PCMJ

Progress in Computer and Mathematics Journal (PCMJ)
volume 3 [November, 2025]
e-ISSN: 3030-6728
Website: fskmjebat.uitm.edu.my/pcmj

INTENT-IQ: CUSTOMER'S REVIEWS INTENT RECOGNITION USING RANDOM FOREST ALGORITHM

NUR FARAHNISRIN MAZLAN
College of Computing, Informatics and Mathematics, Universiti Teknologi MARA
2023388771@student.uitm.edu.my

NOOR HASIMAH IBRAHIM TEO*
College of Computing, Informatics and Mathematics, Universiti Teknologi MARA
shimateo@uitm.edu.my

Article Info | Abstract

Customer review is a written evaluation provided by the consumer. The evaluation will cover the product, services provided, delivery service and experience. Customer intent is the root cause or purpose that drives a customer's behaviors or actions when they interact with the business, website, or product. In this research, we are focusing on customer intent through their reviews. The main problem is with the large-scale manufacturer relies on consumer reviews, ratings, and opinions regarding the quality and design of the products and the manual analysis of these ratings is time-consuming, hence diminishing effectiveness. The problem of information overload in online review platforms has substantially affected many buyers' abilities to properly evaluate the quality of the item or organizations while making decisions about purchases. In order to overcome this problem, a classification model for intent recognition is developed. Dataset from Kaggle which contains English reviews from Shopee is downloaded to be used for the modelling process. Data annotation using semi-supervised learning which is self-training technique need to be accomplished as the dataset is unlabeled. Two machine learning model is chosen to build the classification models which are Random Forest (RF) algorithm and Multinomial Naïve Bayes (MNB) algorithm. Intent-IQ is a web application system which allows users to input Shopee product link and it leads to the intent classification, where the reviews can be classified into its intent categories such as praise, complaint and suggestion. As for the result, the dataset that has gone through data annotation using self-training technique with SVM model is used for further analysis as it achieved 90.0% accuracy and F1-score. The RF classification model achieved accuracy of 81.94%, while MNB classification model with 71.38%. Therefore, the RF classification model is chosen to be integrated into the Intent-IQ system. The validation and functionality testing conducted on the system reflects that the system works as expected. The usability test achieved 97.3% SUS score which falls in the range of excellent ratings. The future recommendation for this project is to build a classification model for Malay reviews and explore other algorithms which could gain better accuracy by capturing more contextual meanings in the reviews such as BERT.

Received: March 2025
Accepted: September 2025
Available Online: Nov. 2025

Keywords: Customer Intent, Data Annotation, Machine Learning, Classification, Functionality Testing, Usability Testing.

INTRODUCTION

Electronic commerce (e-commerce) has rapidly expanded in market size and user base, transforming how businesses operate, and consumers shop online (Zhang & Li, 2023). Unlike traditional business models, e-commerce utilizes the internet as its primary channel, offering both virtual and physical products (Wu & Li, 2022). Advancements in mobile technology and secure transactions have contributed to its continuous growth, providing businesses with opportunities for expansion and consumers with a seamless shopping experience.

Customer reviews have become an essential part of online shopping, influencing purchasing decisions and providing valuable insights into products and services (Chatterjee et al., 2021). Reviews vary in format, including star ratings, multimedia content, and text-based feedback. Understanding customer intent—whether a review expresses praise, a complaint, or a suggestion—is crucial for businesses to assess consumer satisfaction and identify areas for improvement. Nasr et al. (2014) classify customer feedback into five categories: compliments, complaints, valence-free comments, concerns, and suggestions.

One major challenge in e-commerce is the overwhelming volume of customer reviews. Large-scale manufacturers and businesses rely on these reviews to improve product quality and meet customer expectations (Alotaibi, 2023). However, manually analysing reviews is time-consuming, inefficient, and prone to misinterpretation. Quality Assurance teams often struggle to process large datasets effectively, leading to potential strategic errors. Additionally, information overload hinders customers' ability to evaluate product quality, as lengthy reviews may contain mixed sentiments, making it difficult to distinguish between praise, complaints, and constructive feedback (AlQahtani, 2021).

To address these issues, intent recognition can be applied to classify reviews based on their content, categorizing them into praise, complaint, and suggestion. By automating this process, businesses can efficiently analyse customer feedback, improve product offerings, and enhance user satisfaction. Data visualization tools, such as graphs, can further simplify the interpretation of classified reviews, making it easier for businesses and consumers to extract meaningful insights. This approach enhances customer experience by enabling quicker issue resolution, personalized responses, and data-driven decision-making in e-commerce.

LITERATURE REVIEW

Because they offer important information about consumer preferences, product quality, and overall user experience, customer reviews are a crucial part of e-commerce (Kanakamedala et al., 2023). These evaluations address topics including product performance, service quality, and delivery efficiency and can be posted on forums, social media, and e-commerce sites. Reviews have a big impact on decisions to buy since they are publicly available (Chatterjee et al., 2021). While unfavorable evaluations point out areas for development, positive feedback increases consumer trust. Reviews are also used by companies and manufacturers to determine consumer sentiment and improve their goods (Yao et al., 2022). Reviews are available in a variety of formats, such as written descriptions, multimedia content, and numerical ratings, and each one offers varying degrees of insight into customer satisfaction.

Customer intent in reviews represents the intention behind a consumer’s comments, whether it is to praise a product, express dissatisfaction or recommend improvements. Businesses may improve decision-making and get a deeper understanding of customer demands by classifying reviews according to their intent, such as praise, complaint and suggestion. Businesses may improve user experience, improve product offers, and effectively handle complaints by understanding consumer intent. Additionally, praise reviews serve as valuable marketing tools, reinforcing positive brand perception. Understanding customer intent benefits both businesses and consumers by ensuring a more transparent and responsive e-commerce environment.

Intent Recognition

Intent recognition or intent classification is classifying user input text into predetermined categories based on domains and intents (Al-Tuama & Nasrawi, 2022). It is a crucial component of natural language understanding (NLU) and is widely utilised in applications such as chatbots, virtual assistants, customer service automation, and more. The text's context is defined by its intent, which typically consists of a verb and a noun (V. Khan & Meenai, 2021). The aim is to precisely identify the user's intention so that the system or business can act accordingly. Businesses benefit from classifying intents since it enables them to be more customer centric (Al-Tuama & Nasrawi, 2022).

Multinomial Naïve Bayes Algorithm

Naïve Bayes is an approach that uses algorithms based on the Naïve Bayes theorem. It relies on naïve assumptions of conditional independence among predictors to forecast unknown data sets (Ismail et al., 2020). Three popular Naïve Bayes Classifiers are Gaussian Naïve Bayes Classifier, Multinomial Naïve Bayes Classifier and Bernoulli Naïve Bayes Classifier. Multinomial Naive Bayes is a version of the Naive Bayes method that is especially well-suited for classification jobs with discrete features. It is often utilized in text classification issues. It is commonly used as a baseline in text classification since it is quick and simple to implement (Xu et al., 2017). Multinomial Naive Bayes is an effective yet simple technique for text classification and other discrete data issues that strikes a fair compromise between performance and computational efficiency.

The Multinomial Naive Bayes model implies that features such as word counts have a multinomial distribution. This is suited for discrete data, with each feature representing the number of occurrences within an observation. Naïve Bayes classifier uses the concept of probability. Attributes are crucial in Naïve Bayes algorithm as it relates to classification. Bayes' theorem provides a way to update the probability estimate of a class based on new features. Below, Eq 1 is the formula used for Bayes theorem:

$$P(C|X) = \frac{P(X|C).P(C)}{P(X)} \quad (1)$$

Random Forest Algorithm

Random Forest is an ensemble learning approach that is commonly used for classification and regression applications. During training, it constructs numerous decision trees and outputs the class that is the mode of the classes for classification or the mean prediction for regression of each tree. The random forest uses bootstrap resampling to create decision tree models for each sample set (L. Wei, 2023). This method improves the model's accuracy and resilience over a single decision tree. Each subset of the data will be trained with a decision tree. All the subsets differ from each other, that is why each tree has a unique structure and will produce different predictions. As a result, we might consider RF as a means of combating overfitting using ensemble techniques (M. Y. Khan et al., 2021).

Progress in Computer and Mathematics Journal (PCMJ)
volume 3 [November, 2025]
e-ISSN: 3030-6728
Website: fskmjebat.uitm.edu.my/pcmj

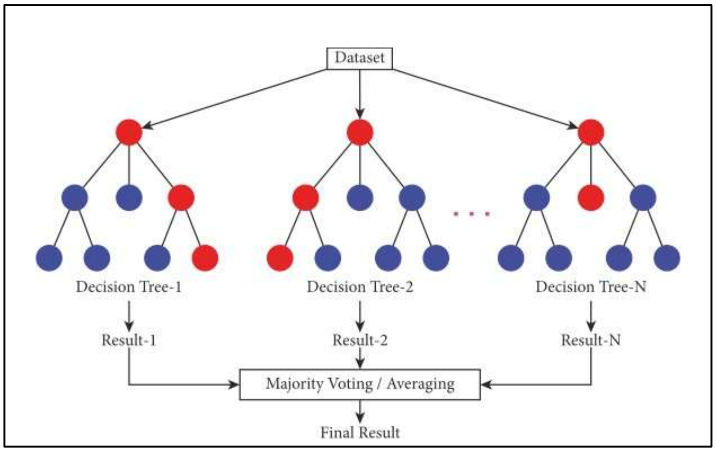

Figure 1: Random Forest Structure

(*Source* : M. Y. Khan et al., 2021)

METHODOLOGY

As for this project, classification model using Random Forest algorithm and Multinomial Naïve Bayes algorithm will go through modelling process to categorize the customers' reviews intent, which falls into Text Analytics area makes it suitable to use CRISP-DM process model as the methodology. CRISP-DM is a process model with six phases. The phases include business understanding, data understanding, data preparation, modelling, evaluation, and deployment where it naturally captures the data science life cycle (Martinez-Plumed et al., 2021). Figure 2 shows the research design framework for this project which includes the overall process.

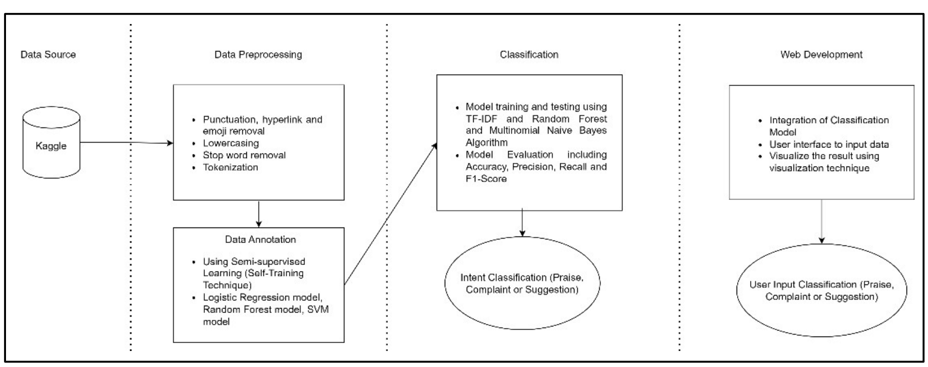

Figure 2: Research Design Framework

For the starter, it begins with business understanding which the primary goal is to ensure the project is aligned with the targeted goals and objectives. This phase lays the groundwork for the whole project by outlining what the research wants to achieve. This phase is where the research topic needs to be defined, and the problem statement will be identified. The research and the analysis objectives need to be established, and the goals of the research will be determined. In data understanding phase, it includes data collection process and discover the data quality concerns and early insights into the data. Exploratory Data Analysis (EDA) is used to discover the insights and intriguing subsets to create hypotheses about the hidden information. The data will be obtained from Kaggle, an open-source dataset site which was contributed by Tony Ng (2020) named Shopee Text Reviews and Kritanjali Jain (2021) named Amazon Reviews.

Data preparation phase includes data preprocessing. Data annotation will be carried out in this phase where it will be using semi-supervised learning self-training technique. First, the data will be gone through a process for punctuation, hyperlink and emoji removal, lowercasing, stop word removal and tokenization. As the data that has been obtained from Kaggle is unlabelled, further data preprocessing needs to be done which is data annotation. A machine learning technique called semi-supervised learning uses both labelled and unlabelled data to enhance model performance, especially in situations where labelled data is hard to come by. Self-training technique is a popular method in semi-supervised learning, in which a model is trained on a small amount of labelled data before it is being applied to the unlabelled data to predict labels. The model is improved over several rounds by iteratively adding the most certain predictions to the training set. Three distinct algorithms such as Logistic Regression, Random Forest, and Support Vector Machine (SVM) are used in this research to accomplish self-training.

As this project is focusing on intent recognition, modelling phase will be focusing on building a classification model. To find the best classification model for this project, there are two models that will go through modelling and training at the same time. Machine learning algorithms that will be used are Multinomial Naïve Bayes algorithm and Random Forest algorithm. After the classification model modelling is done, the best classification model will be chosen by comparing the model performance. Hyperparameter tuning with K-fold cross validation also will be included in this phase to achieve the best model performance for both classification models.

Evaluation phase is an important stage that involves reviewing the performance of the models. This step verifies that the models match the specified requirements and perform effectively with real-world data. As mentioned before, two types of datasets will be created which are training dataset and testing dataset. The dataset will be randomly shuffled to ensure the data is evenly distributed. The model will be evaluated using accuracy, F1-score, precision and recall. Confusion matrix will be generated as well to visually displaying how well it predicts different classes, showing the number of correct and incorrect classifications.

The deployment phase is when the web application will be constructed and followed by integrating the classification model into the system. Intent-IQ web application is a user-friendly system for the end user and also interactive with good UI design where it allows the user to enter their input for the classification process. It is built using HTML, CSS and JavaScript. The classification model is integrated into the web application using Flask API to make sure the system is able to classify the reviews input by the user. To make sure the system works as desired and easy for the user, functionality testing and usability testing is carried out.

RESULT AND DISCUSSION

Intent-IQ aims to classify customer's reviews on Shopee e-commerce platform into intent categories such as praise, complaint and suggestion. This section includes the result for the data annotation process, classification models' performance, functionality testing and usability testing for the system.

Data Annotation Using Self-Training Technique Evaluation

For the data annotation process, the self-training techniques using three machine learning models have been accomplished and the results have been obtained to see which model has the higher accuracy and F1-score. It will show the model with the best performances in labelling the dataset. The dataset that has been produced by the machine learning model with the highest accuracy and F1-Score will be used for further analysis and modelling process. Table 1 shows the results for the three machine learning models in producing the labels for the dataset.

Table 1: Comparison of Data Annotation Using Self-Training Technique Result

Machine Learning Model	Accuracy (%)	F1-Score (%)
Logistic Regression	85.0	84.8
Random Forest	80.0	80.3
SVM	90.0	90.0

Based on the results, it shows that SVM is the model that performs the best in terms of both accuracy and F1-score. These findings show that SVM is successfully striking a balance between accuracy and recall in addition to producing accurate predictions. This suggests that SVM is the most effective for this dataset, as it is able to classify the instances correctly and also maintain a good balance between precision and recall.

Classification Model Evaluation

A few metrics are used to evaluate the classification model's performance, including accuracy, F1-score, precision, recall, and support. The classification model was first carried out using default settings, which means that no changes were made to the default hyperparameter values in order to evaluate the model's performance. It continues with the hyperparameter tuning and cross validation process to figure out the hyperparameter sets that can achieve highest accuracy. A few sets of param grids with different values has been used to find the best hyperparameter set. Table 2 shows the best results for both classification model that has been achieved after the hyperparameter tuning with k-fold cross validation process.

Table 2: Comparison of Classification Model Result

Model	Accuracy (%)	Intent	Precision (%)	Recall (%)	F1-score (%)
Random Forest	81.94	Praise	88.00	78.00	83.00
		Complaint	77.00	92.00	84.00
		Suggestion	83.00	74.00	79.00
Multinomial Naïve Bayes	70.38	Praise	74.00	68.00	71.00
		Complaint	69.00	84.00	76.00
		Suggestion	69.00	57.00	63.00

Based on the results, it shows that Random Forest classification model achieve higher result in terms of accuracy rather than Multinomial Naïve Bayes classification model which are 81.94% and 70.38% respectively. Random Forest classification model also shows a better

PCMJ
Progress in Computer and Mathematics Journal (PCMJ)
volume 3 [November, 2025]
e-ISSN: 3030-6728
Website: fskmjebat.uitm.edu.my/pcmj

result for its precision, recall and F1-score rather than Multinomial Naïve Bayes classification model which make it obvious that Random Forest classification model should be chosen to be integrated into the Intent-IQ web application.

Functionality Testing

Functionality testing has been done to verify that the web application operates as anticipated and offers users the desired functions. Each function is evaluated by entering different Shopee product URLs, verifying that the system accurately obtains and classifies customers' reviews, and making sure the visual representations change dynamically. It is also tested to ensure the navigation between pages works as planned. Validation testing is also included in this test, making sure that error messages provide users with clear instructions and looking for empty inputs. The solution reduces the possibility of mistakes in the analytical process and improves user experience. Table 3 shows the overall result for the functionality testing.

Table 3: Overall Result for Functionality Testing

Functionality Test	Expected Output	Success/Fail
View Landing Page	The user directed to Landing page	Success
View Home Page	The user is redirected to Home page	Success
View Analysis Page	The user is redirected to Analysis page	Success
Input Field on Analysis Page	Correct Shopee Product Link - The alert indicating the link is valid will pop-up	Success
	Incorrect Shopee Product Link - The alert indicating the link is invalid will pop-up	Success
	Random Text Input - The error prompt "Please enter a URL" shows at the input field	Success
	Empty Input Field - The error prompt "Please fill in the field" will show up.	Success
Scrape Review Button	The Scraped Reviews table containing date, review and intent column will be displayed	Success
Download CSV File Button	The alert indicating the CSV file has been successfully downloaded will pop up.	Success

Visualize Button	The user will be redirected to Visualization page that contain complete data visualization	Success
View Visualization Page	The user will be redirected to Visualization page that contain complete data visualization that has been done on the scraped reviews before	Success
View Comparative Page	The user is redirected to Comparative page	Success
Input Field on Comparative Page	Correct Shopee Product Links - The alert indicating the links are valid will pop-up	Success
	Incorrect Shopee Product Links - The alert indicating the link is invalid will pop-up	Success
	Random Text Input - The error prompt “Please enter a URL” shows at the input field	Success
	Empty Input Field - The error prompt “Please fill in the field” will show up	Success
Compare Button	The system will display complete data visualization on both products	Success

Based on the results, it shows that all functionality testing test cases achieve Success, meaning that it works as expected and fulfils the requirements.

Usability Testing

Usability testing is a crucial assessment procedure in system development where it determines how simple it is for people to engage with a system, application or website. It has been conducted face-to-face, which allows the users to assess and try the system on a computer under observation. A total of 20 participants have been gathered for the usability testing. The System Usability Scale (SUS), a standardized questionnaire intended to gauge user satisfaction, efficiency and simplicity of use, is used to evaluate the system’s overall usability. User’s responses are gathered for analysis using a five-point Likert scale, with 1 denoting “Strongly Disagree” and 5 denoting “Strongly Agree”. Table 4 shows the usability testing result.

Table 4: Summary of Usability Testing Result

Subcomponent	**Final Score (%)**
Usability	96.60
Learnability	97.50
Overall	97.30

Based on the results, the SUS resulting in a final score of 97.3% for the overall while 96.6% and 97.5% for usability and learnability respectively. These scores fall within the excellent range for usability testing, as measured by the SUS.

CONCLUSION

The "Intent-IQ: Customer's Reviews Intent Recognition Using Random Forest Algorithm" project aims to classify and visualize customer reviews from Shopee product links, enabling users to make informed purchase decisions. By employing the Random Forest classification model, the system effectively categorizes reviews into intent-based classes such as praise, complaint, and suggestion. The application provides various data visualizations, including bar charts, pie charts, line charts, and word clouds, for a clearer understanding of customer sentiments. Additionally, users can compare two Shopee products by entering their respective links, allowing for side-by-side visualization of review-based insights, which simplifies the decision-making process.

The project's machine learning approach focuses on intent recognition using supervised learning algorithms. Both Multinomial Naïve Bayes and Random Forest models were evaluated, with Random Forest selected for its superior handling of complex text patterns and reduced overfitting through ensemble learning. Performance comparisons indicated that Random Forest achieved higher accuracy (81.94%) compared to Multinomial Naïve Bayes (70.38%), making it the optimal choice for the system. Furthermore, a semi-supervised self-training technique was implemented for data annotation, with SVM achieving the highest accuracy at 90%.

To ensure system reliability, extensive testing was conducted, including accuracy assessment, functionality checks, output validation, and usability testing. Usability testing with 20 participants yielded a high System Usability Scale (SUS) score of 97.3%, indicating excellent user experience. The system met all project objectives, successfully automating customer review analysis and enhancing decision-making for both businesses and consumers in the e-commerce landscape.

REFERENCES

Al-Tuama, A. T., & Nasrawi, D. A. (2022). Intent Classification Using Machine Learning

Algorithms and Augmented Data. *2022 International Conference on Data Science and Intelligent Computing, ICDSIC 2022*, *Icdsic*, 234–239. https://doi.org/10.1109/ICDSIC56987.2022.10075794

Alotaibi, F. M. (2023). *A Machine-Learning-Inspired Opinion Extraction Mechanism for Classifying Customer Reviews on Social Media*.

Chatterjee, I., Zhou, M., Abusorrah, A., Sedraoui, K., & Alabdulwahab, A. (2021). Statistics-based outlier detection and correction method for amazon customer reviews. *Entropy*, *23*(12), 1–24. https://doi.org/10.3390/e23121645

Ismail, M., Hassan, N., & Bafjaish, S. S. (2020). Comparative Analysis of Naive Bayesian Techniques in Health-Related for Classification Task. *Journal of Soft Computing and Data Mining*, *1*(2), 1–10. https://doi.org/10.30880/jscdm.2020.01.02.001

Kanakamedala, V. C., Singh, S. H., & Talasani, R. (2023). Sentiment Analysis of Online Customer Reviews for Handicraft Product using Machine Learning: A Case of Flipkart. *2023 International Conference for Advancement in Technology, ICONAT 2023*, 1–6. https://doi.org/10.1109/ICONAT57137.2023.10080169

Khan, M. Y., Qayoom, A., Nizami, M. S., Siddiqui, M. S., Wasi, S., & Raazi, S. M. K. U. R. (2021). Automated Prediction of Good Dictionary EXamples (GDEX): A Comprehensive Experiment with Distant Supervision, Machine Learning, and Word Embedding-Based Deep Learning Techniques. *Complexity*, *2021*. https://doi.org/10.1155/2021/2553199

Khan, V., & Meenai, T. A. (2021). Pretrained Natural Language Processing Model for Intent Recognition (BERT-IR). *Human-Centric Intelligent Systems*, *1*(3–4), 66. https://doi.org/10.2991/hcis.k.211109.001

Martinez-Plumed, F., Contreras-Ochando, L., Ferri, C., Hernandez-Orallo, J., Kull, M., Lachiche, N., Ramirez-Quintana, M. J., & Flach, P. (2021). CRISP-DM Twenty Years Later: From Data Mining Processes to Data Science Trajectories. *IEEE Transactions on Knowledge and Data Engineering*, *33*(8), 3048–3061. https://doi.org/10.1109/TKDE.2019.2962680

Nasr, L., Burton, J., Gruber, T., & Kitshoff, J. (2014). Exploring the impact of customer feedback on the well-being of service entities ATSR perspective. *Journal of Service Management*, *25*(4), 531–555. https://doi.org/10.1108/JOSM-01-2014-0022

S. M. AlQahtani, A. (2021). Product Sentiment Analysis for Amazon Reviews. *International Journal of Computer Science and Information Technology*, *13*(3), 15–30. https://doi.org/10.5121/ijcsit.2021.13302

Wei, L. (2023). Genetic Algorithm Optimization of Concrete Frame Structure Based on Improved Random Forest. *Proceedings - 2023 International Conference on Electronics and Devices, Computational Science, ICEDCS 2023*, 249–253. https://doi.org/10.1109/ICEDCS60513.2023.00051

Wu, L., & Li, C. (2022). Explore the Application of Computer Network Technology in E-

Commerce. *Proceedings - 2022 International Conference on Computer Network, Electronic and Automation, ICCNEA 2022*, 163–167. https://doi.org/10.1109/ICCNEA57056.2022.00045

Xu, S., Li, Y., & Wang, Z. (2017). Bayesian multinomial naïve bayes classifier to text classification. *Lecture Notes in Electrical Engineering*, *448*(November), 347–352. https://doi.org/10.1007/978-981-10-5041-1_57

Yao, D., Chatterjee, I., & Zhou, M. C. (2022). Conditioning Customers' Product Reviews for Accurate Classification Performance. *ICNSC 2022 - Proceedings of 2022 IEEE International Conference on Networking, Sensing and Control: Autonomous Intelligent Systems*, 1–5. https://doi.org/10.1109/ICNSC55942.2022.10004165

Zhang, Y., & Li, C. (2023). Personalized Recommendation Algorithm for Electronic Commerce Based on Artificial Intelligence Technology. *International Conference on Integrated Intelligence and Communication Systems, ICIICS 2023*, 1–5. https://doi.org/10.1109/ICIICS59993.2023.10420971