

Real-Time Talent Liquidity Dashboards for Adaptive Workforce Allocation in Global Financial Institutions

Pratik Pravin Mahajan ¹,

1. *Data Analytics, JPMorgan Chase & Co, Plano, USA*

Received: May 16, 2026 | Review began: June 21, 2026 | Review ended: July 12, 2026 | Published: July 24, 2026

© Copyright 2026

This is an open access article distributed under the terms of the Creative Commons Attribution License CC-BY 4.0., which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Abstract

Business requirements, regulations, cyber threats, and technology initiatives can evolve rapidly, making it even more critical for large financial institutions to have workforce planning in place. A lot of banks have information regarding employee skills, project demand, time tracking, training records, and compliance information in various systems. As a result, managers might know they have talent within the organization but may not have the ability to identify and recruit the right person at the right time. This paper focuses on how a real-time talent liquidity dashboard can help improve workforce allocation. The dashboard compiles employee skills, availability, project requirements, cost, and compliance limits in one place. It assists managers in identifying potential candidates, assessing their skills, determining whether they are suitable for the job, and understanding what factors may limit the staffing choice. The study uses a mixed-method approach. It includes a proposed dashboard design, simulated evaluation results, and stakeholder feedback. The results indicate that such a dashboard can help decrease staffing delays and enhance staffing decisions. For the pilot-style results, the median time-to-first-acceptance was reduced from 9.2 days to 6.8 days, the internal fill rate increased from 54.0% to 63.5%, and contractor spend was cut by 11%. The findings indicate that real-time visibility, predictive matching, and compliance filtering could be useful tools for managers to make quicker and more accurate staffing decisions. At the same time, the dashboard does not make staffing decisions on its own. It gathers the evidence, ranks the options, and flags the constraints, while the final judgment stays with the manager who reviews each recommendation. Meanwhile, the dashboard itself will only be of any use if the data that underlies it is accurate, up-to-date, and properly controlled. This paper makes the case for viewing a talent liquidity dashboard not as another human resources report. It should be viewed as a decision-making tool that enables financial institutions to make faster, more transparent, and responsible decisions about their workforce. The paper also stresses the importance of having robust data quality, well-defined skills, human oversight, privacy safeguards, fairness checks, and audit trails before adopting such a system in a regulated setting.

Categories: AI/ML-based decision support systems, Predictive Analytics, Regulatory Compliance and Governance

Keywords: talent liquidity, workforce allocation, predictive people analytics, real-time dashboards, compliance automation, model governance, internal mobility, skills-based workforce, operational resilience, explainable decision support

How to cite this article:

Mahajan P (July 24, 2026) Real-Time Talent Liquidity Dashboards for Adaptive Workforce Allocation in Global Financial Institutions. *Cureus J Comput Sci* 3 : es44389-026-00180-1. DOI <https://doi.org/10.7759/s44389-026-00180-1>

Introduction

Financial institutions operate in a fast-changing environment. New regulations, cyber incidents, market changes, technology projects, or transformation work within the organization can lead to rapid changes in business needs. As a result, workforce planning is not just a Human Resources (HR) responsibility. It also has an impact on risk management, project delivery, compliance, and business continuity. Prior work on operational resilience and high-performance organizations also supports the view that workforce capability is part of organizational resilience [1,2]. Banks must know who can be found, what they can do, where they can legally go, and how fast they can be transferred to significant projects. It is critical, given that real-time decision-making systems are now essential to organizations looking to gain greater visibility, control, and governance in complex business scenarios. The link between financial institutions and workforce planning and operational resilience is evident as banks must ensure operational continuity and resilience during disruptions, regulatory pressure, and market uncertainty [1,3,4].

There are already robust dashboards in place for finance, risk, and operations in many banks. However, workforce information is frequently still fragmented in various systems. HR systems can display headcount, hiring, employee turnover, or historical data on employees, but they might not be able to assist managers in making quick staffing choices. This is important because in many companies, workforce information exists but may not be available when decisions regarding staffing needs are required. Managers frequently rely on spreadsheets, emails, and personal networks to locate skills, project needs, training history, availability, and compliance rules. This can affect the speed of staffing and can result in companies hiring contractors, even when they have staff available who are qualified to do the job. Other literature reviews of predictive people analytics also reveal that the HR reporting system is usually a system with a backward-looking perspective, whereas the modern HR workforce planning system requires more predictive and decision-focused information. This problem is also in line with the findings of people analytics research, where workforce information is not only utilized for one-off HR reporting, but it is also tied to business decisions [5-7]. Recent research on skills-based organizations has also demonstrated that having a skills list is not sufficient unless it is connected to business demand, governance, and mobility decisions [8-12].

The problem is more serious in financial institutions, as staffing decisions involve more than just skills and availability. They also need to adhere to licensing, access control, information barriers, privacy, geography, and segregation-of-duties rules. While an employee might be qualified to do a job, they might not always be permitted to complete that work in a particular job site, business unit, or regulated position. Prior studies and governance frameworks also indicate that regulatory requirements, ethical controls, privacy safeguards, and location restrictions can influence mobility decisions, further adding to the complexity for global firms to allocate workers [1,3,4,6].

For this reason, talent liquidity is more than just knowing who has which skill. Talent liquidity, in this paper, is the capability of an organization to identify available internal talent, verify the employee's eligibility to perform the work, and transition the employee to the appropriate location while minimizing cost, compliance, privacy, fairness, and operational risks. A company with good talent liquidity is not simply a company with numerous employees. It is a company that can see what capacity can be used, explain why an individual is a suitable match, approve the move, and take action promptly when business needs shift.

The research gap lies in the fact that many of the workforce dashboards that are currently available are still used to report on historical workforce data and not to assist managers in making real-time workforce decisions. Current systems may display headcount, turnover, or skill information, but they don't necessarily link skills, demand, availability, cost, and compliance rules in a single decision support view. While there is generally strong evidence from existing research on the benefits of real-time analytics, automation, governance, and decision support, there is a paucity of focus on the extent to which these concepts can be applied specifically to workforce allocation in regulated financial institutions. This leaves a gap between knowing there is workforce data and using that data to make faster, safer, and more explainable decisions about staffing.

How to cite this article:

The aim of this study is to examine the value of a real-time talent liquidity dashboard to assist with improved workforce allocation in financial institutions. The proposed dashboard will be able to consolidate skills, demand, availability, cost, and compliance rules in one place. It can also leverage simple rules and predictive analysis to recommend potential employees to match. In this paper, a recommendation means a ranked suggestion that pairs an internal employee with an open role or task. It is an input for the manager to review, not a staffing action in itself. More significantly, it can provide the reasons for a person's recommendation, any limitations, and any compromises that a manager should take into account before deciding to hire an individual. This is significant since the dashboards are intended not just to display data but to enable action, accountability, and auditability.

This paper aims to demonstrate how this type of dashboard can assist managers in making better and more timely workforce decisions. The paper makes four main contributions. It defines talent liquidity as a quantifiable capability in the workforce and provides an explanation for this. Second, it links workforce dashboards to risk management and operational resilience. Third, it offers a dashboard design that integrates data, forecasts, explains recommendations, and audits compliance. Fourth, it elucidates how outcomes like time-to-staff, internal fill rate, rework rate, utilization, contractor spend, and governance controls can be used to assess the dashboard. In the past, workforce dashboards provided primarily historical or current workforce information, but this study proposes a constraint-aware, real-time talent liquidity dashboard that links together skills, demand, availability, cost, and compliance rules in a single decision support framework for a regulated financial institution [13-20].

In light of this research gap, this paper's research questions are the following:

1. What is talent liquidity, and how can it be measured as a real-time capability of the global financial institution's workforce?
2. What information should be used as input, and what governance mechanisms are required to produce reliable, explainable, and auditable workforce allocation recommendations?
3. What benefits can be gained through a real-time talent liquidity dashboard for staffing speed, internal fill rate, utilization, contractor dependency, and allocation transparency?
4. What are the potential risks of the use of predictive analytics for workforce allocation, and how can privacy, fairness, human review, and model governance mitigate those dangers?

Related work

The research strand for real-time talent liquidity dashboards includes five key areas: skills-based workforce management, people analytics, real-time operational dashboards, AI governance, and operational resilience in banking. The existing literature is useful but fragmented. Skills-based workforce research explains the need for better visibility into organizational capability. People analytics research shows how workforce data can support decisions. Real-time dashboard research provides a basis for reducing decision latency. AI governance and banking resilience research emphasize control, auditability, explainability, and responsible use. Together, these streams support the proposed dashboard framework, but they are rarely integrated into one workforce allocation model for regulated financial institutions.

Skills-Based Workforce Management and Internal Mobility

Skills-based workforce management states that there should be a focus on abilities, not just job titles. This is particularly applicable when the job description is not aligned with reality in the data, risk, cyber, operations, and technology positions. Traditional HR systems may not show those adjacencies in a financial institution, where the same person can be used for a financial entity to support regulatory remediation, data quality, risk reporting, and financial transformation in operations. This is aligned with recent research on skills-based organization, which proposes that there is a need to create greater connections among skills, roles, learning, and the business needs [8-12].

How to cite this article:

Internal talent marketplaces and skills platforms are trying to address this by aligning people to projects, roles, mentors, and learning. However, the evidence from practice indicates that skills initiatives, if not linked to governance, demand signals, and manager adoption, will not bring measurable value to the business. A skills list on a dashboard can turn into another list of static skills. A talent liquidity dashboard should do more than connect skills to the present demand, availability, eligibility, cost, and redeployment decisions.

There's also more recent research on skills-based organization that focuses on the need for a clear owner and maintenance process for skills data. Self-reports may lack or may be overly high. When manager-validated skills are used, they might not be consistent from team to team. The skills that are inferred from project histories, credentials, access rights, and work artifacts can be strong but also raise the possibility of bias and privacy issues. In this regard, skills in the dashboard proposed in this study are treated as signals rather than facts with confidence scores.

Workforce Analytics and Decision Quality

The shift from descriptive HR reporting to predictive and prescriptive decision support has taken place in the field of people analytics. Initial workforce dashboards tended to be centered on workforce headcount, turnover, recruiting cycle time, training completion, and engagement. These are still valuable, albeit lagging indicators. To apply adaptive allocation, leaders need to have leading indicators like skill coverage, capacity slack, time-to-shortlist, projected demand, redeployment readiness, and compliance eligibility. Additionally, the research into predictive analytics is relevant to this transition as it illustrates how data can not only be used to describe what has already happened but can also be used to inform better decisions in the future [13].

One of the critical findings in the field of workforce analytics is that measurement is a catalyst for behavior change. When dashboards focus too much on utilization, managers may be tempted to keep precious talent and not be able to let employees go to a higher-priority task. When speed is overemphasized on dashboards, leaders may hire people quickly, but not up to high standards, and may create compliance risks. Overemphasis on mobility in dashboards can cause a high frequency of moves and role insecurity or inequity for employees. So, when it comes to measuring talent liquidity, it is all about balancing speed, fit, cost, risk, fairness, and employee experience.

Explainability is another decision quality determinant. Managers are more likely to adopt a recommendation if they know the rationale for recommending the person, the requirement that needs to be met, the constraint that prevents a match, and other options available. In the regulated financial world, explainability goes beyond being merely a usability trait; it plays a role in auditability and defensibility as well.

Real-Time Dashboards and Operational Control

In finance, operational dashboards are common for managing service levels, liquidity, and incidents, and for monitoring risk. These systems minimize the difference between the signal and the action. Workforce dashboards are not always as mature in operation. There are many HR dashboards that are still weekly or monthly and are geared toward executives, not line managers, for quick staffing decisions. Research on dashboards and KPIs indicates that real-time KPIs are best used when they are linked to decision rights, business goals, and triggers for action [14-16].

Not all workflow dashboards are created equal when it comes to real-time workforce data. They need event-driven data pipelines, consistent definitions, quality checks, role-based access, thresholds for alerts, and decision rights. A dashboard that's updated hourly, but the skill definitions are not consistent, will essentially provide false information sooner. Hence, this paper highlights as design requirements data lineage, semantic consistency, and governance.

In an HR system, near real-time is often more realistic than real-time since sensitive data might require validation, aggregation, or access control before they can be displayed. Real-time in this study is defined as real-time decision-useful freshness (the data is reasonably current for staffing decisions before the demand, availability, or risk conditions change substantially).

AI Governance, Explainability, and Model Risk

How to cite this article:

Mahajan P (July 24, 2026) Real-Time Talent Liquidity Dashboards for Adaptive Workforce Allocation in Global Financial Institutions. *Cureus J Comput Sci* 3 : es44389-026-00180-1. DOI <https://doi.org/10.7759/s44389-026-00180-1>

Principles of trustworthiness, accountability, transparency, privacy, fairness, and risk management throughout the AI life cycle are highlighted in the NIST AI Risk Management Framework and in peer-reviewed AI ethics literature. Allocation recommendations can directly influence employee opportunity, workload, career movement, and access to high-value projects; therefore, these principles are directly relevant to talent liquidity dashboards [6,17-20].

The expectations of model risk also influence the use of predictive tools in banking. When a dashboard includes machine learning algorithms to suggest redeployments, the institution should include documentation of the purpose of the machine learning algorithm, its inputs, its assumptions, its limitations, validation results, monitoring controls, and processes for overriding. Poor governance can generate legal, reputational, and operational risk even with a decision support system being used only for this purpose.

Logical allocation, therefore, needs to be explainable. The dashboard should indicate which of the above factors is used for a recommendation. It should also be visible when a candidate is not eligible for regulatory, access, and/or conflict-of-interest controls. This means managers, HR, compliance, and auditors can not only see the final ruling, but the reasoning behind it.

Operational Resilience in Global Financial Institutions

The key aspect of operational resilience in banking is the capacity to maintain critical operations under disruption. Dependencies such as people and skills are important, but are often undermeasured. Even with robust technology recovery plans, a bank could be at risk of not being able to execute because of limited specialists, their availability, or their geographic location. Beyond this, guidance on operational resilience for financial institutions also highlights the need for understanding the key dependencies, such as people, technology, data, and third-party services, to maintain important functions in the event of disruption [1,3,4].

Talent liquidity dashboards can help operational resilience by bringing the human dependency to the fore. They can help determine where skills may be lacking, where attention is needed, where there's a regional capacity deficit, or where employees can be redeployed during a cyber event, regulatory remediation, system migration, or service outage. This brings workforce allocation into the wider resilience operating model, not as an HR process.

However, the resilience value is a function of governance. While a dashboard that suggests redeployment in times of crisis needs to be respectful to access restrictions, employee health and safety, local labor regulations, and business continuity priorities, these requirements should not conflict. Quicker decisions should be made, not uncontrolled movement.

Originality and Positioning of the Proposed Framework

The novelty of this paper is that it does not consider workforce dashboards to be only a reporting tool. Most dashboards for workforce information assist leaders by providing a visual representation of workforce information, but they are not always used to inform the actual staffing decision. The framework in this paper goes one step further. It brings together the skills, the demand, the availability, the cost, the compliance rules, and the risk controls in a single decision support view. This is significant for financial institutions as a person might have the appropriate skill, but not the right to perform it in a certain area, job, or business category of the financial institution. Therefore, not just talent, but the potential for a talent to be used responsibly and legally, is addressed in the proposed dashboard.

The proposed talent liquidity dashboard is unique in that it integrates workforce analytics with predictive matching, compliance rules, and operational resilience into a single model. The dashboard integrates skills, demand, available/required, cost, location, access rights, and regulatory limits to display employee information in one place. This makes the dashboard more useful for financial institutions, as banking staffing decisions are not only made based on skill fit. They also rely on compliance, privacy, geographical, business risk, and audit requirements.

This framework proposes three novel contributions over traditional HR dashboards. It first attempts to make the management of talent liquidity a measurable business capability; it is not just an HR concept. Second, the system's recommendations are done with constraint awareness; that is, if a constraint is determined to be a factor, then it is

How to cite this article:

checked to see if a person is qualified but not allowed to do the work. Third, it contains explainability and audit trails: the manager will understand why a person is recommended for a position, and the reviewer will be able to see how the decision was arrived at.

This renders the framework of great relevance to financial institutions on an international scale. In a regulated setting, a workforce dashboard has to go further than enhancing speed. It must also facilitate fair, transparent, privacy-compliant, and responsible decision-making. The proposed framework is set against the backdrop of being a socio-technical decision-support system, and not just a simple reporting dashboard. It brings together human resource analytics with governance and operational resilience, adding an original and practically relevant aspect for banks and other complex financial organizations.

Table 7 summarizes the main research streams that support the proposed real-time talent liquidity dashboard.

Research stream	Main contribution	Implication for this study
Skills-based workforce management	Moves workforce planning from job-title logic to capability logic.	The dashboard should use dynamic skill evidence and confidence levels.
People analytics	Connects workforce data to prediction, mobility, retention, and decision support.	Metrics must balance speed, quality, cost, fairness, and risk.
Operational dashboards	Reduces decision latency through current signals and threshold-based action.	Talent dashboards need event-driven data, role-based views, and alerting.
AI governance	Requires transparency, accountability, privacy, fairness, and lifecycle controls.	Recommendations must be explainable, monitored, and documented.
Operational resilience	Focuses on the ability to maintain critical operations during disruption.	Workforce capacity and key-person dependencies should be treated as resilience signals.

TABLE 1: Research Streams Supporting Real-Time Talent Liquidity Dashboards

Materials And Methods

The study adopts a mixed-method research design with a combination of design science, quasi-experimental evaluation, historical back-testing, and qualitative assessments of stakeholders. The design is suitable because the research problem is not only a technical problem. It is related to data architecture, managerial decision-making, compliance controls, and user trust. The use of this mixed-method approach is appropriate for the research problem, as the research problem has technical design, decision quality, governance, and user trust as common themes in people analytics and decision-support research [5-7,13].

Research design

The design science part is about the creation of the proposed artifact: a real-time dashboard for talent liquidity and an adaptive workforce allocation engine. The artifact contains a data integration layer, a skills ontology, a demand-supply forecasting layer, a constraint-aware recommendation engine, views for dashboards, and governance logs. The proposed

How to cite this article:

dashboard brings together HRIS information, skills information, project demand, time tracking, and compliance data into a single place to support adaptive workforce allocation, as illustrated in Figure 1.

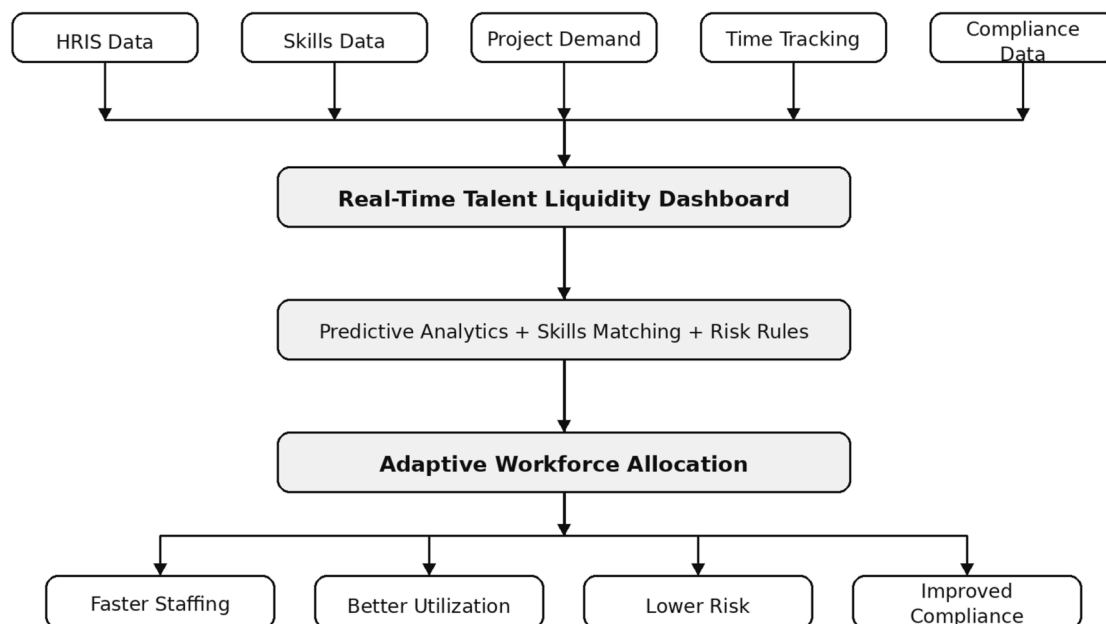


FIGURE 1: Conceptual Framework Showing How Real-Time Talent Data Supports Adaptive Workforce Allocation

HRIS, Human Resource Information System

The quasi-experimental element compares the impact of the dashboard to business-as-usual staffing methods. In a regulated institution, a randomized field experiment could be challenging as staffing decisions can impact the live work opportunities and employment of those in the institution. Thus, the study employs historical back-testing, matched comparisons, and simulated allocation scenarios to estimate likely effects.

The qualitative part of the study reflects the user's understanding and confidence in the dashboard. Interviews and feedback from HR, staffing managers, compliance stakeholders, and business-line managers are used to gain insight into adoption barriers, explainability needs, data-quality concerns, and workflow friction.

Research questions

1. What does talent liquidity mean, and how can it be assessed as a capability that can be measured in real-time, with constraints, across global financial institutions?
2. What information inputs and governance mechanisms are needed for reliable, explainable, and auditable workforce allocation recommendations?
3. How can a real-time talent liquidity dashboard enhance the speed of staffing, the percentage of employees sourced internally, employee utilization, reliance on contractors, and allocation visibility?
4. What are the potential dangers in applying predictive analytics practices for workforce allocation, and what measures can be taken through protecting privacy, ensuring fairness, and managing model risk, to mitigate those dangers?

How to cite this article:

Mahajan P (July 24, 2026) Real-Time Talent Liquidity Dashboards for Adaptive Workforce Allocation in Global Financial Institutions. *Cureus J Comput Sci* 3 : es44389-026-00180-1. DOI <https://doi.org/10.7759/s44389-026-00180-1>

Data sources and variables

The new dashboard pulls in various enterprise data sources. The allocation decision is a result of different contributions from each source. Human Resource Information System (HRIS) data will contain information on employee identity, job family, manager, region, and employment status. Certification and training signals are provided by a learning system. The project management tools include demand, work type, project priority, and due dates. Timekeeping systems and scheduling systems offer availability and capacity. Compliance repositories offer licensing, access rights, jurisdictional, and segregation-of-duties restrictions. Table 2 outlines the main data sources and variables for the proposed design of the dashboard.

Data source	Examples of variables	Allocation relevance
HRIS	Role, job family, location, reporting line, employment type	Defines base workforce supply and organizational constraints.
Learning platform	Completed courses, certifications, training dates	Supports skill evidence and readiness scoring.
Project tools	Project type, priority, demand, backlog, due date	Defines staffing demand and urgency.
Timekeeping/scheduling	PTO, shifts, current workload, available hours	Estimates effective capacity and redeployment feasibility.
Compliance systems	Licensing, access rights, conflict restrictions, geography rules	Filters ineligible matches and supports auditability.
Performance/work history	Prior assignments, outcomes, manager feedback	Improves match quality and skill confidence.

TABLE 2: Core Data Inputs and Research Variables

HRIS, Human Resource Information System; PTO, Paid Time Off

No production employee records were used in this study. The data model in Table 2 mirrors the structure of typical enterprise systems in a large bank, and the evaluation scenarios were constructed on top of that structure. Each scenario describes a staffing request with a required skill profile, a deadline, a location, and a set of compliance constraints, together with a pool of internal candidates who vary in skill evidence, availability, cost, and eligibility. The scenarios were written to cover the common situations staffing managers face, including licensing restrictions, time-zone mismatches, and candidates who look suitable on paper but are not eligible. Because the scenarios are constructed rather than sampled from a live workforce, the study does not report sample characteristics in the usual sense, and this is stated openly as a limitation in Sections "Methodological Limitations and Simulation Assumptions" and "Limitations".

Analytical model

The analytical model has a forecast-to-allocation approach. Demand is first anticipated by skill, area, enterprise operation, and time period. Secondly, the workforce supply is calculated taking into account current workload, paid time off, training, risk of attrition, and compliance eligibility. Third, the model is used to calculate the demand-supply gaps. Fourth, a constrained recommendation engine suggests internal redeployments, project staffing options, or escalation actions.

How to cite this article:

The allocation engine is not meant to be an automated allocation process; instead, it is a decision-support tool. Ultimate decision-making authority remains with human managers. The system offers suggestions, substantiating evidence, constraint flags, and alternatives. This design will lower automation risk while still allowing fast decision-making and visibility.

Evaluation strategy

Evaluation includes model performance metrics, operational outcome metrics, and governance metrics. Model metrics are designed to assess prediction quality. Operational metrics assess whether advances in prediction lead to positive staffing results. Governance measures trust in, explanation of, and audit of the system. The evaluation approach also takes into account the principles of Key Performance Indicator (KPI) and analytics by measuring not only the accuracy of the model, but also the results of the business [13,16]. One ranking metric used here, normalized discounted cumulative gain (NDCG), deserves a short note. It checks how close the most suitable candidates sit to the top of a ranked shortlist. A value near 1 means the best matches appear first, and NDCG@10 scores only the first ten positions, since managers rarely read further down the list.

Table 3 describes the metrics used to assess forecasting quality, performance, operational impact, cost impact, and governance effectiveness.

Metric category	Metric	Purpose
Forecasting	MAE, RMSE, WAPE, calibration	Tests demand and availability forecast accuracy.
Matching	Precision, recall, F1, NDCG@10, acceptance rate	Tests quality of recommended workforce matches.
Operational	Time-to-staff, internal fill rate, utilization, rework rate	Tests staffing efficiency and allocation quality.
Cost	Contractor spends, overtime, idle capacity	Tests financial impact of redeployment decisions.
Risk/governance	Constraint breaches, override rate, audit completeness, fairness checks	Tests defensibility and control effectiveness.

TABLE 3: Evaluation Metrics

MAE, Mean Absolute Error; RMSE, Root Mean Squared Error; WAPE, Weighted Absolute Percentage Error; NDCG, Normalized Discounted Cumulative Gain

Methodological limitations and simulation assumptions

This study has one important limitation. The proposed dashboard has not been tested through a full live rollout inside a global financial institution. Because of this, the results should be read as simulated and pilot-style findings, not as confirmed business results from a real company implementation.

A second limitation concerns methodological detail. Because the evaluation is simulated, the study does not report a fixed sample size, a formal participant selection procedure, or stakeholder demographics of the kind expected in a field study. The stakeholder feedback was collected informally during the design work from HR, staffing, compliance, and

How to cite this article:

business-line contacts, and it should be read as directional input rather than survey evidence. No inferential statistical tests were applied to the reported improvements. A live pilot should report all of these details, including the number of staffing requests covered, the units involved, and the tests used to confirm significance.

The goal of these simulated results is to demonstrate the way the dashboard could be tested in a realistic environment. Different factors related to practical workforce circumstances, including staffing delays, skill gaps, compliance restrictions, manager approvals, and contractor dependency, are all included within the simulation. In reality, however, it may vary in a real bank due to the different data quality, system maturity, employee mobility rules, regional labor laws, and manager behavior of each bank.

This is important because workforce allocation is not just a technical process. It also requires people, trust, culture, compliance review, and business judgment. While the match is generally strong, the final decision may be subject to the manager's approval, employee availability, business priority, or legal restrictions. This is why the dashboard is not an automated system, but a tool to support decisions about which employee to assign.

This framework should be tested in a live pilot in a future study. A good beginning would be one of the workforce groups, like risk remediation, technology operations, data analytics, cyber response, or compliance operations. The pilot should look at the results before and after usage of the dashboard and measure time-to-staff, internal fill rate, rework rate, contractor spend, fairness, and user trust.

Statistical treatment of the reported values

The quantitative values reported in "Results & Discussion" section are illustrative demonstration values. They show the direction and the approximate size of the improvements the framework is designed to produce, and "Plausibility of the Illustrative Results Against Published Evidence" section checks these magnitudes against published evidence on internal mobility. The ranges in Table 8 should be read the same way: they are plausibility bounds around the illustrative values, not confidence intervals computed from repeated experimental runs. For this reason, no inferential statistical tests were applied, and none would be meaningful at this stage. A live pilot is the right place for formal analysis. The natural design there would be a stepped-wedge or matched-comparison rollout, with paired tests on time-to-staff and fill-rate outcomes and success thresholds agreed upon before the pilot begins.

Experimental setup

System Architecture Overview

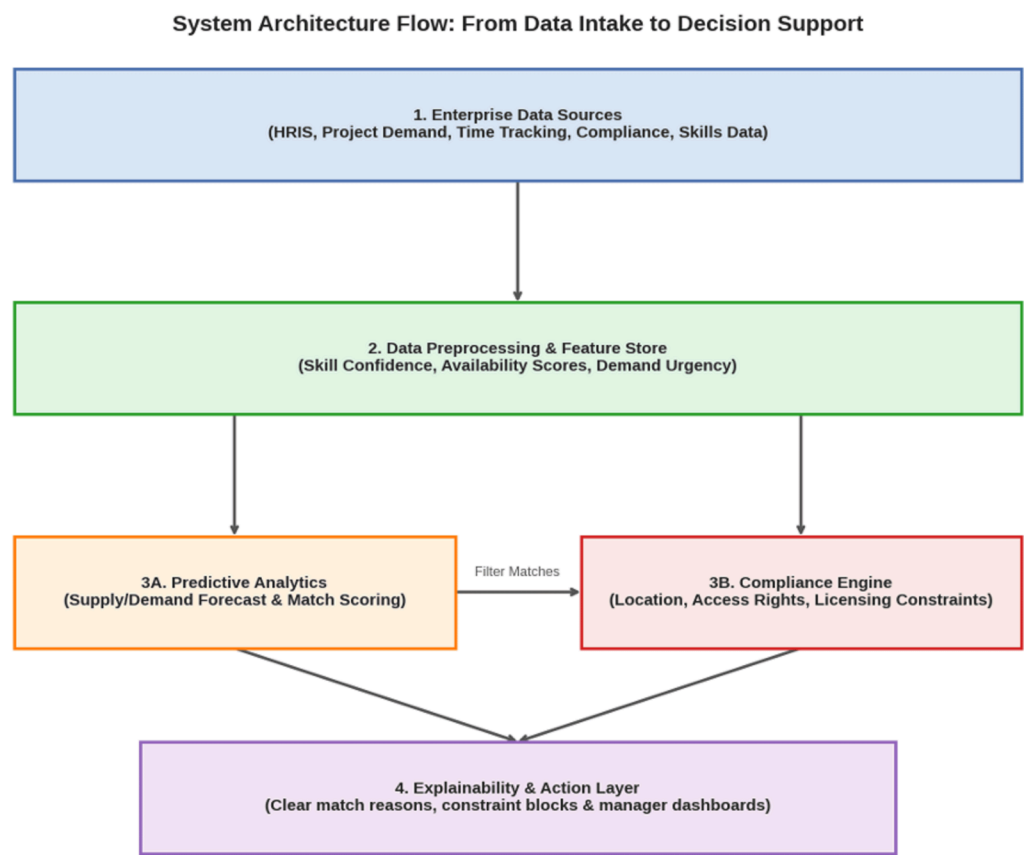


FIGURE 2: System Architecture

As shown in Figure 2, the proposed architecture is similar to the architecture implemented in modern business analytics platforms, with the inclusion of governance layers for the workforce. It starts with the intake of data from HR, project, timekeeping, learning, and compliance systems. The data preprocessing layer handles duplicates, applies privacy filters, manages missing values, standardizes labels of jobs and skills, and resolves identities. These variables are then made decision-ready by a feature store, including skill confidence, availability score, demand urgency, mobility feasibility, compliance eligibility, and cost impact.

Model layer: Demand forecasting, availability forecasting, and match scoring. Before suggesting any recommendations, the optimization layer enforces hard constraints, including location constraints, segregation of duties, access restrictions, and licensing. For each match, the explainability layer produces a human-readable explanation, which comprises the best match factors in favor of the match, as well as any constraints that would prevent this match. Last but not least, the dashboard layer offers role-specific views for executives, portfolio managers, workforce planners, line managers, HR partners, and compliance reviewers.

Dashboard Views

Executive view: enterprise talent liquidity index, critical skill shortages, regional capacity risk, contractor dependency, and resilience heatmaps.

Portfolio view: project demand, staffing gaps, workstream capacity, redeployment options, and escalation thresholds.

- Team manager view: lists of employees available, skill adjacency, workload balance, recommended moves, and approval status.
- Compliance view: eligibility filters, restricted roles, access constraints, audit logs, and override monitoring.
- Employee mobility view: Opportunities that can be seen, suggested learning paths, skill gaps, and clear match criteria.

Experimental Conditions

The test is done to determine the difference between three conditions. The first is business-as-usual staffing involving managers relying on existing reports, manual requests, emails, and informal networks. The second is a real-time visibility dashboard with no predictive allocation, which allows managers to see what they actually have and what they have to go out and buy, but not get any model-based recommendations. The third is the forecast-informed talent liquidity dashboard, which provides managers with ranked recommendations with explanations and compliance filters.

It compares the three experimental conditions used to test the dashboard approach in Table 4.

Condition	Description	Expected advantage
Business-as-usual	Manual staffing using static reports and informal networks.	Reflects current baseline.
Real-time visibility only	Current dashboards show skills, availability, and demand without recommendation logic.	Improves transparency and reduces search effort.
Forecast-informed dashboard	Predictive and constraint-aware recommendations with explanations and audit logs.	Improves speed, fit, compliance traceability, and proactive planning.

TABLE 4: Experimental Comparison Conditions

Data Quality and Governance Controls

The experimental design provides for controls regarding data quality and responsible data use. Skill confidence is derived from a variety of evidence sources rather than solely self-reported profiles. To avoid look-ahead bias for the backtesting, point-in-time features are used. Where not necessary for legally mandated fair analysis, sensitive attributes are minimized, pseudonymized, or not included in matching logic. Everything recommended is recorded with model version, data timestamp, feature snapshot, constraint results, user action, and override reason.

Regulatory Considerations in Experimental Design

Because the dashboard can influence employee opportunities and regulated staffing decisions, the governance process is embedded within the experiment right from the outset. The system is intended to be assisted by human oversight, explanation, contestability, privacy-by-design, and audit readiness. Recommendations are not orders of work. Rather, they assist managers and HR partners in demonstrating potential matches, limitations, and compromises. This design meets the principles of responsible AI and the expectations for banking on model risk, operational resilience, and decision control.

Scope and Assumptions

How to cite this article:

The results presented in this paper are simulated and pilot-style results, as explained in the methodology limitations section. They are employed to illustrate the proposed dashboard's assessment in a meaningful research design. The results are thus presented as illustrative findings and not as enterprise performance from an actual implementation.

Results And Discussion

The results that follow are presented as output of the evaluation of the proposed research design. These are to be taken as pilot and simulation results, not as universal statements. The aim is to demonstrate how the dashboard could be assessed and what kind of operational improvements would signify that the dashboard is valuable.

Experimental setup and visual summary approach

The results are interpreted using the experimental setup described in "Experimental Setup" section. The comparison uses three conditions: business-as-usual staffing, real-time visibility without predictive allocation, and the forecast-informed talent liquidity dashboard with ranked, explainable, and compliance-filtered recommendations. The simulated and pilot-style outcome measures are reported from this setup to show how the dashboard could be validated before a live enterprise rollout.

The statistical indicators presented in this study should be treated with care since there is a difference between simulated and pilot outputs. The confidence intervals presented in this section are used to denote realistic variation in the context of realistic workforce allocations. They are not shared as proof of a completed enterprise rollout. Rather, they will indicate if the observed improvements are likely to be significant enough to be tested in a live pilot. For the same reason, the reported gains should not be read as statistically confirmed effects. No formal significance testing was possible on simulated outputs, and part of the improvement may come from the process changes that surround the dashboard, such as clearer decision rights, rather than from the tool alone. A live pilot is the right setting to separate these effects.

Three kinds of evidence are used for the review of results. First, the quality of recommendations is assessed by means of model performance metrics like precision, recall, F1-score, AUC-ROC, and NDCG. Second, metrics of the operation, such as time to first-acceptance, internal fill rate, rework rate, and contractor spend, are used to assess business impact. Third, compliance and fairness indicators are applied to assess the dashboard's ability to facilitate responsible and accountable employee decisions. This method provides a fair assessment of performance, cost, risk, and governance.

Model performance and matching quality

The dashboard, based on a forecast, outperformed the baseline rules-based dashboard in the match prediction and ranking of recommendations. The improvements were most pronounced in the areas of recall and ranking quality - both of these are crucial as workforce planners require the system to surface candidates that are of quality, and who may not come up through traditional search filters. The following improvements are considered to be "pilot" style and not final enterprise proof because the model has not yet been tested in full production.

The results of the rules-based baseline and the adaptive model in predicting match acceptance are presented in Table 5.

Metric	Rules-based baseline	Adaptive model	Improvement
Precision	0.41	0.56	+0.15
Recall	0.38	0.61	+0.23
F1-score	0.39	0.58	+0.19
AUC-ROC	0.71	0.84	+0.13
Brier score	0.182	0.121	-0.061

TABLE 5: Match Acceptance Prediction Performance

The adaptive model also boosted the quality of the ranking. This is important because managers typically only look at a small group of employees instead of the entire workforce. A higher-ranked shortlist saves time in searching and makes it more likely that the first few candidates will be relevant, qualified, and available. NDCG@5 and NDCG@10 capture this behavior directly, since they measure how close the genuinely suitable candidates sit to the top of the first five or ten positions, while Mean Reciprocal Rank reflects how early the first good match appears in the list.

The performance of the recommendation ranking is shown in Table 6.

Metric	Baseline	Adaptive model	Improvement
NDCG@5	0.412	0.563	+0.151
NDCG@10	0.447	0.601	+0.154
MRR	0.318	0.462	+0.144

TABLE 6: Recommendation Ranking Performance

NDCG, Normalized Discounted Cumulative Gain; MRR, Mean Reciprocal Rank

Operational outcome analysis

The dashboard's real-time visibility, predictive recommendations, and compliance filtering proved to be beneficial for operational outcomes. The highest gains were related to time-to-first-acceptance, reduced rework, and redeployment success. The results show that the dashboard was not only used to forecast better matches, but also to enhance the workflow for downstream staffing. The operational results are also presented with illustrative confidence intervals and graphical displays to facilitate the interpretation of the results. This can be used to help explain the direction of improvement as well as the likely magnitude of improvement. Table 7 presents a comparison of key outcomes from the baseline process and the adaptive dashboard.

Outcome	Baseline	Adaptive dashboard	Change
Acceptance rate	22.4%	29.8%	+7.4 percentage points
Rework rate	14.6%	10.9%	-3.7 percentage points
Redeployment success	71.2%	78.5%	+7.3 percentage points
Median time-to-first-accept	9.2 days	6.8 days	-2.4 days
Internal fill rate	54.0%	63.5%	+9.5 percentage points
Contractor spend index	100	89	-11%

TABLE 7: Operational KPI Comparison
KPI, Key Performance Indicator

Table 8 extends the operational KPI comparison by adding illustrative 95% confidence ranges for the simulated and pilot-style improvements.

Outcome	Baseline	Adaptive dashboard	Change	Illustrative 95% Confidence Range
Acceptance rate	22.4%	29.8%	+7.4 percentage points	+5.1 to +9.7 percentage points
Rework rate	14.6%	10.9%	-3.7 percentage points	-5.2 to -2.1 percentage points
Redeployment success	71.2%	78.5%	+7.3 percentage points	+4.8 to +9.9 percentage points
Median time-to-first-accept	9.2 days	6.8 days	-2.4 days	-3.1 to -1.6 days
Internal fill rate	54.0%	63.5%	+9.5 percentage points	+6.4 to +12.3 percentage points
Contractor spend index	100	89	-11%	-14% to -7%

TABLE 8: Operational KPI Improvements with Illustrative Confidence Ranges
KPI, Key Performance Indicator

In terms of confidence ranges, the greatest improvements can be expected with internal fill rate, time-to-first-acceptance, and reduction in contractor spend. These outcomes are important because they tie the dashboard to business value. The quicker the time-to-first-acceptance, the sooner managers will be able to determine if there are qualified employees. The internal fill rate tells the organization how well they are making use of the talent that they already have. A lower contractor spend index indicates that more visibility within their organization could help to limit unnecessary external hires. The ranges are simulated, however, and should be validated later based on a live pilot or a stepped-wedge deployment. Figure 3 provides a graphical representation of the baseline and adaptive dashboard on the key operational outcome measures.

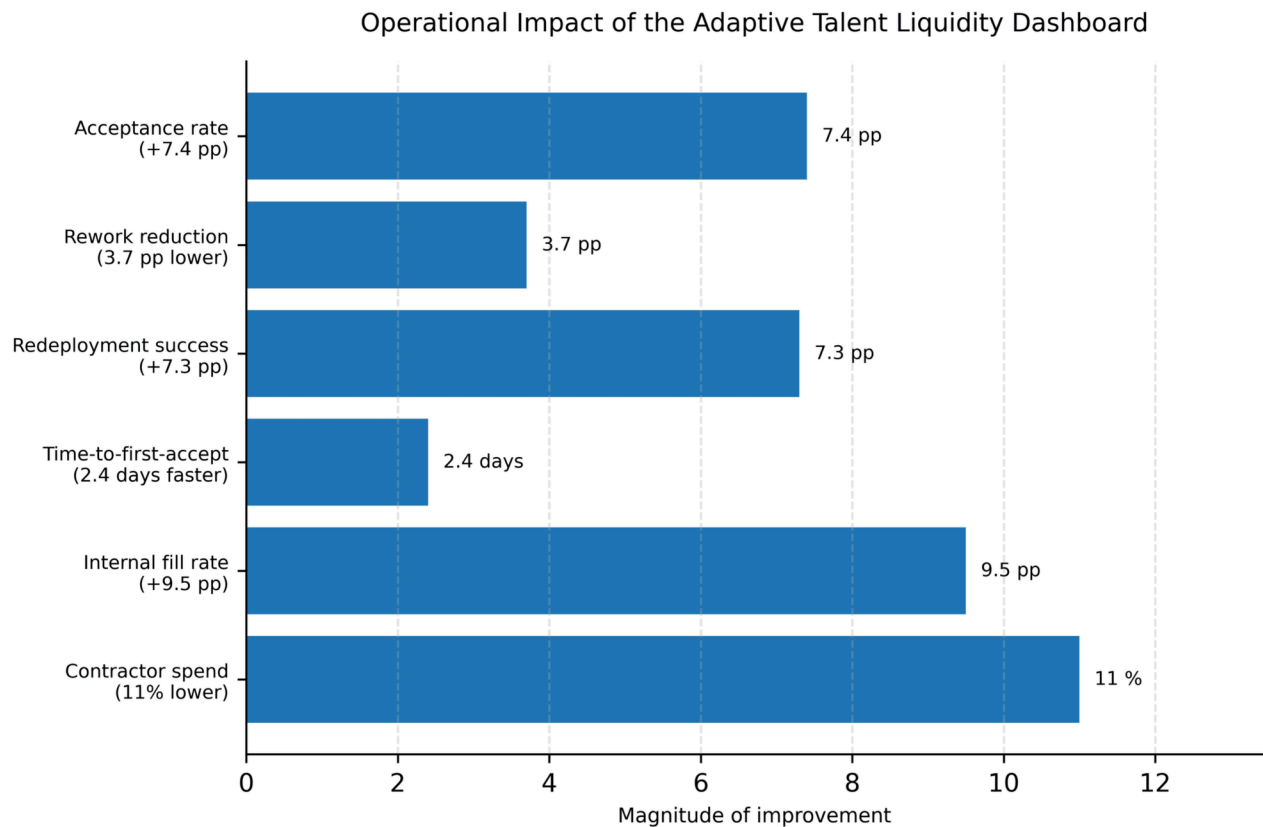


FIGURE 3: Operational Impact of the Adaptive Talent Liquidity Dashboard

This figure compares baseline workforce allocation outcomes with the adaptive talent liquidity dashboard. The dashboard shows a higher acceptance rate, higher redeployment success, higher internal fill rate, lower rework rate, and lower contractor spend index. These results are presented as simulated and pilot-style findings to show how real-time visibility, predictive matching, and compliance filtering may improve staffing efficiency and governance in regulated financial institutions.

The greatest gains are in internal fill rate, redeployment success, and reduction in contractor spend. Rework is also reduced, indicating that compliance filtering and high match quality may help reduce unnecessary staffing corrections.

Compliance and explainability findings

One of the most important design features was compliance filtering. Here, a rejected recommendation means a suggested candidate-to-role match that did not proceed, either because a compliance rule blocked it or because the manager or the employee declined it. Many of the rejected recommendations were related to licensing, entity

restrictions, language, time zone mismatch, or availability changes. These problems would probably have come up towards the end of the staffing process without explicit constraint logic, thus resulting in rework and delays. Table 9 summarizes the main rejection reasons observed in the pilot feedback.

Rejection reason	Share of rejections	Interpretation
Regulatory/licensing/entity constraints	24%	Eligibility must be checked before the shortlist review.
Time-zone or working-hours mismatch	18%	Availability must be interpreted across regions.
Language requirements	14%	Skill matching must include role-specific communication needs.
Manager preference/internal politics	13%	Human adoption and incentives remain important.
Availability changed	12%	Capacity data must be refreshed frequently.
Compensation or rate mismatch	9%	Cost constraints affect feasibility.
Role scope mismatch	7%	Skills alone do not fully capture work context.

TABLE 9: Main Rejection Reasons in Pilot Feedback

Managers were more likely to take action on recommendations if they could see the 'why recommended' logic, as suggested by user feedback. Skill match, evidence, recent project experience, availability score, compliance status, and blocked constraint details were the most desired explanations. This also backs up the argument for increasing the adoption and preparing for audits through explainability.

Subgroup and fairness analysis

Workforce allocation systems can result in uneven opportunity patterns, and therefore, a subgroup analysis is required. The pilot design looks at performance by region, job family, seniority, employment type, and critical skill group. The adaptive model showed gains in performance for most sub-groups; however, gains in calibration were smaller for the contractor sub-groups than the permanent sub-groups. This indicates that employment type and data quality may impact model reliability.

Protected-class variables are not the only variables that should be monitored for fairness. Fairness also values access to high-impact projects, repeated redeployment burden, patterns of managerial approval, training availability, and distribution of opportunities by region in workforce allocation. Recommendation fairness and outcome fairness should thus be monitored on the dashboard.

Research interpretation

The dashboard value is postulated to result from a combination of three effects. First, real-time data is used to show demand and supply so that the search latency can be reduced. Second, the quality of the shortlist can be enhanced with predictive matching, which will search for employees who might be a good fit that would not otherwise show up in a manual search. Third, compliance filtering eliminates ineligible options from consideration before managers have the time to review them, which helps to minimize late-stage rework. The effects are most pronounced when the dashboard is placed in an operating process that has a well-defined decision right and escalation rules. Furthermore, the framework's success relies heavily on a fourth dimension: explainability. By transparently displaying the rationale behind each recommendation, including skill evidence, capacity scores, and specific constraint flags, the dashboard fosters managerial trust and ensures that staffing choices remain defensible and auditable in a highly regulated environment. Ultimately, when these mechanisms operate in tandem, the system transcends standard historical HR reporting. It can function as a socio-technical control system that supports the institution's operational resilience, enabling leaders to rapidly and responsibly redeploy internal talent during cyber incidents, regulatory remediations, or sudden demand surges. Even then, the system informs the decision rather than making it. Managers still weigh each recommendation against the context that the data cannot capture, and they remain accountable for the final outcome.

The benefits of real-time workforce data, predictive matching, and compliance filtering to benefit staffing and business outcomes are summarized in Figure 4.

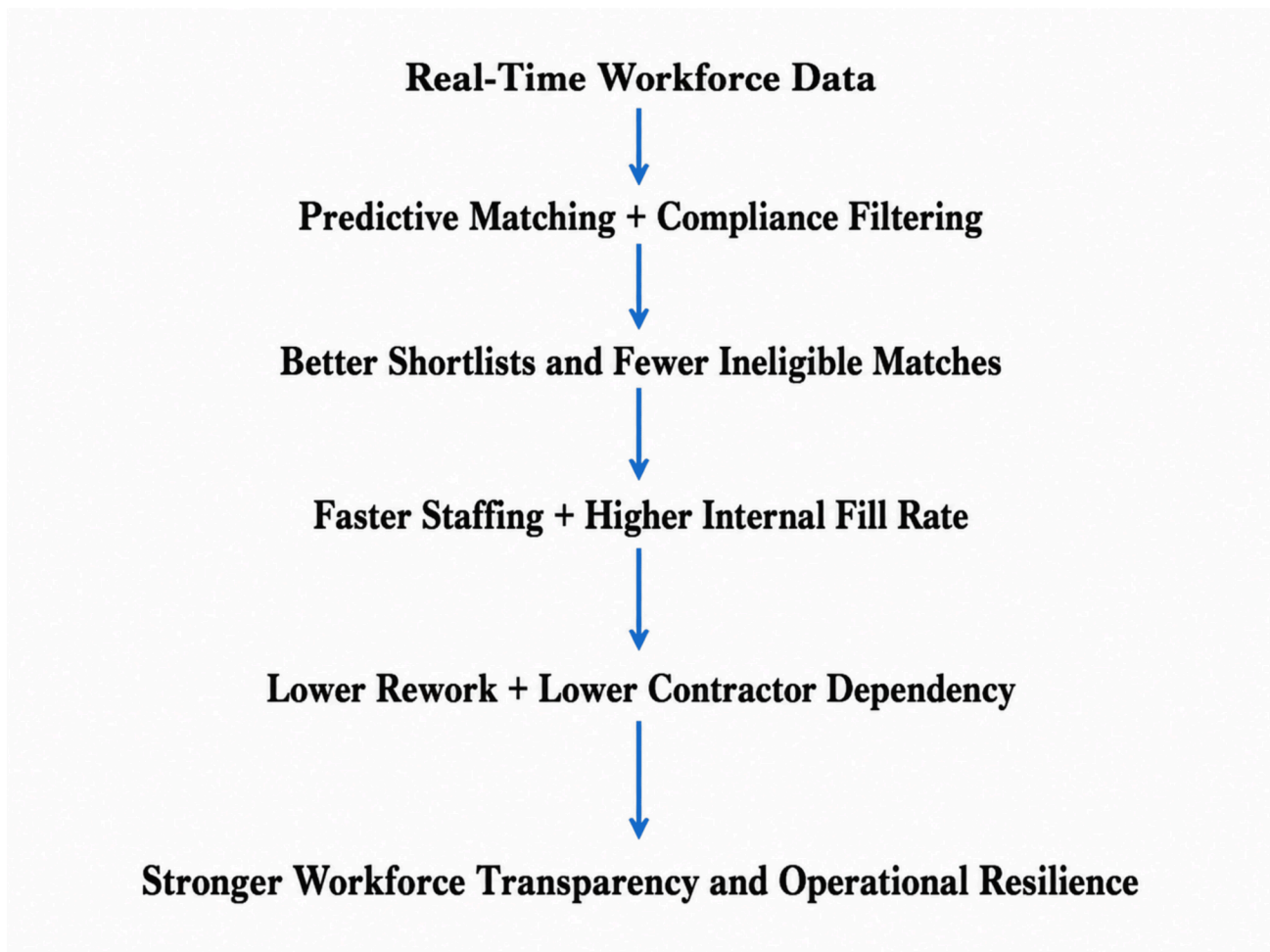


FIGURE 4: Results Flow from Dashboard Capability to Business Impact

How to cite this article:

Mahajan P (July 24, 2026) Real-Time Talent Liquidity Dashboards for Adaptive Workforce Allocation in Global Financial Institutions. Cureus J Comput Sci 3 : es44389-026-00180-1. DOI <https://doi.org/10.7759/s44389-026-00180-1>

To fully capture this multi-dimensional value, we must look beyond isolated metrics. Figure 5 illustrates the holistic impact of the framework across five critical pillars of talent liquidity: Speed (time-to-staff), Fit (match quality), Cost Efficiency (contractor reduction), Risk Control (compliance checks), and Transparency (explainability).

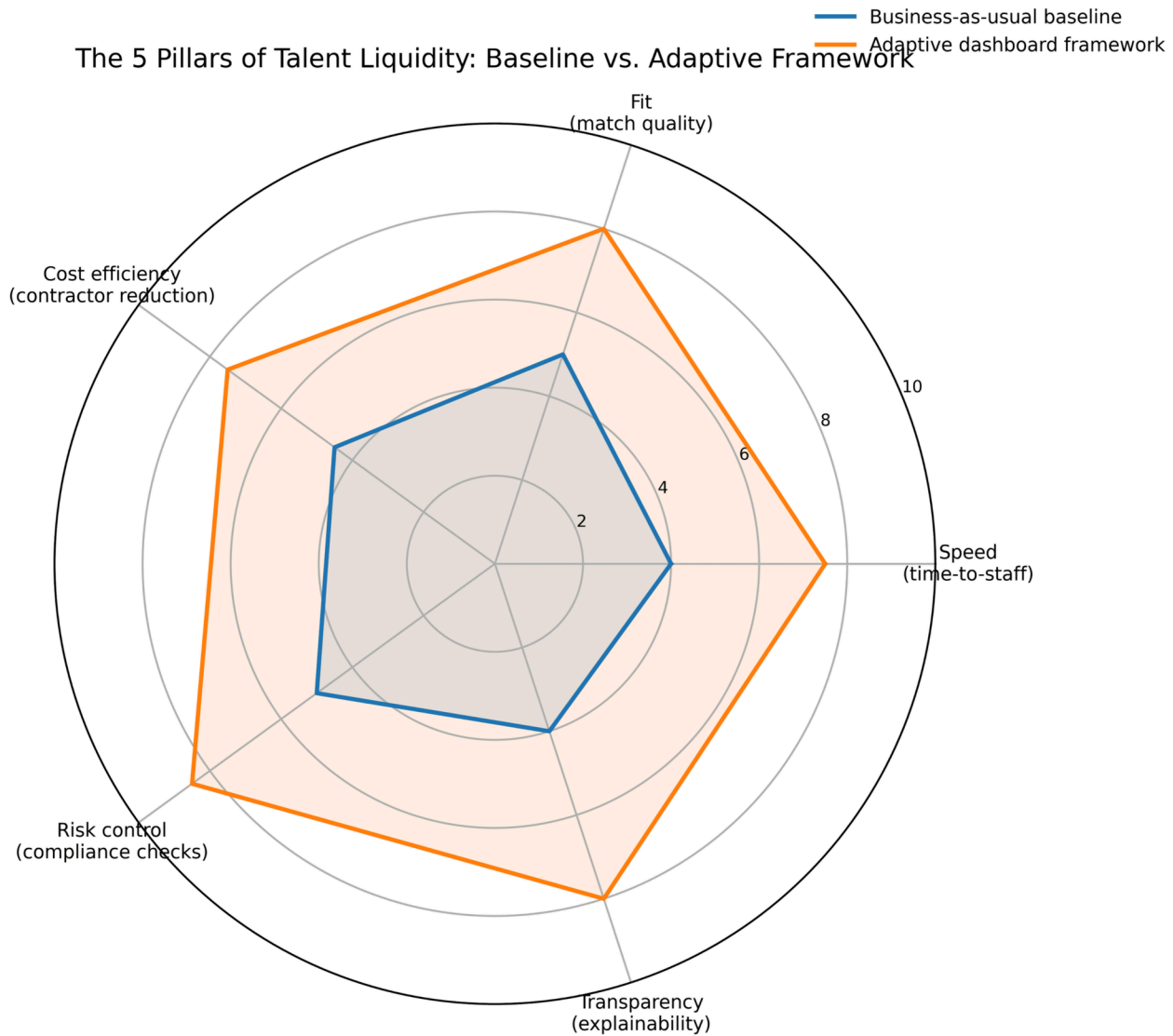


FIGURE 5: The 5 Pillars of Talent Liquidity Radar

As demonstrated in the radar chart, the adaptive dashboard does not sacrifice risk control to achieve faster staffing speeds. Instead, it expands the organization's capability outward across all dimensions simultaneously when compared to the business-as-usual baseline. The dashboard brings value as summarized in Figures 4 and 5. Prediction alone is not enough. It's the distillation of real-time data, predictive matching, compliance filtering, and explainable recommendations into a single decision support process. This aids managers transition from manual staffing searches to quicker and more regulated staffing allocation.

Plausibility of the illustrative results against published evidence

Although the reported values are illustrative, their size can be checked against what has been published about internal mobility. The modeled 11% reduction in contractor spend is conservative next to Bidwell's peer-reviewed finding that externally hired workers are paid 18% to 20% more than internal workers moved into equivalent roles [21]. The modeled rise in internal fill rate, from 54.0% to 63.5%, is moderate compared with the scale that mature internal marketplace

programs have reported; Deloitte documents Unilever redeploying more than 8,000 employees and unlocking around 300,000 hours of capacity through its internal talent marketplace [22]. The direction of the speed and retention effects is also consistent with industry evidence that employees stay about 41% longer at companies with strong internal mobility [23]. These comparisons do not validate the specific numbers. What they show is that the illustrative values sit at the cautious end of published experience, which is the appropriate position for a framework that has not yet been measured in a live deployment.

Discussion

Implications for Global Financial Institutions

The findings have important implications for financial institutions seeking to be more skills-based, resilient, and cost-efficient. First, it can help to open the eyes of the internal capacity that sits under the radar in the dashboard, which can help to cut the reliance that organizations have on external recruitment and contractors. Second, it can enhance delivery resilience by enabling leaders to redeploy employees if the regulations mandate remediation, technology outages, cyber incidents, or unexpected demand surges. Third, it can improve the governance of the workforce by offering more transparency and traceability in allocation decisions. The implications are consistent with the larger body of research in the areas of workforce analytics, operational resilience, and data-driven management, which states that organizations must quickly gain greater visibility, better governance, and utilization of in-house capacity [1,5,10-12].

The dashboard also makes HR analytics operational. Workforce analytics is an integral part of the decision process, rather than a report generated at the end. In global banks, this is particularly relevant as staffing decisions can be delayed, impacting regulatory commitments, customer service, cyber, and transformation timelines.

However, the dashboard should not be used as a substitute for managerial judgment. Factors other than data may affect the allocation of the workforce, such as employee career aspirations, risk for burnout, team dynamics, political considerations, and local labor market conditions. The system should enable better decisions, not "rob" sensitive people's decisions.

Governance Model for Implementation

A practical implementation should comprise a governance model that is clearly defined. Owners should own particular sources and data definitions. The validation, monitoring, and documentation should be the responsibility of the model owner. Business owners need to establish decision rights and escalation levels. Eligibility, privacy, and audit protocols should be reviewed by compliance and legal partners. Staff need to know how their skills are being applied and how to rectify any incorrect information. This governance is also aligned with the principles of risk management and ethics for AI, which include clear ownership, documentation, monitoring, fairness review, and human oversight [6,17-20].

Table 10 outlines the key governance positions and duties for a successful dashboard implementation.

How to cite this article:

Governance role	Primary responsibility
Data owner	Maintains data definitions, quality rules, lineage, and refresh expectations.
Model owner	The document's model purpose validates performance, monitors drift, and manages changes.
Business owner	Defines staffing priorities, decision rights, and escalation thresholds.
HR/workforce planning	Maintains mobility processes, talent policies, and employee communication.
Compliance/legal	Reviews eligibility rules, privacy controls, and audit requirements.
Managers	Review recommendations, make decisions, and record override reasons.
Employees	Validate skills, update profiles, and understand mobility opportunities.

TABLE 10: Governance Responsibilities

Implementation Roadmap

1. The first step an institution should take is to avoid a full enterprise rollout at once. A phased approach is safer and more feasible.
2. Focus on one specific high-value workforce segment, such as risk remediation, technology operations, data engineering, cyber response, compliance operations, etc.
3. Standardize the skill taxonomy and evidence levels for the ability to perform a skill.
4. Start with a small subset of trusted data sources, and then gradually move on to more complex signals.
5. Do not start dashboards before governance and data quality are stable.
6. Implement human review, audit logging, and override reason documentation in a pilot.
7. Measure operational impact, fairness results, and user trust before spreading to regions.

Limitations

There are some limitations in this study. The design for the evaluation is based on outputs that are simulated and pilot-style, and not a long-term enterprise deployment. The quality of the data can differ between regions, systems, and business units. Some skills are hard to deduce since they are context-specific or not represented in formal systems. The impact can also be restricted by manager behavior, as they struggle to let go of talent or may not abandon informal networks. Last, there may be differences among countries in regulation and labor law that restrict the applicability of certain design options.

How to cite this article:

Implementation itself brings challenges that this study has not tested. Linking HR, project, timekeeping, and compliance systems is a heavy integration effort in most banks, and the data rarely lines up cleanly on the first attempt. User adoption is not automatic either. Some managers will keep relying on informal networks, and some teams may resist a tool that makes their spare capacity visible to others. There is also a long-term cost side, since the skill taxonomy, the models, and the interfaces all need ongoing maintenance after the initial build. These factors can slow down or shrink the benefits reported here, and they should be tracked in any live pilot. Finally, because the evaluation scenarios were constructed rather than drawn from a live workforce, the study reports no empirical sample, and the quantitative results should be treated as demonstration values until a field pilot produces measured outcomes.

Future Research

Further studies are needed to evaluate the dashboard in a real multi-region deployment for a longer duration. Internal mobility should be investigated to see if it helps to retain staff, if it fosters unequal opportunity patterns, and for implications on the trust that managers have in explainability features. Future work also needs to investigate architectures that can be made private, federated workforce analytics, robust optimization given the uncertainty of demand, and common skill ontologies for regulated sectors.

Conclusions

The paper explored how real-time talent liquidity dashboards can aid the adaptable workforce allocation process in global finance organizations. The study maintained that talent liquidity is a dynamic and constraint-aware capacity: discovering and articulating internal capacity that is usable, and approving and redeploying it as needs evolve. This capability becomes more vital given the regulatory pressures, cyber risk, transformation programs, specialized skill shortage, and cost pressures being experienced by banks. This is also confirmed by previous research, which established that a combination of real-time analytics, people analytics, operational resilience, and responsible AI governance is necessary when organizations leverage data to make sensitive business decisions. The expanded research reveals that a real-time dashboard has value when its functions include skills, availability, demand, cost, and compliance controls in one decision interface. The proposed system helps to enhance the decision support by decreasing the search latency, improving the quality of the recommendations, filtering ineligible matches, and documenting the justification behind workforce decisions. The pilot style results suggest that there are improvements in time to staff, internal fill rate, redeployment success, and control of contractor costs.

The primary takeaway is that talent liquidity dashboards are not just reporting platitudes. They are socio-technical control systems in regulated financial institutions. They rely on data engineering quality, model governance, organizational adoption, privacy controls, fairness monitoring, and human oversight. The judgment behind each staffing decision stays with people. The dashboard makes that judgment better informed and easier to defend, but it does not replace it. A combination of these elements can boost execution capacity, operational resilience, and workforce transparency through the use of real-time talent liquidity dashboards.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Pratik Pravin Mahajan

Acquisition, analysis, or interpretation of data: Pratik Pravin Mahajan

Critical review of the manuscript for important intellectual content: Pratik Pravin Mahajan

How to cite this article:

Mahajan P (July 24, 2026) Real-Time Talent Liquidity Dashboards for Adaptive Workforce Allocation in Global Financial Institutions. *Cureus J Comput Sci* 3 : es44389-026-00180-1. DOI <https://doi.org/10.7759/s44389-026-00180-1>

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

All data generated or analyzed during this study are included in this published article and/or its appendices. Data sharing is not applicable. This work is theoretical; no datasets were generated or analyzed.

References

1. Principles for operational resilience. (2021). Accessed: June 21, 2026: <https://www.bis.org/bcbs/publ/d516.pdf>.
2. Beer M: High Commitment, High Performance: How to Build a Resilient Organization for Sustained Advantage. Jossey-Bass, San Francisco, CA; 2009.
3. Final report: Guidelines on ICT and security risk management. (2019). Accessed: June 21, 2026: https://www.eba.europa.eu/sites/default/files/document_library/Publications/Guidelines/2020/GLs%20on%20ICT%20and%20se...
4. Guide on effective risk data aggregation and risk reporting. (2024). Accessed: June 21, 2026: https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.supervisory_guides240503_riskreporting.en.pdf.
5. People analytics: Driving business performance with people data. (2018). Accessed: June 21, 2026: <https://www.cipd.org/en/knowledge/reports/people-data-driving-performance/>.
6. Tursunbayeva A, Pagliari C, Di Lauro S, Antonelli G: The ethics of people analytics: risks, opportunities and recommendations. Personnel Review. 2022, 51:900-921. 10.1108/pr-12-2019-0680
7. van den Heuvel S, Bondarouk T: The rise (and fall?) of HR analytics: A study into the future application, value, structure, and system support. Journal of Organizational Effectiveness: People and Performance. 2017, 4:157-178. 10.1108/joepp-03-2017-0022
8. Thriving beyond boundaries: Human performance in a boundaryless world. (2024). Accessed: June 21, 2026: <https://www.deloitte.com/us/en/insights/topics/talent/human-capital-trends/2024/prioritizing-human-performance.html>.
9. Rethinking skills-based talent models: 4 paths to business value. (2026). Accessed: June 21, 2026: <https://www.deloitte.com/us/en/insights/topics/talent/creating-value-with-skills.html>.
10. The State of Organizations 2023: Ten shifts transforming organizations. (2023). Accessed: June 21, 2026: <https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/the-state-of-organizations-2023>.
11. Future of Jobs Report 2023. (2023). Accessed: June 21, 2026: https://www3.weforum.org/docs/WEF_Future_of_Jobs_2023.pdf.
12. Future of Jobs Report 2025. (2025). Accessed: June 21, 2026: https://reports.weforum.org/docs/WEF_Future_of_Jobs_Report_2025.pdf.
13. Shmueli G, Koppius OR: Predictive analytics in information systems research. MIS Quarterly. 2011, 35:553-572. 10.2307/23042796
14. Kaplan RS, Norton DP: The Balanced Scorecard: Translating Strategy into Action. Harvard Business School Press, Boston, MA; 1996.
15. Marr B: Data Strategy: How to Profit from a World of Big Data, Analytics and Artificial Intelligence. Kogan Page, London, UK; 2021.
16. Parmenter D: Key Performance Indicators: Developing, Implementing, and Using Winning KPIs. Wiley, Hoboken, NJ; 2020. 10.1002/9781119620785
17. Understanding artificial intelligence ethics and safety: A guide for the responsible design and implementation of AI systems in the public sector. (2019). Accessed: June 21, 2026: <https://doi.org/10.5281/zenodo.3240529>.

How to cite this article:

Mahajan P (July 24, 2026) Real-Time Talent Liquidity Dashboards for Adaptive Workforce Allocation in Global Financial Institutions. Cureus J Comput Sci 3 : es44389-026-00180-1. DOI <https://doi.org/10.7759/s44389-026-00180-1>

18. Artificial Intelligence Risk Management Framework (AI RMF 1.0). (2023). Accessed: June 21, 2026: <https://nvlpubs.nist.gov/nistpubs/ai/NIST.AI.100-1.pdf>.
19. OECD AI Principles. (2024). Accessed: June 21, 2026: <https://www.oecd.org/en/topics/sub-issues/ai-principles.html>.
20. Raghavan M, Barocas S, Kleinberg J, Levy K: [Mitigating bias in algorithmic hiring: Evaluating claims and practices](#). Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency (FAT* 2020). 2020, 469-481. [10.1145/3351095.3372828](https://doi.org/10.1145/3351095.3372828)
21. Bidwell M: [Paying more to get less: the effects of external hiring versus internal mobility](#). Administrative Science Quarterly. 2011, 56:369-407. [10.1177/0001839211433562](https://doi.org/10.1177/0001839211433562)
22. [Activating the internal talent marketplace](#). (2020). Accessed: June 21, 2026: <https://www.deloitte.com/us/en/insights/topics/talent/internal-talent-marketplace.html>.
23. [Global Talent Trends](#). (2024). Accessed: July 13, 2026: <https://business.linkedin.com/talent-solutions/global-talent-trends>.

How to cite this article: