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Artificial Intelligence and Statistical Models in Business and Management: A Comprehensive Review

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Abstract:

The rapid development of artificial intelligence (AI) and advanced statistical modeling has transformed business and management research, reshaping practices in finance, human resource management, operations, risk assessment, and strategic planning. This review synthesizes insights from eighteen foundational and contemporary studies spanning business analytics, AI-driven decision-making, and statistical approaches to organizational performance. From early statistical approaches such as Altman's (1968) landmark study applied discriminant analysis to bankruptcy prediction, setting an early foundation for statistical approaches in finance and Barney's (1991) resource-based view, to contemporary AI-driven applications in talent analytics, strategic planning, fraud detection, and digital transformation, the review demonstrates how statistical rigor and AI capabilities converge to improve decision-making and firm performance. Drawing on methodologies such as discriminant analysis, structural equation modeling, deep learning, and systematic reviews, the paper highlights the evolution from statistical transparency to AI adaptability. We conclude that combining interpretability with predictive accuracy offers the strongest path for sustainable competitive advantage.

Keywords: Artificial Intelligence, Statistical Models, Business Analytics, Decision-Making, Firm Performance, Talent Analytics, Risk Assessment, Digital Transformation.

Introduction:

Artificial Intelligence (AI) has transitioned from being a technological curiosity to a main stream enabler of competitive advantage in business and management. While classical statistical techniques emphasized transparency and methodological rigor, AI-based approaches have been valued for their flexibility and strong predictive capabilities. This study systematically reviews seminal and recent works, positioning them within a framework of decision-making, performance outcomes, and sustained competitive advantage.

The integration of artificial intelligence (AI) and statistical modeling has redefined how businesses approach decision-making, performance evaluation, and competitive advantage. Early contributions, such as Altman's (1968) seminal work on bankruptcy prediction using discriminant analysis, paved the way for statistical rigor in business research. With advancements in computational power, researchers such as Kraus, Feuerriegel, and Oztekin (2018) demonstrated the potential of deep learning in operations, while Gómez-Caicedo et al. (2022) illustrated AI's growing role in business analytics. This paper reviews both foundational and contemporary research to evaluate the complementarities and contrasts between statistical and AI-driven approaches.

(From early statistical models → AI-driven approaches)

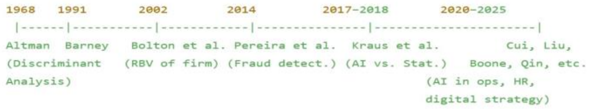

Figure1: Time line of AI & Statistical Models in Business

Literature Review:

1. Statistical Foundations in Business Research:

Altman (1968) pioneered statistical applications in finance by using discriminant analysis to predict bankruptcy, a framework later extended by Pereira, Basto, and Ferreira-da-Silva (2014), who compared statistical and AI models in failure prediction. Bolton et al. (2002) reviewed fraud detection, highlighting the effectiveness of statistical approaches before AI techniques gained prominence. These studies establish the foundation of interpretability and transparency in statistical models.

2. Emergence of AI in Business Analytics:

AI's ability to process large-scale, complex data is exemplified in Gómez-Caicedo, Gaitán-Angulo, and Bacca-Acosta (2022), who details its role in business analytics. Kraus et al. (2018) highlighted how deep learning models could be applied to solve complex problems in operations research, offering improvements over conventional analytics, while Davenport (2018) frames AI as the next evolutionary step after traditional analytics. Gupta (2021) complements this by presenting practical applications of business analytics using hybrid statistical-AI approaches.

3. Talent Management and HR Analytics:

Sharma and Bhatnagar (2017) emphasize talent analytics as a strategic tool for managing workforce outcomes, while Qin et al. (2023) provide a comprehensive AI survey on talent analytics, highlighting statistical and AI synergies in workforce optimization. Amabile (2020) adds a unique perspective by linking AI with creativity, suggesting AI-human collaboration as a catalyst for innovative outcomes.

4. AI in Decision-Making and Strategic Planning:

Chen, Esperança, and Wang (2022) empirically examine AI-enabled decision-making using PLS-SEM, showing its mediating effect on firm performance. Similarly, Fayaz, Amin, and Iqbal (2024) assess AI's role in strategic planning, stressing its transformative effect on managerial decisions. Cui (2025) provides evidence from Chinese enterprises, confirming AI's role in digital transformation and performance enhancement. Liu et al. (2022) extend this by reviewing systematic contributions to AI-enabled digital strategies.

5. AI in Finance and Risk Assessment:

Bahnsen et al. (2020) apply AI in financial risk assessment, demonstrating predictive power in dynamic environments. Boone et al. (2018) demonstrated how unconventional data such as Google Trends can be incorporated into forecasting, enhancing traditional statistical methods with real-time information. Barney (1991), while not AI-specific, introduces the resource-based view (RBV), framing firm resources (including AI capability) as drivers of competitive advantage.

Theoretical Framework:

By leveraging data analytics, talent optimization, and risk evaluation, AI systems support decision-making processes that contribute to better efficiency, stronger performance, and sustainable competitive advantage.

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AI Capabilities
  (Data Analytics,
   Machine Learning,
   Deep Learning)
         ↓
Decision-Making Enhancement
  (Talent Analytics,
   Risk Assessment,
   Strategic Planning)
         ↓
Firm Outcomes
  (Performance ↑,
   Efficiency ↑,
   Competitive Advantage ↑)
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Figure 2: Conceptual Framework: AI → Decision-Making → Firm Performance

Comparative Analysis:

1. Comparative Analysis of Methods:

Feature	Statistical Models (Altman, Bolton, Pereira)	AI Models (Kraus, Qin, Cui, etc.)
Interpretability	High (clear coefficients, ratios)	Medium-Low (black box issue)
Predictive Accuracy	Moderate	High (deep learning, big data)
Data Requirement	Smaller datasets	Large data sets needed
Application Domains	Finance, Bankruptcy prediction	Finance, HR, Operations, Strategy
Flexibility	Rigid assumptions	Adaptive, scalable

2. Comparative study of Foundational and Contemporary Contributions Across Research Domains

Study	Domain	Method/Model	Statistical Concept	Contribution
Altman (1968)	Finance	Discriminant Analysis	Ratios, Z-score	Bankruptcy prediction
Pereira et al. (2014)	Finance	AI vs. Statistics	Comparative modeling	Business failure prediction
Bolton et al. (2002)	Finance	Statistical Review	Fraud detection methods	Early statistical fraud models
Boone et al. (2018)	Marketing	Google Trends	Correlation, forecasting	Sales prediction
Kraus et al. (2018)	Operations	Deep Learning	Optimization	AI in operations research
Chen et al. (2022)	Management	PLS-SEM	Structural modeling	AI decision-making pathways
Liu et al.	Management	Systematic	Thematic coding	Digital transformation

(2022)		Review		
Qin et al. (2023)	HR	AI Survey	Comparative analysis	Talentanalytics
Amabile (2020)	Creativity	Conceptual	Surprise, novelty	AI-human creativity
Barney (1991)	Strategy	RBV Framework	Resource theory	Sustained advantage

3. Statistical Concepts Across Studies:

Statistical Concept	Application in AI Research	Examples from Studies
Regression (linear/logit/probit)	Modeling relationships between business variables	Pereira et al., Cui
Structural Equation Modeling (SEM/PLS-SEM)	Testing mediation, moderation, causal pathways	Cui, PLS-SEM study
Classification Metrics (ROC, AUC, Gini, Confusion Matrix)	Validating AI predictive accuracy	Business failure, fraud detection
Error Analysis (MSE, RMSE)	Measuring predictive performance	Kraus et al., operations forecasting
Hypothesis Testing (t-test, chi-square)	Survey data validation, adoption studies	Fayaz et al.
Survival Analysis	Employee turnover prediction	Qin et al.
Cost-sensitive Modeling	Economic impact of misclassification	Fraud detection papers

Note: *Source: Adapted fromPereiraetal.(2014),Krausetal.(2018),Liuetal.(2022),andothers.*

Findings and Thematic Mapping:

The body of literature suggests four central areas—finance, HR, strategic planning, and operations—where AI has either supplemented or outperformed traditional statistical techniques:-

- Finance & Risk (Altman, Bolton, Bahnsen)
- Human Resources (Sharma & Bhatnagar, Qin, Chakraborty)
- Strategic Planning (Fayaz, Liu, Cui)
- Operations & Creativity (Kraus, Davenport, Amabile)

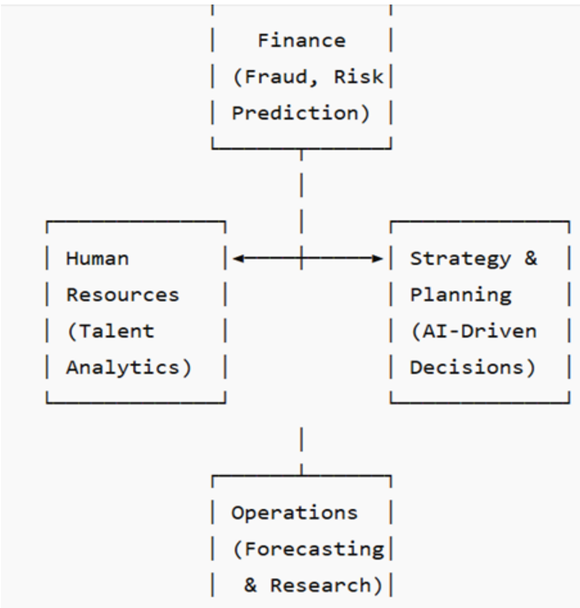

Figure 3: Thematic Map of AI Applications in Business

Figure 4: Application Areas of AI in Business

Discussion:

The reviewed literature reveals a shift from statistical interpretability toward AI adaptability. While statistical methods remain valuable for transparency and theory-building, AI offers superior predictive capacity in complex, dynamic environments. In HR, AI-driven talent analytics highlight its potential for optimizing workforce outcomes. In strategic domains, AI enables data-driven decision-making, aligning with RBV perspectives. However, interpretability and ethical challenges remain central issues requiring further exploration. Findings reveal a recurring balance between the clarity offered by statistical models and the superior predictive power of AI systems. Statistical models remain valuable in domains requiring transparency, while AI excels in large-scale, dynamic environments. The convergence of the two suggests a future of hybrid models combining explain ability and predictive power.

Conclusion and Future Research Agenda:

This review establishes that AI and statistical methods are not substitutes but complementary approaches. Statistical models offer clarity, while AI ensures adaptability and predictive strength. Future research should focus on hybrid frameworks, explainable AI, and cross-domain applications to balance interpretability with innovation. Integrating these methods across finance, HR, operations, and strategy will be essential for sustaining competitive advantage in the digital era. This review emphasizes the complementary roles of AI and statistics in business and management research. While statistics provide robustness and interpretability, AI offers adaptability and predictive strength. Upcoming studies could focus on:

- Developing hybrid approaches that merge the interpretability of statistical inference with the predictive strengths of AI.
- Investigate ethical and governance issues in AI-driven decisions.
- Extend AI applications beyond finance and HR into sustainability, creativity, and organizational innovation.

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