Migration Letters

Volume: 21, No: S4 (2024), pp. 168-177

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)

www.migrationletters.com

E-Commerce Management And Ai Based Dynamic Pricing Revenue Optimization Strategies

Dr Vijayakumar Thota[1] , Dr. Nagalakshmi M[2] , Dr. Kiran Kumar M[3] , Dr. Sanoj Kumar[4] , Uzma Momin[5] , Dr. Prashant Mishra[6]

Abstract

Online pricing is direct and might be the primary considers a purchase. Despite the fact that pricing unpredictability is frequent and used to support sales and productivity, online firms benefit from it. Business success depends on pricing, especially in membership-based models. Albeit successful before, quickly changing market dynamics are making static pricing structures unsuitable for the present businesses and causing significant issues. Computer based intelligence has been used to improve pricing systems in response to these difficulties. Improving e-commerce pricing techniques emphasizes picking the right price over the lowest. The review focuses on inventory-led e-commerce businesses, however online marketplaces without inventory can benefit from the concept. The review uses factual and machine learning methods to anticipate item purchases utilizing adaptive or dynamic pricing. This system is based on several information sources that gather visit attributes, guest details, purchase history, online information, and contextual bits of knowledge. Interestingly, the examination forecasts customer segment purchases higher than individual consumers. Further extensions will be developed after the current research results are released to personalize adaptive pricing and purchase prediction. The review's answer landscape covers machine learning, enormous information, and web mining.

Keywords: *E-Commerce, Management, Artificial Intelligence, Dynamic Pricing, Optimization Strategies.*

1 INTRODUCTION

In the fast-paced world of contemporary business, pricing strategies have undergone significant shift, especially for subscription-based models. While traditional static pricing techniques have proven effective in the past, they today face unanticipated obstacles due to the rapid and unpredictable changes in market dynamics. Given the complexity of today's business environments, pricing strategies must be adaptable enough to change course swiftly when necessary. In response to these challeng[1]es, artificial intelligence (AI) has emerged as a major

[1]Associate Professor, NSB Business School, Bangalore University, Bangalore.
[2]Associate Professor, Schools of Arts, Humanities and Management, Jeppiaar University, Chennai
[3]Assistant Professor, Faculty of Management - Finance, CMS Business School JAIN (Deemed-to-be) UNIVERSITY, Bengaluru, 560009
[4]Director, Department of Management Studies, Pramod Ram Ujagar Tiwari Saket Institute of Management (PRUTSIM), Taluka-Kalyan, Thane, Maharashtra.
[5]Assistant Professor, Department of Commerce, Swayam Siddhi Degree Night College, Thane, Maharashtra.
[6]Assistant Professor, Department of Management Studies, Pramod Ram Ujagar Tiwari Saket Institute of Management (PRUTSIM), Taluka- Kalyan, Thane, Maharashtra.

trend that is transforming how businesses approach pricing. Pricing for subscription-based businesses is very complex. Subscription services are widely available in today's economy and can be found in a variety of industries, including software, streaming media, and e-commerce. The tricky element is figuring up a subscription rate balance that maximises revenue while providing value to customers. It necessitates a deep understanding of market dynamics and consumer behaviour in addition to the adaptability to change with the times. Dynamic pricing is a tactic used by industry leaders like Amazon and Airbnb to modify their pricing strategies in reaction to consumer and market data. By maximising value, this tactic aims to boost profitability while also drawing in a larger customer base. While traditional dynamic pricing models rely on historical data to determine optimal prices, modern dynamic pricing algorithms leverage an even richer dataset in addition to the capabilities of artificial intelligence and machine learning to achieve optimised dynamic pricing and more accurate market trend forecasting. AI-driven dynamic pricing is spearheading this revolution in pricing and is changing the game. By using machine learning algorithms and data analysis to determine the appropriate price for subscription features in real-time, it solves the shortcomings of static pricing systems. Organisations are provided with a valuable tool to navigate the complexities of the modern marketplace by this strategy, which can swiftly adapt to changing market dynamics and consumer preferences.

By utilising these technologies, stores may enhance consumer satisfaction and ensure long-term success in data-driven retail, all while competing in a more cutthroat market. Reduced call costs, increased competition, and improved network infrastructure are the reasons for the impact on the mobile communication sector. Improved coordination between inventory decisions and manufacturing processes improves the automotive industry, leading to a direct-to-consumer business model. Because of increased network connectivity, dynamic pricing is growing in popularity. By lowering menu prices and offering a thorough database of client data, this has helped vendors as well as customers. Customers and purchasers can now self-serve online, saving them time. Suppliers gain from dynamic pricing in a number of ways by combining automation and internet connectivity. Input costs are decreased, customer data is combined into a single database, the vendor's physical presence is removed, and new catalogues can be printed for less money. It likewise gives buyers and vendors a place to examine and exchange reviews, which leads to better services.

Numerous industries utilize dynamic pricing extensively to enhance the trading processes. Numerous businesses, including airlines, hotels, electric utilities, retail, internet shopping, mobile phone systems, automobiles, games, vehicle rentals, and insurance, have made progress with dynamic pricing. In the aviation industry, flexible pricing is frequently referred to as yield or revenue control. The methodology involves the division of travellers into three groups: business, leisure, and hybrid travellers. Dynamic pricing is used in the automotive sector to enhance supply chain management and profitability by combining production plans with inventory selections. Further advantages of dynamic pricing include enhanced customer demand presentation and equipment manufacturer status.

1.1 Dynamic Pricing Driven by AI

AI-driven dynamic pricing refers to the process of using machine learning algorithms and data analysis to decide the best price for features of subscription-based products at any given time. This strategy surpasses traditional pricing strategies, which are frequently static and predicated on predetermined tiers or subscription durations. With the use of AI-driven dynamic pricing, which adjusts to real-time data, companies can establish subscription feature costs that precisely reflect consumer behaviour and market conditions. The impact of pricing and packaging tactics in the dynamic pricing space goes beyond cloud-based applications and affects how companies adjust their pricing structures in response to shifting consumer preferences and market situations.

1.2 AI's Place in Dynamic Pricing

Artificial intelligence (AI), especially when applied to machine learning algorithms, has exceptional powers that make it essential for e-commerce pricing optimisation.

- **Pattern Recognition:** AI systems are able to find intricate patterns in large datasets, providing important new information on consumer behaviour, industry trends, and demand swings.
- **Continuous Learning:** As a result of machine learning models' ability to adapt and learn from new data, pricing strategies are able to change as market conditions do.
- **Predictive Analytics:** By predicting future demand, AI can assist you in proactively modifying prices to satisfy client demands and revenue targets.
- **Automation:** AI-driven dynamic pricing gives you a competitive edge by enabling you to react to market developments in real time. It is automated and can run around the clock.

2 LITERATURE REVIEW

Shah et al., (2020) outlined how various businesses are pursuing the integration of technological applications into their operations at the same time that technical advancements and innovations take shape in the modern world. By generating more money, this strategy aims to increase the company's income and maintain its viability in the face of shifting technology dynamics. The most promising applications in the contemporary corporate environment are machine learning (ML) and artificial intelligence (AI) characteristics because of their adaptability to the optimisation and improvement of product pricing and revenue management strategies.

Weber & Schütte, (2019) explained any organization's revenue management strategy is built on dynamic pricing. Price adjustments are made in accordance with the current conditions, which include market competitiveness and real-time demand. Artificial Intelligence (AI)-powered machine learning technologies facilitate the development of algorithms that are critical to the generation of large amounts of data and enable businesses to react quickly to changes in the market. The organisations that have used this technology have seen a rise in revenue production as a result of these modifications that help assure price optimisation.

Bakakeu et al., (2018) Due to the evolving nature of human behaviour, research on the business landscape has revolutionised, leading to an unparalleled level of dynamism. On the other hand, as a result of technological progress, people's behaviour is changing quickly as they discover new and inventive items that are offered by diverse companies. Additionally, as technology advances and consumer behaviour changes, so do economic conditions, geopolitical developments, and advancements in technology, all of which contribute to the development of pressurised pricing models. The development of the several indispensable instruments necessary for negotiating the convergence of the numerous elements impacting pricing strategies has been aided by the advent of AI and ML. The use of technology, particularly AI-driven technologies, improves real-time data analysis and helps identify the different trends that are crucial for the illusion of human observations. In addition, compared to different traditional approaches, the technologies help the organisation impose precise and effective pricing plans.

Hofmann et al., (2017) explained that due to the enormous potential for revenue management that comes with integrating AI, it is appealing to a variety of difficulties. One of the challenges the technique confronts is the quality of the data used to train and optimise the pricing algorithms. For precise data forecasts and the best price judgements, clean, pertinent, and current data must be incorporated. Pricing techniques powered by AI help shift culture from decision-making methods to cross-functional calibration. Additionally, it guarantees that the teams continue to possess the abilities and know-how required to make effective use of AI tools.

Dash & Gatharia, (2015) analysed to fully utilise product demand prediction, AI and ML must be optimised and integrated. Neural networks are an excellent example of how machine learning (ML) works well when used to the study of historical data in conjunction with other influencing variables. This improves the accuracy of future demand estimates. Furthermore, this strategy is crucial for helping businesses adjust to shifting market trends, which affects their overall viability in the face of shifting market dynamics. Additionally, in contemporary businesses, ML and AI analyse future market projections using historical data. As a result, the forecast has an impact on the marketing standards used in company.

Das et al., (2015) focused on the key improvements in revenue generating performance metrics have resulted from the implementation of AI dynamic pricing algorithms that rely on AI and ML. The creation of revenue has increased significantly, surpassing the predictions provided by conventional pricing methods. As a result, the pricing strategies have demonstrated how well the AI techniques optimise the pricing structures. AI and ML are revolutionising revenue management since the new pricing model has enhanced client acquisition and dynamic pricing in relation to the target market segments. In the e-commerce space, the cutting-edge online retailer uses AI-driven dynamic pricing to adjust to the current state of the market. During the deployment phase, the strategy showed a 30% increase in revenue, illustrating the direct effects of AI-driven tactics to improve revenue production for businesses.

3 RESEARCH METHODOLOGY

The suggested model considers the mix of three particular approaches: determining the client segments, determining the right price for them, and projecting the likelihood that they will make a purchase inside that price range. In Figure 1, the framework is displayed.

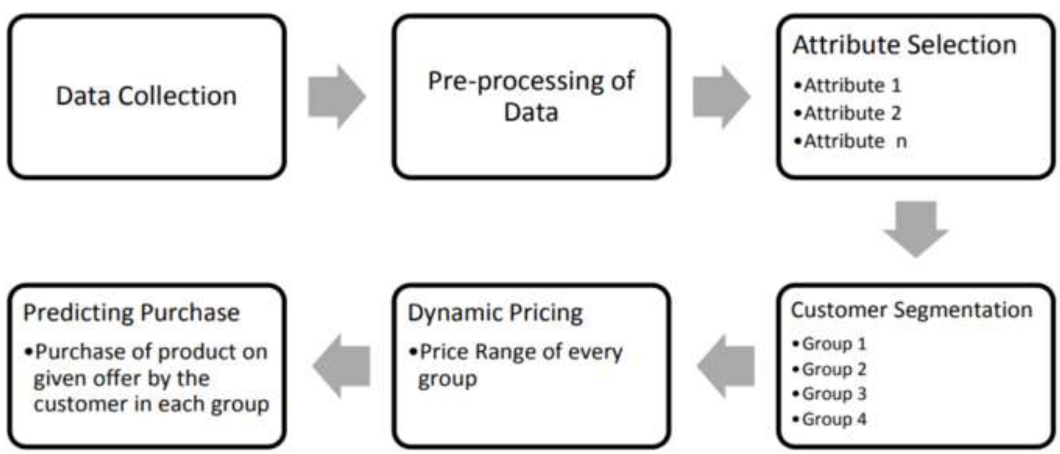

Figure 1: The suggested methodology predicts online client purchases using Dynamic Pricing.

3.1 Data Collection

The first and most significant step in the framework process is the collection of information from numerous information sources combined into a single integrated database. We used a piece of the information from an online marketplace for our review. The schemas of the two datasets used in the review are displayed in Table 1.

Table 1: The primary schema is associated with the exchange database, which holds the customer's all's exchange records, and the second schema is associated with the offer database, which records different price reduction offers for different items, categories, and businesses.

CUSTOMER ID	**Offer ID**
• Store Chain • Store Department • Item Category • Item Organization • Item Brand • Purchase Date • Item Size • Item Measures • Purchase Amount • Purchase Sum	• Item Category • Item Amount • Item Organization • Offer/price Value • Item Brand

Categorical information for some variables made up most of the exchange database, with different IDs corresponding to aspects like client, chain, department, category, firm, brand, size, and measure. Interestingly, the sum and amount of purchases were viewed as persistent variables in this dataset. Similar to this, only the offer value and product quantity in the offers database were continuous; all other variables were categorical. 350 million transactions totalling about 2.4 million unique clients were recorded in the database. Customers who were provided and took advantage of promotions were the subject of our analysis, yielding a dataset consisting

3.2 Pre-Processing Data

Processing every one of the collected information as indicated by the fact that it is so relevant to the price prediction is what this step entails. Pre-processing is additionally necessary to organize information sheets for specific logical projects, for example, Excel, SAS, and R, that were utilized in the review. To improve the information's meaning, extra variables were added because it wasn't initially ceaseless. Purchase by offer (POR), purchase by category (PCT), purchase by amount (PQT), purchase by organization (PCY), purchase by brand (PBD), and purchase by channel (PCN) are some of the derived variables. These variables were calculated by adding up to the number of offers, categories, sums, companies, brands, and channels that were taken into consideration for the client's purchased items, as well as by aggregating the aggregate sum of purchases made by that specific consumer. The two respective sums were divided to get the last values. Outliers were removed, and the information was combined for a number of scientific procedures to guarantee information precision.

3.3 Selection of Attributes

Choosing the right criteria at this stage is essential to carrying out client segmentation. Several attributes from the chosen data should be used for a new client, including visit attributes, demographic profiles, context, past purchases, and buy intentions. But the current study only looks at repeat clients who were picked to give a particular scenario for the project. The fundamental variables considered while investigating repeat consumers are POR, PCT, PQT, PCY, PBD, PCN, purchase sum, and purchase amount. These features are used to find commonalities across different clients, making it easier to order people that share comparative attributes.

3.4 Client Division

Customer grouping is accomplished by using a few chosen attributes and the K-means clustering method to determine user similarities. The clusters that were produced are shown in Tables 1 and 2. 83% is found to be the overall coefficient of variation, which captures a sizable amount of the dataset.

Table 2: For the different customers, clusters emerged.

Variables	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Frequency	5050	223450	86900	94570
RMS- SD	1.35	0.42	0.62	0.95
Variable 1 – PQR	1.36	0.35	0.45	0.94
Variable 2 – PCT	1.58	0.25	0.60	0.78
Variable 3 - PQT	1.22	0.57	2.90	1.35
Variable 4 – PCY	1.48	0.22	1.20	1.10
Variable 5 – PBD	1.97	0.15	0.20	2.15
Variable 6	2.20	0.13	0.15	0.45

3.5 Adjustable Prices

The dynamic price range for every customer segment is determined by using the specified client segments. Using a combination of statistical and machine learning methods, dynamic pricing determines the right price range for each section. It turns out that supervised learning works better, using historical data to provide more precise results. It is advantageous to allocate certain pricing ranges to various segments since this enables a more focused strategy that is adapted to the particular traits of each segment. Here is the expression for the regression equation created for the cluster.

β = PORi+ PCTi+PQTi+PCYi+PBDi+PCNi Di + β6PCNi

where P's are the independent variables and slope coefficients for each cluster, and Pi is the price of the cluster. The customer's buying power is used to depict the price range for each cluster, creating unique pricing ranges for each cluster. Using previous information, the purchasing power of a customer is determined when they make a repeat purchase from the store. They are then placed into a certain cluster based on their spending and buying habits. Based on the cluster, predictions are formed about their price range, and a customer offer value is established. Table 2 displays the purchasing power variable-based regression results for the four clusters. The resulting price range is validated by the large general variation within the clusters. These models are used to calculate the price range for each particular customer.

Table 3: Regression analysis findings for individual cluster price prediction

Constant	0.04220*	0.045*	0.0320*	0.0250*

Variable 1 – PQR	0.0672*	0.025*	0.04370	0.04260*
Variable 2 – PCT	0.423795*	0.255*	0.26882*	0.16328*
Variable 3 – PQT	0.202210	0.245*	0.2570*	0.3455*
Variable 4 – PCY	0.439665*	0.155	0.28220*	0.42870*
Variable 5 – PBD	0.315870*	0.105*	0.2120	0.2750*
Variable 6 – PCN	3.137065*	0.895*	1.21370	1.43747
R-Square	0.75	0.85	0.80	0.90
Price Range	$400- 400	$1000-1500	$2000-4000	$20000-25000

3.6 Modelling Predictively

This stage uses Strategic Regression to predict a client's propensity to purchase or not, given a target price range and an appropriate consumer segment identified through dynamic pricing approach. Picking a twofold predictor is consistent with the above worldview and helps determine the customer's last buying behaviour. Utilizing the dataset, the results of the strategic regression were calculated, considering the buying power and price prediction from multiple regression. A preparation set and a test set were created from the complete dataset in a 4:1 proportion.

4 DATA ANALYSIS AND RESULTS

The system designed for price prediction is examined for purchase forecasts and the possible income gains. Our suggested model shows a more efficient revenue generation system with less mistakes in expecting client purchases when compared to a circumstance where the same item is given at a set price for a specific customer bunch. The results are shown in Figure 2. This approach is quite good at predicting the purchasing behaviour of customers. Supervised learning will get more accurate with time as more data is gathered, which will help with more accurate purchasing behaviour predictions.

Table 4: Skilled at correctly predicting the purchasing habits of customers

	Percentage increase	**Error in Purchase**	**Error in purchase price**	**RMSE**
Cluster 1	0.16	0.15	0.19	0.0
Cluster 2	0.2	0.29	0.15	0.1
Cluster 3	0.1	0.20	0.16	0.2
Cluster 4	0.3	0.14	0.4	0.4

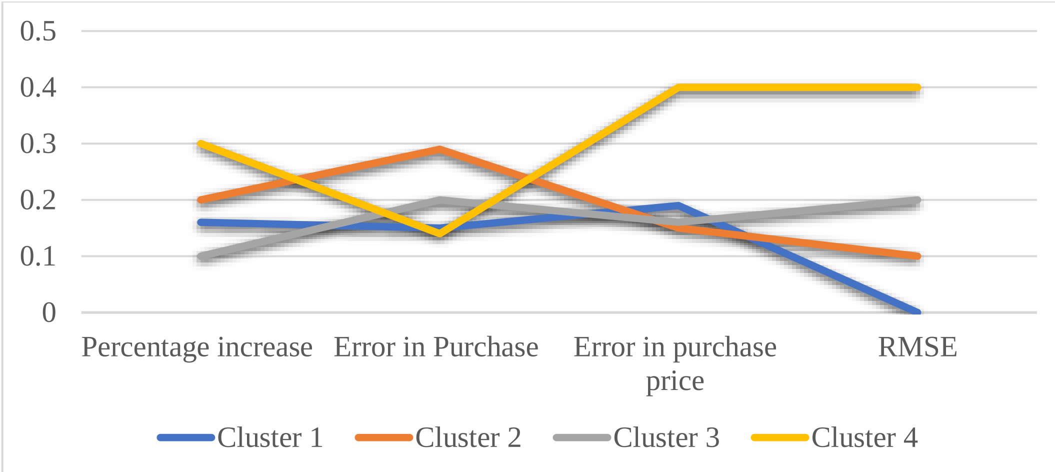

Figure 2: Skilled at correctly predicting the purchasing habits of customers

The review that is being presented presents a complete framework that uses a blend of measurable and machine learning techniques to forecast online client purchases through dynamic pricing. The relevance of personalised and adaptive pricing is highlighted by the focus on ecommerce platform optimisation of pricing methods, with a particular emphasis on choosing the best purchase price. K-means clustering integration makes it easier to segment customers by recognising discrete client groups with different buying habits. Regression equations for every client cluster provide assistance to the dynamic pricing model, which effectively produces customised price ranges. This framework's solid base is created by utilising a variety of data sources, such as visit attributes, purchase history, and contextual insights. The precision of buying decisions based on adaptive pricing strategies is improved by the integration of machine learning calculations.

4.1 Segmenting Customers

When the K-means clustering method is used, it produces unique clusters with particular purchase behaviours and significant consumer segmentation. The total coefficient of variation of 83% indicates that the clusters show high diversity. Because of this strong segmentation, pricing methods may be more precisely tailored to the distinctive qualities of certain consumer groups.

4.2 Regression Analysis Findings

Notable are the regression discoveries for each cluster when buying power factors are considered. The model's effectiveness in catching the variance in buying power based on the chosen variables is demonstrated by the coefficients and R-square values. The pricing ranges that are calculated for every cluster offer critical experiences into the correlation between the attributes of the client base and their potential spending power.

4.3 Using Logistic Regression to Forecast Purchases

The predictive power of the system is further improved by applying Calculated Regression for purchase prediction inside specified price ranges. The double predictor squeezes into the described framework easily and helps determine the last buying behaviour of the clients. The predictive precision of the model is demonstrated by the Area Under the Curve (AUC) study, which adds to the evidence supporting the efficacy of the suggested strategy.

4.4 A Comparative Analysis of Fixed Pricing

The suggested dynamic pricing model offers a better revenue generation system and less mistake in estimating consumer purchases when compared to a scenario with fixed price for particular customer groups. The results, illustrated in Figure 4, feature the possible monetary advantages and enhanced consumer targeting attained through the dynamic pricing system integrating all of this.

5 CONCLUSION

AI-powered dynamic pricing schemes for subscription features mark a dramatic change in the way companies handle price structures. Artificial intelligence and real-time data analysis enable businesses to adjust prices in response to shifting consumer needs and market conditions. Dynamic pricing is expected to play an increasingly bigger role in contemporary corporate strategies as AI technologies develop, especially in the subscription economy. This entails using dynamic pricing to establish a reasonable price range for clients. This study concludes by presenting a comprehensive framework that uses a mix of measurable and machine learning techniques to forecast online client purchases through dynamic pricing. The significance of personalized and adaptive pricing is highlighted by the emphasis on enhancing pricing strategies on ecommerce stages, with an attention on picking the most suited purchase price rather than the very cheapest. K-means clustering is used to help with consumer segmentation by recognising discrete client groups with different purchase patterns. The dynamic pricing model creates customised price ranges with the help of regression models for every cluster, enabling more accurate targeting. By forecasting consumer purchases within these personalised price ranges, logistic regression strengthens the framework even more and adds to a more complex knowledge of consumer behaviour. Examining dynamic pricing techniques in real-time, especially when the market is changing quickly, could improve the framework's effectiveness. Increasing the range of data sources beyond the variables that are now used could yield a more thorough picture of consumer behaviour. The adaptability of the suggested framework would be enhanced by an evaluation of its applicability across various industries and sectors. Lastly, as dynamic pricing changes to adapt to changing consumer landscapes, ethical factors including fairness, transparency, and customer trust deserve more investigation. Essentially, this framework anticipates the creation of more advanced models and approaches that are in step with the ever-changing landscape of online consumer behaviour and e-commerce, thereby providing a strong basis for future research endeavours.

REFERENCES

1. Antonopoulos, I., Robu, V., Couraud, B., Kirli, D., Norbu, S., Kiprakis, A., Flynn, D., ElizondoGonzalez, S., & Wattam, S. (2020). A systematic review of Artificial Intelligence and machine learning approaches to energy demand-side response.
2. Bakakeu, J., Tolksdorf, S., Bauer, J., Klos, H.-H., Peschke, J., Fehrle, A., Eberlein, W., Bürner, J., Brossog, M., Jahn, L., & Franke, J. (2018). An artificial intelligence approach for online optimization of flexible manufacturing systems. Applied Mechanics and Materials,
3. Brunato, M., & Battiti, R. (2020). Combining intelligent heuristics with simulators in hotel revenue management. Annals of Mathematics and Artificial Intelligence,
4. Calvano, E., Calzolari, G., Denicolò, V., & Pastorello, S. (2020). Artificial Intelligence, algorithmic pricing, and collusion. American Economic Review
5. Das, S., Dey, A., Pal, A., & Roy, N. (2015). Applications of Artificial Intelligence in Machine Learning: Review and prospect. International Journal of Computer Applications,
6. Dash, B., & Gatharia, J. (2015). Impact of Digital Transformation on Organizational Behaviors.
7. Neha Sharma, P. William, Kushagra Kulshreshtha, Gunjan Sharma, Bhadrappa Haralayya, Yogesh Chauhan, Anurag Shrivastava, "Human Resource Management Model with ICT Architecture: Solution of Management & Understanding of Psychology of Human Resources and Corporate Social Responsibility", JRTDD, vol. 6, no. 9s(2), pp. 219–230, Aug. 2023.

8. K. Maheswari, P. William, Gunjan Sharma, Firas Tayseer Mohammad Ayasrah, Ahmad Y. A. Bani Ahmad, Gowtham Ramkumar, Anurag Shrivastava, “Enterprise Human Resource Management Model by Artificial Intelligence to Get Befitted in Psychology of Consumers Towards Digital Technology”, JRTDD, vol. 6, no. 10s(2), pp. 209–220, Sep. 2023.
9. Anurag Shrivastava, S. J. Suji Prasad, Ajay Reddy Yeruva, P. Mani, Pooja Nagpal & Abhay Chaturvedi (2023): IoT Based RFID Attendance Monitoring System of Students using Arduino ESP8266 & Adafruit.io on Defined Area, Cybernetics and Systems..
10. P. William, G. R. Lanke, V. N. R. Inukollu, P. Singh, A. Shrivastava and R. Kumar, "Framework for Design and Implementation of Chat Support System using Natural Language Processing," 2023 4th International Conference on Intelligent Engineering and Management (ICIEM), London, United Kingdom, 2023, pp. 1-7, doi: 10.1109/ICIEM59379.2023.10166939.
11. Dash, B., Sharma, P., & Ansari, M. F. (2018). A Data-Driven AI Framework to Improve Urban Mobility and Traffic Congestion in Smart Cities.
12. Gerlick, J. A., & Liozu, S. M. (2020). Ethical and legal considerations of artificial Intelligence and algorithmic decision-making in personalized pricing. Journal of Revenue and Pricing Management,
13. Hofmann, M., Neukart, F., & Bäck, T. (2017). Artificial intelligence and data science in the automotive industry.
14. Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial Intelligence in personalized engagement marketing. California Management Review,
15. Rana, R., & Oliveira, F. S. (2015). Dynamic pricing policies for interdependent perishable products or services using reinforcement learning. Expert Systems with Applications,
16. Shah, N., Engineer, S., Bhagat, N., Chauhan, H., & Shah, M. (2020). Research trends on the usage of machine learning and artificial intelligence in advertising. Augmented Human Research
17. Sharma, P., & Dash, B. (2020). Big Data-IoE Relationships and the Future of Smart Cities.
18. Syam, N., & Sharma, A. (2018). Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial Intelligence in sales research and practice. Industrial Marketing Management,
19. Weber, F., & Schütte, R. (2019). A domain-oriented analysis of the impact of machine learning—the case of retailing. Big Data and Cognitive Computing