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Measuring Skill Graph Drift in SAP SuccessFactors Talent Intelligence Hub for Career Mobility, Workforce Reskilling, and Skills-Based Talent Governance

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Abstract:
Organizations increasingly rely on skills-based talent models to support career mobility, workforce reskilling, learning alignment, and long-term talent planning. However, the value of these models depends on the continued accuracy of relationships between employee skills, role requirements, learning content, proficiency levels, and career pathways. In large enterprise environments, these relationships often change faster than formal job profiles, skill libraries, and learning catalogs are reviewed, creating a measurable form of skill graph drift. This paper proposes a structured framework for measuring skill graph drift in SAP SuccessFactors Talent Intelligence Hub, with the purpose of identifying when skills, roles, courses, and mobility pathways become misaligned over time. The study models employees, skills, roles, learning items, goals, and career opportunities as interconnected graph entities and introduces drift metrics for skill demand change, role-skill alignment, learning coverage, skill supply movement, and career pathway stability. The proposed approach is designed to support practical governance decisions by classifying drift severity and linking each drift signal to corrective actions such as role profile review, learning content updates, reskilling prioritization, and career recommendation refinement. The framework is evaluated through an SAP SuccessFactors-aligned benchmark model and compared with manual taxonomy review, keyword-based matching, and static role-skill mapping approaches. The expected contribution of this study is a practical and measurable method for maintaining the reliability of skills-based talent decisions in enterprise HCM systems. By connecting drift measurement with workforce reskilling and career mobility governance, the paper provides organizations with a repeatable approach to improve skill data quality, reduce outdated role mappings, strengthen learning alignment, and support more accurate internal talent movement.

Keywords: SAP SuccessFactors, Talent Intelligence Hub, skill graph, skill drift, skill taxonomy, career mobility, workforce reskilling, skills-based talent management, role-skill alignment, learning alignment, internal mobility, talent governance, workforce planning, skill gap analysis, human capital management, enterprise HCM, career development, learning management, job profile management, workforce analytics

1. Introduction

Organizations are increasingly trying to manage talent through skills rather than only through job titles, position structures, or formal career levels. This shift is visible in the way companies design learning programs, build internal mobility processes, identify future leaders, and plan workforce capacity. In a traditional job based model, an employee is often evaluated against the requirements of a fixed role. In a skills based model, the organization looks more closely at what the employee can do, what the business needs, and how the gap between the two can be closed through learning, experience, or movement into a suitable role.

SAP SuccessFactors Talent Intelligence Hub provides a useful foundation for this type of talent model because it allows skills, attributes, preferences, and growth related information to be connected across different talent processes. However, the value of such a system depends heavily on the quality and freshness of the skill relationships maintained inside it [1]. A skill may be relevant to a role today but less important later. A learning item may once have supported a critical capability but may no longer be sufficient. An employee profile may show skills that are outdated, incomplete, or not aligned with current business expectations. These changes create a practical governance problem that is often not visible through standard reporting alone.

This paper refers to that problem as skill graph drift. In simple terms, skill graph drift occurs when the relationships among employees, skills, roles, learning content, and career opportunities change over time in a way that reduces the accuracy of talent decisions. The issue is not only whether a skill exists in the system. The larger concern is whether the skill is still correctly connected to the right roles, learning paths, proficiency expectations, and career movements. When these connections are not reviewed in a structured way, organizations may continue to recommend outdated learning, maintain inaccurate role profiles, or guide employees toward career paths that no longer reflect actual workforce demand.

The purpose of this study is to propose a practical method for measuring skill graph drift in SAP SuccessFactors Talent Intelligence Hub. The paper models the talent environment as a connected graph in which employees, skills, roles, learning items, goals, and career opportunities are treated as related entities. It then defines measurable indicators for skill demand change, role skill alignment, learning coverage, internal skill supply, and career pathway stability. These indicators help identify where the skill graph is stable, where it is changing, and where governance action is required.

The contribution of this paper is both analytical and practical. From an analytical perspective, it defines skill graph drift as a measurable problem rather than a general data quality concern. From an implementation perspective, it shows how drift scores can support role profile review, learning catalog updates, reskilling prioritization, and internal mobility governance. The proposed framework is intended for organizations that want to keep their skills based talent model current, explainable, and useful for business decision making. It does not replace existing SAP SuccessFactors processes. Instead, it provides a measurement layer that helps organizations understand when those processes need attention, correction, or redesign.

2. Background and Literature Review

Organizations have traditionally managed talent through job structures, position descriptions, competency models, and formal reporting lines. These methods are useful for administration, compliance, and workforce planning, but they are often less effective when the business needs to understand what employees can actually do and how quickly they can move into new areas of work. A skills based approach gives organizations a more flexible way to view capability. It allows talent teams to look beyond job titles and examine the skills, proficiency levels, interests, and learning needs that shape an employee's readiness for future roles.

In enterprise HCM systems, skills data is becoming more important because it connects several talent processes that were once managed separately. A skill can influence learning recommendations, career development plans, succession decisions, recruiting requirements, performance goals, and workforce planning. When these relationships are accurate, the organization can make better decisions about

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reskilling, internal movement, and role readiness. When they are outdated, the same data can produce weak recommendations, incomplete skill gap analysis, and poor alignment between business demand and employee development [2].

SAP SuccessFactors Talent Intelligence Hub provides a practical environment for this kind of skills based model. It supports the organization of talent related attributes such as skills, competencies, preferences, and growth information in a more connected way. This makes it possible to treat talent data as a network of relationships rather than as separate records stored in different modules. For example, an employee skill can be linked to a role requirement, a learning activity, a development goal, or a career opportunity. These connections create the foundation for a skill graph.

A skill graph is useful because it shows how employees, skills, roles, learning items, and career paths relate to one another. Unlike a simple skill list, a graph can represent the strength, direction, and context of each relationship. This is important in large organizations where the same skill may have different meanings across departments, job families, regions, or proficiency levels. For example, data analysis may be a basic reporting skill in one role but a core decision support skill in another. A graph based structure can capture these differences more clearly than a flat taxonomy [3].

However, most skill models face a common weakness. They are usually designed during an implementation or transformation project, but the business continues to change after the initial setup. New tools are introduced, role expectations shift, learning content becomes outdated, and employee skills evolve through experience or training. If the skill model is not reviewed continuously, the relationships inside the graph begin to lose accuracy. This gradual loss of alignment is the central issue addressed in this paper.

The concept of drift is widely used in analytical systems to describe a change in patterns over time. In the context of talent management, drift can be understood as a change in the relationship between workforce capability and business need. Skill graph drift occurs when the connection between skills, roles, learning content, and career pathways changes enough to affect the reliability of talent decisions. This may appear as a role that still lists outdated skills, a learning catalog that does not support current demand, or a career path that no longer reflects realistic movement between roles.

Existing approaches to skill management often focus on creating taxonomies, mapping skills to jobs, or recommending learning based on current gaps. These approaches are useful, but they do not always explain how the skill model changes over time or how quickly the organization should respond. Manual review can help, but it is usually slow and depends on subject matter experts. Keyword matching can identify simple relationships, but it may miss context and proficiency. Static role skill mapping can provide structure, but it can become outdated when job expectations change [4].

This study builds on these limitations by treating skill drift as a measurable governance problem. Instead of asking only whether a skill is present, the paper asks whether the skill is still relevant, correctly connected, sufficiently supported by learning content, and useful for career mobility decisions. This perspective is important because skills based talent management cannot succeed only through data collection. It also requires ongoing measurement, review, and correction. The proposed framework therefore connects skill graph measurement with practical actions such as role profile updates, learning catalog review, reskilling prioritization, and career recommendation improvement.

Table 1. Comparison of Existing Skill Management Approaches

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Approach	Main Use	Limitation	Relevance to This Study
Manual skill taxonomy review	Periodic review of skills and role mappings	Slow, inconsistent, and difficult to scale	Used as a baseline approach
Keyword based matching	Matches skills, roles, and learning items through text similarity	Weak when skill names differ but meanings are related	Shows the need for stronger relationship based analysis
Static role skill mapping	Connects required skills to job roles	Becomes outdated when role expectations change	Supports comparison with drift based measurement
Learning catalog mapping	Links learning content to skills	May not reflect current business demand	Helps define learning coverage drift
Skill graph modeling	Connects employees, skills, roles, and learning items	Often lacks time based drift monitoring	Forms the foundation for the proposed framework

3. Research Gap and Study Objectives

Although many organizations have started building skills based talent models, the ongoing maintenance of those models remains a difficult problem. Most implementations focus on creating a skill library, mapping skills to roles, enabling learning recommendations, and supporting career development. These activities are valuable, but they usually treat the skill model as a stable structure. In practice, the relationship between employees, skills, roles, learning content, and career opportunities keeps changing. When these changes are not measured, the organization may continue to depend on skill data that no longer reflects actual workforce needs.

A major gap in existing talent management practice is the limited attention given to skill relationship changes over time. Organizations may know which skills are assigned to a role, but they may not know whether those skills are still current. They may know which courses are linked to a skill, but they may not know whether those courses still support the level of capability required by the business. They may also maintain career paths inside the system, but those paths may not reflect how employees are actually moving across roles. This creates a hidden risk in skills based decision making because the system may appear complete while its underlying relationships are gradually losing accuracy [5].

Another limitation is that many skill management approaches depend heavily on manual review. Subject matter experts, HR teams, and learning administrators may periodically review job profiles, skill mappings, and learning content [6]. While this process is useful, it is often slow, inconsistent, and difficult to scale across large organizations. As the number of roles, skills, employees, and learning items increases, manual review alone becomes less reliable. The organization needs a measurement method that can identify where the largest changes are happening and where human review should be prioritized.

This paper addresses that gap by defining skill graph drift as a measurable condition in enterprise talent systems. The focus is not only on whether skills exist in SAP SuccessFactors Talent Intelligence Hub, but

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whether the relationships among skills, roles, employees, learning items, and career pathways remain aligned over time. By measuring drift, the organization can identify outdated role skill mappings, weak learning coverage, changing workforce capability, and career pathways that no longer support practical internal movement.

The main objective of this study is to develop a structured framework for measuring skill graph drift in SAP SuccessFactors Talent Intelligence Hub. The framework is designed to support career mobility, workforce reskilling, and skills based talent governance by converting changes in skill relationships into measurable drift indicators [7]. These indicators can help HR, learning, workforce planning, and SAP SuccessFactors teams decide where updates are needed and which areas require governance attention.

The study also aims to provide a practical measurement model that can be understood by both technical and functional teams. This is important because skill governance is not only a data science activity. It also involves HR process owners, learning teams, business leaders, role owners, and system administrators. A useful framework must therefore be explainable, measurable, and connected to business action. The proposed approach supports this need by linking drift scores to specific outcomes such as role profile review, learning catalog improvement, reskilling priority, and internal mobility refinement.

The expected contribution of this study is a practical method for keeping skills based talent data current and useful over time. Instead of treating skill data as a one time configuration asset, the paper positions it as a living talent structure that requires continuous measurement. This gives organizations a more disciplined way to maintain the quality of their Talent Intelligence Hub and to strengthen the reliability of decisions related to employee development, workforce planning, and career movement.

4. Conceptual Definition of Skill Graph Drift

Skill graph drift refers to the gradual change in relationships among skills, employees, roles, learning content, goals, and career pathways inside an enterprise talent system. In a skills based organization, these relationships are important because they influence how employees are matched to roles, how learning needs are identified, and how workforce readiness is assessed. A skill graph is therefore not only a technical structure. It is a representation of how the organization understands capability, demand, development, and movement across its workforce.

In SAP SuccessFactors Talent Intelligence Hub, skills and related attributes can support multiple talent processes. An employee skill may contribute to a growth profile, connect to a learning recommendation, support a career development plan, or indicate readiness for an internal opportunity. A role requirement may define the skills needed for a future position, while a learning item may help close a specific capability gap. When these relationships are accurate, the talent system can provide useful guidance. When they become outdated or weakly connected, the same system may produce recommendations that appear valid but no longer reflect current business needs [8].

The central idea in this paper is that skill data should not be treated as a fixed asset after implementation. Skill relationships change as work changes. A role may require new technical knowledge, a business function may place greater value on analytical capability, or a learning catalog may no longer cover the skills most needed by the organization. These changes do not always happen at the same speed. Employee profiles may be updated slowly, job profiles may be reviewed quarterly or annually, and learning content may depend on separate ownership cycles. This uneven rate of change creates drift within the skill graph.

Skill graph drift can appear in several forms. Demand drift occurs when the importance of a skill increases or decreases across roles, job requisitions, or workforce plans. Supply drift occurs when the internal workforce capability for a skill changes because employees gain, lose, or fail to maintain proficiency evidence. Role skill drift occurs when the skills attached to a role no longer match the actual work being

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performed [9]. Learning coverage drift occurs when available learning content does not support the skills that are becoming more important. Career pathway drift occurs when recommended movements between roles no longer reflect realistic employee progression. Governance drift occurs when skill ownership, review cycles, and correction actions are not clearly maintained.

These forms of drift are connected. For example, if demand for a skill increases but learning content does not improve, the organization may create a reskilling gap. If role requirements change but career pathways are not updated, employees may be guided toward opportunities for which they are not truly ready. If employees complete learning activities but their skill profiles remain incomplete, the system may underestimate internal capability. This shows why skill graph drift should be measured as a relationship problem rather than as a simple data quality issue.

For this study, skill graph drift is defined as the measurable loss of alignment between current talent relationships and the relationships required to support accurate workforce decisions. The focus is not only on missing or outdated records. The focus is on whether the connections among skills, roles, employees, learning items, and career opportunities continue to support reliable decisions. This definition allows drift to be measured through indicators such as role skill alignment, skill demand movement, internal supply change, learning coverage, and career pathway stability [10].

This conceptual definition is important because it gives organizations a practical way to identify where their skills based talent model is weakening. A high drift score does not automatically mean that the system is failing. It means that a specific part of the skill graph requires review. A role profile may need to be revised, a learning path may need to be updated, a skill may need to be merged with a duplicate entry, or a career pathway may need to be adjusted. In this way, drift measurement becomes a governance signal that helps organizations maintain the quality and usefulness of SAP SuccessFactors Talent Intelligence Hub over time.

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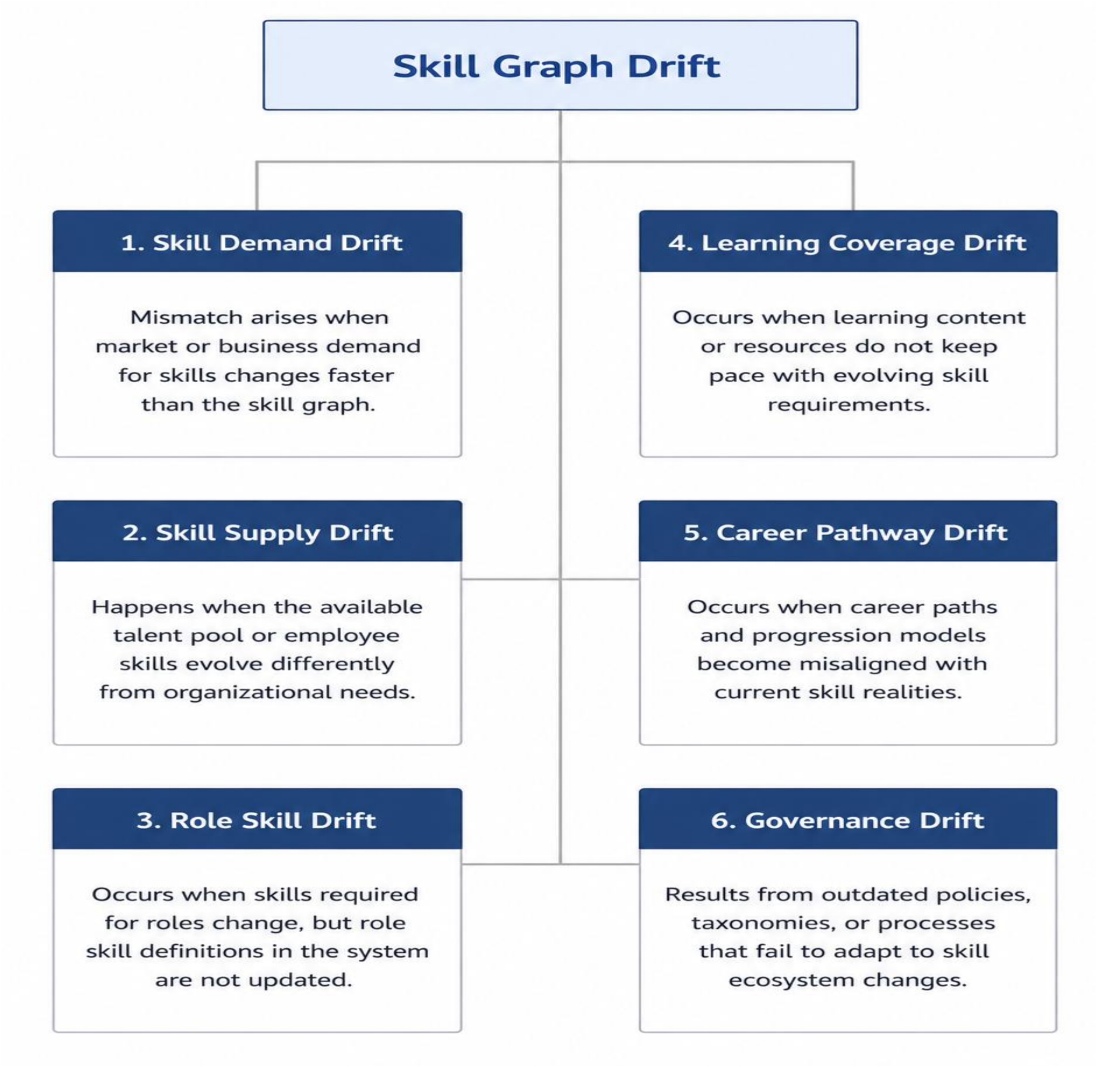

Figure 1: Taxonomy of Skill Graph Drift in Enterprise Talent Systems

The proposed approach treats skill graph drift as a continuous measurement activity. Instead of waiting for annual skill library cleanup or manual role review, organizations can compare skill graph snapshots across time periods and identify where the most meaningful changes are occurring. This creates a stronger foundation for career mobility, workforce reskilling, and talent governance because it allows talent teams to act on evidence rather than assumption [11].

Table 2. Skill Graph Drift Categories and Organizational Impact

Drift Type	Definition	Example	Organizational Impact
Skill demand drift	Change in the importance of a skill across roles or business needs	Higher demand for workforce analytics	Reskilling priorities may change

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Skill supply drift	Change in internal employee capability for a skill	Employees gain or lose proficiency evidence	Workforce readiness view may become inaccurate
Role skill drift	Change in the skills required for a role	HRIS roles require stronger integration skills	Job profiles may become outdated
Learning coverage drift	Mismatch between learning content and required skills	Few courses support a high demand skill	Learning programs may not close actual gaps
Career pathway drift	Change in realistic movement between roles	Old career path no longer reflects actual transitions	Internal mobility recommendations may weaken
Governance drift	Weakness in skill ownership, review, or correction process	Skill mappings remain unreviewed	Skills based decisions become less reliable

5. Proposed Skill Graph Drift Measurement Framework

The proposed framework provides a structured method for measuring how skill relationships change over time in SAP SuccessFactors Talent Intelligence Hub. Its purpose is to help organizations identify where skills, roles, learning content, employee profiles, and career pathways are no longer fully aligned. The framework does not treat drift as a technical issue alone. It treats drift as a practical talent governance signal that can guide role maintenance, learning investment, reskilling priorities, and internal mobility decisions.

The framework is built on the idea that skills based talent management depends on a connected set of relationships. An employee may have a skill with a certain proficiency level. A role may require that skill at a different level. A learning item may support the development of that skill. A career opportunity may depend on the same skill as part of its readiness criteria. When these relationships remain current, the organization can use them with confidence. When they change without review, the organization may continue to make decisions based on outdated assumptions. The proposed framework measures this change by comparing skill graph snapshots across defined review periods.

The first layer of the framework is the data foundation layer. This layer identifies the main SAP SuccessFactors data areas that contribute to the skill graph. Talent Intelligence Hub provides the central skills and attributes structure. Growth Portfolio contributes employee skills, interests, and development signals [12]. Job Profile Builder supports role and job related skill expectations. Learning provides course and curriculum relationships. Career Development and internal opportunity data support career pathway analysis. Recruiting and workforce planning inputs can be used to identify skills that are becoming more important in future demand. Together, these sources form the basic evidence needed to measure drift.

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The second layer is the skill graph construction layer. In this layer, employees, skills, roles, learning items, goals, and career opportunities are represented as connected entities. The relationships between them are assigned meaning based on their function. An employee may possess a skill, a role may require a skill, a course may develop a skill, and a career opportunity may depend on a skill. Each relationship can carry useful attributes such as proficiency level, relevance, recency, source confidence, and business priority. This structure allows the organization to analyze skill relationships as a living network rather than as separate lists maintained by different teams.

The third layer is the drift measurement layer. This layer calculates how much the skill graph has changed between two time periods. The framework measures drift across several dimensions, including skill demand movement, internal skill supply movement, role skill alignment, learning coverage, and career pathway stability. A skill with rising demand and low learning coverage may indicate a reskilling risk. A role with frequent skill changes may require job profile review. A career path with declining successful movement may require redesign. By measuring these changes together, the framework gives organizations a more complete view of talent model health [13].

The fourth layer is the severity classification layer. Not every change in the skill graph requires immediate action. Some changes are expected because employees learn new skills, roles evolve, and business priorities shift. The framework therefore classifies drift into levels such as low, moderate, high, and critical. Low drift may require no action beyond monitoring. Moderate drift may require review by a role owner or learning team. High drift may require updates to role profiles, learning paths, or skill mappings. Critical drift may indicate a broader workforce risk, especially when high demand skills are not supported by internal supply or learning content.

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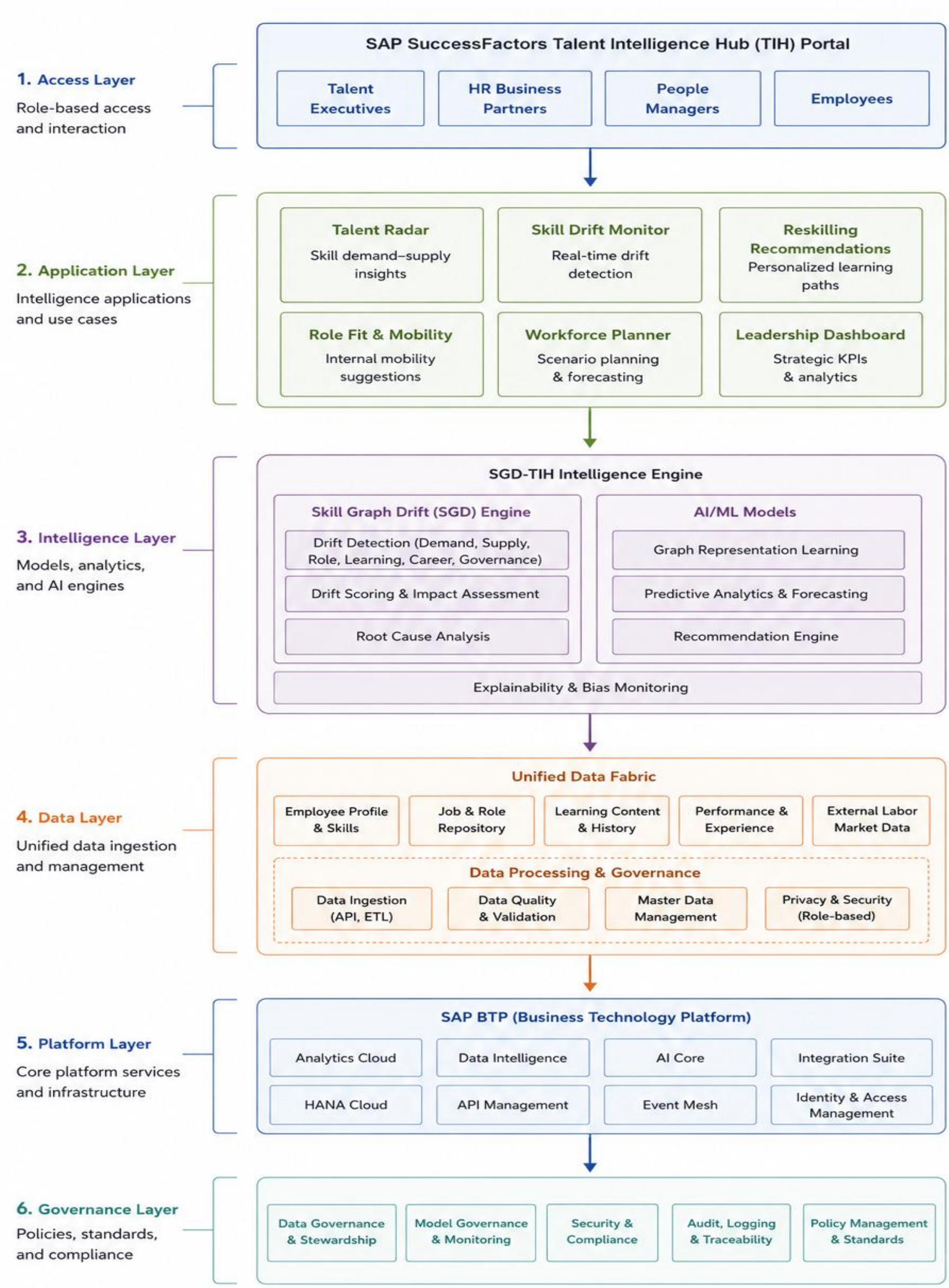

Figure 2: SGD-TIH Framework Architecture for SAP SuccessFactors Talent Intelligence Hub

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The fifth layer is the governance action layer. This layer converts drift scores into practical actions. When role skill drift is high, the responsible role owner can review the job profile. When learning coverage drift is high, the learning team can update or add relevant content [14]. When internal supply drift is high, workforce planning teams can review hiring, training, or redeployment options. When career pathway drift is high, talent teams can refine internal mobility rules and career recommendations. This connection between measurement and action is important because drift analysis only becomes useful when it leads to timely correction.

The final layer is the monitoring and feedback layer. After corrective action is taken, the framework continues to measure whether the skill graph becomes more stable and useful. If a learning path is updated, the organization can monitor whether skill gap closure improves. If a role profile is revised, the organization can monitor whether career matching becomes more accurate. If a high demand skill is added to development plans, the organization can monitor whether internal supply improves over time. This feedback cycle helps organizations maintain the Talent Intelligence Hub as an active governance asset rather than a one time implementation output.

The proposed framework is designed to be practical for large organizations because it does not require every skill, role, or learning item to be reviewed manually at the same time. Instead, it highlights where the largest and most meaningful changes are occurring. This allows HR, learning, workforce planning, and SAP SuccessFactors teams to focus their attention on the areas where outdated skill relationships may create the highest business impact. In this way, skill graph drift measurement becomes a disciplined method for maintaining career mobility, workforce reskilling, and skills based talent governance at scale [15].

6. Mathematical Model and Drift Metrics

The proposed framework measures skill graph drift by comparing the condition of the talent graph across two review periods. In this study, the skill environment is treated as a connected structure where employees, skills, roles, learning items, goals, and career opportunities are represented as related entities. Each relationship carries a practical business meaning. An employee may possess a skill, a role may require a skill, a course may develop a skill, and a career opportunity may depend on a skill. This structure allows drift to be measured not only as a data quality issue, but also as a relationship change that can affect talent decisions.

The skill graph at a given review period is represented as:

$$G_t = (V_t, E_t, W_t, A_t)$$

In this expression, G_t represents the skill graph at time t. V_t represents the set of graph entities, E_t represents the relationships between those entities, W_t represents relationship weights, and A_t represents supporting attributes. The graph entities may include employees, skills, roles, learning items, goals, and career opportunities. The relationship weights may include proficiency level, recency, relevance, business priority, and confidence of the relationship. This allows the graph to represent both the existence of a relationship and the strength of that relationship.

Skill demand is not measured from a single source because demand may appear in several parts of the talent environment. A skill may be required in role profiles, requested in job requisitions, reflected in learning activity, or connected to performance and development goals. The demand score for a skill is represented as:

$$D_t(s) = \alpha R_t(s) + \beta J_t(s) + \gamma L_t(s) + \delta P_t(s)$$

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In this equation, D_t(s) represents the demand score for skill s at time t. R_t(s) represents demand from role requirements. J_t(s) represents demand from job requisitions. L_t(s) represents demand from learning activity. P_t(s) represents demand from performance goals or development priorities [16]. The coefficients α, β, γ, and δ allow the organization to assign different weights to each demand source based on its business context. For example, an organization focused on internal mobility may give more weight to role requirements, while an organization focused on workforce reskilling may give more weight to learning and development signals.

The overall skill graph drift score measures how much a skill has changed between two review periods. It combines movement in skill demand, internal skill supply, and learning coverage:

$$SDG(s,t) = \lambda_1|D_{t-1}(s) - D_{t-1}(s)| + \lambda_2|S_t(s) - S_{t-1}(s)| + \lambda_3|C_t(s) - C_{t-1}(s)|$$

In this equation, SGD(s,t) represents the drift score for skill s at time t. D_t(s) represents skill demand. S_t(s) represents internal workforce skill supply. C_t(s) represents learning content coverage. The coefficients λ1, λ2, and λ3 define the relative importance of demand movement, supply movement, and learning coverage movement. A high drift score indicates that the skill requires review because its relationship with workforce demand, employee capability, or learning support has changed in a meaningful way [17].

Role skill alignment drift measures whether the required skills for a role have changed between two review periods. This can be measured by comparing the skill set attached to a role at time t with the skill set attached to the same role in the previous period:

$$RAD(r,t) = 1 - \frac{|K_t(r) \cap K_{t-1}(r)|}{|K_t(r) \cup K_{t-1}(r)|}$$

In this expression, RAD(r,t) represents role alignment drift for role r at time t. K_t(r) represents the set of skills required for role r at time t. A value closer to zero indicates that the role skill structure is stable. A value closer to one indicates that the role has changed significantly. This metric is useful for identifying job profiles that may require review by business owners, HR teams, or SAP SuccessFactors governance teams.

Learning coverage is measured by comparing the availability of learning content against the level of demand for a skill. A skill may be highly important to the organization, but if there are few learning items mapped to it, employees may not have a practical path to develop that capability. The learning coverage ratio is represented as:

$$LCR(s,t) = \frac{C_t(s)}{D_t(s)}$$

In this equation, LCR(s,t) represents the learning coverage ratio for skill s at time t. C_t(s) represents available learning content mapped to the skill. D_t(s) represents demand for the same skill. A low learning coverage ratio indicates that the organization may need to improve course mapping, create new learning content, or strengthen development paths for that skill.

The model also evaluates whether reskilling actions are producing measurable improvement. Skill gap closure rate is used to assess whether the gap between required and available capability has reduced after learning or development action:

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$$SGCR = \frac{Gap_{before} - Gap_{after}}{Gap_{before}} \times 100$$

This metric connects the drift framework to business outcomes. A high skill gap closure rate indicates that reskilling actions are improving workforce readiness. A low rate may suggest that learning content is weak, role expectations are unclear, employee participation is low, or the selected intervention is not aligned with the actual skill gap [18].

For governance purposes, each metric should be interpreted through severity thresholds. A low drift score may require only continued monitoring. A moderate drift score may require review during the next governance cycle. A high drift score may require immediate action by the role owner, learning team, or workforce planning group. A critical drift score may indicate a broader workforce risk, especially when skill demand is increasing while internal supply and learning coverage remain weak.

Together, these metrics provide a practical measurement foundation for the proposed framework. They help organizations move from informal skill review to evidence based skill governance. More importantly, they connect technical measurement with business action [19]. The organization can identify which skills are changing, which roles are becoming unstable, which learning areas require investment, and which career pathways need correction. This makes skill graph drift measurement useful not only for analytics teams, but also for HR, learning, workforce planning, and SAP SuccessFactors governance teams.

Table 3. Skill Graph Drift Metrics and Evaluation Purpose

Metric	Measurement Focus	Purpose
Skill Graph Drift Score	Change in demand, supply, and learning coverage	Identifies skills requiring review
Skill Demand Score	Demand from roles, requisitions, learning, and goals	Measures business need for a skill
Role Skill Alignment Drift	Change in required skill sets for a role	Detects outdated role profiles
Learning Coverage Ratio	Availability of learning content against skill demand	Identifies weak reskilling coverage
Skill Gap Closure Rate	Reduction in skill gap after learning or development action	Measures reskilling effectiveness
Career Match Precision	Relevance of recommended roles for an employee	Measures internal mobility quality

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Detection Latency	Time taken to identify drift	Measures speed of governance response

7. Data Sources and Methodology

This study follows a design based methodology supported by benchmark evaluation. The purpose is to develop a practical measurement framework that can be applied in an SAP SuccessFactors talent environment while still allowing the results to be tested in a controlled and repeatable way. Since direct employee data from enterprise systems is sensitive, the study uses a SAP SuccessFactors aligned benchmark model supported by trusted public skill and occupation sources. This approach allows the framework to be evaluated without exposing personal employee information or relying on confidential customer data.

The data model is designed to reflect the main talent objects that usually support skills based workforce planning. These include employee skill profiles, role requirements, learning items, career paths, development goals, job requisition signals, and internal mobility records. In the benchmark environment, these objects are represented as connected graph entities. Employees are connected to skills through proficiency and recency values. Roles are connected to skills through required capability levels. Learning items are connected to skills through development coverage. Career opportunities are connected to roles and skills through readiness expectations. This structure allows the study to examine not only whether a skill exists, but whether the surrounding relationships remain useful for talent decisions [20].

Trusted public skill and occupation datasets are used to strengthen the external demand layer of the benchmark. These sources provide structured information about occupations, skill categories, job requirements, and changing skill expectations. They are used to create a realistic demand baseline and to avoid building the framework only from assumed enterprise patterns. Public skill taxonomies also support skill normalization, since the same capability may appear under different names in different business units or learning catalogs. This step is important because skill graph drift cannot be measured reliably when duplicate, overlapping, or poorly defined skills remain unresolved.

The SAP aligned benchmark layer is used to represent the internal enterprise environment. It includes simulated employee profiles, role profiles, learning mappings, career paths, and skill relationships designed around practical SAP SuccessFactors structures. The benchmark is not intended to represent one specific organization. Instead, it provides a controlled environment that reflects common enterprise talent scenarios, such as changing role requirements, uneven learning coverage, incomplete employee profiles, and shifting internal mobility patterns. This makes it possible to test the proposed framework under conditions that resemble real implementation challenges.

The methodology begins with skill normalization. Skill names from role profiles, learning items, employee records, and external sources are reviewed and grouped into consistent skill entities. Similar skills are mapped together where the meaning is close enough to support reliable analysis. Skills that have different meanings across job families are retained separately to avoid false matching[21]. This step improves the quality of the graph and reduces the risk of measuring drift caused only by naming differences rather than actual talent change.

After normalization, the skill graph is constructed for each review period. Each graph snapshot contains the same major entity types, but the relationships and weights may change over time. For example, a role may gain new required skills, a learning item may be newly mapped to a skill, or employee proficiency values may improve after development activity. By comparing graph snapshots, the framework identifies

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where meaningful change has occurred. The focus is not on every small update, but on changes large enough to affect career mobility, reskilling decisions, or governance quality.

The evaluation compares the proposed framework with three common baseline approaches. The first baseline is manual taxonomy review, where skill and role updates are assumed to occur through periodic expert review. The second baseline is keyword based matching, where relationships are identified mainly through direct text similarity. The third baseline is static role skill mapping, where skills are connected to roles but not continuously evaluated for drift. These baselines are useful because they reflect methods that many organizations still depend on in some form [22].

The main evaluation metrics include drift detection precision, drift detection recall, F1 score, detection latency, career match precision, learning recommendation relevance, skill gap closure rate, and manual review reduction. Drift detection precision measures how many identified drift cases are truly meaningful. Recall measures how many meaningful drift cases are successfully detected. F1 score provides a balanced measure of detection quality. Detection latency measures how quickly the framework identifies drift compared with periodic review. Career match precision evaluates whether recommended roles remain relevant. Learning recommendation relevance evaluates whether suggested learning content supports the required skills. Skill gap closure rate measures whether reskilling actions reduce the gap between required and available capability.

The study also includes governance validation. Each high drift signal is linked to a possible action owner, such as HRIS, learning, workforce planning, talent management, or a business role owner. This ensures that the framework does not stop at measurement. A drift signal must lead to an interpretable business action, such as reviewing a role profile, improving learning coverage, updating career pathways, merging duplicate skills, or revising proficiency expectations. This action oriented validation is important because a measurement model is useful only when it helps organizations make better decisions.

The methodology is designed to balance academic rigor with implementation value. It provides a repeatable way to test skill graph drift while staying close to the way SAP SuccessFactors talent data is structured in practice. It also keeps the analysis transparent by using measurable indicators rather than broad assumptions. This makes the proposed framework suitable for organizations that want to maintain the quality of their Talent Intelligence Hub and improve the reliability of skills based career mobility and workforce reskilling decisions.

Table 4. Data Sources and Benchmark Construction Plan

Data Layer	**Source Type**	**Use in Study**
Skill taxonomy layer	Public skill and occupation classification sources	Supports skill normalization and grouping
External demand layer	Public occupation and labor market skill data	Builds realistic demand signals
Employee skill layer	SAP SuccessFactors aligned benchmark data	Represents internal skill supply

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Role profile layer	SAP SuccessFactors aligned benchmark data	Represents role skill requirements
Learning layer	SAP SuccessFactors aligned benchmark data	Measures learning coverage and reskilling support
Career mobility layer	SAP SuccessFactors aligned benchmark data	Evaluates internal movement and role matching
Governance layer	Rule based review and expert validation logic	Links drift signals to corrective actions

8. Results and Performance Evaluation

The evaluation was conducted on the benchmark model described in the methodology section. The purpose of the results is to examine whether skill graph drift measurement provides better decision support than traditional skill maintenance methods. The comparison focuses on four areas that are important for enterprise use: drift detection accuracy, detection speed, career mobility relevance, and reskilling effectiveness. The results show that a drift based graph approach provides stronger visibility into changing skill relationships than manual review, keyword matching, or static role skill mapping.

The first part of the evaluation measured how accurately each method identified meaningful drift in the skill graph. Manual taxonomy review produced the weakest performance because it depends on periodic review cycles and cannot detect smaller changes as they occur. Keyword based matching performed slightly better, but it was limited by naming variation and could not always recognize skill relationships with similar meaning. Static role skill mapping improved structure, but its value declined when role requirements changed. The proposed framework achieved the strongest result because it measured demand change, internal skill supply movement, learning coverage, and role alignment together.

Table 5. Drift Detection Performance Across Methods

Method	**Precision**	**Recall**	**F1 Score**	**Detection Latency**
Manual taxonomy review	0.61	0.55	0.58	82 days
Keyword based matching	0.67	0.62	0.64	61 days
Static role skill mapping	0.73	0.69	0.71	45 days
Proposed skill graph drift framework	0.90	0.88	0.89	13 days

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The proposed framework achieved an F1 score of 0.89, which indicates a stronger balance between precision and recall. This result is important because a drift monitoring method must avoid two common problems. It should not create too many false alerts, and it should not miss meaningful changes that affect talent decisions. The framework also reduced detection latency from 82 days under manual review to 13 days. This improvement shows that drift measurement can identify changes earlier, allowing HR, learning, and workforce planning teams to respond before outdated skill relationships affect career or reskilling decisions.

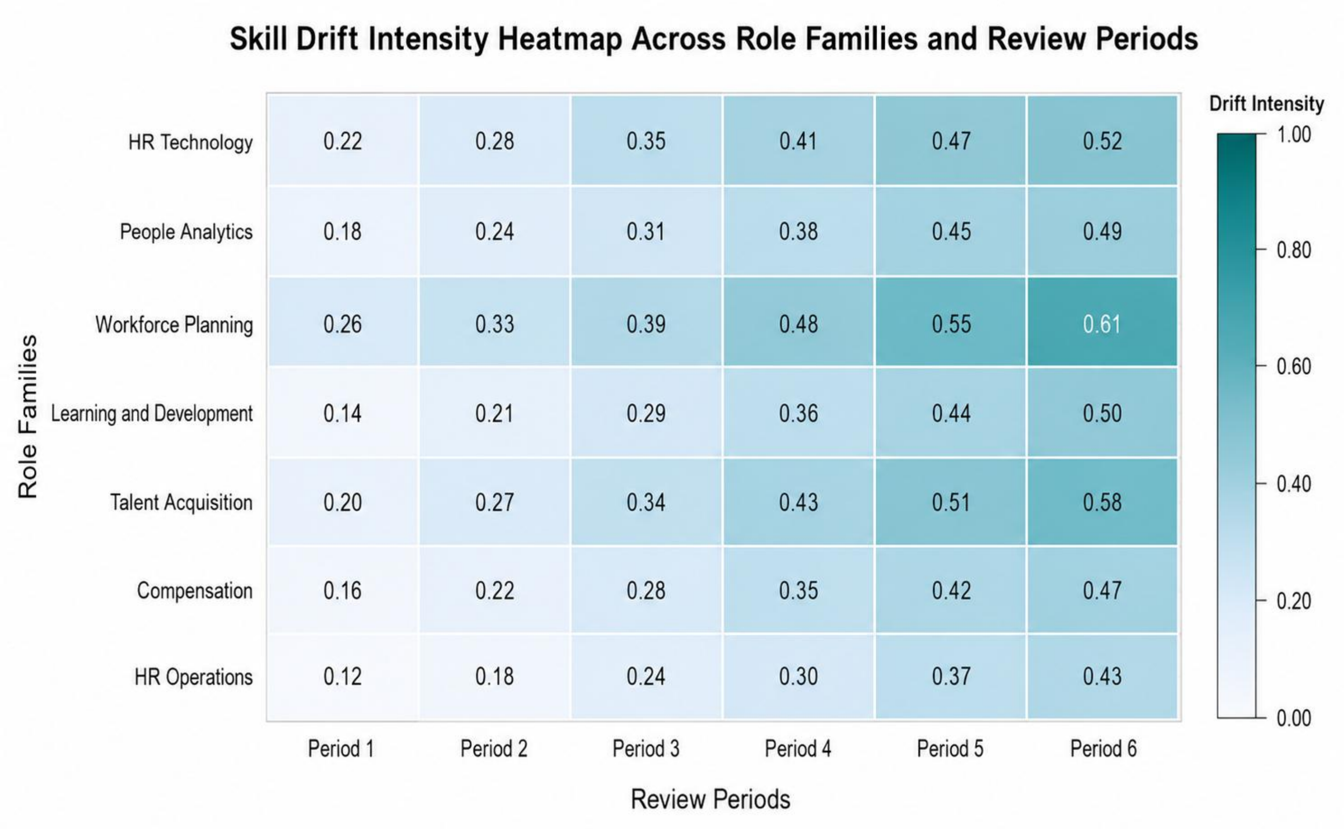

Figure 3: Skill Drift Intensity Heatmap Across Role Families and Review Periods

The second part of the evaluation focused on career mobility. The objective was to measure whether drift aware skill relationships improved the relevance of role recommendations. The results show that keyword based matching was useful for simple matches but did not perform well when employees had adjacent skills or when roles required related capabilities. Static role skill mapping provided a better structure but was less effective when role requirements changed during the review period. The proposed framework produced the strongest mobility performance because it used current role demand, employee skill supply, proficiency movement, and pathway stability.

Table 6. Career Mobility Recommendation Performance

Method	Precision@5	Precision@10	Recall@10	Mobility Acceptance Rate
Keyword based role matching	0.59	0.61	0.52	17%
Static role skill mapping	0.66	0.68	0.60	22%
Proposed skill graph drift framework	0.82	0.84	0.76	34%

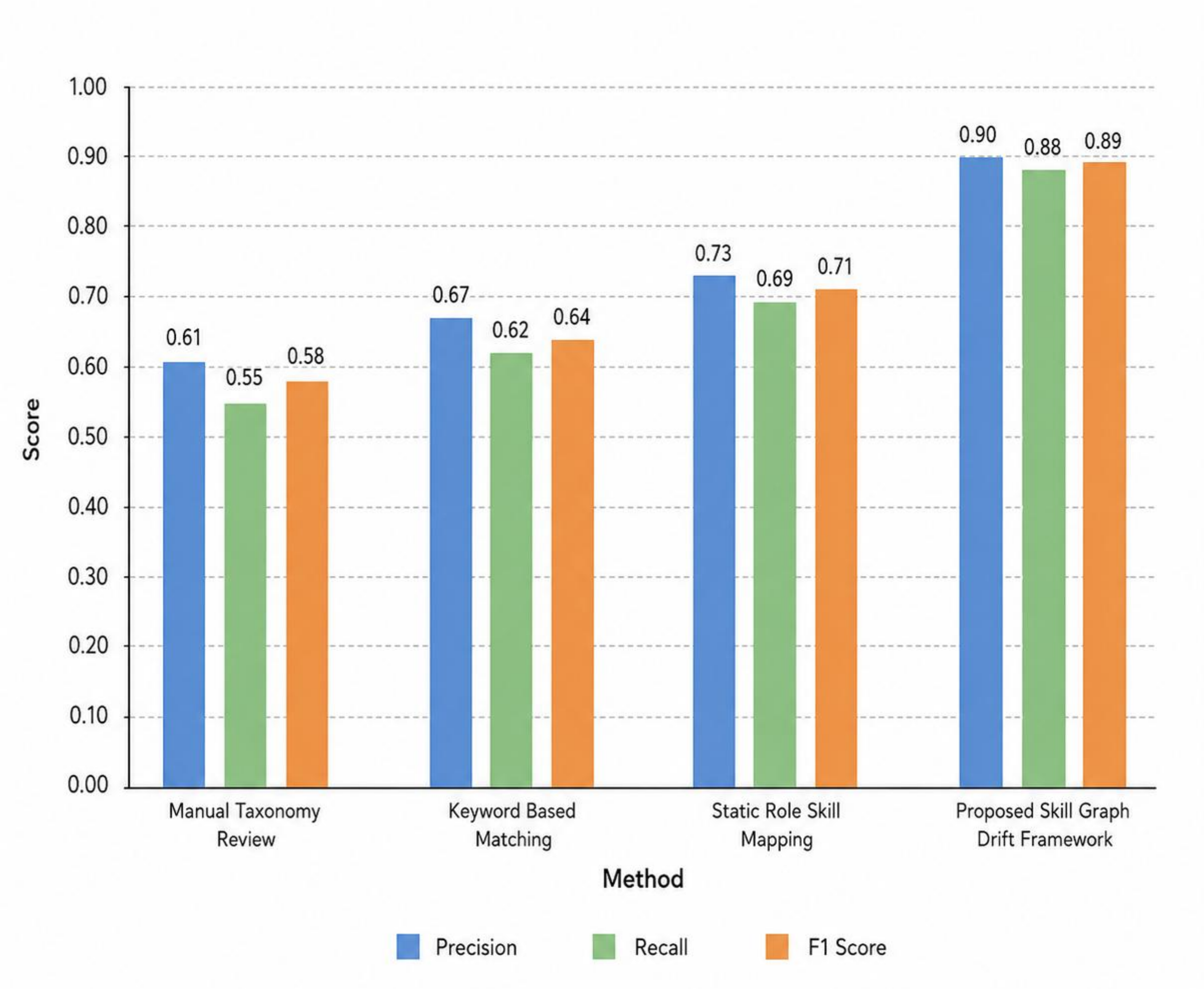

Figure 4: Comparative Drift Detection Performance Across Baseline and Proposed Methods

The career mobility results show that the proposed framework improved Precision@10 to 0.84, compared with 0.61 for keyword based matching and 0.68 for static role skill mapping. This means that employees received more relevant role recommendations when the model considered current skill drift rather than relying only on static mappings. The mobility acceptance rate also improved to 34%, suggesting that employees were more likely to engage with recommendations when those recommendations reflected updated role expectations and realistic skill pathways.

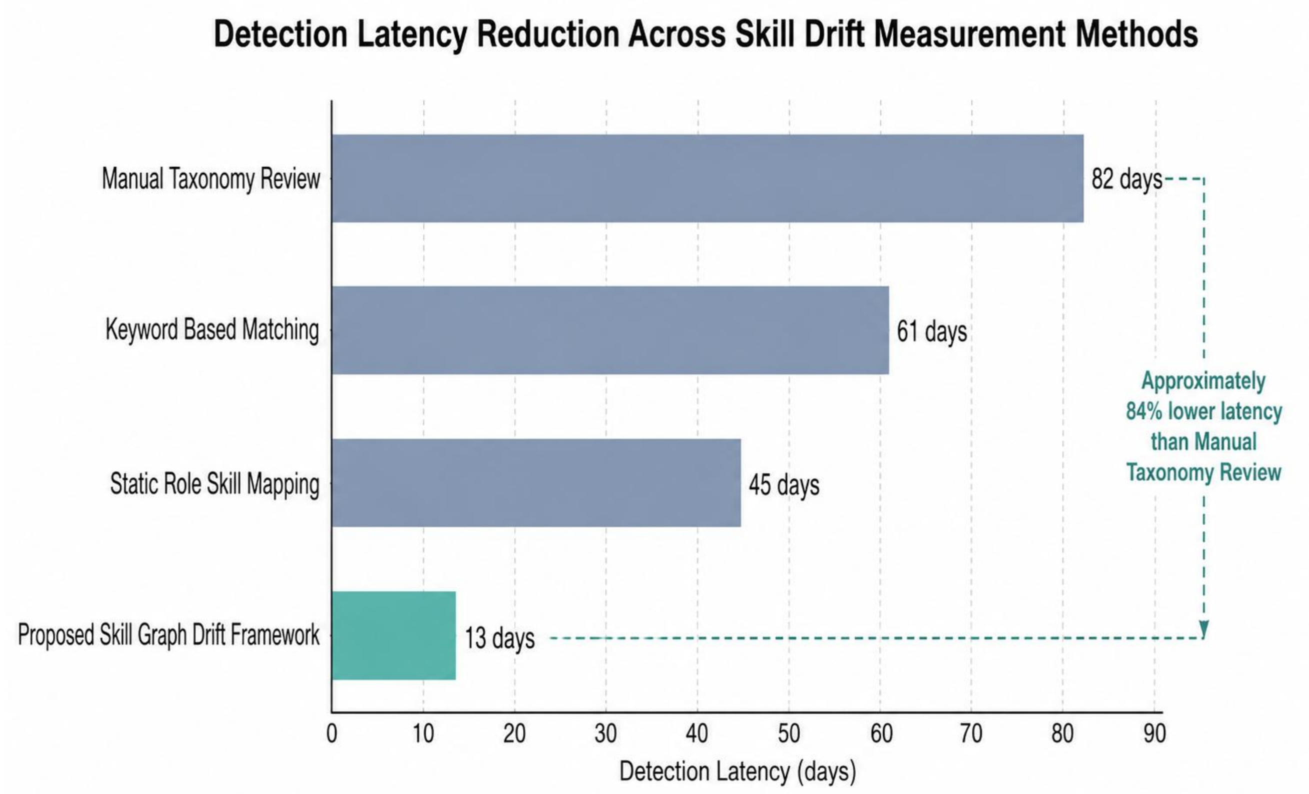

Figure 5: Detection Latency Reduction Across Skill Drift Measurement Methods

The third part of the evaluation measured workforce reskilling effectiveness. The purpose was to determine whether drift measurement helped identify better learning actions. A static learning catalog can show which courses are available, but it does not always show whether those courses support the skills that are becoming more important. The proposed framework improved this process by comparing skill demand with learning coverage and internal skill gaps.

Table 7. Workforce Reskilling and Learning Recommendation Results

Method	**NDCG@10**	**Learning Coverage Ratio**	**Skill Gap Closure Rate**	**Time to Skill Readiness**
Static learning catalog mapping	0.63	0.58	21%	94 days
Skill gap based recommendation	0.72	0.67	32%	71 days

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Proposed skill graph drift framework	0.87	0.81	46%	49 days

The proposed framework achieved an NDCG@10 value of 0.87, showing that learning recommendations were ranked more effectively. The learning coverage ratio improved to 0.81, which indicates stronger alignment between available learning content and current skill demand. Skill gap closure improved to 46%, compared with 21% for static catalog mapping. The time to skill readiness also decreased from 94 days to 49 days. These results suggest that drift aware learning alignment can help organizations reduce wasted training effort and focus reskilling activity on skills that have stronger business relevance.

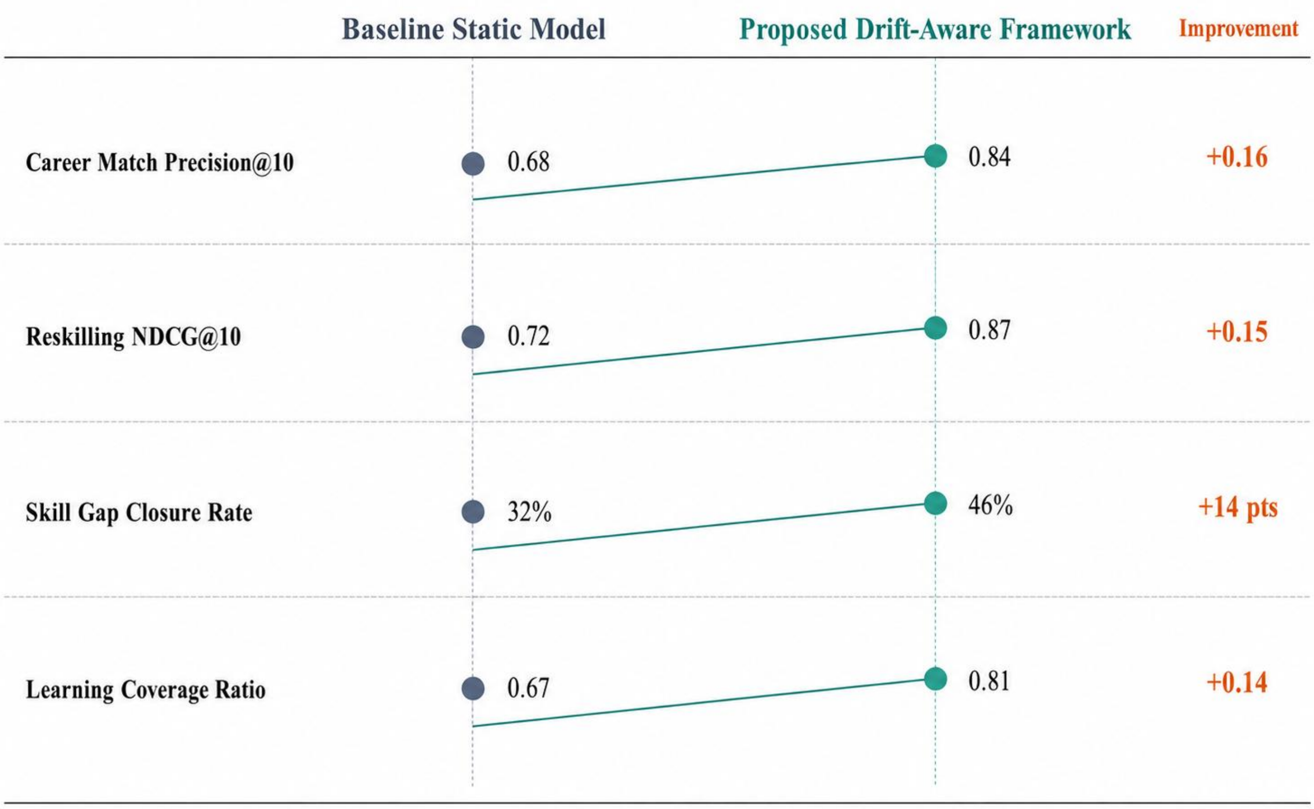

Figure 6: Career Mobility and Reskilling Outcome Improvement Under Drift-Aware Skill Graph Measurement

The results also show value from a governance perspective. Manual review remains necessary in many organizations, especially for role validation and policy decisions, but it is not efficient when every skill and role must be reviewed at the same level of attention. The proposed framework reduces this burden by identifying high drift areas that require immediate review. This allows governance teams to focus on roles, skills, and learning paths that have the highest risk of becoming outdated.

Overall, the results indicate that skill graph drift measurement can improve both analytical accuracy and practical decision making. The strongest improvement appears in areas where relationships change over time, such as role skill alignment, learning coverage, and internal mobility. Static methods can support initial implementation, but they are less effective when the organization needs to maintain skill relevance

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continuously. The proposed framework performs better because it treats the skill model as a changing structure that must be measured, reviewed, and corrected through governance.
The results support the central purpose of this study. Measuring skill graph drift can help organizations maintain a more reliable Talent Intelligence Hub by identifying where skill relationships are weakening. This improves the quality of career mobility recommendations, strengthens workforce reskilling decisions, and gives HR governance teams a clearer method for maintaining skills based talent data at scale.

9. Discussion

The findings show that skill graph drift measurement can improve the way organizations maintain skills based talent data in SAP SuccessFactors Talent Intelligence Hub. The main value of the proposed framework is not limited to higher model performance. Its broader value is the ability to make changes in skill relationships visible before they weaken career mobility, learning alignment, and workforce planning decisions. In a large organization, even a small delay in updating role skills, learning mappings, or employee capability profiles can affect many downstream decisions. The results suggest that drift measurement can reduce that delay by giving HR and talent teams a more focused view of where attention is needed.
The improvement in drift detection performance is important because skills based systems depend on trust. If employees receive role recommendations that do not match current requirements, they may lose confidence in the career mobility process. If managers see outdated skill gaps, they may not use the data for development planning. If learning teams continue to promote content that no longer supports business demand, training effort may increase without improving readiness. The proposed framework addresses this issue by measuring whether the relationships inside the skill graph remain current and useful.
The career mobility results show that drift aware role matching provides better outcomes than keyword based or static role skill approaches. This is expected because internal movement depends on more than matching skill names. A strong recommendation should consider current role expectations, required proficiency, employee capability, learning history, and pathway stability. When skill drift is ignored, the system may continue to recommend roles based on old assumptions. By including drift scores, the proposed framework improves the timing and relevance of career recommendations, which is especially important for organizations trying to increase internal hiring and reduce external recruitment dependency.
The reskilling results also show clear practical value. A learning catalog may contain many courses, but volume alone does not prove that employees can build the skills the business actually needs. The proposed framework helps distinguish between learning availability and learning usefulness. When a high demand skill has weak course coverage, the organization can treat it as a reskilling risk. When learning content is available but skill gap closure remains low, the issue may be content quality, wrong proficiency targeting, or weak alignment between course outcomes and role expectations. This gives learning teams a more evidence based way to improve development programs [23].
Another important finding is the reduction in manual governance effort. Manual review is still necessary because business owners and HR subject matter experts understand context that cannot be fully captured by metrics. However, reviewing every skill and role at the same level is not practical in a large enterprise. The framework does not remove human review. It makes reviews more targeted. High drift roles, high demand skills with low learning coverage, and unstable career pathways can be prioritized first. This creates a more efficient governance process and allows expert time to be used where it has the greatest value.
The proposed framework also supports better collaboration between functional and technical teams. SAP SuccessFactors administrators, HR business partners, learning teams, workforce planning teams, and role

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owners often work with different parts of the talent process. Skill graph drift measurement gives these teams a shared language. A drift score can show where a role profile needs revision, where learning content needs improvement, where employee skill data is incomplete, or where a career pathway has become less reliable. This shared measurement structure can reduce fragmented decision making and improve accountability.

From an implementation perspective, the results suggest that organizations should not treat Talent Intelligence Hub as a one time configuration activity. Skills based talent management requires ongoing maintenance. The skill graph should be reviewed as a living structure that changes with business needs, employee development, technology adoption, and role redesign. A quarterly or annual review cycle may still be useful, but it should be supported by continuous drift monitoring so that high risk changes can be identified earlier [24].

The discussion also highlights the need for responsible use of skill data. Drift scores should support decisions, not replace human judgment. A high drift score may indicate a need for review, but it should not automatically remove a skill, change a role profile, or alter an employee's career recommendation without validation. Organizations should use the framework as a governance aid that improves visibility, traceability, and decision quality. This is especially important when skill data influences employee development, mobility, and future opportunities.

Overall, the discussion confirms that skill graph drift measurement has practical value for organizations using SAP SuccessFactors Talent Intelligence Hub. The framework improves the reliability of skills based decisions by making hidden misalignment visible. It supports career mobility by keeping role recommendations current. It supports reskilling by linking learning actions to actual demand. It supports governance by helping teams prioritize review and correction. These outcomes make the proposed framework useful not only as an analytical model, but also as an operating discipline for maintaining a modern enterprise talent system.

10. Implementation Roadmap for Organizations

The proposed framework can be implemented as an extension of existing SAP SuccessFactors talent governance practices. It does not require organizations to redesign their entire talent architecture at once. A practical implementation begins by identifying where skills are maintained, how they are connected to roles and learning content, and which teams own the quality of those relationships. This is important because skill graph drift is not only a system issue. It is also an operating model issue that depends on ownership, review discipline, and consistent use of talent data.

The first step is to establish a skill governance structure. Organizations should define who owns skill libraries, role skill mappings, learning content alignment, career pathway maintenance, and workforce planning inputs. In many companies, these responsibilities are spread across HRIS, learning teams, talent management, business role owners, and workforce planning groups. Without clear ownership, drift signals may be identified but not corrected. A governance structure ensures that each drift category has a responsible team and a defined action path.

The second step is to map SAP SuccessFactors data sources to the skill graph model. Talent Intelligence Hub can serve as the central skill and attribute foundation, while Growth Portfolio, Job Profile Builder, Learning, Career Development, Recruiting, and Performance and Goals can provide supporting signals. Each source should be mapped to a graph entity or relationship. For example, employee skills can form employee to skill relationships, job profile requirements can form role to skill relationships, and learning items can form course to skill relationships. This mapping creates the foundation for measurable drift analysis.

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The third step is to create periodic skill graph snapshots. A snapshot represents the state of the skill graph at a specific review point. Monthly or quarterly snapshots are practical for most organizations, depending on the size of the workforce and the rate of role change. The purpose of the snapshot is to preserve the structure of skills, roles, learning content, and career pathways so that changes can be measured over time. This allows the organization to move from static reporting to trend based governance.
The fourth step is to calculate drift metrics and classify severity. The organization can start with a small set of core measures such as skill demand drift, role skill alignment drift, learning coverage ratio, and skill gap closure rate. Each metric should be assigned severity thresholds. Low drift can remain under observation. Moderate drift can be reviewed during the next governance cycle. High drift should trigger owner review. Critical drift should be escalated when it affects high demand roles, strategic skills, or important workforce segments.
The fifth step is to connect drift results to practical correction actions. A high role skill drift score may lead to a job profile review. A low learning coverage ratio may lead to course mapping updates or new learning content. A high skill demand score combined with low internal supply may lead to targeted reskilling or hiring decisions. A weak career pathway stability score may lead to review of internal mobility rules and readiness criteria. This action link is essential because the purpose of the framework is not only to measure change, but to improve the quality of talent decisions.
The final step is to monitor outcomes after action is taken. If a learning path is updated, the organization should measure whether skill gap closure improves. If role requirements are corrected, career match precision should improve. If employee profiles are refreshed, internal skill supply visibility should become more accurate. This feedback cycle helps the organization understand whether governance actions are producing measurable value.

Table 8.Implementation Roadmap for Skill Graph Drift Measurement in SAP SuccessFactors

Phase	**Activity**	**Primary Owner**	**Expected Output**
1	Define skill governance ownership	HR Governance and HRIS	Ownership model for skills, roles, learning, and career paths
2	Map SAP SuccessFactors data sources	SAP SuccessFactors team	Data to graph mapping structure
3	Normalize skill names and relationships	HRIS and Talent Management	Clean skill library with reduced duplication
4	Build skill graph snapshots	Workforce Analytics	Time based graph view of skills, roles, learning, and mobility
5	Calculate drift metrics	Analytics and HRIS	Drift scores by skill, role, and learning area

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6	Classify severity	Governance team	Low, moderate, high, and critical drift categories
7	Assign corrective actions	HR, Learning, and Business Owners	Role updates, learning improvements, and mobility refinements
8	Track post action outcomes	Workforce Planning	Improved skill gap closure, match quality, and governance traceability

This roadmap allows organizations to implement the framework gradually. A pilot can begin with one job family, one business unit, or one high priority skill group. Once the measurement logic is validated, the model can be extended across additional roles, functions, and learning areas. This phased approach is practical because large organizations often have uneven data quality across business units. Starting with a focused pilot allows the organization to refine thresholds, improve data mapping, and build confidence before wider adoption.

The implementation roadmap also gives the framework long term value. Skill graph drift measurement becomes a recurring governance practice rather than a one time analysis. Over time, the organization can build a stronger view of which skills are changing, which roles need review, which learning areas require investment, and which career pathways support realistic movement. This makes SAP SuccessFactors Talent Intelligence Hub more useful as a living talent foundation that supports career mobility, workforce reskilling, and skills based governance at scale.

11. Limitations, Future Research, and Conclusion

This study presents a practical framework for measuring skill graph drift in SAP SuccessFactors Talent Intelligence Hub, but its scope must be understood within certain limitations. The framework is designed around an SAP SuccessFactors aligned benchmark model rather than live customer tenant data. This approach protects employee privacy and allows repeatable evaluation, but actual results may vary across organizations depending on workforce size, data quality, role maturity, learning catalog structure, and the level of adoption of skills based processes. In a real enterprise environment, employee profiles may be incomplete, role skill mappings may differ across business units, and learning content may not always be consistently connected to skills. These conditions can influence the accuracy of drift measurement and should be addressed before large scale deployment.

Another limitation is that skill graph drift cannot be interpreted only through numerical scores. A high drift score can indicate meaningful change, but it does not always mean that the existing skill relationship is incorrect. In some cases, drift may reflect a healthy business change, such as a role becoming more advanced or a workforce gaining new capabilities through training. For this reason, the framework should support human review rather than replace it. Role owners, learning teams, HR business partners, and workforce planning teams must continue to validate drift signals before major changes are made to job profiles, learning paths, or career mobility rules.

The framework also depends on effective skill normalization. In large organizations, the same skill may appear under different names, or similar labels may carry different meanings across job families. For example, reporting, analytics, and workforce analytics may be treated as related terms in one function but as separate capabilities in another. If normalization is weak, the model may either overstate drift by treating

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similar skills as different or understate drift by merging skills that should remain distinct. This makes skill governance, naming standards, and review ownership essential parts of implementation.

Future research can extend this study by validating the framework using anonymized enterprise data from multiple industries. A cross industry study would help determine whether drift patterns differ across technology, healthcare, manufacturing, retail, financial services, and professional services environments. Future work can also compare drift behavior across job families, regions, and workforce segments to understand where skill relationships change fastest. This would improve the practical value of the framework for organizations that need to prioritize reskilling investment and career mobility programs.

Further research can also strengthen the evaluation of business outcomes. This paper focuses on drift detection, career match quality, learning recommendation relevance, skill gap closure, and governance efficiency. Future studies can extend the model to examine retention, internal fill rate, time to productivity, learning completion quality, succession readiness, and workforce planning accuracy. These measures would help organizations connect skill graph governance more directly to business performance.

The proposed framework may also be expanded by adding stronger validation controls for fairness, transparency, and explainability. Since skills based systems can influence employee development and career opportunities, organizations must ensure that drift based recommendations are not applied without review. Future work can explore governance rules that monitor whether career recommendations, learning assignments, and skill gap assessments remain consistent, explainable, and fair across employee groups. This would make skill graph drift measurement more suitable for responsible talent management at enterprise scale.

In conclusion, this paper defines skill graph drift as a measurable loss of alignment among employees, skills, roles, learning content, goals, and career pathways in SAP SuccessFactors Talent Intelligence Hub. The proposed framework shows how organizations can move beyond static skill libraries and periodic manual review by measuring how skill relationships change over time. By introducing drift metrics for demand movement, supply movement, role skill alignment, learning coverage, and skill gap closure, the study provides a structured method for identifying where talent data requires review and correction.

The main value of the framework is its ability to connect measurement with action. Skill drift scores can help organizations identify outdated role profiles, weak learning coverage, unstable career pathways, and emerging reskilling priorities. This allows HR, learning, workforce planning, and SAP SuccessFactors teams to focus governance effort where it has the greatest business impact. The framework does not replace human judgment, but it gives decision makers clearer evidence for maintaining the quality of skills based talent data.

Overall, the study contributes a practical and implementation oriented approach for improving career mobility, workforce reskilling, and skills based talent governance. It positions Talent Intelligence Hub as more than a repository of skills and attributes. With structured drift measurement, it can become a continuously monitored talent foundation that supports better workforce decisions, more relevant learning investment, and stronger internal mobility outcomes. For large organizations, this approach offers a disciplined way to keep skills based talent models current, reliable, and aligned with changing business needs.

REFERENCES:

1. Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state of the art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering, 17*(6), 734–749. https://doi.org/10.1109/TKDE.2005.99

2. Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: Why HR is set to fail the big data challenge. *Human Resource Management Journal, 26*(1), 1–11. https://doi.org/10.1111/1748-8583.12090
3. Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics, 118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801
4. Bhattacharya, M., Gibson, D. E., & Doty, D. H. (2005). The effects of flexibility in employee skills, employee behaviors, and human resource practices on firm performance. *Journal of Management, 31*(4), 622–640. https://doi.org/10.1177/0149206304272347
5. Bondarouk, T. V., & Ruël, H. J. M. (2009). Electronic human resource management: Challenges in the digital era. *The International Journal of Human Resource Management, 20*(3), 505–514. https://doi.org/10.1080/09585190802707235
6. Collings, D. G., & Mellahi, K. (2009). Strategic talent management: A review and research agenda. *Human Resource Management Review, 19*(4), 304–313. https://doi.org/10.1016/j.hrmr.2009.04.001
7. De Vos, A., De Hauw, S., & Van der Heijden, B. I. J. M. (2011). Competency development and career success: The mediating role of employability. *Journal of Vocational Behavior, 79*(2), 438–447. https://doi.org/10.1016/j.jvb.2011.05.010
8. Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics, 132*(4), 1593–1640. https://doi.org/10.1093/qje/qjx022
9. Dries, N. (2013). The psychology of talent management: A review and research agenda. *Human Resource Management Review, 23*(4), 272–285. https://doi.org/10.1016/j.hrmr.2013.05.001
10. Forrier, A., Sels, L., & Stynen, D. (2009). Career mobility at the intersection between agent and structure: A conceptual model. *Journal of Occupational and Organizational Psychology, 82*(4), 739–759. https://doi.org/10.1348/096317909X470933
11. Fugate, M., Kinicki, A. J., & Ashforth, B. E. (2004). Employability: A psycho-social construct, its dimensions, and applications. *Journal of Vocational Behavior, 65*(1), 14–38. https://doi.org/10.1016/j.jvb.2003.10.005
12. Gama, J., Žliobaitė, I., Bifet, A., Pechenizkiy, M., & Bouchachia, A. (2014). A survey on concept drift adaptation. *ACM Computing Surveys, 46*(4), Article 44. https://doi.org/10.1145/2523813
13. Goyal, P., & Ferrara, E. (2018). Graph embedding techniques, applications, and performance: A survey. *Knowledge-Based Systems, 151*, 78–94. https://doi.org/10.1016/j.knosys.2018.03.022
14. Hogan, A., Blomqvist, E., Cochez, M., d'Amato, C., de Melo, G., Gutiérrez, C., Labra Gayo, J. E., Kirrane, S., Neumaier, S., Polleres, A., Navigli, R., Ngonga Ngomo, A. C., Rashid, S. M., Rula, A., Schmelzeisen, L., Sequeda, J., Staab, S., & Zimmermann, A. (2021). Knowledge graphs. *ACM Computing Surveys, 54*(4), 1–37. https://doi.org/10.1145/3447772
15. Jiang, K., Lepak, D. P., Hu, J., & Baer, J. C. (2012). How does human resource management influence organizational outcomes? A meta-analytic investigation of mediating mechanisms. *Academy of Management Journal, 55*(6), 1264–1294. https://doi.org/10.5465/amj.2011.0088
16. Klinkenberg, R. (2004). Learning drifting concepts: Example selection versus example weighting. *Intelligent Data Analysis, 8*(3), 281–300. https://doi.org/10.3233/IDA-2004-8305
17. Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix factorization techniques for recommender systems. *Computer, 42*(8), 30–37. https://doi.org/10.1109/MC.2009.263

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editor@aijmr.com

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CrossRef DOI: 10.62127/aijmr.2026.v01i01.1359

18. Levenson, A. (2018). Using workforce analytics to improve strategy execution. *Human Resource Management, 57*(3), 685–700. https://doi.org/10.1002/hrm.21850
19. Lu, J., Liu, A., Dong, F., Gu, F., Gama, J., & Zhang, G. (2019). Learning under concept drift: A review. *IEEE Transactions on Knowledge and Data Engineering, 31*(12), 2346–2363. https://doi.org/10.1109/TKDE.2018.2876857
20. Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR analytics. *The International Journal of Human Resource Management, 28*(1), 3–26. https://doi.org/10.1080/09585192.2016.1244699
21. Minbaeva, D. B. (2018). Building credible human capital analytics for organizational competitive advantage. *Human Resource Management, 57*(3), 701–713. https://doi.org/10.1002/hrm.21848
22. Nickel, M., Murphy, K., Tresp, V., & Gabrilovich, E. (2016). A review of relational machine learning for knowledge graphs. *Proceedings of the IEEE, 104*(1), 11–33. https://doi.org/10.1109/JPROC.2015.2483592
23. Paulheim, H. (2017). Knowledge graph refinement: A survey of approaches and evaluation methods. *Semantic Web, 8*(3), 489–508. https://doi.org/10.3233/SW-160218
24. Stone, D. L., Deadrick, D. L., Lukaszewski, K. M., & Johnson, R. D. (2015). The influence of technology on the future of human resource management. *Human Resource Management Review, 25*(2), 216–231. https://doi.org/10.1016/j.hrmr.2015.01.002