UNIVERSITY ASSIGNMENT

MODULE: BUS4021 — Strategic Management & Technology

The Impact of Artificial Intelligence on Business Decision-Making

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Submission: [Month Year]

Learning Objectives

By the end of this presentation, the audience will be able to:

1. Define artificial intelligence and its key subfields relevant to business contexts (machine learning, NLP, and predictive analytics).
2. Critically evaluate how AI technologies are transforming strategic and operational decision-making in modern organisations.
3. Apply relevant theoretical frameworks — including bounded rationality (Simon, 1955) and the dynamic capabilities view — to AI adoption.
4. Analyse the ethical, social, and governance challenges posed by AI-driven decision-making systems.
5. Assess evidence-based case studies demonstrating measurable business outcomes attributable to AI deployment.
6. Formulate informed conclusions on the future trajectory of AI in business strategy and competitive advantage.

Introduction: What Is Artificial Intelligence?

Defining AI in a Business Context

Artificial Intelligence (AI) refers to the simulation of human cognitive functions — including learning, reasoning, problem-solving, and language comprehension — by computer systems (Russell and Norvig, 2021).

In the context of business, AI is not a single technology but an ecosystem of interconnected techniques, including:

• Machine Learning (ML): Systems that learn from data without explicit programming.
• Natural Language Processing (NLP): Enables machines to understand human language.
• Computer Vision: Allows machines to interpret visual data.
• Predictive Analytics: Statistical models that forecast future outcomes.

77%

of businesses are using or exploring AI (PwC, 2023)

$15.7T

projected contribution of AI to global economy by 2030 (PwC, 2023)

40%

reduction in business costs achievable through AI automation (McKinsey, 2023)

Theoretical Framework

This study draws on four established theoretical lenses to analyse AI-driven decision-making:

Bounded Rationality (Simon, 1955)

Herbert Simon's bounded rationality theory posits that human decision-making is constrained by cognitive limitations, available information, and time. AI systems can extend these boundaries by processing vast datasets at speed — complementing, rather than replacing, human judgement.

Dynamic Capabilities View (Teece et al., 1997)

Dynamic capabilities refer to a firm's ability to sense, seize, and reconfigure resources in response to changing environments. AI investment constitutes a dynamic capability that enables sustained competitive advantage through superior sensing and response mechanisms.

Resource-Based View (Barney, 1991)

The RBV holds that sustained competitive advantage derives from valuable, rare, inimitable, and non-substitutable (VRIN) resources. AI-enabled data assets and proprietary models are increasingly recognised as VRIN resources that are difficult for competitors to replicate.

Agency Theory (Jensen & Meckling, 1976)

Agency theory examines conflicts of interest between principals and agents. AI-driven monitoring and reporting can reduce information asymmetry, improving governance and reducing the costs associated with managerial opportunism.

Literature Review: Key Academic Perspectives

Davenport & Ronanki (2018) — Harvard Business Review

Identified three distinct business applications of AI: automating processes, gaining insights through data analysis, and engaging customers/employees. Emphasised that most successful AI deployments augment human capabilities rather than replace them.

Agrawal, Gans & Goldfarb (2018) — "Prediction Machines" — MIT Press

Reframed AI as a 'prediction machine' that dramatically reduces the cost of prediction. As prediction costs fall, the value of human judgement and actions that complement prediction rises — reshaping the economics of decision-making.

Brynjolfsson & McAfee (2014) — "The Second Machine Age" — W.W. Norton

Argued that AI and digital technologies constitute a new general-purpose technology comparable to the steam engine. Productivity gains are real but unevenly distributed; skill-biased technological change exacerbates income inequality.

Obermeyer & Emanuel (2016) — New England Journal of Medicine

Cautioned that algorithmic decision-making in healthcare reproduced existing racial biases embedded in historical training data — highlighting the critical importance of ethical AI governance and diverse data curation.

AI Applications in Business Decision-Making

Strategic Planning

Scenario modelling, competitive intelligence, market demand forecasting (Chui et al., 2018)

Financial Decisions

Algorithmic trading, credit risk scoring, fraud detection, investment portfolio optimisation (Bholat, 2016)

Operations Management

Supply chain optimisation, predictive maintenance, dynamic pricing, inventory management (Waller & Fawcett, 2013)

Human Resources

AI-assisted recruitment, performance analytics, workforce planning, talent retention modelling (Tambe et al., 2019)

Customer Relationship

Personalisation engines, sentiment analysis, chatbot service delivery, churn prediction (Davenport et al., 2020)

Risk Management

Real-time risk dashboards, regulatory compliance automation, cyber-threat detection (Buchanan, 2020)

Case Study 1: Amazon — AI-Driven Supply Chain Optimisation

Sector: E-commerce & Logistics | AI Application: Predictive Demand Forecasting & Autonomous Warehousing

Background	Amazon processes over 1.6 million orders per day. Managing inventory across 175+ global fulfilment centres demanded decision-making capabilities far beyond human capacity (Brynjolfsson & McAfee, 2014).
AI Intervention	Amazon deployed ML-based anticipatory shipping algorithms that predict customer purchases before orders are placed, positioning inventory closer to predicted demand locations. Additionally, Kiva robots — now Amazon Robotics — autonomously manage warehouse logistics (MacCormack et al., 2020).
Measured Outcomes	40% reduction in operating costs; delivery speed improved to same-day fulfilment for Prime members in 90+ cities; inventory accuracy improved to 99.99% (Amazon Annual Report, 2022).
Critical Analysis	While outcomes are impressive, critics (Delfanti, 2021) raise concerns over algorithmic management of warehouse workers, including productivity surveillance and injury rates — illustrating the social consequences of AI-driven operational decisions.

Case Study 2: JP Morgan — AI in Financial Decision-Making

Sector: Banking & Financial Services | AI Application: Contract Intelligence (COIN) — Natural Language Processing

Background	JP Morgan processes approximately 12,000 commercial credit agreements annually. Each contract review required an estimated 360,000 hours of legal and loan officer time per year, at significant cost and error risk.
AI Intervention	In 2017, JP Morgan deployed COIN — Contract Intelligence — an NLP system that interprets commercial loan agreements. COIN analyses legal documents in seconds, extracting critical data points and flagging anomalies against regulatory requirements (JP Morgan Annual Report, 2019).
Measured Outcomes	360,000 hours of lawyer time replaced annually; error rates fell significantly; the system now processes loans in seconds versus the weeks required for manual review — demonstrating quantifiable gains in both efficiency and accuracy (Davenport & Ronanki, 2018).
Critical Analysis	Agrawal et al. (2018) would frame COIN as a prediction machine reducing the cost of information extraction. However, concerns exist around auditability: when an AI system denies a loan, institutions must ensure regulatory explainability requirements (EU AI Act, 2024) are satisfied.

Critical Analysis: Benefits and Limitations of AI in Decision-Making

Opportunities

- Enhanced speed and scale of data processing
- Reduction of cognitive bias in structured decisions
- New business models enabled by data monetisation
- Competitive differentiation through proprietary AI systems

Limitations

- Opacity of "black-box" ML models (Doshi-Velez & Kim, 2017)
- Data quality dependency: garbage in, garbage out
- Risk of replicating historical biases (Obermeyer et al., 2019)
- High implementation costs for SMEs

Benefits

- Augmented human decision quality (Davenport, 2018)
- Real-time insight generation from unstructured data
- Predictive maintenance reducing operational downtime
- Personalisation at scale improving customer outcomes

Challenges

- Workforce displacement and reskilling requirements
- Regulatory uncertainty (GDPR, EU AI Act 2024)
- Cybersecurity vulnerabilities in AI-enabled systems
- Organisational resistance and change management

Ethical Considerations & AI Governance

Algorithmic Bias

Training data reflecting historical inequalities produces discriminatory outputs. Obermeyer et al. (2019) demonstrated racial bias in US healthcare AI. Mitigation requires diverse datasets and regular bias audits.

Transparency & Explainability

The EU AI Act (2024) mandates that high-risk AI systems be explainable to affected individuals. "Black-box" models used in credit scoring or recruitment violate principles of fairness and accountability (Goodman & Flaxman, 2017).

Privacy & Data Protection

AI systems are data-hungry. GDPR (2018) grants EU citizens the right not to be subject to solely automated decisions with legal effects. Organisations must implement privacy-by-design principles (Cavoukian, 2012).

Labour Displacement

The OECD (2019) estimates 14% of jobs are highly automatable and a further 32% face significant change. Ethical AI deployment requires proactive reskilling investment and fair transition frameworks for affected workers.

Human-AI Collaboration: Augmentation vs. Automation

"The most productive use of AI in business is not to automate human decisions, but to augment human intelligence — combining the computational power of machines with the contextual wisdom of people." — Davenport & Ronanki (2018)

Human Strengths

- Contextual & emotional intelligence
- Ethical & moral reasoning
- Creative problem-solving
- Stakeholder relationship management
- Ambiguous and novel situations

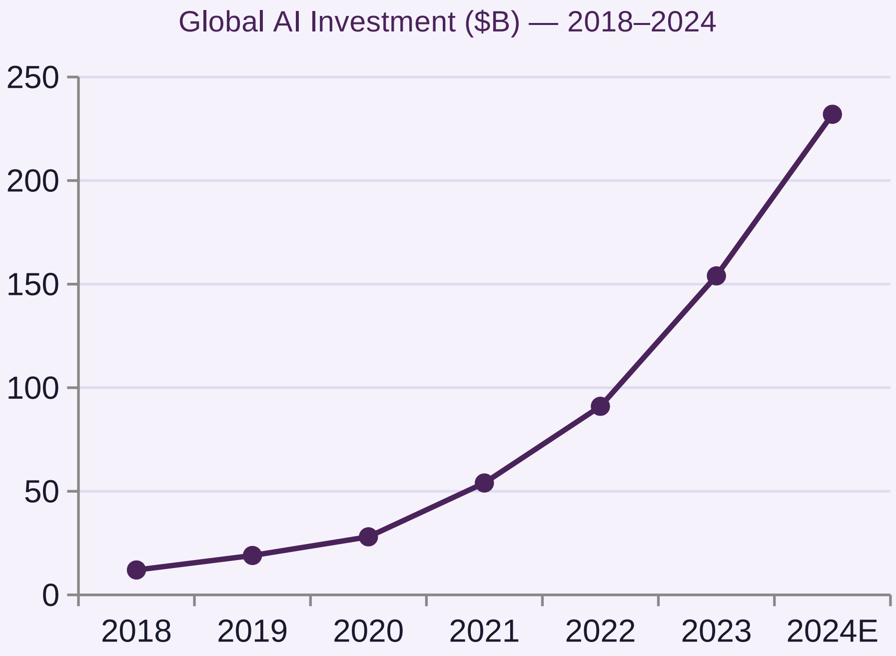
Together (Human + AI)

- Faster, more accurate decisions
- Bias-checked by diverse teams
- Scalable personalised services
- Continuous performance monitoring
- Evidence-based strategy

AI Strengths

- Processing vast structured datasets
- Pattern recognition at scale
- Consistent rule-based execution
- Real-time anomaly detection
- 24/7 operational availability

Future Trends in AI-Driven Business Decision-Making



Source: Stanford AI Index (2024)

Generative AI in Strategy

LLMs (e.g. GPT-4) are enabling real-time synthesis of market intelligence for strategic planning (Dwivedi et al., 2023).

Explainable AI (XAI)

Regulators and stakeholders increasingly demand interpretable models — XAI techniques make AI decisions auditable and accountable.

Autonomous Decision Agents

Fully autonomous AI agents capable of executing multi-step business decisions are emerging in supply chain and trading contexts.

Federated Learning

Enables collaborative AI model training across organisations without sharing raw data — critical for privacy-sensitive sectors like healthcare and banking.

Discussion Questions

Q1 To what extent does AI in business decision-making represent an evolution of, rather than a departure from, Simon's (1955) model of bounded rationality? Justify your answer with reference to specific AI applications.

Q2 Drawing on Barney's (1991) Resource-Based View, under what conditions can an organisation's AI capability constitute a sustained competitive advantage? What factors might erode this advantage over time?

Q3 The EU AI Act (2024) classifies certain AI systems as "high risk" and imposes strict transparency obligations. Is this regulation sufficient to address the ethical concerns raised in the literature, or does it risk stifling innovation?

Q4 How should business leaders balance the efficiency gains offered by fully automated AI decisions against the accountability requirements that come with human oversight in high-stakes domains such as finance and healthcare?

Conclusion

This presentation has demonstrated that Artificial Intelligence is fundamentally reshaping business decision-making across strategic, operational, financial, and human resource functions. Drawing on the theoretical lenses of bounded rationality (Simon, 1955), dynamic capabilities (Teece et al., 1997), and the resource-based view (Barney, 1991), it is evident that AI represents not merely a technological tool but a transformative organisational capability — one that, when thoughtfully governed, can generate significant and sustained competitive advantage.

1. AI extends the cognitive boundaries of decision-makers, consistent with Simon's (1955) bounded rationality framework — enabling processing at scale impossible for individual humans.
2. Evidence from Amazon and JP Morgan confirms measurable, quantifiable benefits: cost reductions, speed improvements, and accuracy gains attributable to AI deployment.
3. Ethical governance is non-negotiable. Algorithmic bias, transparency deficits, and labour displacement require proactive organisational and regulatory responses (EU AI Act, 2024).
4. The future belongs to organisations that pursue human-AI collaboration, not wholesale automation — combining machine computation with irreplaceable human contextual judgement.

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