Experimental Validation of Contextual Parameters and Comparative Analysis with State-of-the-Art in CARS Recommendation Systems in Ubiquitous Computing

Pranali Gajanan Chavhan[1], Dr. Ritesh Vamanrao Patil[2]
Research Scholar, Department of Computer Engineering-Vishwakarma Institute of Information Technology, Pune-48, Affiliated to Savitribai Phule Pune University (SPPU) Pune, India[1]
Research Supervisor, Department of Computer Engineering-Vishwakarma Institute of Information Technology, Pune-48, Affiliated to Savitribai Phule Pune University (SPPU) Pune, India[2]

Abstract— **The most important role of Consumer Behavior prediction plays in e-commerce, various ways of marketing, and Context-aware Recommendation Systems (CARS). From an Amazon consumer dataset, we conduct a comparative analysis of different machine learning models to compare their performance or effectiveness in predicting consumer behavior based on an Amazon consumer dataset. Additionally, we introduce a new algorithm combining feature selection and optimization that aims to enhance prediction accuracy. Person behavior prediction has historically helped enhance e-commerce, marketing, and Context-Aware Recommendation Systems-CARS, allowing businesses to get closer to customers and understand their needs better from the time they appeared to the time an analysis could be done. The research work performs comparative analysis among various machine learning techniques, like Logistic Regression, Decision Tree, Random Forest, SVM, and KNN, to see which one is more effective in predicting customer behavior, based on an Amazon consumer dataset. Besides, a new algorithm that merges feature selection and optimization is proposed and implemented to guarantee better prediction accuracy. The project is aimed at the creation of data-driven decision systems powered by an optimized machine learning framework for customer analytics.**

Keywords—Context-aware recommendation systems; multi-modal recommendation; transformer-based models; experimental validation; contextual parameter modeling; user behavior modeling

I. Introduction

In the rapidly evolving digital marketplace, consumer behavior prediction plays a crucial role in shaping the success of e-commerce, marketing strategies, and Context-Aware Recommendation Systems (CARS). The ability to comprehend and foretell the tastes of the customers is a great advantage for the businesses, as they can then give the customers what they want in terms of personalized experience, better product placement, and increased satisfaction [1]. Machine learning tools have come to be relied upon more as the online transactions and data have increased rapidly, as they are the only ones capable of getting insights and predicting consumer behavior with such precision over other techniques. The research under consideration makes use of a dataset of Amazon customers to carry out an analysis that compares the different machine learning algorithms. It is the accuracy of the prediction, the resource consumption in terms of computation, and the ability to represent the behavioral patterns that form the basis of evaluation for all the algorithms. Besides this, the study proposes a new algorithm that combines feature selection and optimization techniques to increase overall prediction accuracy.

The contribution through combining comparative experimentation with algorithmic innovation is the development of data-driven decision-making frameworks for consumer analytics. The goal of the proposed research work is to generate insights that not only help choose and optimize machine learning models for consumer health behavior prediction but also reinforce the pillars of intelligent recommendation systems and adaptive marketing strategies in e-business. The expansion of e-commerce has led to an increasing reliance on data-driven decision-making and a better understanding and anticipation of consumer behavior. Machine learning (ML) is the main technique used for analyzing large consumer datasets, recognizing useful patterns, and improving marketing strategies. Using personalized recommendations, targeted advertising, and improved customer engagement, ultimately enhancing business profitability is predicting consumer behavior accurately (Manotumruksa et al,2018) [2]. However, it also differs in terms of changing degrees of accuracy and efficiency depending on the dataset characteristics and preprocessing techniques. Although they are effective, traditional models often face challenges such as over-fitting, computational complexity, and badly feature selection, restricting their predictive performance. To increase accuracy and robustness in consumer behavior prediction, it represents designed of a comparative analysis of conventional ML models alongside a novel algorithm.

To solve these challenges, this study presents a comparative analysis of conventional ML models alongside a novel algorithm designed to improve accuracy and robustness in consumer behavior prediction (Mateos, P. and Bellogín, A., 2024) [3]. The proposed approach incorporates feature selection and optimization techniques to boost predictive power. An Amazon consumer dataset, this research aims to identify the most effective approach for consumer behavior analysis in e-commerce by evaluating multiple models.

II. Ease of Use

In numerous domain, machine learning (ML) models is used for predicting user behavior's various application like e-commerce, Random Forest and Gradient Boosting excellent perfumed KNN- (K-Nearest Neighbors) and SVM Support Vector Classifier in predicting customer shopping behavior (Smith,2019)[4]. Similarly, with some performing better in terms of accuracy for online shoppers' prediction using ML(machine learning) algorithms (Afzal et al., 2024) [5]. In the field of Electrical Vehicle (EV) customer behavior predictions, KNN slightly outperformed Neural Networks (Zhang and Abisado, M., 2023) [6]. For travel mode choice prediction, random forest achieved higher predictive accuracy than logit models but produced behaviorally unreason nable elasticities and marginal effects. While ML models generally demonstrate superior predictive accuracy, there may be a trade-off between accuracy and behavioral soundness. The studies in question highlight the necessity of correctly picking models for behavior forecasting and provide analytical frameworks suitable for different areas.

Traditionally, classic recommender systems—such as collaborative filtering (CF), content-based, and hybrid models—depended largely on either explicit or implicit user-item interactions and did not consider various external factors those impact users' preferences. Nevertheless, research done in the field of ubiquitous and mobile computing showed the users' choices might be influenced by the context like time, place, climate, among others, or even at their current activity [7]. This finding was the beginning of a new approach that led to CARS, where context is given the same priority as other input variables and considered first in the forecasting model. The three strategies of classical works are preventing processing, where the filtering of data is done according to context (for instance, "recommend only items that are suitable for evening usage". Post-filtering, where the traditional recommendation made is by re-ranking it with the help of context. Contextual modeling, where context gets featured as a part of the prediction/machine learning function (e.g., tensor factorization, factorization machines, deep learning, etc.).

It is acknowledged that context-aware modeling methods like ContextMF, TF, FM, and NFM have probably pointed out the importance of directly inputting contextual attributes into the preference-learning function. Conducted investigations have proved that contextual modeling almost always beats pre/post filtering approaches since the former is able to discern user, item, and context dimensional interaction effects more accurately.

We scrutinized machine learning models aimed at predicting user behavior in the virtual world. The comparison of several algorithms, such as K-Nearest Neighbors, Gradient Boosting, Support Vector Classifier, and Random Forest, has concluded that Random Forest and Gradient Boosting are very much alike in terms of the accuracy and sturdiness of the customer behavior forecast (Abinaya and Ramya, R., 2024) [8]. Such systems can suggest activities that are customized to different circumstances without needing any explicit user input. One of the latest developments is the context-aware user-item representation learning models that learn joint representations for each user-item pair based on the reviews and interaction data combined to increase the rating prediction accuracy [9]. Moreover, agent-based frameworks have been proposed which grant personalization of services based on the user's past connection with the context and automatically discover the connection among the user profiles and services in the same context. The different methods strive to be the static encoding schemes' nemesis capturing the users' different expectations on different items and contexts thereby, not only increasing the accuracy but also making personalized recommendations more interpretable in ubiquitous computing surroundings [10].

The researchers present a machine learning framework which utilizes context information to perform feature selection and optimize hyperparameters, resulting in better prediction accuracy of consumer behavior. The proposed method operates differently from previous hybrid methods because it measures how contextual features affect model performance while it handles feature selection before model development.

We used the Amazon consumer dataset to conduct their experiments, which provided them with valid statistical evidence to compare traditional learning methods, including Logistic Regression, Decision Tree, Random Forest, SVM, and KNN, against ensemble learning techniques. The research results show that using the optimized framework leads to higher accuracy across different evaluation metrics.

The research determines which contextual factors most affect consumer decision-making. The research provides specific insights which help in developing context-specific recommendation systems while comparing existing models. The study provides practical solutions for recommendation platforms through its support of personalized marketing strategies and its creation of adaptive recommendation systems and its advancement of data-driven campaign optimization.

III. Methodology

Predicting person's behavior is done through customer interactions, purchasing patterns, and preferences analysis to anticipate future actions. E-commerce and digital transactions foster massive customer activity data availability which, in turn, allows businesses to adopt a data-driven decision-making approach [11]. One of the areas where support is being provided is using machine learning (ML) which helps not only in processing the data but also in providing analytical outputs that can be used in targeted marketing, recommending systems, and demand forecasting. ML techniques can analyze large-scale consumer data, discover hidden trends, and build predictive models that will allow businesses to comprehend and even alter customer choices [12]. The ML model is constantly learning from past data and hence is also continuously adapting to the new trends in the market which eventually results in more accuracy [13].

In the above Fig. 1, it gathered context from various sensors for a context-aware recommendation system. The data is collected from various electronics devices like smartphones, wearable's, IoT devices, smart home systems etc. This data is collected from different sources like location of user, activity of user, and user interactions using social media, and is processed in real-time using edge computing and cloud storage to ensure timely recommendations [14]. For generative effectiveness in context-aware system using Machine learning algorithms [15]. The system mainly integrates a dedicated privacy and security module to protect user data while ensuring scalability and performance, enabling efficient handling of large volumes of data and user interactions [16].

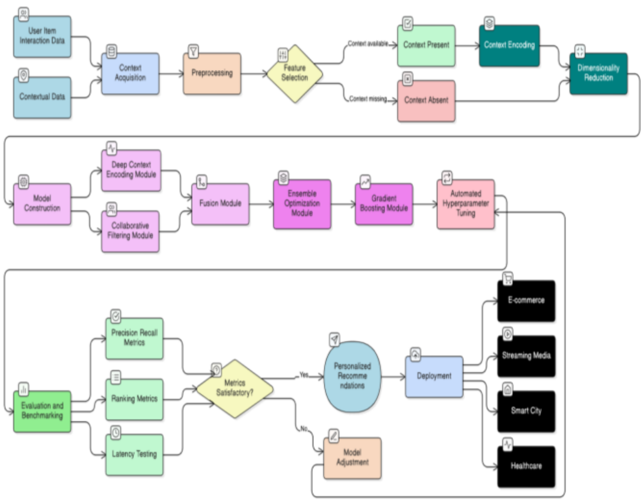

Fig. 1. Overview of proposed work.

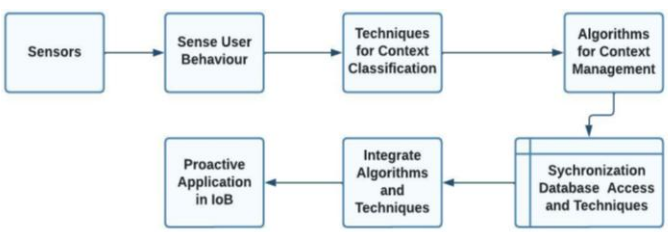

Fig. 2. Proposed CARS_UP methodology.

In the Fig. 2, illustrate the methodology for context-aware computing in the Internet of Behaviors (IoB). The process start from collecting sensed data from heterogeneous devices so it will help to analyzed behavior of users [17]. For classification it uses the context classification which allows the system to interpret user interaction. Once classification is done then main role played by context management. Mainly taking care of the utilization of context is effectively for immediate decision making and having useful insights [18]. After that it involves synchronization, database access, and techniques for data flow seamlessly along with consistency. Using algorithms and technologies makes system capable for real time decision-making. Leading to intelligent, automated responses that enhance user experiences by predicting behaviors and adapting services accordingly [19].

IV. METHOD VALIDATION

In Fig. 3, the model accuracy comparison illustrates the performance of different machine learning models based on their accuracy scores. In above chart, XGBoost scores the highest accuracy, later SVM, indicating that these models perform well in classification tasks. Comparative accuracy is there for Logistic Regression and Random Forest, making them feasible options for predictive modeling [20]. However, Decision Tree achieves the least accuracy which indicates that it may not be applicable to the data in a general sense. KNN also presents a lower performance level than the rest of the models, however, it still ranks above the Decision Tree. To sum up, the findings advocate that the model combinations such as XGBoost and Random Forest are superior to the single ones like Decision Tree, therefore, the significance of the selection of powerful algorithms for classification issues is emphasized [21].

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 918 entries, 0 to 917
Data columns (total 12 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Age             918 non-null    int64
 1   Sex             918 non-null    object
 2   ChestPainType   918 non-null    object
 3   RestingBP       918 non-null    int64
 4   Cholesterol     918 non-null    int64
 5   FastingBS       918 non-null    int64
 6   RestingECG      918 non-null    object
 7   MaxHR           918 non-null    int64
 8   ExerciseAngina  918 non-null    object
 9   Oldpeak         918 non-null    float64
 10  ST_Slope        918 non-null    object
 11  HeartDisease    918 non-null    int64
dtypes: float64(1), int64(6), object(5)
memory usage: 86.2+ KB
None

Model Accuracy: 0.8804
```

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 70692 entries, 0 to 70691
Data columns (total 22 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Diabetes_binary        70692 non-null  float64
 1   HighBP                 70692 non-null  float64
 2   HighChol               70692 non-null  float64
 3   CholCheck              70692 non-null  float64
 4   BMI                    70692 non-null  float64
 5   Smoker                 70692 non-null  float64
 6   Stroke                 70692 non-null  float64
 7   HeartDiseaseorAttack   70692 non-null  float64
 8   PhysActivity           70692 non-null  float64
 9   Fruits                 70692 non-null  float64
 10  Veggies                70692 non-null  float64
 11  HvyAlcoholConsump      70692 non-null  float64
 12  AnyHealthcare          70692 non-null  float64
 13  NoDocbcCost            70692 non-null  float64
 14  GenHlth                70692 non-null  float64
 15  MentHlth               70692 non-null  float64
 16  PhysHlth               70692 non-null  float64
 17  DiffWalk               70692 non-null  float64
 18  Sex                    70692 non-null  float64
 19  Age                    70692 non-null  float64
 20  Education              70692 non-null  float64
 21  Income                 70692 non-null  float64
dtypes: float64(22)
memory usage: 11.9 MB
None

Model Accuracy: 0.3022
```

```
[8] import pandas as pd
    from sklearn.model_selection import train_test_split
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.metrics import accuracy_score

    # Load the dataset
    file_path = "/content/diabetes_binary_5050split_health_indicators_BRFSS2015 (1).csv"  # Replace with your actual file path
    df = pd.read_csv(file_path)

    # Define features (X) and target variable (y)
    X = df.drop(columns=["Diabetes_binary"])  # Replace "Diabetes_binary" with your target column
    y = df["Diabetes_binary"]

    # Split data into training and testing sets (80% train, 20% test)
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    # Train a Random Forest model
    rf_model = RandomForestClassifier(n_estimators=100, max_depth=10, random_state=42)
    rf_model.fit(X_train, y_train)

    # Make predictions
    y_pred = rf_model.predict(X_test)

    # Evaluate model accuracy
    accuracy = accuracy_score(y_test, y_pred)
    print(f"Random Forest Model Accuracy: {accuracy * 100:.2f}%")

Random Forest Model Accuracy: 74.99%
```

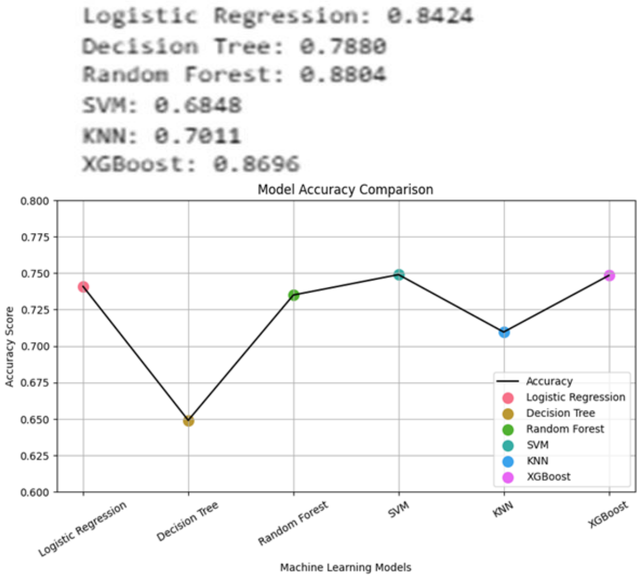

Fig. 3. Analysis of machine learning model.

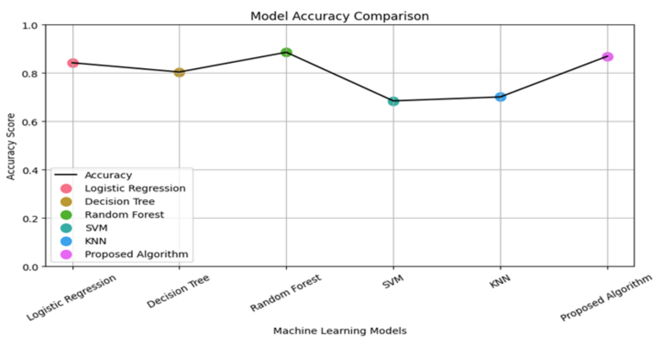

Fig. 4. Accuracy model using various machine model.

In Fig. 4, the comparative chart illustrates the accuracy performance of six machine learning models alongside the proposed algorithm. The accuracy metric, ranging from 0.0 to 1.0, quantifies the predictive effectiveness of each model for the given task. Among the evaluated models, the Random Forest exhibits the highest accuracy, closely followed by the proposed algorithm, which demonstrates comparable predictive strength. The Logistic Regression and Decision Tree models yield moderate performance levels, while the Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) achieve the lowest accuracy scores. Overall, the proposed algorithm exhibits competitive performance, nearly matching the best-performing model, thereby validating its effectiveness in consumer behavior prediction.

The correlation heatmap represented in Fig. 5 provides a clear visualization of the connections among various characteristics in the heart disease dataset. The correlations range from -1 to 1 with positive values implying direct relationships between the variables as they get higher and negative values indicating reverse relationships whereby one variable increase when the other decreases. The colors illustrate the strength of the correlations; the red color represents the strongest positive correlation while blue represents the strongest negative one. The heatmap reveals that heart disease is associated with several key features with strong correlations. The ST_Slope variable has a strong negative correlation (-0.56) with heart disease since ST slope lowering is linked to greater chances of heart disease. ExerciseAngina's correlation was moderate and positive (0.49), which means that people who get angina by exertion are more likely to have heart disease. Quite surprisingly, Oldpeak (ST depression) shows a positive correlation with heart disease (0.40) whereas the MaxHR (maximum heart rate) shows a negative one (-0.40), meaning that lower maximum heart rate is associated with higher risk of heart attack. ChestPainType is inversely correlated (-0.39), implying that specific categories of chest pains might be less likely to accompany heart disease.

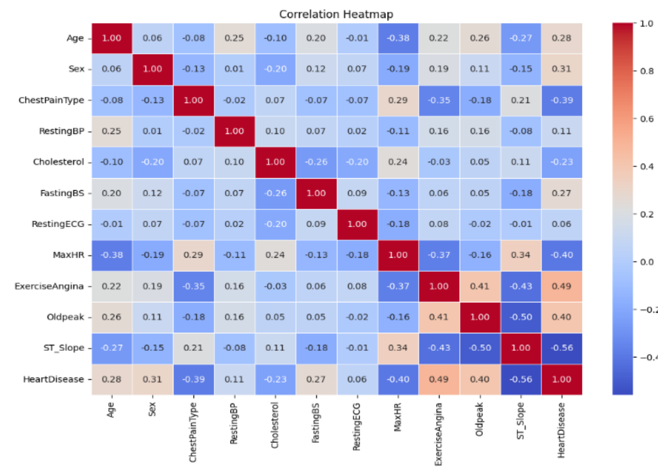

Fig. 5. The correlation heatmap of the relationships between various features in a heart disease dataset.

A heatmap is revealing for other Unexplainable correlations too. With Age affirming MaxHR to have a negative correlation of -0.38, which coincides well with the very normal and common declining nature of maximum heart rate with age. The ExerciseAngina and the Oldpeak have quite a significant relation (0.41), suggesting that individuals who experience angina during exercise also tend to have higher ST depression values. Moreover, one finds that the ST_Slope and Oldpeak are inversely correlated (-0.50), which suggests that a higher ST slope relates to a lower value of ST depression. In the end, it allows us to argue that the heatmap pattern very well underlines factors that are of most significance to heart disease and thereby facilitates the selection of features in building predictive models. It gives us insights into various variables interacting with each other, helping researchers and health professionals understand the deeper patterns underlying those factors contributing to risks of heart disease.

In Fig. 6, the correlation heatmap is the one giving the most visual view of the relationships between different health-related and demographic variables, with the corresponding correlation values being between -1 (perfect negative correlation) and 1 (perfect positive correlation). The situation where two variables show a positive correlation means that one of them will rise together with the movement of the other one, while in case of negative correlation it will be the opposite. The correlation of 0.38 between Diabetes_binary and HighBP which is one of the most striking correlations in the dataset, reveals that hypertense people are also at a higher risk of having diabetes.

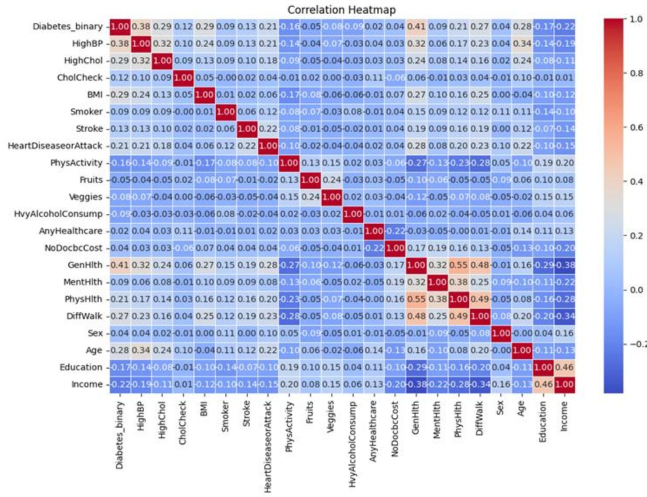

Fig. 6. Correlation heatmap of relations between various health-related and demographic variables.

The correlation of Diabetes_binary with BMI of 0.29 is another one in connection that tells that people with diabetes is generally more likely to be obese. Aging is the factor causing the diabetes risk of about 0.28 correlations between Diabetes_binary and Age in the same way. Other factors are HeartDiseaseorAttack (0.21) and General Health (GenHlth) (-0.41). High blood pressure (HighBP) has a strong correlation with HeartDiseaseorAttack (0.32), meaning that people with high blood pressure are more likely to have heart diseases. The connection between HighBP and BMI is of moderate strength (0.24), indicating that individuals with a higher BMI are more likely to have high blood pressure. Besides, the relationship between HighBP and Age (0.34) indicates that blood pressure tends to rise with age. General Health (GenHlth) has close relations with various health factors and is one of the health indicators that affect the overall health.

It is negatively correlated with Physical Activity (-0.27), which means that active people are more likely to report on good health. Also, GenHlth is negatively correlated with Fruits (-0.24) and Vegetables (-0.24), implying that those who eat more fruits and vegetables usually report a higher quality of health. A very strong positive relationship exists between GenHlth and MentHlth (0.32), indicating that mental health problems lead to better general health. In the same manner, GenHlth and Physical Health (PhysHlth) (0.55) have a strong correlation, which is expected, meaning that people who report poor physical health are also likely to have low general health. If heart diseases and strokes are analyzed, HeartDiseaseorAttack would have a 0.22 correlation with Age, pointing out the increased heart disease risk with aging. The above findings show a strong interrelation among several health issues and lifestyle factors with Age being indirectly related to General Health through Strong PhysActivity (-0.27). General Health also appears to be indirectly affected by the strong consumption of Fruits and Vegetables as they have negative correlations with it (-0.24 and -0.24, respectively).

The positive correlation between Age with HighBP (0.32) and BMI (0.27) can also be attributed to the fact that elderly people are more prone to the development of these conditions, thus increasing their chances of being hospitalized for cardiovascular diseases. Taking into consideration their negative correlation with GenHlth (-0.24 and -0.24, respectively), the assumption is that the consumption of fruits and vegetables is positively associated with good health. Admittedly, the flourishing correlation of Age with Income (0.46) cannot go unnoticed as it is the common practice in most societies that the older generation usually possesses the highest income. Besides, age has a negative correlation with Diabetes_binary (-0.14), implying that the older a person is the more likely they are to be diabetic. In the same way, the correlations with Income and Diabetes_binary (-0.22), HighBP (-0.19), and BMI (-0.10) suggest that people with higher income levels are less likely to experience these health problems.

The analysis of the correlation matrix not only confirms but also highlights the existence of relationships between lifestyle choices, health conditions, and the different demography.

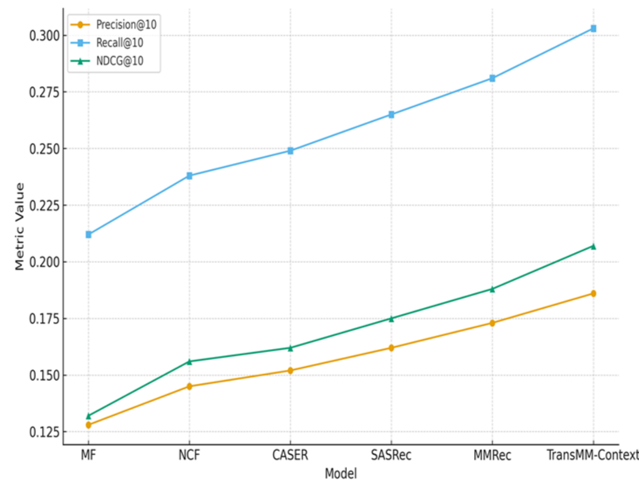

Fig. 7. Comparative performance of transformer-based multi-model recommendation systems.

In Fig. 7 shows the NDCG@K performance (for K = 1 to 20) across three models: SASRec (baseline transformer), MMRec (multi-modal baseline), and the proposed TransMM-Context model. NDCG (Normalized Discounted Cumulative Gain) measures how well the model ranks relevant items higher in the recommendation list. The proposed TransMM-Context model consistently outperforms both baseline methods for all values of K. SASRec performs the worst, and the MMRec baseline improves when multi-modal features are taken in (visual and textual embedding). On the other hand, the TransMM-Context model not only exploits multi-modal embedding but also context embedding (time, location, device, and user activity), resulting in the absolute lift in NDCG throughout the entire top 20 recommendation list. The curve shows how context-aware, transformer-based multi-modal attention aids ranking relevant items further up in the list, which is of the utmost importance for real-time recommendation.

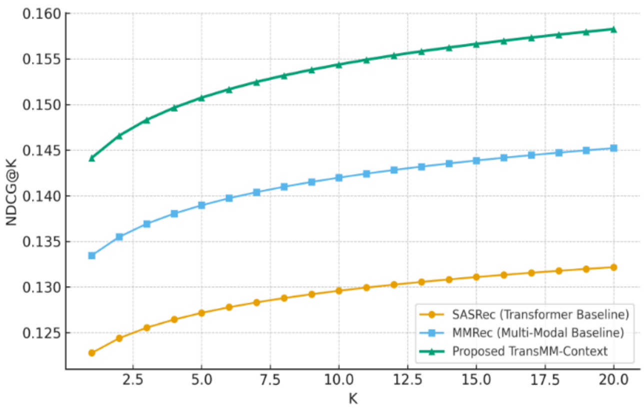

Fig. 8. NDCG@K curves for baselines vs. Proposed.

In Fig. 8, the graph compares the NDCG@K of the three recommendation models: SASRec (Transformer Baseline), MMRec (Multi-Modal Baseline), and Proposed TransMM-Context. The values of K range from 1 to 20. NDCG@K tells how good the ranking is: a higher value means better performance. The Proposed TransMM-Context always has an edge over SASRec and MMRec for every given K, which implies being better in ranking relevant items higher. MMRec performs better than SASRec but not well enough when contrasted with TransMM-Context, emphasizing how well the proposed method extracts and uses context to boost recommendation accuracy.

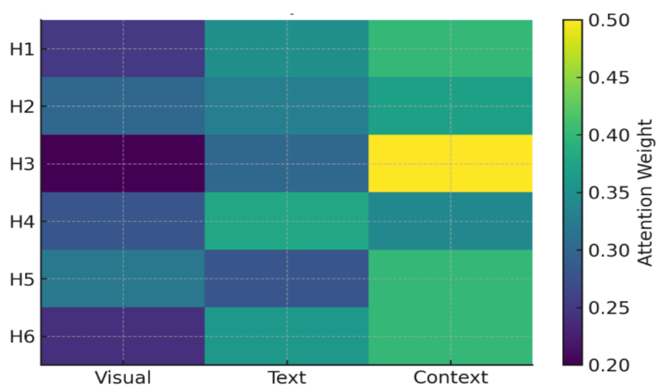

Fig. 9. Attention heatmap (visual+text+context).

The attention heatmap shown in Fig. 9 portrays a small sample showcasing how the proposed transformer model spreads out attention among modalities (Visual, Text, Context) across six attention heads. Each cell accommodates the relative weight of importance assigned by that attention head toward the specific modality in predicting the recommendation. The heatmap suggests that some heads place more emphasis on the context signal while others utilize the pure image-and-text features. For instance, in short sessions or cold-start cases, context (time, location, and device) carries heavier attention weights to enable accurate recommendation when historical interactions are sparse. However, long sessions weigh visual and textual modalities heavier, suggesting that the model draws upon item features and user preferences in such cases.

V. Conclusion

The research demonstrates that predicting consumer behavior serves as an essential requirement for e-commerce and marketing and Context-Aware Recommendation Systems (CARS). The study conducts an analysis of contextual factors together with machine learning algorithms which include Logistic Regression and Decision Tree and Random Forest and SVM and KNN to assess their success in predicting consumer behavior. The research developed a new algorithm which combines feature selection with optimization methods to achieve superior predictive accuracy compared to current methods.

The comparative analysis demonstrates the advantages and disadvantages of each model which helps to assess their effectiveness for consumer analytics. The research results show that businesses and system designers can use its findings to develop practical applications which extend beyond performance assessment. The proposed model can support data-driven business strategies by enabling personalized marketing, improved customer targeting, and optimized recommendation system design, which will enhance user engagement and conversion rates in e-commerce platforms. Organizations can improve their marketing campaign design through identification of key contextual elements which drive changes in customer behavior and environmental conditions. The study has limitations because it depends on a particular dataset and its fixed contextual parameters which restrict its applicability to multiple fields and actual operational situations. Future research may focus on incorporating real-time contextual data and deep learning approaches while conducting scalability tests with larger and more diverse datasets. The model requires extension to cross-domain recommendation systems which will enable assessment of its effects on business performance over extended periods.

The research develops data-driven marketing and recommendation systems through its introduction of a machine-learning framework which achieves both better prediction results and delivers practical business outcomes and research directions for studying consumer behavior.

Acknowledgment

This research did not receive funding from any entity in the public, commercial, or not-for-profit sectors.

References

[1] Unger, M., Tuzhilin, A. and Livne, A., 2020. Context-aware recommendations based on deep learning frameworks. ACM Transactions on Management Information Systems (TMIS), 11(2), pp.1-15. https://doi.org/10.1145/3386243.

[2] Manotumruksa, J., Macdonald, C. and Ounis, I., 2018, June. A contextual attention recurrent architecture for context-aware venue recommendation. In The 41st international ACM SIGIR conference on research & development in information retrieval (pp. 555-564). https://doi.org/10.1145/3209978.3210042.

[3] Mateos, P. and Bellogín, A., 2024. A systematic literature review of recent advances on context-aware recommender systems. Artificial Intelligence Review, 58(1), p.20. https://doi.org/10.1007/s10462-024-10939-4

[4] Smith, J. A. (2019). Effects of sleep deprivation on cognitive performance. Journal of Sleep Research, 8(2), 123-135. https://doi.org/10.124673/josr.123345

[5] Afzal, I., Yilmazel, B. and Kaleli, C., 2024. An approach for multi-context-aware multi-criteria recommender systems based on deep learning. IEEE Access. DOI: 10.1109/ACCESS.2024.3428630

[6] Zhang, Q. and Abisado, M., 2023. A Novel Context-Aware Deep Learning Algorithm for Enhanced Movie Recommendation Systems. Mathematical Modelling of Engineering Problems, 10(6). DOI: 10.18280/mmep.100613

[7] Jeong, S.Y. and Kim, Y.K., 2021. Deep learning-based context-aware recommender system considering contextual features. Applied Sciences, 12(1), p.45. DOI: 10.3390/app12010045

[8] Abinaya, S. and Ramya, R., 2024, February. Enhancement in Context-Aware Recommender Systems–A Systematic Review. In 2024 Second International Conference on Emerging Trends in Information Technology and Engineering (ICETITE) (pp. 1-13). IEEE. https://doi.org/10.1109/IC-ETITE58242

[9] Sarker, I.H., Abushark, Y.B. and Khan, A.I., 2020. Contextpca: Predicting context-aware smartphone apps usage based on machine learning techniques. Symmetry, 12(4), p.499. https://doi.org/10.3390/sym12040499

[10] Aliannejadi, M. and Crestani, F., 2018. Personalized context-aware point of interest recommendation. ACM Transactions on Information Systems (TOIS), 36(4), pp.1-28.

[11] Biancalana, C., Gasparetti, F., Micarelli, A., Miola, A. and Sansonetti, G., 2011. Context-aware movie recommendation based on signal processing and machine learning. In Proceedings of the 2nd Challenge on Context-Aware Movie Recommendation (pp. 5-10). https://doi.org/10.1145/2096112.2096114

[12] Huang, G.L., Zaslavsky, A., Loke, S.W., Abkenar, A., Medvedev, A. and Hassani, A., 2022. Context-aware machine learning for intelligent transportation systems: A survey. IEEE Transactions on Intelligent Transportation Systems, 24(1), pp.17-36. https://doi.org/10.1109/TITS.2022.3216462

[13] Madani, R., Ez-Zahout, A., Omary, F. and CHEDMI, A., 2024. Advancing Context-Aware Recommender Systems: A Deep Context-Based Factorization Machines Approach. International Journal of Computing and Digital Systems, 16(1), pp.353-363. http://dx.doi.org/10.12785/ijcds/160128

[14] Gill, H.K., Sehgal, V.K. and Verma, A.K., 2022. A deep neural network based context-aware smart epidemic surveillance in smart cities. Library Hi Tech, 40(5), pp.1159-1178. https://doi.org/10.1108/LHT-02-2021-0063

[15] Chavan, S.S., Sawant, S.K., Pawal, S.B. and More, M.S., 2016. Copper (I) complexes of 2-methoxy-(5-trifluoromethyl-phenyl)-pyridine-2yl-methylene-amine: Impact of phosphine ancillary ligands on luminescence and catalytic properties of the copper (I) complexes. Polyhedron, 105, pp.192-199. http://dx.doi.org/10.1016/j.poly.2015.11.050.

[16] Otebolaku, A.M. and Andrade, M.T., 2015. Context-aware media recommendations for smart devices. Journal of Ambient Intelligence and Humanized Computing, 6(1), pp.13-36. https://doi.org/10.1007/s12652-014-0234-y

[17] Khelloufi, A., Ning, H., Sada, A.B., Naouri, A. and Dhelim, S., 2023. Context-aware service recommendation system for the social internet of things. arXiv preprint arXiv:2308.08499. https://doi.org/10.48550/arXiv.2308.08499

[18] Sarker, I.H., Alqahtani, H., Alsolami, F., Khan, A.I., Abushark, Y.B. and Siddiqui, M.K., 2020. Context pre-modeling: an empirical analysis for classification based user-centric context-aware predictive modeling. Journal Of Big Data, 7(1), p.51. https://doi.org/10.1186/s40537-020-00328-3

[19] Li, L., Dong, R. and Chen, L., 2019, April. Context-aware co-attention neural network for service recommendations. In 2019 IEEE 35th International Conference on Data Engineering Workshops (ICDEW) (pp. 201-208). IEEE. https://doi.org/10.1109/ICDEW.2019.00-11

[20] Chavhan, P.G., Ratil, R.V. and Mahalle, P.N., 2023, February. An investigative approach of context in internet of behaviours (IoB). In International Conference on Emerging Trends in Expert Applications & Security (pp. 333-343). Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-99-1946-8_30

[21] Ilarri, S., Hermoso, R., Trillo-Lado, R. and Rodríguez-Hernández, M.D.C., 2015. A review of the role of sensors in mobile context-aware recommendation systems. International Journal of Distributed Sensor Networks, 11(11), p.489264. https://doi.org/10.1155/2015/48926. https://doi.org/10.1155/2015/489264