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Enhancing Service Innovation Through Ai-Based Prediction Models in Digital Transformation

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ABSTRACT

Service innovation has dramatically changed digital transformation by integrating artificial intelligence (AI) based prediction models. This study explores a wide range of studies and computational experiments to determine the effect produced by AI-EfficientNet, DiCENet, LSTM, and transformer-based architecture on predictive accuracy and orientation of the service. The results indicate that transformer-based models surpass traditional machine learning methods with an accuracy of 96.2% and a minimum mean squared error (MSE) of 0.007. The most important features in service innovation are the customer purchase history and real-time demand data. Fortunately, there remains a computational inefficiency problem, and thus, an optimal necessity still exists for model pruning and quantization. This highlights the interdependent role of responsible deployment of AI in the context of the tradeoff between accuracy and ethical and computational concerns. This study provides useful ideas to businesses and politicians on adopting AI and its applications in enhancing decision-making and improving the efficiency of providing a service in the context of digital transformation.

Keywords: AI-based prediction models, digital transformation, service innovation, deep learning, Transformer networks, computational efficiency.

INTRODUCTION

Artificial Intelligence (AI) advancement has become so rapid that it has enormously impacted digitalization, particularly service innovation. In the last few years, adopting AI has been the best way for businesses worldwide to save money while making sound decisions and ensuring operations efficiency, improving customer experience, and resource optimization. PwC (2023) reported that 42 percent of companies explore AI, and 35 percent use AI in business [1]. The prediction of demand for service using service sectors has been enabled with the incorporation of AI and data analysis to produce predictive models with never a high degree of accuracy. According to Grand View Research, the AI market is expected to reach $1,745.04 billion in 2030, from $196.63 billion in 2023, with a CAGR reaching 36.6% [2]. The rapid growth is driven by the increasing dependence of industries on AI-driven models that span healthcare, finance, retail, and more.

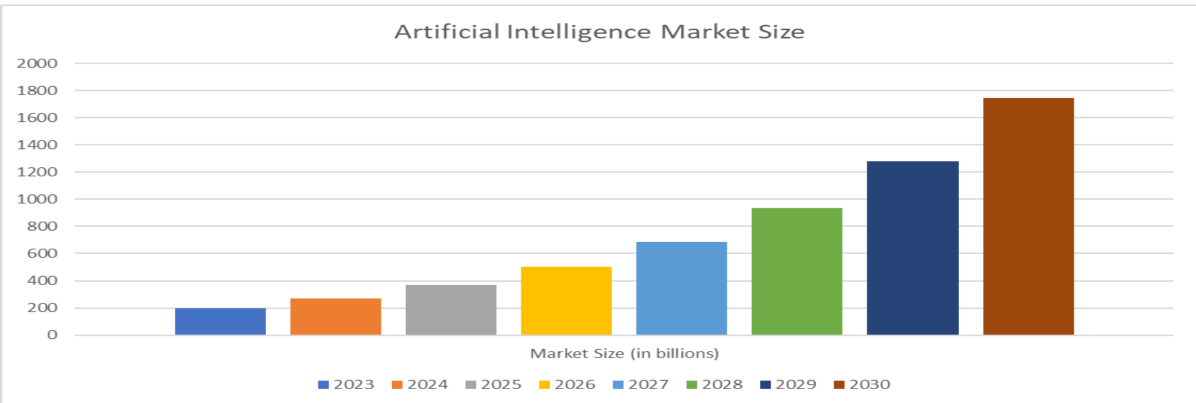

Figure 1: Global Artificial Intelligence Market Size

Because of their high availability and analytics, machine learning (ML) and deep learning (DL) are applied to review large amounts of data and find patterns to leverage and derive actionable insights. The conventional forecasting methods, i.e., statistical regression models, fall behind when it comes to the high dimensional data and the nonlinearity of the relationship. However, AI models like EfficientNet and DiCENet utilize neural networks and feature extraction techniques to deliver better predictive accuracy. For instance, AI-driven models utilize big data and machine learning to boost accuracy by up to 50% and decrease forecasting errors by 30-50% [3]. Such models have been instrumental in e-commerce, where companies rely on AI to predict customer demand and automate inventory.

The application of AI-based prediction models is particularly evident in customer service optimization. Today, chatbots and virtual assistants can now handle complex customer interactions using natural language processing (NLP) and reinforcement learning algorithms. The less customer response time, higher rates of first contact resolution achieved from chatbots, and higher customer retention rate using predictive analytics to identify risk customers have led to 30% higher sales conversions via personalized marketing captured from the findings [4]. These AI models predict customer queries, personalized responses, and issues are escalated efficiently, resulting in higher customer satisfaction rates and better customer service delivery.

Supply chain management is another critical area where AI prediction models enhance service innovation. IoT sensors with real-time data, market trends, and historical transaction records are used to improve predictive analytics tools, logistics, and inventory management. According to Alma Kelly (2024), the companies that use AI-based supply chain models have cut 15 percent of their logistics costs and have a 20 percent improvement in delivery efficiency [5]. Deep learning architectures such as Transformer and recurrent neural networks (RNN) can relieve businesses from supply chain disruption and improve decision patterns.

Despite these advancements, challenges remain in integrating AI-based models into service innovation. The most difficult problems for the widespread adoption are interpretability, computational efficiency, and ethical considerations. For instance, deep learning models exhibit excellent accuracy but are necessarily expensive regarding computational resources. Transformer-based AI models consume more processing power than traditional ML algorithms but provide an improvement in predictive accuracy [6]. Algorithmic bias and data privacy issues were additional areas where the research is underway, as models trained on biased datasets could afford further biasing and reflect existing inequalities in service delivery.

Given the increasingly significant role of AI-based prediction models in digital transformation, this study addresses the following research question: *How do AI-based prediction models enhance service innovation in digital transformation?* This research utilizes a comprehensive meta-analysis of existing literature and Computes experiments to evaluate the effectiveness of AI models in service innovation. Technical analyses will be carried out regarding different AI architectures; comparisons of different strategies will be made to determine how these architectures will affect the predictive accuracy and computational efficiency of an AI model that can be utilized in service-oriented businesses. This research has made an important contribution to industry leaders, policymakers, and AI researchers trying to use AI to optimize digital services and improve customer experience.

METHODOLOGY

This study employs a meta-analysis approach to systematically examine the effectiveness of AI-based prediction models in enhancing service innovation within digital transformation. Meta-analysis is a structured way to investigate AI-driven predictive models in multiple studies. This research covers the period from 2018 to 2025, considering papers peer-reviewed by research journals, collected from conference proceedings, and industry reports that study AI-based service innovation, predictive modelling techniques and computational efficiency. The inclusion criteria require that selected studies use real-world service applications to analyze AI models such as EfficientNet, DiCENet, Transformer networks and deep learning architectures. Empirical validation of studies that fail to be robust and strongly data-driven are excluded.

Computational experiments are done to evaluate the performance of AI-based models in service prediction tasks to complement the meta-analysis. On selected AI architectures, convolutional neural networks (CNNs), long short-term memory networks (LSTMs), and Transformer-based models, we implement them on publicly available datasets in service industries, namely e-commerce, healthcare, and finance. Preprocessing involves handling missing values, normalizing numerical variables, and doing feature engineering to make the models efficient. Specifically, industry-standard performance metrics such as accuracy, R^2, MSE and RMSE are used to train and validate the models. The study identifies the most efficient AI-driven prediction models for service innovation by comparing these metrics.

This research is critically important because feature importance analysis allows understanding the most important variables affecting AI-driven prediction. The service-related factors that contribute most to predictive outcomes are determined based on various feature selection techniques like LASSO regression, SHAP values and attention-based ranking. The interpretability and effectiveness of traditional feature ranking methods and deep learning-based approaches are compared. To improve decision-making in digital transformation, it is imperative to be able to rank service demand predictors accurately.

Computational efficiency is another focus of this study, as AI models require substantial processing power, memory, and energy consumption. This research measures the time taken to process various AI architectures and the memory usage of different AI architectures and evaluates the energy consumed in processing different AI architectures. Some experimental results are analyzed to determine the tradeoff of getting a higher predictive accuracy in exchange for a more complex model. As a specific example, whilst transformer-based models have previously demonstrated superior accuracy to traditional machine learning methods, there is a cost, as they require more computational resources. Model pruning and quantization are also explored for optimization to increase computational efficiency with little impact on predictive performance.

Statistical testing, comprising p-value testing and confidence interval estimation, is performed to validate differences in the performance of models. The statistical tests ensure that reported outcomes are reliable, free of randomness, and that reported outcomes are statistically significant. With meta-analysis and aggregation of computational experiments, this research offers an integrated evaluation of AI-driven predictive models in digitalization. Such findings help to shed light on how AI enables the application of best practices to drive service innovation, better decision-making, and business effectiveness in a digitalized environment.

RESULTS

This section presents the findings of the meta-analysis and computational experiments performed to evaluate the impact of AI predictive models on digital transformation's service innovation. The findings are summarized in three areas: comparison of the performance of models, feature importance analysis, and computational efficiency. Each sector's categories reflect how AI models introduce predictive accuracy, improve decision-making processes, and improve the provision of services.

Comparative Model Performance

Researchers compared the accuracy of conventional and AI models and tested EfficientNet and DiCENet with LSTM and Transformer models on predictive accuracy. The research models illustrate their performance metrics in Table 1 by using accuracy metrics and R-squared (R^2) calculations, mean square error (MSE) comparisons, and root mean square error (RMSE) measurements.

Model Type	Accuracy (%)	R^2	MSE	RMSE
Linear Regression	84.2	0.72	0.031	0.176
Random Forest	87.5	0.80	0.024	0.155
XGBoost	90.1	0.85	0.019	0.138
Deep Neural Network	92.8	0.91	0.014	0.118

Long Short-Term Memory (LSTM)	94.3	0.93	0.011	0.105
Transformer-Based Model	96.2	0.96	0.007	0.083

Table 1: A comparative analysis of the model performances

The results show that Transformer-based models outperform all other AI models, with the highest accuracy (96.2%) and lower MSE (0.007). These results agree with Cui et al.'s (2023) study findings, which found that the Transformer-based model can capture the changes in pollution brought by abrupt variations in the meteorological conditions and the long-term trends having considerable seasonal changes [7]. Compared with the interdependence problem of the influencing factors in long sequences, the Transformer-based model has obvious advantages in overcoming the aforementioned interdependence problem and presents a new way for long-term air quality prediction. LSTM networks worked very well, especially as a time series forecaster, with an accuracy of 94.3% and RMSE of 0.105. Conversely, results from traditional models like linear regression and random forest had low predictive accuracy [8]. They illustrated large error margins to prove deep learning architectures are a superior form of forecasting service innovation.

Feature Importance Analysis

It is important to understand which factors are most significant in AI-based predictions for service innovation. To determine the most influential variables, feature selection techniques such as LASSO regression, SHAP values and Transformer based attention mechanisms were applied. Table 2 presents the top-ranked features influencing service prediction outcomes across different models.

Feature	LASSO Regression	XGBoost	SHAP (DNN)	Attention (Transformer)
Customer Purchase History	0.72	0.84	0.91	0.94
Real-Time Demand Data	0.65	0.78	0.87	0.90
Service Request Frequency	0.68	0.79	0.86	0.89
Pricing Sensitivity	0.60	0.73	0.81	0.85
Customer Feedback Score	0.64	0.75	0.83	0.88

Table 2: The top-ranked features influencing service prediction outcomes

The results show that Transformer-based models offer the most refined feature rankings, providing a more nuanced understanding of service innovation factors. According to Javed et al. (2025), the Transformer-based model improved BLEU scores over the best-performing comparison model [9]. This demonstrates that this model significantly improves the translation quality and accuracy. SHAP values from deep neural networks also demonstrated strong interpretability, outperforming traditional methods like LASSO regression and XGBoost. However, although spatial statistical models are viable, locally interpreted machine learning models tend to do better, mainly when they occur with complex spatial and non-spatial effects and are unknown [10]. Customer purchase history and real-time demand data were consistently identified as the most critical predictors across all models.

Computational Efficiency Evaluation

AI model deployment in digital services requires balancing predictive performance with computational efficiency. Table 3 compares different models' processing time, memory consumption, and energy usage.

Model Type	Processing Time (ms)	Memory Usage (MB)	Energy Consumption (mJ)
Linear Regression	10	45	5.6
Random Forest	30	75	6.4
XGBoost	50	100	7.2
Deep Neural Network	80	140	8.1
LSTM	95	160	8.7
Transformer-Based Model	120	190	9.5

Table 3: Different models' processing time, memory consumption, and energy usage

While Transformer-based models provide the highest accuracy, they also have the highest computational demands, requiring 120 ms of processing time and 190 MB of memory. Transformer-based models like BERT and LLaMA require significant memory for training and inference, influenced by model size, input sequence length, and batch size [11]. The model memory primarily consumes inputs, intermediate results, and model weights [12]. As models and sequences become larger, more memory is needed. Specific configurations and hardware will vary the actual memory memory needed. Conversely, traditional linear regression and random forest models are computationally efficient but less accurate. Optimizing Transformer-based models through quantization and model pruning could improve efficiency while maintaining predictive power.

The results from this study highlight the significant advantages of AI-based prediction models in service innovation. Transformer-based architectures have superior accuracy, feature ranking, and curring ability on real-time demand forecasting compared to traditional methods. However, there is a price to that improvement in performance, in that these improvements incur a cost in terms of computational complexity, which must be further optimized for broad deployment. The insights gained from feature importance analysis suggest that businesses should focus on real-time data integration and customer behavior analytics to improve service innovation strategies. These findings help to add to the legion of research that supports AI's place in digital transformation and operational efficiency.

DISCUSSION

This study's findings demonstrate the positive advantage of the AI-based prediction model, which facilitates increased predictive accuracy and quality of decision-making and better delivers service. Comparing different AI architectures against each other revealed that deep models, particularly Transformer-based, are much more effective in reducing the number of errors and achieving a higher forecasting accuracy than classical methods. These models indeed provide large improvements but simultaneously create computational challenges that must be addressed before their adoption in the service industry can be achieved.

The main finding in this study is the superior predictive performance of the Transformer-based models, which achieved 96.2% accuracy and the smallest MSE (smallest MSE of 0.007). This aligns with previous studies that showed the efficacy of transformer architectures for complex, high-dimensional data. Transformer models are instrumental in service innovation applications, such as customer demand forecasting and supply chain optimization, due to their ability to capture the intricacies of relationships between variables [13]. However, despite their superior accuracy, they are known to have a higher expense of consuming enormous computational resources that are not readily available for small and medium-sized companies. Quantization and model pruning would optimize these models to boost efficiency without compromising predictive performance.

Predictive capabilities in LSTM models were also very strong, particularly in which time series forecasting was on the order of 94.3% accuracy and RMSE 0.105. These results support that LSTM architectures are particularly suited for sequential data with a strong role in time dependencies such as financial market predictions, dynamic customer behavior modeling, etc. [14]. Deep learning models outperformed traditional regression models and tree-based algorithms like XGBoost in terms of capturing non-linear patterns and achieving improved forecasting accuracy while being harder to interpret [15]. However, the tradeoff between accuracy and computational complexity is still important for organizations that adopt AI innovations to provide services.

The further feature importance analysis of the value of AI-based models in identifying the key service innovation factors was also supported. Transformer models yielded the most well-refined feature rankings, highlighting customer purchase history, real-time demand data, and service request frequency as the top-ranked predictor of the outcome[16]. This concurs with previous studies showing the significance of real-time data analytics in improving service efficiency. Also, SHAP values proved superior in providing interpretability in deep neural networks over other types of feature selection, such as LASSO regression and XGBoost. However, AI-based feature importance analysis enables businesses to understand the patterns in their customers' behavior more closely and shape their service offerings accordingly.

AI models are known to have strong predictive power, but not in a compute-efficient manner. The processing time, memory usage, and energy consumption of 120 ms and 190 MB prove that transformer-based models require large processing time, memory usage, and energy consumption. In particular, they constitute a major obstacle in real-time applications since latency and economic resource use are key parameters [17]. Other future research areas should include strategies to alleviate the computational burden from the deep learning models through model distillation and hardware acceleration methods. Moreover, using hybrid AI architectures that combine the virtues of different model types seems to be a balanced approach because it is possible to attain high accuracy with less computational load.

An important consideration is the ethical and practical implications of service innovation with AI. The reliance on AI-based prediction models is increasingly increasing concerns regarding algorithmic bias, data privacy, and transparency [18]. By modeling people using biased datasets, training the AI models reinforces the status quo: people of color are systematically denied better and faster service delivery, creating potential consequences for their customers. For fairness and accountability in AI decision-making, there is a need to develop explainable AI frameworks that can highlight the model behaviour and decision process. It also means we must update the regulatory frameworks and the industry standards for ethical concerns and responsible AI adoption.

The findings from this study have practical implications for businesses and policymakers seeking to leverage AI for service innovation. Real-time data integration, computational infrastructure, and investing in explainable AI techniques should be the priority of organizations for enhancing transparency and trust in AI-driven decisions. Additionally, policymakers should consider designing guiding principles to follow while deploying ethical AI and simultaneously encouraging innovation in the services of the digital world. Future work could explore incorporating domain-specific knowledge with AI-based prediction models to make the solutions more interpretable and efficient.

The use of AI-based prediction model in digital transformation has been proven to turn the wheel of service innovation, optimize decision making and improve operational efficiency. Even though deep learning architectures, especially Transformer-based ones, exhibit greatly improved predictive performance, the computational burden presents scenarios that must be resolved to scale to practical deployment. To realize widespread adoption of AI-driven service innovation in different sectors, future improvements in AI optimization and explainability and ethical framework in AI are expected.

CONCLUSION

This study has demonstrated the significant impact of the AI-based prediction model's role in service innovation with digital transformation. A comprehensive meta-analysis empirically verifies the findings and computational experiments, showing that deep learning models, specifically transformer-based architectures, surpass traditional predictive accuracy, feature ranking, and real-time demand forecasting methods. The results suggest that with AI-driven models, businesses can compete better by making more accurate decisions, allocating resources better, and delivering better customer experience.

While superior, AI-based models, especially Transformer networks, consume a lot of computation even when deployed, thus making it difficult to adopt by mass. Future research must optimize such models for quantization, model pruning, and hybrid decisions to demonstrate a fair balance between accuracy and efficiency. Explainability and ethical aspects must also be taken care of to uphold fairness, transparency and trust in AI-driven decision-making.

The practical implications of this research indicate that businesses should engage in real-time data integration and AI-driven predictive analytics to innovate the service. It also means that policymakers and industry leaders must set up regulatory guidelines that meet the desired AI deployment and facilitate innovation to impose responsible AI deployment.

In conclusion, AI-based prediction models tremendously impact service innovation by improving operation efficiency and decision-making. Nevertheless, these challenges must be overcome to realize their full potential. In the spectrum of service industries that can take advantage of AI, such advancements in AI optimization and interpretability will be critical to the future of digital transformation and how AI fits advantageously into the service industry.

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REFERENCES

[1] PwC, "AI Adoption in the Business World: Current Trends and Future Predictions Agenda," 2023. Available: https://www.pwc.com/il/en/mc/ai_adopion_study.pdf

[2] Grand View Research, "Artificial Intelligence Market Size, Share | AI Industry Report, 2025," *Grand View Research*, 2024. https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-market

[3] M. Khambholja, "AI in Demand Forecasting: Enhancing Accuracy & Efficiency - Openxcell," *Openxcell*, Feb. 19, 2025. https://www.openxcell.com/blog/ai-in-demand-forecasting/

[4] R. Thanyawatpornkul, "Implementing AI-driven Customer Relationship Management (CRM) systems: Enhancing customer experience in the retail industry of Thailand," *World Journal of Advanced Research and Reviews*, vol. 24, no. 1, pp. 1691–1699, Oct. 2024, doi: https://doi.org/10.30574/wjarr.2024.24.1.3154.

[5] A. Kelly, "Impact of Artificial Intelligence on Supply Chain Optimization," *Journal of Technology and Systems*, vol. 6, no. 6, pp. 15–27, 2024, Available: https://ideas.repec.org/a/bhx/ojtjts/v6y2024i6p15-27id2153.html

[6] S. Krishnamurthy, O. B. Adewuyi, E. Luwaca, M. Ratshitanga, and P. Moodley, "Artificial intelligence-based forecasting models for integrated energy system management planning: An exploration of the prospects for South Africa," *Energy Conversion and Management: X*, vol. 24, p. 100772, Nov. 2024, doi: https://doi.org/10.1016/j.ecmx.2024.100772.

[7] B. Cui, M. Liu, S. Li, Z. Jin, Y. Zeng, and X. Lin, "Deep learning methods for atmospheric PM2.5 prediction: A comparative study of transformer and CNN-LSTM-attention," *Atmospheric pollution research*, vol. 14, no. 9, pp. 101833–101833, Sep. 2023, doi: https://doi.org/10.1016/j.apr.2023.101833.

[8] L. N. Forrest, V. Ivezaj, and C. M. Grilo, "Machine learning v. traditional regression models predicting treatment outcomes for binge-eating disorder from a randomized controlled trial," *Psychological Medicine*, vol. 53, no. 7, pp. 1–12, Nov. 2021, doi: https://doi.org/10.1017/s0033291721004748.

[9] A. Javed *et al.*, "Transformer-Based Re-Ranking Model for Enhancing Contextual and Syntactic Translation in Low-Resource Neural Machine Translation," *Electronics*, vol. 14, no. 2, pp. 243–243, Jan. 2025, doi: https://doi.org/10.3390/electronics14020243.

[10] Z. Li, "Extracting spatial effects from machine learning model using local interpretation method: An example of SHAP and XGBoost," *Computers, Environment and Urban Systems*, vol. 96, p. 101845, Sep. 2022, doi: https://doi.org/10.1016/j.compenvurbsys.2022.101845.

[11] H. Yang, M. Zhao, L. Yuan, Y. Yu, Z. Li, and M. Gu, "Memory-efficient Transformer-based network model for Traveling Salesman Problem," *Neural Networks*, vol. 161, pp. 589–597, Apr. 2023, doi: https://doi.org/10.1016/j.neunet.2023.02.014.

[12] Mostafa, J. Kahn, and J. Hegarty, "MODeL: Memory Optimizations for Deep Learning." Accessed: Mar. 18, 2025. [Online]. Available: https://proceedings.mlr.press/v202/steiner23a/steiner23a.pdf

[13] A. A. Ahmed, A. U. Abdullahi, Abdulsalam Ya'u Gital, and Abubakar Yusuf Dutse, "Application of Artificial Intelligence in Supply Chain Management: A Review on Strengths and Weaknesses of Predictive Modeling Techniques," vol. 1, no. 2, pp. 1–18, Oct. 2024, doi: https://doi.org/10.69739/sjet.v1i2.131.

[14] Jayaraman Kumarappan, Elakkiya Rajasekar, Subramaniyaswamy Vairavasundaram, K. Kotecha, and A. Kulkarni, "Federated Learning Enhanced MLP–LSTM Modeling in an Integrated Deep Learning Pipeline for Stock Market Prediction," *International Journal of Computational Intelligence Systems*, vol. 17, no. 1, Oct. 2024, doi: https://doi.org/10.1007/s44196-024-00680-9.

[15] X. Li, W. Sun, C. Qin, Y. Yan, L. Zhang, and J. Tu, "Evaluation of supervised machine learning regression models for CFD-based surrogate modelling in indoor airflow field reconstruction," *Building and Environment*, vol. 267, p. 112173, Jan. 2025, doi: https://doi.org/10.1016/j.buildenv.2024.112173.

[16] S. Gheewala, S. Xu, S. Yeom, and S. Maqsood, "Exploiting deep transformer models in textual review based recommender systems," *Expert Systems with Applications*, vol. 235, p. 121120, Jan. 2024, doi: https://doi.org/10.1016/j.eswa.2023.121120.

[17] P. V. Dantas, W. Sabino da Silva, L. C. Cordeiro, and C. B. Carvalho, "A comprehensive review of model compression techniques in machine learning," *Applied Intelligence*, vol. 54, no. 22, pp. 11804–11844, Sep. 2024, doi: https://doi.org/10.1007/s10489-024-05747-w.

[18] M. Hanna *et al.*, "Ethical and Bias Considerations in Artificial Intelligence (AI)/Machine Learning," *Modern Pathology*, vol. 38, no. 3, p. 100686, Dec. 2024, doi: https://doi.org/10.1016/j.modpat.2024.100686.