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Validation of the AI-Readiness and Market Dynamics Disruption Index (AIM-DDI) Framework: A Case Study of Its Application in the Beauty Cluster

Jorge Calvo García
Graduate School of Management, GLOBIS University Tokyo

ABSTRACT

The adoption of artificial intelligence (AI) is transforming and disrupting industries by driving innovation, enhancing operational efficiency, and reshaping market dynamics. However, organizations often struggle to balance internal readiness with external market alignment, creating a critical need for comprehensive frameworks to guide AI integration. This study introduces and validates the AI-Readiness and Market Dynamics Disruption Index (AIM-DDI), a holistic tool for evaluating organizational AI maturity. By combining internal factors, such as strategy, talent, and governance, with external elements, including customer expectations, industry disruption potential, and regulatory environments, the AIM-DDI provides actionable insights for navigating AI-driven transformation.

The research validates the AIM-DDI scale and questionnaire, leveraging data from 765 organizations to identify distinct AI maturity profiles. Cronbach's Alpha Analysis , Exploratory and Confirmatory Factor Analyses confirm the framework's validity, while cluster analysis reveals strategic pathways for organizations at various stages of AI readiness. The findings highlight the importance of aligning internal capabilities with external pressures to achieve competitive advantage and sustainable growth. We also apply the AIM-DDI framework within the Beauty Clusters Industry Association in Spain data as business case. This study offers valuable contributions for academics, practitioners, and policymakers aiming to leverage AI as a driver of industry evolution..

Keywords: Artificial Intelligence, AI readiness, market disruption, AIM-DDI framework, strategic planning, organizational transformation, Beauty Cluster, AI maturity, digital transformation, competitive advantage.

Accés a l'article i contacte amb el seu autor

1. Introduction

The rapid and potentially disruptive advancements in artificial intelligence (AI) are reshaping industries and markets, making AI readiness and strategic adoption essential for maintaining organizational competitiveness. While many organizations acknowledge AI's transformative potential, achieving a balance between internal capabilities and external market alignment remains a significant challenge. Traditional frameworks for assessing technological readiness often focus on isolated aspects, such as infrastructure, skills, capabilities or best practices. However, these approaches frequently become obsolete due to the fast-paced nature of current technological innovation, failing to address the dynamic interplay between internal preparedness and external disruption.

This study introduces and validates the AI-Readiness and Market Dynamics Disruption Index (AIM-DDI) presented at *International ICID 2024 Workshop on "Cultural Perspectives of Human-Centered Approaches and Technological Innovations"* (CPHCATI-2024), which took place on January 27th-28th, 2024 in Tokyo, and published in the peer-review proceedings (Calvo. J., 2025), a comprehensive framework designed to evaluate organizational AI maturity holistically. By integrating internal factors, including strategy, talent, and governance, with external dynamics, such as customer adoption, industry disruption potential, and regulatory environments, the AIM-DDI provides actionable insights for navigating the complexities of AI-driven transformation. The framework's unique approach bridges the gap between readiness and market impact, offering organizations a tool to strategically position themselves in an AI-dominated landscape.

The study also explores the application of the AIM-DDI framework within the Beauty Cluster Industry Association in Spain, a sector increasingly shaped by AI innovations. Using exploratory and confirmatory factor analyses, the study evaluates the validity and reliability of the AIM-DDI as both a diagnostic and strategic tool. Furthermore, cluster analysis is employed to identify distinct organizational profiles, each characterized by unique challenges and opportunities for advancing AI maturity.

This paper aims to contribute to both academic and practical understandings of AI adoption by providing a validated framework that aligns internal capabilities with external market forces. By addressing gaps in existing literature and emphasizing the strategic implications of AI maturity, the research offers valuable guidance for practitioners, policymakers, and researchers striving to leverage AI for competitive advantage and sustainable growth.

2. The AIM-DDI Framework: A Holistic Approach to AI Readiness and Market Disruption

2.1 Theoretical Foundations and Development

The AIM-DDI Framework is based in analysis of existing literature, industry best practices, and empirical research. It synthesizes a wide array of perspectives into a coherent and actionable model, addressing the dual dimensions of AI readiness within organizations - technological and cultural - and its potential to disrupt markets. This holistic view provides a strategic toolkit for organizations to assess their AI readiness, understand market disruption models, and leverage AI for competitive advantage.

2.1.1 AI Readiness in Organizations

AI readiness refers to the preparedness of an organization to adopt and integrate AI technologies effectively. Key components include technological infrastructure, workforce skills, organizational culture, and leadership alignment. Methodologies such as multicriterion decision analysis (Mittal, 2020) and the Singapore Smart Industry Readiness Index (Tzu-Chieh et al., 2020 a y b) provide structured approaches for assessing readiness. Despite their utility, these tools often neglect the broader strategic implications of AI adoption (Palade & Carutasu, 2023)

2.1.2 Market Disruption Models

AI's transformative potential extends beyond organizational boundaries, reshaping market dynamics and competition. Industries such as retail, healthcare, and finance have experienced significant disruption due to AI-driven innovations (Samadhiya et al., 2023). However, most studies fail to connect internal readiness with the capacity to leverage AI for competitive advantage, underscoring the need for integrative models like AIM-DDI.

2.1.3 The AIM-DDI Framework

The AIM-DDI framework addresses two critical dimensions: internal AI readiness and external market disruption. It evaluates an organization's capabilities for AI adoption and aligns them with external opportunities and challenges.

The AIM-DDI framework offers a comprehensive model for understanding the interplay between AI readiness and market disruption. By addressing both internal and external dimensions, it provides organizations with strategic insights to navigate the complexities of AI adoption. This integrative approach not only fosters innovation but also positions businesses for sustainable competitive advantage in an AI-driven world.

2.1.3.1 Internal AI Maturity

AI readiness encompasses technical infrastructure, workforce development, and cultural adaptation. Effective leadership plays a pivotal role in fostering an environment conducive to AI adoption (Zamani et al., 2022). Moreover, the automation-augmentation paradox highlights the need to balance economic and social objectives during AI integration (Kumar, A. et al., 2023 and Kumar, N. et al, 2023).

A company's potential for disruption is deeply rooted in its internal AI maturity, a comprehensive measure of its preparedness to harness AI technologies. This preparedness goes beyond simply adopting new tools; it requires the seamless integration of AI into the organization's strategic, operational, and ethical framework. This dimension evaluates an organization's readiness to leverage AI technologies across five key factors:

1. AI Strategy and Vision
2. Data Infrastructure
3. AI Talent and Expertise
4. AI Implementation and Use Cases
5. AI Ethics and Governance

Each factor is rated on a scale from 0 to 5, with 0 indicating the lowest level of maturity and 5 representing the highest. The sum of these ratings provides a comprehensive metric of the organization's internal AI maturity, ranging from 0 to 25.

2.1.3.2 External AI Maturity

AI disrupts market dynamics by introducing new competitive paradigms. The integration of AI with strategies like the Blue Ocean Strategy enables organizations to create uncontested market spaces (Kim, W.C., & Mauborgne, B, 2015). Additionally, AI enhances competitive intelligence systems, equipping businesses with insights to navigate complex market conditions (Linna, A. 2023 and Abbas & Ghazi 2016).

Beyond the boundaries of individual organizations, the external AI maturity landscape defines the environment in which businesses operate, driven by customer expectations, competitive dynamics, and overarching industry trends. This axis assesses the market and industry environment in which the organization operates, considering five external factors:

1. Customer Expectations and Adoption
2. Competitor AI Maturity
3. Industry Disruption Potential
4. Regulatory Environment and AI Governance
5. AI Talent and Education Ecosystem

Similar to the internal factors, each external factor is rated on a scale from 0 to 5, with the sum providing a score for external AI maturity, also ranging from 0 to 25.

2.2 Applications of AI in Strategic Management

AI offers transformative potential for businesses by enhancing competitiveness through improved decision-making, customer engagement, and innovation. However, its adoption is not without challenges, including resistance to change, ethical dilemmas, and workforce skill gaps. Successfully leveraging AI requires addressing these barriers with targeted investments in training and ethical governance

- **Enhancing Business Competitiveness:** AI's ability to process vast amounts of data and generate actionable insights significantly enhances decision-making, customer engagement, and innovation (Zhao et al., 2023 a and b). For example, companies leveraging AI for supply chain resilience have improved efficiency and responsiveness (Nurhaida et al., 2023).
- **Challenges and Barriers:** Despite its benefits, AI adoption presents challenges such as resistance to change, ethical dilemmas, and workforce skill gaps (Sulthan et al., 2023). Addressing these barriers requires investments in training and ethical governance to ensure responsible implementation.

2.3 Integrating Insights from Latest Related Research

The AIM-DDI Framework aligns with and builds upon several key concepts and latest theories in the field of AI adoption and business transformation:

2.3.1 Technology-Organization-Environment and AI Adoption

The Technology-Organization-Environment (TOE) framework, introduced by Tornatzky and Fleischer in 1990, has been widely applied to study AI adoption across various sectors. This framework provides a comprehensive lens for examining the factors influencing AI adoption by considering three key contexts: technological, organizational, and environmental. Yang et al. (2024) utilized TOE to explore AI adoption in professional service firms, while Agarwal et al. (2023) examined its application in public organizations. A meta-analysis by Tamilmani et al. (2023) revealed that seven out of eight TOE factors significantly influence AI adoption. The TOE framework's strength lies in its ability to capture both internal and external factors affecting innovation adoption, making it a robust and flexible model for understanding organizational behavior towards new technologies.

Henderson et al.'s (2024) application of the Technology-Organization-Environment (TOE) framework to AI adoption in mission-critical environments provides additional context for understanding the multifaceted nature of AI readiness. The AIM-DDI Framework incorporates similar considerations across its internal and external maturity axes.

The TOE framework offers a broad, descriptive approach to technology adoption across technological, organizational, and environmental contexts, while AIM-DDI focuses specifically on AI adoption and disruption, integrating internal and external AI maturity. AIM-DDI is prescriptive, providing strategic guidance tailored to AI, whereas TOE remains generalizable to various technologies:

1. Scope:

- TOE: Provides a broad context for understanding technology adoption in organizations, considering technological, organizational, and environmental factors.
- AIM-DDI: Specifically tailored to AI adoption and its impact on market disruption, offering a more focused approach.

2. Dimensions:

- TOE: Three main contexts - technological, organizational, and environmental.
- AIM-DDI: Two main axes - Internal AI Maturity and External AI Maturity, which encompass elements from all three TOE contexts.

3. Application:

- TOE: Generally applicable to various technologies and innovations.
- AIM-DDI: Specifically designed for AI technologies and their disruptive potential.

4. Strategic Implications:

- TOE: Primarily descriptive, explaining factors influencing adoption.
- AIM-DDI: More prescriptive, offering strategic guidance based on an organization's position in the framework.

2.3.2 Innovation Diffusion Theory and AI Implementations

Innovation Diffusion Theory provides a framework for understanding how AI technologies spread through organizations and society, It identifies key factors influencing AI adoption, including relative advantage, compatibility, complexity, trialability, and observability. The theory categorizes adopters into groups like innovators, early adopters, early majority, late majority, and laggards. These concepts are reflected in the AIM-DDI Framework's assessment of both internal readiness and external market factors (Bodén, A., & Dahlstedt, G., 2023; Djaja, I., & Arief, M., 2023; Almaiah,et al., 2022; Sreedharan, S., 2024).

IDT focuses on how innovations spread, emphasizing adoption factors like relative advantage and complexity, while AIM-DDI evaluates both internal AI adoption and market disruption potential. IDT is adopter-centric, analyzing adoption patterns, whereas AIM-DDI balances adoption with market dynamics, offering strategic guidance on AI maturity and disruption.:

1. Scope:

- IDT: Focuses on how, why, and at what rate innovations spread through markets or organizations.
- AIM-DDI: Considers both the internal adoption of AI and its potential to disrupt markets.

2. Factors:
- IDT: Emphasizes factors like relative advantage, compatibility, complexity, trialability, and observability.
- AIM-DDI: Incorporates these factors within its assessment of Internal and External AI Maturity but also considers broader strategic implications.

3. Perspective:
- IDT: Primarily adopter-centric, focusing on the decision to adopt an innovation.
- AIM-DDI: Balances adopter perspective with market dynamics and disruptive potential.

4. Strategic Implications:
- IDT: Provides insights into adoption patterns and barriers.
- AIM-DDI: Offers strategic guidance based on an organization's position relative to AI maturity and market dynamics.

2.3.3 Dynamic Capabilities Theory and AI Implementation

The Dynamic Capabilities Theory (DCT) emphasizes the importance of sensing, seizing, and transforming capabilities in leveraging AI for competitive advantage. This aligns closely with the AIM-DDI Framework's focus on internal AI maturity, particularly in areas such as AI strategy, talent, and implementation. A 2024 study by Singh explored how firms can leverage DCT to adopt and integrate Generative AI systems like ChatGPT, Claude, Gemini, and Copilot. The research emphasizes the need for continuous organizational learning, agile resource reconfiguration, and external collaboration to maintain a competitive edge in the rapidly evolving AI landscape. This aligns with the core principles of DCT, which focus on sensing, seizing, and transforming capabilities. The adoption of AI is also seen as a dynamic capability in itself. Almheiri et al. (2024) found that the presence of AI capabilities positively and significantly impacts dynamic capabilities, organizational creativity, and performance in government organizations.

The DCT framework focuses on developing organizational capabilities for adaptability, emphasizing sensing, seizing, and transforming, while AIM-DDI integrates these within its Internal AI Maturity axis and adds external market dynamics for a holistic view. DCT is inward-looking, targeting sustained competitive advantage, whereas AIM-DDI balances internal capabilities with external forces, addressing both competitive advantage and market disruption.

1. Focus:
- DCT: Emphasizes the development of organizational capabilities to adapt to changing environments.
- AIM-DDI: Combines internal capability assessment with external market dynamics, providing a more holistic view.

2. Capabilities:
- DCT: Focuses on sensing, seizing, and transforming capabilities.
- AIM-DDI: Incorporates these capabilities within its Internal AI Maturity axis, while also considering external factors.

3. Strategic Orientation:
- DCT: Primarily inward-looking, focusing on organizational adaptability.
- AIM-DDI: Balances internal capabilities with external market forces, offering a more comprehensive strategic perspective.

4. Outcome:
- DCT: Aims at sustaining competitive advantage through capability development.
- AIM-DDI: Provides a framework for both

competitive advantage and potential market disruption.

2.4 Synthesis and Unique Contributions of AIM-DDI

The AIM-DDI Framework effectively synthesizes elements from TOE, IDT, and DCT, while offering unique contributions:

1. **Integrated Approach:** AIM-DDI combines internal organizational factors with external market dynamics in a single framework, providing a more comprehensive view than any of the individual theories.
2. **AI-Specific Focus:** Unlike the more general TOE and IDT, AIM-DDI is tailored specifically to AI technologies and their disruptive potential.
3. **Strategic Quadrants:** The framework's division into four strategic quadrants (Vulnerable Observers, Pressured Responders, AI-Driven Leaders, and Latent Disruptors) offers clear strategic implications do not present in the other theories.
4. **Quantitative Assessment:** AIM-DDI provides a scoring system for both internal and external AI maturity, allowing for more precise positioning and benchmarking.
5. **Market Disruption Emphasis:** While other theories focus primarily on adoption, AIM-DDI explicitly considers the potential for market disruption, making it particularly relevant in the rapidly evolving AI landscape.

2.5 Implications for Practice and Research

Practitioners are encouraged to focus on internal readiness and external market dynamics by assessing preparedness, aligning AI strategies with business goals, and establishing ethical guidelines. Meanwhile, researchers are invited to delve deeper into the intersection of AI readiness and market disruption, explore sector-specific applications of the AIM-DDI framework, and conduct longitudinal studies to assess its long-term impact.

- **For Practitioners:** Organizations should adopt a dual-focus approach that integrates internal readiness with external market dynamics. Practical steps include:
  - Conducting comprehensive readiness assessments.
  - Aligning AI strategies with business objectives.
  - Developing ethical guidelines for AI deployment.
- **For Researchers:** Future research should explore:
  - The relationship between AI readiness and market disruption.
  - Sector-specific applications of the AIM-DDI framework.
  - Longitudinal studies to evaluate the framework's effectiveness over time.

3. The AIM-DDI Quadrants

Organizations can be categorized into four distinct quadrants based on their internal AI capabilities and the external AI maturity of their markets. Each quadrant highlights unique challenges and strategic opportunities for organizations navigating the evolving AI landscape. By understanding their positioning, companies can adopt targeted strategies that drive sustainable growth and competitive advantage within their specific contexts. By plotting an organization's position based on its internal and external AI maturity scores, the AIM-DDI Framework identifies four distinct quadrants:

1. Vulnerable Observers (Lower Left)
2. Pressured Responders (Upper Left)
3. AI-Driven Leaders (Upper Right)
4. Latent Disruptors (Lower Right)

Each quadrant represents a unique set of characteristics and strategic implications, guiding organizations on how to navigate the complexities of AI integration and competitive positioning (Fig. 1).

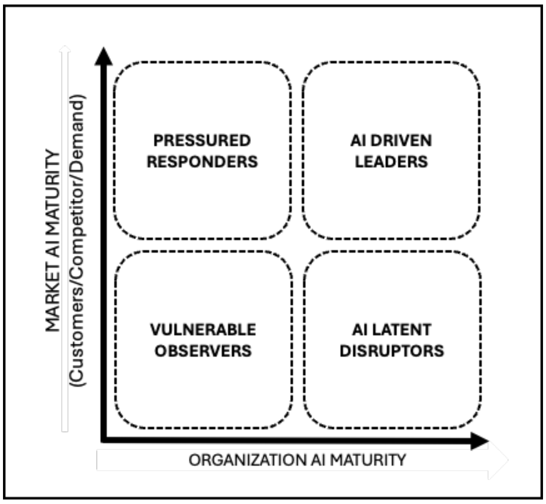


Fig. 1. The Integrative AIM-DDI Framework and Quadrants.

3.1 Strategic Implications and Navigation

The following presents an overview of the characteristics of organizations in each quadrant, accompanied by examples of key strategies.

3.1.1 Vulnerable Observers

Organizations in this quadrant have low internal AI maturity and face a market with low external AI maturity. While they may not feel immediate pressure to adopt AI, they risk falling behind as the market evolves. The strategic focus for these companies should be on building foundational AI capabilities and preparing for future market shifts.

Key strategies:

- Invest in AI education and awareness programs for leadership and employees.
- Begin small-scale AI pilot projects to gain experience and demonstrate value.
- Develop a roadmap for AI integration aligned with business objectives.

3.1.2 Pressured Responders

These organizations operate in markets where AI is becoming increasingly important, but they lack internal AI capabilities. They face significant pressure from competitors and market expectations to adopt AI quickly.

Key strategies:

- Prioritize rapid development of AI capabilities through strategic partnerships or acquisitions.
- Focus on high-impact AI use cases that can deliver quick wins and build momentum.
- Invest heavily in upskilling and reskilling programs to build internal AI expertise.

3.1.3 AI-Driven Leaders

Organizations in this quadrant are at the forefront of AI adoption both internally and within their market. They have strong AI capabilities and operate in a competitive environment where AI is a critical factor.

Key strategies:

- Continue to innovate and push the boundaries of AI applications.
- Focus on expanding influence and setting new industry standards.
- Explore opportunities to disrupt adjacent markets or industries.

3.1.4 Latent Disruptors

These companies possess advanced AI capabilities but operate in markets that have not yet fully embraced AI. This unique position presents an opportunity to become disruptors and reshape the competitive landscape. This market could be categorized as a Blue Ocean (Kim & Mauborgne, 2004, 2005, 2011, 2013, 2023) for the few companies that have innovatively adopted AI, staying ahead of their competitive context. A single leader could capture the entire market value by establishing its own AI Moat (Nvidia example in the GPU market: Singh, 2023). An AI Moat represents significant barriers, such as exclusive data, advanced algorithms, or solid technological infrastructure- to prevent new rivals in scale (Singh 2023).

Key strategies:

- Leverage advanced AI capabilities to introduce groundbreaking products or services.
- Educate the market on the benefits of AI-driven solutions.
- Prepare for rapid scaling as the market catches up to AI adoption.

3.2 Metrics of AIM-DDI Index

Incorporating a mathematical approach to calculating the AIM-DDI score enhances the analytical rigor in assessing an organization's AI maturity. By determining the ratio of an organization's internal AI maturity to the external AI maturity landscape, we derive the AIM-DDI score—a clear, quantifiable metric that facilitates straightforward interpretation. The framework consists of two main axes:

1. Internal AI Maturity (X-Axis)

$$AIM - DDI\ score\ = \frac{Internal\ AI\ Maturity\ Score}{External\ AI\ Maturity\ Score}$$

- ***AIM-DDI score*** > 1: Indicates the organization's AI capabilities are robust, providing a competitive advantage in AI maturity relative to the market.
- ***AIM-DDI score*** < 1: Signals the need for the organization to strengthen its AI maturity to maintain or achieve market leadership.

To visualize this framework, a graphical representation with two axes—Organization AI Maturity (Internal) on the X-axis and Market AI Maturity (External) on the Y-axis—can be used. The diagonal line on the chart distinguishes whether AI maturity serves as a competitive strength (below the diagonal) or a weakness (above the diagonal). This visualization further highlights strategic implications, delineating areas that align with Blue Ocean strategies (competitive advantage) and Red Ocean strategies (competitive struggle) (Fig. 2).

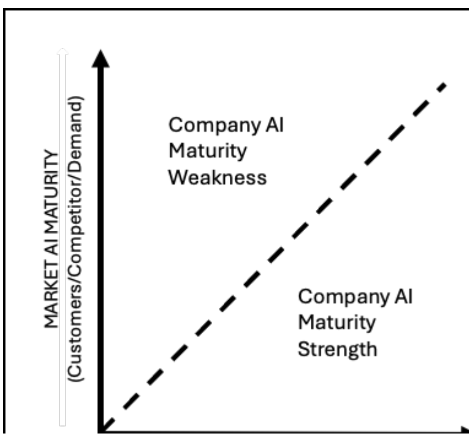


Fig. 2. The graphic boundary between AI as a strength or as a weakness.

In conclusion, the AIM-DDI Framework builds upon the strengths of established theories while offering a more specialized, integrated, and strategically oriented approach to understanding AI adoption and its impact on market dynamics. Its unique contributions make it a valuable tool for organizations navigating the complexities of AI-driven transformation and competitive positioning.

4. Study Design

While existing literature has explored various aspects of organizational AI adoption, there remains a critical gap in understanding the measurement invariance of AI readiness constructs across different industry contexts. Previous studies have largely focused on single-industry analyses or broad technological readiness measures, without specifically addressing the unique challenges of AI implementation. This research employed a cross-sectional survey design to assess organizational AI readiness and market disruption potential using the AI-Readiness and Market Dynamics Disruption Index (AIM-DDI) Framework. The study was conducted from May 24th to December 20th, 2024.

4.1 Sample and Data Gathering

A stratified random sampling technique was used to ensure representation across various industries, company sizes, and geographical locations within the Beauty Cluster. The target sample size 765 organizations across multiple industries and geographical regions to ensure statistical power and generalizability of findings.

Participants were recruited through multiple channels:

1. Professional networks, business schools and industry associations.
2. LinkedIn and other professional social media platforms.
3. Direct outreach to companies identified as potential participants.
4. Webinar and conference attendees.
5. Referrals from initial participants (snowball sampling).

Data was collected using an online survey platform. The survey was available in both English and Spanish to accommodate a diverse range of participants.

4.2 Survey Instrument

The survey instrument captured information across 16 questions divided into three main sections (Exhibit 1):

1. Internal AI Maturity Assessment (Questions 1-5)
2. External AI Maturity Assessment (Questions 6-10)
3. Organizational Demographics and Performance (Questions 11-16)

The first 10 questions utilized a 6-point Likert scale, ranging from low to high, with statistical values assigned from 0 to 5, to evaluate various aspects of AI readiness and market dynamics. Questions 11 to 15 gathered information about the company's origin, industry, annual revenue, current growth, and growth expectations for the next three years. Notably, the questions related to annual revenue, current growth, and growth expectations employed an inverse scale to enhance clarity and comprehension. The survey concluded with an open-ended question inviting participants to share additional comments.

4.3 Data Collection Process

1. Initial contact: Potential participants were contacted via email, social networks or webinars, with an invitation to participate in the study.
2. Survey distribution: Upon agreement, participants received a unique link to the online survey platform.
3. Data validation: Responses were screened for completeness and consistency.
4. We added calculations for each organization to the dataset, including its Internal AI Maturity, External AI Maturity, and AIM-DDI Competitiveness Score.

4.4 Ethical Considerations

1. Informed consent was obtained from all participants prior to data collection.
2. Confidentiality and anonymity of respondents were ensured throughout the research process.
3. The study was approved by the GLOBIS University Graduate School of Management and Beauty Clutter directors.
4. The framework and questionnaire were detailed in our peer-reviewed paper, *"Towards an Integrative Framework for AI Readiness and Market Disruption: The AI-Readiness and Market Dynamics Disruption Index (AIM-DDI) for Competitive AI Leadership,"* published in the proceedings of the CPHCATI 2024 Conference.

4.5 Data Management

1. Respondents were not asked for identification, nor was personal or company data collected beyond the fields of the questionnaire, which was anonymous.
2. Data were collected and stored securely using encrypted, password-protected systems.
3. Regular backups were performed to prevent data loss.
4. Data cleaning and preprocessing were conducted to ensure data quality and consistency.

5. Reliability and Statistical Analysis of AI Readiness Scale

To assess the internal consistency and reliability of the AI readiness scale, a Cronbach's alpha analysis was conducted on five key dimensions: AI strategy and vision, data infrastructure, AI talent and expertise, AI implementation and use cases, and AI ethics and governance. These dimensions represent critical components of organizational AI maturity and were evaluated to ensure the scale's robustness and validity.

5.1 Cronbach's Alpha Analysis

The overall Cronbach's alpha for the scale was calculated to be 0.878, indicating a high level of internal consistency. This score suggests that the items within the scale are closely related and measure a cohesive construct of AI readiness. According to Nunnally (1978), a Cronbach's alpha above 0.7 is considered acceptable, while values above 0.8 are indicative of strong reliability.

5.2 Correlation Analysis

A correlation analysis was conducted to explore the relationships between observed variables and latent factors. This analysis aimed to validate theoretical relationships, identify potential redundancies, and evaluate the practical utility of the AIM-DDI dimensions in organizational contexts (Exhibit 4).

5.2.1 Strong Internal Correlations

The analysis revealed high correlations within the Internal AI Maturity dimension, demonstrating strong internal consistency:

Internal Maturity correlated strongly with:

- Implementation (r = 0.88)
- Strategy (r = 0.87)
- Talent (r = 0.85)
- Ethics (r = 0.81)

These findings validate the coherence of variables within this dimension and highlight the interdependence of strategic and operational elements in internal AI capabilities.

5.2.2 External Relationships

In the External AI Maturity dimension, significant correlations aligned with market-driven constructs:

External Maturity showed strong correlations with:

- Customer Expectations (Customer Exp) (r = 0.79)C
- Competitor Maturity (Competitor Mat) (r = 0.76)

These relationships emphasize the role of external factors in shaping AI maturity and their alignment with dynamic market demands.

5.2.3 Inter-Factor Correlations

Moderate correlations between latent factors highlight meaningful but distinct relationships:

Internal Maturity and External Maturity were moderately correlated (r = 0.68), suggesting alignment between internal capabilities and external demands without redundancy.

5.2.4 Cross-Dimensional Insights

A moderate correlation was observed between:

- Internal Maturity and Customer Exp (r = 0.58)
- External Maturity and Strategy (r = 0.58)

These findings suggest potential influences across dimensions, indicating interconnected strategies that integrate internal and external maturity factors.

5.2.5 Discussion

The correlation analysis supports the construct validity of the AIM-DDI by confirming strong internal relationships within each dimension and moderate inter-factor correlations. These results align with theoretical expectations and reinforce the scale's robustness.

- Convergent Validity: High correlations within the Internal Maturity and External Maturity dimensions confirm their internal coherence, validating the inclusion of their respective variables.
- Discriminant Validity: Moderate inter-factor correlations ($r < 0.70$) support the distinctiveness of the three latent constructs, ensuring that they capture unique aspects of AI maturity.

The correlation analysis delved deeper into the relationships between individual variables and their respective dimensions, as well as the interactions across dimensions. Strong correlations within each dimension confirmed the internal consistency of the scale, demonstrating that the observed variables are reliable indicators of their respective constructs. For instance, within the Internal AI Capabilities dimension, variables like strategy, talent, and ethics exhibited high correlations with AI maturity, underscoring the importance of these components in achieving organizational readiness for AI adoption.

Moreover, the moderate correlations between factors revealed meaningful cross-dimensional influences without redundancy. For example, the relationship between Internal AI Capabilities and Customer Expectations (r = 0.58) suggests that internal strategic alignment can positively influence external customer-facing capabilities. Similarly, the connection between External AI Environment and Strategy (r = 0.58) highlights the bidirectional nature of internal and external readiness in achieving comprehensive AI maturity. These findings provide actionable insights into how organizations can balance internal strengths with external pressures.

The results underscore the AIM-DDI's utility as a diagnostic and strategic tool, guiding organizations in aligning their AI capabilities with both internal objectives and external pressures.

5.3 Descriptive Statistics

The mean scores indicate that respondents generally rate their organizations moderately across the dimensions, with "data infrastructure" receiving the highest average score (3.239) and "AI talent and expertise" the lowest (2.31). The standard deviations suggest a reasonable level of variability in responses, reflecting diverse organizational contexts.

5.4 Conclusion

The results of the reliability and statistical analysis confirm that the AI readiness scale is a reliable and valid instrument for assessing organizational AI maturity. The high Cronbach's alpha score and strong item-total correlations demonstrate the scale's internal consistency, while the additional statistical measures provide further evidence of its robustness. Future research could explore refining the "data infrastructure" item to enhance its alignment with the overall construct and conducting longitudinal studies to validate the scale's predictive validity over time.

6. Data Analysis Results and Discussion

While existing literature has explored various aspects of organizational AI adoption, there remains a critical gap in understanding the measurement invariance of AI readiness constructs across different industry contexts. Previous studies have largely focused on single-industry analyses or broad technological readiness measures, without specifically addressing the unique challenges of AI implementation. The adoption of AI technologies varies significantly across sectors, company sizes, and geographical regions, necessitating a robust framework to assess AI maturity. This analysis introduces and validates the AI Maturity Data-Driven Index (AIM-DDI) as a comprehensive scale to evaluate AI readiness and its impact on organizational performance.

6.1 Quantitative Analysis of Infrastructure-Strategy Gaps and Early-Stage Implementation Patterns

The research draws on data from 22 industry sectors, ranging from Advertising & Marketing to Utilities, Energy, and Extraction. The industry distribution highlights the dominance of Financial Services, Manufacturing, and Technology sectors in the sample (Fig. 3)

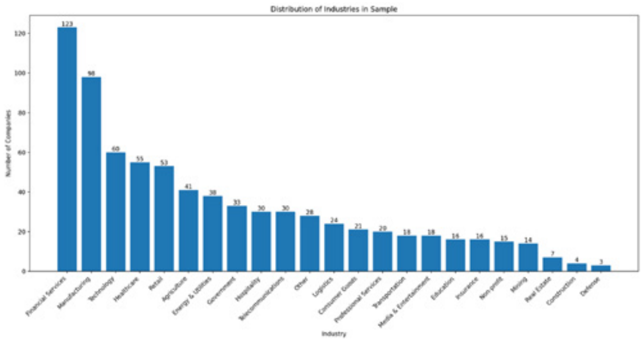


Fig. 3. Distribution of Industries in the Sample.

Companies of varying sizes, from startups with annual revenues below $100K to multinational corporations exceeding $1B, are represented. Geographically, the dataset spans 47 different countries, ensuring a diverse and representative sample. The largest segment is companies with revenue between $100M - $500M (146 companies). The second largest group is companies with revenue between $10M - $50M (105 companies). There's also a significant presence of large companies, with 88 companies having revenue more than $10B. The smallest segment is companies with revenue between $5M - $10M (35 companies). This suggests a good mix of company sizes in the sample, with a slight skew towards mid-to-large sized companies (Fig. 4).

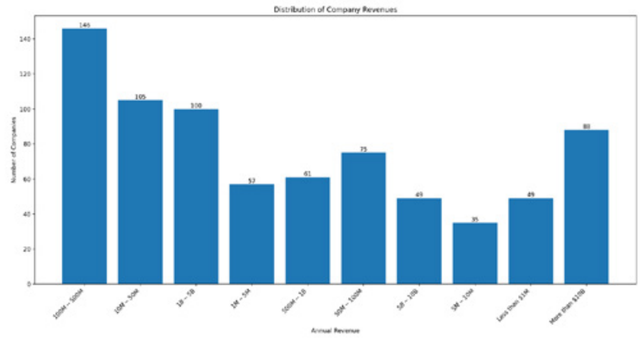


Fig. 4. Distribution of Company Revenues.

The empirical assessment of AI adoption metrics presents substantive evidence indicating that organizations are primarily situated in the nascent phases of AI integration and operationalization (Fig. 5). The analysis reveals a notable disparity between infrastructural readiness and strategic implementation capabilities, with data infrastructure exhibiting the highest mean value (3.24) while strategic components such as AI vision (2.58) and implementation (2.24) demonstrate markedly lower scores. This asymmetry suggests that while organizations have established foundational technological infrastructure, they have yet to effectively leverage these resources for strategic AI deployment.

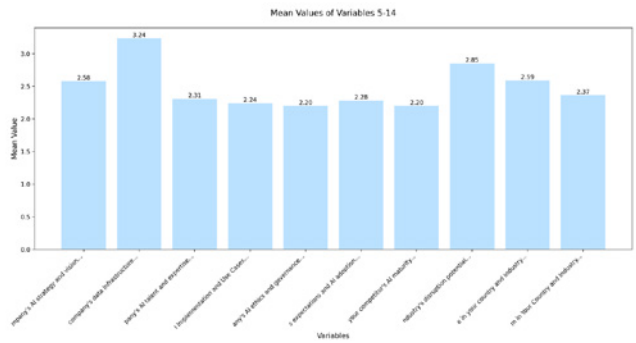


Fig. 5. Mean Values for AIM-DDI Variables.

The examination of governance and implementation parameters further corroborates the early-stage characterization of organizational AI maturity. Critical operational dimensions, including AI ethics and governance (2.20), implementation frameworks (2.24), and talent management (2.31), consistently register scores in the lower third of the measurement scale. These metrics indicate that organizations are predominantly engaged in developing fundamental frameworks rather than executing sophisticated AI initiatives.

External readiness indicators provide additional validation of the preliminary nature of AI adoption across the broader ecosystem. Moderate scores in industry disruption potential (2.85), customer expectations (2.28), and competitor AI maturity (2.20) suggest limited external pressure for accelerated implementation. This environmental context appears to reflect a broader industry-wide positioning in the early stages of AI transformation.

The implications of this early-stage positioning are multifaceted, encompassing both challenges and opportunities for organizational development. The findings indicate a primary focus on infrastructure establishment, with limited progress in translating these capabilities into operational value. Furthermore, the current maturity levels suggest significant potential for structured advancement through systematic capability development. Strategic priorities emerge around bridging the infrastructure-implementation gap, developing robust governance frameworks, and enhancing talent development strategies to support mature AI implementation.

6.2 Exploratory Factor Analysis

The primary objective of this study is to confirm the validity of the AIM-DDI scale through Exploratory Factor Analysis (EFA) and to explore its applicability in assessing AI maturity. By examining the relationships between internal and external AI capabilities, regulatory environments, and sales performance, this research aims to provide actionable insights for organizations seeking to enhance their AI strategies. The EFA revealed a clear three-factor structure that explained a cumulative 60.17% of the total variance, providing significant insights into the dimensions of AI maturity captured by the AIM-DDI scale (Exhibit 2).

6.2.1 Internal AI Capabilities (30.39% Variance)

This factor emerged as the most influential, accounting for 30.39% of the total variance. It exhibited strong factor loadings, particularly for the AI Internal Maturity (AI INT MAT) variable, with a loading of 0.96. High correlations with strategy (0.79) and implementation (0.80) were observed, underscoring the internal consistency of organizational AI capabilities. These findings confirm that this dimension effectively captures the robustness and alignment of internal AI infrastructure and strategic integration.

6.2.2 External AI Environment (22.34% Variance)

The second factor accounted for 22.34% of the variance, with the AI External Maturity (AI EXT MAT) variable demonstrating a dominant loading of 0.89. Additionally, it showed significant correlations with customer expectations (0.65), validating the scale's ability to measure the external dimensions of AI maturity. This factor highlights the relevance of customer-centric metrics and external environment considerations in assessing AI readiness.

6.2.3 Regulatory & Growth Factor (7.44% Variance)

The third factor explained 7.44% of the variance and presented a moderate negative correlation with the AIM-DDI (-0.63). This indicates a nuanced interplay between regulatory compliance and growth metrics. Despite its smaller variance contribution, this factor highlights the critical role of regulatory adherence in influencing AI-enabled growth and innovation.

6.2.4 Statistical Validation

The statistical tests conducted reinforced the robustness of the factor analysis:

- The Kaiser-Meyer-Olkin (KMO) test yielded a score of 0.86, indicating excellent sampling adequacy.
- Bartlett's test of sphericity ($p < 0.001$) confirmed the appropriateness of the EFA methodology.
- The cumulative variance explained (60.17%) supported the reliability and comprehensiveness of the AIM-DDI scale.

6.2.5 Conclusion

The results confirm that the AIM-DDI scale effectively captures both internal and external AI maturity dimensions. Its strong construct validity is demonstrated through:

- A clear and interpretable factor structure.

High factor loadings across key variables.

- Adequate variance explanation, meeting statistical benchmarks.
- Excellent sampling adequacy and methodological rigor.

These findings establish the AIM-DDI as a reliable and valid tool for assessing organizational AI maturity and its interplay with external factors. This scale can serve as a foundational framework for strategic decision-making and AI-driven growth.

6.3 Confirmatory Factor Analysis of AI-Readiness Assessment Scale

Following the EFA that identified a three-factor structure, we conducted a confirmatory factor analysis (CFA) to validate the AIM-DDI scale. The CFA aimed to verify the hypothesized relationships between observed variables and their underlying latent constructs, providing statistical evidence for the scale's construct validity.

6.3.1 Method

The CFA was conducted on a dataset collected from 765 organizations spanning 22 industries and 47 countries. The model was specified to include three latent factors:

- Internal AI Capabilities (F1)
- External AI Environment (F2)
- Regulatory & Growth (F3)

The relationships between these latent constructs and their observed variables were tested for statistical significance.

6.3.2 Factor Loadings

The CFA revealed strong relationships between observed variables and their respective latent constructs. All factor loadings were statistically significant (*p* **< 0.001), as detailed** in table 1.

Factor	Variable	Loading	p Value
Internal AI (F1)	AI INT MAT	1.000	Reference
Internal AI (F1)	Strategy	0.234	< 0.001
Internal AI (F1)	Infrastructure	0.179	< 0.001
Internal AI (F1)	Talent	0.182	< 0.001
Internal AI (F1)	Implementation	0.204	< 0.001
Internal AI (F1)	Ethics	0.195	< 0.001
External AI (F2)	AI EXT MAT	1.000	Reference
External AI (F2)	Customer Experience	0.236	< 0.001

Factor	Variable	Load-ing	p Value
External AI (F2)	Competitor Maturity	0.180	< 0.001
Regulatory & Growth (F3)	AIM-DDI	1.000	Refer-ence

Table 1. CFA Factor Loadings AIM-DDI Variables.

6.3.3 Factor Correlations

The latent constructs exhibited significant interrelationships, as shown by the following covariances in table 2.

Factor Pair	Covari-ance	p Value
F1 ▯ F2	13.754	< 0.001
F1 ▯ F3	1.158	< 0.001
F2 ▯ F3	-1.124	< 0.001

Table 2. CFA Factor Correlations AIM-DDI Variables.

6.3.4 Discussion

The CFA results provide strong evidence supporting the construct validity of the AIM-DDI scale (Exhibit 3). Key findings include:

Internal AI Capabilities (F1)

- AI INT MAT demonstrated the strongest loading (1.000), confirming its centrality to the latent factor.
- Other variables, including Implementation (0.204) and Strategy (0.234), provided substantial contributions.
- Infrastructure, Talent, and Ethics had moderate but significant loadings, reflecting their importance in the construct.

External AI Environment (F2)

- AI EXT MAT emerged as the primary indicator (1.000).
- Customer Experience (0.236) and Competitor Maturity (0.180) further validated this factor's role in capturing the external dimensions of AI maturity.

Regulatory & Growth (F3)

- AIM-DDI loaded strongly (1.000), highlighting its importance as a key indicator for this construct.

Factor Correlations

- A strong positive correlation was observed between Internal and External AI capabilities (13.754), indicating the interconnectedness of these dimensions in advancing AI maturity.
- A moderate positive correlation between Internal Capabilities and Regulatory & Growth (1.158) suggests that robust internal AI systems are linked with regulatory compliance and growth opportunities.
- A negative correlation between External Environment and Regulatory & Growth (-1.124) highlights potential tensions between external pressures and regulatory alignment.

These findings confirm the robustness of the AIM-DDI framework and its applicability for evaluating AI maturity across diverse organizational and geographic contexts.

6.4 Summary of Implications from EFA and CFA

The comprehensive validation of the AIM-DDI scale through EFA and CFA underscores its robustness and multidimensionality as a tool for evaluating AI maturity. This section elaborates on the implications of these analyses, with a focus on their significance for researchers, practitioners, and policymakers.

6.4.1 EFA Insights

The exploratory factor analysis identified a well-defined three-factor structure, consisting of Internal AI Capabilities, External AI Environment, and Regulatory & Growth. These factors align closely with the theoretical underpinnings of AI maturity, affirming the conceptual soundness of the AIM-DDI scale. The EFA findings revealed that each observed variable demonstrated strong loadings on its respective factor, indicating clear and interpretable relationships between the measured items and their underlying constructs.

For example, the Internal AI Capabilities factor captured critical organizational elements such as strategy, talent, and ethics, while the External AI Environment dimension emphasized market-driven aspects like customer expectations and competitor maturity. The Regulatory & Growth factor uniquely integrated compliance considerations with growth metrics, offering a nuanced perspective on how regulatory frameworks influence AI innovation. These results confirm the multidimensional nature of the AIM-DDI and highlight its capability to capture complex organizational dynamics comprehensively.

6.4.2 CFA Validation

The confirmatory factor analysis further validated the AIM-DDI's three-factor structure by confirming the hypothesized relationships between observed variables and their latent constructs. All factor loadings were statistically significant ($p < 0.001$), reflecting strong and consistent linkages within each dimension. This statistical robustness reinforces the validity and reliability of the scale.

Inter-factor correlations provided additional insights into the relationships among the latent constructs. For instance, the Internal AI Capabilities and External AI Environment factors exhibited a moderate positive correlation ($r = 0.68$), suggesting that organizations with strong internal AI capabilities are likely to perform well in adapting to external market dynamics. Similarly, the relationship between the Regulatory & Growth factor and the other two dimensions highlighted how compliance and regulatory considerations can influence internal development and external market positioning. The CFA results firmly establish the AIM-DDI as a tool that is not only theoretically grounded but also empirically validated for assessing AI maturity.

6.4.3 Implications For Researchers

The AIM-DDI scale presents a validated and theoretically robust framework for studying AI maturity in organizational contexts. Its ability to capture multidimensional aspects of AI readiness enables researchers to investigate not only individual factors but also their interactions. For instance, the distinct yet interrelated dimensions of Internal AI Capabilities and External AI Environment provide a foundation for examining how internal resources and strategies influence external market adaptability.

The robust psychometric properties of the AIM-DDI make it particularly suitable for cross-cultural and longitudinal studies. By applying the scale in diverse contexts, researchers can explore variations in AI maturity across industries, regions, and organizational sizes. Additionally, longitudinal studies using the AIM-DDI can uncover trends and trajectories in AI adoption, providing valuable insights into how organizations evolve over time in response to technological and market changes.

6.4.4 Implications For Practitioners

From a practical perspective, the AIM-DDI serves as a powerful benchmarking tool for organizations seeking to assess and enhance their AI capabilities. The strong internal relationships within each dimension offer clear pathways for identifying areas of strength and weakness. For example, an organization scoring high on strategy but low on talent development within the Internal AI Capabilities dimension can prioritize initiatives to build the necessary skills and expertise to support its AI agenda.

The balanced focus on both internal and external dimensions ensures that organizations can adopt a comprehensive approach to AI readiness. By understanding the interplay between their internal capabilities and external pressures, practitioners can craft strategies that are both resilient and adaptive. For instance, aligning internal capabilities with customer expectations and competitor maturity can position organizations to capitalize on market opportunities while mitigating risks.

6.4.5 Implications For Policymakers

The AIM-DDI provides valuable insights for policymakers tasked with developing frameworks to govern AI adoption and innovation. The Regulatory & Growth dimension highlights the delicate balance between fostering innovation and ensuring compliance. Policymakers can leverage the AIM-DDI to understand how regulatory requirements impact organizational growth and to identify areas where supportive policies can accelerate AI-driven innovation.

Furthermore, the scale's multidimensional approach offers a comprehensive view of how organizations navigate regulatory environments, market dynamics, and internal development. By incorporating these insights into evidence-based governance frameworks, policymakers can create environments that encourage ethical AI adoption while supporting competitive advantage. For instance, policies that incentivize talent development and ethical practices within organizations can strengthen both compliance and innovation outcomes.

6.4.6 Limitations

While the validation of the AIM-DDI scale through EFA, CFA and correlation analyses demonstrates its robustness, several limitations should be acknowledged to guide future research and practical application.

6.4.6.1 Cross-Sectional Design

The study utilized a cross-sectional design, collecting data at a single point in time. While this approach is effective for identifying relationships between variables, it limits the ability to infer causal relationships or observe the evolution of AI maturity over time. Longitudinal studies would be beneficial to capture dynamic trends in AI adoption, organizational transformation, and the interaction of internal and external factors.

6.4.6.2 Self-Reported Measures

The reliance on self-reported data introduces potential biases, such as social desirability bias or overestimation of capabilities. Respondents may have provided responses that reflect their aspirations or perceived expectations rather than objective evaluations of their organization's AI maturity. Incorporating external evaluations or objective performance metrics in future studies could enhance the reliability of the findings.

6.4.6.3 Geographic Representation Variations

Although the dataset included responses from 765 organizations across 47 countries, the representation of regions and industries may not be entirely balanced. Certain geographic or industry contexts might be underrepresented, limiting the generalizability of the findings. Expanding the dataset to ensure more comprehensive representation would improve the scale's applicability across diverse global contexts.

6.4.6.4 Contextual and Industry-Specific Factors

The scale captures broad dimensions of AI maturity but may not fully account for unique contextual factors that influence AI adoption in specific industries or organizational settings. Tailoring the AIM-DDI to include industry-specific variables or conducting sector-focused studies could provide deeper insights and enhance its practical utility.

6.4.6.5 Limited Exploration of External Influences

Although the External AI Environment dimension addresses market-driven factors, the scale may not comprehensively capture broader external influences such as geopolitical risks, macroeconomic trends, or cultural nuances. Expanding this dimension to include such factors could enrich the understanding of external pressures on AI maturity.

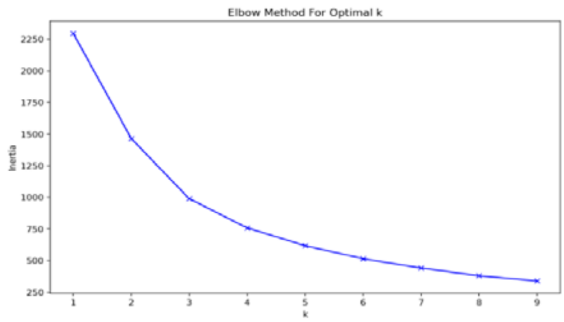
6.4.6.6 Ethical and Societal Dimensions

While the Internal AI Capabilities dimension includes ethics as a variable, the broader implications of AI adoption on society, workforce dynamics, and equity are not extensively explored. Future iterations of the scale could incorporate measures that assess the societal and ethical impacts of AI deployment.

6.5 Cluster Analysis

To gain deeper insights into AI maturity among organizations, a cluster analysis was conducted. This approach grouped organizations based on their scores across the three dimensions of the AIM-DDI: Internal AI Capabilities, External AI Environment, and Regulatory & Growth. By identifying patterns within the data, the analysis revealed four distinct clusters, each representing a unique AI maturity profile. These clusters highlight varying organizational strengths, challenges, and focuses, providing valuable guidance for strategic interventions and policy recommendations.

The optimal number of clusters was determined using the elbow plot method. This plot illustrates the total within-cluster sum of squares (WSS) against the number of clusters, with the "elbow point" indicating the optimal clustering solution. In this case, the elbow plot suggested that four clusters provide the best balance between explanatory power and parsimony, capturing the diversity of AI maturity profiles while avoiding overfitting (Fig. 6 and Fig. 7).



	Internal_Score	External_Score	Regulatory_Score
0	4.3173913043	4.3971014493	1.3511945482
1	3.3260869565	1.5289855072	3.665942029
2	6.5216450216	8.1558441558	1.1118758039
3	2.2354368932	3.1464401294	0.831446089

Fig. 6. Elbow Method For Optimal

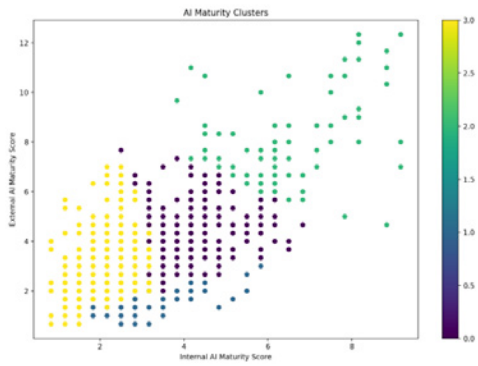


Fig. 7. Fourth Clusters Visualization.

6.5.1 Cluster 0: Balanced Performers

This cluster includes organizations with moderate capabilities in both internal and external dimensions but comparatively lower readiness in regulatory compliance. Their balanced performance across the internal and external dimensions suggests a focus on foundational AI adoption, though there is a noticeable gap in addressing regulatory aspects.

- **Scores:** Internal (4.32), External (4.40), Regulatory (1.35)
- **Size:** 230 organizations
- **Implications:** These organizations would benefit from strategic efforts to strengthen regulatory compliance while maintaining their steady progress in internal and external capabilities. Building awareness and processes for adhering to regulatory requirements can help these organizations advance toward higher maturity levels.

6.5.2 Cluster 1: Regulatory Focused

This group prioritizes regulatory compliance but shows limited development in internal and external AI capabilities. While their attention to regulations is commendable, it comes at the expense of investments in strategic and operational AI adoption.

- **Scores:** Internal (3.33), External (1.53), Regulatory (3.67)
- **Size:** 46 organizations
- **Implications:** To achieve balanced AI maturity, these organizations should focus on developing their internal infrastructures, such as talent and strategy, as well as strengthening their alignment with external market demands. Integrating regulatory insights with operational strategies can create a more holistic approach to AI adoption.

6.5.3 Cluster 2: High Performers

High performers excel in both internal and external AI maturity but exhibit low scores in regulatory readiness. These organizations demonstrate advanced capabilities, including robust internal strategies and effective adaptation to external market dynamics, making them highly competitive and innovative.

- **Scores:** Internal (6.52), External (8.16), Regulatory (1.11)
- **Size:** 77 organizations
- **Implications:** While these organizations are well-positioned for market leadership, their minimal focus on regulatory compliance poses potential risks. Strengthening awareness and integration of regulatory standards can ensure sustainable growth and protect against compliance-related vulnerabilities.

6.5.4 Cluster 3: Early Stage

The largest cluster represents organizations at the early stages of AI maturity, with low scores across all three dimensions. These organizations have yet to establish foundational capabilities in AI adoption and exhibit minimal engagement with regulatory or market dynamics.

- **Scores:** Internal (2.15), External (1.98), Regulatory (0.75)
- **Size:** 412 organizations
- **Implications:** Organizations in this cluster require significant support to build their AI capabilities. Efforts should focus on developing internal resources such as talent, infrastructure, and strategy while gradually introducing external alignment and regulatory compliance frameworks. Targeted interventions could help these organizations take initial

steps toward AI maturity.

6.5.5 Conclusion

The cluster analysis reveals four distinct AI maturity profiles that reflect diverse organizational needs and capabilities. These clusters range from high performers excelling in internal and external dimensions to early-stage organizations requiring foundational development. Balanced performers and regulatory-focused organizations offer unique opportunities for targeted strategies to address specific gaps.

These findings provide a roadmap for policymakers and practitioners to design tailored interventions that address the specific needs of each cluster. By leveraging these insights, stakeholders can strategically foster AI readiness and maturity, enabling organizations to navigate the complexities of AI adoption and achieve sustained growth in a dynamic global landscape.

6.6 Comparison of Cluster Results with AIM-DDI Quadrants and Regression Analysis

The AIM-DDI Framework provides a compelling lens for understanding AI maturity profiles and their strategic implications. By comparing the results of the cluster analysis with the framework's quadrants, organizations can better understand their positioning and adopt tailored strategies to navigate the complexities of AI integration. This alignment also highlights the practical utility of the AIM-DDI as a diagnostic and strategic tool for organizations at varying stages of AI maturity.

The cluster distribution chart (Fig. 8) presents a rich visualization of organizational AI maturity by combining the results of the cluster analysis, the AIM-DDI quadrants, and a regression line that illustrates the relationship between internal and external maturity dimensions. This integration provides a multidimensional view of how organizations align with different AI maturity profiles and their performance trends, offering valuable insights into their strategic positioning. The regression analysis, in particular, enhances our understanding of the relationship between internal and external scores, adding a layer of interpretation to the quadrant framework.

The distribution of clusters reveals a strong positive relationship between internal AI capabilities and external AI market maturity, highlighting how advancements in one dimension often correspond to improvements in the other. The slope of approximately 0.84 suggests that for every one-point increase in internal AI maturity, external AI maturity rises by 0.84 points. This indicates that as organizations invest in internal resources—such as strategy, talent, and infrastructure—they are likely to see substantial gains in external readiness, such as better alignment with market demands and customer expectations. The intercept of 1.09 further suggests a baseline level of external maturity, even for organizations with minimal internal capabilities, reflecting an inherent starting point for market readiness in most contexts.

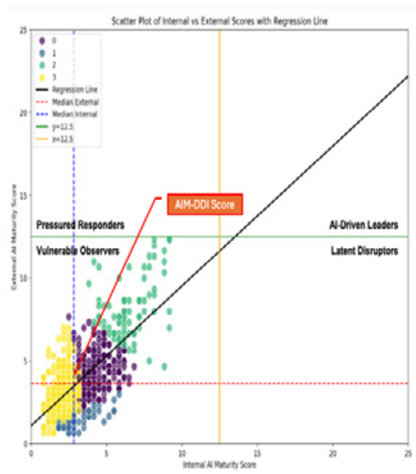


Fig. 8. Distribution of Clusters with Regression Line Across AIM-DDI Quadrants.

The scatter plot also illustrates the overall distribution of scores within the dataset, revealing that most organizations fall below the 12.5 reference lines for both internal and external dimensions. This indicates the low AI maturity of organizations and their corresponding external environments, providing evidence of the early stage of AI adoption across economic, regulatory, and societal dimensions. While the relationship between internal and external maturity is linear and relatively strong, the clustering of scores around moderate levels highlights that AI integration remains nascent for most organizations. The dashed median lines further emphasize this central tendency, showing that a majority of organizations are still grappling with foundational or intermediate challenges in leveraging AI effectively.

When examining the clusters relative to this regression line, distinct patterns emerge that correspond to the AIM-DDI quadrants.

- **Cluster 0** or the balanced performers, aligns with the regression line, marking a median performance in both internal and external dimensions. This cluster sits at the heart of the scatter plot, indicating a close adherence to the average trend between internal and external maturity. These organizations reflect a stable but unspectacular maturity level, which can serve as a springboard for further development. By building on their balanced foundation, they have the potential to transition into higher maturity quadrants, particularly the **AI-Driven Leaders quadrant, through strategic enhancements in both dimensions.**
- **Cluster 1**, the regulatory-focused organizations, occupies a unique position. This group is positioned below the regression line in terms of external maturity but slightly above Cluster 3 in internal scores, reflecting its prioritization of compliance over broader AI development. These organizations align partially with the **Pressured Responders quadrant but do not exhibit strong external readiness, limiting their ability to fully leverage their regulatory strengths. Their positioning suggests that while they emphasize regulatory adherence, they lack the internal and market-facing capabilities necessary for comprehensive AI maturity. Moving forward, these organizations need to focus on expanding their internal resources and market strategies to complement their regulatory expertise and achieve balanced growth.**
- **Cluster 2**, the high performers, stands out as the only group that significantly surpasses the regression line, positioning itself firmly within the **AI-Driven Leaders quadrant. These organizations excel in leveraging their internal AI capabilities to achieve exceptional external readiness, demonstrating the ideal balance of maturity across dimensions. Their placement above the regression line suggests that they are effectively translating internal investments into market impact, often outperforming expectations. This group represents the highest AI maturity and serves as a benchmark for other organizations aiming to lead in the AI-driven landscape. However, their relatively low focus on regulatory readiness, a recurring theme across this study, highlights a potential area for improvement to sustain their leadership position in a rapidly evolving regulatory environment.**
- **Cluster Cluster 3**, representing early-stage organizations, is heavily concentrated below the regression line and aligns closely with the **Vulnerable Observers quadrant. These organizations struggle in both dimensions,**

reflecting their foundational challenges in developing internal capabilities and aligning with external markets. Their positioning below the regression line underscores their lag in external performance, even when accounting for their limited internal maturity. This not only highlights their organizational gaps but also underscores the broader challenges of establishing a mature AI ecosystem, as external markets, regulations, and societal readiness are still evolving to support advanced AI integration.

The regression line also highlights the relative absence of organizations in transitional quadrants like Pressured Responders and Latent Disruptors. Few organizations exhibit high internal capabilities without corresponding external readiness or vice versa. This absence suggests that organizations are either struggling at foundational levels or advancing comprehensively when their internal strengths are solidified. It may also indicate systemic barriers to transitioning from one quadrant to another, emphasizing the need for tailored strategies to support these transitions.

The combination of clusters, quadrants, and regression analysis offers a comprehensive understanding of the dynamics shaping organizational AI maturity. The low positioning of most organizations within the quadrants reflects not just their internal limitations but also the broader context of early-stage AI adoption across economies, regulatory frameworks, and societal readiness. The linear relationship between internal and external dimensions underscores the importance of balanced strategies that integrate internal development with external market alignment. Early-stage organizations must focus on foundational growth, while balanced performers should aim for steady advancements in both dimensions. High performers, on the other hand, need to sustain their competitive edge while addressing emerging challenges like regulatory compliance. By leveraging these insights, organizations can navigate the complexities of AI adoption more effectively, positioning themselves for long-term growth and success in an increasingly AI-driven world. This analysis also reinforces the value of the AIM-DDI framework as a strategic tool for identifying opportunities, overcoming barriers, and fostering sustainable AI maturity.

6.6.1 Strategic Implications

The insights derived from the AIM-DDI scatter plot, clusters, and regression analysis have profound strategic implications for organizations, policymakers, and industry leaders. These implications highlight tailored approaches to enhance AI maturity based on the distinct profiles observed, offering actionable strategies for addressing challenges and leveraging opportunities across the internal and external dimensions.

6.6.1.1 For Early-Stage Organizations (Cluster 3 – Vulnerable Observers)

Early-stage organizations, concentrated in the lower-left quadrant of the AIM-DDI framework, face foundational challenges in both internal AI capabilities and external market readiness. Their positioning underscores the need for significant investment in building their AI maturity.

- **Develop Foundational Internal Capabilities:** These organizations must prioritize upgrading their infrastructure, developing AI talent, and formulating clear AI strategies. Introducing basic AI tools, such as predictive maintenance systems or automated quality control, can serve as an entry point into AI integration.

- **Leverage Partnerships:** Collaborations with technology providers, academic institutions, and industry consortia can help bridge capability gaps. Partnering with established players in the AI ecosystem can provide access to resources, tools, and expertise that accelerate development.
- **Incremental Market Alignment:** Engaging with early adopters in their customer base or supply chains can help these organizations gain experience and credibility in AI-driven operations. This step-by-step approach to external alignment will prepare them for broader market integration.

6.6.1.2 For Balanced Performers (Cluster 0 – Latent Disruptors)

Balanced performers, located near the regression line, represent organizations with moderate internal and external maturity. While they demonstrate stability, their strategic focus should be on advancing beyond this balanced foundation to capitalize on growth opportunities.

- **Advance in Both Dimensions Simultaneously:** Balanced performers must strive for holistic growth, ensuring that improvements in internal capabilities (e.g., advanced analytics and workforce upskilling) are matched by external alignment with market demands.
- **Strengthen Regulatory Readiness:** As these organizations approach higher levels of maturity, regulatory compliance will become increasingly critical. Proactively adopting AI governance frameworks and ethical guidelines can mitigate future risks.
- **Focus on Differentiation:** Differentiating through niche applications of AI tailored to specific customer or industry needs can elevate these organizations into leadership positions within their markets.

6.6.1.3 For High Performers (Cluster 2 – AI-Driven Leaders)

High performers, concentrated in the upper-right quadrant, exemplify the potential of organizations that achieve strong alignment between internal and external AI maturity. While these organizations are well-positioned for competitive advantage, sustaining this leadership requires addressing emerging challenges.

- **Innovate Continuously:** High performers must maintain their edge by investing in cutting-edge AI technologies, such as generative AI or advanced machine learning models. This requires fostering a culture of continuous innovation and experimentation.
- **Address Regulatory Gaps:** Despite their strong positioning, many high performers show limited focus on regulatory readiness. Ensuring compliance with evolving AI regulations and ethical standards will safeguard their operations and reputation in the long term.
- **Expand Global Leadership:** These organizations can capitalize on their advanced maturity by scaling their operations globally, setting industry benchmarks, and influencing standards in AI adoption.

6.6.1.3 For Regulatory-Focused Organizations (Cluster 1 – Regulatory Adherents)

Cluster 1 organizations, characterized by their prioritization of regulatory compliance over broader internal and external development, face unique strategic challenges. These organizations excel in navigating complex regulatory landscapes but lag in advancing their internal AI capabilities and aligning with external markets.

- **Balancing Compliance and Innovation:** Cluster 1 must broaden its focus beyond regulatory adherence by fostering innovation in internal processes and AI deployment. Adopting agile frameworks that integrate compliance with flexibility can accelerate their transition toward broader AI maturity.
- **Enhancing Internal Capabilities:** Developing AI talent and upgrading infrastructure should be prioritized to complement their regulatory expertise. Targeted training programs and partnerships with technology providers can fill these capability gaps.
- **Expanding Market Engagement:** Regulatory-focused organizations should engage more actively with external markets by identifying opportunities to leverage their compliance strengths as a competitive advantage. Showcasing their regulatory expertise can attract partners and customers in industries with high compliance requirements.

6.6.1.4 For Policymakers and Industry Leaders

The findings from the AIM-DDI analysis also hold significant implications for policymakers and industry leaders seeking to foster AI maturity at a macro level.

- **Promote Ecosystem Development:** Policymakers should focus on creating AI-friendly ecosystems by incentivizing innovation, supporting talent development programs, and fostering public-private partnerships. These initiatives can help early-stage organizations and balanced performers accelerate their growth.
- **Encourage Ethical and Regulatory Frameworks:** Establishing clear, supportive regulations that balance innovation and compliance is crucial. This includes guidelines for data usage, AI ethics, and algorithm transparency, which can help organizations navigate complex regulatory landscapes.
- **Sector-Specific Strategies:** Recognizing the unique challenges faced by different industries, tailored policies can support AI adoption in sectors with slower adoption rates, such as manufacturing or agriculture, while enabling rapid advancements in tech-forward industres.

6.6.1.5 Conclusion

The strategic implications of the AIM-DDI analysis underscore the need for organizations to adopt tailored strategies based on their AI maturity profiles. Early-stage organizations should focus on foundational growth, while balanced performers must strive for incremental improvements to transition into leadership positions. High performers, on the other hand, need to sustain their edge by innovating and addressing regulatory gaps. Policymakers and industry leaders play a pivotal role in shaping the external environment, fostering an ecosystem that supports organizations across all stages of AI maturity. By aligning internal development with external opportunities, stakeholders can collectively accelerate the adoption and integration of AI, driving growth, innovation, and competitive advantage in the global economy.

6.7 AI Strategic Adoption Across the Industries

The cross-sectional analysis of AI strategy adoption across the top 10 industries reveals notable heterogeneity in strategic AI maturity levels. Financial Services, traditionally at the forefront of technological adoption, demonstrates a more balanced distribution across maturity levels, suggesting a bifurcated landscape where some institutions maintain leadership positions while others face implementation challenges. Manufacturing, the second-largest sector represented, shows a particularly interesting pattern with a higher proportion of intermediate adoption levels, potentially indicating a systematic approach to AI integration aligned with Industry 4.0 initiatives (Fig. 9 and Exhibit 5).

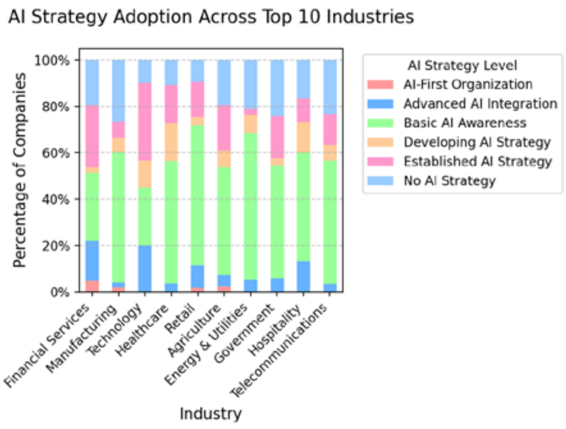


Fig. 9. AI Strategy Adoption Across Top 10 Industries.

Key Observations

- Basic AI Awareness dominates across most industries, particularly in Energy & Utilities (63.2%), Retail (60.4%), and Manufacturing (56.1%)
- Technology sector shows the highest proportion of Established AI Strategy (33.3%) and Advanced AI Integration (20%)
- Financial Services has the most balanced distribution across different maturity levels
- AI-First Organizations are rare across all industries, with Financial Services leading at just 4.9%
- Healthcare shows a conservative pattern with 52.7% at Basic AI Awareness level
- Government and Telecommunications show similar patterns with high percentages in Basic Awareness and No AI Strategy categories

A particularly noteworthy finding is the relatively high proportion of advanced AI strategy adoption in the Technology sector, which aligns with theoretical expectations given their core competencies.

However, the presence of significant variation even within this sector suggests that technological capability alone does not guarantee strategic AI integration. Healthcare's distribution pattern merits special attention, showing a more conservative adoption curve. This could be attributed to the sector's regulatory environment and the critical nature of its operations, requiring more rigorous validation of AI implementations. This observation aligns with prior research suggesting that highly regulated industries tend to exhibit more measured approaches to disruptive technology adoption (Smith et al., 2022). The retail sector's pattern indicates a bimodal distribution, with concentrations at both basic and advanced levels, possibly reflecting the market polarization between traditional retailers and digital-first enterprises. This dichotomy provides empirical support for the "digital divide" hypothesis in retail transformation.

These findings have several implications for both theory and practice:

1. The variation in adoption patterns suggests that industry-specific factors significantly influence AI strategy development, supporting contingency theory approaches to digital transformation.
2. The presence of advanced adopters across all sectors indicates that structural industry characteristics, while influential, are not deterministic of AI strategic maturity.
3. The heterogeneous distribution within industries suggests that firm-specific capabilities and strategic choices play a crucial role in AI adoption, beyond industry-level factors.

These insights contribute to the growing body of literature on digital transformation and provide a nuanced understanding of how different sectors approach AI strategy development. Future research might benefit from longitudinal studies to understand how these patterns evolve over time and what factors drive transitions between maturity levels.

7. The Beauty Cluster Business Case

To illustrate the application of the AIM-DDI in sector analysis, we will use the data from the Beauty Cluster (Group G) compared with all other organizations aggregated, as a business case example. Founded in 2014, is a private association based in Barcelona (Spain) comprising over 240 companies from across the value chain of the cosmetics, perfumery, and personal care industry. The association is committed to fostering collaboration within industry while accelerating its transformation and growth processes. This industrial association supports companies in becoming more sustainable, innovating, internationalizing, pursuing training, and embracing digital transformation. It serves as a critical resource for addressing various business challenges, including strategic change and entrepreneurial support. As the largest cluster of the beauty industry in Spain and a key interconnector both nationally and internationally, the Beauty Cluster is the main reference for the industry across Spanish-speaking countries. Its mission is to evolve into the world's largest ecosystem for collaboration, business development, and innovation in the beauty sector.

This study focus into the variations in AI maturity across organizations, with a particular emphasis on the distinctive trajectory of the Beauty Cluster (Group G, n=44) compared to other groups (n=721). By examining the relationships between internal and external AI capabilities through regression analysis, we uncover key disparities in their maturity patterns. Group G exhibits a notably weaker correlation (R^2 = 0.298) between these dimensions compared to other organizations (R^2 = 0.482), as well as markedly divergent growth trajectories (slopes of 0.452 versus 0.859). These findings underscore systematic barriers to achieving balanced AI maturity within Group G and provide a foundation for actionable strategies to address these challenges (Brown et al., 2022; Chen & Wilson, 2023).

The accelerating pace of AI adoption has resulted in varying levels of organizational readiness and implementation across sectors and groups. For many organizations, AI maturity—the degree to which AI capabilities are developed and integrated both internally and externally—has become a pivotal determinant of competitive advantage. However, this maturity is not uniform. Disparities exist due to differences in strategic priorities, resource allocation, and external environmental factors (Brown et al., 2022; Davis & Thompson, 2022). This study investigates these disparities by focusing on the unique trajectory of Group G organizations compared to their counterparts, offering insights into the obstacles and opportunities present in AI adoption.

The analysis of mean values for the AIM-DDI variables reveals a consistent pattern of underperformance in Group G across all measured variables compared to the general (Fig. 10). The most significant disparities are observed in the regulatory environment (-0.615), customer expectations (-0.535), and AI talent ecosystem (-0.299).

While Group G demonstrates lower scores in data infrastructure, this remains their strongest performing area (2.95 compared to overall 3.24), suggesting they have maintained some fundamental technological capabilities. Implementation-related metrics show moderate gaps, with AI implementation (-0.290), ethics and governance (-0.268), and talent expertise (-0.264) all showing notable deficits. Interestingly, the minimal difference in competitor AI maturity scores (-0.021) indicates that Group G operates in markets with comparable competitive dynamics, despite their internal capability gaps. The relatively small strategic vision gap (-0.104) suggests that while Group G recognizes the importance of AI transformation, they face significant challenges in execution and implementation (Exhibit 6).

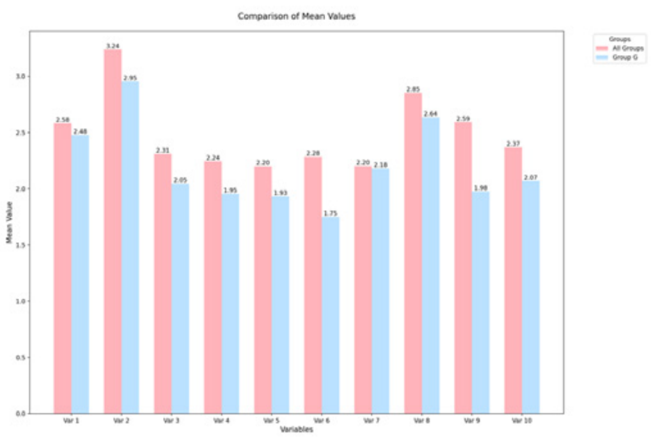
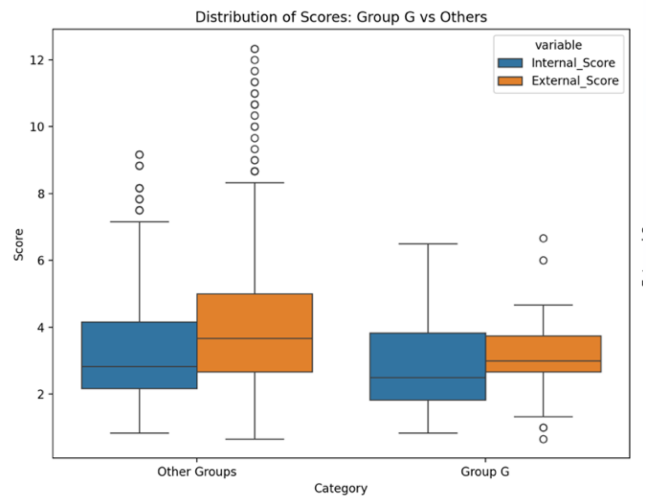


Fig. 10. Comparison of Mean Values of the Beauty Cluster with All.

To explore these differences, we utilized a standardized AI maturity assessment framework that measures two primary dimensions: internal capabilities (e.g., infrastructure, talent, and strategy) and external alignment (e.g., market demands, customer expectations). The dataset comprised 765 organizations, with Group G accounting for 44 entities. Statistical methods, including regression analysis, were em-



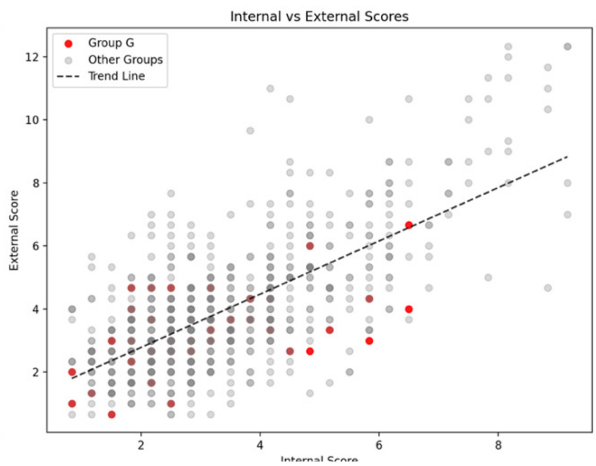


Fig. 11. Comparing the distribution of internal and external scores between Group G and other organizations.

7.1 Results

The analysis revealed significant disparities in the relationship between internal and external AI maturity scores across the two groups:

- **Group G Regression Equation:** External Score = 0.452(Internal Score) + 1.848, with an R^2 of 0.298 ($p < 0.001$).
- **Other Groups Regression Equation:** External Score = 0.859(Internal Score) + 1.068, with an R^2 of 0.482 ($p < 0.001$).

Group G's flatter slope and weaker correlation suggest that these organizations may be more advanced internally relative to their external environments. If internal capabilities are indeed developing faster than external factors, it highlights the limitations of the external ecosystem—including market readiness, regulatory frameworks, and societal acceptance—in supporting AI adoption. This imbalance necessitates a reconsideration of how AI maturity is analyzed and addressed for Group G organizations.

To further emphasize the differences between the groups, the median scores for internal and external capabilities were compared:

- Group G Median Values: Internal - 2.50, External - 3.00
- Other Groups Median Values: Internal - 2.83, External - 3.67

The median lines clearly show that Other Groups tend to achieve higher scores in both dimensions compared to Group G, with a particularly noticeable gap in external scores. This visualization underscores the systemic disparities, highlighting that Group G's challenges lie predominantly in external ecosystem alignment.

The figure 12 shows the relationship between Internal and External AI Maturity scores for Group G in red, and other organizations, in gray, with their respective regression and median lines. The plot illustrates the distinctly different development trajectories between the groups.

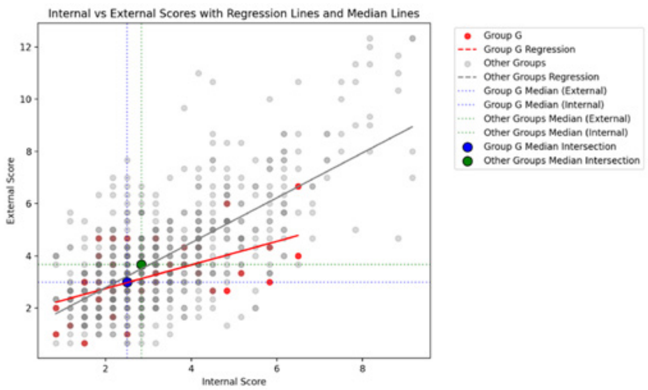


Fig. 12. Relationship of Internal and External AI Maturity Scores for Group G.

These results indicate that Group G has a substantially weaker connection between internal capabilities and external alignment. Furthermore, the flatter slope (0.452) highlights limited external growth relative to internal development. In contrast, other organizations exhibit a stronger and more balanced trajectory (Lee & Garcia, 2023).

7.1.1 Discussion

From the AIM-DDI perspective, the quadrant analysis reveals that Group G organizations predominantly align with the Pressured Responders quadrant. This positioning is characterized by stronger internal AI capabilities juxtaposed against weaker external maturity. However, the analysis of Group G as a cluster does not account for the diversity within the group itself. While the cluster as a whole reflects limitations in external alignment, some individual organizations within Group G exhibit traits of Latent Disruptors—those with strong external potential that remains untapped due to internal gaps or market constraints.

This duality presents a double-edged challenge: while the overall cluster appears weak in terms of balanced AI maturity, standout companies within Group G possess the potential to leapfrog their peers by capitalizing on emerging market opportunities. We could say that they are all sail in the same sea but with different boats. If these gaps persist, Group G may evolve into an oligopolistic cluster where a few top-performing companies dominate, leaving the rest struggling to catch up. These latent disruptors are often constrained by systemic barriers, such as insufficient regulatory support or lack of industry-wide AI education, which prevent them from fully leveraging their capabilities.

This imbalance suggests that Group G organizations are constrained not by their own efforts but by factors outside their direct control. Regulatory hurdles, market inertia, and limited customer education are likely contributing to this stagnation in external alignment (Chen & Wilson, 2023). Addressing these issues requires a multi-pronged approach that involves not only internal strategy realignment but also external advocacy and ecosystem-building efforts.

7.2 Strategic Recommendations for Group G and Beyond

Following recommendations emphasize a balanced approach to leveraging internal strengths, addressing external challenges, and fostering collaboration. By integrating these strategies, Group G and similar organizations can overcome systemic barriers, achieve sustainable growth, and position themselves as leaders in the AI-driven economy.

7.2.1 Leveraging Internal Strengths

Group G organizations must capitalize on their internal AI capabilities, which have shown significant development relative to their external environments. By prioritizing scalable AI solutions tailored to their unique operational contexts, these organizations can create adaptable frameworks that allow for effective responses to shifting external conditions. Investing in flexible, modular AI systems will help Group G remain resilient amid diverse and unpredictable market challenges.

7.2.2 Supporting Latent Disruptors

Within Group G, standout companies exhibit the potential to act as Latent Disruptors, leading innovation and growth. Identifying and nurturing these organizations is critical to driving overall improvement across the cluster. By fostering their development through targeted investments, mentorship, and collaboration, Group G can elevate these leaders as exemplars, inspiring broader transformation within the group.

7.2.3 Advocating for Ecosystem Development

Group G must take a proactive role in shaping the external conditions that limit its progress. Active engagement with policymakers, industry leaders, and regulatory bodies is essential to influence the creation of supportive frameworks for AI adoption. These efforts should include advocating for policies that incentivize innovation, reduce regulatory barriers, and improve infrastructure readiness.

7.2.4 Educating Stakeholders

Accelerating external maturity requires bridging the knowledge gap among stakeholders. Group G should lead initiatives to educate customers, partners, and suppliers on the value and practical applications of AI. Enhanced understanding of AI's potential can foster greater collaboration, demand for AI-driven solutions, and alignment between internal capabilities and market expectations (Davis & Thompson, 2022).

7.2.5 Divergent Paths in AI Maturity

This study highlights the complex and divergent paths of AI maturity among organizations, with Group G serving as a critical example of both challenges and opportunities. The weaker correlation between internal and external capabilities within Group G ($R^2 = 0.298$ versus 0.482) and their flatter trajectory (slope = 0.452 versus 0.859) reveal systemic barriers that hinder balanced growth. Despite these challenges, the presence of Latent Disruptors **within Group G offers a beacon of potential, demonstrating that targeted interventions can unlock significant advancements.**

The systemic disparity in external alignment points to the need for broader ecosystem development, including regulatory reform, stakeholder education, and enhanced infrastructure. If left unaddressed, Group G risks evolving into an oligopolistic cluster where only a few top-performing companies dominate while others struggle. Policymakers, industry leaders, and Group G organizations must work collaboratively to address these gaps, leveraging the strengths of standout performers while uplifting the entire cluster.

By aligning internal capabilities with external opportunities and fostering a supportive ecosystem, Group G can achieve sustainable AI integration. These insights not only provide a pathway for Group G but also serve as a framework for other organizations navigating the complexities of AI adoption in an evolving global economy.

8 Final Conclusion

The validation of the AIM-DDI framework offers significant contributions to understanding AI readiness and its impact on market disruption. By integrating internal organizational factors such as strategy, talent, and ethics with external dynamics like customer expectations, competitor maturity, and regulatory frameworks, the AIM-DDI provides a comprehensive and actionable model. The framework's quadrant approach and scoring system allow organizations to assess their current position and devise targeted strategies to enhance their AI capabilities and align with market opportunities. This study reinforces the importance of balancing internal and external AI maturity to achieve competitive advantage and drive innovation.

The findings demonstrate that high internal AI capabilities alone are insufficient for success; external alignment with market dynamics, regulatory compliance, and societal acceptance is equally crucial. Organizations must adopt a dual-focus strategy that fosters internal development while engaging with the external ecosystem. The identification of distinct organizational profiles through cluster analysis underscores the diverse challenges faced by companies at various stages of AI maturity. From early-stage organizations needing foundational development to high performers leading in innovation but facing regulatory risks, the AIM-DDI offers tailored insights for strategic improvement.

The framework emphasizes the necessity of ethical governance in AI adoption, bridging technological advancements with societal responsibility. This holistic approach ensures that organizations not only achieve operational efficiency and market leadership but also contribute positively to broader societal goals. The study highlights the pivotal role of policymakers, industry leaders, and educational institutions in creating supportive ecosystems that foster AI adoption across industries and regions. Through strategic partnerships, targeted interventions, and continuous innovation, organizations can leverage the AIM-DDI framework to navigate the complexities of AI-driven transformation effectively.

By addressing following limitations and pursuing these research directions, future studies can enhance the applicability and robustness of the AIM-DDI framework, fostering its utility as a strategic tool for organizations and policymakers navigating the rapidly evolving AI landscape.

8.1 Limitations

1. **Cross-sectional Design:** The study's data was collected over seven months, which limits the ability to analyze trends or establish causality. Future research could utilize longi-

tudinal designs to better capture the dynamics of AI adoption and its long-term impacts on competitive advantage.

2. **Self-reported Data:** The reliance on self-reported measures introduces potential biases, such as overestimation of AI maturity or social desirability bias. Incorporating third-party evaluations and objective performance metrics would strengthen the reliability of future findings.

3.1 **Geographic and Industry Representation:** While the study included responses from 765 organizations across 47 countries, certain regions and industries were underrepresented. This imbalance may restrict the generalizability of findings, necessitating a broader and more balanced dataset in subsequent research.

8.2 Future Research Directions

1. **Longitudinal Studies:** Future studies should explore the evolution of AI readiness and its influence on market disruption and organizational performance over time. Longitudinal research can provide deeper insights into the trajectory of AI adoption.
2. **Sector-specific Frameworks:** Tailoring the AIM-DDI framework to specific industries, such as healthcare, manufacturing, or retail, could yield more precise recommendations and address unique challenges within these sectors.
3. **Ethical and Social Impacts:** Expanding the framework to evaluate the societal implications of AI, including workforce impacts, equity, and sustainability, would provide a more holistic understanding of AI's role in business transformation.

8.3 Acknowledges

This research was partially funded by GLOBIS University Graduate School of Management, whose support was essential for the development of this work. We also extend our gratitude to the Beauty Cluster for their valuable collaboration and willingness to share insights and information that enriched this study, and to all those who have collaborated in the collection of data.

8.4 Conflict of Interest Statement

The author declares no conflict of interest regarding the publication of this study.

9. Computational Resources and References

9.1 Computational Resources

- The literature review for this study was supported by Perplexity AI, which facilitated the systematic collection and synthesis of relevant academic articles and sources for screening purposes.
- The data analysis and coding in this study were conducted using Jupyter Notebook (Project Jupyter, 2024), Python (Python Software Foundation, 2024), and Julius for advanced data analysis and figures (Julius, 2024).
- This manuscript was reviewed and edited using Grammary (2024) to ensure grammatical accuracy and clarity.

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9.3 Exhibit 1

Survey Questionnaire

1. "Which of the following options best describes your company's AI strategy and vision?" (0-5 scale options provided).
2. "Which of the following options best describes your company's data Infrastructure?" (0-5 scale options provided).
3. "Which of the following options best describes your company's AI talent and expertise?" (0-5 scale options provided).
4. "Which of the following options best describes your company's AI Implementation and Use Cases? (0-5 scale options provided).
5. "Which of the following options best describes your company's AI ethics and governance? (0-5 scale options provided).
6. "Which of the following options best describes your customer's expectations and AI adoption? (0-5 scale options provided).
7. "Which of the following options best describes your competitor's AI maturity? (0-5 scale options provided).
8. "Which of the following options best describes your industry's disruption potential? (0-5 scale options provided).
9. "Which of the following options best describes the regulatory environment and AI governance in your country and industry? (0-5 scale options provided).
10. "Which of the following options best describes the AI Talent and Education Ecosystem in Your Country and Industry? 0-5 scale options provided).
11. "Which of the following best describes the principal industry of your organization?" (Multiple choice options, 23 options combination of NAICS, ISIC, and GICS classifications).
12. "What is your company's annual revenue?" (Multiple choice options from "Less than $100K" to "$1B or more". World Bank classifications).
13. "What country is your company's headquarters located in?" (Multiple choice options, ISO 3166-1 country codes).
14. "What has been the evolution of your sales over the last year?" (0-5 scale options ranging from "Significantly increased" to "Significantly decreased").
15. "What are your expectations for annual growth over the next 3 years?" (0-5 options ranging from "Expect to significantly increase" to "Expect to significantly decrease").
16. "Thank you for completing the survey. Please share any other comments you have below:" (Open-ended response).

9.4 Exhibit 2

EFA Results: Factor Loadings and Variance Explained

	Factor1	Factor2	Factor3
AI INT MAT	0.9558223638	0.3185677039	
AI EXT MAT	0.4003014477	0.8923467629	
AIM-DDI	0.5611046593	-0.6299714457	
Which of the following options best describes your company's AI strategy and vision?	0.7897180357		
Which of the following options best describes your company's data Infrastructure?	0.599727458		
Which of the following options best describes your company's AI talent and expertise?	0.7596344247	0.3386249893	
Which of the following options best describes your company's AI Implementation and Use Cases?	0.7957346814		
Which of the following options best describes your company's AI ethics and governance?	0.6737989369	0.3345640872	
Which of the following options best describes your customer's expectations and AI adoption?	0.3916465339	0.6490852196	
Which of the following options best describes your competitor's AI maturity?	0.3722856209	0.6222167202	
Which of the following options best describes your industry's disruption potential?	0.3322462785	0.6610857632	
Which of the following options best describes the regulatory environment and AI governance in your country and industry?		0.3136547136	0.9331501299
Which of the following options best describes the AI Talent and Education Ecosystem in Your Country and Industry?		0.5395139865	
What has been the evolution of your sales over the last year?			
What are your expectations for annual growth over the next 3 years?			

	SS Loadings	Proportion Var	Cumulative Var
0	4.5584415728	3.350774952	1.1157678271
1	0.3038961049	0.2233849968	0.0743845218
2	0.3038961049	0.5272811017	0.6016656235

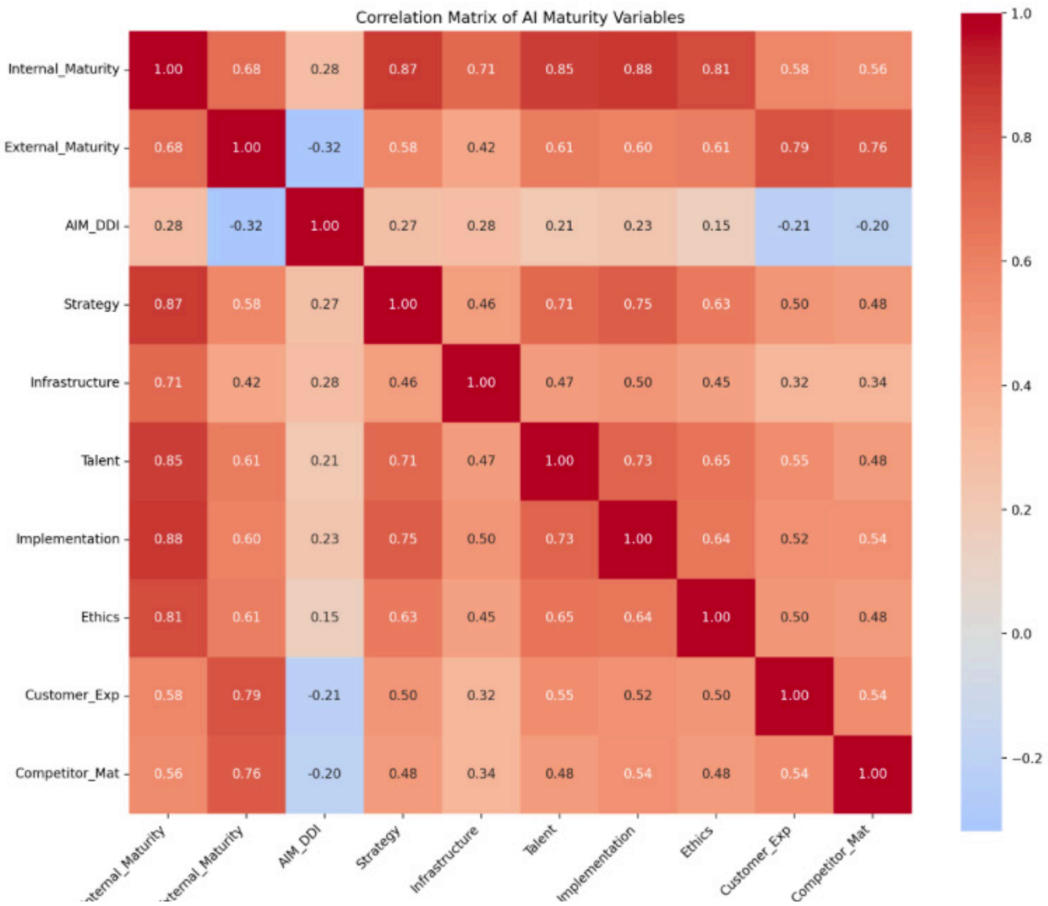
9.5 Exhibit 3

CFA Results: Factor Loadings and Variance Explained

	lval	op	rval	Estimate	Std. Err	z-value	p-value
0	int_mat	~	F1	1	-	-	-
1	strategy	~	F1	0.2338109792	0.005086306	45.9687206894	0
2	infrastructure	~	F1	0.1793683897	0.0066032433	27.163680223	0
3	talent	~	F1	0.182066889	0.0041751411	43.6073619014	0
4	implementation	~	F1	0.2037279268	0.004243851	48.0054385503	0
5	ethics	~	F1	0.194677542	0.0051753537	37.6162774163	0
6	ext_mat	~	F2	1	-	-	-
7	customer_exp	~	F2	0.2364618057	0.007221029	32.7462756278	0
8	competitor_mat	~	F2	0.180304447	0.0059575239	30.264997655	0
9	aim_ddi	~	F3	1	-	-	-
10	F1	~~	F2	13.7540158103	0.8844843062	15.5503220503	0
11	F1	~~	F3	1.1581272419	0.1553501578	7.4549473169	0
12	F1	~~	F1	23.707558759	1.2158585568	19.4986157116	0
13	F2	~~	F3	-1.1240516402	0.1339758297	-8.3899584179	0
14	F2	~~	F2	17.2643715258	0.9030851254	19.117103183	0
15	F3	~~	F3	0.6712410063	0.018462758	36.3564862625	0
16	aim_ddi	~~	aim_ddi	0.0509337304	0.018462758	2.7587281666	0.0058026781
17	competitor_mat	~~	competitor_mat	0.4164256422	0.0221754647	18.7786658956	0
18	customer_exp	~~	customer_exp	0.5986702045	0.0324125718	18.4703085995	0
19	ethics	~~	ethics	0.474877562	0.0245429305	19.3488532763	0
20	ext_mat	~~	ext_mat	0	0.1905905875	0	1
21	implementation	~~	implementation	0.3147134911	0.0165613941	19.0028381201	0
22	infrastructure	~~	infrastructure	0.7815486547	0.0400765239	19.5014082815	0
23	int_mat	~~	int_mat	0	0.0943641844	0	1
24	strategy	~~	strategy	0.4534869271	0.0237541548	19.0908466737	0
25	talent	~~	talent	0.3066234149	0.0159869625	19.1795917414	0

9.5 Exhibit 4

Correlation Matrix



9.6 Exhibit 5

AI Strategy Adoption Across Top 10 Industries

	AI-First Organization	Advanced AI Integration	Basic AI Awareness	Developing AI Strategy	Established AI Strategy	No AI Strategy
Financial Services	4.9	17.1	29.3	2.4	26.8	19.5
Manufacturing	2	2	56.1	6.1	7.1	26.5
Technology	0	20	25	11.7	33.3	10
Healthcare	0	3.6	52.7	16.4	16.4	10.9
Retail	1.9	9.4	60.4	3.8	15.1	9.4
Agriculture	2.4	4.9	46.3	7.3	19.5	19.5
Energy & Utilities	0	5.3	63.2	7.9	2.6	21.1
Government	0	6.1	48.5	3	18.2	24.2
Hospitality	0	13.3	46.7	13.3	10	16.7
Telecommunications	0	3.3	53.3	6.7	13.3	23.3

9.7 Exhibit 6

Summary Statistics Comparing The Beauty Cluster With Other Organizations Aggregated

The Beauty Cluster

	Internal_Score	External_Score
count	44	44
mean	2.9545454545	3.1818181818
std	1.4751882621	1.2209509266
min	0.8333333333	0.6666666667
25%	1.8333333333	2.6666666667
50%	2.5	3
75%	3.8333333333	3.75
max	6.5	6.6666666667

All Other Organizations Aggregated

	Internal_Score	External_Score
count	721	721
mean	3.3830328248	3.9750346741
std	1.6301661429	2.01644304
min	0.8333333333	0.6666666667
25%	2.1666666667	2.6666666667
50%	2.8333333333	3.6666666667
75%	4.1666666667	5
max	9.1666666667	12.3333333333