Skill Mismatch Over The Technology Lifecycle

Prasanna Tambe, Wharton School, U. Pennsylvania

with Ashwini Agrawal (LSE) and Daniel Kim (University of Waterloo)

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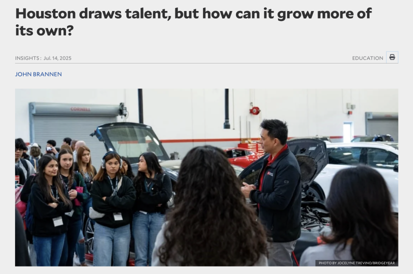
University of Houston

Preliminary and Incomplete - Do not Circulate

Current Labor Market Challenges

Intensifying Competition for Workers:

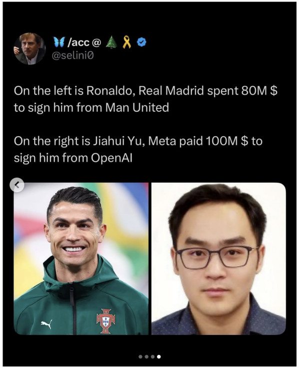
- 74% of employers struggle to find skilled talent (ManpowerGroup 2024)
- Specialized roles: 120+ days to fill, up from 44 days average (LinkedIn 2024)
- 40% of firms restructuring workforce due to AI capabilities (WEF 2025)
- Skills-based hiring: 81% adoption in 2024 vs 56% in 2022 (TestGorilla)



Source: Houston Chronicle, July 2025

How do mismatches affect technology diffusion?

Case Study: AI Talent Competition



Source: Twitter/@selini0

Meta's $100M AI Hiring Spree:

- Mark Zuckerberg offering $100M+ packages
- Personal outreach to hundreds of top AI talent
- Cold emails from Zuckerberg personally
- Dinners at CEO's private homes

Cutting-edge technology adoption constrained by talent scarcity

Case Study: Legacy System Skills

As mainframes turn 60, skill gaps threaten the enterprise workhorse

"Great technology doesn't really go away — it finds the niche that it was made for," Forrester Senior Analyst Brent Ellis said.

Published April 5, 2024 • Updated April 12, 2024

Matt Ashare
Senior Reporter

Engineers assemble an IBM Z system mainframe. The sixtieth anniversary of the first commercial available mainframe, IBM's System/360, is April 7, 2024 *Courtesy of IBM image gallery*

Source: Enterprise Workforce

Legacy Technology Crisis:

- Average COBOL programmer age: 58 years
- 10% retiring annually, no replacements
- 220 billion lines of COBOL code active
- 85% of universities dropped curriculum

Legacy technologies challenged by disappearing skills

Labor Markets and Technology Adoption

Central Question in Information Systems Literature:

- Technology adoption and productivity effects extensively studied
- Focus on firm characteristics, market conditions, technology features
- Well-established: technology complementarities, organizational factors

GAP: Labor market factors have been understudied

- Limited attention to skill availability and alignment
- Workforce characteristics treated as static or exogenous
- Missing link between technology lifecycle and labor market dynamics

Evidence of Skills Mismatch?

Scale of the Challenge

- 74% of employers struggle to find skilled workers (ManpowerGroup 2024)
- $8.5T potential revenue loss by 2030 due to skill gaps (Korn Ferry)
- 600K manufacturing job openings unfilled (BLS 2024)

Key Question:

How can we measure and understand skill-technology alignment to guide better policy and firm decisions?

Research Question

How does skill mismatch between firms and workers vary across the technology lifecycle?

1. Do skill gaps follow patterns as technologies evolve?
2. What types of skills are most affected by technological change?
3. How do firms respond to skill mismatch through investment?

Our Contribution

1. **Novel Methodology**: Leverage large language models (LLMs) with matched data from worker resumes and firm job postings to measure skill mismatch
2. **New Empirical Facts**: Document systematic patterns in skill mismatch over technology lifecycles
3. **Economic Insights**: Provide evidence on firm responses to skill gaps through capital investment

Preview of Main Findings

1. **U-Shaped Mismatch Pattern**:
   - Highest mismatches for new and legacy technologies
   - Lowest for mid-vintage technologies

2. **Non-Technical Skills Most Affected**:
   - Management and support roles show largest gaps
   - Technical specialists better aligned across lifecycle

3. **Firm-Level Consequences**:
   - 2.5% productivity loss per SD of mismatch
   - Firms invest more in intangible capital

Skill mismatches create systematic costs across the technology adoption cycle

Prior Work on Skill Measurement

Existing Measurement Approaches:

- Survey-based methods: Limited scale and subjectivity (NFIB surveys)
- Administrative data: Lack granular skill information
- O*NET matching: Only 40% job coverage, static classifications

Empirical Evidence of Skill Gaps:

- 36% of small businesses cite "lack of soft skills" as hiring obstacle
- 74% of hiring managers agree there is a skills gap in labor market
- Average job sees 37% skills requirement change in 5 years

Our Contribution: First large-scale LLM-based measurement enabling systematic skill gap analysis across technology lifecycle

Conceptual Framework: Technology Lifecycle

Technology Age and Skill Mismatch:

- **New IT**: Technology weights tilt toward frontier tasks faster than workforce can adapt → High mismatch
- **Mature IT**: Task weights closer to market modal technology, firms have time to reallocate workers → Low mismatch
- **Obsolete IT**: Required tasks tilt toward legacy capabilities that are scarce in labor market → High mismatch

Key Prediction: U-shaped relationship between technology age and skill mismatch

Theoretical Framework

Period 1 (New Technology): Technology vintage V^{new}

- Skill demand vector: $\{F_j^1\}$ for $j = 1, ..., J$ skills
- Worker supply: $\{W_j^1\}$ with existing skill distributions

Period 2 (Mature Technology): Technology vintage V^{mature}

- Adjusted skill demand: $\{F_j^2\}$ after learning
- Worker adaptation: $\{W_j^2\}$ after training/adjustment

Period 3 (Obsolete Technology): Technology vintage V^{old}

- Legacy skill demand: $\{F_j^3\}$ for outdated systems
- Scarce legacy skills: $\{W_j^3\}$ as market moves forward

Empirical Methodology: Data Collection & Analysis

Step 1: Collect matched data on:

- Firm job postings (technology requirements, skill demands)
- Worker resumes (current skill profiles)

Step 2: Use LLMs to:

- Extract technology and classify skills into standardized categories
- Measure skill alignment between demand and supply

Step 3: Construct firm-level measures of:

- Technology vintages (age of IT systems)
- Skill mismatch across different skill categories

Measuring Skill Mismatch with BERT

BERT (Bidirectional Encoder Representations from Transformers):

- Zero-shot classification approach for skill detection
- Context-aware bidirectional text understanding
- Consistent, objective measurement across millions of documents

Skill Mismatch Calculation:

- 25 skill categories from Revelio Labs taxonomy
- Euclidean distance formula: $m(f, w) = \sqrt{\sum_j (f_j - w_j)^2}$
- Captures multidimensional skill-technology relationships
- Provides continuous rather than binary measures

Measurement Approach (Part 1)

BERT-Based Approach:

- Analyze job postings and worker resumes using BERT language model
- Extract skill requirements and capabilities across 25 categories
- Create firm-level skill demand and supply vectors

Measurement Framework:

- For each firm i in year t across skill categories $s = 1, ..., 25$
- Calculate average skill demands from job postings
- Calculate average skill supplies from worker resumes
- Measure multidimensional distance between demand and supply

Key Innovation: Continuous measurement of skill alignment rather than binary matching

Measurement Approach (Part 2)

Mathematical Formulation:

$$\text{Demand}_{i,t,s} = \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} \text{BERT\_Score}(\text{Job Posting}_j, \text{Skill}_s) \tag{1}$$

$$\text{Supply}_{i,t,s} = \frac{1}{M_{i,t}} \sum_{k=1}^{M_{i,t}} \text{BERT\_Score}(\text{Resume}_k, \text{Skill}_s) \tag{2}$$

Interpretation:

- $N_{i,t}$ = number of job postings for firm i in year t
- $M_{i,t}$ = number of worker resumes matched to firm i in year t
- BERT scores range from 0 to 1 for each skill category

Measurement Approach (Part 3)

Final Mismatch Calculation:

$$\text{Mismatch}_{i,t} = \sqrt{\sum_{s=1}^{25} (\text{Demand}_{i,t,s} - \text{Supply}_{i,t,s})^2} \tag{3}$$

Key Features:

- Euclidean distance captures multidimensional skill gaps
- Covers all 25 Revelio skill categories
- Provides continuous measure of firm-worker skill alignment
- Higher values indicate greater skill mismatch

Key Innovation: Continuous measurement of skill alignment rather than binary matching

Data Sources

Job Postings Data:

- Large-scale database of online job postings with technology requirements and skill demands; Firm identifiers and temporal coverage

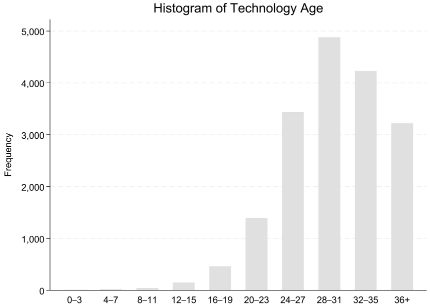
Worker Resume Data:

- Professional profiles from LinkedIn and similar platforms
- Current skill sets and work experience
- Matched to job postings through employer information

Firm Financial Data:

- Compustat for firm characteristics and investment
- Intangible investments

Technology Age Distribution



Key Observations:

- Wide distribution of technology vintages across firms
- Many firms still using **legacy systems** (high technology age)
- Opportunities to study mismatch across *full technology lifecycle*

Skill Categories and Summary Statistics

Technical Skills with High Mismatch:

- Data Analysis/C++, Advanced Manufacturing, Network Security
- Software Development, Data Science/Machine Learning, Engineering

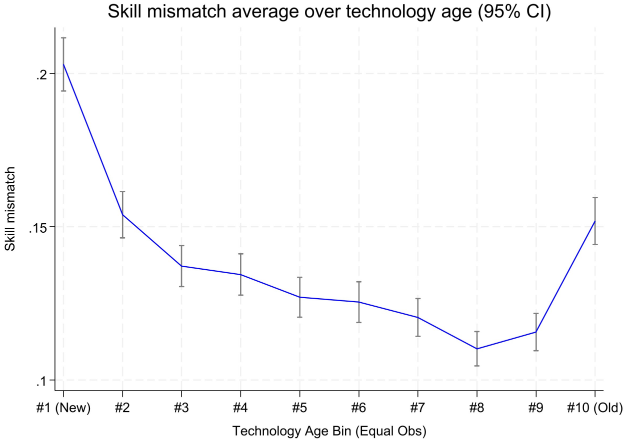
Non-Technical Skills with High Mismatch:

- Management/Leadership, Financial Analysis, Strategic Planning
- Project Management, Quality Assurance, Business Analysis

Low Mismatch/Oversupplied Skills:

- Customer Service, Sales, Administrative Support
- Human Resources, Marketing/Advertising, Hospitality

Main Result: U-Shaped Mismatch



Key Results:

Technology Age:
-2.292***
(0.421)

Technology Age^2:
3.464***
(0.698)

Robust across all specifications

Understanding the U-Shape Pattern

Young Technologies (High Mismatch):

- New task requirements emerge faster than workforce can adapt
- Limited experience with complementary skills

Mature Technologies (Low Mismatch):

- Market has time to develop relevant skills
- Training programs and education catch up

Obsolete Technologies (High Mismatch):

- Legacy skills become scarce in labor market
- Firms struggle to maintain aging technology

Within-Firm and Cross-Sectional Evidence

The U-shaped pattern appears in both:

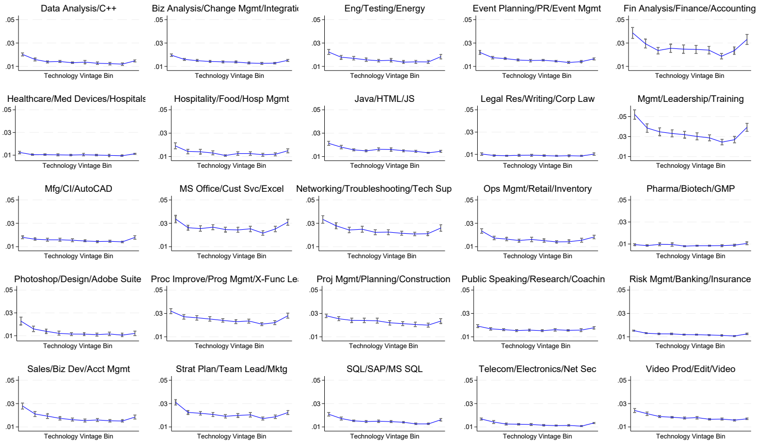
- **Cross-sectional variation**: Across different firms at a point in time
- **Within-firm variation**: Same firm over time as technology ages

Heterogeneity Across Firms - Stronger U-Shape Effects for:

- **Younger firms**: Less experience managing technology transitions
- **Smaller firms**: Fewer resources for adjustment and training
- **Financially constrained firms**: Limited skill investment capacity
- **High-tech industries**: Rapid pace of technological change

Economic Mechanism: Adjustment frictions delay convergence to optimal skill mix, amplifying mismatch during technology transitions

Skill-Specific Patterns



Skill-Specific Patterns

High Mismatch Skills (Follow U-Shape):

- **Technical**: Advanced manufacturing, network security, data science
- **Non-technical**: Management, financial analysis, strategic planning
- Both show pronounced U-shaped relationship with technology vintage

Skill-Specific Patterns

Low/No Mismatch Skills:

- Routine/legacy tasks: Hospitality, basic sales, legacy programming
- Often oversupplied except when firms use very old IT systems
- Generally stable across technology vintages

Finding

Complementary non-technical skills show the largest gaps across the technology lifecycle

Implication: Skills gaps extend far beyond technical competencies to include managerial and strategic capabilities

Comparing Skill Types

Key Finding: Both technical AND non-technical skills show U-shaped mismatch

Skill Type	Coefficient	Std. Error
Technical Skills	0.12	(0.03)
Non-Technical Skills	0.29	(0.05)

Critical Insight

Managerial skills show 2.4x larger gaps than technical skills on average

Firm Investment Response

- **Total capital investment**
- **Intangible investments**: Training, software customization, organizational processes
- **Tangible IT spending**: Hardware, software, equipment

Consistent with:

- General-purpose technologies require complementary investments
- Firms invest in training and process optimization
- Skill gaps drive capital deepening

Evidence: Part of investment response targets mismatch directly through worker training and process customization

Investment Results

Investment Type	Coefficient
Training & Development	0.198***
Intangible Assets	0.156***
Tangible IT Investment	0.063*

Key Finding: **Intangible investments** most responsive to skill mismatch

Firms adapt through human capital rather than technology substitution

Effect Size Comparisons

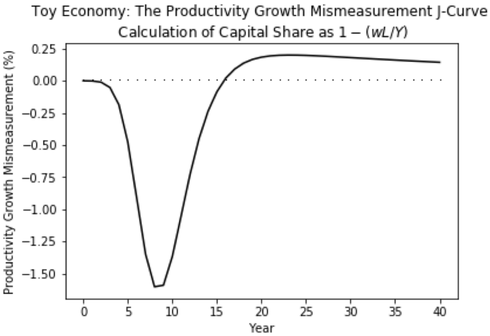
How Big Are Skill Mismatch Effects?

Factor	Productivity Effect	Source
Skill Mismatch (1 SD)	-2.5%	This Study
R&D Intensity (1 SD)	+3.1%	Literature
IT Capital (1 SD)	+2.8%	Literature
Management Quality (1 SD)	+4.5%	Literature

Key Finding: Skill mismatch effects are **larger** than many established productivity drivers

Implication: Skill mismatch is a **first-order** economic concern

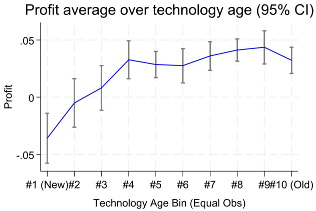
The Expected Timing of Productivity Returns

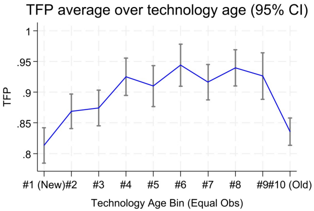


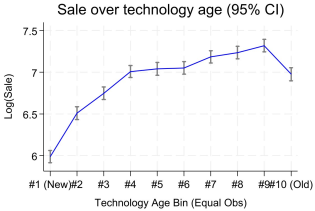
Source: Brynjolfsson, Rock & Syverson (2021)

- New technologies initially reduce productivity due to learning costs and skill gaps
- Skill mismatches amplify the initial productivity dip
- Recovery depends on how quickly firms can close skill gaps through hiring/training

Technology Age and Firm Performance: Specific Results







U-Shaped Effects:

Profitability

Age: **0.639*****

Age^2: **-0.785*****

TFP

Age: **2.918*****

Age^2: **-4.263*****

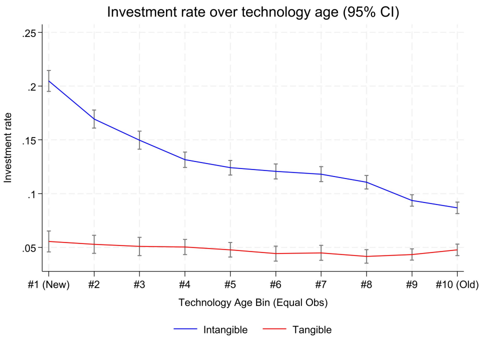
Sales Growth

Age: **20.92*****

Age^2: **-25.64*****

All effects significant

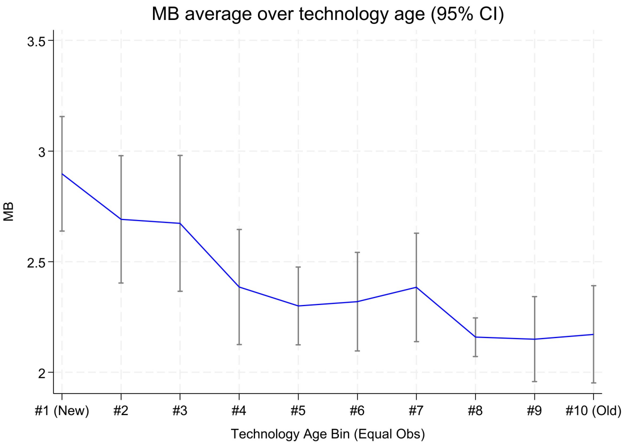
Investment Over the Technology Lifecycle



Key Pattern: Investment response follows skill mismatch U-shape

- High investment needs when adopting new technologies
- Lower, stable investment during mature phase

Market Valuation Patterns



Robustness Tests

Baseline Result: TechAge: -2.292***, $TechAge^2$: 3.464***

Robustness Checks Show Consistent U-Shape:

- **ModernBERT**: Effects get stronger
- **Alternative technology measures**: Robust patterns
- **Excluding Microsoft Office**: Results remain consistent
- **Different hiring windows**: Results remain consistent

Summary: U-shaped pattern is not driven by methodological choices

Question: What other robustness checks should we consider?

Heterogeneous Effects by Firm Type

U-Shape Stronger for Resource-Constrained Firms:

Paper finding: Effects are "especially pronounced among younger, smaller, and financially constrained firms"

Key Insight: Limited resources amplify skill mismatch effects across the technology lifecycle; Larger firms have more resources to manage skill mismatches.

Heterogeneous Effects by Industry

Industry Heterogeneity (coefficient magnitudes):

Strongest U-Shape Effects:

- **Technology/Software**: Steepest U-curves, highest mismatch volatility
- **Financial Services**: Strong coefficients, complex skill bundles
- **Manufacturing**: Pronounced patterns, technical-managerial complementarity

Economic Implications: Tech-intensive sectors show 2-3x stronger mismatch responses

Economic Mechanisms

1. **Adjustment Costs**: Training, hiring, and organizational change are costly and time-consuming
2. **Learning Effects**: Firms and workers learn optimal skill combinations over technology lifecycle
3. **Market Development**: Education and training markets develop around mature technologies
4. **Skill Obsolescence**: Legacy skills become scarce as market moves to newer technologies

Policy Implications

For Education:

- Emphasize both technical AND non-technical skills
- Create flexible, adaptable curricula

For Firms:

- Target high-mismatch skills: Management, Data Analysis
- Focus on SMEs: 3x stronger mismatch effects

Timing Matters:

- Early intervention with new technologies
- Support legacy skill transitions

Economic Magnitude

The Costs of Skill Mismatch:

- Firm-level: +2.5% productivity from mismatch reduction (our estimates)
- Worker-level: -11.8% salary penalty (our estimates)

Policy interventions might generate substantial returns

Implications for Technology Adoption

- **Productivity paradoxes**: Why new technologies don't immediately boost productivity
- **Adoption delays**: Why firms wait to adopt new technologies
- **Investment complementarity**: Why technology adoption requires broad organizational investment

Connection to macro trends:

- Slowdown in productivity growth despite technological advances
- Rising inequality as skill premiums change
- Importance of human capital in technology diffusion

Summary of Contributions

1. **Methodological Innovation**:
   - Novel LLM-based approach to measure skill mismatch at scale
   - Matched firm-worker data robust across multiple specifications
2. **New Empirical Facts**:
   - U-shaped relationship between technology age and skill mismatch
   - Both technical and non-technical skills affected systematically
   - Investment responses to skill gaps, especially in intangibles
3. **Economic Insights**:
   - Skill alignment crucial for technology diffusion and productivity
   - Adjustment frictions create persistent inefficiencies
   - Challenges frictionless models of technology adoption

Limitations and Future Research

Current Limitations:

- Sample selection toward technology-intensive, online-active firms
- Measurement based on job postings and resumes (revealed preferences)
- Limited temporal coverage for full technology lifecycles

Future Research Directions:

- Optimal timing of technology adoption given skill constraints
- Others?

Conclusion

Key Takeaway

Skill alignment between workers and firms plays a central role in the diffusion patterns of new technologies

Implications:

1. Understanding skill mismatch patterns can improve technology adoption decisions
2. Investment in human capital complements technology investment
3. Policy attention to skill transitions during technological change

Questions?

Skill Mismatch Over The Technology Lifecycle

Ashwini K. Agrawal, Daniel Kim, Prasanna Tambe

Comments: tambe@wharton.upenn.edu