Education Vintage and Knowledge Depreciation: Board Technical Competency in the Era of Generative AI

The integration of artificial intelligence (AI) into the strategic core of the modern enterprise represents a pivotal juncture in corporate history, comparable to the advent of the internet or the electrification of industry. Specifically, the emergence of Generative AI (GenAI), catalyzed by the public release of ChatGPT in November 2022, has created a competence-destroying technological discontinuity (Anderson & Tushman, 2018). Unlike incremental technological advances that reward accumulated experience and existing institutional knowledge, competence-destroying discontinuities render vast swaths of prior expertise obsolete. In this volatile environment, the board of directors serves as the ultimate steward of organizational adaptation, tasked with navigating the firm through the gale of creative destruction (Ma, 2025).

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Wed, 1 April 2026

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Project Details

Item	Value
Owner	Tony, Jongcnaglu
Type	Research
Status	초기화
Created	2026-03-29
Collaboration	collaboration
People	채충일
Deadline	2026-05-30

Description

The integration of artificial intelligence (AI) into the strategic core of the modern enterprise represents a pivotal juncture in corporate history, comparable to the advent of the internet or the electrification of industry. Specifically, the emergence of Generative AI (GenAI), catalyzed by the public release of ChatGPT in November 2022, has created a competence-destroying technological discontinuity (Anderson & Tushman, 2018). Unlike incremental technological advances that reward accumulated experience and existing institutional knowledge, competence-destroying discontinuities render vast swaths of prior expertise obsolete. In this volatile environment, the board of directors serves as the ultimate steward of organizational adaptation, tasked with navigating the firm through the gale of creative destruction (Ma, 2025).

Research Logs

Research Log

xxxx-xx-xx

- `entry.`

Meeting Log

xxxx-xx-xx

- [x] 10:00-10:30: Kick-off meeting

Analysis Version

Version 0.0.1

- Starting draft

Draft Version

Ver 0.0.1

- Starting draft

Research Note

Ideas and Thoughts

Research Q & A

Q1: Why “Education Vintage” instead of simply “age”?

A: Age captures general experience and generational identity, but Education Vintage specifically measures the technological paradigm under which a director's cognitive framework was formed. Two directors of the same age could have vastly different vintages if one pursued a late-career STEM degree. Vintage isolates the knowledge-relevance dimension from the broader age construct.

Q2: Why is ChatGPT the right exogenous shock?

A: ChatGPT's release (November 30, 2022) satisfies three conditions for a valid DiD shock: (1) it was discrete and identifiable, (2) it was largely unanticipated in timing and magnitude, and (3) it created a clear demarcation between pre-GenAI and post-GenAI strategic environments. Unlike gradual AI adoption, ChatGPT forced an immediate strategic response from boards.

Q3: How do you distinguish GenAI adoption from general AI adoption?

A: We use a validated keyword dictionary that separates GenAI-specific terms (``Large Language Model,'' ``Transformer,'' ``GPT,'' ``Foundation Model'') from generic technology terms (``Big Data,'' ``Cloud,'' ``Machine Learning''). This ensures we capture the specific competence-destroying discontinuity of GenAI rather than incremental AI investment.

Q4: What about reverse causality – don't innovative firms just hire younger directors?

A: This is our primary endogeneity concern. We address it through: (1) firm fixed effects controlling for time-invariant firm characteristics, (2) instrumental variable strategy using director birth year, and (3) the DiD design itself, which measures within-firm changes around an exogenous shock rather than cross-sectional correlations.

Q5: Can the Reskilling Index truly capture lifelong learning?

A: The Reskilling Index is an imperfect proxy. It captures formal certifications and degrees from BoardEx but misses informal learning (online courses, self-study, conference attendance). We acknowledge this limitation and suggest future research incorporating richer reskilling data.

Q6: Why pre-2012 as the vintage cutoff for "modern AI"?

A: 2012 marks the AlexNet breakthrough in deep learning (ImageNet competition), which fundamentally shifted the AI paradigm from rule-based/symbolic approaches to neural network/deep learning methods. This represents a natural technological discontinuity point in AI education curricula. We conduct robustness checks with alternative cutoffs (2010, 2015).

Q7: How does this differ from studies on board digital literacy?

A: Existing studies measure digital literacy as a binary (has/doesn't have tech experience). Our contribution is adding the temporal dimension -- not just whether directors have technical knowledge, but when that knowledge was acquired and whether it remains relevant to the current technological regime.

Procedures

Research Workflow

Phase 1: Literature Review (4 weeks)

1. Systematic search across Web of Science, Scopus, SSRN, NBER
2. Three rounds of keyword-based searches (see `lr_search_incl_excl.qmd`)
3. PRISMA-compliant screening and selection
4. Literature classification (A/B/C grades)
5. Conceptual model refinement based on literature gaps

Phase 2: Data Collection & Variable Construction (6 weeks)

1. Week 1-2: Extract BoardEx education data
   - Download director-level data with education fields
   - Identify STEM-classified qualifications
   - Extract AwardDate for vintage calculation
2. Week 2-3: Classify STEM vs. non-STEM qualifications
   - Create classification dictionary
   - Manual validation of ambiguous cases
   - Compute TKL for each STEM director
3. Week 3-4: Download and parse 10-K filings
   - Bulk download from SEC EDGAR (XBRL full-text)
   - Extract relevant text sections (MD&A, Risk Factors, Business Description)
4. Week 4-5: Run GenAI keyword extraction
   - Apply validated keyword dictionary
   - Compute TF-IDF weighted scores
   - Calculate AI Adoption Speed (quarters to first mention)
5. Week 5-6: Merge and validate

- Link BoardEx → Compustat → CRSP → EDGAR via CIK/GVKEY
- Handle missing data (imputation for AwardDate)
- Construct panel dataset (firm-quarter)
- Winsorize outliers (1st/99th percentile)

Phase 3: Empirical Analysis (4 weeks)

1. Week 1: Descriptive statistics and correlations
   - Sample composition by vintage category
   - Industry distribution
   - Temporal trends in GenAI adoption
2. Week 2: Main DiD estimation
   - Triple DiD model (H1)
   - Tech Committee interaction (H2)
   - Vintage faultline analysis (H3)
   - Reskilling moderation (H4)
3. Week 3: Robustness and supplementary analyses
   - Event study (parallel trends verification)
   - IV estimation (birth year instrument)
   - Placebo tests (non-GenAI technologies)
   - Alternative vintage cutoffs (2010, 2012, 2015)
   - Heterogeneity by industry and firm size
4. Week 4: Results compilation
   - Tables and figures
   - Sensitivity analysis summary
   - Effect size interpretation

Phase 4: Writing & Submission (4 weeks)

1. Week 1: Draft Introduction, Theory, Hypotheses
2. Week 2: Draft Method, Results
3. Week 3: Draft Discussion, Conclusion
4. Week 4: Internal review, revision, journal formatting

Quality Checkpoints

Checkpoint	Criteria	Phase
Literature saturation	No new themes emerging in final round	Phase 1
Data validation	<5% imputation rate for AwardDate	Phase 2
Parallel trends	Non-significant pre-treatment coefficients	Phase 3
Robustness	Results stable across alternative specifications	Phase 3
Internal review	Co-author sign-off on all sections	Phase 4

Theoritical Framework

Related Theories

Primary Theories (Currently Employed)

1. Resource Dependence Theory (RDT)

- Origin: Pfeffer & Salancik (1978)
- Core idea: Organizations must interact with their environment to acquire critical resources; boards manage these dependencies
- Application: Directors provide technical expertise as a resource to reduce environmental uncertainty
- Extension in this study: Introduction of ``Resource Fossilization'' and temporal validity constraint

2. Human Capital Theory

- Origin: Becker (1964)
- Core idea: Education is an investment with returns; knowledge is an asset
- Application: Education vintage determines the depreciation rate of technical human capital
- Key insight: Half-life of engineering knowledge is 2.5-5 years (Shearer & Steger, 1975)

3. Technological Discontinuities Theory

- Origin: Anderson & Tushman (1990, 2018)
- Core idea: Distinguishes competence-enhancing from competence-destroying technological change
- Application: GenAI is a competence-destroying discontinuity for traditional IT governance

Supplementary Theories (Proposed)

4. Upper Echelons Theory

- Origin: Hambrick & Mason (1984)
- Core idea: Strategic choices reflect executives' cognitive bases shaped by their backgrounds
- Application: Education timing forms cognitive frames that determine how directors interpret and respond to GenAI
- Relevance: Explains why vintage matters -- educational era creates lasting cognitive imprints

5. Absorptive Capacity

- Origin: Cohen & Levinthal (1990)
- Core idea: A firm's ability to absorb new knowledge depends on related prior knowledge
- Application: Temporal dimension of ``related prior knowledge'' -- outdated technical education weakens capacity to absorb GenAI-related new knowledge
- Relevance: Supports H1 -- recent vintage directors face lower absorption costs

6. Dynamic Capabilities

- Origin: Teece (2007)
- Core idea: Sensing-Seizing-Transforming framework for organizational adaptation
- Application: Board's ``sensing'' capability varies with education vintage
- Relevance: Complements RDT's static limitations with a dynamic perspective

7. Institutional Theory

- Origin: DiMaggio & Powell (1983)
- Core idea: Organizations adopt structures for legitimacy, not just efficiency
- Application: Decoupling phenomenon -- appointing technical directors for institutional legitimacy rather than substantive competence
- Relevance: Explains why Tech Committees may be ineffective (H2)

8. Negative Transfer Theory

- Origin: Educational Psychology
- Core idea: Prior learning can interfere with acquisition of new knowledge
- Application: Deterministic thinking from older CS education hinders understanding of probabilistic GenAI
- Relevance: Provides psychological mechanism for H1's old vintage effect

9. Competence Trap

- Origin: Levitt & March (1988)
- Core idea: Past success with existing competencies suppresses exploration of new approaches
- Application: Directors with track records in legacy tech exploitation resist AI exploration
- Relevance: Explains inertia beyond simple knowledge gaps

Theoretical Relationship

How the Theories Connect

The theoretical framework integrates multiple streams into a coherent causal model centered on the Education Vintage construct.

Theoretical Integration Map

```
                   Upper Echelons Theory
                   (Cognitive Imprint Formation)
                         |
                         v
   Human Capital Theory -----> Education Vintage (Core Construct)
   (Knowledge Depreciation)             |
                                        |
         +------------------------------+------------------------------+
         |                              |                              |
         v                              v                              v
  Absorptive Capacity          RDT + Dynamic                Institutional Theory
  (Reduced Knowledge           Capabilities                 (Decoupling/
   Absorption)                (Resource Fossilization)       Ceremonial Response)
         |                              |                              |
         v                              v                              v
  Negative Transfer            Competence Trap              Tech Committee
  (Old Knowledge Interferes)   (Success Trap)               Ineffectiveness (H2)
         |                              |
         v                     +-------+-------+
     H1: Vintage Affects       |               |
     Adopting Speed            v               v
                        H3: Cognitive      H4: Reskilling
                        Faultlines         Offsets Depreciation
```

Theory-to-Hypothesis Mapping

Hypothesis	Primary Theory	Supporting Theories
H1: Recent vintage → faster AI adoption	Human Capital Theory (Vintage Effect)	Absorptive Capacity, Negative Transfer, Upper Echelons
H2: Old vintage Tech Committee → negative/null effect	RDT (Resource Fossilization)	Institutional Theory (Decoupling), Competence Trap
H3: High vintage variance → slower adoption	Cognitive Faultlines	Upper Echelons, Dynamic Capabilities
H4: Reskilling mitigates old vintage	Human Capital Theory (Reinvestment)	Absorptive Capacity, Dynamic Capabilities

Causal Mechanism

1. Formation: Education vintage creates cognitive imprints during formative years (Upper Echelons)
2. Depreciation: Technical knowledge decays rapidly in high-tech fields (Human Capital Theory)
3. Shock: GenAI arrives as a competence-destroying discontinuity (Anderson & Tushman)
4. Differential Response: Directors respond based on their vintage:
    - Recent vintage: High absorptive capacity, cognitive alignment with probabilistic AI → faster adoption
    - Old vintage: Low absorptive capacity, negative transfer, competence trap → resistance or misguided governance
    - Mixed vintage: Cognitive faultlines create communication breakdown → delayed consensus
5. Mitigation: Reskilling refreshes vintage capital, restoring absorptive capacity

From "Possessed Knowledge" to "Effective Knowledge"

Traditional governance research operates on the premise of Possessed Knowledge: once a director acquires a credential, they permanently possess the associated utility.

This study proposes a shift to Effective Knowledge: accounting for the temporal erosion of relevance.

> Effective Knowledge = Possessed Knowledge x Vintage Alignment Factor
>
> Where Vintage Alignment = f(graduation year, current technological regime, reskilling investment)

Theoretical Framework

Overview

This study integrates three distinct theoretical streams to unpack the relationship between education vintage and AI governance:

1. Resource Dependence Theory (RDT) -- Dynamic View
2. Economics of Human Capital -- Obsolescence
3. Theory of Technological Discontinuities

1. Reframing Resource Dependence Theory: The Decay of Board Capital

Resource Dependence Theory (RDT) asserts that organizations must interact with their environment to acquire resources. Boards are the primary mechanism for managing these external dependencies (Hoppmann et al., 2019). In high-tech industries, the most critical resource is information processing capability and technical foresight.

Limitation of Standard RDT: Board capital is treated as static. A director appointed for their technical expertise is assumed to deliver that resource continuously throughout their tenure.

Extension -- Resource Fossilization: The phenomenon where a strategic resource degrades into a liability due to environmental shifts. When a technological paradigm shifts (e.g., from on-premise to cloud, from analytical AI to generative AI), the ``resource'' provided by a director trained in the old paradigm loses its strategic value.

> RDT must be extended to include a temporal validity constraint: The provision of technical resources is contingent on the alignment between the vintage of the resource and the current technological regime.

2. Human Capital Obsolescence and the "Vintage Effect"

Becker's human capital theory views education as an investment with a rate of return. However, this capital depreciates. The depreciation rate in high-technology fields is significantly higher than in law, finance, or management (Boone et al., 2008).

- Half-life of engineering knowledge: 2.5 to 5 years (Shearer & Steger, 1975)
- Cognitive imprinting: Executives' cognitive bases are formed by their educational backgrounds and are resistant to change (Upper Echelons Theory)
- Negative transfer: A director trained in control and determinism will struggle with the probabilistic and emergent nature of GenAI

3. Technological Discontinuities: Competence-Destroying Change

The distinction between competence-enhancing and competence-destroying discontinuities (Anderson & Tushman, 1990, 2018):

Type	Description	Director Impact
Competence-Enhancing	Innovations building upon existing know-how	Experienced directors thrive
Competence-Destroying	Innovations rendering existing skills obsolete	Experienced directors may hinder

GenAI acts as a competence-destroying discontinuity for traditional IT governance:

- Previous IT eras: process automation, structured data, logical determinism
- GenAI era: content creation, unstructured data, probabilistic outcomes

Competence Trap: Directors with obsolete expertise may actively resist new technology -- not out of ignorance, but out of the belief that their methods remain superior.

Hypothesis

H1: Education Vintage and AI Adoption Speed

In the post-ChatGPT period, the positive relationship between board technical competence and firm AI adoption speed is significantly stronger for firms whose technical directors have more recent educational vintages (lower Tech Knowledge Latency).

H2: Technology Committee Vintage Effect

The presence of a Technology Committee will have a negative or insignificant effect on GenAI adoption if the average Education Vintage of its members predates the modern AI era (pre-2012).

H3: Cognitive Vintage Faultlines

Boards with high variance in technical education vintage will exhibit slower AI adoption compared to boards with low variance.

H4: Reskilling Mitigation

The negative effect of Old Vintage is mitigated by the Reskilling Index (frequency of technical certifications or degrees obtained after age 45).

Methodology and Method

Methodology

Research Paradigm

This study employs a positivist research paradigm with a quantitative, archival research design. The goal is to establish causal relationships between education vintage and GenAI adoption using large-scale panel data and quasi-experimental methods.

Research Design: Difference-in-Differences (DiD)

The study exploits the sudden and largely unanticipated release of ChatGPT in November 2022 as an exogenous shock, creating a natural experiment that demarcates ``pre-GenAI'' and ``post-GenAI'' periods.

Why DiD?

- ChatGPT's release was a discrete, identifiable event
- It was largely unanticipated in its timing and impact
- It allows comparison of firms with different board vintage compositions before and after the shock
- Firm and time fixed effects control for unobserved heterogeneity

Key Assumptions

1. Parallel Trends: Absent the ChatGPT shock, firms with different board vintages would have followed similar AI adoption trajectories
2. No Anticipation: Firms did not systematically alter board composition in anticipation of ChatGPT
3. SUTVA: One firm's treatment does not affect another firm's outcome

Validation Strategy

- Event Study: Plot quarterly coefficients around the ChatGPT launch to visually verify parallel trends
- Placebo Test: Test whether vintage effects appear for non-GenAI technologies (cloud, blockchain)
- Robustness: Vary vintage cutoff points (2010, 2012, 2015)

Unit of Analysis

Firm-quarter panel, covering U.S. publicly listed firms with available BoardEx and Compustat data.

Time Period

- Pre-treatment: 2019 Q1 -- 2022 Q3
- Treatment event: 2022 Q4 (ChatGPT release, November 30, 2022)
- Post-treatment: 2022 Q4 -- 2025 Q4

Population and Sample

- Population: All U.S. publicly listed firms in BoardEx universe
- Sample criteria: Firms with at least one STEM-degreed director, available financial data in Compustat, and 10-K filings in SEC EDGAR
- Expected sample: ~3,000-5,000 firms, ~50,000+ firm-quarter observations

Method

Econometric Model

Main Specification (Triple DiD)

```
GenAI_Adoption_{it} = beta_0
                    + beta_1 * Post_ChatGPT_t
                    + beta_2 * TechBoard_i
                    + beta_3 * (Post x TechBoard)
                    + beta_4 * (Post x TechBoard x Vintage_i)
                    + gamma * Controls_{it}
                    + alpha_i    (firm fixed effects)
                    + delta_t    (time fixed effects)
                    + epsilon_{it}
```

Key coefficient: `beta_4` captures whether education vintage moderates the effect of board technical competence on GenAI adoption in the post-ChatGPT period.

Hypothesis-Specific Models

H1 (Vintage → Adoption Speed):

```
AI_Adoption_Speed_{it} = ... + beta * TKL_{it} + ...
```

Where TKL = Tech Knowledge Latency (Current Year - STEM Degree Year)

H2 (Tech Committee Vintage):

```
GenAI_Adoption_{it} = ... + beta_1 * TechCommittee_i
                          + beta_2 * (TechCommittee x OldVintage_i) + ...
```

H3 (Vintage Faultlines):

```
GenAI_Adoption_{it} = ... + beta * Vintage_Variance_{it} + ...
```

```
H4 (Reskilling Mitigation):
```

```
GenAI_Adoption_{it} = ... + beta_1 * OldVintage_i
                          + beta_2 * (OldVintage x ReskillingIndex_i) + ...
```

Supplementary Analyses

Analysis	Method	Purpose
Event Study	Quarterly coefficient plot	Verify parallel trends assumption
Heterogeneity	Subgroup DiD	Industry (tech vs. non-tech), firm size effects
Instrumental Variable	2SLS with birth year	Address endogeneity of vintage
Robustness	Varying cutoffs	Sensitivity to vintage classification (2010, 2012, 2015)
Mediation	Baron-Kenny / Causal Mediation	Board decision process as mediator
Placebo	Alternative tech DiD	Cloud/blockchain should show no vintage effect

Software and Tools

- Statistical software: Stata / R
- Text analysis: Python (for 10-K keyword extraction)
- Visualization: R (ggplot2) / Stata

Data Collection

Primary Data Sources

Database	Provider	Variables	Access
BoardEx	WRDS	Director education (AwardDate, Qualification, Subject), Committee membership, Employment history	University subscription
Compustat	S&P Global via WRDS	Total assets, Revenue, R&D expenditure, SIC/NAICS codes	University subscription
CRSP	WRDS	Stock returns, market capitalization	University subscription
SEC EDGAR	SEC	10-K annual filings (full text for NLP analysis)	Public access

Variable Construction

Independent Variables

Tech Knowledge Latency (TKL)

- Formula: `Current Year - STEM Degree Award Year`
- Source: BoardEx AwardDate field for STEM-classified qualifications
- Board-level aggregation: Mean TKL across all STEM-degreed directors

Education Vintage Category

Category	Graduation Period	Technological Era
Legacy Vintage	Pre-2000	Mainframe, early internet
Transitional Vintage	2000-2012	Web 2.0, mobile, early ML
Modern Vintage	Post-2012	Deep learning, transformers

Cognitive Vintage Faultline

- Formula: Variance of TKL within the board
- Measures: Intra-board heterogeneity in technical education recency

Reskilling Index

- Formula: Count of technical certifications or degrees obtained after age 45
- Source: BoardEx additional qualifications with AwardDate

Dependent Variables

GenAI Adoption Score

- Method: NLP-based keyword extraction from 10-K filings
- Keywords: ``Large Language Model,'' ``Transformer,'' ``Generative AI,'' ``GPT,'' ``Foundation Model,'' ``Prompt Engineering,'' ``AI-generated,'' ``LLM''
- Scoring: TF-IDF weighted frequency per 10-K filing
- Exclusion: Generic tech terms (``Big Data,'' ``Cloud,'' ``Machine Learning'') to isolate GenAI-specific adoption

AI Adoption Speed

- Formula: Number of quarters from ChatGPT launch (2022 Q4) to first GenAI keyword appearance in 10-K
- Lower values = faster adoption

Control Variables

Variable	Source	Measurement
Firm Size	Compustat	Log(Total Assets)
R&D Intensity	Compustat	R&D Expenditure / Revenue
Industry	Compustat	SIC 2-digit / NAICS codes
Board Size	BoardEx	Number of directors

Variable	Source	Measurement
Board Independence	BoardEx	% independent directors
CEO Tenure	BoardEx	Years as CEO
Firm Age	Compustat	Years since IPO
Prior IT Investment	Compustat	IT capital expenditure

Missing Data Strategy

BoardEx AwardDate Imputation

When AwardDate is missing but QualificationType is available:

Degree	Imputation Rule
Bachelor's	Birth Year + 22
Master's	Birth Year + 24
Doctoral	Birth Year + 28

Validation

- Compare imputed vs. actual dates where both are available
- Report imputation rate and sensitivity analysis excluding imputed observations

Data Collection Timeline

Step	Activity	Duration
1	Extract BoardEx education data	Week 1-2
2	Classify STEM vs. non-STEM qualifications	Week 2-3
3	Download and parse 10-K filings from EDGAR	Week 3-4
4	Run GenAI keyword extraction	Week 4-5
5	Merge BoardEx + Compustat + CRSP + EDGAR	Week 5-6
6	Data cleaning and validation	Week 6

Data

Sample Description

- Population: U.S. publicly listed firms in the BoardEx universe
- Time period: 2019 Q1 -- 2025 Q4 (28 quarters)
- Treatment event: ChatGPT release, November 30, 2022 (2022 Q4)
- Expected sample size: ~3,000-5,000 firms, ~50,000+ firm-quarter observations

Inclusion Criteria

1. Listed on NYSE, NASDAQ, or AMEX
2. At least one director with a STEM-classified degree in BoardEx
3. Financial data available in Compustat for the study period
4. At least one 10-K filing available in SEC EDGAR post-2022

Exclusion Criteria

1. Financial firms (SIC 6000-6999) -- different regulatory environment
2. Utility firms (SIC 4900-4999) -- regulated industry dynamics
3. Firms with fewer than 3 board members in BoardEx
4. Firms with missing key financial variables (total assets, revenue)

STEM Classification

Degrees classified as STEM based on BoardEx Subject field:

STEM	Non-STEM
Computer Science, Engineering, Mathematics, Physics, Statistics, Information Technology, Data Science, Artificial Intelligence, Electrical Engineering, Mechanical Engineering, Chemical Engineering, Bioinformatics	Law, Finance, Accounting, MBA (general), Economics, Political Science, History, English, Philosophy, Marketing

Key Data Fields from BoardEx

Field	Description	Use
`DirectorID`	Unique director identifier	Linking
`CompanyID`	Unique company identifier	Linking
`Qualification`	Degree name (BS, MS, PhD, etc.)	STEM classification
`QualSubject`	Field of study	STEM classification
`AwardDate`	Degree conferral date	Vintage calculation
`DOB`	Date of birth	Imputation, age controls
`CommitteeName`	Board committee assignments	Tech Committee identification
`RoleStartDate`	Director appointment date	Tenure calculation

Descriptive Statistics (Expected)

To be populated after data collection

Variable	N	Mean	SD	Min	Max
TKL (years)					
GenAI Adoption Score					

Variable	N	Mean	SD	Min	Max
AI Adoption Speed (quarters)					
Vintage Faultline (variance)					
Reskilling Index					
Board Size					
Firm Size (log assets)					
R&D Intensity					

Literature Review

Searching and Inclusion & Exclusion

Round 1

Search keywords and category

Category: Board Composition and AI/Digital Transformation

Keywords: - Board: ``board of directors,'' ``corporate governance,'' ``board composition,'' ``board expertise'' - AI: ``AI adoption,'' ``artificial intelligence adoption,'' ``digital transformation,'' ``generative AI,'' ``GenAI,'' ``ChatGPT''

Keywords combination

```
("board of directors" OR "corporate governance" OR "board composition")
AND
("AI adoption" OR "digital transformation" OR "generative AI" OR "ChatGPT")
```

Databases: Web of Science, Scopus, SSRN Expected results: 200-400 articles Inclusion: Empirical studies on board-level factors affecting technology/AI adoption Exclusion: Non-board-level analysis, purely technical AI papers, conference proceedings without peer review

Round 2

Search keywords and category

Category: Knowledge Obsolescence and Human Capital Depreciation

Keywords: - Knowledge: ``knowledge obsolescence,'' ``human capital depreciation,'' ``knowledge depreciation,'' ``education vintage,'' ``skill obsolescence'' - Domain: ``technology,'' ``STEM,'' ``engineering,'' ``technical expertise,'' ``high-tech''

Keywords combination

```
("knowledge obsolescence" OR "human capital depreciation" OR "education vintage"
 OR "skill obsolescence" OR "knowledge decay")
AND
("technology" OR "STEM" OR "engineering" OR "technical" OR "high-tech")
```

Databases: Web of Science, Scopus, NBER Working Papers Expected results: 100-200 articles Inclusion: Studies measuring temporal dimension of knowledge/skill value Exclusion: General education returns without temporal analysis, non-technical domains

Round 3

Search keywords and category

Category: Board Technical Expertise and Innovation

Keywords: - Board: ``tech committee,'' ``technology committee,'' ``director expertise,'' ``board human capital,'' ``STEM directors'' - Innovation: ``innovation,'' ``technology adoption,'' ``R&D,'' ``technological change,'' ``disruptive technology''

Keywords combination

```
("tech committee" OR "technology committee" OR "director expertise"
 OR "board human capital" OR "STEM director*")
AND
("innovation" OR "technology adoption" OR "R&D" OR "disruptive technology")
```

Databases: Web of Science, Scopus, SSRN Expected results: 150-300 articles Inclusion: Empirical studies linking board-level technical expertise to firm innovation outcomes Exclusion: CEO-only studies (unless board-level analysis included), theoretical-only papers

Additional Keywords (during writing)

```
("cognitive faultlines" OR "age diversity" OR "generational diversity")
AND
("top management team" OR "board" OR "executive" OR "TMT")
```

PRISMA

PRISMA flow diagram to be completed after systematic search

Stage	Round 1	Round 2	Round 3	Total
Identified				
Screened (title/abstract)				
Full-text assessed				
Included				
Excluded (with reasons)				

Exclusion reasons to track: 1. Not board-level analysis 2. No temporal/vintage dimension 3. No empirical component 4. Duplicate across databases 5. Not in English 6. Conference proceedings only (no journal version)

Reference List

Category, Classification and Decision Note for Selected Literature in Rounds

Round 1: Board Composition & AI

#	Reference	Category	Decision	Note
1	Hoppmann, Naegele, & Girod (2019). Boards as a source of inertia. AMJ	Board Inertia	Include (A)	Core reference: boards can resist change during discontinuities
2	Montagnani & Passador (2020). AI for Companies: Tech Committees in EU and US	Tech Committee	Include (A)	Empirical analysis of tech committee presence and AI
3	Ma (2025). Technological obsolescence. Review of Financial Studies	Obsolescence	Include (A)	Recent finance perspective on technological obsolescence

Round 2: Knowledge Obsolescence

#	Reference	Category	Decision	Note
1	Boone, Ganeshan, & Hicks (2008). Learning and knowledge depreciation. Management Science	Knowledge Depreciation	Include (A)	Foundational: knowledge depreciation in professional services
2	Shearer & Steger (1975). Manpower obsolescence. AMJ	Skill Obsolescence	Include (B)	Classic: half-life of engineering knowledge
3	Goldin (2014). A grand gender convergence. AER	Education Returns	Include (C)	Vintage of education affects wages and productivity

Round 3: Board Expertise & Innovation

#	Reference	Category	Decision	Note
1	Anderson & Tushman (1990). Technological discontinuities. ASQ	Tech Discontinuity	Include (A)	Foundational: competence-enhancing vs. destroying
2	Anderson & Tushman (2018). Technological discontinuities (reprint). Routledge	Tech Discontinuity	Include (A)	Updated version of the cyclical model

#	Reference	Category	Decision	Note
3	Lavie (2006). Capability reconfiguration. AMR	Dynamic Capabilities	Include (B)	Incumbent responses to techno-logical change
4	Kunze & Bruch (2010). Age-based faultlines. Small Group Research	Faultlines	Include (B)	Age-based cognitive faultlines in teams
5	Mundlamuri et al. (2025). Evolution of AI. IEEE Access	AI History	Include (C)	AI eras classifica-tion for vintage categoriza-tion

Additional (during and after writing)

#	Reference	Category	Decision	Note
	Hambrick & Mason (1984). Upper Echelons. AMR	Upper Echelons	Include (B)	Cognitive imprinting from educational backgrounds
	Cohen & Levinthal (1990). Absorptive Capacity. ASQ	Absorptive Capacity	Include (B)	Prior knowledge affects new knowledge absorption
	Teece (2007). Dynamic Capabilities. Strategic Management Journal	Dynamic Capabilities	Include (C)	Sensing-Seizing-Transforming framework

#	Reference	Category	Decision	Note
	DiMaggio & Powell (1983). Institutional Isomorphism. ASR	Institutional Theory	Include (C)	Decoupling: form vs. substance in governance
	Levitt & March (1988). Organizational Learning. Annual Review of Sociology	Competence Trap	Include (C)	Exploitation vs. exploration trade-off

Classification Key: A = Directly relevant to core argument, B = Supports theoretical framework, C = Provides background context

Research Problems

The Core Paradox

The integration of artificial intelligence (AI) into the strategic core of the modern enterprise represents a pivotal juncture in corporate history. The emergence of Generative AI (GenAI), catalyzed by the public release of ChatGPT in November 2022, has created a competence-destroying technological discontinuity (Anderson & Tushman, 2018).

While boards of directors are increasingly populated with individuals possessing technical backgrounds, many firms remain sluggish, misguided, or defensively reactive in their adoption of transformative AI technologies. The prevailing frameworks for assessing board competence rely on static indicators (e.g., STEM degree possession, Technology Committee existence). These binary metrics implicitly assume that knowledge is a durable asset with a negligible depreciation rate.

Central Research Question

> Does the vintage of directors' technical education moderate the relationship between board technical competence and the firm's adoption of Generative AI?

Sub-Questions

1. Latency: Does a shorter time-since-graduation for technical directors predict faster AI adoption?
2. Cognitive Faultlines: How does the variance in education vintage (the gap between the ``Old Guard'' and ``AI Natives'') affect strategic consensus?
3. Reskilling: Can continuous education (lifelong learning) mitigate the effects of knowledge depreciation?

Theoretical Gap

The corporate governance literature fails to account for Knowledge Obsolescence in technical domains. While labor economics has long recognized that the vintage of education affects wages and productivity (Goldin, 2014), governance research has largely ignored this dimension, treating a 40-year-old engineering degree as equivalent to a fresh doctorate.

This oversight is critical: stale knowledge does not merely fail to help; it may actively hinder. Directors entrenched in obsolete technical paradigms (deterministic, rule-based computing) could view the probabilistic, unstructured nature of GenAI as a risk to be contained rather than a capability to be unleashed (Lavie, 2006).

Key Construct: Education Vintage

Technical knowledge is not a stock variable but a flow subject to rapid radioactive decay. A director who obtained a Computer Science degree in 1985 (mainframe computing, symbolic AI) possesses a cognitive framework fundamentally distinct from one who graduated in 2020 (deep learning, transformer models, neural networks). Although both are classified as ``technically competent'' by traditional measures, the vintage of their education dictates the relevance, utility, and validity of their human capital in the face of the GenAI shock.

Key References

Foundational References by Theory

Resource Dependence Theory

- Hoppmann, J., Naegele, F., & Girod, B. (2019). Boards as a source of inertia: Examining the internal challenges and dynamics of boards of directors in times of environmental discontinuities. Academy of Management Journal, 62(2), 437-468.
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- Boone, T., Ganeshan, R., & Hicks, R. L. (2008). Learning and knowledge depreciation in professional services. Management Science, 54(7), 1231-1236.
- Goldin, C. (2014). A grand gender convergence: Its last chapter. American Economic Review, 104(4), 1091-1119.
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- Ma, S. (2025). Technological obsolescence. The Review of Financial Studies, hhaf059.

Technological Discontinuities

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- Anderson, P., & Tushman, M. L. (2018). Technological discontinuities and dominant designs: A cyclical model of technological change. In Organizational Innovation (pp. 373-402). Routledge.

Board Composition & AI Governance

- Montagnani, M. L., & Passador, M. L. (2020). Artificial Intelligence for Companies in a Post Covid World: An Empirical Analysis of Tech Committees in the EU and US.

Cognitive Faultlines

- Kunze, F., & Bruch, H. (2010). Age-based faultlines and perceived productive energy: The moderation of transformational leadership. Small Group Research, 41(5), 593-620.

AI Evolution

- Mundlamuri, R., Gunnam, G. R., Mysari, N. K., & Pujuri, J. (2025). The Evolution of AI: From Classical Machine Learning to Modern Large Language Models. IEEE Access.

Dynamic Capabilities

- Lavie, D. (2006). Capability reconfiguration: An analysis of incumbent responses to technological change. Academy of Management Review, 31(1), 153-174.

Key Model: Conceptual Framework

```
Board Technical           Education              GenAI
Competence      ------>   Vintage      ------>   Adoption
(STEM directors)          (Moderator)            (Speed & Depth)
                              |
                    +---------+---------+
                    |                   |
              Tech Committee      Reskilling
              Vintage (H2)       Index (H4)
                    |
              Cognitive
              Faultlines (H3)
```

Literature Gaps Addressed

Gap	How This Study Addresses It
Static measurement of board technical competence	Introduces temporal dimension via Education Vintage
Binary STEM degree classification	Continuous TKL measure + vintage categories
Ignoring knowledge depreciation in governance	Integrates labor economics vintage concept
Assuming Tech Committee = effective oversight	Tests moderation by committee member vintage
No causal identification for board-AI relationship	DiD design with ChatGPT as exogenous shock

Quotes and Paraphrases

On Knowledge Obsolescence

> ``The depreciation rate of knowledge in high-technology fields is significantly higher than in law, finance, or management.'' -- Boone, Ganeshan, & Hicks (2008), Management Science

> ``The half-life of engineering knowledge is as short as 2.5 to 5 years.'' -- Shearer & Steger (1975), Academy of Management Journal

On Competence-Destroying Discontinuities

> ``Unlike incremental technological advances that reward accumulated experience and existing institutional knowledge, competence-destroying discontinuities render vast swaths of prior expertise obsolete.'' -- Anderson & Tushman (2018)

Paraphrase: Competence-destroying discontinuities fundamentally differ from incremental innovations because they invalidate existing expertise rather than building upon it. GenAI represents such a discontinuity for traditional IT governance frameworks.

On Board Inertia

> ``Boards as a source of inertia: Examining the internal challenges and dynamics of boards of directors in times of environmental discontinuities.'' -- Hoppmann, Naegele, & Girod (2019), Academy of Management Journal

Paraphrase: Hoppmann et al. demonstrate that boards can become sources of organizational inertia rather than drivers of change, particularly during periods of environmental discontinuity. This supports our argument that vintage-misaligned boards may resist rather than enable GenAI adoption.

On Cognitive Imprinting

Paraphrase: Upper Echelons Theory (Hambrick & Mason, 1984) suggests that executives' strategic choices reflect their cognitive bases, which are formed during formative educational experiences. These cognitive imprints are resistant to change, meaning a director trained in deterministic computing paradigms will approach GenAI through that established cognitive lens.

On the Vintage Effect

Paraphrase: A director who obtained a Computer Science degree in 1985 (the era of mainframe computing and symbolic AI) possesses a cognitive framework fundamentally distinct from one who graduated in 2020 (deep learning and transformer models). Although both are classified as technically competent by traditional databases, the vintage of their education dictates the relevance and utility of their human capital when confronting GenAI.

On Resource Fossilization

Paraphrase (original concept): We introduce ``Resource Fossilization'' to describe the phenomenon where a strategic resource provided by a board member degrades into a liability due to environmental paradigm shifts. When the technology landscape moves from on-premise to cloud, or from analytical AI to generative AI, expertise in the old paradigm loses its strategic value and may actively impede adaptation.

On Capability Reconfiguration

> ``Capability reconfiguration: An analysis of incumbent responses to technological change.'' -- Lavie (2006), Academy of Management Review

Paraphrase: Lavie argues that incumbents' responses to technological change depend on their ability to reconfigure existing capabilities. Directors entrenched in obsolete technical paradigms may view GenAI's probabilistic nature as a risk to be contained rather than a capability to be unleashed.

Products

Expected Deliverables

Primary Output

1. Journal Manuscript: ``Education Vintage and Knowledge Depreciation: Board Technical Competency in the Era of Generative AI''
    - Target: Academy of Management Journal / Strategic Management Journal
    - Format: APA 7th edition (apaquarto template)
    - Length: ~12,000 words (excluding references and appendices)

Supplementary Materials

2. Online Appendix
    - Full variable definitions and sources
    - STEM classification dictionary
    - GenAI keyword dictionary with validation
    - Additional robustness tables
    - Event study plots
3. Replication Package
    - Stata/R code for all analyses
    - Data construction scripts (Python for NLP)
    - Variable codebook

Presentation Materials

4. Conference Presentation
    - Target venues: AOM Annual Meeting, SMS Annual Conference
    - 15-minute presentation deck

Data Products

5. Education Vintage Dataset

    - Board-level vintage measures for U.S. public firms
    - Potential for data sharing with research community (subject to BoardEx license)

Target Journal Priorities

Priority	Journal	Impact Factor	Fit
1	Academy of Management Journal	~13.0	Board human capital + tech change
2	Strategic Management Journal	~8.6	Dynamic capabilities + board composition
3	Journal of Management	~13.5	Human capital theory extension
4	Corporate Governance: An Intl Review	~5.0	Direct topical fit
5	Organization Science	~5.4	Competence trap, cognitive faultlines

Timeline to Submission

Milestone	Target Date
Literature review complete	2026-04-30
Dataset constructed	2026-05-15
Analysis complete	2026-06-15
Draft complete	2026-07-15
Internal review	2026-07-30
Journal submission	2026-08-15

References