Journal of Information Systems Engineering and Management
2025, 10(26s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Return Policy and Consumer Behavior: Examining Return Frequency and Patterns of Computer Products in India

[1]Bhavya N, [2]Dr N.S. Viswanath, [3]Dr Navya Gubbi Sateeshchandra, [4]Dr Deepak R, [5]Dr Samrat Ray
[1]Manipal Academy of Higher Education, Bangalore, India
naidu.bhavya@gmail.com
ORCID: https://orcid.org/0009-0005-6526-3041
Google Scholar: Bhavya Naidu
[2]Director Bhavan's Management Research Centre Manipal Academy of Higher Education Bangalore, India.
viswanathns19@gmail.com
[3]Academic Faculty, Berlin School of Business and Innovation, Berlin, Germany.
navya.gubbi@berlinsbi.com
ORCID: https://orcid.org/0009-0003-9461-9831
[4]Google Scholar :Dr.Navya Gubbi Sateeshchandra HOD, Ramaiah Institute of Technology.
[5]Dean and Head of International Relations, IIMS,Pune,s.ray@iimspune.edu.in

ARTICLE INFO

Received: 22 Dec 2024

Revised: 14 Feb 2025

Accepted: 25 Feb 2025

ABSTRACT

The rapid expansion of e-commerce in India has brought about a fundamental shift in consumer purchasing patterns, with a notable impact on the computer hardware industry. The increased access and choice have also led to a rise in product returns, as customers may not always be satisfied with their purchases or their expectations may not be fully met, posing a significant challenge for companies in the sector. The increasing prevalence of e-commerce in India has amplified product return rates, making return policies a crucial factor in shaping consumer purchase and return behavior. This study examines the return frequency of computer products in India and its relationship with return policies. Using data collected from 224 consumers in Bengaluru through a primary questionnaire, this research applies machine learning techniques—including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest, Decision Tree, Logistic Regression, and Naïve Bayes to predict return frequency based on various independent variables.

The study identifies the best-performing model for understanding return policy factors and assesses the impact of return policies on consumer purchase and return decisions. This research contributes to the growing literature on consumer return behavior in India's electronics market, offering practical insights for retailers, policymakers, and manufacturers to optimize return policies. The findings reveal that policy flexibility, return window duration, refund processing time, restocking fees, and ease of return procedures speed, and associated costs significantly influence consumer return behavior. A well-structured return policy can enhance consumer trust and satisfaction while minimizing unnecessary returns, thus benefiting both businesses and consumers.

Keywords: Return Policy, Consumer Behavior, Return Frequency, Machine Learning, Computer Products, India.

INTRODUCTION

The Indian electronics industry has faced substantial hurdles in forecasting and managing product returns for recycling, as studies have highlighted the stochastic and uncertain nature of these returns. The management of product returns has become a crucial aspect of inventory management, particularly in the Indian electronics industry. Studies have highlighted the stochastic and uncertain nature of these returns, posing challenges for forecasting and effective management.(Ambilkar et al., 2021; Blackburn et al., 2004; Griffis et al., 2012;) While consumers may return products for a variety of reasons, such as poor functionality, damage during shipment, or regret over impulsive purchases, retailers often provide lenient return policies to signal high quality and act as risk relievers for purchasing decisions (Ülkü & Gürler, 2018). Computers have become integral to modern life, serving as versatile tools that facilitate a wide range of activities, from professional tasks and productivity applications to educational purposes and online entertainment.

The unpredictable nature of product returns has posed significant obstacles for the various reverse supply chain management activities, such as repair, refurbishing, and remanufacturing, that have been examined in the context of the Indian consumer electronics industry. (Mayo et al., 2006). Researchers have attempted to categorize returned goods based on factors such as recency, usability, and residual value, and have analyzed the contribution of different return streams to the overall reverse supply chain operations. The ubiquity of computers in various facets of daily life underscores the importance of understanding the factors that shape consumer return behavior for these products, as this knowledge can inform more effective inventory management strategies and enhance operational efficiency to better meet the evolving needs and preferences of consumers in the Indian market. (Das & Chaudhari, 2015)

The existing literature provides valuable insights into the management of product returns in the Indian context. Existing research has explored the design of value recovery networks for various categories of post-consumer product returns in India, finding that while these activities are generally profitable, the economic viability of remanufacturing has not yet been established as a viable proposition (Shaharudin et al., 2015; Ülkü & Gürler, 2018). The impact of abusing return policies has also been investigated, with research highlighting the importance of understanding consumer return behavior in the context of single-period inventory models. (Ülkü & Gürler, 2018) Given the significance of computers in Indian consumers' lives, a deeper examination of the factors that influence return behavior for these products could yield crucial insights to assist retailers and manufacturers in developing more responsive and effective inventory management strategies, ultimately enhancing their ability to cater to the evolving needs and preferences of the Indian market. While there is limited research on the specific influence of return policies on consumer purchase decisions for computer products in India, this is an area that warrants further investigation. (Ariffin et al., 2018; Chen & Ma, 2020; Fan et al., 2013; Jatav & Gupta, 2020; Pei et al., 2014; Rokonuzzaman et al., 2020; Xu et al., 2014)

A study on the management of product returns highlighted the growing importance of reverse logistics in the era of e-commerce, where product returns have become a common occurrence. According to the authors, as the e-commerce sector continues to grow in India, understanding the relationship between the purpose of computer usage and product returns is crucial for optimizing reverse logistics processes. (2006) (Das et al., 2020; Frei et al., 2020; Jatav & Gupta, 2020; Ren et al., 2020; Wang et al., 2021)

The widespread adoption of computers in various aspects of life, from professional tasks to educational activities, has further emphasized the need to understand the factors that drive consumer purchase decisions. Moreover, the availability of a wide range of computer products, coupled with increasingly flexible return policies, has contributed to a rise in impulse purchases, which are closely linked to higher rates of product returns. (Iyer et al., 2019; Kumar & Kaur, 2018; Ülkü et al., 2013) Existing research has also revealed that dissatisfaction due to unmet expectations is a primary reason for product returns, particularly in industries where visual representations play a significant role in the purchasing process, such as electronics (Mayo et al., 2006) The present literature review aims to provide an in-depth understanding of consumer return patterns for computer products in India, with a particular focus on the role of return policies in purchase decisions.

To address the research objectives, this study employed a quantitative research approach, wherein primary data was collected through a structured questionnaire distributed to 223 customers in Bengaluru, India. The data was then analyzed using various statistical and Machine Learning techniques, including Random Forest, K-nearest Neighbors, Logistic Regression, and Support Vector Machines were assessed to identify the best-performing model for predicting purchase decision factors and computer hardware product returns by consumers.

The following objectives were considered in the study namely:

1. Predicting "Return Frequency" based on a variety of independent variables
2. To identify the best-performing model for return policy factors.
3. To examine the impact of return policies on consumer purchase and return decisions for computer products in the Indian market.

Thus, the hypothesis of the study was to come up with a classification model which would help in prediction of best models obtained in return policies. Thus, we tested the following hypothesis:

Null Hypothesis (H_0): The independent variables do not have a significant impact on Return Frequency and

Alternative Hypothesis (H_1): At least one independent variable has a significant impact on Return Frequency

RESEARCH SCOPE AND IMPLICATION

Businesses can utilize the insights from this model to identify key drivers of product returns and address them strategically. For instance, improving return policies, customer support, or product specifications could potentially reduce return rates. The study helps in optimizing return policies to reduce return rates while maintaining customer satisfaction. Retailers can refining post-purchase support, warranty services, and exchange policies to reduce unnecessary returns. The study Provides insights into consumer return behavior, enabling better inventory and logistics management. The study further helps to assists in developing strategies and insights into patterns of returns to minimize fraudulent or unnecessary returns.

For computer product manufacturers the study offers data-driven insights into product defects, usability concerns, and customer dissatisfaction factors leading to returns. Also Encourages improvements in product design, quality control, and after-sales support to reduce return frequency and highlights the need for clear product specifications, description, feature disclosures, and enhanced customer education to manage expectations.

For policymakers and regulators the study Supports the development of uniform return frameworks across online and offline retailers to protect both businesses and consumers. Helps policymakers design awareness campaigns on responsible return practices to reduce unnecessary product returns. Provides empirical evidence to guide the formulation of consumer protection laws and establishment of standardized return policies in India's electronics market. And for the consumers the study encourages responsible purchasing behavior, minimizing waste and environmental impact associated with frequent returns, helps consumers make more informed decisions while purchasing computer products online or offline and encourages ethical return behavior to ensure sustainability and fairness in the retail ecosystem.

RESULT ANALYSIS AND INTERPRETATION

The study on "Return Frequency and Its Relationship with Return Policies in the Indian Computer Hardware Sector" provides critical insights into consumer behavior in the burgeoning e-commerce environment. Utilizing data from 224 respondents in Bengaluru, India, the research systematically investigates the impact of various independent variables on return frequency, employing machine learning models for predictive analysis. Here, we delve deeply into the key findings of the study, emphasizing the practical implications for businesses, policymakers, and consumers. The findings of this study underscore the relevance of independent variables such as demographic factors (age, gender), job type, income levels, and product-specific variables like computer usage and customer perceptions in shaping return behaviors. These variables serve as important predictors of whether a consumer is likely to return a product. Among these, factors like ease of return policies, perceived product quality, and refund processing times emerge as especially influential. This insight emphasizes that understanding and catering to these factors is essential for businesses aiming to reduce return rates while maintaining customer satisfaction.

The study's hypothesis testing confirmed the significance of these variables, rejecting the null hypothesis (H0) and supporting the alternative hypothesis (H1). This conclusion highlights the intricacies of consumer decision-making processes, driven by policy structures and individual expectations.

The research rigorously evaluated six machine learning models to identify the best approach for predicting return frequency. These models included Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbors (KNN), Naïve Bayes, Random Forest, and Logistic Regression. Each model was assessed based on its accuracy.

The results provide a clear performance comparison of six machine learning models used to predict the *Return Frequency* of computer products. These accuracy scores (or possibly another evaluation metric) offer valuable insights into the predictive power and usability of each model.

Variable	SVM	Decision Tree	KNN	Naïve Bayes	Random Forest	Logistics Regression	Best Model
Return Frequency	0.64444	**0.6667**	0.57777	0.64444	0.64444	0.62222	Decision Tree

1. **Decision Tree**: With a score of **0.6667**, the Decision Tree model outperformed the other models, making it the most suitable tool for this study. Its superior performance can be attributed to its ability to capture non-linear relationships and handle categorical and continuous data effectively. Additionally, Decision Trees are interpretable, allowing businesses to identify the key drivers influencing return behavior.
2. **Support Vector Machine (SVM)** and **Random Forest**: Both models achieved scores of **0.644444**, which is commendable. SVM is known for its robustness in handling high-dimensional datasets and defining clear decision boundaries, whereas Random Forest, as an ensemble method, combines multiple decision trees to improve predictive accuracy. These models are reliable but slightly less effective compared to the Decision Tree in this context.
3. **Naïve Bayes**: The Naïve Bayes model also achieved a score of **0.644444**, demonstrating its efficiency in probabilistic classification. However, its assumption of feature independence may have limited its ability to model complex interactions between variables in this dataset.
4. **Logistic Regression**: With a score of **0.622222**, Logistic Regression performed adequately but fell short of more complex models like Decision Tree or Random Forest. As a linear model, its predictive power might be constrained when dealing with non-linear relationships in the data.
5. **K-Nearest Neighbors (KNN)**: KNN was the least effective model, achieving a score of **0.577778**. While simple and intuitive, KNN's sensitivity to noisy data and its computational cost likely contributed to its comparatively lower performance.

The performance of the Decision Tree model surpasses that of others, such as SVM (0.6444), Random Forest (0.6444), and Logistic Regression (0.6222). This highlights the importance of model selection in analyzing return policies and predicting consumer behavior. The Decision Tree model, with its interpretable structure and focus on feature importance, proved to be particularly well-suited for this study's objectives.

One of the most insightful aspects of the study lies in the identification of key drivers affecting return frequency. Factors such as return window duration, refund processing time, restocking fees, and associated costs were found to be pivotal. Consumers tend to favor policies that offer flexibility and transparency, and any bottlenecks in these areas often lead to dissatisfaction and increased returns. On the other hand, brands with well-designed return policies, prioritizing customer convenience and minimizing return-related costs, tend to experience reduced return rates and higher customer loyalty.

The research findings offer valuable implications for businesses operating in the e-commerce and computer hardware sectors. Firstly, the insights derived from the Decision Tree model can guide companies in shaping their return policies. For example, simplifying the return process by offering longer return windows or quicker refund processing times can address key pain points for consumers. Additionally, reducing restocking fees or ensuring a transparent communication channel with consumers can help build trust and mitigate unnecessary returns.

Retailers can also employ predictive tools, like the Decision Tree model, to anticipate return frequency for certain products or categories. This would enable targeted interventions, such as improved product descriptions, enhanced customer education, or quality checks for high-return items. By leveraging these predictive insights, businesses can strike a balance between minimizing operational costs and maximizing customer satisfaction. The study highlights how critical consumer-centric return policies are in influencing purchase decisions. Modern consumers value convenience and trust in their interactions with brands. Factors such as ease of initiating returns, perceived fairness in policy enforcement, and overall product quality play a substantial role in shaping consumer behavior. Retailers must recognize that these preferences go beyond mere transactional experiences; they contribute to long-term brand loyalty and positive word-of-mouth promotion.

Additionally, the study underscores that consumers may view returns as a safety net, allowing them to make confident purchasing decisions in an online marketplace. Companies that foster this sense of security are more likely to thrive in the competitive e-commerce landscape, as they address the inherent uncertainties associated with online shopping.

CONCLUSIONS

Overall, this study provides valuable insights into the factors that influence consumer purchase decisions for computer products and their impact on product returns in Bengaluru, India. The findings highlight the importance of considering the intended purpose of computer usage when developing marketing strategies and product offerings, as this factor has a significant influence on the likelihood of product returns. The application of advanced statistical and machine learning techniques, such as the random forest model, has enabled the identification of the most significant factors driving consumer behavior and the development of predictive models for computer hardware product returns. These insights can help businesses in the computer industry improve their operations, reduce costs, and enhance the overall customer experience, ultimately contributing to the long-term sustainability of the industry.

Broader Implications for Policymakers

Beyond individual businesses, the findings have implications for industry stakeholders and policymakers. The high rate of product returns in the e-commerce sector not only impacts business profitability but also has environmental consequences due to increased logistical demands. Policymakers can encourage the adoption of sustainable practices by incentivizing businesses to optimize their return policies. For instance, promoting the use of eco-friendly packaging or offering repair and refurbishment options can help minimize the environmental impact of returns. Furthermore, policymakers can facilitate consumer education initiatives to raise awareness about the cost implications of returns for both businesses and the environment. By fostering a more informed consumer base, such initiatives can contribute to more mindful purchasing behaviors.

Future Research

1. Future studies can explore return behavior across other consumer industries, such as mobile phones, televisions, fashion, home appliances and accessories, to compare return trends and adopt best practices in return policy formulation.

2. A time-series study tracking changes in consumer return behavior over time can provide deeper insights into evolving e-commerce policies and consumer habits.

3. Investigating how emotions, cognitive biases, and post-purchase dissonance influence consumer return decisions.

4. Examining how return behavior differs between India and other global markets with varying return policies and consumer protection laws.

5. Provides a foundation for predictive modeling of return behaviors, allowing businesses to implement AI-driven return management systems.

REFERENCES

[1] Thommandru, A., Espinoza-Maguiña, M., Ramirez-Asis, E., Ray, S., Naved, M., & Guzman-Avalos, M. (2023). Role of tourism and hospitality business in economic development. *Materials Today: Proceedings*, *80*, 2901-2904.

[2] Voumik, L. C., Islam, M. A., Ray, S., Mohamed Yusop, N. Y., & Ridzuan, A. R. (2023). CO2 emissions from renewable and non-renewable electricity generation sources in the G7 countries: static and dynamic panel assessment. *Energies*, *16*(3), 1044.

[3] Bhargava, A., Bhargava, D., Kumar, P. N., Sajja, G. S., & Ray, S. (2022). Industrial IoT and AI implementation in vehicular logistics and supply chain management for vehicle mediated transportation systems. *International Journal of System Assurance Engineering and Management*, *13*(Suppl 1), 673-680.

[4] Rakhra, M., Sanober, S., Quadri, N. N., Verma, N., Ray, S., & Asenso, E. (2022). Implementing machine learning for smart farming to forecast farmers' interest in hiring equipment. *Journal of Food Quality*, *2022*.

[5] Al Ayub Ahmed, A., Rajesh, S., Lohana, S., Ray, S., Maroor, J. P., & Naved, M. (2022, June). Using Machine Learning and Data Mining to Evaluate Modern Financial Management Techniques. In *Proceedings of Second International Conference in Mechanical and Energy Technology: ICMET 2021, India* (pp. 249-257). Singapore: Springer Nature Singapore.

[6] Pallathadka, H., Leela, V. H., Patil, S., Rashmi, B. H., Jain, V., & Ray, S. (2022). Attrition in software companies: Reason and measures. *Materials Today: Proceedings*, *51*, 528-531.

[7] Sharma, A., Kaur, S., Memon, N., Fathima, A. J., Ray, S., & Bhatt, M. W. (2021). Alzheimer's patients detection using support vector machine (SVM) with quantitative analysis. *Neuroscience Informatics*, *1*(3), 100012.

[8] Mehbodniya, A., Neware, R., Vyas, S., Kumar, M. R., Ngulube, P., & Ray, S. (2021). Blockchain and IPFS integrated framework in bilevel fog-cloud network for security and privacy of IoMT devices. *Computational and Mathematical Methods in Medicine*, *2021*.

[9] Ray, S. (2020). How COVID-19 changed dimensions of human suffering and poverty alleviation: economic analysis of humanitarian logistics. *Вестник Астраханского государственного технического университета. Серия: Экономика*, (4), 98-104.

[10] Akbar, A., Akbar, M., Nazir, M., Poulova, P., & Ray, S. (2021). Does working capital management influence operating and market risk of firms?. *Risks*, *9*(11), 201.

[11] Dutta, A., Voumik, L. C., Ramamoorthy, A., Ray, S., & Raihan, A. (2023). Predicting Cryptocurrency Fraud Using ChaosNet: The Ethereum Manifestation. *Journal of Risk and Financial Management*, *16*(4), 216.

[12] Polcyn, J., Voumik, L. C., Ridwan, M., Ray, S., & Vovk, V. (2023). Evaluating the influences of health expenditure, energy consumption, and environmental pollution on life expectancy in Asia. *International Journal of Environmental Research and Public Health*, *20*(5), 4000.

[13] Sajja, G. S., Jha, S. S., Mhamdi, H., Naved, M., Ray, S., & Phasinam, K. (2021, September). An investigation on crop yield prediction using machine learning. In *2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA)* (pp. 916-921). IEEE.

[14] Ali, N. G., Abed, S. D., Shaban, F. A. J., Tongkachok, K., Ray, S., & Jaleel, R. A. (2021). Hybrid of K-Means and partitioning around medoids for predicting COVID-19 cases: Iraq case study. *Periodicals of Engineering and Natural Sciences*, *9*(4), 569-579.

[15] Gupta, S., Geetha, A., Sankaran, K. S., Zamani, A. S., Ritonga, M., Raj, R., ... & Mohammed, H. S. (2022). Machine learning-and feature selection-enabled framework for accurate crop yield prediction. *Journal of Food Quality*, *2022*, 1-7.

[16] Gupta, S., Geetha, A., Sankaran, K. S., Zamani, A. S., Ritonga, M., Raj, R., ... & Mohammed, H. S. (2022). Machine learning-and feature selection-enabled framework for accurate crop yield prediction. *Journal of Food Quality*, *2022*, 1-7.

[17] Ma, W., Nasriddinov, F., Haseeb, M., Ray, S., Kamal, M., Khalid, N., & Ur Rehman, M. (2022). Revisiting the impact of energy consumption, foreign direct investment, and geopolitical risk on CO2 emissions: comparing developed and developing countries. *Frontiers in Environmental Science*, 1615.

[18] Shukla, S. (2017). Innovation and economic growth: A case of India. *Humanities & Social Sciences Reviews*, *5*(2), 64-70.

[19] Soham, S., & Samrat, R. (2021). Poverty and financial dearth as etiopathogen of psychotic and neurotic diseases. *Заметки ученого*, (4-1), 568-578.

[20] Park, J. Y., Perumal, S. V., Sanyal, S., Ah Nguyen, B., Ray, S., Krishnan, R., ... & Thangam, D. (2022). Sustainable marketing strategies as an essential tool of business. *American Journal of Economics and Sociology*, *81*(2), 359-379.

[21] Роков, А. И., Дубаневич, Л. Э., & Рэй, С. (2021). Повышение экономической эффективности труда за счет изменения системы оплаты. *E-Scio*, (9 (60)), 53-62.

[22] Ray, S. (2021). How Emotional Marketing can help better understand the Behavioral Economic patterns of Covid-19 pandemic: Economic Judgments and Falsifications from India Samrat Ray-Alagappa University, Tamil Nadu, India. samratray@ rocketmail. com. *Вестник МИРБИС*, (2), 26-34.

[23] Ravi, S., Kulkarni, G. R., Ray, S., Ravisankar, M., krishnan, V. G., & Chakravarthy, D. S. K. (2023). Analysis of user pairing non-orthogonal multiple access network using deep Q-network algorithm for defense applications. *The Journal of Defense Modeling and Simulation*, *20*(3), 303-316.

[24] Priya, P. S., Malik, P., Mehbodniya, A., Chaudhary, V., Sharma, A., & Ray, S. (2022, February). The relationship between cloud computing and deep learning towards organizational commitment. In *2022 2nd*

International Conference on Innovative Practices in Technology and Management (ICIPTM) (Vol. 2, pp. 21-26). IEEE.

[25] Ray, S., & Leandre, D. Y. (2021). How entrepreneurial university model is changing the Indian COVID–19 Fight?. *Путеводитель предпринимателя*, *14*(3), 153-162.

[26] Inthavong, P., Rehman, K. U., Masood, K., Shaukat, Z., Hnydiuk-Stefan, A., & Ray, S. (2023). Impact of organizational learning on sustainable firm performance: Intervening effect of organizational networking and innovation. *Heliyon*, *9*(5).

[27] Rajendran, R., Sharma, P., Saran, N. K., Ray, S., Alanya-Beltran, J., & Tongkachok, K. (2022, February). An exploratory analysis of machine learning adaptability in big data analytics environments: A data aggregation in the age of big data and the internet of things. In *2022 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM)* (Vol. 2, pp. 32-36). IEEE.

[28] Elkady, G., & Samrat, R. (2021). An analysis of Blockchain in Supply Chain Management: System Perspective in Current and Future Research. *International Business Logistics*, *1*(2).

[29] Korchagina, E., Desfonteines, L., Ray, S., & Strekalova, N. (2021, October). Digitalization of Transport Communications as a Tool for Improving the Quality of Life. In *International Scientific Conference on Innovations in Digital Economy* (pp. 22-34). Cham: Springer International Publishing.

[30] Kumar, A., Nayak, N. R., Ray, S., & Tamrakar, A. K. (2022). Blockchain-based Cloud Resource Allocation Mechanisms for Privacy Preservation. In *The Data-Driven Blockchain Ecosystem* (pp. 227-245). CRC Press.

[31] Wawale, S. G., Bisht, A., Vyas, S., Narawish, C., & Ray, S. (2022). An overview: Modeling and forecasting of time series data using different techniques in reference to human stress. *Neuroscience Informatics*, *2*(3), 100052.

[32] Batool, A., Ganguli, S., Almashaqbeh, H. A., Shafiq, M., Vallikannu, A. L., Sankaran, K. S., ... & Sammy, F. (2022). An IoT and Machine Learning-Based Model to Monitor Perishable Food towards Improving Food Safety and Quality. *Journal of Food Quality*, *2022*.

[33] Verma, K., Sundararajan, M., Mangal, A., Ray, S., & Kumar, A. (2022, April). The Impact of COVID-19 to the Trade in India Using Digital, IOT and AI Techniques. In *2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)* (pp. 01-05). IEEE.

[34] Bangare, J. L., Kapila, D., Nehete, P. U., Malwade, S. S., Sankar, K., & Ray, S. (2022, February). Comparative Study on Various Storage Optimisation Techniques in Machine Learning based Cloud Computing System. In *2022 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM)* (Vol. 2, pp. 53-57). IEEE.

[35] Kiziloglu, M., & Ray, S. (2021). Do we need a second engine for Entrepreneurship? How well defined is intrapreneurship to handle challenges during COVID-19?. In *SHS Web of Conferences* (Vol. 120, p. 02022). EDP Sciences.

[36] Samajpaty, S., & Ray, S. (2020). Innovation strategies in health economics: a force that makes blood move and game of gravity in it-futuristic economic plans. *Московский экономический журнал*, (9), 397-409.

[37] Nikam, R. U., Lahoti, Y., & Ray, S. (2023). A Study of Need and Challenges of Human Resource Management in Start-up Companies. *Mathematical Statistician and Engineering Applications*, *72*(1), 314-320.

[38] Yanbin, X., Jianhua, Z., Wang, X., Shabaz, M., Ahmad, M. W., & Ray, S. (2023). Research on optimization of crane fault predictive control system based on data mining. *Nonlinear Engineering*, *12*(1), 20220202.

[39] Ray, S., Abinaya, M., Rao, A. K., Shukla, S. K., Gupta, S., & Rawat, P. (2022, October). Cosmetics Suggestion System using Deep Learning. In *2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS)* (pp. 680-684). IEEE.

[40] Bhaskar, T., Shiney, S. A., Rani, S. B., Maheswari, K., Ray, S., & Mohanavel, V. (2022, September). Usage of Ensemble Regression Technique for Product Price Prediction. In *2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA)* (pp. 1439-1445). IEEE.

[41] Kanade, S., Surya, S., Kanade, A., Sreenivasulu, K., Ajitha, E., & Ray, S. (2022, April). A Critical analysis on Neural Networks and Deep Learning Based Techniques for the Cloud Computing System and its Impact on Industrial Management. In *2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)* (pp. 325-331). IEEE.

[42] Pallathadka, H., Tongkachok, K., Arbune, P. S., & Ray, S. (2022). Cryptocurrency and Bitcoin: Future Works, Opportunities, and Challenges. *ECS Transactions*, *107*(1), 16313.

[43] Li, Y. Z., Yu, Y. H., Gao, W. S., Ray, S., & Dong, W. T. (2022). The Impact of COVID-19 on UK and World Financial Markets. *Jundishapur Journal of Microbiology*, 373-399.
[44] Samrat, R., Elkadyghada, E. G., Rashmi, N., & Elena, K. (2022). UPSKILLING AND RESKILLING FOR A GREENER GLOBAL BUSINESS ECOSYSTEM: WEB 4.0 PERSPECTIVE. *Журнал прикладных исследований*, *1*(11), 49-60.
[45] Ray, S. (2022). Fraud detection in e-Commerce using machine learning. *BOHR International Journal of Advances in Management Research*, *1*(1).
[46] Samrat, R. (2021). WHY ENTREPREUNERAL UNIVERSITY FAILS TO SOLVE POVERTY ERADICATION?. *Вестник Тувинского государственного университета.№ 1 Социальные и гуманитарные науки*, (1), 35-43.
[47] Ray, S. (2021). Are Global Migrants At Risk? A Covid Referral Study of National Identity. In *Трансформация идентичностей: опыт Европы и России* (pp. 26-33).
[48] Saravanan, A., Venkatasubramanian, R., Khare, R., Surakasi, R., Boopathi, S., Ray, S., & Sudhakar, M. POLICY TRENDS OF RENEWABLE ENERGY AND NON RENEWABLE ENERGY.
[49] Varma, A., & Ray, S. (2023). The case of amazons E-commerce digital strategy in India.
[50] Ray, S. (2023). Can Change Management Be Disrupted Through Leadership Stretegies?: Evidence From Start-Up Firms in Asia. In *Change Management During Unprecedented Times* (pp. 100-127). IGI Global.
[51] Al Noman, M. A., Zhai, L., Almukhtar, F. H., Rahaman, M. F., Omarov, B., Ray, S., ... & Wang, C. (2023). A computer vision-based lane detection technique using gradient threshold and hue-lightness-saturation value for an autonomous vehicle. *International Journal of Electrical and Computer Engineering*, *13*(1), 347.
[52] Nayak, N. R., Kumar, A., Ray, S., & Tamrakar, A. K. (2023). *Blockchain-Based Cloud Resource Allocation Mechanism for Privacy Preservation* (No. 9700). EasyChair.
[53] Ray, S. (2023). XA-GANOMALY: AN EXPLAINABLE ADAPTIVE SEMI-SUPERVISED LEARNING METHOD FOR INTRUSION DETECTION USING GANOMALY IN GLOBAL ECONOMIC DYNAMIC SHIFTS©. *ЭКОНОМИЧЕСКАЯ СРЕДА*, 4.
[54] Zamani, A. S., Rajput, S. H., Bangare, S. L., & Ray, S. (2022). Towards Applicability of Information Communication Technologies in Automated Disease Detection. *International Journal of Next-Generation Computing*, *13*(3).
[55] Korchagina, E. V., Barykin, S. E., Desfonteines, L. G., Ray, S., Shapovalova, I. M., & Repnikova, V. (2022). Digitalisation of Ecosystem-Based Management and the Logistics Potential of the Arctic Region. *Journal of Environmental Assessment Policy and Management*, *24*(03), 2250034.
[56] Zamani, A. S., Rajput, S. H., Bangare, S. L., & Ray, S. (2022). Towards Applicability of Information Communication Technologies in Automated Disease Detection. *International Journal of Next-Generation Computing*, *13*(3).
[57] Ray, S., Korchagina, E. V., Druzhinin, A. E., Sokolovskiy, V. V., & Kornev, P. M. (2022, April). Emergence of the New Start Up Ecosystem: How Digital Transformation Is Changing Fintech and Payment System in Emerging Markets?. In *International Scientific Conference "Digital Transformation on Manufacturing, Infrastructure & Service"* (pp. 621-638). Cham: Springer Nature Switzerland.
[58] Wagh, S., Nikam, R., & Ray, S. (2022). Exploration of the Higher Education System's Mechanism and Impact on More Than Just the Effective Growth of the Indian Economy. *Globsyn Management Journal*, *16*(1/2), 85-91.
[59] Ray, S., Korchagina, E. V., Druzhinin, A. E., Sokolovskiy, V. V., & Kornev, P. M. (2022, April). Emergence of the New Start Up Ecosystem: How Digital Transformation Is Changing Fintech and Payment System in Emerging Markets?. In *International Scientific Conference "Digital Transformation on Manufacturing, Infrastructure & Service"* (pp. 621-638). Cham: Springer Nature Switzerland.
[60] Chakraborty, T., & Ray, S. (2022). STRATEGIES OF CYBERLOAFING AND PHUBBING WHICH AFFECT WORKPLACE DIGITAL TRANSFORMATION. *Московский экономический журнал*, (10), 430-446.
[61] Ray, S., & Pal, R. P. (2022). IMPORTANCE OF ENTREPRENEURSHIP AND INNOVATION IN THE HEALTHCARE INDUSTRY DURING THE COVID-19 PANDEMIC. *Beneficium*, (2 (43)), 85-93.
[62] Samrat, R., Pratap, P. R., & Korchagina, E. V. (2022). WORLD ECONOMY AND INTERNATIONAL COOPERATION· МИРОВАЯ ЭКОНОМИКА И МЕЖДУНАРОДНОЕ СОТРУДНИЧЕСТВО.

[63] Ray, S., & Pal, R. P. (2021). ARE WE TRANSFORMING OUR PAYMENT THROUGH INNOVATION IN FINTECH AND THE DIGITAL ECONOMY? PERSPECTIVES FROM ASIAN DRAMA IN FINTECH INNOVATION©.
[64] Samrat, R. (2021). NEUROMARKETING EVIDENCES FROM THE ECONOMICS OF BOOKSELLERS ON THE STREETS: COVID-19 PERSPECTIVES AND IMPLICATIONS ON LUXURY BRANDS GLOBALLY. *Экономика и управление инновациями*, (2), 83-90.
[65] Korchagina, E. V., & Ray, S. (2021). TRIPLE HELIX CONCEPT IN INNOVATIVE UNIVERSITY DEVELOPMENT MODEL.
[66] Ray, S., & Pal, R. P. (2021). ARE WE TRANSFORMING OUR PAYMENT THROUGH INNOVATION IN FINTECH AND THE DIGITAL ECONOMY? PERSPECTIVES FROM ASIAN DRAMA IN FINTECH INNOVATION©.
[67] Самрат, Р. (2021). НЕЙРОМАРКЕТИНГ В ЭКОНОМИКЕ КНИЖНЫХ МАГАЗИНОВ НА УЛИЦАХ: ПЕРСПЕКТИВЫ ГЛОБАЛЬНОГО ВЛИЯНИЯ COVID-19 НА ЛЮКСОВЫЕ БРЕНДЫ. *ЭКОНОМИКА И УПРАВЛЕНИЕ*, (2), 83-90.
[68] Ray, S., Muhammad, G., & Adnan, M. The administrative role of principals: Insights and implication in secondary schools of.
[69] Pradhan, D., Ray, S., & Dash, A. A Critical Review on Sustainable Development of Green Smart Cities (GSCs) for Urbanization. *communities (Fig. 1)*, *13*, 15.
[70] Van Minh, N., Huu, N. N., & Ray, S. Responses of varied quinoa (Chenopodium quinoa Willd.) genotypes grown in Central Highlands, Vietnam.
[71] Ray, S., Nikam, R., Vanjare, C., & Khedkar, A. M. Comparative Analysis Of Conventional And Machine Learning Based Forecasting Of Sales In Selected Industries.
[72] Karim, S., Ahluwalia, G. K., Nakhate, V., Swami, V. I., Kumar, D., & Ray, S. Debt Trap Diplomacy and Debt Sustainability: A South Asian Countries Perspective.
[73] Roy, S., Gupta, V., & Ray, S. (2023). ADOPTION OF AI CHAT BOT LIKE CHAT GPT IN HIGHER EDUCATION IN INDIA: A SEM ANALYSIS APPROACH©. *Economic environment*, 130-149.

Author’s Profile

Author 1: Bhavya N, Research Scholar
Manipal Academy of Higher Education, Bangalore, India
naidu.bhavya@gmail.com
ORCID: https://orcid.org/0009-0005-6526-3041
Google Scholar: Bhavya Naidu
Author 2: Dr N S Viswanath
Director Bhavan’s Management Research Centre
Manipal Academy of Higher Education Bangalore, India.
viswanathns19@gmail.com
Author 3: Dr.Navya Gubbi Sateeshchandra
Academic Faculty, Berlin School of Business and Innovation, Berlin, Germany.
navya.gubbi@berlinsbi.com
ORCID: https://orcid.org/0009-0003-9461-9831
Google Scholar :Dr.Navya Gubbi Sateeshchandra
Author 4: Dr.Deepak R
HOD, Ramaiah Institute of Technology.
dnaikr@gmail.com
Author 5
Dr Samrat Ray,
Dean and Head of International Relations, IIMS,Pune,s.ray@iimspune.edu.in