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MODELING THE IMPACT OF RECOMMENDATION ALGORITHMS ON GEN Z E-COMMERCE CONSUMPTION BEHAVIOR

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Abstract

The consumptive behavior of Generation Z (Gen Z) in e-commerce platforms is strongly influenced by recommendation algorithms, which often drive impulsive purchasing decisions. This issue is further exacerbated by low levels of financial literacy and the widespread availability of Buy Now Pay Later (BNPL) services, which increase the risk of a recurring debt cycle. This study aims to model and quantitatively estimate the level of impulsive behavior using a deep learning approach. Two neural network architectures were tested and compared. The first architecture, an Artificial Neural Network (ANN), was employed as a preliminary analytical model to map the nonlinear relationships between preprocessed static variables and impulsivity levels. The second architecture, a hybrid model combining a Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM), was specifically designed to capture temporal patterns and the dynamic evolution of impulsive behavior over time. Quantitative evaluation results demonstrate that the RNN-LSTM hybrid model achieved superior performance with exceptionally high estimation accuracy, as indicated by a Mean Absolute Error (MAE) of 0.0821 and a coefficient of determination (R^2) of 0.9767. In comparison, the static ANN model achieved only an MAE of 0.2078 and an R^2 of 0.8924. These findings explicitly confirm that impulsive behavior is a dynamic phenomenon, and thus, the hybrid RNN-LSTM architecture proves significantly more effective in analyzing sequential behavioral patterns.

Keywords: Generation Z (GEN Z); Impulsive; Recommendation Algorithms; Deep Learning

Abstrak

Prilaku konsumtif Generasi Z (Gen Z) di e-commerce sangat dipengaruhi oleh adanya algoritma rekomendasi, hal ini yang mendorong keputusan pembelian impulsif. Permasalahan ini diperburuk oleh rendahnya literasi keuangan dan ketersediaan layanan Buy Now Pay Later (BNPL), yang memperbesar risiko siklus utang konsumtif. Penelitian ini bertujuan untuk memodelkan dan mengestimasi tingkat prilaku impulsif tersebut secara kuantitatif menggunakan pendekatan deep learning. Dua arsitektur jaringan saraf diuji lalu dibandingkan. Untuk arsitektur pertama, Artificial Neural Network (ANN), digunakan sebagai komponen analisis awal untuk memetakan hubungan antar nonlinear dan variable static hasil preprocessing terhadap tingkat impulsifitas. Arsitektur kedua, model hibrida yang mengkombinasikan Recurrent Neural Network (RNN) dan Long Short-Term Memory (LSTM), digunakan secara spesifik untuk mempelajari pola temporal dan dinamika perubahan perilaku impulsif yang terjadi dari waktu ke waktu. Hasil dari evaluasi kuantitatif menunjukkan bahwa model hibrida RNN-LSTM memberikan performa yang jauh lebih baik dengan akurasi estimasi yang sangat tinggi, dibuktikan oleh nilai Mean Absolute Error (MAE) sebesar 0,0821 dan koefisien determinasi (R2) sebesar 0.9767. Sebagai pembanding, model ANN statik hanya mampu mencapai MAE sebesar 0,0278 dan R2 sebesar 0,8924. Temuan ini secara eksplisit mengkonfirmasi bahwa perilaku impulsive adalah fenomena dinamis, sehingga arsitektur hibrida RNN-LSTM secara signifikan lebih efektif dalam melakukan analisis pola perilaku sekuensial tersebut.

Kata kunci: Generasi Z (Gen z); Impulsif; Algoritma Rekomendasi; Deep Learning

INTRODUCTION

The rapid growth of e-commerce has fundamentally transformed consumer behavior, particularly among Generation Z (Gen Z), who are closely connected to digital technology and tend to make purchasing decisions instantaneously. Recommendation algorithms implemented in e-commerce platforms play a crucial role in shaping Gen Z's shopping habits by providing personalized

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product exposure, thereby triggering impulsive buying behavior (Salim et al., 2021). In Indonesia, this phenomenon is further reinforced by the convenience of digital payment systems and the proliferation of social media promotions that encourage instant gratification in online shopping (Joseph & Balqiah, 2022). The combination of technological and psychological factors contributes to the increasing prevalence of unplanned purchases among young consumers in digital marketplaces.

This issue has become more complex with the emergence of Buy Now Pay Later (BNPL) services, which allow users to defer payments and make purchases without immediate financial consequences. Such convenience has been shown to encourage more frequent transactions and short-term borrowing tendencies among young consumers. Recent studies highlight that BNPL is increasingly associated with hedonistic consumption patterns among youth, especially Generation Z, who tend to prioritize instant gratification and exhibit lower levels of financial discipline (Rochma & Suryandari, 2025). Literacy significantly affects personal financial management, this condition can lead to cycles of consumptive debt and reduced long-term financial well-being (Nuri et al., 2025).

Several previous studies have examined social and economic factors influencing impulsive buying behavior using conventional statistical methods such as regression analysis and Structural Equation Modeling (SEM) (Hegawan et al., 2023). However, these approaches have not fully captured the temporal dynamics of consumer purchasing patterns. In this context, deep learning- based approaches are more relevant due to their ability to learn nonlinear relationships and sequential patterns among consumer behavior variables (Ayu et al., 2021). Recent studies have shown that the architecture of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) is superior in identifying long-term dependencies in user behavior data, as LSTM is designed with memory cells and gating mechanisms that enable the model to retain information across multiple time steps (Melati et al., 2024).

Based on these research gaps, this study aims to model and estimate the level of impulsive behavior among Gen Z consumers quantitatively using a deep learning approach. Two neural network architectures are tested and compared: the Artificial Neural Network (ANN) as the baseline for analyzing nonlinear relationships among static variables, and a hybrid RNN–LSTM model designed to capture the temporal dynamics of impulsive behavior. The main contribution of this research is to provide empirical evidence that impulsive buying is a dynamic phenomenon that should be modeled as a sequential behavioral pattern. These findings are expected to serve as a foundation for developing ethical e-commerce recommendation systems and supporting the improvement of financial literacy among Gen Z consumers.

RESEARCH METHODS

Based on the problem formulation and research objectives previously described, this study adopts an experimental quantitative approach designed to model impulsive buying behavior among Generation Z through the integration of questionnaire-based behavioral data and deep learning techniques. The questionnaire responses are transformed into numerical variables representing impulsivity indicators, which serve as the input features for the ANN, RNN, and LSTM models. This establishes a direct connection between the behavioral constructs measured through the questionnaire and the computational modeling process.

The methodological workflow consists of several stages. First, the raw questionnaire data are collected and converted into structured datasets. Second, preprocessing procedures are applied, including data cleaning, normalization, and encoding to ensure that all variables meet the requirements of deep learning model training. Third, the dataset is divided into two portions—80% for training and 20% for testing—to enable a balanced evaluation of model performance. Fourth, the processed data are fed into the selected deep learning architectures, where ANN processes static relationships, while RNN and LSTM learn sequential and temporal patterns within the behavioral data. Fifth, the models generate predicted impulsivity scores, which are then evaluated using MAE and R^2 to assess predictive accuracy.

The sequence of procedures used in this study is illustrated, which models the complete workflow from questionnaire data processing to preprocessing, train–test splitting, model training, prediction generation, and final evaluation.

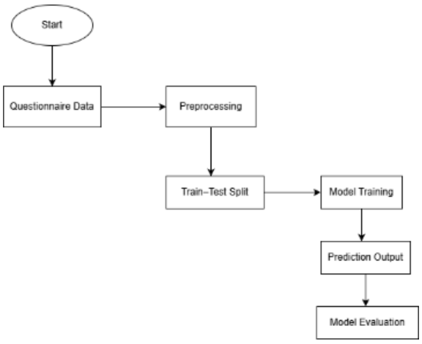

Figure 1. Flowchart of Deep Learning Modeling Process

Data Collection

The data collection process in this study was conducted online using a questionnaire distributed through Google Forms, shared across several social media platforms such as Instagram, WhatsApp, and TikTok. This strategy was chosen because social media serves as the dominant communication channel among Generation Z, making it more effective in reaching respondents relevant to the topic of digital consumer behavior. The online survey approach has been widely applied in studies of impulsive buying behavior on e-commerce platforms, particularly among young consumers who are digitally active and highly responsive to social media-based content (Andika et al., 2025).

The research data were obtained from 320 respondents, all belonging to the Generation Z category aged between 17 and 20 years, who actively shop online through platforms such as Shopee, Tokopedia, and Lazada. The questionnaire consisted of 15 items designed to measure various indicators of consumer behavior, including online shopping frequency, the use of Buy Now Pay Later (BNPL) services, and responses to product recommendation algorithms. Each question was measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) to obtain a quantitative overview of impulsive behavior levels and the influencing factors.

The data collection process adhered to the principles of validity, reliability, and research ethics. Before completing the questionnaire, each respondent was provided with a brief explanation of the research objectives and asked for consent to participate. Data collection was carried out from March to May 2025, and the survey results were compiled in CSV format. The subsequent stage involved a data cleaning process to remove incomplete entries, ensuring the quality of data used during the preprocessing stage of the deep learning model.

Planning

The planning phase of this research focuses on developing a responsive web-based application designed to measure the level of impulsive buying behavior among individuals, particularly within Generation Z. The platform is built to be optimally accessible across multiple devices such as computers and smartphones without requiring any additional installation. The rationale behind this development stems from the growing ease of online shopping among Generation Z, who, as digital natives, often blur the boundary between needs and wants, making them more susceptible to impulsive purchase behavior (Mariyani & Risanta, 2025)

Therefore, this system is designed as an online platform that assists users in monitoring and understanding their impulsive buying tendencies in real-time and across multiple devices. The application includes several key features such as login, questionnaire completion, dashboard visualization, impulsive behavior history, account management, and logout, enabling users to continuously track and analyze their consumption patterns over time.

The main features planned in this application include:

Table 1. Main features of the Impulse Tracker system

No	Feature	Brief Description
1	Login	Provides secure and personalized user access through individual accounts.
2	Questionnaire Module	Enables users to complete an online impulsivity scale to assess their shopping behavior.
3	Dashboard	Display users' impulsivity scores in a visual and informative manner.
4	Impulsivity History	Stores and presents users' impulsivity trends over time.
5	Profile Management	Allows users to manage personal information and preferences.

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6	Logout	Ensures users can safely exit the system while maintaining privacy.

All of the designed features are intended to support the process of data collection and visualization in this research. The online questionnaire enables efficient accumulation of quantitative data, while the interactive dashboard presents survey results through visual graphs that help researchers analyze trends and patterns of impulsive behavior among Generation Z. Therefore, the combination of these features ensures that the system can collect data accurately and present information effectively for further analytical purposes.

Design

In the Impulse Tracker design, the Admin actor is tasked with system supervision and data management duties, which reflects common practices in web-based information system management. Typically, an administrator role in such systems has full control to manage users, data, and overall system operations. For example, the admin usually can create or approve user accounts, update content, and configure system settings (Hasibuan & Ikhwan, 2024)

This corresponds to the Impulse Tracker's admin capabilities for managing user data and monitoring the model's prediction outputs. Moreover, administrators are responsible for maintaining the system's consistency and reliability through routine maintenance tasks. Best practices in information systems suggest performing regular data backups, database maintenance, and software updates to ensure the system remains stable and to prevent data loss.

Prior case studies of web-based systems have emphasized the importance of such maintenance recommending periodic backups and hardware or software upkeep so the system operates optimally and preserves data integrity. In the Impulse Tracker, the Admin's ability to export data for research and perform database maintenance aligns with these standard administrative duties. By implementing strong administrative controls (user management, output monitoring, and database upkeep), the system follows established norms for web-based system administration aimed at keeping the platform secure, consistent, and reliable for all users (Roselyn Charity Nebore et al., 2024).

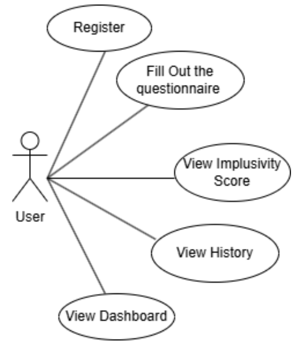

Figure 2. Design Use Case User

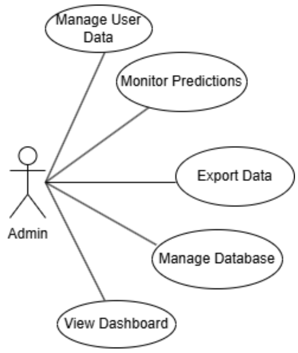

Figure 3. Design Use Case Admin

Coding

The system implementation stage was carried out using the Python programming language, integrated with the Flask framework as the core of responsive web application development. Additionally, TensorFlow and Keras libraries were utilized to activate artificial intelligence models based on Artificial Neural Network (ANN), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM). The developed system, named Impulse Tracker, is an interactive web-based platform designed to measure and monitor impulsive consumer behavior among Generation Z within the context of online shopping. Flask was chosen due to its ease of building lightweight and modular web APIs and its flexibility in integrating machine learning systems, as demonstrated in previous research on responsive Flask-based helpdesk systems (Gea & Susetyo, 2023).

The user interface was developed using HTML5, Bootstrap 5, and Jinja to display dynamic content, while impulsivity scores were visualized using the Chart.js library. The system integrates all previously mentioned features. Data collected from the questionnaire were converted into numerical values, normalized, and processed using the ANN,

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RNN, and LSTM models. The prediction results were categorized into three levels of impulsivity: low, medium, and high. All outputs were automatically stored in the SQLite database and managed through SQL-Alchemy. To support model training the ANN and RNN-LSTM models, with the first row representing the ANN configuration and the second row corresponding to the RNN-LSTM setup.

The following table outlines the key hyperparameters employed in training the ANN and RNN–LSTM models:

Table 2. Hyperparameter Settings for ANN and RNN–LSTM Models

Epochs	Batch Size	Optimizer	Learning Rate	Loss Function
100	16	Adam	0.0008	MSE
100	16	Adam	0.0005	MSE

By combining web, AI modeling, and behavioral–psychological considerations, Impulse Tracker serves not only as an automated survey tool but also as an adaptive, data-driven impulsive behavior tracking system for digitally native young consumers.

Testing

The testing phase of the Impulse Tracker system was conducted to ensure that every component, both from the web application functionality and the artificial intelligence model performance, operated optimally and in accordance with the initial design. The testing process was divided into two main approaches: system testing and model testing. The system testing stage was carried out using the black-box testing method, which evaluates system functionality from the user's perspective without inspecting internal source code. Core features such as login, questionnaire submission, impulsivity score processing, graphical visualization, and data storage were tested to ensure that the entire workflow operated smoothly, without logical errors, and remained responsive across multiple devices.

Meanwhile, the AI model testing involved evaluating the performance of the ANN, RNN, and LSTM models in predicting impulsivity scores based on user data. The dataset was divided into 80% training and 20% testing portions, and the model performance was assessed using Mean Absolute Error (MAE) and the Coefficient of Determination (R^2). The main models and their performance results are summarized as follows.

The results indicated that the RNN–LSTM model demonstrated superior capability in capturing temporal patterns and fluctuations in Gen Z's impulsive buying behavior. This is because LSTM networks are designed to process sequential data and retain information across time steps, allowing the model to learn behavioral shifts that occur rapidly in response to short-lived digital stimuli something that static models like ANN and basic RNN architectures cannot capture as effectively. These characteristics explain why the RNN–LSTM model achieved the highest predictive accuracy during testing.

Overall, this testing process confirmed that the system is not only stable and functionally reliable but also capable of providing highly precise estimations of impulsive behavior. These findings validate the system's practicality for use in digital behavior research and data-driven intervention studies.

RESULTS AND DISCUSSION

This research focuses on evaluating the level of impulsive behavior among users, particularly Generation Z, within the context of e-commerce platforms. The evaluation encompasses two primary components: (1) assessing the performance of deep learning-based predictive models, including the Artificial Neural Network (ANN) and the combined Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM), and (2) examining the functional reliability of the web-based system utilized for data collection and visualization.

The discussion is structured progressively, beginning with numerical performance assessment using standard evaluation metrics, followed by visual interpretation of prediction outcomes to observe emerging behavioral patterns. These results are then analyzed critically and compared with relevant existing studies to highlight the contribution, originality, and strengths of the methodological approach applied in this research.

Model Evaluation Metrics

To measure the predictive accuracy of the deep learning models implemented in the Impulse Tracker system, two primary evaluation metrics were applied: Mean Absolute Error (MAE) and the Coefficient of Determination (R2). These metrics are widely adopted in regression model evaluation since they provide insight into the average

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prediction error and the model's ability to account for variance in the target data.

MAE quantifies the average magnitude of the absolute difference between actual values and model predictions, while R2 reflects the proportion of variability in the target variable that can be explained by the model. In general, lower MAE values and R2 scores approaching 1 indicate a stronger and more accurate predictive model.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \qquad (1)$$

$$\mathrm{MSE} = \frac{1}{n}\sum(y_i - \hat{y}_i)^2 \qquad (2)$$

The use of MAE and R2 in this study is supported by prior research involving consumer behavior prediction as well as deep learning-based forecasting models such as CNN-LSTM in financial analytics (Fozap, 2025). Therefore, the selection of these metrics aligns with contemporary evaluation practices considered effective for analyzing complex regression models that capture non-linear behavioral patterns.

The performance results of the ANN and RNN–LSTM models are summarized as follows:

Table 3. Performance comparison of ANN and RNN–LSTM models

Model	Type of Analysis	Mean Absolute Error (MAE)	Coefficient of Determination (R^2)
Artificial Neural Network (ANN)	Static	0.2078	0.8924
Recurrent Neural Network (RNN) & Long Short-Term Memory (LSTM)	Dynamic	0.0821	0.9767

Based on the evaluation results presented, the RNN–LSTM model demonstrated superior performance compared to the ANN model, as reflected by its lower MAE and higher R^2 values. Conceptually, this improvement is attributed to the LSTM architecture, which incorporates memory cells and gating mechanisms that enable the model to retain long-term dependencies and capture temporal fluctuations that static models like ANN cannot learn. Recent studies also support the effectiveness of LSTM for time-series forecasting and behavioral prediction. For instance, reported that LSTM-based architectures consistently achieve more stable predictive accuracy in dynamic regression tasks (Al-Selwi et al., 2024)

This temporal learning capability is particularly relevant to impulsive buying behavior among Generation Z, which is strongly influenced by rapidly shifting digital stimuli such as flash sales, personalized recommendations, and short-lived social media trends. A recent found that online impulsive buying among Indonesian Gen Z consumers is significantly shaped by digital stimulus exposure and self-regulation patterns (Uppalidevi Jaya Mudra & Toto Rusmanto, 2024). Another empirical work focusing on Gen Z behavior on Shopee similarly demonstrated that their impulsive responses are driven by fast-changing digital cues and momentary emotional triggers (Susanto et al., 2024)

Result Implementation

This stage displays the final web-based interface of the Impulse Tracker system, showing that all designed features have been successfully implemented and are ready for use.

The figure shows the Login Page, designed with a clean and minimalist layout. Users enter their email and password to access the system, while new users can register via the "Sign up now" link. This login process ensures secure and personalized access to each user's behavioral data.

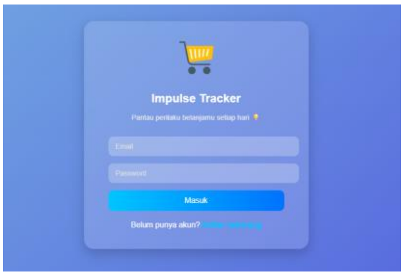

Figure 4. Login Process

Users are required to input their email and password credentials to access the system. For new users, a "Sign up now" link is provided, directing them to the account registration page. This login process is essential for ensuring data privacy and personalization, as each user will have a dedicated history of impulsive behavior stored and visualized within the system.

The following three figures showcase the main interface of the Impulse Tracker system used for completing the daily impulsivity assessment. This form captures key indicators of impulsive behavior and short-term financial habits through a structured and user-friendly format.

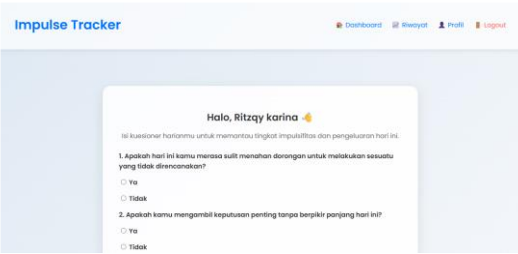

Figure 5. The process of filling out the questionnaire

Upon accessing the page, users are greeted personally by name and prompted to complete the day's self-assessment. This feature is designed to increase user engagement by creating a sense of familiarity and interaction.

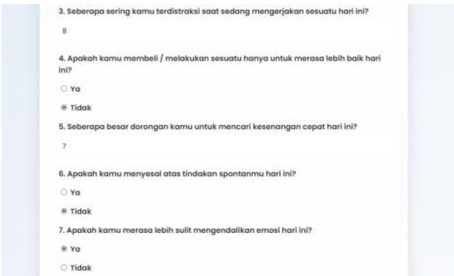

Figure 6. Continued process of filling out the questionnaire

The questionnaire consists of eight items measuring various dimensions of impulsive behavior, such as difficulty controlling urges, spontaneous decision-making, and susceptibility to distraction. Responses are collected using binary (Yes/No) or numerical inputs, which are then processed directly by the AI models.

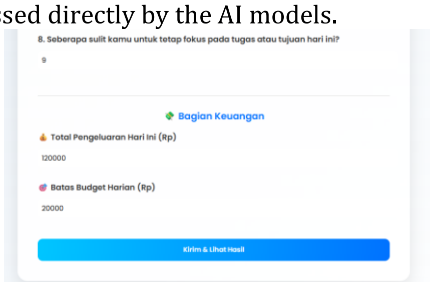

Figure 7. Continued process of filling the budget

At the end of the form, users are asked to input their daily spending and budget limits. These financial variables are used to calibrate the impulsivity score according to individual spending patterns. The "Submit & View Results" button triggers the predictive algorithm and instantly displays the analysis outcome.

These three interface elements are integrated to form a complete feedback loop from behavioral input to predictive insight enabling users to continuously monitor their impulsive buying tendencies in a digital environment. Therefore, it is essential to include all three stages in the system visualization, as each plays a critical role in the user's behavioral tracking experience.

Figure 8. history page to see the level of impulsivity

The figure shows the History page displaying a line chart of the user's impulsivity scores over time. The X-axis represents the dates of submissions, while the Y-axis shows the predicted impulsivity scores (0–1). Each point indicates the score generated by the system on that day.

Tanggal	Skor	Kategori
20 October 2025	0.33	Sedang
20 October 2025	0.33	Sedang
20 October 2025	0.00	Rendah

Figure 9. Summary of user impulsivity scores and categories.

The table above presents a summary of predicted impulsivity scores based on users' questionnaire submissions. Each row represents an individual entry, showing the corresponding date, predicted score, and its associated impulsivity category. Categories are classified into three levels: Low (≤ 0.3), Moderate (0.31–0.6), and High (> 0.6), visually distinguished using color coding for easy interpretation.

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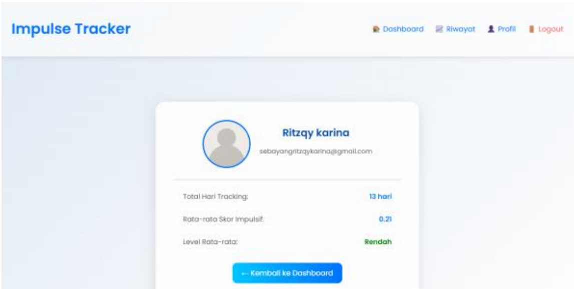

Figure 10. User profile page showing summary of impulsivity monitoring

The image above displays the user profile interface within the Impulse Tracker system. This page provides personalized information for logged-in users, including their email address and a summary of their impulsivity tracking activities.

Three key indicators are presented: the total number of days tracked, the average impulsivity score across all questionnaire sessions, and the overall impulsivity level based on that score in this case, the user has tracked their behavior for 13 days, with an average score of 0.21, categorized as Low.

Black Box Testing

To ensure that the Impulse Tracker system performs according to its intended functionality and meets user expectations, a Black Box Testing procedure was conducted. This testing approach focuses on evaluating the system's observable behavior by providing various input scenarios and examining whether the outputs match the expected results, without inspecting the internal code or algorithmic logic.

The main features tested in this application and their results are summarized as follows:

Table 4. Functional testing results of the Impulse Tracker system.

No	Feature Tested	Expected Output	Status
1	Login	Access dashboard	Pass
2	Registration	Account successfully created	Pass
3	Questionnaire Submission	Warning message displayed	Pass
4	Prediction Output	Impulsivity score generated correctly	Pass
5	History Display	Graph and table display correctly	Pass
6	Profile Page	Correct data and average score showm	Pass

The results demonstrate that all core features of the Impulse Tracker system performed correctly and met the predefined functional requirements. No major errors or unexpected behaviors were found during testing. Minor usability observations, such as input validation feedback timing, were noted for potential refinement but did not affect system stability.

CONCLUSIONS AND SUGGESTIONS

Conclusion

This research successfully developed and evaluated the Impulse Tracker, a web-based intelligent system designed to measure and predict impulsive buying behavior among Generation Z e-commerce users. The integration of Artificial Neural Network (ANN) and Recurrent Neural Network–Long Short-Term Memory (RNN–LSTM) models achieved strong predictive performance, as indicated by low MAE values and high R2 scores, demonstrating the capability of deep learning to capture complex behavioral tendencies.

The implementation and functionality were validated through Black Box Testing, confirming that all modules—from user authentication to behavioral visualization performed reliably and as expected. These results prove that the Impulse Tracker is technically stable and user- oriented, supporting its practical use for behavioral monitoring and research purposes.

The findings of this study are consistent with several previous works in Indonesian e-commerce behavior research. (Reky Dewantara et al., 2025) found that emotional and hedonic factors significantly affect impulsive buying among Shopee users, which aligns with the behavioral dimensions modeled in this study. Similarly, (Fahriansah et al., 2023) emphasized that hedonic value, word- of-mouth, and influencer endorsement are major predictors of impulsive buying among Generation Z, supporting the psychological constructs represented in the Impulse Tracker questionnaire. Moreover, (Yanti Nasution et al., 2022) revealed that social commerce features and online engagement significantly increase impulsive purchase intentions among young consumers, which resonates with the behavioral fluctuation trends observed in this research's predictive results.

In conclusion, the Impulse Tracker system not only validates the theoretical insights proposed by earlier behavioral studies but also contributes methodologically by applying AI-based prediction to psychological constructs. This integration of technology and behavioral science offers a new, data-driven perspective for understanding and managing impulsive tendencies in Indonesia's digital consumer landscape.

Suggestion

Suggestions can be input for the next researcher and can also be implicative recommendations from the research findings. First, future research should consider expanding the dataset to include more diverse behavioral and psychological indicators, such as emotional states, time pressure, and financial self-control, as emphasized by (Nabila et al., 2025), who found that emotional and time-related factors significantly influence impulse buying among Generation Z e-commerce users. By integrating these variables, predictive accuracy can be further enhanced.

Second, the integration of intervention features for instance, personalized spending alerts or reflective feedbac could transform the Impulse Tracker from a diagnostic tool into a preventive system that helps users manage impulsive tendencies. This aligns with (Chandra et al., 2025), who suggested that technological interaction and engagement features in social commerce strongly shape consumer behavior and decision-making.

Third, conducting broader empirical testing across various demographics and regions would improve the model's generalizability. Studies such as (Saputra & Naufal Wala, 2025)emphasized that socio-cultural context plays a significant role in shaping impulsive buying, thus cross-region validation would add depth to behavioral analysis.

Lastly, future development should focus on mobile optimization and data privacy enhancement to ensure user accessibility and ethical compliance. This will not only improve usability but also strengthen public trust in AI-driven behavioral analytics platforms.

By implementing these suggestions, subsequent studies can expand upon the Impulse Tracker's foundation and contribute to a more comprehensive understanding of impulsive consumer behavior in the era of digital commerce.

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