How Skill Demand Is Changing — And What Comes Next

A Skill-Level View of Data & IT Skill Demand Dynamics (2015–2027)

Author: Ezequiel Rios

Project Description

Problem Statement

Data & IT labour markets have undergone profound transformation over the past decade, with the pace of change accelerating markedly after 2020. Advances in technology, increased digitalization, and shifts in organizational operating models have altered not only which roles are in demand, but more fundamentally, which skills employers require.

In this environment, organizations increasingly struggle to distinguish between skills that are becoming strategically critical, those that remain foundational, and those whose relevance is declining. Traditional labour market analyses, which often focus on job titles or occupations, tend to obscure these dynamics by aggregating heterogeneous skill requirements under static role definitions.

This limitation reduces the ability of organizations, policymakers, and educators to anticipate workforce needs and to design effective hiring, upskilling, and reskilling strategies.

This project addresses that gap by shifting the unit of analysis from jobs to skills. It examines how skill demand has evolved over time, identifies a structural break in demand dynamics after 2020, and differentiates between skills that are emerging, accelerating, persistent, or declining. Rather than relying on predictive forecasting models, the analysis adopts a forward-looking, scenario-based approach grounded in observed historical trends.

This analysis focuses specifically on skill demand within data-related and technology-oriented roles, based on job postings associated with data science, analytics, machine learning, and closely related technical functions. It does not aim to represent the full labour market across all occupations, but rather a high-change segment where skill dynamics are most pronounced.

This project examines the evolution of skill demand within data-related and technology-oriented roles, using job postings to analyse how required capabilities have changed between 2015 and 2024.

Project Objectives

The objectives of this project are to:

• Analyze the evolution of skill demand between 2015 and 2024 using job posting data
• Identify a structural break in skill demand dynamics after 2020
• Classify skills based on their observed demand trajectories over time
• Extend recent post-2020 trends (2022–2024) into plausible forward-looking scenarios for 2025–2027, without relying on hard forecasting

The overarching goal is to provide interpretable, evidence-based insights that support workforce planning, talent strategy, and skills development decisions in a rapidly changing labour market.

Potential Impact

The insights generated by this analysis can support decision-making across multiple domains:

• Workforce planning and talent strategy, by identifying skills that are likely to remain strategically relevant in the near term

• Upskilling and reskilling initiatives, by distinguishing emerging and accelerating skills from those showing signs of decline

• Policy and education alignment, by highlighting shifts in skill demand at a granular level rather than relying on occupation-based signals

By focusing on skills rather than job titles, the analysis provides a more flexible and forward-looking perspective on labour market dynamics.

Datasets Used

The datasets used in this project primarily capture skill demand in data and technology-related roles and are selected to support skill-level analysis within this domain.

- Job Postings Dataset (Skill Demand)

  Source: Hugging Face Datasets Hub
  Dataset: Data Science Job Postings (Naukri)
  Original Platform: Naukri.com (India)
  License: Open Data (as documented on Hugging Face)

This dataset contains job postings for data-related roles collected from the Naukri job portal. It includes job identifiers, posting dates, job descriptions, and extracted skill tags.

This dataset contains job postings for data-related roles collected from the Naukri job portal. After normalization, the dataset contains 105,320 skill–year observations covering 6,761 unique skills. It includes job identifiers, posting dates, job descriptions, and extracted skill tags.

The dataset serves as the primary source for analyzing historical skill demand. Skills are normalized into a canonical skill-level structure (jobId | year | skill), which forms the foundation for all temporal, comparative, and forward-looking analyses in this project.

- O*NET Skills Database

  Source: U.S. Department of Labor – O*NET Resource Center
  License: Public Domain

The O*NET database is used as a taxonomy and interpretation layer rather than as a direct measure of demand. It provides a standardized framework for skill definitions, supporting structured comparison and contextual interpretation of skills extracted from job postings.

- Eurostat Labour Market Data

Source: Eurostat Data Explorer (European Commission)
License: European Union Open Data Licence

Eurostat employment data is used to provide historical labour market context within the European Union. These indicators support interpretation of broader employment dynamics alongside observed skill demand trends.

- U.S. Bureau of Labor Statistics (BLS) – OEWS

  Source: U.S. Bureau of Labor Statistics
  License: Public / Open Data

BLS Occupational Employment and Wage Statistics are included as a structural reference snapshot for the U.S. labour market, providing context on employment scale and wage structure within a major global economy.

Analytical Approach (High-Level)

- Skill-level analysis rather than occupation-level analysis
- Longitudinal time-series analysis covering 2015–2024
- Identification of post-2020 structural shifts in skill demand
- Classification of skills into:
  - Emerging
  - Accelerating
  - Persistent
  - Sunsetting

Scenario-based forward-looking extension to 2025–2027 without predictive modeling.

Executive Summary

Data & IT labour markets are undergoing a profound transformation driven by technological change, digitalization, and evolving organizational needs. While these shifts are often discussed at the level of jobs or occupations, such perspectives can obscure more granular and actionable changes occurring at the skill level. As a result, organizations and policymakers increasingly struggle to identify which skills are becoming strategically relevant, which remain foundational, and which are losing importance over time.

This project adopts a skill-level perspective to analyze how skill demand has evolved between 2015 and 2024, using job postings as a proxy for employer demand. By transforming job postings into a normalized skill-level dataset and contextualizing findings with selected labour market indicators, the analysis provides a detailed view of how the skill landscape has changed over the past decade.

A central finding of the analysis is the presence of a clear structural break in skill demand dynamics after 2020. The post-2020 period is characterized not only by a sharp increase in the volume of demanded skills, but also by a rapid expansion in skill diversity. This combination indicates a qualitative shift in how skills are defined and combined in the labour market, rather than a simple continuation of pre-existing trends.

Building on this structural break, skills are classified into distinct regimes based on their observed demand patterns. A large group of skills emerges only after 2020, reflecting the adoption of new tools, platforms, and practices. At the same time, a smaller but stable core of persistent skills continues to anchor labour demand across periods, while a limited set of skills shows declining relevance in the post-2020 landscape.

Rather than relying on predictive forecasting, the project adopts a scenario-based forward-looking approach grounded in recent demand trajectories observed between 2022 and 2024. These trajectories are extended qualitatively into plausible scenarios for 2025–2027, distinguishing emerging and accelerating skills from mature, uncertain, and sunsetting ones. This approach prioritizes interpretability and analytical honesty over numerical precision.

Overall, the analysis highlights that future-relevant skills are shaped less by gradual evolution and more by rapid reconfiguration following systemic change. By focusing on skills rather than job titles, the project provides evidence-based insights that can support workforce planning, talent strategy, and skills development decisions in an increasingly dynamic labour market.

Key Takeaways

• Skill demand has shifted structurally after 2020, showing a clear break from pre-2020 patterns. The post-2020 period is characterized by simultaneous growth in both the volume and diversity of demanded skills, indicating a qualitative reconfiguration of labour market needs rather than incremental change.

• The majority of future-relevant skills are not long-established ones, but skills that emerge or accelerate only after 2020. This highlights the limits of relying exclusively on historical dominance when designing hiring or training strategies.

• A relatively small core of skills remains persistent across time, continuing to anchor labour demand despite rapid change. These foundational skills provide stability but no longer define the full skill profile required for many roles.

• Forward-looking insights can be generated without hard forecasting by extending recent, observed demand trajectories. Scenario-based approaches grounded in empirical momentum offer a more interpretable and responsible alternative to predictive models in volatile skill environments.

• Analysing labour markets at the skill level, rather than at the level of job titles or occupations, reveals patterns that are otherwise obscured and enables more flexible, adaptive workforce planning in the face of ongoing structural change.

Building a Skill-Level View of Data & IT Demand

Understanding changes in labour demand requires shifting the unit of analysis from job titles to skills. Job titles evolve slowly and often mask meaningful changes in the capabilities employers actually seek. By contrast, skills provide a more granular and flexible lens through which labour market dynamics can be observed.

This project adopts a skill-level perspective by combining job posting data with selected labour market indicators that provide structural context. The focus of this section is not only to describe the data used, but to explain the analytical choices that shape how skill demand is measured and interpreted throughout the analysis.

Skill Demand from Job Postings

Job postings serve as the primary source of skill demand in this project. They capture the skills employers explicitly request at the moment of hiring, offering a timely signal of changing labour market needs that traditional statistics often lag behind.

The job posting data used in this analysis was sourced from the Hugging Face Datasets Hub (Data Science Job Postings – Naukri), originally collected from the Naukri job portal in India. The dataset includes job identifiers, posting dates, and extracted skill tags, enabling a longitudinal analysis of skill demand over time.

While job postings do not represent the entire labour market, they provide a uniquely detailed view of how required skills evolve, particularly in fast-changing technical and analytical roles.

Constructing a Canonical Skill-Level Dataset

To support consistent analysis across time, raw job postings were transformed into a normalized skill-level dataset. Each job posting was decomposed into individual skill mentions and represented in a canonical structure:

jobId | year | skill

Several design decisions underpin this transformation. Skill text was normalized conservatively to preserve the original signal of market demand, avoiding aggressive semantic consolidation or fuzzy matching. Duplicate skill mentions within the same job posting and year were removed to prevent overrepresentation, ensuring that each skill contributes equally to demand counts.

These choices reflect a deliberate trade-off: prioritizing transparency and interpretability over maximum compression of the skill space. As a result, observed changes in skill demand remain closely tied to how employers describe their requirements.

Labour Market Context (Macro Indicators)

In addition to job postings, selected labour market indicators are used to contextualize the analysis. Data from Eurostat, the U.S. Bureau of Labor Statistics, and the OECD provide macro-level information on employment structure, workforce size, and labour market conditions across regions. These indicators provide macro context and do not change the project's core scope: Data & IT skill demand measured from job postings.

Importantly, these datasets are not used to infer skill demand directly. Instead, they offer structural context that helps situate observed changes in skill demand within broader labour market dynamics, avoiding interpretations that rely solely on job posting data.

Why This Perspective Matters

By centering the analysis on skills rather than occupations, this project captures both the expansion and the fragmentation of labour demand observed over the past decade. The resulting skill-level view enables the identification of emerging, persistent, and declining skills, and forms the foundation for the forward-looking scenarios developed later in the analysis.

How Skill Demand Changed Over Time (2015–2024)

The evolution of skill demand over the past decade reveals more than a gradual shift in employer requirements. When examined at the skill level, the data shows a profound transformation in both the scale and the diversity of demanded skills, particularly in the years following 2020.

This section presents a longitudinal view of skill demand from 2015 to 2024, focusing on two fundamental dimensions:
(1) the overall volume of skill demand, and
(2) the breadth of skills requested by employers.

Growth in Skill Demand Volume

Between 2015 and 2024, the total number of skills mentions extracted from job postings increased dramatically. While early years show relatively limited activity, the post-2020 period is characterized by a sharp acceleration in the volume of skills requested.

This increase is not driven by a small number of roles becoming more verbose in their descriptions. Instead, it reflects a broader expansion in the number of skills explicitly required across job postings. By 2024, the volume of skill demand is an order of magnitude higher than in the pre-2020 period.

Crucially, this trend remains robust after controlling for data preparation choices. Each skill is counted at most once per job posting and year, preventing artificial inflation due to repeated mentions within individual postings. As a result, the observed growth reflects genuine changes in employer requirements rather than artifacts of job description length or formatting.

Expansion in Skill Diversity

Alongside growth in volume, the diversity of skills demanded by employers has expanded significantly. The number of unique skills appearing in job postings increases steadily from 2015 onward, with a pronounced acceleration after 2020.

This expansion indicates that labour demand is not simply intensifying around a fixed set of core competencies. Instead, employers are drawing from a broader and more heterogeneous skill landscape, incorporating new technical, analytical, and operational capabilities into their requirements.

The rise in skill diversity suggests increasing specialization and hybridization of roles. Positions that were previously defined by a narrow skill set now often combine competencies across domains, reinforcing the importance of analyzing labour demand at the skill level rather than relying solely on job titles or occupational categories.

Early Signals of Structural Change

While gradual growth is visible throughout the late 2010s, the post-2020 period stands out as qualitatively different rather than merely an extension of prior trends. The simultaneous surge in both the volume and diversity of skills marks the emergence of a new regime in skill demand dynamics.

This observation motivates the analytical distinction between the pre-2020 period (2015–2019) and the post-2020 period (2020–2024) used throughout the remainder of the project. Rather than assuming 2020 as a turning point by convention, the split is grounded in clear empirical changes observed in the data.

The following sections build on this foundation to examine how skill demand reorganizes after this structural break, identifying which skills emerge, which persist, and which lose relevance over time.

A Structural Break After 2020

The changes observed in skill demand over time are not evenly distributed across the 2015–2024 period. While the second half of the 2010s shows gradual growth, the years following 2020 exhibit a markedly different pattern. This shift is not limited to an increase in scale; it reflects a structural break in how skills are demanded and combined in the labour market.

This section formalizes that break and explains why the post-2020 period is treated separately in the remainder of the analysis.

Skill Demand Expansion Without Concentration

While total skill demand expands dramatically after 2020, this growth is not accompanied by a corresponding increase in concentration. The share of total demand captured by the top 10 and top 20 skills remains remarkably stable across periods, with only marginal variation.

At the same time, the number of unique skills increases more than ninefold between the pre-2020 and post-2020 periods. This combination indicates that post-2020 growth is driven primarily by the introduction of new, peripheral skills rather than by an intensification of demand for an existing core set.

In structural terms, the labour market is expanding horizontally rather than vertically. A stable core of foundational skills continues to anchor demand, but the surrounding skill landscape becomes significantly more fragmented. This pattern reflects increasing specialization, tool proliferation, and hybrid skill requirements, rather than consolidation around dominant competencies.

Evidence of a Structural Shift

Two empirical signals jointly support the existence of a structural break after 2020.

First, the volume of skill demand increases sharply. The number of distinct skill mentions extracted from job postings grows at a pace that exceeds trends observed in prior years. This acceleration persists even after accounting for data preparation choices designed to avoid artificial inflation, such as deduplicating skill mentions within individual job postings.

Second, the diversity of demanded skills expands simultaneously. Rather than concentrating demand around a stable set of core skills, the post-2020 period introduces a large number of previously unseen skills. This expansion suggests that labour demand is reorganizing, with roles increasingly combining new tools, platforms, and competencies.

The concurrence of these two dynamics—scale and diversity—indicates a qualitative change in skill demand, not merely a continuation of pre-existing trends.

Why 2020 Marks a Turning Point

The analytical distinction between the pre-2020 period (2015–2019) and the post-2020 period (2020–2024) is grounded in observed data patterns rather than external assumptions. While 2020 is often treated as a special year by convention, this project does not assume its importance a priori.

Instead, the data itself motivates the split. Prior to 2020, changes in skill demand are incremental and relatively stable. After 2020, the skill landscape becomes more volatile, more fragmented, and more dynamic. New skills appear at scale, while others rapidly gain or lose relevance.

This behaviour is inconsistent with a smooth, linear evolution of labour demand and is better understood as a regime shift in how skills are defined, valued, and combined by employers.

Analytical Implications of the Break

Recognizing this structural break has important implications for analysis. Treating the entire 2015–2024 period as homogeneous would obscure meaningful differences between earlier and later dynamics, potentially conflating slow-moving trends with rapid post-2020 reconfiguration.

For this reason, subsequent analyses explicitly compare skill demand across the two periods. This enables a clear distinction between skills that persist across regimes, skills that emerge only after the break, and skills whose relevance diminishes in the post-2020 landscape.

This framework provides the foundation for classifying skills based on their demand trajectories and for constructing forward-looking scenarios grounded in recent behaviour.

From Structural Break to Skill Regimes

The identification of a structural break after 2020 reframes the core question of the analysis. Rather than asking whether skill demand is increasing, the focus shifts to how different skills respond to the new regime.

The following section builds on this insight by categorizing skills into distinct regimes—emerging, persistent, and fading—based on their presence and evolution before and after the post-2020 break.

Emerging, Accelerating, and Fading Skills

The structural break identified after 2020 raises a central question: how do individual skills behave under this new regime? Rather than treating skill demand as a single aggregate trend, this section differentiates skills based on their presence and evolution before and after the post-2020 shift.

By examining how skills appear, persist, or disappear across periods, the analysis identifies distinct regimes of skill demand that characterize the current labour market landscape.

Skill Persistence and Volatility

Beyond identifying which skills emerge or disappear across periods, it is critical to understand how long skills remain relevant once they appear. To capture this dimension, skill persistence was

measured as the number of distinct years in which each skill appears in job postings.
Only **8.58%** of skills persist across the structural break, while **89.35%** are classified as emerging, indicating a highly volatile and long-tailed skill distribution
The majority of emerging skills exhibit very short lifespans, often appearing for only a single year, while persistent skills represent a small minority of the skill space (**8.58%**)
This pattern becomes even more pronounced when comparing pre-2020 and post-2020 cohorts. Skills that first appear after 2020 exhibit substantially lower persistence, typically remaining active for fewer years than those introduced earlier. In contrast, skills originating in the pre-2020 period show longer active spans and greater continuity over time.
These findings suggest that recent growth in skill demand is driven less by the accumulation of durable capabilities and more by rapid experimentation, tool turnover, and short-lived technological adoption. While a stable core of foundational skills continues to anchor labour demand, the post-2020 environment is characterized by increased volatility and reduced skill longevity.
From a strategic perspective, this implies that organizations face a dual challenge: maintaining long-term capabilities built around persistent skills, while simultaneously adapting to a fast-moving layer of transient competencies that may not sustain long-term relevance.

Skill Demand Concentration and Core Fragility

The rapid expansion in the number of demanded skills raises an important question: whether labour market demand has become more evenly distributed across skills, or whether it remains concentrated around a relatively small core.
To examine this, skill demand concentration was measured by calculating the share of total skill mentions accounted for by the top 10 and top 20 most demanded skills in each period.
Despite a nearly tenfold increase in the number of unique skills after 2020, concentration levels remain remarkably stable. In the pre-2020 period, the top 10 skills account for approximately 17 percent of total demand, while the top 20 represent around 24 percent. In the post-2020 period, these shares remain at comparable levels, with the top 20 skills accounting for an even slightly larger share of total demand.
This indicates that growth in skill diversity has not been accompanied by a proportional dispersion of demand. Instead, the labour market combines a stable concentration of demand around a small core of highly dominant skills with a rapidly expanding long tail of low-frequency and often short-lived skills.

From an analytical perspective, this reveals a form of core fragility. While a small set of skills continues to anchor labour demand, the surrounding skill ecosystem is increasingly fragmented and volatile. Organizations therefore face a labour market in which strategic capability remains concentrated, even as the surface complexity of skill requirements grows.

Defining Skill Regimes

Skills are classified into three primary regimes using explicit, rule-based criteria derived from observed demand patterns:

Emerging skills: skills that appear only after 2020 and were absent from job postings in the pre-2020 period.

Persistent skills: skills that are present both before and after 2020, maintaining relevance across regimes.

Fading skills: skills that appear in the pre-2020 period but disappear from job postings after 2020.

This classification is intentionally mechanical. Skills are assigned to regimes based solely on their empirical presence in each period, avoiding subjective judgments or semantic grouping.

Emerging Skills: Signals of a New Regime

Emerging skills constitute the largest group identified in the analysis. These skills were not present in job postings between 2015 and 2019 but appear at scale in the post-2020 period.

The size of this group highlights the extent to which the skill landscape has been reshaped. Many emerging skills are associated with modern data infrastructures, cloud platforms, machine learning frameworks, and orchestration tools, reflecting changes in how organizations build, deploy, and scale analytical capabilities.

The emergence of these skills suggests that the post-2020 labour market is not merely demanding more of the same competencies, but actively incorporating new tools and practices into standard job requirements.

Persistent Skills: The Stable Core

Persistent skills form a comparatively smaller but highly significant group. These skills appear consistently across both pre- and post-2020 periods, indicating their role as foundational competencies that remain relevant despite broader changes in the skill landscape.

Examples include general programming, data analysis, and core analytical concepts. Their persistence underscores the fact that while the skill environment is expanding and diversifying, certain competencies continue to anchor labour demand.

This stable core provides continuity across regimes, offering insight into which skills retain long-term value even as new ones emerge.

Fading Skills: Declining Relevance

A third group of skills appears in job postings prior to 2020 but disappears in the post-2020 period. These fading skills represent competencies whose relevance diminishes under the new regime.

In many cases, these skills are more narrowly defined, role-specific, or tied to legacy systems and practices. Their disappearance does not necessarily imply obsolescence across the entire economy, but it does signal a reduced presence in the types of roles captured by the job posting data.

Interpreting Skill Regimes

Together, these three regimes reveal a labour market that is simultaneously expanding and reorganizing. The dominance of emerging skills points to rapid innovation and tool adoption, while the persistence of a stable core highlights the enduring importance of fundamental competencies.

This regime-based view of skill demand moves beyond simple rankings and provides a structured way to understand how the skill landscape adapts to systemic change.

From Regimes to Trajectories

While regime classification captures whether skills appear or persist across periods, it does not capture how quickly demand for those skills is changing. The next section extends this analysis by examining recent demand trajectories and constructing forward-looking scenarios based on observed post-2020 dynamics.

Core vs Long-Tail Skill Demand

To assess whether rising skill demand is driven by a small set of dominant skills or by broader diversification, skill mentions were split into a “core” group (top 20 skills per period) and a long tail comprising all remaining skills.

Across both periods, the long tail accounts for the majority of total skill mentions, indicating that demand growth is driven primarily by expansion at the margins rather than consolidation around a narrow core. While the share of core skills increases slightly after 2020, this change is marginal relative to the overall expansion in demand. The core remains stable, but it does not absorb the majority of post-2020 growth.

This pattern indicates that recent increases in skill demand are driven primarily by expansion at the margins rather than consolidation around a narrow skill set. Employers are not converging on a fixed bundle of standardized skills; instead, they are drawing from an increasingly diverse and specialized pool of capabilities.

From a labour market perspective, this reinforces the view that post-2020 dynamics reflect fragmentation and recombination of skills rather than simple scaling of existing competencies.

Long-Tail Depth and Structural Fragmentation

Analyzing the depth of the long tail reveals that skill demand is not only diverse, but highly fragmented. 51.45% of all skills appear only once in the dataset, and 71.61% appear three times or fewer. This indicates that the majority of skills demanded by employers are highly transient rather than recurrent.

At the same time, the long tail is not composed exclusively of one-off mentions. A non-trivial middle layer of skills (23.57%) appears between 4 and 50 times, suggesting the presence of semistable competencies that gain traction without becoming part of the dominant core. Only a small fraction of skills reaches high-frequency levels, reinforcing the idea that labour demand is anchored by a limited core while continuously experimenting at the margins.

Importantly, this structure remains consistent across periods, even as total demand increases sharply after 2020. Rather than collapsing the long tail into the core, growth extends the tail further—indicating increasing specialization, tool turnover, and role fragmentation.

From Long-Tail Depth to Forward-Looking Skill Scenarios

The observed depth of the skill demand long tail has direct implications for how future skill relevance should be interpreted. A labour market dominated by transient, low-frequency skills is not well suited to traditional forecasting approaches based on trend extrapolation or stable rankings.

Instead, the structure revealed by the data suggests a regime in which skills continuously enter, compete, and exit the demand landscape. In such an environment, forward-looking analysis must focus less on predicting specific outcomes and more on identifying patterns of momentum, stability, and decay.

For this reason, the forward-looking component of this project adopts a scenario-based approach grounded in observed post-2020 trajectories. By combining evidence of high volatility, limited persistence, and a deep long tail of experimental skills, the analysis distinguishes between emerging, accelerating, mature, uncertain, and sunsetting skills without claiming deterministic forecasts.

Observed Skill Transition Probabilities (2020–2024)

This subsection documents empirically observed skill transitions between two consecutive time windows: W1 (2020–2022) and W2 (2022–2024). Using PostgreSQL as the sole source of truth, skills were classified based on their observed presence and relative change in demand across the two windows. Conditional transition probabilities were then computed with respect to skill status in W1 (Active vs. Absent), without applying any forecasting models or temporal extrapolation.

Observed transition probabilities indicate a highly asymmetric structure. Among skills that were Active in W1, the dominant transition is toward an Accelerating regime in W2, accounting for approximately 79.8% of cases. Smaller but non-negligible shares of Active skills transition into Fading (11.5%) and Mature (7.6%) regimes, while only 1.2% transition into Sunsetting, indicating observed disappearance or near-disappearance over the period.

In contrast, skills that were Absent in W1 transition exclusively into the Emerging regime in W2. This reflects observed entry into the skill space without prior presence in the earlier window, rather than growth or decline from an existing baseline.

All transition probabilities are empirically derived from observed data covering the 2020–2024 period and computed and validated in PostgreSQL. The resulting transition matrix is visualized in Tableau (Figure X). These results do not imply future outcomes; instead, they provide a descriptive foundation for the scenario framing that follows.

From Observed Transitions to Scenario Framing

The transition probabilities documented above provide a structured empirical summary of how skills have behaved across the most recent post-2020 period. Rather than extrapolating these probabilities into numerical forecasts, the analysis uses them to inform a qualitative scenario framework. The scenarios that follow are therefore grounded in observed momentum, stability, and decline patterns between 2022 and 2024, and represent interpretive extensions of recent behaviour rather than predictions of future outcomes.

Looking Ahead Without Predicting: Skill Scenarios for 2025–2027

Note: throughout this analysis, “persistent” refers to skill presence across the pre- and post-2020 period, while “accelerating” refers specifically to recent growth dynamics observed between 2022 and 2024.

This section translates observed post-2020 skill demand patterns into forward-looking scenarios for the 2025–2027 horizon. Rather than relying on predictive forecasting models, the analysis adopts a scenario-based approach grounded in recent, observable demand trajectories between 2022 and 2024.

Skills are classified according to their empirical behaviour following the post-2020 structural break, distinguishing between emerging, accelerating, mature, sunsetting, and uncertain trajectories. These scenarios are designed to support strategic reasoning about future skill relevance, not to generate deterministic predictions.

The objective is not to predict which skills will dominate in 2027, but to outline plausible future paths based on how skills have behaved in the most recent and data-rich period of the dataset.

While all five scenarios are empirically observed in the data, the 2022–2024 window shows an extreme concentration in emerging and accelerating skills. Mature and sunsetting skills do exist, but represent only a very small fraction of the observed skill space. This asymmetry reflects the current structure of skill demand rather than a methodological artifact.

Table X summarises representative skills within each forward-looking scenario. Skills are ranked within each scenario based on cumulative demand observed between 2022 and 2024.

Scenario	Skill	Trajectory	2022	2023	2024	Rationale
Emerging	Azure Databricks	spike_2024	0	0	244	New signal concentrated in 2024 (spike pattern).
Emerging	Azure	spike_2024	0	0	244	New signal concentrated in 2024 (spike pattern).
Emerging	TensorFlow	spike_2024	0	0	213	New signal concentrated in 2024 (spike pattern).
Emerging	Data Bricks	spike_2024	0	0	192	New signal concentrated in 2024 (spike pattern).
Emerging	PyTorch	spike_2024	0	0	179	New signal concentrated in 2024 (spike pattern).
Emerging	Airflow	spike_2024	0	0	160	New signal concentrated in 2024 (spike pattern).
Emerging	Machine Learning Algorithms	spike_2024	0	0	143	New signal concentrated in 2024 (spike pattern).

Emerging	Kubernetes	spike_2024	0	0	141	New signal concentrated in 2024 (spike pattern).
Emerging	Azure Data Lake	spike_2024	0	0	124	New signal concentrated in 2024 (spike pattern).
Emerging	NLP	spike_2024	0	0	119	New signal concentrated in 2024 (spike pattern).
Accelerating	Python	growing	26	94	2421	Consistent growth across 2022–2024.
Accelerating	Machine Learning	growing	106	220	2162	Consistent growth across 2022–2024.
Accelerating	SQL	growing	45	179	2031	Consistent growth across 2022–2024.
Accelerating	Data Analysis	growing	54	171	1817	Consistent growth across 2022–2024.
Accelerating	Analytical	growing	90	202	1295	Consistent growth across 2022–2024.
Accelerating	Agile	growing	64	149	1008	Consistent growth across 2022–2024.
Accelerating	Data Modeling	growing	24	120	1059	Consistent growth across 2022–2024.
Accelerating	Analytics	growing	46	126	1018	Consistent growth across 2022–2024.
Accelerating	Computer Science	growing	51	87	892	Consistent growth across 2022–2024.
Accelerating	Data Engineering	growing	11	35	961	Consistent growth across 2022–2024.
Mature	Adobe Acrobat	stable	1	1	1	Stable demand across 2022–2024.
Mature	Business Analyst Lead	stable	1	1	1	Stable demand across 2022–2024.
Mature	LINQ	stable	1	1	1	Stable demand across 2022–2024.
Mature	Product Planning	stable	1	1	1	Stable demand across 2022–

						2024.
Mature	Storage Management	stable	1	1	1	Stable demand across 2022–2024.
Sunsetting	IT Business Analyst	declining	3	2	1	Declining demand across 2022–2024.
Sunsetting	Social Media Analytics	declining	2	2	0	Declining demand across 2022–2024.
Sunsetting	Network Analysis	declining	2	2	0	Declining demand across 2022–2024.
Sunsetting	Biometrics	declining	1	1	0	Declining demand across 2022–2024.
Sunsetting	Improvement	declining	1	1	0	Declining demand across 2022–2024.
Uncertain	Snowflake	other	2	0	266	Mixed or volatile pattern across 2022–2024.
Uncertain	Java	other	1	0	258	Mixed or volatile pattern across 2022–2024.
Uncertain	Neural Networks	other	16	14	159	Mixed or volatile pattern across 2022–2024.
Uncertain	Product Engineering	other	6	5	113	Mixed or volatile pattern across 2022–2024.
Uncertain	Financial Planning	other	2	0	68	Mixed or volatile pattern across 2022–2024.

While the table highlights individual skill trajectories, it does not capture how demand is distributed across scenarios. To address this limitation, the following visualisation compares the 2024 demand volume of skills by scenario, highlighting differences in concentration and fragmentation.

Distribution of 2024 skill demand across forward-looking scenarios.

Accelerating skills exhibit high concentration around a small core of dominant capabilities, while emerging skills display a fragmented, long-tail structure.

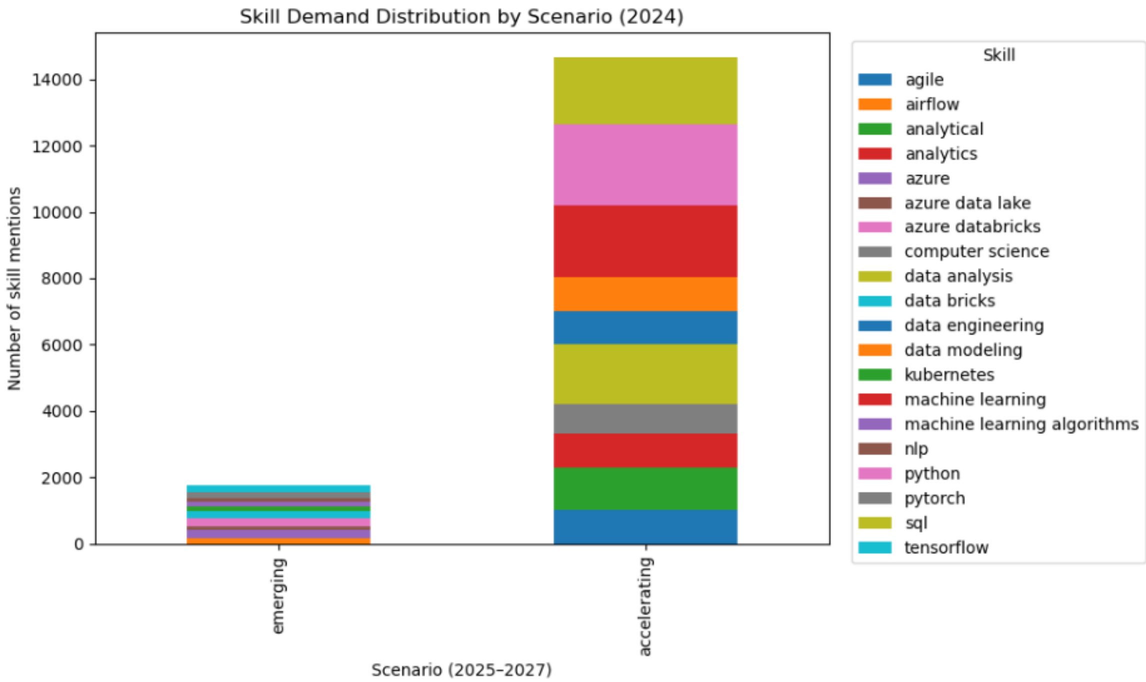

Figure — Distribution of 2024 skill demand across emerging and accelerating scenarios. Accelerating skills exhibit high concentration around a small core, while emerging skills display a fragmented, long-tail structure.

The contrast between scenarios reveals two distinct demand structures. Accelerating skills concentrate a large share of total demand in a small number of well-established competencies such as programming, machine learning, and core analytical skills, reflecting consolidation around a stable technical core. Emerging skills, by contrast, show lower absolute volumes but substantially higher fragmentation, indicating experimentation and rapid turnover rather than long-term stabilisation.

Together, these patterns suggest that post-2020 skill demand operates on two interconnected layers: a concentrated core of accelerating skills that anchor workforce demand, and a dynamic periphery of emerging skills that reflects ongoing technological exploration. Strategic workforce planning therefore requires balancing sustained investment in persistent capabilities with the flexibility to adapt to an expanding and volatile skill frontier.

Why Not Forecast?

Skill demand data derived from job postings is inherently noisy and sensitive to short-term shocks, platform effects, and changes in posting behaviour. Forecasting such data several years into the future risks amplifying these uncertainties and obscuring underlying structural signals.

Rather than producing point estimates or probabilistic forecasts, this analysis focuses on directional momentum. By examining how skill demand evolves immediately after the post-2020 structural break, it is possible to identify patterns of continuation, acceleration, stabilisation, or decline without claiming predictive certainty. This represents a deliberate trade-off: sacrificing numerical precision in favour of interpretability and analytical honesty.

Observed Trajectories as a Foundation

Forward-looking scenarios are constructed using observed skill demand trajectories between 2022 and 2024, the most recent and data-rich period in the dataset.

For each skill, demand patterns over these three years are classified into simple trajectory types based on their relative movement. This step preserves transparency by relying on explicit, rule-based comparisons rather than model-driven inference.

The resulting trajectories capture whether a skill appears suddenly and gains traction, shows sustained acceleration, remains stable, or exhibits signs of decline.

These observed behaviours form the empirical foundation for extending insights into the near future.

From Trajectories to Scenarios

Observed trajectories are mapped into forward-looking scenarios for 2025–2027 using a qualitative extension of recent patterns:

Emerging skills reflect sudden post-2020 appearance with growing presence in recent years.

Accelerating skills demonstrate consistent growth across the most recent period.

Mature skills show stable demand without significant growth or decline.

Sunsetting skills exhibit declining demand relative to recent history.

Uncertain skills follow mixed or volatile patterns that resist clear classification.

These scenarios do not imply inevitability. Instead, they provide a structured way to reason about potential future relevance based on empirical momentum.

Strategic Implications of the Forward-Looking View

The scenario-based framework highlights a key insight: most future-relevant skills are not long-established ones, but those that have either recently emerged or are rapidly accelerating.

This observation has important implications for workforce planning and skill development. It suggests that focusing exclusively on historically dominant skills may leave organizations underprepared for near-term changes, while overreacting to every new skill risks chasing transient trends.

By distinguishing emerging and accelerating skills from stable and uncertain ones, the analysis supports more nuanced decision-making around hiring priorities, training investments, and strategic capability building.

Interpreting Scenarios with Caution

It is important to emphasize that these scenarios are interpretive tools, not forecasts. External shocks, technological breakthroughs, regulatory changes, and shifts in business models can alter skill demand trajectories in ways not captured by recent data.

For this reason, the forward-looking analysis is best understood as a framework for thinking about the future, rather than a prediction of what will occur.

Limitations and Next Steps

No analysis of labour market dynamics is without limitations. Rather than viewing these constraints as weaknesses, this section makes them explicit to clarify the scope of the findings and to outline directions for future work.

Limitations

Reliance on job postings as a proxy for demand.

Skill demand in this project is inferred from job postings, which reflect employer requirements at the point of hiring rather than actual skill utilization or workforce composition. While postings provide timely and granular signals, they do not capture informal hiring channels, internal mobility, or on-the-job skill development.

Partial representation of the labour market.

The primary dataset focuses on job postings from a single platform and geography. As a result, observed trends may not fully generalize across all regions, industries, or labour market segments. The analysis emphasizes internal consistency and longitudinal patterns rather than universal representativeness.

Conservative skill normalization.

Skill text was normalized minimally to preserve the original signal expressed by employers. This choice avoids imposing artificial semantic structures but may lead to fragmented representations of conceptually similar skills. The resulting skill space prioritizes transparency over maximal consolidation.

Scenario-based, non-predictive forward-looking approach.

The forward-looking component deliberately avoids numerical forecasting. While this reduces the risk of overclaiming, it also means that scenarios should be interpreted qualitatively rather than as quantitative projections.

Next Steps

Several extensions could deepen and broaden the analysis:

- Semantic consolidation of skills, using controlled vocabularies or embedding-based approaches, to explore higher-level skill groupings while retaining interpretability.

- Cross-regional comparison, incorporating additional job posting sources to assess whether observed post-2020 dynamics are consistent across labour markets.

- Integration with education and training data, to examine alignment between emerging skill demand and skill supply.

- Longer post-2020 observation windows, as additional data becomes available, to validate whether emerging and accelerating trajectories persist over time.

- These extensions would build on the current framework while preserving its emphasis on transparency and empirical grounding.

Concluding Remarks

By focusing on skills rather than job titles, identifying a clear post-2020 structural break, and adopting a forward-looking approach grounded in observed trajectories, this project provides a structured and interpretable view of how skill demand is evolving.

The analysis demonstrates that the future of skill demand is shaped less by gradual change and more by rapid reconfiguration, underscoring the importance of continuous monitoring and adaptive workforce strategies.