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From Predictive Modelling to Prescriptive Strategy: The Evolving Role of Analytics in HR and Marketing

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ABSTRACT

In a volatile business environment defined by talent shortages, shifting consumer expectations, and digital acceleration, the role of analytics in organisational strategy has undergone a fundamental transformation. Once confined to descriptive reporting, analytics has advanced into predictive modelling and, more recently, into prescriptive strategy formulation. This study explores the evolving role of analytics across human resource management (HRM) and marketing, investigating how predictive insights can be systematically converted into prescriptive interventions that enhance workforce stability and customer engagement simultaneously. Drawing on a primary dataset of 360 respondents—including employees and customers from the technology, retail, and financial services sectors—the research applies a combination of statistical and machine learning techniques to forecast critical outcomes such as employee turnover risk and customer churn probability. Logistic regression, Random Forest, and Extreme Gradient Boosting (XGBoost) models are employed, with performance compared through accuracy, precision, recall, F1-score, and ROC-AUC metrics. Complementary analyses, including correlation, chi-square testing, and t-tests, provide interpretive depth. The findings reveal that skill adaptability, workload flexibility, and digital proficiency significantly influence HR-related outcomes, while campaign responsiveness, cross-channel engagement, and segmentation alignment emerge as the strongest predictors of marketing success. Random Forest achieved the highest predictive accuracy (AUC = 0.88), while SHAP-based feature importance analysis highlighted the centrality of both structural flexibility in HR and personalised engagement in marketing. This research demonstrates that predictive analytics, when embedded within a prescriptive framework, enables organisations to not only anticipate risks but also design targeted interventions—ranging from reskilling programmes to personalised marketing strategies. The study contributes to academic discourse by integrating HR and marketing analytics within a unified predictive–prescriptive framework and offers practitioners actionable pathways for fostering workforce resilience and customer loyalty.

Keywords: *Predictive modelling; Prescriptive analytics; Human resource analytics; Marketing analytics; Machine learning; Random Forest; XGBoost; SHAP; Employee turnover; Customer churn*

1. INTRODUCTION

In today's volatile, uncertain, complex, and ambiguous (VUCA) environment, organisations are under relentless pressure to balance internal workforce stability with external customer engagement. On one hand, firms grapple with high employee turnover, shifting skill requirements, and the need for agile workforces. On the other, they must navigate fragmented consumer journeys, rising customer churn, and intensifying competition across digital markets. Traditional decision-making, often grounded in managerial intuition or historical trends, is proving insufficient in such a dynamic context.

Analytics has emerged as a decisive enabler of resilience and adaptability. Initially, analytics in both HR and marketing was largely descriptive, providing dashboards and reports that explained what had already happened. Over time, predictive models advanced this capacity, allowing leaders to forecast outcomes such as employee attrition, workforce productivity, customer churn, and campaign responsiveness. Yet, the evolution has not stopped there. Contemporary organisations increasingly require prescriptive strategies—data-driven recommendations that go beyond predicting future risks to prescribing optimal courses of action tailored to specific workforce and market conditions.

In human resource management (HRM), predictive analytics has been used to estimate turnover likelihood, recruitment success, or training effectiveness. However, the true strategic value lies in prescriptive analytics, which can inform targeted interventions such as personalised learning paths, dynamic workforce planning, or flexible work policies. Similarly, in marketing, predictive models identify customer churn or responsiveness to campaigns, but prescriptive analytics prescribes interventions such as personalised offers, optimal channel selection, and real-time engagement strategies. This shift from prediction to prescription reflects a broader movement toward decision intelligence—where analytics is embedded directly into strategic and operational choices.

The academic discourse on HR and marketing analytics has often remained siloed. HR analytics research has predominantly focused on employee outcomes such as agility, engagement, or turnover, while marketing analytics has concentrated on consumer behaviours and digital channel optimisation. Few studies have integrated these domains to explore analytics as a unifying capability that strengthens both workforce and market adaptability. Given that both HR and marketing fundamentally deal with human behaviour—albeit in different contexts—integrating these perspectives offers fertile ground for advancing both scholarship and practice.

This study addresses that gap by developing and empirically testing a dual-domain framework that links predictive modelling to prescriptive strategy in HR and marketing. Drawing on primary data collected from 360 respondents across technology, retail, and financial services sectors, the research evaluates the performance of logistic regression, Random Forest, and XGBoost models. It further employs interpretability tools such as SHAP analysis to ensure that predictive insights are not only statistically robust but also practically actionable. By comparing and contrasting HR and marketing outcomes, the study demonstrates how analytics can evolve into a prescriptive toolset capable of simultaneously reducing employee turnover and customer churn.

The contribution of this paper is threefold. First, it expands the conversation on analytics by framing HR and marketing not as separate domains but as interconnected arenas where predictive insights can be unified into prescriptive strategies. Second, it empirically tests the performance of both traditional statistical and modern machine learning approaches, providing practitioners with evidence on model choice. Third, it integrates explainability into prescriptive strategy design, ensuring that data-driven insights are transparent, actionable, and aligned with organisational objectives.

By situating analytics as both a predictive and prescriptive capability, this research underscores its strategic role in navigating uncertainty. In an era where human capital and customer loyalty are equally critical, embedding analytics into HR and marketing decision-making provides a foundation for sustainable competitiveness.

2. LITERATURE REVIEW

The growing reliance on analytics as a foundation for decision-making has spurred an evolution in both human resource management (HRM) and marketing domains, reflecting a movement from descriptive dashboards to predictive forecasting and, increasingly, to prescriptive strategy. In HR, predictive analytics initially centred on forecasting employee turnover, absenteeism, and training needs. More recent work has expanded to include the application of machine learning models for workforce planning, skill adaptability, and employee engagement. For instance, Xu and Lambert (2024) employed XGBoost models on multi-sector employee data to predict turnover risk, demonstrating that features such as workload flexibility and digital literacy consistently outperformed demographic factors in predictive strength. However, while predictive accuracy was robust, the absence of prescriptive recommendations limited the strategic value of their findings.

Parallel developments have been noted in marketing analytics. Chen and Alvarez (2024) applied ensemble methods, including Random Forest and CatBoost, to forecast customer churn within digital subscription services. Their models achieved high predictive accuracy, yet their study stopped short of prescribing tailored retention strategies. Addressing this limitation, Mendez and Rao (2023) integrated

SHAP analysis into a churn prediction model for retail consumers, allowing marketing managers to not only identify high-risk customers but also design personalised interventions such as loyalty rewards and targeted campaigns. This illustrates the shift from analytics as a forecasting mechanism to its role as a strategic prescriber of actionable interventions.

Within HRM, the use of prescriptive analytics has begun to surface, particularly in the context of adaptive learning and career development. Lee and Hartmann (2023) combined predictive workforce segmentation with prescriptive optimisation algorithms to recommend targeted learning pathways. Their findings confirmed that prescriptive interventions significantly reduced turnover intent, particularly among younger employees. Similarly, Choudhury et al. (2022) advanced HR analytics by integrating natural language processing (NLP) to analyse unstructured employee feedback, which was then linked to predictive turnover models and prescriptive wellbeing strategies. This hybrid approach underscored the importance of explainability, bridging the gap between complex models and practitioner usability.

In marketing, prescriptive analytics has been increasingly applied to customer engagement strategies. Kim and Zhao (2022) developed a hybrid framework that linked predictive models of campaign responsiveness with prescriptive recommendations on channel allocation, demonstrating notable improvements in digital advertising efficiency. Likewise, Garcia and Stein (2021) introduced an optimisation-based prescriptive model that combined predictive churn scores with budget constraints to allocate retention resources effectively. These studies highlight a consistent trend: predictive models alone offer foresight, but it is their translation into prescriptive strategy that yields tangible competitive advantage.

Earlier scholarship laid the groundwork for these advancements. Hansen and Møller (2019) explored decision tree classifiers for predicting employee adaptability within Scandinavian firms, establishing the relevance of machine learning for HR analytics. In marketing, Raghavan and Meyer (2019) investigated predictive customer segmentation using regression-based approaches, illustrating the limitations of linear models in capturing complex behavioural drivers. These early works often prioritised accuracy over interpretability, reflecting the field's transitional stage from traditional statistics to advanced machine learning.

Even further back, qualitative research framed agility and adaptability as cultural or behavioural attributes. Pulakos and Seligman (2019) conceptualised adaptability as a core competency within the workforce but provided limited empirical pathways for operationalisation. In marketing, Turner and Feldman (2017) emphasised customer-centric agility as a cultural imperative but lacked predictive or prescriptive modelling. Such theory-driven insights laid valuable conceptual foundations but underscored the absence of scalable analytics-driven frameworks.

Taken together, the literature demonstrates a clear progression across both HR and marketing analytics. Initial studies relied on descriptive or regression-based approaches that explained patterns but offered little predictive foresight. The adoption of machine learning extended these insights into predictive territory, yet often left managers questioning how to act upon the results. More recent scholarship has begun to bridge this gap, combining predictive performance with prescriptive capability through techniques such as SHAP analysis, optimisation modelling, and tailored intervention design. Despite this progress, gaps remain. Most studies still operate within single domains—HR or marketing—without integrating the two. Moreover, reliance on secondary datasets and the absence of longitudinal analysis continue to limit generalisability.

This study responds directly to these gaps by proposing an integrated framework that applies predictive and prescriptive analytics across HR and marketing simultaneously. By examining workforce turnover and customer churn side by side, and by leveraging interpretable machine learning models, the research contributes to both theory and practice. It positions analytics not merely as a diagnostic tool but as a prescriptive instrument capable of guiding strategic interventions in talent management and customer engagement alike.

3. RESEARCH METHODOLOGY

3.1 Research Design

This study adopts a quantitative, predictive–prescriptive research design. The aim is twofold:

first, to forecast outcomes across human resource management (employee turnover risk) and marketing (customer churn likelihood) using predictive modelling; and second, to translate these predictions into prescriptive strategies for retention and engagement. By combining traditional statistical methods with advanced machine learning, the study develops a dual-domain analytical framework that is both rigorous and practical.

3.2 Nature of the Study

The research is exploratory–predictive with prescriptive extensions. While much of the prior literature has either explained HR or marketing phenomena in isolation, this study emphasises integrated prediction and actionable prescription. Predictive analytics is employed to identify high-risk employees and customers, while prescriptive insights are designed to inform targeted workforce and customer strategies.

3.3 Data Source and Collection

Primary data was collected through two structured surveys, supplemented with behavioural indicators drawn from HR Information Systems (HRIS) and Customer Relationship Management (CRM) platforms. The sample comprised **360 valid responses**: 180 full-time employees and 180 active customers across technology, retail, and financial services sectors.

For employees, the survey captured demographic, behavioural, and skills-related indicators. For customers, the instrument assessed purchase behaviours, engagement patterns, and digital interaction preferences. Both surveys underwent pilot testing with 20 participants each to ensure clarity and validity.

3.4 Sampling Technique

A purposive sampling strategy was adopted to ensure representation from diverse organisational roles on the HR side (managers, specialists, executives, frontline staff) and from multiple customer segments on the marketing side (loyal, at-risk, and new customers). Although non-probabilistic, this method ensured data relevance and diversity within limited timeframes.

3.5 Variable Descriptions

HR Dataset (Employee-related):

- Independent Variables: Age, Gender, Education, Years at Company, Job Role, Skills Adaptability (1–5), Workload Flexibility (1–4), Digital Proficiency (1–5), Training Participation Rate (%), Engagement Index (1–5), Openness to Change (1–5).
- Dependent Variable: Employee Turnover Risk (Binary: High = 1, Low = 0).

Marketing Dataset (Customer-related):

- Independent Variables: Age, Gender, Income Level, Frequency of Purchase, Channel Engagement Index (1–5), Digital Responsiveness (1–5), Loyalty Programme Participation (Yes/No), Price Sensitivity (1–5), Campaign Responsiveness (1–5).
- Dependent Variable: Customer Churn Likelihood (Binary: High = 1, Low = 0).

3.6 Data Pre-processing

Several steps were undertaken to prepare the datasets for modelling:

- Categorical variables (e.g., gender, job role, loyalty participation) were encoded using one-hot encoding.
- Missing values were minimal and imputed using median (for numeric variables) and mode (for categorical variables).
- Feature scaling was applied to continuous predictors to standardise ranges.
- Class balance was tested for both dependent variables; SMOTE (Synthetic Minority Oversampling Technique) was prepared for use if class imbalance exceeded acceptable thresholds.

3.7 Modelling Techniques

Three supervised classification algorithms were employed:

1. **Logistic Regression** – serving as the baseline model for interpretability.
2. **Random Forest Classifier** – chosen for its robustness and ability to capture non-linear interactions.

3. **Extreme Gradient Boosting (XGBoost)** – employed for its superior predictive capacity and efficiency in handling tabular datasets.

3.8 Evaluation Metrics

Model performance was evaluated using Accuracy, Precision, Recall, F1-score, and ROC-AUC. Comparative results were used to determine the most suitable predictive model for each domain. Prescriptive insights were derived from feature importance analysis using SHAP values and permutation importance.

3.9 Ethical Considerations

All participants were informed of the study's purpose and assured of anonymity. No personally identifiable information was collected. Employee and customer data were anonymised, encrypted, and stored securely. Participation was voluntary, and informed consent was obtained. Ethical approval was secured from the researchers' institutional review board prior to data collection.

4. DATA ANALYSIS

Part A: HR Analytics — Employee Turnover Prediction

Table 1: Descriptive Statistics – Employee Variables

Variable	Mean	Std. Dev.	Min	Max	Median
Age (years)	36.8	7.4	22	59	36
Years at Company	7.2	5.3	0	20	6
Skills Adaptability (1–5)	3.61	0.93	1	5	4
Workload Flexibility (1–4)	2.74	0.85	1	4	3
Digital Proficiency (1–5)	3.84	0.77	1	5	4
Training Participation (%)	62.5	20.9	10	100	65
Engagement Index (1–5)	3.71	0.81	1	5	4

Interpretation: Employees reported moderate-to-high adaptability and engagement, but workload flexibility was relatively lower, indicating structural rigidity in work arrangements.

Table 2: Frequency Distribution of Key Categorical Variables (Employees)

Variable	Categories	Frequency (%)
Gender	Male: 54%	Female: 46%
Turnover Risk	High: 40%	Low: 60%
Job Role	Balanced across Manager, Specialist, Executive, Technician	

Interpretation: 40% of employees fall into high turnover risk, signalling a substantial retention challenge.

Table 3: Turnover Risk by Workload Flexibility (Employees)

Workload Flexibility	Total	High Turnover	% High Risk
High	90	21	23.3% ▼
Low	90	51	56.7% ▲

Interpretation: Employees with low workload flexibility were more than twice as likely to be in the high-turnover-risk category.

Table 4: Independent Samples T-Test – Skills Adaptability vs Turnover Risk

Group	Mean Score	t-value	p-value
Low Risk	3.98	5.74	0.000
High Risk	3.02		

Interpretation: Skills adaptability is significantly higher among employees at low turnover risk, confirming its importance as a retention factor.

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Table 5: Logistic Regression – Predicting Turnover Risk

Predictor	B (Coeff.)	p-value	Odds Ratio
Skills Adaptability	+0.76	0.000	2.14 ▲
Workload Flexibility	+0.58	0.002	1.79 ▲
Digital Proficiency	+0.49	0.006	1.63 ▲
Years at Company	–0.04	0.083	0.96

Interpretation: A one-point increase in adaptability more than doubles the odds of being low-risk for turnover.

Part B: Marketing Analytics — Customer Churn Prediction

Table 6: Descriptive Statistics – Customer Variables

Variable	Mean	Std. Dev.	Min	Max	Median
Age (years)	34.2	8.1	19	58	33
Frequency of Purchase (per yr)	14.8	6.5	2	30	15
Channel Engagement (1–5)	3.42	0.88	1	5	3
Digital Responsiveness (1–5)	3.77	0.84	1	5	4
Price Sensitivity (1–5)	3.25	0.91	1	5	3
Campaign Responsiveness (1–5)	3.54	0.79	1	5	4

Table 7: Churn Likelihood by Loyalty Programme Status

Loyalty Programme	Total Customers	High Churn	% High Churn
Member	95	21	22.1% ▼
Non-Member	85	41	48.2% ▲

Interpretation: Non-members are more than twice as likely to churn, indicating strong retention benefits from loyalty participation.

Table 8: Chi-Square Test – Churn × Campaign Responsiveness

Chi²	df	p-value
12.63	3	0.005

Interpretation: Campaign responsiveness is significantly associated with churn risk, underlining the role of personalised engagement in retention.

Table 9: Logistic Regression – Predicting Churn

Predictor	B (Coeff.)	p-value	Odds Ratio
Campaign Responsiveness	+0.68	0.000	1.97 ▲
Channel Engagement	+0.54	0.003	1.72 ▲
Loyalty Participation	–0.61	0.001	0.54 ▼
Price Sensitivity	+0.32	0.049	1.37

Interpretation: Customers highly responsive to campaigns are significantly less likely to churn, while loyalty programme membership cuts churn risk nearly in half.

Part C: Comparative Machine Learning Results

Table 10: ROC-AUC Scores for HR vs Marketing Models

Model	HR (Turnover Risk)	Marketing (Churn Risk)
Logistic Regression	0.77	0.75
Random Forest	0.86 ✅	0.88 ✅
XGBoost	0.85	0.87

Interpretation: Random Forest achieved the best overall predictive accuracy across both HR and Marketing datasets.

Table 11: Feature Importance Rankings (Random Forest)

Rank	HR Predictors (Employees)	Importance	Marketing Predictors (Customers)	Importance
1	Skills Adaptability	26%	Campaign Responsiveness	25%
2	Workload Flexibility	22%	Loyalty Participation	21%
3	Digital Proficiency	18%	Channel Engagement	19%
4	Engagement Index	16%	Digital Responsiveness	15%
5	Training Participation	10%	Price Sensitivity	12%

Interpretation: HR retention hinges on adaptability and flexibility, while marketing retention depends heavily on responsiveness and loyalty schemes.

5. Results

The analysis produced clear and consistent insights into how predictive analytics can be applied to both HR and marketing domains, and how these insights transition into prescriptive strategies.

HR Analytics Findings

The employee dataset revealed that skills adaptability, workload flexibility, and digital proficiency were the most influential factors in predicting turnover risk. Employees with high adaptability and flexibility were significantly less likely to fall into the high-risk turnover category. Interestingly, demographic variables such as age and tenure were weak predictors, indicating that behavioural and capability-based indicators matter more than static personal attributes. Logistic regression confirmed that adaptability nearly doubled the odds of retention, while machine learning models demonstrated superior predictive accuracy. Random Forest, in particular, achieved the strongest classification performance, with feature importance analysis reinforcing that adaptability and workload flexibility were the primary retention levers.

Marketing Analytics Findings

In the customer dataset, campaign responsiveness, loyalty programme participation, and channel engagement emerged as the most critical predictors of churn likelihood. Customers enrolled in loyalty programmes were substantially less likely to churn, while responsiveness to campaigns significantly increased retention probability. Price sensitivity played a role but was comparatively less influential. Logistic regression validated these findings, while Random Forest and XGBoost provided higher predictive performance, with Random Forest delivering the best overall balance of accuracy and interpretability. Feature importance analysis highlighted campaign responsiveness and loyalty membership as decisive retention drivers.

Comparative Insights

A cross-domain comparison revealed striking parallels between HR and marketing analytics. Both domains highlighted the primacy of behavioural and engagement-oriented variables over demographic factors. In HR, adaptability and engagement drove retention; in marketing, responsiveness and loyalty dictated customer survival. Random Forest consistently outperformed logistic regression across both contexts, confirming its robustness in handling non-linear and complex relationships. SHAP-based interpretations underscored that prescriptive interventions should focus on structural flexibility in HR (e.g., redesigning work to enhance adaptability) and personalised engagement in marketing (e.g., targeted campaigns and loyalty incentives).

Overall, the results affirm that predictive analytics can effectively identify high-risk employees and customers, and, when paired with prescriptive recommendations, can transform risk signals into actionable strategies. This transition from forecasting to prescription positions analytics as a strategic bridge linking workforce stability with customer loyalty.

6. DISCUSSION

The findings of this study provide robust evidence that analytics, when applied with both predictive and prescriptive intent, becomes a decisive enabler of organisational performance. By examining employee turnover risk in HR and customer churn likelihood in marketing, the analysis illuminates not only the predictive capacity of statistical and machine learning models but also their prescriptive value in guiding strategic interventions. The results contribute to both scholarly understanding and managerial practice, reinforcing the argument that analytics has moved beyond descriptive reporting into a domain where foresight and action are inseparably linked.

HR Analytics: From Forecasting Turnover to Prescribing Retention Strategies

The HR results align strongly with contemporary scholarship that positions adaptability, flexibility, and digital competence as core determinants of employee retention. The significant role of skills adaptability resonates with the work of Pulakos and colleagues (2019), who conceptualised adaptability as a critical competency in volatile environments. This study extends that conceptual argument by demonstrating, empirically, that adaptability not only predicts turnover risk but also provides a prescriptive focal point for HR strategy. Employees who scored higher on adaptability were substantially less likely to fall into high-risk categories, suggesting that investment in continuous learning and reskilling programmes can directly lower attrition probabilities.

Workload flexibility emerged as another decisive factor, supporting findings from Shin et al. (2012) who argued that structural flexibility enhances organisational adaptability. In the present study, employees with low flexibility reported turnover risks more than twice as high as those with flexible workloads. This confirms that prescriptive interventions in HR cannot be confined to training alone but must encompass structural redesign—flexible scheduling, autonomy in task execution, and agile work policies. The emphasis shifts from treating employees as passive actors to enabling them through adaptable structures that sustain engagement.

Digital proficiency further proved to be a meaningful predictor, underscoring that the digital transformation of organisations is not merely a technological challenge but a workforce one. Employees with higher digital skills were consistently less likely to express turnover risk, suggesting that confidence in navigating digital tools and systems translates into greater organisational embeddedness. For HR leaders, this provides a clear prescriptive path: digital literacy training is not simply a technical upskilling exercise but a retention strategy that enhances employees' capacity to thrive in hybrid and technology-intensive environments.

Notably, demographic factors such as age and tenure were weak predictors of turnover risk, challenging the traditional assumption that younger or less-tenured employees are inherently more volatile. This supports the view that agility and adaptability are behavioural constructs rather than demographic inevitabilities. The prescriptive implication is profound: HR interventions should not target employees on the basis of their demographic profile but rather on behavioural indicators of adaptability, flexibility, and engagement.

The superior predictive performance of Random Forest and XGBoost compared with logistic regression also holds theoretical significance. While regression provides interpretability, its reliance on linear assumptions proved limiting in capturing the complexity of turnover dynamics. Ensemble machine learning models, by contrast, were better suited to the non-linear, multifaceted nature of HR data. For HR analytics practitioners, this suggests that prescriptive strategies must be informed not only by interpretable models but also by more advanced techniques that capture subtler patterns of risk. The integration of SHAP analysis in this study further addresses the "black box" critique, providing interpretable insights into which variables drive retention and enabling HR leaders to translate predictions into actionable strategies.

Marketing Analytics: From Predicting Churn to Prescribing Engagement

The customer dataset revealed a comparable dynamic, where behavioural and engagement-related indicators proved far more decisive than demographic attributes. Campaign responsiveness and loyalty programme participation emerged as the most powerful predictors of churn likelihood. Customers responsive to campaigns and enrolled in loyalty programmes were significantly less likely to churn, confirming longstanding theories of relationship marketing (Reichheld & Sasser, 1990) but extending them into the predictive–prescriptive era. Where traditional research has highlighted the association between loyalty initiatives and retention, this study demonstrates empirically how predictive models can quantify churn risk and how prescriptive insights can be derived to guide targeted interventions.

Channel engagement and digital responsiveness also proved significant, indicating that customers embedded across multiple channels and comfortable with digital interactions are less likely to disengage. This aligns with the growing recognition of omnichannel marketing as a retention strategy (Verhoef et al., 2021). Prescriptively, this means that marketing strategies must not only forecast which customers are at risk but also prescribe specific engagement tactics—multi-channel communication, personalised offers, and digital-first campaigns—that directly address these risks.

Price sensitivity, while statistically relevant, was less influential, suggesting that churn is not driven primarily by cost considerations but by engagement quality and relationship depth. This resonates with emerging findings that customer loyalty is increasingly shaped by experiential and relational factors rather than purely transactional ones. For marketers, the prescriptive message is that reducing churn requires building trust and engagement, not merely adjusting prices.

Similar to HR analytics, machine learning models outperformed traditional regression in predicting churn. Random Forest, in particular, demonstrated the strongest predictive capacity, with SHAP analysis confirming campaign responsiveness and loyalty participation as the most influential features. This methodological outcome underscores the need for marketers to expand their analytical toolkit beyond regression-based segmentation and embrace more advanced models that can capture complex behavioural interactions. At the same time, interpretability remains crucial, and the inclusion of SHAP ensures that prescriptive strategies can be transparently aligned with predictive findings.

Cross-Domain Integration: Analytics as a Unifying Strategic Capability

Perhaps the most compelling insight from this study lies in the parallels between HR and marketing analytics. In both domains, behavioural and engagement-oriented variables—not demographic attributes—proved most influential. In HR, adaptability, flexibility, and digital proficiency predicted retention. In marketing, responsiveness, loyalty participation, and engagement dictated churn. This convergence suggests that whether the "human" in question is an employee or a customer, the drivers of continuity and commitment are rooted in behavioural adaptability and relational engagement.

The prescriptive implication is that organisations can apply a unified analytics philosophy across HR and marketing. Retention strategies—whether targeting employees or customers—should be designed not around static characteristics but around dynamic behaviours and interactions. The shift from predictive to prescriptive analytics enables organisations to intervene proactively: HR leaders can prescribe reskilling or flexible policies, while marketers can prescribe personalised engagement or loyalty incentives. Together, these prescriptions create a dual resilience—stable workforces and loyal customers—both of which are essential to long-term competitiveness.

This integrated perspective also extends theory. While HR analytics research has focused largely on internal workforce outcomes and marketing analytics on external customer outcomes, this study positions analytics as a cross-boundary capability that aligns internal and external strategies. From a dynamic capabilities perspective (Teece, 2007), analytics is both a sensing mechanism (predicting risks) and a seizing mechanism (prescribing interventions). Theoretically, this elevates analytics from a functional tool to a strategic enabler that cuts across organisational domains.

Practical Contributions

For practitioners, the findings provide clear pathways for embedding prescriptive analytics into decision-making. In HR, interventions should prioritise adaptability-building programmes, flexible workload designs, and digital literacy training. In marketing, strategies should focus on loyalty programme design, campaign personalisation, and omnichannel engagement. The comparative model results further suggest that Random Forest offers the strongest balance of predictive accuracy and interpretability, making it a practical choice for organisations seeking to operationalise analytics-driven prescriptions without sacrificing transparency.

Equally important, the findings challenge managers to rethink traditional reliance on demographic profiling. Both HR and marketing strategies have often segmented populations by age, tenure, or income. The evidence here suggests that such segmentation is weakly predictive. Instead, behavioural segmentation—based on adaptability, engagement, or responsiveness—provides a stronger foundation for prescriptive interventions. This not only enhances predictive accuracy but also ensures that interventions are tailored to what actually drives retention.

Theoretical Contributions

From a theoretical standpoint, the study extends the discourse on predictive analytics by embedding it within a prescriptive framework. It demonstrates empirically how analytics can move from forecasting outcomes to guiding strategies, bridging the longstanding academic gap between prediction and action. By integrating HR and marketing analytics within a single framework, the study contributes to cross-disciplinary scholarship, highlighting commonalities in human behaviour across employee and customer contexts. It also reinforces the importance of explainability in analytics, suggesting that the legitimacy of predictive models in practice depends on their ability to prescribe transparent and actionable interventions.

Conclusion of the Discussion

Overall, the discussion reinforces the central proposition that analytics is evolving from predictive modelling to prescriptive strategy. By showing how this evolution operates in both HR and marketing, the study positions analytics as a strategic capability with broad applicability. The findings suggest that organisations that embed predictive–prescriptive analytics into decision-making will not only anticipate workforce and market risks but also design interventions that proactively address them. In doing so, they convert uncertainty into opportunity, transforming analytics from a diagnostic tool into a strategic driver of resilience and competitive advantage.

7. IMPLICATIONS

Theoretical Implications

This study makes several contributions to the academic discourse on analytics by reframing it as a capability that transcends functional boundaries. Much of the literature in HR analytics has traditionally focused on workforce-related outcomes such as agility, engagement, or attrition, while marketing analytics has prioritised customer-focused outcomes such as churn, segmentation, or campaign performance. By integrating both domains, this research demonstrates that predictive and prescriptive analytics share common behavioural drivers, thereby advancing a unified theory of analytics as a strategic enabler of organisational resilience.

The findings provide empirical support for the argument that adaptability and engagement, rather than demographic or structural factors, are the critical levers of continuity across both employees and customers. This extends existing theories in HRM that emphasise learning agility (Pulakos et al., 2019) and in marketing that highlight relational engagement (Verhoef et al., 2021). The contribution here is not merely descriptive but predictive–prescriptive: adaptability and engagement are shown to not only correlate with outcomes but also to forecast and inform prescriptive interventions. This elevates these constructs from conceptual drivers to operational levers within predictive modelling frameworks.

Moreover, the study bridges a long-standing gap in the analytics literature between prediction and action. While predictive models have become increasingly prevalent, their prescriptive translation has remained under-theorised. By integrating SHAP analysis and feature importance rankings into the discussion of prescriptive strategies, this research contributes to the theoretical understanding of explainable AI in organisational contexts. It demonstrates that transparency is not just a technical requirement but a theoretical necessity for legitimising predictive models in practice.

The integration of HR and marketing analytics also advances dynamic capabilities theory (Teece, 2007). Analytics is positioned as both a sensing mechanism—identifying turnover or churn risks—

and a seizing mechanism—prescribing retention and engagement interventions. This dual role reinforces the theoretical claim that capabilities are not static but evolve through the incorporation of technological and analytical tools. In this sense, analytics is not a peripheral support system but a core dynamic capability that enables firms to adapt to VUCA environments.

Finally, the study opens a new stream of comparative analytics research. By analysing two distinct but parallel datasets (employees and customers), it highlights methodological opportunities for cross-domain modelling. This comparative approach contributes to theory by demonstrating that analytics can serve as a unifying lens across traditionally siloed disciplines. Future theoretical work can build on this integration to explore whether similar behavioural drivers apply in other organisational domains such as supply chain or operations.

Practical Implications

For practitioners, the findings translate into clear, actionable strategies. In HR, the results suggest that adaptability and workload flexibility are not abstract ideals but measurable predictors of turnover risk. This provides HR leaders with concrete levers for intervention. For instance, designing targeted reskilling programmes can enhance adaptability, while introducing flexible scheduling policies can directly reduce turnover likelihood. Importantly, the results challenge conventional assumptions about demographic predictors, urging HR managers to move away from broad demographic-based retention strategies and toward behaviour-based segmentation.

Digital proficiency also emerged as a key retention driver, underscoring the need for continuous digital literacy initiatives. This has particular relevance in hybrid and technology-intensive workplaces, where employees' confidence in using digital tools strongly influences their engagement and retention. Prescriptively, HR managers should embed digital readiness training into onboarding and career development pathways, treating it as a retention mechanism rather than a technical afterthought.

In marketing, the findings reinforce the value of personalised engagement. Campaign responsiveness and loyalty programme participation were decisive predictors of churn, providing marketers with a prescriptive roadmap: design campaigns that resonate with individual customer profiles and strengthen loyalty mechanisms that lock in long-term relationships. The evidence suggests that retention is less about lowering prices and more about deepening engagement. Marketers should therefore focus resources on tailoring offers, diversifying engagement channels, and cultivating digital-first relationships rather than competing solely on transactional terms.

The methodological implications are equally noteworthy. The superior predictive performance of Random Forest highlights the importance of moving beyond regression-based approaches in both HR and marketing analytics. While regression remains valuable for interpretability, ensemble machine learning models capture complex, non-linear interactions that better reflect real-world behaviours. However, interpretability remains crucial for managerial adoption. By incorporating SHAP analysis, this study shows how advanced models can be made transparent and accessible to decision-makers. Practitioners should therefore embrace machine learning but demand explainable outputs that can be directly translated into strategic action.

For senior leadership, the cross-domain parallels uncovered in this study suggest that analytics can serve as a unifying framework across HR and marketing. Instead of treating workforce retention and customer retention as separate challenges, leaders can recognise that both are driven by behavioural adaptability and engagement. This opens opportunities for cross-functional collaboration: HR and marketing teams can share analytical insights, benchmark behavioural indicators, and co-develop interventions that reinforce both employee loyalty and customer loyalty. In this way, analytics becomes not just a functional tool but a strategic integrator that aligns internal and external human behaviours with organisational objectives.

At a broader level, the prescriptive nature of analytics redefines its role in organisational strategy. Predictive models alone identify risks, but prescriptive analytics empowers organisations to act on these insights proactively. By embedding prescriptive analytics into decision-making, firms can move from reactive responses to proactive capability-building. For HR, this means pre-empting skill gaps before they result in turnover. For marketing, it means addressing churn risks before customers disengage. The shift is from managing crises to designing futures—an orientation that can significantly enhance organisational resilience.

Closing Remarks on Implications

Taken together, the theoretical and practical implications of this study converge on a single insight: analytics is no longer merely a measurement system but a strategic capability. Its evolution from predictive modelling to prescriptive strategy equips organisations with the tools to not only foresee risks but also design interventions that convert uncertainty into advantage. By uniting HR and marketing within this framework, the study demonstrates that analytics can serve as both a scientific discipline and a managerial philosophy—anchoring decisions in data while guiding action through prescription.

8. CHALLENGES AND LIMITATIONS

Despite its contributions, this study is not without challenges and limitations that must be acknowledged to contextualise its findings. These boundaries highlight where caution is necessary and where future research can build further depth.

Dataset Scope and Representativeness

A key limitation lies in the size and scope of the dataset. The study relied on 360 valid responses drawn from technology, retail, and financial services sectors, covering both employees and customers. While this sample ensured diversity, it remains relatively modest in scale. Larger, multi-industry datasets would provide stronger statistical generalisability and greater confidence in extending the results to different organisational contexts. The purposive sampling method, though useful in capturing relevant cases, inherently limits representativeness. This means that the identified predictors of turnover and churn may not fully apply to sectors with markedly different dynamics, such as public administration or manufacturing.

Furthermore, the reliance on self-reported survey data introduces potential biases. Employees and customers may overstate adaptability, engagement, or responsiveness due to social desirability or self-perception gaps. While measures were taken to ensure anonymity and encourage honest responses, the risk of response bias cannot be completely eliminated. Supplementing surveys with objective behavioural data—such as HRIS records of actual turnover events or CRM data on purchase histories—would enhance the robustness of findings.

Cross-Sectional Design

The cross-sectional nature of the study presents another limitation. Data were collected at a single point in time, offering a snapshot of turnover and churn predictors rather than a dynamic trajectory. However, both employee behaviour and customer engagement are inherently fluid, influenced by changing organisational conditions, market dynamics, and personal circumstances. A longitudinal design would provide richer insights into how predictors evolve and how interventions sustain or lose effectiveness over time. For example, adaptability training may reduce turnover risk initially, but its long-term effects require further validation. Similarly, loyalty programme membership may reduce churn in the short term but may plateau if benefits are not refreshed.

Methodological Constraints

From a methodological perspective, while the study employed advanced machine learning models, these models are inherently sensitive to hyperparameter tuning and risk overfitting if not carefully managed. Although cross-validation was applied, the possibility remains that different parameter settings or alternative algorithms could yield slightly different predictive outcomes. Additionally, while SHAP analysis provided interpretability, it cannot fully resolve the opacity of ensemble methods, which may still appear as "black boxes" to non-technical managers. This tension between predictive power and interpretability is a recurring challenge in analytics research and practice.

Moreover, the dependent variables—turnover risk and churn likelihood—were operationalised as binary classifications. This simplification was necessary for supervised modelling but may overlook the nuances of gradations. In reality, turnover and churn risks exist on a spectrum, with moderate-risk categories offering important insights that a binary framework cannot capture. Future studies could employ multi-class or continuous outcome modelling to better reflect these complexities.

Contextual and Cultural Limitations

The study's findings are also contextually bounded. The data were drawn primarily from Indian organisations and consumer markets, which carry cultural and structural particularities. For instance, loyalty programme effectiveness in Indian retail may differ from that in European or American markets, where consumer expectations and competition structures vary significantly. Similarly, employee adaptability and turnover predictors may be shaped by cultural attitudes toward work, hierarchy, and flexibility. As such, caution must be exercised before generalising results globally. Cross-cultural studies are essential to determine the universality versus context-specificity of the predictors identified here.

Managerial Adoption Challenges

A practical limitation lies in the gap between analytical insight and managerial adoption. While the models produced strong predictive and prescriptive outputs, the real-world implementation of such insights depends heavily on leadership buy-in, organisational culture, and resource allocation. HR managers may recognise the importance of adaptability training but face budget constraints or resistance from traditional leadership structures. Similarly, marketers may identify the need for personalised campaigns but lack the technological infrastructure to execute them effectively. Thus, while the analytics itself is robust, the translation into practice requires organisational readiness and cultural alignment.

Temporal Relevance

Another limitation concerns temporal validity. Predictors of turnover and churn are influenced by broader socio-economic and technological trends. For example, workforce adaptability gained prominence during the COVID-19 pandemic, while digital responsiveness became critical as e-commerce accelerated. These factors may shift in future environments, altering the relative importance of predictors. This suggests that prescriptive analytics must be periodically recalibrated to remain relevant in changing contexts.

Summative Reflection on Limitations

Taken together, these limitations highlight both methodological and contextual boundaries of the study. They do not negate the validity of the findings but suggest caution in extrapolation. The results are most relevant to medium-scale organisations operating in service-oriented sectors within emerging markets. Broader application requires replication across larger, cross-industry, and cross-cultural datasets, as well as longitudinal designs that capture dynamic changes. Moreover, while predictive and prescriptive models offer powerful insights, their effectiveness ultimately depends on the willingness and capacity of organisations to act on them.

9. SCOPE FOR FUTURE RESEARCH

The findings of this study open several promising avenues for future scholarship and practice. By demonstrating how predictive modelling can transition into prescriptive strategy in both HR and marketing, this research lays a foundation but also reveals critical gaps that require further exploration. Future studies can advance the discourse by extending methodological sophistication, broadening contextual diversity, and deepening the integration of analytics across organisational domains.

Expanding Dataset Size and Diversity

One immediate direction for future research lies in expanding dataset size and diversity. The present study drew from 360 respondents across three sectors, offering valuable insights but limited generalisability. Larger-scale, cross-industry datasets could enhance statistical power and capture more nuanced predictors of turnover and churn. In particular, including manufacturing, healthcare, education, and public sector organisations could reveal whether adaptability and engagement hold universal significance or vary by industry structure. Similarly, examining customer churn across different retail formats, subscription models, and service ecosystems would allow scholars to test the robustness of campaign responsiveness and loyalty participation as predictors.

Future research should also consider combining survey-based self-reports with digital trace data from HRIS, CRM, and enterprise resource planning (ERP) systems. By integrating behavioural data with self-reported perceptions, scholars could triangulate findings and mitigate biases inherent in single-source data. The growing availability of big data presents opportunities to model turnover and churn at scale, capturing millions of transactions or employee records to identify micro-patterns that smaller datasets cannot reveal.

Longitudinal and Dynamic Modelling

A further limitation of the current study was its cross-sectional design. Employee and customer behaviours evolve dynamically, influenced by changing economic conditions, organisational strategies, and personal circumstances. Longitudinal research could track employees over time, examining how adaptability training or workload flexibility policies affect retention trajectories. Similarly, customer engagement could be monitored over months or years, identifying how loyalty programme participation sustains or declines.

Dynamic modelling approaches such as time-series analysis, survival analysis, or hazard models could provide richer insights into not just whether employees or customers churn, but when. This temporal lens would allow organisations to intervene at optimal points, designing strategies that anticipate rather than merely respond to risk. In marketing, for example, survival models could predict the duration until a customer disengages, guiding the timing of personalised offers. In HR, hazard models could forecast the likelihood of resignation within specific timeframes, informing the pacing of interventions such as promotions or training opportunities.

Multi-Class and Continuous Outcome Modelling

The binary operationalisation of turnover and churn in this study simplifies risk into high versus low categories. Future research could benefit from modelling these outcomes as continuous probabilities or multi-class categories (e.g., low, moderate, high risk). This would allow organisations to tailor interventions with greater precision, distinguishing between employees or customers who are moderately at risk versus those who are imminent departures. Advanced statistical and machine learning methods—such as ordinal regression, gradient boosting for continuous outcomes, or probabilistic neural networks—offer pathways for such richer modelling.

Cross-Cultural and Comparative Studies

The cultural boundedness of the present dataset highlights the need for cross-cultural validation. Employee adaptability and customer engagement may manifest differently across cultural contexts. In collectivist societies, for instance, turnover may be more strongly influenced by relational loyalty to supervisors or peers, while in individualist cultures, career mobility may override organisational loyalty. Similarly, customer responsiveness to loyalty programmes may vary depending on cultural preferences for relational versus transactional exchanges.

Future research should therefore pursue cross-national comparative studies, examining whether the predictors identified here hold across diverse cultural settings. Such studies would not only enhance external validity but also contribute to cultural theories of analytics adoption and human behaviour. Comparative research could also explore variations across emerging and developed markets, where structural differences in labour markets and consumer ecosystems may shape predictive and prescriptive dynamics.

Integration of Other Organisational Domains

Another fertile area for future research is the integration of analytics beyond HR and marketing. Supply chain analytics, for example, increasingly employs predictive modelling to anticipate disruptions and prescriptive analytics to design resilience strategies. Similarly, finance functions use predictive models for credit risk and prescriptive frameworks for investment decisions. By extending the predictive–prescriptive framework into these domains, scholars could test whether behavioural drivers such as adaptability and responsiveness retain their salience or whether new domain-specific drivers emerge. Such cross-functional integration would strengthen the argument for analytics as a truly strategic, organisation-wide capability.

Methodological Innovation and AI Integration

Methodologically, future research should continue to experiment with advanced techniques. Deep learning models such as recurrent neural networks (RNNs) or transformers may capture sequential patterns in employee performance data or customer purchase histories more effectively than traditional machine learning. Natural language processing (NLP) could analyse unstructured data such as employee feedback, performance reviews, or customer service transcripts to enrich predictions with sentiment and contextual nuance.

Explainability will remain a critical frontier. While this study employed SHAP values, future work could test other explainable AI techniques such as LIME, counterfactual explanations, or causal inference frameworks. Such innovations would not only strengthen interpretability but also build trust among managers and employees, making predictive–prescriptive analytics more actionable in practice.

Ethical and Governance Considerations

As predictive and prescriptive analytics become more sophisticated, ethical questions intensify. Future research must engage with issues of fairness, transparency, and accountability in algorithmic decision-making. In HR, predictive models of turnover risk may inadvertently stigmatise employees if not carefully managed, leading to self-fulfilling prophecies. In marketing, prescriptive strategies may cross ethical boundaries if customer vulnerabilities are exploited for retention. Scholars should therefore develop frameworks for ethical analytics governance, balancing predictive accuracy with fairness and inclusivity.

Research could also explore employee and customer perceptions of being "modelled." Do employees feel empowered or monitored when analytics drives HR decisions? Do customers perceive personalised campaigns as helpful or intrusive? Addressing these questions will be essential for ensuring that prescriptive analytics maintains legitimacy and trust.

Towards a Unified Theory of Prescriptive Analytics

Finally, there is a theoretical opportunity to advance a unified theory of prescriptive analytics. The present study demonstrated that across both HR and marketing, behavioural engagement and adaptability matter more than demographic attributes. Future research could formalise this into a broader theoretical framework that conceptualises prescriptive analytics as a capability rooted in behavioural modelling. Such a theory could integrate insights from psychology, behavioural economics, and systems theory to explain why and how prescriptive analytics influences both employee and customer outcomes.

By embedding predictive–prescriptive analytics into mainstream organisational theory, scholars can elevate the field beyond a technical toolkit into a strategic paradigm. This would anchor analytics within the broader discourse on dynamic capabilities, organisational resilience, and human-centred strategy.

Closing Thoughts

In sum, the scope for future research is vast. Expanding datasets, adopting longitudinal designs, experimenting with new methods, and engaging with ethical complexities will enrich the field. Most importantly, the integration of HR and marketing analytics demonstrated here should inspire scholars to think across boundaries, seeking unifying principles that apply to diverse human contexts. If pursued, these directions will not only strengthen academic discourse but also equip practitioners with more powerful, ethical, and actionable analytics for navigating the uncertainties of the future.

10. CONCLUSION

This study set out to explore the evolving role of analytics in organisational decision-making, moving from predictive modelling to prescriptive strategy across two critical domains: HR and marketing. By examining employee turnover and customer churn side by side, it demonstrated how analytics can illuminate risk, guide intervention, and ultimately function as a strategic capability that integrates internal workforce stability with external customer loyalty.

The findings make it clear that behavioural and engagement-oriented variables consistently outweigh demographic factors in shaping continuity. In HR, adaptability, workload flexibility, and digital proficiency emerged as the strongest predictors of turnover risk. In marketing, campaign responsiveness, loyalty participation, and channel engagement dictated customer retention. Across both contexts, predictive analytics proved its value in identifying high-risk cases, but it was prescriptive interpretation that provided the actionable levers for intervention. Random Forest emerged as the most effective modelling approach, balancing predictive strength with interpretability when supported by SHAP analysis.

The implications are significant. For scholars, the study extends theory by positioning analytics not only as a tool of prediction but as a prescriptive capability embedded within dynamic capabilities theory. It suggests that organisations do not merely forecast risks; they actively design strategies that transform risk signals into opportunities for resilience. For practitioners, the message is equally powerful: HR leaders can prescribe adaptability training and structural flexibility to retain employees, while marketers can prescribe loyalty programmes and personalised campaigns to sustain customers. Together, these prescriptions reinforce organisational continuity on both the inside and outside.

Equally important are the integrative insights. By analysing HR and marketing in tandem, the study revealed striking parallels in how human behaviour operates across domains. Whether dealing with employees or customers, the drivers of retention are rooted in adaptability, responsiveness, and engagement. This convergence suggests that analytics should not be confined to functional silos but understood as a unifying organisational capability. Leaders who recognise this integration can break down barriers between HR and marketing, fostering cross-functional collaboration that strengthens both employee experience and customer experience.

At the same time, the study acknowledges its boundaries. Its scope was limited by dataset size, cultural context, and cross-sectional design, signalling the need for future research that is larger, longitudinal, and cross-cultural. These limitations do not diminish the validity of the findings but rather point towards opportunities for refining and extending them. Future scholarship must also engage with ethical dimensions, ensuring that prescriptive analytics empowers rather than exploits, and builds trust rather than erodes it.

Ultimately, the study underscores a broader transformation: analytics is no longer a retrospective mirror nor merely a forecasting tool. It has become a compass—guiding organisations through uncertainty with prescriptions that convert insight into action. The shift from predictive to prescriptive is not just a technical evolution but a philosophical one. It reframes analytics as a strategic partner in decision-making, capable of shaping the futures of both employees and customers.

For organisations navigating an era defined by volatility and complexity, this evolution carries profound significance. Firms that embed prescriptive analytics will not only anticipate risks but design futures—strengthening resilience, sustaining loyalty, and building a competitive edge grounded in data-driven foresight. In doing so, they will affirm the central proposition of this study: analytics is no longer peripheral but central, no longer descriptive but prescriptive, no longer reactive but strategic.

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