Predictive Modeling to Determine Key Variables Supporting the Success of B2B Transformation Using CatBoost

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Abstract— PT Telkom Indonesia's strategic shift from B2C to B2B aims to capture opportunities in a market valued at IDR 155.8 trillion, where it currently holds a 32% share and 14% revenue contribution, lagging global peers like Telstra and Vodafone. To address this gap, PT Telkom Indonesia seeks to expand B2B digital services, including IT and ecosystem-based solutions. This study aims to identify key variables supporting successful B2B transformation using predictive modelling with CatBoost-based Gradient Boosting. It examines factors such as workforce readiness, product readiness, operational models, organizational mindset and culture, and IT system support, integrating the Organizational Health Index (OHI) to assess organizational readiness and the DeLone & McLean model to evaluate information system effectiveness. The integrated approach aims to develop a predictive model for B2B transformation success in telecommunications. Findings are expected to guide PT Telkom Indonesia and similar firms in designing data-driven strategies to optimize transformation outcomes and enhance competitiveness.

Keywords— B2B Transformation, CatBoost Gradient Boosting, Organizational Readiness, Predictive Modeling, Telecommunication Strategy.

I. BACKGROUND

The Indonesian vertical industry presents substantial growth opportunities, with a market potential of IDR 156 trillion across sectors such as finance, manufacturing, and government. PT Telkom Indonesia currently holds a 32% market share, underscoring its significant yet expandable position in this landscape. To capture these opportunities and remain competitive, PT Telkom Indonesia has strategically shifted its business model from B2C to B2B, requiring organizational and operational transformation across its territorial units. This transformation aligns with the company's "Strengthening B2B Territory" initiative, emphasizing four strategic domains: Business Development, Business Operation, Business Governance, and Business Enablement. These domains guide the company in capturing new business opportunities, enhancing operational efficiency, reinforcing transparent governance, and empowering technology and talent.

Effective B2B transformation requires a comprehensive change in product portfolios, operating models, organizational culture, and technological readiness to meet the complex demands of B2B clients, including enterprises, government, and MSMEs. Drawing from Kotter's change management principles and supported by evidence [1], successful transformation necessitates talent readiness, product readiness, and a mindset shift toward collaboration and data-driven decision-making. Drawing from Kotter's change management principles and supported by evidence from previous research [1], successful transformation necessitates talent readiness, product readiness, and a mindset shift toward collaboration and data-driven decision-making. This study applies predictive analytics, particularly Gradient Boosting with CatBoost, to model and identify key success variables impacting business and operational performance during transformation. Additionally, the Organizational Health Index (OHI) is integrated to assess organizational readiness,

while the DeLone & McLean framework evaluates information systems' effectiveness in supporting business change.

Literature emphasizes six generic drivers critical for B2B transformation success: transformational leadership, discovery-driven decision-making, customer-specific industry orientation, content-oriented communication, self-initiative collaboration, and phased separation strategies [2]. Moreover, effective change management is driven by clear vision, structured planning, stakeholder engagement, consistent communication, and continuous monitoring [3].

By leveraging data-driven predictive modeling and integrated frameworks, this study aims to determine which variables most significantly influence the success of B2B transformation within PT Telkom Indonesia. The outcomes are expected to provide actionable insights for PT Telkom Indonesia and similar firms in optimizing transformation strategies, strengthening market positioning in the B2B telecommunications sector, and enhancing competitiveness in Indonesia's dynamic digital economy.

Notably, Organizational transformation is critical for maintaining competitiveness, yet 60–70% of such initiatives fail [3]. At PT Telkom Indonesia, a leading Indonesian telecommunications company, the shift from B2C to B2B, targeting SMEs, private enterprises, SOEs, and government sectors, necessitates comprehensive organizational, strategic, and operational restructuring. Despite a target of IDR 4 trillion in SME revenues from a potential IDR 16 trillion market, effective management across units remains challenging. Notably, no existing studies have identified the most dominant factors driving successful transformation using Gradient Boosting while integrating quantitative analysis with machine learning in this context.

This study aims to: (1) identify Quick Win transformation variables in PT Telkom Indonesia's B2B strengthening initiatives across territories, aligned with 12 characteristics synthesizing 37 change models and 72 sub-factors for organizational transformation success; (2) determine key variables influencing the B2C-to-B2B transformation at PT Telkom Indonesia using OHI for organizational health and DeLone & McLean's seven elements for information system success; and (3) develop a predictive model integrating OHI and DeLone & McLean frameworks with Gradient Boosting to identify the most critical variables driving B2B transformation success, ensuring data-driven strategy formulation for sustainable competitive advantage.

II. METHOD

The methodology of this study employs a systematic literature review utilizing the PRISMA (*Preferred Reporting Items for Systematic Reviews and Meta-Analysis)* framework. This study aims to answer the following questions: (1) the key variables supporting B2B transformation success based on PT Telkom Indonesia's B2C-to-B2B program dimensions; (2) employee perceptions of organizational aspects in B2B transformation; (3) information system variables impacting B2B transformation success; and (4) the effectiveness of Gradient Boosting in predictive analysis for assessing B2B transformation success within the organizational and technological context.

The literature that searched and cross-checked across database i.e Elsevier (Scopus), ScienceDirect, and IEEE databases by combining the search terms "Key Variables", "Key Drivers", "Business Transformation", "Change Management", "B2B", and "Gradient Boosting". The search produced more than 86.840 records spanning from 2020 to 2025. To ensure the quality and academic rigor, only peer-reviewed articles from major publishers such as IEEE, ScienceDirect and Elsevier were included. In this stage, the researcher reviews 31 prior studies on machine learning methods, focusing on business development, organizational health index, organizational transformation, and B2B-focused business. This review identifies research gaps and opportunities to develop a predictive model

for determining key variables in organizational transformation using Gradient Boosting.

Each article was systematically coded using a structured framework capturing publication year, application domain, category of optimization challenge, research objective, types of base or meta learners utilized, optimization methods applied, and the novelty of the proposed approach. A PRISMA flow diagram was also employed to document the review process (**Figure 1**).

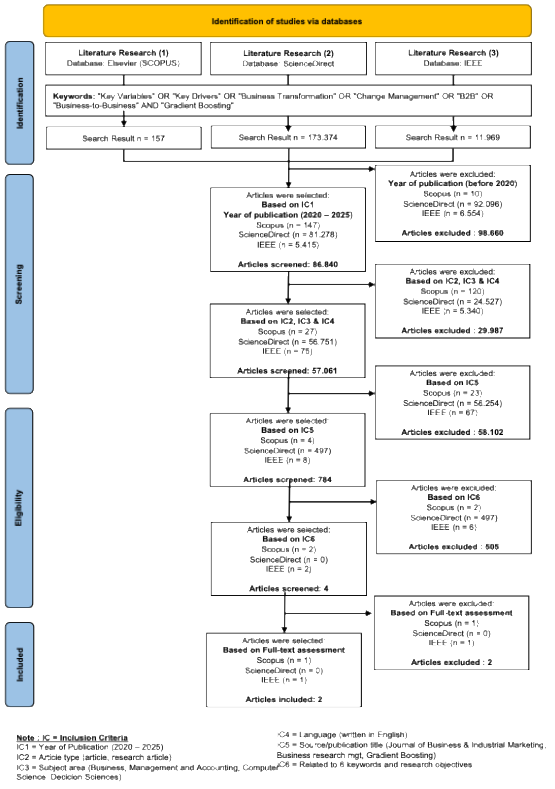

Figure 1. PRISMA flow diagram of the paper selection process

III. RESULTS AND DISCUSSION

Recent studies highlight the growing utilization of Gradient Boosting algorithms, including XGBoost and CatBoost, for predictive modeling within organizational transformation contexts. [4] and [5] demonstrate the superior predictive accuracy, computational efficiency, and adaptability of Gradient Boosting in various domains, making it a reliable method for identifying critical variables influencing transformation success. Such methods are further applied to enhance decision-making and risk mitigation in digital transformation initiatives, demonstrating their potential for providing data-driven strategic insights during complex organizational changes.

In the domain of B2B transformation, prior studies emphasize the strategic shift from B2C to B2B models to strengthen competitiveness in dynamic markets. Research by [6] identifies leadership, customer-specific strategies, and agile processes as critical enablers of successful B2B transitions, while acknowledging the complexity of organizational restructuring across systems, talent, and processes. The adoption of B2B-focused strategies has been shown to expand market reach, enhance tailored solutions, and align organizational capabilities with evolving enterprise and public sector demands, supporting sustainable business growth.

The Organizational Health Index (OHI), as developed by McKinsey [6] and further refined by Camp et al. [7], has been validated as a robust tool to measure organizational readiness and health, correlating with improved financial performance and resilience. Concurrently, the DeLone & McLean Information Systems Success Model remains central in evaluating the effectiveness of information systems during transformation initiatives, focusing on system quality, user satisfaction, and organizational impact. The integration of Gradient Boosting with OHI and IS success models in predictive frameworks presents a research opportunity to identify key variables driving transformation success, bridging gaps in the literature while equipping firms with actionable, data-driven strategies for effective B2B transformation within the telecommunications and digital services sectors.

A. Gap And Novelty in Predictive Modeling Research

Although predictive modeling has advanced significantly, notable research gaps remain in its application to B2B organizational development models. As outlined in 31 prior studies, these gaps highlight limitations in methodological

approaches, research variables, industry context, and the integration of machine learning within organizational transformation frameworks. Addressing these gaps is essential to advance predictive capabilities and develop effective transformation strategies within the B2B context, particularly in dynamic and emerging markets.

First, there is a clear methodological gap in current research on predictive models for organizational transformation. Most studies continue to rely on linear regression and classical statistical models, while the application of Gradient Boosting in analysing transformation success factors remains limited [8]. Few frameworks explicitly integrate technical, organizational, and environmental factors within Gradient Boosting predictive models, thereby reducing their practical effectiveness in organizational transformation contexts [9]. Additionally, existing models often fail to accommodate dynamic factors that evolve over time, leading to an inability to capture the progressive structural changes occurring within organizations during transformation processes [10].

Second, there is a lack of exploration of critical research variables within current models. Psychosocial factors such as adaptive leadership, employee engagement, and organizational culture are rarely classified as primary variables in predictive models of organizational transformation [11]. Furthermore, there is an absence of integrative approaches that measure the combined impact of structural factors (processes, technology) and non-structural factors (culture, employee behaviour) on transformation success [12]. External variables, including government regulations, industry trends, and market shifts, which significantly influence organizational change strategies, are also insufficiently considered within existing predictive frameworks [5].

Third, industry and geographical context gaps are evident in current studies. Much of the research on predictive modeling in business transformation has focused on large enterprises within developed countries, while studies highlighting predictive model applications in SMEs and emerging markets remain scarce [13]. Additionally, there is a lack of granular analysis on how transformation success factors differ across industry sectors. Few studies compare predictive transformation models across industries such as manufacturing, telecommunications, and service-based organizations, despite these sectors facing unique transformation challenges [14]. Moreover, the use of Gradient Boosting in B2B business contexts has not been thoroughly explored, even though the complexity of B2B dynamics requires distinct approaches compared to B2C business models [15].

While machine learning techniques, particularly Gradient Boosting, are widely applied in project and financial success prediction, their application within organizational change management remains underexplored [16]. Additionally, comparative studies assessing the performance of Gradient Boosting against other methods such as Random Forest and Deep Learning in organizational transformation contexts are limited [17].

There is a need for a comprehensive framework that integrates dynamic capabilities with predictive analytics to support decision-making in organizational change initiatives. Despite the potential of combining these elements to enhance the effectiveness of transformation strategies, there is currently no unified framework addressing this integration [18]. This gap limits the capacity of organizations to leverage predictive insights for strategic adaptation during transformation processes.

In addition, the implementation of predictive models within B2B transformation specifically remains underdeveloped. Given the increasing need for organizations to transition from B2C to B2B models to capture market opportunities and ensure competitiveness, the development of predictive models that account for B2B complexities is critical. The absence of such models reduces the effectiveness of

transformation initiatives in leveraging market insights and organizational readiness to drive performance outcomes.

Finally, addressing these research gaps offers a significant opportunity for advancing predictive modeling within organizational transformation studies. By integrating Gradient Boosting with organizational health measures (OHI), information system success frameworks (DeLone & McLean), and contextual B2B business strategies, future research can contribute to developing robust predictive frameworks. These frameworks will enhance decision-making, reduce transformation risks, and facilitate sustainable competitive advantage in rapidly evolving market environments, particularly within the telecommunications and digital services sectors.

B. Categorical Boosting (CatBoost) and X-Y model approach

In selecting an appropriate predictive modeling method, a comparison of popular gradient boosting algorithms, including XGBoost, CatBoost, LightGBM, Gradient Boosting, and AdaBoost, was conducted. XGBoost offers high performance and regularization for large datasets but requires complex tuning. CatBoost efficiently handles categorical features with stability, while LightGBM provides speed and low memory usage, although it is less suitable for small or imbalanced data. Gradient Boosting is simple for baseline models but slower on large data, and AdaBoost is easy to implement but less accurate with complex data. This comparison guides model selection based on research direction and dataset characteristics (**Table 1**). Table 1 presents a comparative overview of several gradient boosting algorithms, including XGBoost, CatBoost, LightGBM, Gradient Boosting (sklearn), and AdaBoost. Each algorithm demonstrates distinct advantages and limitations depending on the nature of the dataset and computational objectives. XGBoost is widely recognized for its high performance and strong regularization capabilities, making it particularly efficient for handling large datasets. However, its tuning process is complex, and if not properly managed, it carries a high risk of overfitting due to its model flexibility.

CatBoost offers a notable advantage by automatically processing categorical variables without extensive preprocessing, which minimizes the risk of target leakage and enhances model stability. Nevertheless, its training time is relatively longer, and documentation and community support are still developing compared to XGBoost. LightGBM, on the other hand, is known for its high computational efficiency and low memory usage, enabling fast execution on large-scale problems. Its main limitation lies in its reduced accuracy when dealing with small or imbalanced datasets, where it may produce biased results.

Gradient Boosting from sklearn serves as a simpler baseline model, suitable for experimentation and educational purposes. However, it lacks scalability and becomes less efficient with larger datasets. AdaBoost provides ease of implementation and performs well with moderate noise levels, but its sensitivity to outliers and lower accuracy on complex data restrict its performance in real-world applications. Overall, while each method offers unique strengths, their selection depends heavily on dataset characteristics, computational resources, and the balance between accuracy, interpretability, and efficiency.

CatBoost (Category Boosting) is a Gradient Boosting algorithm designed to address categorical data challenges and overfitting, efficiently managing categorical features without one-hot encoding by using ordered boosting and symmetric trees for stability. Compared with XGBoost and LightGBM, CatBoost demonstrates high stability in handling categorical data,

although it has lower flexibility in grid search and lacks feature fraction support. However, it effectively manages missing values and leverages GPU utilization. Studies, such as [19], highlight CatBoost's accuracy in predicting electric vehicle ownership based on household income,

Table 1. Comparison of Gradient Boosting Methods

No	Algorithm	Advantages	Disadvantages
1	XGBoost	High performance, regularization, efficient for large datasets	Complex tuning process, potential for overfitting if not managed
2	CatBoost	Automatically handles categorical features, stable, minimizes target leakage	Longer training time, limited documentation
3	LightGBM	Fast and efficient, low memory usage	Not suitable for small or imbalanced datasets
4	Gradient Boosting (sklearn)	Simple, suitable for baseline models	Slow for large datasets, less efficient
5	AdaBoost	Easy to implement, resistant to moderate noise	Sensitive to outliers, less accurate for complex data

identifying commuting distance as a critical factor. Overall, Gradient Boosting, including CatBoost, XGBoost, and LightGBM, has proven effective across various domains such as fraud detection, credit risk analysis, and stock price prediction, offering higher accuracy and interpretability compared to traditional regression methods within predictive modeling research (**Table 2**). CatBoost shows lower flexibility for grid search compared to XGBoost and LightGBM, which offer broader hyperparameter spaces and higher adaptability. In terms of hyperparameter optimization, CatBoost is moderate, while XGBoost and LightGBM provide more extensive tuning options. Unlike the other two, CatBoost does not support feature fraction or boosting variants, which limits certain customization options available in LightGBM.

However, CatBoost excels in stability when handling categorical data, as it automatically processes such variables without requiring additional preprocessing. This stability is a key advantage in practical implementations involving diverse datasets. Regarding computational performance, XGBoost delivers the fastest GPU multitasking, while CatBoost remains competitive with good GPU support. LightGBM, despite being efficient, performs less optimally when using its GOSS boosting type. Overall, CatBoost stands out for its robustness with categorical features and its ease of use, whereas XGBoost and LightGBM offer greater flexibility and hyperparameter control.

The comparison highlights that CatBoost is often preferred for complex categorical data scenarios, while XGBoost and LightGBM are suitable for tasks demanding speed and tuning flexibility.

In Addition to CatBoost, The X-Y Model, introduced by [20], categorizes managerial assumptions into Theory X, viewing employees as inherently lazy requiring control, and Theory Y, which sees employees as intrinsically motivated and capable of self-direction. Empirical studies show that Theory Y fosters innovation, employee satisfaction and productivity [21], [22]. Flexible application of this model allows managers to balance control with employee empowerment

Table 2. Advantages of Catboost Compared to LightGBM and XGBoost

Criterion	CatBoost	XGBoost	Light GBM
Flexibility (Grid Search)	Low (limited features)	Moderate	High (supports boosting type)
Hyperparameter Optimization Space	Moderate	High	Very High
Feature Fraction Support	Not Available	High	Available
Boosting Variants	Not Available	Not Available	Available (gbdt, goss)
Stability for Categorical Data	Very Stable	Less Stable	Require preprocessing
GPU Multitasking Support	Good	Very Fast	Less Optimal for GOSS

[23], [24]. In the digital era, Theory Y aligns with transformational leadership, enhancing innovation and change management [25], [26]. Additionally, the X-Y Model supports data-driven human resource strategies, predicting outcomes of flexible work policies on employee retention and satisfaction [27], [28].

C. Predictive Modeling Using Catboost Approach

This study employed the X & Y model methodology to develop a machine learning predictive model using CatBoost, focusing on evaluating organizational performance and information system success. The research began by identifying independent variables (X), including Quick Wins indicators, organizational performance metrics, Organizational Health Index (OHI) dimensions, and DeLone and McLean's information system success indicators (**Figure 2**). The dataset used in this study consists of four integrated components that collectively provide a comprehensive foundation for analyzing organizational transformation.

The first component is the set of 20 Quick Win variables, which represent short-term, high-impact initiatives designed to accelerate performance improvements during the transformation process. The second component includes 32 performance indicators derived from PT XYZ, serving as internal organizational metrics that capture operational effectiveness, leadership engagement, and strategic alignment. The third component draws upon the Organizational Health Index (OHI), a widely recognized framework that measures an organization's ability to align, execute, and renew itself over time. Finally, the fourth component incorporates the DeLone and McLean Information Systems Success Model, which evaluates system quality, information quality, and user satisfaction as determinants of digital transformation success.

By combining these datasets, the study creates a multidimensional foundation for identifying the dominant variables that influence the success of organizational change from B2C to B2B models.Dependent variables (Y) were selected based on theoretical relevance to measure the effectiveness of organizational interventions and system implementations.

Random splitting of datasets into training and testing subsets was conducted to ensure objectivity in model evaluation, adopting an 80-20 split to optimize learning while maintaining representativeness for performance testing.

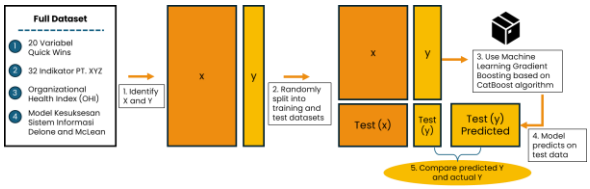

Figure 2. Predictive model algorithm using CatBoost approach

The CatBoost algorithm, a gradient boosting method designed for categorical data, was implemented due to its ability to handle heterogeneous datasets without extensive preprocessing. The model training utilized quantitative survey data on OHI, transformation variables, business and operational performance, and system success indicators. CatBoost's ordered boosting and oblivious decision trees enhanced computational efficiency and interpretability while reducing overfitting risks. Hyperparameter tuning was conducted using grid search and Bayesian optimization to refine model parameters for optimal predictive performance. Evaluation employed metrics such as accuracy, precision, recall, F1-score for classification, and RMSE or R^2 for regression tasks.

Finally, the model was tested on unseen data to generate predictive outputs for system success and organizational performance, validating results through comparison with actual data (**appendix**). Feature importance analysis highlighted key predictors, supporting data-driven decision-making while aligning theoretical frameworks with empirical validation. This approach offers a practical and replicable predictive modeling

methodology for organizational and system performance evaluation using CatBoost.

IV. CONCLUSION

This study contributes theoretically by enriching the literature on predictive modeling through the integration of the Organizational Health Index (OHI), the DeLone & McLean Information Systems Success Model, and Gradient Boosting machine learning algorithms within the context of B2C-to-B2B business transformation in the telecommunications industry. This integration offers a novel perspective for evaluating key variables influencing organizational transformation success, addressing gaps in current literature by demonstrating how predictive modeling frameworks can be aligned with organizational health and information system effectiveness. The findings also provide a reference for future research in information systems and change management employing predictive modeling approaches.

Additionally, from a practical perspective, the study offers a data-driven foundation for strategic decision-making within PT Telkom Indonesia and similar firms undertaking B2B transformation initiatives. By identifying significant variables that influence transformation success, this research provides clear guidance to stakeholders on critical factors requiring focused attention to ensure successful transformation outcomes. The insights generated can support organizations in effectively allocating resources, designing targeted strategic interventions, and enhancing the likelihood of successful B2B transformation initiatives, thereby improving organizational agility and competitiveness in the evolving telecommunications landscape.

Furthermore, this study aligns 12 determinants of organizational change management success and their 74 sub-factors [3] with PT Telkom Indonesia's 17 defined variables, 20 quick wins, and 32 indicators that implemented within corporate policies. This alignment ensures that the developed predictive modeling framework can accurately predict organizational transformation success, providing a structured and evidence-based approach to anticipating the outcomes of B2B transformation initiatives.

This study concludes that integrating the Organizational Health Index, DeLone & McLean Information Systems Success Model, and Gradient Boosting will enable the identification of key variables influencing successful B2C-to-B2B transformation in the telecommunications industry. The expected result is a predictive model capable of determining which determinants factors is most impacting result on transformation performance.

This model is anticipated to provide actionable, data-driven recommendations for PT Telkom Indonesia and similar firms, enhancing strategic decision-making during B2B transformation initiatives. Additionally, the research contributes to bridging gaps in the literature by demonstrating the efficacy of machine learning in organizational change management, supporting future development of adaptable predictive frameworks for digital transformation in dynamic business environments.

In constructing predictive modeling to determine key dominant variables within B2B transformation initiatives, this study employs Gradient boosting specifically CatBoost method, a high-performance gradient boosting algorithm known for its ability to handle categorical variables and produce accurate, interpretable results.

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Appendix

Critical Factors	Sub-Factors	Quick Win	Dimension	Defined Variable	Variable	Variable OHI	Variable D&M
Change Vision and Strategy	Clear definition of change	1. Product Indibiz Packaging for SME Market	Product	Product Readiness	Total Revenue	Direction	System Quality
Stakeholder Engagement and Commitment	Clear and shared change vision	2. Integration of Product & FAB Tools			Small and Medium Enterprise Revenue	Accountability	User Quality
	Change strategy and objectives	3. Monetizing new LKPP platform.	Solution	Ecosystem SME	Large Enterprise & Government Revenue	Coordination & Control	Information Quality
	Alignment with mission and strategy	4. Development of Vertical Industry Priority Solution			New Go to Market Revenue	Leadership	Information Use
	Engagement and commitment of supervisors, mid-level managers, & senior managers	5. Accelerate Partnership with Global & Credible Local Partners	Partnership	Subsidiaries Collaboration	Digital Product Revenue	External Orientation	User Satisfaction
	Stakeholder engagement					Innovation	Net Benefit
	Personal and employee commitment					Capability	
	Organizational engagement					Motivation	
	Internal support					Environment & Values	
Change Team Performance	Change agents capacity	1. Sharpening Market Potential & Customer Needs	GTM	New Model Operation	Total Sales		
	Change team has the necessary training and expertise in change management						
	Power and stamina of change agents						
	Preparation of change management team						

Critical Factors	Sub-Factors	Quick Win	Dimension	Defined Variable	Variable	Variable OHI	Variable D&M
Effective and Constant Communication	Clear change agent's roles and responsibilities	2. GTM Alignment to win SME, LEGS		ADO	HSI Sales		
Motivation of Employees and Change Agents	High-performance team	3. Ensuring Project & Delivery Management Excellent	Project Management	Control Delivery Order	Bandwidth Sales		
	Skilled and experienced change team	4. Improvement After Sales Management	Channel Management	Customer Engagement	Digital Product Sales		
	Organizational change competency	5. AM & Channel Management Alignment		Channel Readiness	New Go to Market Sales		
	Communication of the change vision and strategy to all people						
	Constant communication with stakeholders						
	Assessment of communication needs and channels						
	Development and implementation of a communication strategy and plan						
	Monitoring and evaluating communication effectiveness						
	Motivation of change agents						
	Creating short wins						
	Motivation						
	Rewards, celebration, and recognition						
	Incentives						
	Building a support system for change agents						
	Consideration of individual needs and values						

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Critical Factors	Sub-Factors	Quick Win	Dimension	Defined Variable	Variable	Variable OHI	Variable D&M
Monitoring and Measurement	Tracking, measuring, reporting, and feedback	1. Evaluation of Policy and Risk Management	Risk & Process Management	Policy & Governance	AM Productivity		
Leadership and Sponsorship	Progress monitoring	2.Improvement of customer contract involving partners.			SA, AR Productivity		
Resistance Management	Political support and external support	3.Digitize Business Processes & Electronic Document	Strategy Alignment & KPI	KPI B2B	Digital Channel Productivity		
Approach and Planning for Change	Leadership-enabled leaders	4.Strategy of B2B Telkomsel Business Transfer			Collection Ratio		
	Champions and sponsors	5.Operating Model of Regional, HQ Organization and KPI	Operating Model	Structure Territory B2B	C3MR		
	Sponsorship				First Billing		
	Transition management				Churn		
	Resistance management				NPS		
	Behaviour management				Order Management (AOSODOMORO)		
	Pursue comprehensive and systemic change						
	Structured change methodology						
	Integration of project and change management						
	Defined procedures and planning						
	Governance and PMO						
	Action planning						
	Planning and road mapping						
	Structure, policies, and procedures						

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Critical Factors	Sub-Factors	Quick Win	Dimension	Defined Variable	Variable	Variable OHI	Variable D&M
Training, Coaching, and Empowerment	Coaching of employees	1. People Capacity & Capability Fulfilment	People Readiness	People Readiness	Marketing Account Plan Summary Update		
	Individual skills and abilities						
	External support						
	Change agents' commitment						
Change Readiness and Capacity for Change	Mobilizing commitment	2. Reskilling and Upskilling B2B Talent			Organizational Health Index		
Reinforcement and Sustainment of Change	Knowledge, ability, and learning development	3. Digital Touch Point & IT Tools Alignment	IT Support & Tools	FAB Tools	Information System Success Model		
	Training	4. End-to-End B2B IT Capabilities		IT Tools Readiness			
	Employee empowerment	5. Ensuring B2B Transformation & B2B Readiness Measurement	Change Management	B2B Mindset			
	Skill development			Leader Direction			
	Sense of urgency			Leader Comm			
	Need for change						
	Case for change						
	Capacity for change						
	Enabling structures						
	Organizational competencies						
	Infrastructure and conditions to support change						
	Sufficient resources						

Critical Factors	Sub-Factors	Quick Win	Dimension	Defined Variable	Variable	Variable OHI	Variable D&M
	Organizational and individual readiness						
	Organizational culture/cultural fit						
	Reinforce new behaviours						
	Maintain and institutionalize change						
	Anchors change in the corporate culture						
	Consolidate gains and improvements						
	Integrate lessons learned						
	Establish best practices						
	Develop reinforcement strategy and create cultural fit						

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