International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

Implementing Business Intelligence And Predictive Analytics In Data-Driven Decision-Making: A Comparative Case Study Of Telkomsel And Netflix

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Abstract

Organizations invest heavily in Business Intelligence (BI) and Predictive Analytics (PA), yet the value of these investments does not materialize automatically. This study analyzes how BI and PA are implemented in data-driven decision-making and which factors determine their success. A qualitative comparative case study design was employed, combining a critical review of peer-reviewed literature published between 2015 and 2025 with a document analysis of two contrasting organizations, Telkomsel and Netflix, using five analytical dimensions derived from the literature. The critical review shows that the evidence is not uniform: the effect of BI and analytics on performance is largely indirect and mediated by decision quality and decision speed, whereas the roles of data-driven insight, data culture, and user–tool fit remain contested; moreover, most studies rely on cross-sectional perception data. The case analysis shows that Netflix, as a digital-native organization, has reached a mature stage, with its advantage lying in embedding predictions into operational decisions and in continuous experimentation. Telkomsel is in a transition stage from BI to predictive analytics: its data assets are rich, but evidence of impact is still largely based on company and vendor claims. The differences between the two organizations are explained more by decision integration, experimentation culture, and data structure than by analytics technology itself. Six strategic recommendations are proposed: integrated data governance and architecture, integration of predictions into decision flows, controlled experimentation, data culture and human capital development, credible value measurement, and management of privacy, bias, and regulatory compliance.

Keywords: Business intelligence; Predictive analytics; Data-driven decision-making; Telkomsel; Netflix.

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INTRODUCTION

Digital transformation has positioned data as a strategic organizational asset. Organizations increasingly regard data as a core asset, and this view has shifted organizational culture toward decision-making grounded in analytics (Hurbean et al., 2023). Business Intelligence and Analytics (BI&A) systems enable organizations to understand their business better and to improve the quality of managerial decisions (Hurbean et al., 2023). In practice, BI is used to understand performance that has already occurred, whereas *predictive analytics* is used to estimate what is likely to happen, for example which customers are at risk of churning or which content a viewer is likely to enjoy.

However, investment in analytics technology does not automatically generate business value. The question of what actually translates *big data* into business value has become the focus of a meta-analysis of the impact of business analytics on firm performance (Oesterreich et al., 2022). Empirical studies show that outcomes depend on complementary factors such as *data-driven insight* (Awan et al., 2021), decision-making speed (Khaddam et al., 2023), and a data-driven culture (Hurbean et al., 2023). Wang (2025) further argues that analytics investment is not merely a technological change but an organizational transformation, with decision quality acting as the link between analytics and performance. Large-scale evidence from United States manufacturing likewise shows that the benefits of predictive analytics are conditional: productivity gains materialize mainly when PA is combined with organizational complements such as information technology (IT) capital and educated workers (Brynjolfsson et al., 2021).

A research gap also remains. Hurbean et al. (2023) note that few studies have examined how BI&A adoption affects individual decision-making effectiveness and managerial work performance. In addition, many studies treat BI, analytics, and big data as a single construct, which makes the specific contribution of predictive analytics difficult to isolate. Case studies of real organizations can help bridge this gap by showing how these capabilities operate in concrete settings.

This study selects two contrasting organizations. **Telkomsel** is the largest mobile operator in Indonesia, serving approximately 156.1 million mobile subscribers at the end of 2025 (Telkomsel, 2026) and holding very large volumes of customer, network, and billing data. **Netflix** is a global streaming entertainment company whose recommender system has become a classic reference for the application of predictive analytics to product decisions (Gomez-Uribe & Hunt, 2015). Comparing the two makes it possible to analyze how industry context, data architecture, and organizational culture shape the outcomes of BI and PA implementation. Accordingly, this study addresses four research questions:

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1. How are BI, predictive analytics, and data-driven decision-making conceptualized in recent scholarly literature?
2. How do the theories, approaches, and findings of prior studies compare regarding the relationship between BI/analytics, decision quality, and organizational performance?
3. How are BI and predictive analytics implemented at Telkomsel and Netflix, and what are the differences and similarities between the two?
4. Which strategies are recommended so that BI and predictive analytics implementation produces better decisions on a sustainable basis?

Theoretically, this study contributes a critical synthesis of the BI&A literature and a case-analysis framework that can be used in further research. Practically, it offers guidance for managers in designing BI and predictive analytics initiatives that are tied to real decisions rather than treated as mere technology projects.

LITERATURE REVIEW

Business Intelligence

Business Intelligence is understood as a set of processes, technologies, and practices that transform data into meaningful information to support decisions. BI&A enables organizations to understand their business and to improve the quality of managerial decisions so that organizational performance improves (Hurbean et al., 2023). Phillips-Wren et al. (2021) propose reconciling BI, analytics, and decision support systems (DSS), which have long developed in separate traditions; with more data, the ultimate goal is deeper insight for decision makers. The implication is that BI should not be viewed merely as a reporting tool but as part of a decision system involving data, models, and people (Phillips-Wren et al., 2021).

Predictive Analytics

Predictive analytics uses statistical and machine learning models to estimate the probability of future events, such as classifying customers who are likely to churn or estimating viewer interest in a title. In the commonly used typology of analytics, descriptive and diagnostic BI answer “what happened and why”, predictive analytics answers “what is likely to happen”, and prescriptive analytics answers “what should be done” (Lepenioti et al., 2020). The quality of predictive models is usually assessed with metrics such as accuracy, precision, recall, and AUC, but business value emerges only when predictions change managerial actions. Evaluation of PA therefore needs to combine model performance measures with measures of decision impact.

Large-scale empirical evidence on PA is provided by Brynjolfsson et al. (2021), who, in collaboration with the U.S. Census Bureau, surveyed more than 30,000 American

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manufacturing establishments. Productivity was significantly higher in plants that used PA, and instrumental-variable estimates and the timing of the gains suggest a causal relationship. However, the pay-off occurred only when PA was combined with at least one workplace complement: significant accumulation of IT capital, educated workers, or workplaces designed for high flow-efficiency production. From an implementation perspective, Chen et al. (2024) conducted structured interviews with IT and analytics executives in 11 U.S. organizations and identified the sociotechnical components that are key to PA implementation, noting that although analytics investment is increasing, little research has examined how analytics assets are converted into business performance. Both studies indicate that PA is a sociotechnical capability rather than merely a model. In the Indonesian telecommunications context, Asror and Nuryana (2025) illustrate PA through a churn classification model developed with the CRISP-DM method.

Data-Driven Decision-Making

Data-driven decision-making (DDDM) is the practice of basing decisions on analytical evidence rather than solely on intuition or experience. Wang (2025) argues that the impact of business analytics on firm performance depends on improvements in decision quality, which encompass accuracy, timeliness, relevance, and actionability. Hurbean et al. (2025) find that a data-driven culture, together with BI&A, shapes managerial performance. DDDM is therefore a sociotechnical phenomenon in which technology, processes, and culture must be aligned.

Theoretical Lenses

Three theoretical perspectives underpin this study. First, the Resource-Based View (RBV) and the Dynamic Capability View (DCV) are used by Chatterjee et al. (2023) to explain that big data analytics adoption affects decision-making processes, forecasting, and firm performance. Within this framework, data and analytics are valuable resources when combined with organizational capabilities that are difficult to imitate. Second, the decision support systems tradition (Phillips-Wren et al., 2021) emphasizes the interaction among information, models, and decision makers. Third, the organizational culture perspective (Hurbean et al., 2023, 2025) stresses that the value of analytics emerges only when organizational norms support the use of data. These three perspectives are used jointly as the analytical framework of this study.

The three lenses are complementary. RBV/DCV explains *why* analytical capabilities are valuable, the DSS tradition explains *how* that value flows through decisions, and the cultural perspective explains *when* that value occurs. No single lens is sufficient on its own. A common weakness of all three is the tendency to explain

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relationships at the organizational level, whereas decisions are actually made by individuals and teams, a gap also highlighted by Hurbean et al. (2023).

Prior Empirical Studies

Table 1 summarizes the eight peer-reviewed studies that form the main foundation of this article. Oesterreich et al. (2022) are used to frame the research problem, whereas Gomez-Uribe and Hunt (2015) and Jannach and Jugovac (2019) are used in the Netflix case analysis.

Table 1. Summary of prior studies underpinning this article

No	Author (year) and source	Context and method	Main finding or contribution
1	Phillips-Wren et al. (2021), *Decision Support Systems*	Conceptual review of the relationship between BI, analytics, and DSS	Proposes reconciling BI, analytics, and DSS into a single decision-support continuum with more data and deeper insight.
2	Awan et al. (2021), *Technological Forecasting and Social Change*	109 Czech manufacturing firms; PLS-SEM	BDA capability and BI&A are positively associated with decision quality; the effect is stronger when firms use data-driven insight, but insight does not mediate the BDA–decision relationship.
3	Chatterjee et al. (2023), *Technological Forecasting and Social Change*	366 respondents from Indian firms; RBV and DCV; PLS-SEM	BDA adoption affects decision-making processes, forecasting, and firm performance; the authors acknowledge the limitations of cross-sectional data (causality and endogeneity).
4	Khaddam et al. (2023), *The Service Industries Journal*	Survey of respondents in leadership positions across Jordanian industries; PLS-SEM	BI increases decision-making speed; decision speed mediates the BI–performance relationship; person–tool fit weakens the BI–decision speed relationship.

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No	Author (year) and source	Context and method	Main finding or contribution
5	Hurbean et al. (2023), *Scientific Annals of Economics and Business*	Research model of BI&A adoption among managers	Proposes that BI&A adoption affects decision-making effectiveness and managerial work performance, and that a data-driven culture drives adoption.
6	Wang (2025), PESD 2025 proceedings (Atlantis Press)	Literature synthesis and conceptual model	The effect of business analytics on performance depends on improved decision quality (accurate, timely, relevant, actionable).
7	Brynjolfsson et al. (2021), *Business Economics*	Survey of more than 30,000 U.S. manufacturing plants with the Census Bureau; administrative data	PA-using plants are more productive (up to US$918,000 higher sales than similar competitors); causal indication; gains occur only with complements (IT capital, educated workers, high flow-efficiency workplaces).
8	Chen et al. (2024), *Journal of International Technology and Information Management*	Structured interviews with IT and analytics executives in 11 U.S. organizations	Identifies key sociotechnical components of PA implementation; analytics investment is increasing, but research on converting analytics assets into performance remains scarce.

Source: compiled by the authors from the cited articles. Studies 7 and 8 specifically strengthen the predictive analytics foundation.

Conceptual Framework

Based on the review above, this study views the value of BI and PA as the outcome of a chain: data and infrastructure are processed through BI and PA, linked to decision flows, and produce improvements in decision quality and speed that ultimately affect performance. This chain is conditioned by a data-driven culture, human capital, and governance (Figure 1).

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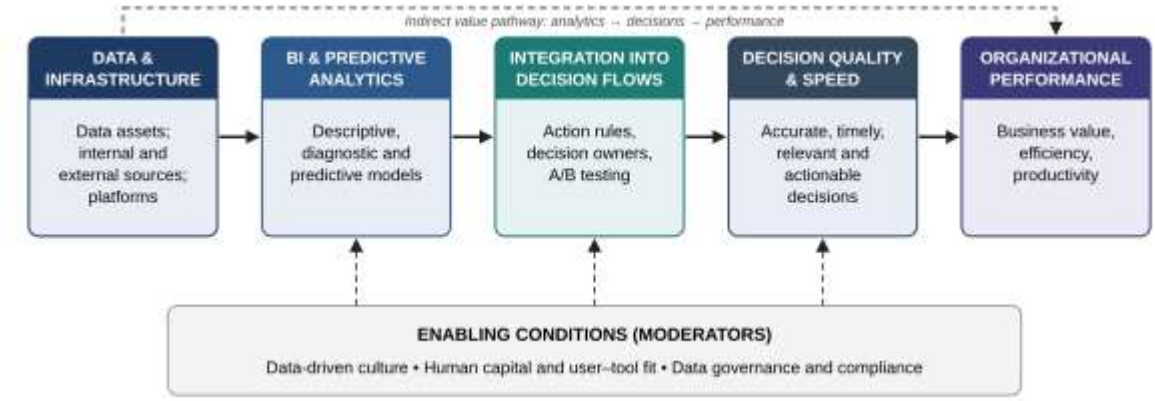


Figure 1. Conceptual framework of the study

Source: authors' synthesis of Awan et al. (2021), Chatterjee et al. (2023), Khaddam et al. (2023), Hurbean et al. (2023), and Wang (2025).

RESEARCH METHOD

This study adopts a qualitative design that combines a critical literature review with a comparative case study. Case studies are suitable for examining contemporary phenomena in their real-life context and for building theoretical insight through cross-case comparison (Eisenhardt, 1989). The literature component draws on peer-reviewed articles published between 2015 and 2025 that address BI, business analytics, predictive analytics, decision quality, and performance; each reference was checked for bibliographic validity before use.

The two cases were selected purposively as contrasting cases. Telkomsel represents a large, regulated, customer-intensive incumbent in an emerging market, whereas Netflix represents a digital-native platform organization in which user interaction and product delivery occur within the same system. Case data were collected through document analysis (Bowen, 2009) of publicly available sources, namely company press releases, letters to shareholders, technical publications by company engineers, vendor and consultant case studies, industry news, and scholarly articles.

The analysis uses five dimensions derived from the literature synthesis (Table 2). Because most performance claims originate from the companies themselves or from their technology vendors, every such claim is treated as a self-reported indication rather than as causal evidence. This critical stance follows the methodological concerns identified in the literature, particularly regarding cross-sectional designs, perception data, and the measurement of business value (Chatterjee et al., 2023; Jannach & Jugovac, 2019).

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Table 2. Dimensions of case analysis

Dimension	Analytical question	Theoretical basis
D1. Data and infrastructure	What data does the organization own, and what platforms does it use?	RBV/DCV (Chatterjee et al., 2023)
D2. BI and PA capability	What types of analytics are used (from descriptive to predictive)?	Phillips-Wren et al. (2021)
D3. Integration into decisions	Do predictions trigger operational or strategic actions?	Wang (2025); Khaddam et al. (2023)
D4. Culture and organization	Does the organization support the use of data in decisions?	Hurbean et al. (2023)
D5. Evidence of impact and governance	How credible is impact measurement, and how are risks managed?	Chatterjee et al. (2023); Jannach and Jugovac (2019)

Source: authors' analysis.

RESULTS AND DISCUSSION

Critical Analysis of the Literature

Table 3 compares the empirical findings on the relationship between BI/analytics, decisions, and performance, together with the critical notes of the authors.

Table 3. Comparison of empirical findings on BI/analytics, decisions, and performance

Study	Main relationship	Mediator or moderator	Critical note
Awan et al. (2021)	BDA and BI&A → decision quality (positive)	Data-driven insight strengthens the effect but is not a mediator	Small sample (109) from one country and one sector; limited generalizability.
Chatterjee et al. (2023)	BDA adoption → decisions, forecasting, performance	Financial and operational performance as intermediate factors	Cross-sectional data; the authors acknowledge causality and endogeneity risks.

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Study	Main relationship	Mediator or moderator	Critical note
Khaddam et al. (2023)	BI → decision speed → performance	Decision speed as mediator; person–tool fit as a weakening moderator	Focus on speed rather than decision accuracy; counter-intuitive moderation result.
Hurbean et al. (2023)	BI&A adoption → decision effectiveness → managerial work performance	Data-driven culture as a driver of adoption	Model-based; needs broader testing across contexts.
Wang (2025)	Analytics → decision quality → performance	Decision quality as the link; a direct effect on performance is not assumed	Conceptual synthesis rather than an empirical test.
Brynjolfsson et al. (2021)	PA → productivity (positive, with causal indication)	Complements: IT capital, educated workers, flow-efficient workplaces	U.S. manufacturing data, mostly pre-generative-AI methods; limited generalization to services.
Chen et al. (2024)	PA implementation success is determined by sociotechnical components	Technical and organizational factors	Qualitative, 11 U.S. organizations; does not test performance effects quantitatively.

Source: authors' analysis based on the cited articles.

Points of agreement. All studies agree that BI and analytics are positively associated with better decisions, and most position decisions as the link to performance (Awan et al., 2021; Chatterjee et al., 2023; Khaddam et al., 2023; Wang, 2025). Studies that specifically examine PA are consistent with this view: Brynjolfsson et al. (2021) find productivity benefits, and Chen et al. (2024) emphasize the sociotechnical nature of implementation.

Points of divergence. First, regarding mediators, Awan et al. (2021) find that data-driven insight does not mediate the relationship between BDA capability and decision quality, whereas Khaddam et al. (2023) find that decision speed mediates the

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relationship between BI and performance. This difference likely stems from differences in constructs (quality versus speed), context (Czech manufacturing versus various Jordanian industries), and sample size, so the two should not be read as a direct contradiction. Second, regarding person–tool fit, Khaddam et al. (2023) find that a high fit actually weakens the relationship between BI and decision speed. In the authors' interpretation, decision makers who are already well matched with their tools may already decide quickly, so the marginal benefit of BI becomes smaller; this interpretation requires further testing. Third, regarding direct effects, Chatterjee et al. (2023) report an effect of BDA adoption on performance, whereas Wang (2025) argues that the effect is indirect and passes through decision quality. Fourth, regarding the strength of evidence, Brynjolfsson et al. (2021) use large-scale administrative data with instrumental variables and timing analysis, making their study causally stronger than cross-sectional perception surveys; their study also shows that the benefits of PA are conditional on organizational complements.

Methodological and conceptual critique. Five limitations emerge from the literature:

- *Cross-sectional design and perception data.* Survey-based PLS-SEM studies show associations rather than causality; Chatterjee et al. (2023) themselves acknowledge causality and endogeneity risks. Better-performing firms may be more likely to adopt analytics, rather than the reverse.
- *Construct ambiguity.* BI, BDA, and predictive analytics are often combined into a single construct, making the specific contribution of predictive analytics difficult to identify. This matters because descriptive BI and PA require different data, skills, and decision processes.
- *Contextual generalization.* Samples come from a single country or sector (Czech Republic, India, Jordan, and U.S. manufacturing), so application to mass-customer industries in Indonesia requires caution.
- *Focus on benefits rather than negative outcomes.* The reviewed literature tends to highlight benefits; risks such as model bias, privacy, and vendor dependence are rarely research variables.
- *Gap between model accuracy and decision value.* Technical evaluations of PA usually stop at model metrics, whereas business value requires evidence that predictions change actions and outcomes.

Synthesis. Four synthesis points are formulated as guidelines for the case analysis. **S1:** the value of BI and PA emerges mainly indirectly through improved decision quality and speed. **S2:** that value is conditioned by a data-driven culture, user–tool fit, and human capital. **S3:** the value of PA depends on integrating predictions into action flows, not on model accuracy alone. **S4:** analytical capabilities need to be built and

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renewed dynamically (the DCV perspective) and demonstrated through credible impact measurement.

Case 1: Telkomsel

Profile and context

Telkomsel is the largest mobile operator in Indonesia, serving approximately 156.1 million mobile subscribers at the end of 2025 (Telkomsel, 2026). Its business is characterized by mass customer services with very large and diverse data, ranging from network data, transactions, and billing to customer service interactions. These characteristics make churn prediction and offer personalization important decision issues.

From a managerial perspective, the urgency of predictive analytics at Telkomsel is also driven by the characteristics of Indonesian mobile consumers. The market is highly price-sensitive, and many subscribers readily switch operators to obtain competitors' data-package promotions. In a market with such low loyalty, mass blanket promotions are costly and increasingly ineffective. Predictive analytics offers an alternative: instead of discounting to all customers, models can detect early anomalies, such as a sudden decline in data usage or top-up frequency, and trigger targeted retention offers before the customer actually leaves. In the authors' view, the ability to anticipate customer intent in this way is central to sustaining margins in Indonesian telecommunications.

Implementation of BI and predictive analytics

- *Voice-of-customer analytics.* In a vendor case study, Telkomsel is described as having been able to act on only a small fraction of its customer interaction data, which slowed management reporting and decisions. Text and sentiment analytics solutions were then used to extract patterns from unstructured multichannel data, replacing manual daily categorization with an automated hourly cycle; the vendor claims faster responses, higher satisfaction, and reduced churn, without reporting churn figures (SAS Institute, n.d.).
- *Analytics platform for personalization.* McKinsey & Company (2021) describes the development of a modular analytics platform with thousands of data points per customer, supported by AI-driven tools to identify customer needs across thousands of microsegments; the digital brand by.U reportedly reached nearly two million subscribers fifteen months after launch.
- *AI for marketing.* A Telkomsel press release reports the "AI Marketing Brain" project, which integrates customer, network, and billing big data into AI models to predict behavior and personalize offers, with a claimed 28% increase in new 5G

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customer conversion and a 35% reduction in operational costs; the project received a TM Forum Outstanding Catalyst Award (Telkomsel, 2025).

- *Data monetization for enterprise customers.* In September 2025, Telkomsel partnered with Mobileum to apply machine learning-based network analytics to provide insights for enterprises, with processing claimed to comply with local data sovereignty principles (Le Maistre, 2025).
- *Academic research on churn.* Asror and Nuryana (2025) developed a Telkomsel churn classification model using CRISP-DM and compared six algorithms, finding that the previous churn-status attribute was the most influential. Their data were collected through an online questionnaire administered to university students rather than from Telkomsel's operational data.

Critical analysis

D1 and D2. Telkomsel owns rich data assets and shows progress from descriptive analytics (voice-of-customer monitoring) toward segmentation and predictive AI. This evidence is consistent with the DCV perspective that capabilities are built incrementally and often through technology partnerships, but reliance on multiple vendors creates fragmentation and lock-in risks that need to be managed.

D3. The claims on 5G conversion and cost savings indicate that predictions are linked to marketing decisions, which is consistent with S3. However, public sources do not clarify who the decision makers are, how quickly actions are taken, or how actions are tested.

D4. Public sources are insufficient to assess data culture directly. Indirect indications include the use of analytics in customer service, marketing, and network operations; however, culture can only be assessed through internal data such as manager interviews or surveys, as proposed in the model of Hurbean et al. (2023).

D5. This is the weakest point in terms of evidence. The impact figures (28% and 35%) come from a company press release about an award-winning project, and the churn-reduction claim comes from a vendor case study without figures. The academic churn study uses student data, so its external validity for Telkomsel's customer base is limited. By the standards of the critique above, all of these claims should be treated as indications rather than causal evidence.

Overall, Telkomsel is at a **transition stage**: it has moved from descriptive BI toward segmentation, personalization, and predictive AI for marketing, service, network, and data monetization. Its strengths are the scale and variety of its data, its technology partnerships, and the application of analytics across several business functions. Its weaknesses are that evidence of impact relies on company and vendor claims, the feedback loop from prediction to action is not visible, and multi-vendor dependence risks

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fragmentation. Telkomsel has great potential to make BI and PA the basis of its decisions, but this value has not yet been independently demonstrated.

Case 2: Netflix

Profile and context

Netflix is a global streaming service that reported 301.6 million paid memberships at the end of 2024 and announced that it would no longer report quarterly membership figures from 2025 onward (Netflix, 2025). As a digital-native organization, all user interactions occur within its own platform, so behavioral data are continuously available and can be tested through experiments.

Implementation of BI and predictive analytics

- *A recommender system as a collection of algorithms.* Gomez-Uribe and Hunt (2015) explain that the Netflix recommender system is not a single algorithm but a collection of algorithms that jointly shape the user experience, most of which appears on the homepage. The business need is clear: users quickly lose interest if they cannot find something to watch, so recommendations must be relevant.
- *Business value claims.* The authors, who were Netflix executives, state that personalization and recommendations reduce churn and save more than US$1 billion per year (Gomez-Uribe & Hunt, 2015).
- *Continuous experimentation.* Algorithm improvements are evaluated through offline testing and online A/B testing before deployment, linking predictions to measured effects on real behavior (Gomez-Uribe & Hunt, 2015).
- *Foundation model.* Hsiao et al. (2025) describe a shift from many specialized models to a centralized, transformer-based foundation model that learns from sequences of user interactions, handles the cold-start problem for new titles using metadata, and is integrated into various personalization applications.

Critical analysis

D1 and D2. Integrated behavioral data and an experimentation platform make Netflix strong in predictive analytics. The shift to a foundation model demonstrates dynamic capabilities that are continuously renewed, consistent with S4, including an efficiency motive to reduce model duplication.

D3. Predictions are embedded directly in operational decisions (what is shown to each user and in what order), and outcomes are tested through A/B testing. This is a strong example of integrating predictions into action flows, consistent with S3, and the feedback loop is far shorter than in the telecommunications industry.

D4. A culture of experimentation and test-based decision-making is evident from the A/B testing practices described by Gomez-Uribe and Hunt (2015); this culture is

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consistent with the model of Hurbean et al. (2023), although the causal effect of culture on performance cannot be established from public sources.

D5. The credibility of measurement must be viewed critically. The US$1 billion claim originates from company insiders and was published in 2015, and the review by Jannach and Jugovac (2019) cautions that the business value of recommender systems is often not adequately defined, measured, and analyzed in the literature. Moreover, the discontinuation of quarterly membership reporting from 2025 limits external verification. Other risks, in the authors' assessment, include the homogenization of content choices and the privacy of behavioral data, which require dedicated governance.

Overall, Netflix is at a **mature stage**: predictive analytics is the core of the product rather than merely a support tool. Its advantage lies in integrating predictions into decisions and in its experimentation culture rather than in algorithmic sophistication alone. Its challenges are maintaining transparency in measurement and governing behavioral data.

Comparative Analysis

Table 4. Comparison of BI and PA implementation at Telkomsel and Netflix

Dimension	Telkomsel	Netflix	Comparative implication
D1. Data and infrastructure	Customer, network, and billing data; multiple platforms and partners (e.g., SAS, Mobileum)	Behavioral data within its own platform; centralized foundation model	Netflix has closed, integrated data; Telkomsel needs integration across systems and partners.
D2. BI and PA capability	From voice-of-customer analytics and segmentation toward AI marketing; churn prediction is a key issue	Recommendation, personalization, and ranking with a foundation model	Netflix is more mature in PA; Telkomsel is moving up from BI to PA.
D3. Integration into decisions	Predictions linked to 5G offers and efficiency; testing mechanisms not publicly visible	Predictions determine product display; tested with A/B testing	Netflix has a short decision–feedback loop; Telkomsel needs to close the same loop for campaigns and retention.

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Dimension	Telkomsel	Netflix	Comparative implication
D4. Culture and organization	Cannot be fully assessed from public sources	Experimentation culture evident from A/B testing practice	Culture needs to be measured through internal data at Telkomsel.
D5. Evidence and governance	Company and vendor claims; academic study uses student data	Executive claims (2015); membership reporting reduced	Both rely on internal claims; credibility should be strengthened with transparent measurement.
Maturity stage	Transition from BI to predictive analytics	Mature; predictive analytics is the core of the product	Netflix is more advanced.
Main challenge	Closing the decision loop and managing multiple vendors	Measurement transparency, homogenization, privacy	Different, but both rest on governance.

Source: authors' analysis of the sources cited in the case sections.

The main difference lies in data structure and the distance between prediction and action. At Netflix, decisions (recommendations) and their outcomes (viewing, retention) occur within the same platform, so feedback is fast and testable. At Telkomsel, predictions (e.g., churn risk) must be translated into cross-functional actions (marketing, customer service, network), so success depends more on organizational coordination and data culture. In common, both cases show that the value of analytics depends on integration into decisions, and both still face the challenge of transparent evidence of impact. These findings support S1, S3, and S4, while S2 (culture and user–tool fit) is only partially supported because of the limitations of public data.

These results reinforce the conclusion of Brynjolfsson et al. (2021) that predictive analytics pays off only in the presence of organizational complements, and they are in line with Wang (2025), who places decision quality as the bridge between analytics and performance. The differences in outcomes between the two organizations are explained more by decision integration, experimentation culture, and data structure than by their analytics technology. Telkomsel can learn from Netflix by applying control groups, shortening the cycle from prediction to action, and assigning clear decision owners.

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Strategic Recommendations

The following recommendations are derived from the synthesis points and the comparative findings. They are directed primarily at Telkomsel, as the organization with greater room for improvement in integration and impact demonstration, while incorporating transferable lessons from Netflix that are relevant to other organizations (Table 5).

Table 5. Strategic recommendations based on the analysis and scientific evidence

No	Recommendation	Evidence base	Key actions	Success indicators
R1	Build integrated data governance and architecture	D1 analysis: multiple platforms and partners; DCV (Chatterjee et al., 2023)	Establish a data governance council; standardize customer definitions and metrics; consolidate platforms; manage vendor lock-in risk	Data preparation time; share of quality data; number of integrated data sources
R2	Integrate predictions into operational decision flows	S3; Wang (2025); Brynjolfsson et al. (2021); Netflix pattern (Gomez-Uribe & Hunt, 2015)	Map priority decisions (retention, offers, network); assign decision owners and action rules for prediction scores; ensure complements (IT capital, skilled staff, efficient processes)	Time from prediction to action; share of predictions acted upon
R3	Adopt controlled experiments as the standard of proof	D3 and D5; Netflix A/B testing	Use holdout control groups for retention and offer campaigns; document internal measurement methods	Uplift in retention or conversion against control groups

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International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

No	Recommendation	Evidence base	Key actions	Success indicators
R4	Develop data culture and human capital	Hurbean et al. (2023); Khaddam et al. (2023); Chen et al. (2024)	Data literacy training for managers; role-appropriate BI tools; monitor adoption	Dashboard usage; trust-in-data surveys; manager-rated decision quality
R5	Strengthen credible value measurement	Jannach and Jugovac (2019); limitations of claims in the cases	Separate model metrics (AUC, precision) from business metrics (retention, ARPU, cost); periodic independent audits	Impact reports with documented methods
R6	Manage privacy, bias, and compliance risks	Both cases; Law No. 27 of 2022 on Personal Data Protection (Republic of Indonesia, 2022)	Data protection impact assessments; data minimization; model bias testing; model-drift monitoring	Audit findings; data incidents; bias-test results

Source: authors' analysis.

Implementation can follow a three-phase roadmap. In **Phase 1 (0–6 months, foundation)**, R1 and R6 are applied in priority domains, baseline metrics and control groups are established (R3, R5), and one or two priority decisions are selected (R2). In **Phase 2 (6–18 months, integration)**, prediction models are operationalized in priority decisions with action rules, training and adoption are expanded (R4), and controlled experiments are run routinely. In **Phase 3 (18–36 months, optimization)**, the approach is extended to other domains, models and platforms are consolidated, and independent impact audits and periodic capability renewal are institutionalized.

Several implementation risks should be anticipated. Low-quality or fragmented data can produce inaccurate models and misleading insights, mitigated through governance and data standardization (R1). Predictions that are not acted upon render the investment valueless (S3), mitigated through decision owners and action rules (R2). Non-credible impact claims bias investment decisions, mitigated through control groups and audits (R3 and R5). Privacy violations or model bias may lead to sanctions, reputational damage, and unfairness, mitigated through impact assessments and bias testing (R6). Finally, vendor dependence raises costs and reduces flexibility, mitigated through open standards and a multi-vendor strategy (R1).

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CONCLUSION

This study concludes that BI is best understood as part of a decision system and predictive analytics as a forward-looking capability whose value depends on decision quality and on integration into action (Phillips-Wren et al., 2021). The effect of BI and analytics on performance is generally indirect; findings differ in their mediators (quality, speed, insight), moderators, and contexts, while the limitations of cross-sectional designs and perception data constrain causal claims (Awan et al., 2021; Chatterjee et al., 2023; Khaddam et al., 2023). The strongest evidence on predictive analytics shows productivity benefits that are conditional on organizational complements (Brynjolfsson et al., 2021), and its implementation is a sociotechnical rather than a purely technical issue (Chen et al., 2024).

In the case studies, Telkomsel is in transition from descriptive BI toward predictive analytics. Its data assets are large and its applications span marketing, customer service, network operations, and data monetization, but its impact has not been independently demonstrated because public evidence consists of company and vendor claims. Netflix is at a mature stage: predictive analytics is the core of its product, is tested through A/B testing, and is continuously renewed through a foundation model; its critical issues are internally sourced value claims, reduced reporting transparency, and risks of homogenization and privacy. Netflix is more advanced in decision integration, feedback loops, and predictive maturity, mainly because of its data structure and experimentation culture. Therefore, the success of BI and predictive analytics in data-driven decision-making is determined by the combination of data, decision integration, culture, and governance, not by technology alone.

This study has limitations. It relies on public documents, many of which are self-reported by the companies or their vendors, and it covers only two cases. Future research should use internal organizational data, such as manager interviews or surveys and controlled field experiments, to assess data culture and measurable impact. For practitioners, Telkomsel is advised to apply control groups to retention and offer campaigns, assign decision owners for prediction scores, and consolidate data governance across platforms and partners; other organizations are advised to start from clear priority decisions, separate model metrics from business metrics, build managers' data literacy, and comply with personal data protection regulations.

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