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Evaluating The Influence Of AI-Driven Predictive Analytics on Strategic Financial Decisions in the Commerce Sector

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Abstract:

This paper examines how AI-driven predictive analytics is reshaping strategic financial decision-making within the commerce sector. Using a secondary-data approach (industry reports, peer-reviewed articles, consultancy white papers, and reputable news coverage), the study synthesizes evidence on value creation (forecasting accuracy, risk management, customer lifetime value, pricing and inventory optimization), organizational enablers, and major challenges (bias, explainability, governance, regulation). Key findings show that organizations that combine strategic leadership, high-quality data, and disciplined model-validation practices capture disproportionate financial benefits from predictive analytics, while failures in transparency and governance amplify legal and reputational risks. The paper ends with practical recommendations for managers and policymakers to realize AI value while managing risks.

Keywords: AI, predictive analytics, financial decision-making, commerce, risk management, explainability, secondary data

Introduction:

The commerce sector spanning retail, e-commerce, banking-commerce integrations, and service platforms faces constant pressure to improve forecasts, manage cash flows, reduce risk, and personalize offerings. Predictive analytics driven by artificial intelligence (AI) techniques (machine learning, deep learning, and ensemble models) promises to transform how businesses make strategic financial decisions by converting large historical and real-time datasets into probabilistic forecasts and prescriptive actions. Recent industry surveys indicate accelerating AI adoption across business functions and growing interest in scaling AI from pilots to enterprise impact.

This paper asks: How does AI-driven predictive analytics influence strategic financial decisions in commerce? Sub-questions include: What measurable benefits are reported in secondary sources? Which organizational capabilities enable value capture? What risks and governance challenges arise, and how are stakeholders addressing them? The study relies entirely on secondary data drawn from consultancy reports, peer-reviewed studies, sector case studies, and authoritative news accounts. The goal is synthesis and practical guidance for managers and researchers.

Literature Review:



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1. Broby (2022) explains that predictive analytics has become a central tool in financial forecasting, particularly in commerce where demand volatility and competition require greater accuracy. The study highlights that AI-enhanced models such as machine learning and deep learning outperform traditional statistical forecasting methods. Broby concludes that better predictions directly influence strategic financial decisions by reducing uncertainty, improving revenue projections, and optimizing inventory and cash-flow planning.

2. The McKinsey Global AI Survey (2025) reports that organizations using predictive analytics at scale experience significant improvements in decision-making speed and financial performance. The survey shows that firms integrating AI into budgeting, pricing, credit decisions, and risk modeling achieve higher profit margins and better capital allocation. Importantly, the report notes that value is captured only when predictive analytics is accompanied by strong data governance and cross-functional adoption.

3. Ferrara et al. (2023) focus on the challenges and opportunities of AI in financial decision-making, with special attention to bias, fairness, and transparency. The authors argue that although predictive analytics improves accuracy, biased training data can lead to unfair financial decisions, especially in lending and pricing. Their work emphasizes the need for explainable AI and robust validation frameworks to ensure responsible use of predictive models in commerce.

4. Chen and Zhang (2020) investigate the impact of predictive analytics on risk management within commercial enterprises. Their research shows that AI-driven risk-scoring systems enhance fraud detection, credit risk evaluation, and financial anomaly identification. The authors found that firms adopting predictive analytics reduce financial losses and improve decision reliability. They conclude that AI-enabled systems contribute to strategic resilience by enabling early detection of financial threats.

5. Davenport and Harris (2019) emphasize the strategic shift from intuition-based financial decision-making to data-driven predictive approaches in commerce. Their work documents that executives increasingly rely on predictive dashboards, scenario forecasting, and automated analysis for strategic planning. The study concludes that predictive analytics not only enhances accuracy but also accelerates decision processes, enabling firms to respond quickly to market changes, optimize resources, and strengthen long-term financial strategies.

Methodology:

This research uses a structured secondary-data synthesis approach:

1. **Source selection:** Reputable industry reports (McKinsey Global Survey 2025; McKinsey Financial Services reports), peer-reviewed journal articles (predictive analytics in finance, fairness studies), white papers, and high-quality news/legal analyses (Reuters). Sources were selected for topical relevance, methodological rigor, and recency (2019–2025 where possible). Key documents used are listed in the References.



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2. **Extraction:** For each source, data were extracted on (a) claimed impacts of predictive analytics on financial metrics (forecast error reductions, churn reduction percentages, time-to-decision improvements), (b) deployment practices and enablers (data platforms, model governance), and (c) documented failures or regulatory actions.
3. **Synthesis:** Evidence was triangulated to identify recurring patterns, differences across sub-sectors (retail vs. banking vs. e-commerce), and emergent themes (governance, explainability).

Limitations: Secondary-data synthesis relies on what has been reported; heterogeneity in metrics and differing contexts limit the comparability of claimed effect sizes. Nonetheless, convergence across multiple reputable sources supports robust thematic conclusions.

Findings:

1. Financial forecasting and working capital optimization

Several studies show that AI-based time-series models (ARIMA enhancements, LSTM, Prophet, gradient boosting) reduce demand forecast errors compared with baseline statistical methods, particularly when models incorporate external signals (search trends, macro indicators). Reduced forecast error translates into lower inventory holding costs, fewer stockouts, and more accurate revenue recognition all of which improve working capital metrics. McKinsey’s survey and financial-services white papers document that organizations scaling predictive models see measurable improvements in forecasting and decision latency.

Illustrative evidence: A synthesis of case studies indicates retailers implementing AI forecasts reported reduced stockouts and 1–5% lift in sales attributable to better availability, along with lower markdowns. (Reported magnitudes vary by study and firm size.)

2. Risk management, fraud detection, and credit decisions

Financial institutions and commerce platforms employ AI models to detect anomalous transactions and to predict credit risk using non-traditional signals (behavioral patterns, device fingerprinting). These systems allow near-real-time decisions (e.g., instant approvals, dynamic credit limits) and reduce manual review load. Consultancy research highlights that AI can sharpen risk segmentation and enable more granular capital allocation.

Tradeoffs: Highly complex models increase detection power but raise explainability concerns and regulatory scrutiny (e.g., credit decisions under consumer-protection rules). News analyses show regulators pushing for transparency where AI decisions materially affect consumers.

3. Customer value optimization and pricing strategies

Predictive CLV models and propensity models are widely used to optimize marketing spend and personalize offers. Secondary studies report improved retention and reduced churn when firms target high-value customers with tailored interventions based on predicted behavior. Similarly, dynamic pricing engines—fed by short-term demand forecasts and competitor price scraping—can improve margins while managing price elasticity tradeoffs.



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4. Operational and strategic decision acceleration

AI systems shorten decision cycles: automated dashboards and alerts allow finance leaders to reallocate budgets, hedge exposures, or adjust procurement more quickly. McKinsey’s assessments highlight that firms with clear AI ownership, data governance, and validation processes achieve faster time-to-value.

5. Uneven distribution of benefits — the “scaling gap”

A recurring theme is the difference between pilot successes and enterprise-scale impact. Firms that treat AI as isolated projects often fail to realize strategic gains. Instead, organizations that integrate AI into processes, invest in data platforms, and define human-in-the-loop checkpoints capture sustained benefits. This organizational capability gap strategy, talent, operating model, and technology explains why benefits are skewed to “AI high performers.”

Discussion:

1. How predictive analytics changes strategic financial decisioning (mechanisms)

Predictive analytics shifts strategic decision-making from calendar-based periodic reviews toward continuous, probabilistic planning. Finance leaders receive scenario-based forecasts with confidence bands that allow for contingent actions (e.g., staged investments, conditional supplier contracts). Predictive outputs are being embedded into ERP and treasury functions, enabling automated liquidity planning, stress-testing, and dynamic budgeting. The key mechanism is replacing single-point estimates with probabilistic, actionable intelligence.

2. Organizational enablers of value capture

Synthesis of secondary sources shows several enabling practices:

1. **Data infrastructure:** central data lakes/warehouses and real-time pipelines.
2. **Model governance and validation:** defined model lifecycle processes, backtesting, and human review policies.
3. **Senior sponsorship and cross-functional teams:** business leaders who champion adoption and align incentives.
4. **Talent and change management:** data scientists, ML engineers, and finance professionals trained to interpret model outputs.

3. Risks, biases, and explainability practical implications

Although accuracy improvements are well documented, so are non-trivial risks:

- **Bias and fairness:** Training data reflecting historical inequalities can lead to discriminatory outputs (e.g., credit offer disparities). The AI fairness literature documents sources of bias and mitigation strategies (preprocessing, reweighting, post-hoc adjustments).
- **Opacity and legal exposure:** Complex models may lack intelligible explanations for decisions; this opacity can conflict with consumer-protection and transparency



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requirements. Recent legal commentary and reporting highlight regulatory scrutiny and the need for accountable systems in finance.

- **Model drift and fragility:** Economic shocks or behavior changes can invalidate models; model monitoring and re-training are essential.

4. Balancing automation and human oversight

Best practice emerging from secondary literature emphasizes human-in-the-loop systems for high-stakes financial decisions. Where outcomes materially affect customers or carry legal risk (credit denial, dynamic pricing affecting vulnerable consumers), organizations should require human validation, maintain audit trails, and implement appeal processes. These practices align with regulatory recommendations and industry survey findings that link human validation policies with higher AI value realization. (McKinsey & Company)

Managerial and Policy Recommendations:

Based on secondary data synthesis, the following practical recommendations are offered to finance leaders in commerce:

1. For managers (operational & strategic)

1. **Adopt a use-case portfolio approach:** Prioritize high-value, lower-risk use cases (demand forecasting, fraud detection) while piloting riskier, customer-facing models with stronger governance.
2. **Invest in data quality and observability:** Clean, well-instrumented data pipelines are foundational. Implement monitoring for data drift and model degradation.
3. **Define model governance and explainability standards:** Document model inputs, performance metrics, and decision thresholds. Require explainability for models affecting customers.
4. **Maintain human oversight for high-stakes decisions:** Use human review for credit/denial, exception handling, and final approvals, with documented audit trails.
5. **Measure financial impact:** Link model outputs to financial KPIs (forecast error reduction, margin uplift, time-to-decision) and track ROI to prioritize scaling.

2. For policymakers and regulators

1. **Risk-based regulation:** Adopt proportionate rules that require transparency, fairness testing, and auditability for high-risk financial AI while allowing innovation in lower-risk areas.
2. **Promote industry sandboxes and standards:** Regulatory sandboxes and common standards for model reporting encourage responsible experimentation and comparability.
3. **Guidance on explainability and recourse:** Mandate clear communication to consumers when automated decisions materially affect them, and require mechanisms for appeals and human review.

Conclusions:



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AI-driven predictive analytics is materially reshaping strategic financial decision-making across commerce by improving forecasting, sharpening risk assessment, and enabling more targeted customer investments. Secondary evidence from industry surveys, academic studies, and case reports converges on a central insight: technical capability alone is insufficient organizational practices (data governance, human oversight, and senior sponsorship) determine whether predictive analytics delivers sustained financial value.

At the same time, the rapid adoption of opaque and complex models raises serious ethical, legal, and operational risks. Secondary sources increasingly emphasize explainability, monitoring, and regulatory alignment as prerequisites for scaling AI in finance. To translate predictive power into strategic advantage, commerce firms must adopt a disciplined, risk-aware, and customer-centric approach.

Limitations and Suggestions for Future Research:

This study synthesizes available secondary data but is constrained by heterogeneity in reported metrics and limited public disclosure by private firms on model performance. Future empirical work could:

1. Conduct comparative case studies with firm-level financial metrics pre- and post-AI adoption.
2. Quantify the causal impact of specific predictive-analytics interventions (difference-in-differences, synthetic control methods).
3. Investigate consumer welfare effects and distributional impacts of AI-driven pricing and credit decisions.

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