Interdisciplinary Journal of Information, Knowledge, and Management

An Official Publication of the Informing Science Institute InformingScience.org

IJIKM.org

Volume 19, 2023

RECOMMENDATION SYSTEM FOR AN ONLINE SHOPPING PAY-LATER SYSTEM USING A MULTISTAGE APPROACH: A CASE STUDY FROM INDONESIA

Wiwin Suwarningsih*	Research Center for Information and Data Sciences, National Research and Innovation Agency, Bandung, Indonesia	wiwi005@brin.go.id
Nuryani	Research Center for Information and Data Sciences, National Research and Innovation Agency, Bandung, Indonesia	nury012@brin.go.id

* Corresponding author

ABSTRACT

Aim/Purpose	In this study, we developed a recommendation system model designed to support decision-makers in identifying consumers eligible for pay-later options via consensus-based decision-making. This approach was chosen due to the high and complex risks involved, such as delayed payments, challenges in reaching consumers, and issues of bad credit.
Background	The "pay-later" option, which allows consumers to postpone payment for e-commerce purchases, offers convenience and flexibility but also introduces several challenges: (i) by enabling payment deferral, merchants face financial risks, including potential delays or defaults in payment, adversely affecting their cash flow and profitability; and (ii) this payment delay can also heighten the risk of fraud, including identity theft and unauthorized transactions.
Methodology	This study initiated a risk analysis utilizing the ROAD process. Considering contemporary economic developments and advancements in neural networks, integrating these networks into risk assessment has become crucial. Consequently, model development involved the amalgamation of three deep learning methods – CNN (Convolutional Neural Networks), RNN (Recurrent Neural Networks), and LSTM (Long Short-Term Memory) – to address various risk alternatives and facilitate multi-stage decision-making recommendations.

Accepting Editor Tharrenos Bratitsis │Received: April 17, 2024│ Revised: July 29, August 13, 2024 │ Accepted: August 16, 2024.

Cite as: Suwarningsih, W., & Nuryani. (2024). Recommendation for an online shopping pay-later system using a multistage approach: A case study from Indonesia. *Interdisciplinary Journal of Information, Knowledge, and Management, 19,* Article 24. https://doi.org/10.28945/5366

Contribution	Our primary contribution is threefold. First, our study identified potential consumers by prioritizing those with the smallest associated problem consequence values. Second, we achieved an optimal recall value using a candidate generator. Last, we categorized consumers to assess their eligibility for pay-later rights.
Findings	The findings from this study indicate that our multi-stage recommendation model is effective in minimizing the risk associated with consumer debt repayment. This method of consumer selection empowers policymakers to make informed decisions regarding which consumers should be granted pay-later privileges.
Recommendations for Practitioners	This recommendation system is proposed to several key parties involved in the development, implementation, and use of pay-later systems. These parties include E-commerce Executive Management for financial analysis and risk evaluation, the Risk Management Team to assess and manage risks related to users utilizing Pay-Later services, and Sales Managers to integrate Pay-Later services into sales strategies.
Recommendations for Researchers	Advanced fraud detection mechanisms were implemented to prevent unauthorized transactions effectively. The goal was to cultivate user confidence in the safety of their financial data by ensuring secure payment processing.
Impact on Society	Ensuring consumers understand the terms and conditions of pay-later arrangements, including interest rates, repayment schedules, and potential fees, is crucial. Providing clear and transparent information, along with educating consumers about their financial responsibilities, helps prevent misunderstandings and disputes.
Future Research	Our future development plans involve the ongoing assessment of the system's performance to enhance prediction accuracy. This includes updating models and criteria based on feedback and changes in economic or market conditions. Upholding compliance with security and data privacy regulations necessitates the implementation of protective measures to safeguard consumer information. The implementation of such a system requires careful consideration to ensure fairness and adherence to legal standards. Additionally, it is important to acknowledge that algorithms and models may evolve over time through the incorporation of additional data and continuous evaluations.
Keywords	pay-later, system recommendation, multi-stage analysis, ROAD, CNN, RNN, LSTM

INTRODUCTION

In recent years, the global e-commerce market has witnessed a significant shift towards "buy now, pay later" (BNPL) systems, driven by the evolving financial preferences of consumers seeking more flexible payment options. This trend is not confined to developed nations but is also rapidly gaining traction in emerging markets, including Indonesia. Indonesia, with its burgeoning digital economy and expanding middle class, presents a unique landscape for the implementation of BNPL systems. However, the adoption of these systems faces distinct challenges, such as varying consumer creditworthiness, regulatory landscapes, and technological infrastructure disparities. Additionally, the COVID-19 pandemic has further accelerated the need for innovative payment solutions that can support both consumers and merchants in navigating economic uncertainties.

Despite the growing popularity of BNPL systems globally, there is a dearth of comprehensive studies examining their implementation in the Indonesian context. A multistage approach, considering factors such as market readiness, consumer behavior, and risk management, is essential to develop an effective and sustainable BNPL system tailored to the Indonesian market.

The pay-later application offers functionalities and benefits similar to a credit card, enabling consumers to "buy now, pay later" (C+R Research, 2021). This payment option has gained popularity in Indonesia, enhancing payment system innovation among e-commerce giants such as Shopee, Tokopedia, Traveloka, Bukalapak, Kredivo, Akulaku, Gojek, IndoDana, and LinkAja. Its widespread acceptance among millennials underscores the appeal of the pay-later feature, especially for those without access to traditional credit cards. Pay-later services represent a collaboration between multi-finance companies, peer-to-peer (P2P) fintech, and e-commerce platforms (Gerrans et al., 2022). Decision-making processes for these services scrutinize consumer shopping behavior, incorporating data such as account history, transaction frequency, payment methods, and the types of goods purchased (Agustin, 2022).

However, issues like bad credit, including late payments or defaults, present significant challenges. For instance, a recent study indicated that 30% of BNPL users missed at least one payment in the past year, and 15% defaulted on their pay-later obligations (Gerrans et al., 2022). Another study found that defaults in pay-later schemes contributed to a 20% increase in consumer credit delinquencies (Wadud et al., 2020). To address these challenges, we propose a recommendation model designed to identify consumers most likely to fulfill their payment obligations. By leveraging a multistage approach, this study will evaluate the feasibility, potential benefits, and risks associated with implementing a BNPL system. The findings are expected to offer valuable insights not only for Indonesia but also for other emerging markets considering similar financial innovations.

The approaches and methods used for recommendation systems in various case studies – including choosing jobs, schools, food, films, music, books, TV programs, news articles, and more – focus on user profiles (age, gender, occupation, and location) (Benkaddour et al., 2018; Bourkoukou et al., 2017; Widiyaningtyas et al., 2021), user ratings (e.g., Silver, Gold, Platinum) (Yin et al., 2022), purchasing patterns (Ali Abumalloh et al., 2020; Yin et al., 2022), and content information (Ali Abumalloh et al., 2020; Kim et al., 2023). User profile and behavior data are utilized to determine the weight of user ranking values in assessing film genre data (Goyani & Chaurasiya, 2020; Z. Wang et al., 2014). In the research by Z. Wang et al. (2014), the UPC Sim method is employed to calculate similarity values between user rating values, user behavior values, and similarity weighting. In another study, Luna et al. (2015) use user profiles to measure future user interest in specific items. Similarly, Bourkoukou et al. (2017) explore user profiles as a hierarchical concept to enhance the recommendation system for selecting books and music on Amazon.com. Moreover, Benkaddour et al. (2018) demonstrate how user profiles can support diagnostic recommendations made by industrial operators through the stages of prediction, evaluation, and improvement of recommendation results.

User ratings influence the recommendation system with temporal characteristics in film ratings (Kumar et al., 2015; W. Zhang & Wu, 2024), and user tastes can also be treated as a level of ground truth in calculating the validation of film ratings (Amatriain et al., 2009). In this research, user-level patterns were created and analyzed using the Collaborative Filtering (CF) algorithm. Additionally, the user level can be used to create economic models in online film recommendation systems (Tahir & Ali, 2023).

To increase e-commerce sales, customer purchasing patterns can serve as a basis for taxonomic analysis in recommendation systems (W. Zhang & Wu, 2024). The categorization of user purchasing patterns becomes representative data for recommending consumption trends on certain items (P. Wang et al., 2019). Furthermore, user purchasing patterns can enhance the efficiency, prediction, and accuracy of recommendations for purchasing mobile sample products (Guo et al., 2017).

Content-based recommendation systems emphasize providing information in the form of item descriptions (Patra et al., 2020; Puglisi et al., 2015), which are sourced from purchasing patterns and user profiles. Item descriptions displayed on e-commerce pages form the basis of the types of items that users prefer (Pawełoszek, 2021; Wijaya & Mudjahidin, 2021) and represent one of the ways that information is projected to the right people on e-commerce websites (Karthik & Ganapathy, 2021; Mishra et al., 2015).

Finally, building a recommendation system can address problems with a content-based approach that also involves user profiles, purchasing patterns, and user ratings. Collaborative methods for solving problems all have one or more limitations. The results of our analysis indicate that in the recommendation system in previous research, there was no "one-size-fits-all and all using a single stage" technique. Therefore, the opportunity to develop a multi-stage recommendation system is possible (D. Das et al., 2017; Udokwu et al., 2023). The reasons behind using multi-stage recommendations are: (i) consumer classification can utilize a large corpus of items (Fata et al., 2019); (ii) balance in dividing the model workload to achieve optimal precision and recall values (X. Li et al., 2019); and (iii) at the ranking stage, fewer categories and classifications of candidates will be obtained (Khouja, 2003), making it easier for the system to determine the purpose of its recommendations.

Our main contribution has threefold significance. First, our study generates consumer candidates based on the smallest problem consequence value. Second, we achieve the best recall value through the utilization of a candidate generator. Finally, we rank consumers based on categories deserving of pay-later rights.

The remainder of this paper is organized as follows. The next section reviews the literature on recommendation systems, emphasizing the need for a process-oriented approach. This is followed by a detailed methodology and materials used, including an exploratory research design and an analytical framework. This section also discussed the case study and linked the analysis results to existing literature. Next, the experimental findings, theoretical contributions, and managerial implications are presented. The article concludes with a discussion of its limitations and directions for future research.

Literature Review on Recommendation Systems

Recommendation systems, essential to information filtering, are widely used in e-commerce to provide personalized suggestions (Gatzioura & Sànchez-Marrè, 2015; Shah et al., 2017). They leverage personal, implicit, and local information to generate recommendations (Shah et al., 2017). The effectiveness of these systems depends on the techniques, methods, and algorithms used (Bell et al., 2007) and can be categorized into content-based, collaborative, and hybrid approaches (Khan, 2020). Below, we explain these categories and recent research developments in each area (a summary of recent advances in recommender systems can be seen in Table 1).

Collaborative Filtering Recommendation

Recent research in collaborative filtering has produced various advancements. Bobadilla et al. (2023) developed synthetic datasets with adjustable characteristics, allowing for better simulation and evaluation of recommendation algorithms by creating tailored datasets that reflect diverse user behaviors and preferences. Jia et al. (2014) introduced a genetic algorithm-based approach that optimizes the recommendation process by evolving solutions over time, thereby improving the accuracy of recommendations based on user data. Yang et al. (2021) proposed a method using multiple ranked domains to enhance recommendation precision, incorporating various levels of user preferences into the recommendation process. Alharbe et al. (2023) developed an algorithm that accounts for user preference order, addressing the issue of rank rating dependencies and improving the relevance of recommendations. This research also delves into user characteristics, the relationship between users and items, and implicit feedback.

- **User Characteristics:** Ji et al. (2020) proposed algorithms that emphasize time-interest weight, offering a dynamic approach to capturing user preferences. S. Li and Li (2020) integrated user traits and registration details, providing a more personalized recommendation experience. S. Wang et al. (2019) introduced time weighting to address temporal variations in user interests, while J. Zhang et al. (2014) combined item attributes with user preferences for improved recommendations.
- **Relationship Between Users and Items:** Chow et al. (2012) designed a privacy-preserving clustering system that maintains user anonymity while clustering similar users, which is crucial for privacy-conscious applications. Yao et al. (2014) addressed challenges in one-class settings to improve recommendation accuracy despite data sparsity. Sandholm and Ung (2011) emphasized location-aware collaborative filtering to enhance recommendation diversity and reduce bias towards popular items. Chen et al. (2010) developed an algorithm that considers changes in user interests and rating credibility, which improves recommendation quality.
- **Implicit Feedback:** Liu et al. (2018) introduced Logistic Matrix Factorization for analyzing music listening behavior, which outperformed traditional matrix factorization methods. Zheng et al. (2016) proposed implicit CF-NADE, a neural autoregressive model that showed significant improvements in recommendation accuracy. Lian et al. (2016) developed a sparse Bayesian framework for implicit feedback, showcasing its effectiveness in various recommendation contexts. Hu et al. (2008) created a factor model specifically for implicit feedback datasets, enhancing recommendation systems' ability to handle implicit user interactions.

CONTENT-BASED FILTERING RECOMMENDATION SYSTEMS

Content-based filtering systems have also seen notable advancements. Thannimalai and Zhang (2021) introduced a hybrid system combining collaborative and content-based filtering with a Naïve Bayes Classifier, improving the efficiency of tourist spot recommendations by leveraging both user preferences and item features. Iwahama et al. (2004) developed a content-based filtering system for MIDI music data, focusing on feature parameters to generate relevant recommendations, enhancing the effectiveness of music recommendation systems. Son and Kim (2017) addressed cold start and data sparsity issues by applying content-based filtering techniques, offering solutions for common challenges faced by recommender systems. H. Li et al. (2012) utilized Hidden Markov Models (HMM) to capture user interests more accurately, providing a robust method for modeling user preferences over time. This body of work underscores the significance of research in content-based filtering, particularly regarding user attributes and the complex dynamics between users and items, while also exploring the potential of implicit feedback to refine recommendation processes.

- **User Characteristics:** H. Zhou et al. (2005) developed a personalized search algorithm that improved upon the vector space model, capturing user interests more effectively. Hashim and Waden (2023) applied content-based filtering on social media to analyze user activities and profile data, enhancing social media recommendations. F. Zhao et al. (2017) introduced a hybrid approach for personalized mobile searches, merging content-based and collaborative filtering to increase precision. Vivek Arvind et al. (2012) advanced web personalization by combining item-based collaborative filtering with association rule mining.
- **Relationship Between Users and Items:** Kazienko (2007) utilized positive and negative usage patterns for web recommendations, improving the relevance of recommended items. Yoshida et al. (2012) suggested tag ranking to enhance item recommendations, providing a method for better item categorization. J. Wang et al. (2020) modeled user and item preferences for personalized recommendations, refining how user preferences are matched with items. W. Zhao et al. (2022) compared user and item-based collaborative filtering methods on sparse data, addressing their respective challenges and potential benefits.

- **Implicit Feedback:** T. Lee et al. (2008) and Roy (2020) proposed methods that incorporate temporal information and matrix factorization to improve recommendations. Liu et al. (2018) introduced a sparse Bayesian framework for implicit feedback, enhancing recommendation systems' ability to handle sparse data. S. Lee et al. (2016) reviewed the role of implicit feedback in recommender systems, highlighting its impact and associated challenges.

HYBRID RECOMMENDATION SYSTEMS

Hybrid recommendation systems combine multiple techniques to enhance accuracy and user satisfaction. Chikhaoui et al. (2011) and Trabelsi et al. (2021) emphasized the importance of hybrid approaches in overcoming the limitations of individual recommendation methods, demonstrating improved recommendation performance by integrating different techniques. Ristoski et al. (2014) introduced a model leveraging Linked Open Data (LOD) to combine base recommenders with global popularity scores, broadening the scope of recommendations while tailoring them to individual users. Anjali et al. (2021) combined association rule mining with content-based techniques, excelling in generating accurate recommendations in complex information spaces. Dooms et al. (2015) developed a hybrid method integrating collaborative and content-based filtering, focusing on user-specific optimizations to enhance recommendation quality. These investigations contribute to a deeper understanding of how hybrid systems can adapt and evolve to meet the diverse needs and preferences of users, further solidifying the importance of hybrid approaches in the development of effective and efficient recommendation systems.

- **User Characteristics:** Grivolla et al. (2014) and Anjali et al. (2021) highlighted the importance of incorporating user demographics and item characteristics to refine recommendations. Ristoski et al. (2014) introduced user-profile groups within a multicriteria decision-making framework, and Dooms et al. (2015) emphasized online optimization for enhancing system responsiveness and scalability.

- **Relationship Between Users and Items:** Ghazanfar and Prügel-Bennett (2010) demonstrated how detailed user and item information improves recommendation quality. Aguiar et al. (2020) incorporated customer personality traits into the recommendation process, outperforming contemporary algorithms. Chikhaoui et al. (2011) merged multiple filtering techniques, achieving significant improvements in accuracy and coverage.

- **Implicit Feedback:** Garden and Dudek (2005) and Kavinkumar et al. (2015) discussed leveraging both external and internal user feedback to enhance system performance. S. Lee et al. (2016) and Yu et al. (2013) illustrated how combining diverse feedback data improves recommendation outcomes, showcasing the critical role of implicit feedback in hybrid systems.

Table 1. Summary of recent advances in recommendation systems

Approach	Contribution
Collaborative Filtering	Developed synthetic datasets with adjustable characteristics for better simulation and evaluation of algorithms (Bobadilla et al., 2023)
	Introduced a genetic algorithm-based approach to optimize the recommendation process by evolving solutions over time (Jia et al., 2014)
	Proposed a method using multiple ranked domains to enhance recommendation precision by incorporating various levels of user preferences (Yang et al., 2021)
	Developed an algorithm accounting for user preference order, addressing rank rating dependencies to improve relevance (Alharbe et al., 2023)
Content-Based Filtering	Introduced a Naïve Bayes Classifier for improved tourist spot recommendations (Thannimalai & Zhang, 2021)
	Developed MIDI music data, focusing on feature parameters to enhance recommendation effectiveness (Iwahama et al., 2004)

Approach	Contribution
	Addressed cold start and data sparsity issues to common recommender system challenges (Son & Kim, 2017)
	Utilized Hidden Markov Models (HMM) to capture user interests more accurately, providing a robust method for modeling preferences over time (H. Li et al., 2012)
Hybrid Recommendation Systems	Highlighted the importance of hybrid approaches in overcoming limitations of individual methods by integrating different techniques (Chikhaoui et al., 2011; Trabelsi et al., 2021)
	Introduced a model leveraging Linked Open Data (LOD) to combine base recommenders with global popularity scores for broader and tailored recommendations (Ristoski et al., 2014)
	Combined association rule mining with content-based techniques, excelling in generating accurate recommendations in complex information spaces (Anjali et al., 2021)
	Developed a hybrid method integrating collaborative and content-based filtering, focusing on user-specific optimizations to enhance quality (Dooms et al., 2015)

MULTISTAGE RECOMMENDATION SYSTEM

The exploration of multistage recommendation systems represents a significant advancement in the field of recommender systems, offering sophisticated frameworks that cater to the complexities of modern digital ecosystems. Through the integration of diverse methodologies and considerations, these systems aim to enhance user satisfaction, market coverage, and overall system effectiveness. R. Das and Singh (2022) and Fata et al. (2019) both propose multistage recommendation models, with R. Das and Singh (2022) focusing on a two-stage embedding model that leverages multimodal auxiliary information items, and Fata et al. (2019) introducing a two-level monotonic property to enhance prediction accuracy. These models aim to improve recommendation performance by considering user-item-stage dependencies and enhancing the accuracy of learning. However, both models have limitations in terms of scalability and the ability to handle missing observations. Khouja (2003) discusses the concept of multi-stakeholder recommendation, which considers the needs of both end users and other stakeholders. This approach presents a potential solution to the limitations of the existing multistage recommendation models.

Köse and Yaslan (2023) introduce an innovative multi-stage ensemble model tailored for cross-market recommendations. This model leverages data from various markets to improve the accuracy of ranking predictions, showcasing the potential of cross-market insights to refine recommendation processes. Palomares and Kovalchuk (2017) explore the realm of multi-view data approaches within recommender systems, shedding light on their capability to overcome prevalent challenges in the field. By employing advanced learning techniques for the aggregation of information from multiple viewpoints, Palomares and Kovalchuk (2017) demonstrate how these approaches can significantly enrich the recommendation process, offering more personalized and accurate suggestions to users.

Collectively, these studies underscore the transformative potential of multistage recommendation systems. By embracing complexity and diversity, these systems pave the way for more sophisticated, equitable, and effective recommendation practices that cater to the nuanced demands of digital environments and their myriad participants. See Table 2 for a summary of the multistage recommendation system and the contribution of this study.

Table 2. Summary of multistage recommendation systems and contribution of this study

Approach	Contribution
Two-stage embedding model (R. Das & Singh, 2022)	Leverages multimodal auxiliary information items to enhance recommendation performance.
Two-level monotonic property (Fata et al., 2019)	Enhances prediction accuracy by considering user-item-stage dependencies.
Multi-stakeholder recommendation (Khouja, 2003)	Considers the needs of both end users and other stakeholders, addressing scalability and missing data issues.
Multi-stage ensemble model (Köse & Yaslan, 2023)	Tailored for cross-market recommendations, improving the accuracy of ranking predictions using cross-market data.
Multi-view data approaches (Palomares & Kovalchuk, 2017)	Uses advanced learning techniques to aggregate information from multiple viewpoints for personalized recommendations.
This study (multi-stage using ROAD analysis and CNN Architecture)	• Identified potential consumers by prioritizing those with the smallest associated problem consequence values. • Achieved an optimal recall value using a candidate generator. • Categorized consumers to assess their eligibility for pay-later rights.

METHOD AND MATERIAL

METHOD

The construction of a recommendation system, as described (refer to Figure 1), employs a nuanced multi-stage approach designed to enhance decision-making processes and recommendation accuracy. This method integrates diverse analytical techniques and stakeholder insights, culminating in a sophisticated framework for evaluating consumer eligibility for pay-later rights. Below is an elaboration on the described methodology, broken down by stages.

Stage 1: Scientific model analysis using hybrid deep learning methods

The initial stage of the recommendation system leverages a hybrid deep learning approach. This methodology combines the strengths of various deep learning architectures to analyze consumer data comprehensively. By processing user profiles, ratings, buying patterns, and content-related information, the system can uncover intricate patterns and preferences that might not be evident through traditional analytical methods. The hybrid model ensures a robust understanding of consumer behavior, facilitating personalized and accurate recommendations.

Stage 2: Risk analysis of decision selection using the ROAD process

Following the deep learning analysis, the system engages in a risk assessment phase utilizing the Risk Option Assessment for Decision Making (ROAD) process. This stage is critical for evaluating the potential risks associated with granting pay-later rights to consumers. The ROAD process systematically assesses various decision options, considering factors such as financial stability, purchase history, and consumer reliability. This structured approach to risk analysis ensures that decisions are made with a comprehensive understanding of potential outcomes, thereby minimizing financial risk and enhancing decision-making accuracy.

ROAD enables decision-makers to understand and address complex risks through a systems-based approach to risk assessment that integrates different tools and types of knowledge (https://www.fe2wnetwork.org/ROADguide). Its main feature is the participatory development of a causal model of the risk system, which provides a basis for decision-making.

Stage 3: Analysis of knowledge originating from stakeholders

The third stage involves incorporating insights and knowledge from stakeholders. This includes feedback from financial analysts, consumer behavior experts, and other relevant parties who can provide additional context or identify potential oversights in the analysis. By integrating stakeholder knowledge, the system gains a more holistic view of the consumer and the marketplace, ensuring that the recommendation process is grounded in a wide range of perspectives and expertise.

Stakeholders should possess the following knowledge and skills: financial knowledge, including credit scoring, risk assessment, and financial regulations; and analytical skills, such as proficiency in analyzing financial data to identify trends, patterns, and anomalies that may indicate creditworthiness or potential risk. Additionally, they should have experience in issuing credit, understanding the criteria for approval, and managing the lifecycle of credit accounts.

Final analysis and decision-making

The culmination of these stages is a thorough analysis process that determines which consumers are eligible for pay-later rights. The multi-stage approach ensures that the decision is informed by a deep understanding of consumer behavior (Stage 1), a comprehensive risk assessment (Stage 2), and the valuable insights of stakeholders (Stage 3). This methodological rigor enhances the accuracy and reliability of the recommendation system, making it a powerful tool for businesses looking to offer pay-later options to their consumers.

By adopting this multi-stage approach, the recommendation system not only personalizes its suggestions but also ensures that such recommendations are viable and sustainable from a financial perspective. This holistic and rigorous methodology exemplifies the potential of combining advanced analytical techniques with stakeholder insights to make informed, strategic decisions in the realm of financial services and consumer credit.

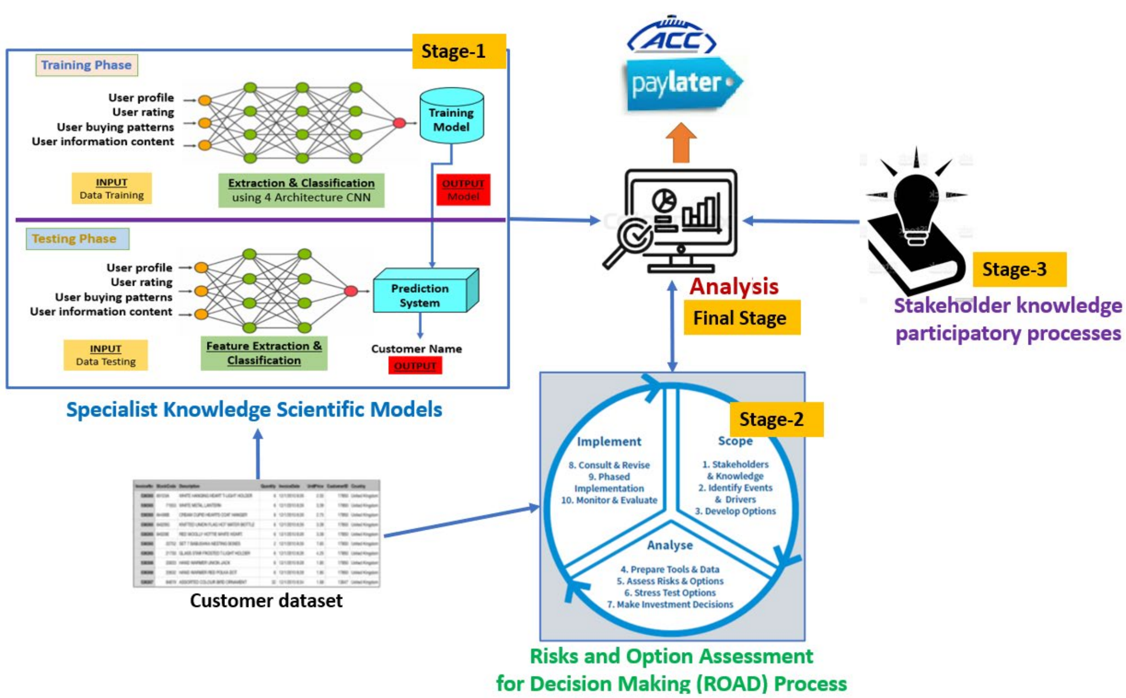

Figure 1. Pay-later recommendation multistage method

Based on Figure 1, each component contributes to the overall recommendation system, leading to the selection of consumers for pay-later services:

Specialist Knowledge Scientific (SKS) Model

- Input: Customer dataset (user profiles, ratings, buying patterns, and content information).
- Process: The SKS model applies scientific analysis to this dataset, evaluating consumers' eligibility for pay-later services based on a pay-later value classification. This classification likely incorporates predictive analytics and customer segmentation techniques to identify those with the highest potential.
- Output: A prioritized list of consumers deemed to have the highest potential for pay-later eligibility. This list represents individuals who, according to the model, are most likely to use pay-Later services responsibly and profitably.

Risks Option Assessment for Decision Making (ROAD) Process

- Input: Same customer dataset as used in the SKS model.
- Process: The ROAD process focuses on evaluating the risks and consequences associated with extending pay-later services to different consumers. This involves a detailed risk assessment to pinpoint consumers who present minimal risk and have a high potential for successful engagement with pay-later services.
- Output: An analysis highlighting consumers with the most favorable risk-to-benefit ratio for pay-later services. This output identifies the safest and most promising opportunities for service extension.

Stakeholder Knowledge Participatory (SKP) Analysis

- Input: Outputs from both the SKS model and the ROAD process.
- Process: The SKP involves stages such as the identification of relevant stakeholders, clarification of their influences, consensus-building on the involvement process, and managing stakeholder relationships. This participatory approach ensures that the insights and concerns of various stakeholders are incorporated into the final decision-making process.
- Output: A refined and stakeholder-informed list of consumers recommended for pay-later services. This list is optimized not only based on scientific analysis and risk assessment but also on the practical insights and strategic considerations of stakeholders.

Final Recommendation System

- Integration: The system integrates the analytical outputs from the SKS model and the ROAD process, further refined by stakeholder inputs through the SKP analysis.
- Function: It facilitates automatic recommendations for pay-later providers, enabling them to identify and select consumers with the highest potential for successfully obtaining and using pay-later service rights.
- Application: Particularly useful for evaluating new customers classified by the model, this system streamlines the process of extending pay-later services to those deemed most eligible, thereby enhancing service provision and minimizing risk.

This multi-faceted approach exemplifies a thorough and nuanced method for determining pay-later eligibility, combining data-driven insights with risk assessment and stakeholder participation. It offers a comprehensive framework that balances scientific analysis with practical risk management and stakeholder engagement, ensuring a well-rounded and informed selection process for pay-later service provision.

MATERIAL

The dataset we utilized comprises consumer data randomly sampled from four pay-later providers: Shopee, Bukalapak, Gojek, and LinkAja. These providers were selected based on attributes relevant to consumer prediction assessments. Shopee is a leading e-commerce platform in Southeast Asia and

Taiwan, known for its wide range of products and integrated pay-later solutions. Bukalapak is a major e-commerce player in Indonesia, offering a variety of products and financial services, including pay-later options. Gojek, a leading on-demand service provider in Southeast Asia, integrates pay-later solutions into its multi-service platform. LinkAja is a digital payment platform backed by major Indonesian state-owned enterprises, offering pay-later options as part of its financial services.

The total data collected comprised 438 entries, which were randomly divided into 70% for training and 30% for testing. The dataset features ten predictor attributes: age, income, marital status, shopping patterns, types of goods purchased, price of goods purchased, payment patterns, installment tenor, payout interest, and payout limit. To enhance output accuracy, we categorized the data into three groups: low, middle, and high, as outlined in Table 3. The dataset was then converted into a categorical format, where output values are represented as 1 for low, 2 for medium, and 3 for high. These ten factors are crucial for predicting the credit risk evaluation process, as determined through consultations and discussions with expert staff in public finance.

Table 3. Predictor attribute data

Code#	Attribute description	Low	Medium	High
UP1	Income	< 2 million IDR	Rp. 3-5 million IDR	> 5 million IDR
UP2	Age	17-20 years	21-39 years	> 40 years
UP3	Marital Status	single	married	single parent
UP4	Shopping Pattern	once a month	2 weeks	once a week
UP5	Types of goods purchased	food	Clothing	tools/electronics
UP6	Price of goods purchased	< 500.000 IDR	500.000-1.000.000 IDR	>1.000.000 IDR
UP7	Pattern / history of paying	COD	transfer	digital wallet
UP8	Installment Tenor	1 month	6 months	12 months
UP9	Pay-latter Interest	2%	3%	4%
UP10	Pay-latter Limit	750.000 IDR	3.000.000 IDR	6.000.000 IDR

The system's output consists of '1', representing risk-free credit, and '2', representing credit risk, as illustrated in Table 4. The classification for determining risk or no risk utilizes the consumer credit scoring process. We conclude that a score above 70% is classified as risk-free, while scores below 70% indicate potential risk. Due to the sensitive and high-risk nature of consumer decisions regarding pay-later payouts, we opted for binary classification, simplifying the data into two distinct categories: approved and denied. This choice was made to enhance model clarity and focus on the critical decision-making outcomes. Additionally, to address ethical concerns, all customer data were anonymized to protect personal information and ensure compliance with privacy regulations.

Table 4. Classification of output values

Limiting variable	Class	Pay later
>= 0,70	1	Not risky
< 70	2	Risky

Table 4 outlines the "Limiting Variable" as a threshold score, likely derived from a scoring model, to evaluate the risk associated with specific actions or decisions, such as extending "pay-later" credit. This variable is expressed as a decimal, normalized between 0 and 1, where a value of 1 indicates the highest likelihood of a positive outcome or the lowest risk. The "Class" column categorizes outcomes into two distinct groups based on the "Limiting Variable": Class 1 for outcomes deemed "Not Risky," indicating that the conditions or criteria meet a certain level of safety or confidence (Limiting

Variable ≥ 0.70), and Class 2 for outcomes labeled as "Risky," reflecting lower confidence in the outcome or a higher risk of unfavorable results (Limiting Variable < 0.70). The "pay-later" decision column identifies the risk associated with deciding to "pay-later." A Limiting Variable of 0.70 or above is considered "Not Risky," suggesting that allowing a later payment is relatively safe under these conditions. Conversely, a value below 0.70 is deemed "Risky," indicating a higher likelihood of non-payment or default. By categorizing risk into clear, actionable classes, this classification table simplifies the decision-making process and accelerates the evaluation of "pay-later" decisions, proving especially useful in high-volume settings.

RESULTS AND DISCUSSION

In this section, we present the outcomes of our research activities and observations, which encompass four key areas:

(1) the development of a Specialist Knowledge Scientific model through deep learning techniques;
(2) the evaluation of Risk and Option Assessment within the Decision-Making Process;
(3) the engagement in Stakeholders Knowledge Participatory Processes; and
(4) the Analysis of Recommendation Results.

The specifics of these observations and their implications are delineated in the subsequent points.

SPECIALIST KNOWLEDGE SCIENTIFIC MODEL

At this stage of our research, we aim to identify the optimal model through the comparative analysis of three advanced deep learning architectures: Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM). According to P. Zhou et al. (2016), the integration of RNN and LSTM algorithms is particularly effective for analyzing data that exhibit inherent sequential relationships. Concurrently, Jain et al. (2021) highlight that combining LSTM and CNN can significantly improve the accuracy of consumer classification tasks. Motivated by these insights, our study delves into the application of deep learning technologies for the extraction and classification of consumer data, specifically targeting eligibility for pay-later services.

Data preparation

The data we collected underwent a preparation stage using the Pandas library, where it was converted into a format readable by CNN, RNN, and LSTM models. This preparation involved cleansing the database to eliminate noise, address missing values and rectify inconsistencies. Specifically, data cleaning was crucial because real-time database information often arrived incomplete and inconsistent, leading to inaccurate data mining results. Therefore, to enhance the quality of the data for analysis, we performed data preparation steps.

The data cleaning process was essential as the recently collected data contained many irrelevant components and some missing parts. This involved handling missing values and noise. Missing values occurred when data in the database was incomplete or absent. Dealing with missing values could involve either ignoring the records or filling in the missing data. Ignoring records was suitable for large datasets where several values in a record were missing. Filling in missing values could be accomplished in various ways, such as manually replacing them with the mean or other values based on the data type. Noise refers to irrelevant or erroneous data that cannot be interpreted by tools, often arising from incorrect data collection or inaccurate data entry. The illustration of data cleaning and normalization can be seen in Figure 2.

Data Cleaning Steps

Step 1: Handling Missing Values

For this illustration, let's assume that the original data had some missing values (e.g. colored cells).

Consumer ID	Income (IDR)	Age (Years)	Marital Status	Shopping Pattern	Types of Goods Purchased	Price of Goods Purchased (IDR)	Pattern / History of Paying	Installment Tenor (Months)	Pay-later Interest (%)	Pay-later Limit (IDR)
1	4,500,000	25	Married	Once a Week	Clothing	750.000	Transfer	6	3	3.000.000
2	6,200,000	40	Single Parent	Every 2 Weeks	Tools/ Electronics	1.500.000	Digital Wallet	12	4	6.000.000
3	1,800,000		Single	Once a Month	Food	300.000	COD	1	2	750.000
4	3,200,000	32	Married	Every 2 Weeks		550.000	Transfer	6	3	3.000.000
5		28	Single	Once a Week	Clothing	1.200.000	Digital Wallet	12	4	6.000.000

Step 2: Imputing Missing Values

Consumer ID 5 has a missing value for Income. We can impute this with the mean income.

Mean Income: (4,500,000 + 6,200,000 + 1,800,000 + 3,200,000) / 4 = 3,425,000 IDR

Updated value for Consumer ID 5: **3,425,000 IDR**

Consumer ID 3 has a missing value for Age. We can impute this with the mean age.

Mean Age: (25 + 40 + 32 + 28) / 4 = 31.25 years

Updated value for Consumer ID 3: **31 years** (rounded to the nearest whole number)

Consumer ID 4 has a missing value for Types of Goods Purchased. We can impute this based on the mode of the column.

Mode: Clothing (appears most frequently)

Updated value for Consumer ID 4: **Clothing**

Step3: Normalization

Income (IDR):

Min-Max scaling to transform values to a range [0, 1].

Min: 1,800,000 IDR, Max: 6,200,000 IDR

Normalized Income:

Consumer ID 1: (4,500,000 - 1,800,000) / (6,200,000 - 1,800,000) = 0.75
Consumer ID 2: (6,200,000 - 1,800,000) / (6,200,000 - 1,800,000) = 1.00
Consumer ID 3: (1,800,000 - 1,800,000) / (6,200,000 - 1,800,000) = 0.00
Consumer ID 4: (3,200,000 - 1,800,000) / (6,200,000 - 1,800,000) = 0.35
Consumer ID 5: (3,425,000 - 1,800,000) / (6,200,000 - 1,800,000) = 0.45

Age (Years):

Min-Max scaling to transform values to a range [0, 1].

Min: 19 years, Max: 40 years

Normalized Age:

Consumer ID 1: (25 - 19) / (40 - 19) = 0.286
Consumer ID 2: (40 - 19) / (40 - 19) = 1.000
Consumer ID 3: (31 - 19) / (40 - 19) = 0.571
Consumer ID 4: (32 - 19) / (40 - 19) = 0.619
Consumer ID 5: (28 - 19) / (40 - 19) = 0.429

Price of Goods Purchased (IDR):

Min-Max scaling to transform values to a range [0, 1].

Min: 300,000 IDR, Max: 1,500,000 IDR

Normalized Price:

Consumer ID 1: (750,000 - 300,000) / (1,500,000 - 300,000) = 0.375
Consumer ID 2: (1,500,000 - 300,000) / (1,500,000 - 300,000) = 1.000
Consumer ID 3: (300,000 - 300,000) / (1,500,000 - 300,000) = 0.000
Consumer ID 4: (550,000 - 300,000) / (1,500,000 - 300,000) = 0.208
Consumer ID 5: (1,200,000 - 300,000) / (1,500,000 - 300,000) = 0.750

Cleaned and Normalized Data

Consumer ID	Income (Normalized)	Age (Normalized)	Marital Status	Shopping Pattern	Types of Goods Purchased	Price (Normalized)	Pattern / History of Paying	Installment Tenor (Months)	Pay-later Interest (%)	Pay-later Limit (IDR)
1	0.75	0.286	Married	Once a Week	Clothing	0.375	Transfer	6	3	3000000
2	1.00	1.000	Single Parent	Every 2 Weeks	Tools/ Electronics	1.000	Digital Wallet	12	4	6000000
3	0.00	0.571	Single	Once a Month	Food	0.000	COD	1	2	750000
4	0.35	0.619	Married	Every 2 Weeks	Clothing	0.208	Transfer	6	3	3000000
5	0.45	0.429	Single	Once a Week	Clothing	0.750	Digital Wallet	12	4	6000000

Step4: Discretization

1. Income (Normalized):		2. Age (Normalized):		3. Price (Normalized):		4. Installment Tenor (Months):	
Bins	**Discretized Values**	**Bins**	**Discretized Values:**	**Bins**	**Discretized Values**	**Bins**	**Discretized Values**
Low: 0.0 - 0.4	0.75 → High	Young: 0.0 - 0.4	0.286 → Young	Low: 0.0 - 0.3	0.375 → Medium	Short: 1 - 6 months	6 → Short
Medium: 0.4 - 0.7	1.00 → High	Middle-aged: 0.4 - 0.7	1.000 → Old	Medium: 0.3 - 0.7	1.000 → High	Medium: 7 - 12 months	12 → Medium
High: 0.7 - 1.0	0.00 → Low	Old: 0.7 - 1.0	0.571 → Middle-aged	High: 0.7 - 1.0	0.000 → Low	Long: 13+ months	1 → Short
	0.35 → Low		0.619 → Middle-aged		0.208 → Low		6 → Short
	0.45 → Medium		0.429 → Middle-aged		0.750 → High		12 → Medium

Discretization Data

Consumer ID	Income (Discrete)	Age (Discrete)	Price (Discrete)	Installment Tenor (Discrete)	Marital Status	Shopping Pattern	Types of Goods Purchased	Pattern / History of Paying	Pay-later Interest (%)	Pay-later Limit (IDR)
1	High	Young	Medium	Short	Married	Once a Week	Clothing	Transfer	6	3000000
2	High	Old	High	Medium	Single Parent	Every 2 Weeks	Tools/ Electronics	Digital Wallet	12	6000000
3	Low	Middle-aged	Low	Short	Single	Once a Month	Food	COD	1	750000
4	Medium	Middle-aged	Low	Short	Married	Every 2 Weeks	Clothing	Transfer	6	3000000
5	Medium	Middle-aged	High	Medium	Single	Once a Week	Clothing	Digital Wallet	12	6000000

Figure 2. Illustration of cleaned, normalized, and discretization data

Feature engineering

In this stage, we select and engineer the features to be used as input for the CNN, RNN, and LSTM models. The variables selected include the type of goods purchased, the amount of the pay-later loan, income, debt-to-income ratio, payment patterns, employment status, and credit score. Next, we normalize or scale features to improve model performance. This step involves data transformation, which changes data into a form appropriate for the data mining process. Some techniques for data transformation include normalization, attribute selection, and discretization.

Normalization is conducted to scale data values to a specific range, such as -1 to 1 or 0 to 1. The second technique, attribute selection, involves choosing the most relevant attributes for the data mining process. Lastly, the discretization technique replaces raw numeric attribute values with interval values.

Model architecture

The architectural model we constructed leverages existing libraries in Keras, involving the creation of a novel architecture that combines layers of (CNN + LSTM) with (RNN + LSTM). This intricate process includes specifying a particular number of cells and hidden layers, as well as determining the activation function used in each layer. Our inspiration for this innovative combination of CNN and LSTM was drawn from the research findings of Donahue et al. (2017), which we aimed to adapt for text data analysis. In this model, the weights of CNN and LSTM are utilized to scale long sequences in the input data effectively. CNN is tasked with extracting features from the input data, whereas LSTM processes these features to predict sequences. The decision to combine CNN with LSTM is grounded in the unique capability of these two algorithms to address prediction challenges involving distinct inputs. This synergistic combination enhances the model's ability to manage and predict complex data sequences, as illustrated in Figure 3.

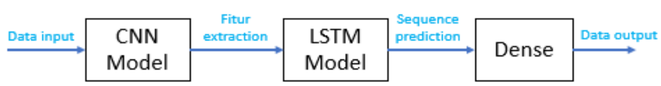

Figure 3. CNN-LSTM Architecture model

Another combination that we employ is RNN + LSTM, as depicted in Figure 4, with the goal of attaining the optimal model for our recommendation system. The embedding results manifest as a matrix with a dictionary size and embedding size. The resultant dimensions encompass batch size, sequence, and embedding size. The embedding dimension encapsulates a set of features for words akin to the number of hidden units.

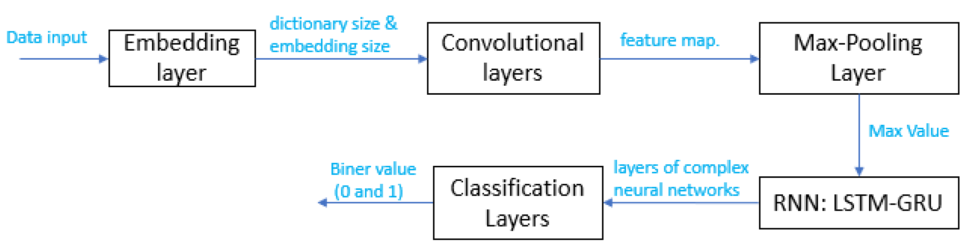

Figure 4. RNN-LSTM Architecture model

The results of the embedding are represented in a matrix format with a length corresponding to the dictionary size and embedding dimensions. Following this, we incorporate an RNN Layer with Simple RNN from the TensorFlow module. The subsequent step entails integrating the LSTM memory block, which comprises specialized units known as memory blocks within the recurrent hidden layer. Subsequently, we introduce a dense layer to enhance complexity and a dropout neural network layer to mitigate the issue of overfitting. The final step involves the representation of Output Data, which is depicted by binary values (0 and 1).

Fase training data

The training of deep learning architecture models (CNN, RNN, LSTM) involves utilizing annotated historical data, which is partitioned into training and validation sets. Training algorithms, such as stochastic gradient descent (SGD), are then applied to optimize model parameters. Moreover, we explored variations in epoch values, adjusted learning rates, and manipulated the number of epochs to optimize the performance of the constructed model. From the results of our conducted training, it is evident that combining these two methods (CNN+LSTM and RNN+LSTM) leads to improved accuracy compared to when the three methods are implemented separately (see Figure 5).

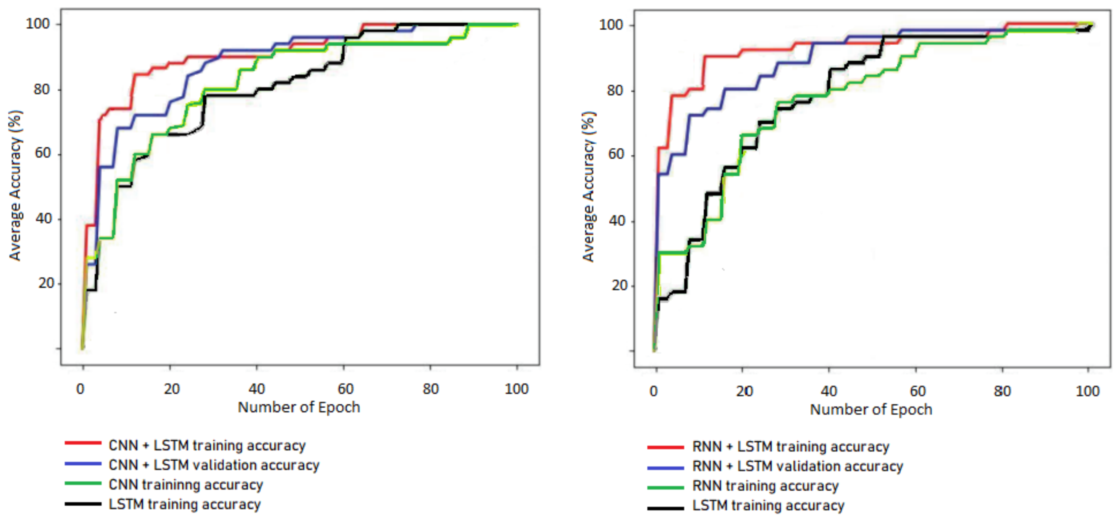

Figure 5. Comparison of training phases for the combination of CNN+LSTM and RNN+LSTM

According to Figure 5, the training process, spanning from the initial iteration to the 60th, consistently shows that each combination of CNN+LSTM and RNN+LSTM achieves accuracy above 80%. We use approximately 85-90 iterations to determine the number of epochs for evaluating and testing the performance of the neural network model on validation data. After the 91st iteration, we halt to prevent overfitting. These findings underscore that the implemented combination yields superior accuracy compared to using the methods individually.

Fase testing data

To further assess the impact of CNN-LSTM and RNN-LSTM models on pay-later evaluation, we conducted a comparative analysis experiment involving five different models (see Table 5). The selected comparison objects were RNN, CNN, LSTM, CNN-LSTM, and RNN-LSTM. Initially, a comparative experiment was carried out to analyze and compare the evaluation results of the five models with variations in dropout rates and learning levels. The experiments demonstrate that the RNN-LSTM model consistently exhibits optimal performance among the five models, regardless of different learning rates. Additionally, the RNN-LSTM model maintains the best results across various dropout rates.

Table 5. Testing result

Method	Accuracy	Precision	Recall	F1-score
RNN + LSTM	**89.4%**	**87.7**	**88.7**	**88.2**
CNN + LSTM	88.8%	86.7	87.9	87.3
RNN	82.4%	85.6	86.7	86.1
CNN	83.2%	88.5	87.6	88.0
LSTM	85.3%	89.6	88.9	89.2

Table 5 presents the testing results of different methods used, including their accuracy, precision, recall, and F1-score. The methods tested include RNN + LSTM, CNN + LSTM, RNN, CNN, and LSTM. Accuracy represents the percentage of correctly classified instances out of the total instances tested. RNN + LSTM achieved the highest accuracy at 89.4%, indicating its effectiveness in making accurate predictions. Precision indicates the proportion of true positive predictions out of all positive predictions made by the model. LSTM had the highest precision at 89.6%, suggesting it made fewer false positive predictions compared to other methods. Recall measures the ability of the model to correctly identify true positives out of all actual positive instances. LSTM also achieved the highest recall at 88.9%, indicating its ability to capture a high percentage of actual positive instances. F1-Score represents the harmonic mean of precision and recall, providing a balance between the two metrics. LSTM obtained the highest F1-score at 89.2%, reflecting its overall performance in terms of precision and recall.

Overall, the results suggest that LSTM performed consistently well across all metrics, followed closely by RNN + LSTM. CNN also demonstrated competitive performance, while RNN showed slightly lower accuracy and F1-score compared to the other methods. These findings provide insights into the effectiveness of different methods for the task at hand and can guide the selection of the most suitable approach for future applications.

Next, we present the data grouping for the comparison of the four models. The results reveal that all four types of models exhibit their best performance when the parameters are set to Optimizer = SGD, Dropout = 0.3, and CNN and LSTM models demonstrate relatively better performance under Learning Rate = 0.005. To ensure objectivity, we opted for two distinct sets of parameters, ensuring that the evaluation of each model approximates the best results. The classification results of the five types of models were tested across three separate datasets. The experimental outcomes indicate that the RNN-LSTM model consistently achieves the highest accuracy across most instances compared to the other three models on the three different datasets.

RISK OPTION ASSESSMENT FOR DECISION-MAKING PROCESS

At this stage, we institute a participatory process that integrates various types of knowledge into decision-making. We adapt the process by modifying steps, stages, and tasks to align with the decision context we are constructing. The steps taken are elucidated in the following subsection.

Scope: Identify risk event and driver

We begin with the definition of a risk event, which is an event with uncertain consequences, such as consumers being late in paying installments, unable to pay off part of their debt, and unwilling to pay their debt at all. Each of these three risk events has a trigger (the direct cause of the risk event) and a driver (a threat, trend, or other source of the risk event that causes the trigger). The triggers for these risk events are:

(a) debtor character with drivers, including customer's intention, responsibility, and honesty/openness,
(b) capacity with financial management, priority, and policy-making drivers, and
(c) economic conditions with development drivers of financial conditions and relative income.

The scheme for defining risk events, triggers, and drivers can be seen in Figure 6. Referring to this scheme, the next stage is to define the consequences, which are the results of a risk event affecting the goal. The consequences or impacts for the pay-later provider can include the non-return of funds that have been spent, unacceptable interest income, and a decrease in total income. Bad credit conditions will not only affect borrowers or customers but will also impact pay-later providers. These unfavorable credit conditions result in the pay-later provider lacking funds, negatively impacting their business activities.

Analyses: Develop option control and mitigation

Every financial institution offering pay-later funds must maintain a low NPL (Non-Performing Loans) value to sustain its business operations. This necessitates control actions, which involve modifying potential drivers/triggers that can lead to risk events (refer to Figure 6). Controls for debtor character include:

(i) having a fixed income,
(ii) being 21 years old or married with a minimum age of 17 years,
(iii) using pay-later as needed.

Meanwhile, controls for capacity include:

(i) setting the maximum ceiling for goods purchased at twice the monthly income,
(ii) limiting the maximum payout interest to 3% per month.

The control for economic conditions involves the ability to set aside sufficient income and savings to meet needs. Defining controls involves using available resources to mitigate risk events by identifying external factors beyond the control of decision-makers. This includes conducting an initial evaluation of consumers' priority choices regarding the use of pay-later based on criteria established by the pay-later credit service provider. This assessment analysis can also be measured through feedback, which serves as input for drivers/events derived from consequences.

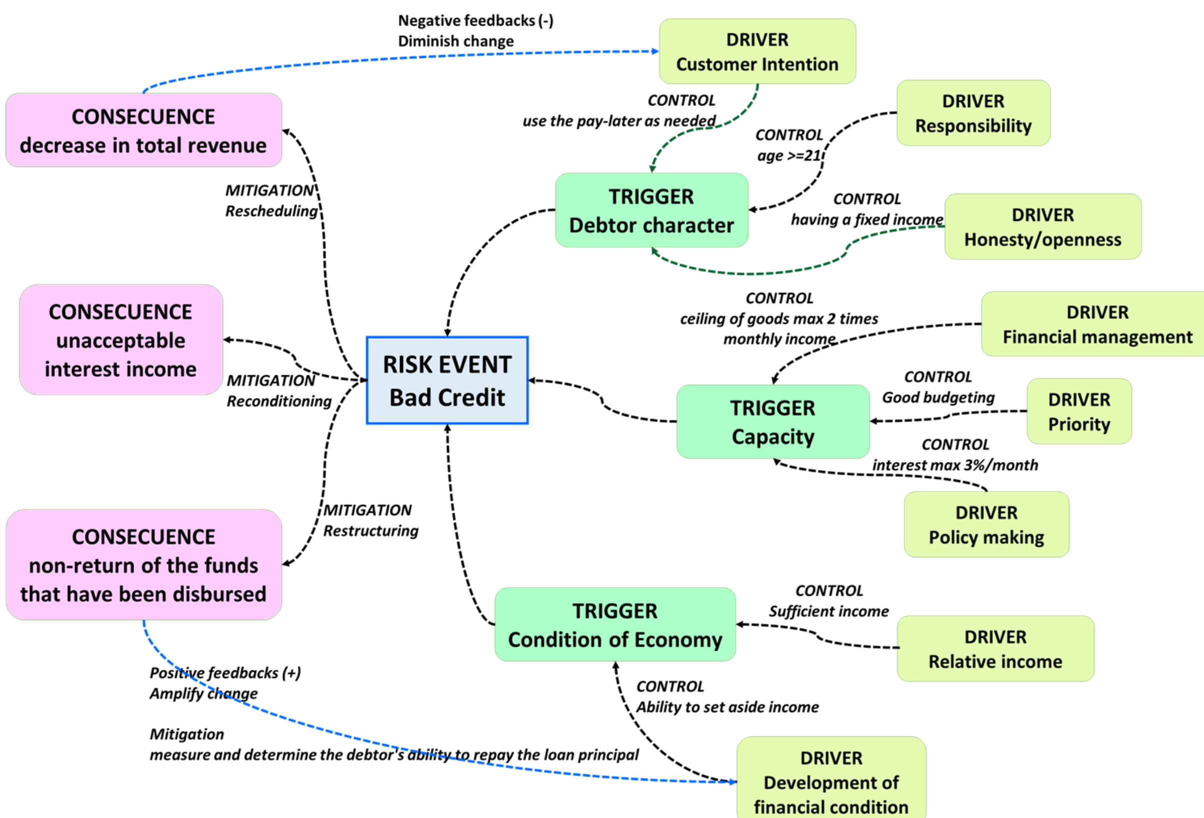

Figure 6. ROAD concept for bad credit

Mitigating is an action that alters the magnitude or potential consequences (refer to Figure 6). Mitigation strategies for bad credit include:

(i) measuring and understanding the extent of the debtor's ability to repay the principal and interest on the loan,

(ii) rescheduling, involving adjustments to payment terms, interest amounts, or fund deposit payments,
(iii) reconditioning, entailing a change in the interest rate to facilitate the debtor in meeting monthly obligations, and
(iv) restructuring, wherein the creditor may reduce credit interest rates, waive fines, or extend installment periods, among other measures.

Implementation: revise, monitor, and assess

In this revising stage, monitoring and assessing pay-latter models are crucial for maintaining their effectiveness and dependability throughout their lifespan. Below are actions for the review, oversight, and evaluation of pay-latter models:

(a) *Monitoring Data Quality:* Consistently oversees the quality of consumer data, ensuring models are trained on the most current information. We employ methods like data profiling, cleaning, and verification to guarantee data accuracy, completeness, and consistency.

(b) *Performance Oversight:* Continuously supervise model performance, assessing metrics such as accuracy, precision, recall, and F1 score. We implement techniques like drift detection, model calibration, and performance analysis to verify that the model meets performance expectations.

(c) *Model Updating:* If a pay-latter model's performance declines over time, consider retraining it with the latest data. Efficient retraining can be achieved through methods such as transfer learning, incremental learning, and active learning.

(d) *Explainability Monitoring:* Regularly monitor the model's explainability to ensure ongoing interpretability. We employ techniques like feature importance ranking, partial dependency plots, and SHAP (Shapley Additive Explanations) values to observe and interpret model behavior.

(e) *Deployment Oversight:* Continually monitor model deployment to ensure its proper functionality in the pay-latter environment. Techniques such as error logging, performance monitoring, and security audits can confirm the correct and secure utilization of the model.

Stakeholders' Knowledge Participatory Processes

Participatory Stakeholder Knowledge is a collaborative process that integrates various types of stakeholder knowledge into decision-making. Stakeholders' experiences and expertise in managing bad credit serve as input for analyzing consumer eligibility in obtaining pay-later rights. In this participatory process, individuals' expertise is incorporated into the calculation parameters of a predefined model. The model utilized is MACTOR (Matrix of Alliances and Conflicts: Tactics, Objectives, and Recommendations). Consequently, the output of this process is a recommendation for consumers who are eligible for pay-later rights.

The stages of MACTOR analysis in this research are as follows:

(i) determine the system trigger;
(ii) establish a set of goals;
(iii) describe the relationship between triggers and drivers, measured on a scale of 0 (no influence) to 4 (very high influence); and
(iv) describe the trigger's attitude (level of resistance) towards the goal, measured on a scale of (+) supporting, (0) neutral, and (-) opposing, and determine the salience of the goal for the trigger, measured on a scale of 0 (not important) to 4 (very important) (Rees & MacDonell, 2017).

Formulating definitive strategic recommendations made by stakeholders requires consideration of the power balance among actors, particularly pay-latter consumers, who can adjust their positions and involvement based on strategic goals. In this research, the relative strength of each trigger parameter is determined using MACTOR software. This involves considering the influence and dependence of assessment parameters on their positions, reflected in the scalar calculation results of the Matrix Direct and Indirect Influences (MIDI)ij matrix (Mayer-Pinto et al., 2015). The formula below illustrates the concrete calculations of assessment parameters for each actor.

$$R_i = \frac{I_i - MIDI_{ii}}{\sum I_i} \frac{I_i}{I_i + D_i} \tag{1}$$

where:

- Ii: the degree of direct and indirect influence of each parameter trigger (by summing the lines of the MIDI);
- Di: the degree of direct and indirect dependence of each parameter trigger (by summing the columns).

In this case study, we compiled assessment parameters grouped into three clusters: the first cluster, 'Debtor Character,' consisting of A1: customer intention, A2: responsibility, and A3: honesty. The second cluster, 'Capacity,' comprises A4: financial management, A5: priority, and A6: policy making. The third cluster, 'Economic Conditions,' includes A7: relative income and A8: development of financial conditions.

The results of calculations using MIDI reveal that the assessment parameters A7: relative income, A8: development of financial condition, A5: priority, and A3: honesty generally demonstrate a very favorable balance of power across all systems, as indicated by Ri values higher than 1. However, factor A6, namely policy making, is entirely dominated with an Ri value of 0.2, as can be seen in Figure 7.

Figure 7. Calculations using MIDI based on the assessment parameters

The direct transaction analysis, as depicted in Figure 7, is relatively straightforward, even when determining the assessment parameters of a complex credit scoring system. In contrast, indirect transactions that influence assessment parameters represent a complex concept that can support multi-stage recommendation systems.

Here, we define a direct relationship as a direct pairwise interaction between two parameters within several clusters, assessing the feasibility of this pay-latter system. An indirect relationship is defined as a pairwise interaction between two clusters through other parameters. Both directly and indirectly, the primary focus of this paper is to determine the most dominant assessment parameters that influence new concepts in both direct and indirect transactions, which are crucial in determining the provision of pay-later to consumers. These are defined as pairs between two parameters in different clusters and individually. Explicitly, we formulate a matrix of requirements and coefficients related to requests for pay-latter approval from consumers.

ANALYSIS OF RECOMMENDATION RESULT

The analysis of the results from these recommendations involves evaluating and reviewing the recommendations provided by the SKS model and the ROAD model. This analysis aims to assess the extent to which the recommendations derived from the SKS model constitute a list of consumer names with the highest potential eligibility for pay-later services based on the pay-later value classification (refer to Table 6) and potential consumer eligibility (refer to Table 7).

Meanwhile, the ROAD model generates risk and consequence analyses related to consumer data, identifying events with minimal issues and significant potential for offering pay-later services (refer to Table 7). Analyzing the results of these recommendations is crucial to ensuring that the provided recommendations can deliver added value and meet the expectations of decision-makers.

Table 6. Pay-later value classification

Pay-later value	Category	Risk-level
800 – 850	Excellent	Low-risk
740 – 799	Very good	Low-risk
670 – 739	Good	Low-risk
580 – 669	Fair	High-risk
300 – 579	Poor	High-risk

The "pay-later Value Classification" in Table 6 categorizes consumer credit scores into five distinct groups, each labeled with a corresponding category name and associated risk level. Here is an analysis of each segment:

- 800 – 850: Excellent – Low-risk

Interpretation: Consumers in this range are considered to have excellent creditworthiness. The classification as "low-risk" indicates that these individuals have a high probability of repaying their debts on time and are very reliable borrowers.

Implications: Financial institutions can offer these consumers the best terms for pay-later services, including lower interest rates or higher borrowing limits, due to their lower risk of default.

- 740 – 799: Very Good – Low-risk

Interpretation: This range is also indicative of strong credit health, albeit slightly below the top tier. Being labeled as "low-risk" suggests that these consumers are also dependable, with a very good track record of meeting financial obligations.

Implications: Similar to those in the excellent category, these consumers are likely to receive favorable pay-later offers, though possibly not as advantageous as those given to consumers with scores in the 800-850 range.

- 670 – 739: Good – Low-risk

Interpretation: Consumers with scores in this range have good credit standings, though they are at the lower end of what is typically considered low-risk. They are generally reliable but might have had a few late payments or other minor financial issues.

Implications: They should still qualify for pay-later services but may encounter slightly less favorable terms than those in higher score brackets.

- 580 – 669: Fair – High-risk

Interpretation: This category marks a significant shift to a higher risk level. Scores in this range suggest that the consumer has encountered financial difficulties in the past, such as consistent late payments or defaults.

Implications: Consumers in this bracket are considered risky; they might still be able to secure pay-later services but with stringent conditions, such as higher interest rates or lower credit limits, to mitigate potential losses for the lender.

- 300 – 579: Poor – High-risk

Interpretation: Scores in this range are considered poor, indicating serious financial reliability issues, possibly including multiple defaults, bankruptcies, or other adverse financial events.

Implications: Consumers with these scores pose a significant risk to lenders. They might be ineligible for standard pay-later services or might only receive offers with very restrictive terms.

Table 6 is a vital tool for assessing credit risk in financial lending, particularly for pay-later services. It not only classifies individuals based on their credit scores into comprehensible categories but also aligns these categories with corresponding risk levels. This provides a dual function:

(i) Credit Assessment: By dividing the scores into distinct categories, lenders can easily gauge the creditworthiness of potential borrowers. The labels (Excellent, Very Good, Good, Fair, Poor) serve as quick indicators of a borrower's past financial behavior and their ability to manage credit.
(ii) Risk Management: Associating each category with a risk level (Low-risk, High-risk) helps lenders manage and mitigate potential risks. Low-risk categories suggest a high likelihood of timely repayments, whereas high-risk categories warn of potential difficulties in recovering lent funds.

This structured approach allows for tailored financial products and services, ensuring that borrowers receive offers that match their financial stability and lenders can balance their risk exposure. Moreover, this classification can influence the terms of the credit offers, such as interest rates, credit limits, and repayment terms, aligning them with the borrower's risk profile. Thus, Table 8 is essential not only for credit decision-making but also for strategic financial planning within lending institutions.

Table 7. Potential consumer eligibility

ID-consumer	Eligibility value	Category	Potential eligibility
PL-45633	810	Excellent	Feasible
PT-12221	584	Fair	Not Feasible
PY-32445	688	Good	Feasible
PL-11234	758	Very good	Feasible
PL-89908	305	Poor	Not Feasible
PT-23445	701	Good	Feasible

Table 8. Results of consumer risk analysis

Id-Consumer	Consequences value	Risk-Level
PL-45633	815	Low-risk
PT-12221	589	High-risk
PY-32445	692	Low-risk
PL-11234	763	Low-risk
PL-89908	310	High-risk
PT-23445	707	Low-risk

Table 7 presents potential consumer eligibility for a pay-later system based on their eligibility value, category, and potential eligibility. Each entry in the table is identified by a unique consumer ID, which likely represents individual consumers or accounts within the pay-later system. The "Eligibility Value" denotes the numerical value associated with each consumer, reflecting their creditworthiness or eligibility for the pay-later system. Higher values typically indicate better creditworthiness. The "Category" column specifies the qualitative category associated with each consumer's eligibility value. Categories range from "Excellent" to "Poor," providing a descriptive assessment of the consumer's credit standing. "Potential Eligibility" indicates whether the consumer is deemed potentially eligible for the pay-later system based on their eligibility value and category. Entries are categorized as either "Feasible" or "Not Feasible," suggesting whether the consumer meets the criteria for participation in the pay-later system.

The table serves as a tool for evaluating consumer eligibility for the pay-later system. Consumers with higher eligibility values and categories such as "Excellent" or "Very Good" are generally considered feasible candidates for participation. In contrast, consumers with lower values and categories such as "Fair" or "Poor" may not meet the eligibility criteria.

While there is no definitive "magic number" that ensures loan approval or improved interest rates, many widely used pay-later scoring models consider a minimum score of 670 as "good" for consumer pay-later eligibility. In general, a higher pay-later score enhances consumer attractiveness to lenders. Elevated credit scores suggest a history of responsible credit management, making consumers more likely to secure favorable terms and lower interest rates from lenders.

The outputs from the two tables (Tables 7 and 8) are then analyzed with input from Stakeholder Knowledge Participatory (SKP), involving stages such as identification, clarification of influences, consensus on the engagement process, and management of relationships with stakeholders. Stakeholders are presented with the results of the consumer rating model.

Based on Table 9, the analysis of the recommendation system for determining whether consumers are eligible for pay-later privileges involves several key aspects, including the data utilized, algorithms applied, assessment criteria, and performance evaluation.

Table 9. Consumer ranking for Pay-later

ID-consumer	Potential eligibility	Risk-level	Pay-later status
PL-45633	Feasible	Low-risk	Accepted
PT-12221	No Feasible	High-risk	Rejected
PY-32445	Feasible	Low-risk	Accepted
PL-11234	Feasible	Low-risk	Accepted
PL-89908	No Feasible	High-risk	Rejected
PT-23445	Feasible	Low-risk	Accepted

This recommendation system functions effectively and can aid decision-makers or pay-later providers in determining the eligibility of numerous consumers categorized as low-risk. In this study, the features or variables deemed crucial for assessing the eligibility of consumers to receive pay-later privileges are A7: relative income and A8: development of financial conditions (refer to subsection 4.3). These features significantly contribute to predictions about consumer eligibility for pay-later privileges.

Table 9 provides a consumer ranking for the pay-later system, detailing each consumer's ID, potential eligibility, risk level, and pay-later status. Each row corresponds to a unique consumer, identified by their consumer ID. These IDs likely represent individual consumers or accounts within the pay-later system. The potential eligibility of each consumer is categorized as either "Feasible" or "Not Feasible," suggesting whether they meet the criteria for participation. The risk-level column classifies consumers based on their risk within the system, categorizing them as either "Low-risk" or "High-risk," which indicates their potential risk profile in terms of default likelihood or adverse outcomes. The pay-later status column denotes each consumer's pay-later application status, labeling them as either "Accepted" or "Rejected," which reflects the approval or denial of their application for the service.

The table provides a comprehensive overview of consumer ranking and eligibility for the pay-later system. Here are key insights from Table 9:

- Correlation between Eligibility and Risk: There is a clear correlation between "Potential Eligibility" and "Risk Level" with the "pay-later Status." Consumers assessed as "Feasible" and "Low-risk" are consistently accepted, suggesting that these criteria are critical in the decision-making process for pay-later services.
- Impact of Risk Assessment: Risk level plays a significant role in the pay-later decision-making process. All consumers classified as "Low-risk" in this table were accepted, regardless of their ID prefix, indicating that risk assessment is possibly the most crucial factor in determining pay-later approvals.
- Efficiency of the Eligibility System: The eligibility criteria appear efficient in predicting which consumers will be low-risk and thus suitable for pay-later services, as indicated by the consistent outcomes for each consumer category.

Table 9 effectively demonstrates how potential eligibility and risk assessment influence the pay-later status of consumers. It shows that the system used to evaluate consumers aligns well with the objective to minimize risk and target creditworthy individuals for pay-later services. This kind of data analysis is crucial for businesses to fine-tune credit offerings, manage risk, and ensure financial stability.

FINDINGS

During the evaluation of the model we constructed, we utilized metrics such as precision and recall. This evaluation serves as the foundation for a comprehensive analysis of the elements, ensuring that the recommendation system can deliver fair, accurate, and business-aligned pay-latter recommendations. In this study, we prioritized recall as it is more crucial for identifying consumers eligible for pay-latter privileges. Additionally, we employed precision to minimize the number of consumers incorrectly deemed ineligible for pay-latter. In Table 10, where we present the performance evaluation of the built recommendation system, we compare it with several methods used by previous researchers. The results of this matrix comparison indicate that our constructed model has significant values and can accomplish business objectives by providing correct and accurate recommendations.

Analyzing the performance evaluation of a multistage approach for a recommendation system, as provided in Table 10, allows for a comprehensive understanding of how different methodologies compare in terms of precision and recall. The following is an analysis based on precision value, recall value, and the overall best performance approach.

Table 10. Performance evaluation multistage approach for recommendation system

Multistage approach	Precision	Recall
Collaborative filtering and content-based (Rastin & Zolghadri Jahromi, 2014)	0.83	0.85
Association rules mining and content-based (Alsalama, 2015)	0.86	0.84
Combining individual base recommenders and global popularity scores (Ristoski et al., 2014)	0.84	0.83
Two-stage embedding model (R. Das & Singh, 2022)	0.84	0.85
Two-level monotonic property (Fata et al., 2019)	0.85	0.84
SKS Methode & ROAD (this study)	**0.87**	**0.86**

A. Analysis Based on Precision Value

Precision measures the accuracy of the recommendations, indicating the proportion of relevant items among the recommended items. Higher precision values imply more accurate recommendations. In the table, the precision values for various approaches are as follows. Collaborative filtering and content-based (Rastin & Zolghadri Jahromi, 2014) has a precision of 0.83, association rules mining and content-based (Alsalama, 2015) has a precision of 0.86, combining individual base recommenders and global popularity scores (Ristoski et al., 2014) has a precision of 0.84, the two-stage embedding model (R. Das & Singh, 2022) has a precision of 0.84, and the two-level monotonic property (Fata et al., 2019) has a precision of 0.85. The SKS Method & ROAD achieves the highest precision value of 0.87, outperforming all other approaches listed in the table. This suggests that the SKS Method & ROAD provides the most accurate recommendations, making it the most effective method in terms of precision.

B. Analysis Based on Recall Value

Recall measures the ability of the recommendation system to identify all relevant items for the user. Higher recall values indicate a more comprehensive retrieval of relevant items. In the table, the recall values for various approaches are as follows: Collaborative filtering and content-based (Rastin & Zolghadri Jahromi, 2014) has a recall of 0.85, association rules mining and content-based (Alsalama, 2015) has a recall of 0.84, combining individual base recommenders and global popularity scores (Ristoski et al., 2014) has a recall of 0.83, the two-stage embedding model (R. Das & Singh, 2022) has a recall of 0.85, and the two-level monotonic property (Fata et al., 2019) has a recall of 0.84. The SKS Method & ROAD achieves the highest recall value of 0.86, slightly better than the other methods. This indicates that it is more effective in retrieving all relevant items for the user, making it the most comprehensive method in terms of recall.

Considering both precision and recall, the SKS Method & ROAD approach shows the best performance with the highest scores in both metrics (precision: 0.87, recall: 0.86). This suggests a well-balanced system that not only recommends items that are relevant (high precision) but also ensures a comprehensive coverage of the items of interest to the user (high recall).

The multi-stage approach that we propose, the SKS Method & ROAD, stands out as the most effective for the pay-later recommendation system. Its leading performance in both precision and recall indicates a highly accurate system capable of delivering relevant recommendations while also ensuring broad coverage of users' interests. This balance is crucial for pay-later recommendation systems, as it ensures not only reliability in suggestions but also comprehensiveness, enhancing user satisfaction and engagement. The success of the SKS Method & ROAD approach could be attributed to its potential to leverage both the strengths of knowledge-based techniques (SKS) and the robustness of optimization algorithms (ROAD). This approach provides valuable insights for the development of future recommendation systems, suggesting a focus on integrating diverse methods for improved accuracy and coverage.

CONCLUSION

Our study using the multi-stage approach of the SKS & ROAD Method demonstrates the most effective results for the pay-later recommendation system. This is evident from the comparison results with five baselines in Table 10, where the SKS & ROAD Method shows superior performance in both precision and recall. The SKS & ROAD Method is capable of presenting a list of consumers who are either accepted or rejected for pay-later privileges, making it a viable application for use by pay-later service providers or financing entities.

The success of the SKS & ROAD approach can be attributed to its ability to leverage the strengths of knowledge-based techniques (SKS) and optimization algorithms (ROAD). This system operates by evaluating various factors to determine the eligibility of each consumer, including purchase history, spending, payment habits, income, financial obligations, credit scores, and credit history. Based on the analysis results, consumers are classified as accepted, rejected, or potentially requiring further evaluation, with reasons or justifications provided for each decision. Future exploration and refinement of multi-stage approaches, such as the SKS & ROAD Method, can enhance the accuracy and coverage of the recommendation system.

The study has some limitations. First, the dataset is incomplete as consumers only provide the necessary data, necessitating data cleaning, normalization, and discretization to facilitate analysis and model development. Second, the involvement of Stakeholder Knowledge Participatory (SKP) introduces complexities, including difficulties in stakeholder identification, challenges in consensus building, subjectivity in insights, resource intensity, the risk of overemphasis on opinions, and a dynamic stakeholder environment. These issues must be carefully managed to ensure that the participatory approach benefits without compromising the scientific and analytical rigor of the recommendations.

Future work will focus on several key areas to further refine the multi-stage approaches, such as the SKS & ROAD Method. First, expanding the framework to include additional stages may enhance its capability to capture more nuanced aspects of consumer behavior and improve overall recommendation accuracy. This could involve integrating more sophisticated data analysis phases or additional layers of consumer profiling. Second, increasing the dataset size and diversity will be crucial for verifying and strengthening the existing framework. More comprehensive and varied data can provide deeper insights and improve the robustness of the recommendation system, helping to address potential gaps identified in the current analysis. Third, exploring advanced deep learning techniques, such as neural collaborative filtering, recurrent neural networks (RNNs), or transformers, could offer new ways to enhance the system's predictive power and handle complex patterns in user data. These techniques might offer improved performance over traditional methods and help in capturing intricate user preferences and interactions. Overall, future research will aim to optimize the integration of these approaches, validate the framework with more extensive data, and leverage emerging deep learning technologies to advance the recommendation system's effectiveness and applicability. This direction promises to enhance the adaptability and precision of multi-stage recommendation methodologies, making them more effective in real-world scenarios.

REFERENCES

Aguiar, J. J., Fechine, J. M., & Costa, E. D. (2020). Collaborative filtering strategy for product recommendation using personality characteristics of customers. *Proceedings of the Brazilian Symposium on Multimedia and the Web* (pp. 157-164). Association for Computing Machinery. https://doi.org/10.1145/3428658.3430969

Agustin, L. (2022). Evaluation of factors influencing the Shopee PayLater adoption in Indonesia. *Management Science and Business Decisions, 2*(2), 5–18. https://doi.org/10.52812/msbd.49

Alharbe, N., Rakrouki, M. A., & Aljohani, A. (2023). A collaborative filtering recommendation algorithm based on embedding representation. *Expert Systems with Applications, 215,* 119380. https://doi.org/10.1016/j.eswa.2022.119380

Ali Abumalloh, R., Ibrahim, O., & Nilashi, M. (2020). Loyalty of young female Arabic customers towards recommendation agents: A new model for B2C e-commerce. *Technology in Society, 61,* 101253. https://doi.org/10.1016/j.techsoc.2020.101253

Alsalama, A. M. K. (2015). A hybrid recommendation system based on association rules. *World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering, 9*(1), 55-62. https://api.semanticscholar.org/CorpusID:20197623

Amatriain, X., Pujol, J. M., & Oliver, N. (2009). I like it ... I like it not: Evaluating user ratings noise in recommender systems. In G. J. Houben, G. McCalla, F. Pianesi, & M. Zancanaro (Eds.), *User modeling, adaptation, and personalization.* Springer. https://doi.org/10.1007/978-3-642-02247-0_24

Anjali, A., Sandhu, J. K., & Goyal, D. (2021, February). User profiling in travel recommender system using hybridization and collaborative method. *Proceedings of the International Conference on Computing, Communication, and Intelligent Systems, Greater Noida, India,* 143-148. https://doi.org/10.1109/ICCCIS51004.2021.9397099

Bell, R. M., Koren, Y., & Volinsky, C. (2007). Modeling relationships at multiple scales to improve accuracy of large recommender systems. *Proceedings of the 13th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 95-104). Association for Computing Machinery. https://doi.org/10.1145/1281192.1281206

Benkaddour, F. Z., Taghezout, N., Kaddour-Ahmed, F. Z., & Hammadi, I.-A. (2018). An adapted approach for user profiling in a recommendation system: Application to industrial diagnosis. *International Journal of Interactive Multimedia and Artificial Intelligence, 5*(3), 118-130. https://doi.org/10.9781/ijimai.2018.06.003

Bobadilla, J., Gutiérrez, A., Yera, R., & Martínez, L. (2023). Creating synthetic datasets for collaborative filtering recommender systems using generative adversarial networks. *Knowledge-Based Systems, 280,* 111016. https://doi.org/10.1016/j.knosys.2023.111016

Bourkoukou, O., El Bachari, E., & El Adnani, M. A. (2017). Recommender model in e-learning environment. *Arab Journal of Science and Engineering, 42,* 607–617. https://doi.org/10.1007/s13369-016-2292-2

C+R Research. (2021, May 13). *Buy now, pay later statistics and user habits.* https://www.crresearch.com/blog/buy_now_pay_later_statistics

Chen, Z., Jiang, Y., & Zhao, Y. (2010). A collaborative filtering recommendation algorithm based on user interest change and trust evaluation. *Journal of Digital Content Technology and its Application, 4,* 106-113. https://doi.org/10.4156/jdcta.vol4.issue9.13

Chikhaoui, B., Chiazzaro, M., & Wang, S. (2011, March). An improved hybrid recommender system by combining predictions. *Proceedings of the IEEE Workshops of International Conference on Advanced Information Networking and Applications, Biopolis, Singapore,* 644-649. https://doi.org/10.1109/WAINA.2011.12

Chow, R., Pathak, M. A., & Wang, C. (2012, December). A practical system for privacy-preserving collaborative filtering. *Proceedings of the IEEE 12th International Conference on Data Mining Workshops, Brussels, Belgium,* 547-554. https://doi.org/10.1109/ICDMW.2012.84

Das, D., Sahoo, L., & Datta, S. (2017). A survey on recommendation system. *International Journal of Computer Applications, 160*(7), 6–10. https://doi.org/10.5120/ijca2017913081

Das, R., & Singh, T. D. (2022). A multi-stage multimodal framework for sentiment analysis of Assamese in low resource setting. *Expert Systems with Applications, 204,* 117575. https://doi.org/10.1016/j.eswa.2022.117575

Donahue, J., Anne Hendricks, L., Guadarrama, S., Rohrbach, M., Venugopalan, S., Saenko, K., & Darrell, T. (2017). Long-term recurrent convolutional networks for visual recognition and description. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 39*(4), 677-691. https://doi.org/10.1109/TPAMI.2016.2599174

Dooms, S., Pessemier, T. D., & Martens, L. (2015). Online optimization for user-specific hybrid recommender systems. *Multimedia Tools and Applications, 74,* 11297-11329. https://doi.org/10.1007/s11042-014-2232-7

Fata, E., Ma, W., & Simchi-Levi, D. (2019). Multi-stage and multi-customer assortment optimization with inventory constraints. *Inventory Management eJournal.* https://doi.org/10.2139/ssrn.3443109

Garden, M., & Dudek, G. (2005, March). Semantic feedback for hybrid recommendations in Recommend. *2005 IEEE International Conference on e-Technology, e-Commerce, and e-Service, Hong Kong, China,* 754-759. https://doi.org/10.1109/EEE.2005.115

Gatzioura, A., & Sànchez-Marrè, M. (2015). A case-based recommendation approach for market basket data. *Proceedings of the IEEE Intelligent Systems, 30*(1), 20-27. https://doi.org/10.1109/MIS.2014.57

Gerrans, P., Baur, D. G., & Lavagna-Slater, S. (2022). Fintech and responsibility: Buy-now-pay-later arrangements. *Australian Journal of Management, 47*(3), 474–502. https://doi.org/10.1177/03128962211032448

Ghazanfar, M. A., & Prügel-Bennett, A. (2010). A scalable, accurate hybrid recommender system. *Proceedings of the Third International Conference on Knowledge Discovery and Data Mining, Phuket, Thailand,* 94-98. https://doi.org/10.1109/wkdd.2010.117

Goyani, M., & Chaurasiya, N. (2020). A review of movie recommendation system: Limitations, survey and challenges. *Electronic Letters on Computer Vision and Image Analysis, 19*(3), 18–37. https://doi.org/10.5565/rev/elcvia.1232

Grivolla, J., Campo, D., Sonsona, M., Pulido, J.-M., & Badia, T. (2014, March). A hybrid recommender combining user, item and interaction data. *Proceedings of the International Conference on Computational Science and Computational Intelligence, Las Vegas, NV, USA,* 297-301. https://doi.org/10.1109/CSCI.2014.58

Guo, Y., Wang, M., & Li, X. (2017). Application of an improved Apriori algorithm in a mobile e-commerce recommendation system. *Industrial Management and Data Systems, 117*(2), 287-303. https://doi.org/10.1108/IMDS-03-2016-0094

Hashim, S., & Waden, J. (2023). Content-based filtering algorithm in social media. *Wasit Journal of Computer and Mathematics Science, 2*(1), 14-17. https://doi.org/10.31185/wjcm.112

Hu, Y., Koren, Y., & Volinsky, C. (2008, December). Collaborative filtering for implicit feedback datasets. *Proceedings of the Eighth IEEE International Conference on Data Mining, Pisa, Italy,* 263-272. https://doi.org/10.1109/ICDM.2008.22

Iwahama, K., Hijikata, Y., & Nishida, S. (2004, January). Content-based filtering system for music data. *Proceedings of the International Symposium on Applications and the Internet Workshops, Tokyo, Japan,* 480-487. https://doi.org/10.1109/SAINTW.2004.1268677

Jain, P. K., Saravanan, V., & Pamula, R. (2021). A hybrid CNN-LSTM: A deep learning approach for consumer sentiment analysis using qualitative user-generated contents. *Transactions on Asian and Low-Resource Language Information Processing, 20*(5), Article 84. https://doi.org/10.1145/3457206

Ji, R., Tian, Y., & Ma, M. (2020, October). Collaborative filtering recommendation algorithm based on user characteristics. *Proceedings of the 5th International Conference on Control, Robotics and Cybernetics, Wuhan, China,* 56-60. https://doi.org/10.1109/CRC51253.2020.9253466

Jia, Y., Ding, Q. Q., Liu, D. L., Zhang, J. F., & Zhang, Y. L. (2014). Collaborative filtering recommendation technology based on genetic algorithm. *Applied Mechanics and Materials, 599-601,* 1446-1452. https://doi.org/10.4028/www.scientific.net/AMM.599-601.1446

Karthik, R. V., & Ganapathy, S. (2021). A fuzzy recommendation system for predicting the customers' interests using sentiment analysis and ontology in e-commerce. *Applied Soft Computing, 108,* 107396. https://doi.org/10.1016/j.asoc.2021.107396

Kavinkumar, V., Reddy, R. R., Balasubramanian, R., Sridhar, M., Sridharan, K., & Venkataraman, D. (2015, August). A hybrid approach for recommendation system with added feedback component. *Proceedings of the International Conference on Advances in Computing, Communications, and Informatics, Kochi, India,* 745-752. https://doi.org/10.1109/ICACCI.2015.7275700

Kazienko, P. (2007). Filtering of web recommendation lists using positive and negative usage patterns. In B. Apolloni, R. J. Howlett, & L. Jain (Eds.), *Knowledge-based intelligent information & engineering systems* (pp. 1016-1023). Springer. https://doi.org/10.1007/978-3-540-74829-8_124

Khan, M. M. (2020). A review on filtering techniques used for classification of recommender systems. *Proceedings of the International Conference on Innovative Computing & Communications.* https://doi.org/10.2139/ssrn.3563557

Khouja, M. (2003). Optimizing inventory decisions in a multi-stage multi-customer supply chain. *Transportation Research Part E: Logistics and Transportation Review, 39*(3), 193-208. https://doi.org/10.1016/S1366-5545(02)00036-4

Kim, S., Shin, W., & Kim, H. W. (2023). Predicting online customer purchase: The integration of customer characteristics and browsing patterns. *Decision Support Systems, 177,* 114105. https://doi.org/10.1016/j.dss.2023.114105

Köse, E., & Yaslan, Y. (2023, September). Cross-market recommendation with two-stage graph learning. *Proceedings of the 8th International Conference on Computer Science and Engineering, Burdur, Turkiye*, 1-5. https://doi.org/10.1109/UBMK59864.2023.10286769

Kumar, M., Yadav, D., Singh, A. K., & Gupta, V. (2015). A movie recommender system: MOVREC. *International Journal of Computer Applications, 124*(1), 7-11. https://doi.org/10.5120/ijca2015904111

Lee, S., Chandra, A., & Jadav, D. (2016). An empirical study on hybrid recommender system with implicit feedback. In J. Bailey, L. Khan, T. Washio, G. Dobbie, J. Huang, & R. Wang (Eds.), *Advances in knowledge discovery and data mining* (pp. 514-526). Springer. https://doi.org/10.1007/978-3-319-31753-3_41

Lee, T., Park, Y., & Park, Y. (2008). A time-based approach to effective recommender systems using implicit feedback. *Expert Systems with Applications, 34,* 3055-3062. https://doi.org/10.1016/j.eswa.2007.06.031

Li, H., Cai, F., & Liao, Z. (2012, August). Content-based filtering recommendation algorithm using HMM. *Proceedings of the Fourth International Conference on Computational and Information Sciences, Chongqing, China,* 275-277. https://doi.org/10.1109/ICCIS.2012.112

Li, S., & Li, X. (2020). Collaborative filtering recommendation algorithm based on user characteristics and user interests. *Journal of Physics: Conference Series, 1616,* 12032. https://doi.org/10.1088/1742-6596/1616/1/012032

Li, X., Zhuang, Y., Lu, B., & Chen, G. (2019). A multi-stage hidden Markov model of customer repurchase motivation in online shopping. *Decision Support Systems, 120,* 72-80. https://doi.org/10.1016/j.dss.2019.03.012

Lian, D., Ge, Y., Yuan, N. J., Xie, X., & Xiong, H. (2016). Sparse Bayesian content-aware collaborative filtering for implicit feedback. *Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence* (pp. 1732-1738). AAAI Press. https://dl.acm.org/doi/abs/10.5555/3060832.3060863

Liu, Y., Zhao, L., Liu, G., Lu, X., Gao, P., Li, X.-L., & Jin, Z. (2018). Dynamic Bayesian logistic matrix factorization for recommendation with implicit feedback. *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence* (pp. 3463–3469). AAAI Press. https://doi.org/10.24963/ijcai.2018/481

Luna, V., Quintero, R., Torres, M., Moreno-Ibarra, M., Guzmán, G., & Escamilla, I. (2015). An ontology-based approach for representing the interaction process between user profile and its context for collaborative learning environments. *Computers in Human Behavior, 51*(Part B), 1387-1394. https://doi.org/10.1016/j.chb.2014.10.004

Mayer-Pinto, M., Underwood, A. J., & Marzinelli, E. M. (2015). The matrix influences direct and indirect effects of an anthropogenic disturbance on marine organisms. *Environmental Research, 136,* 15-20. https://doi.org/10.1016/j.envres.2014.10.006

Mishra, R., Kumar, P., & Bhasker, B. (2015). A web recommendation system considering sequential information. *Decision Support Systems, 75,* 1-10. https://doi.org/10.1016/j.dss.2015.04.004

Palomares, I., & Kovalchuk, S. V. (2017). Multi-view data approaches in recommender systems: An overview. *Procedia Computer Science, 119,* 30-41. https://doi.org/10.1016/j.procs.2017.11.157

Patra, B. G., Maroufy, V., Soltanalizadeh, B., Deng, N., Zheng, W. J., Roberts, K., & Wu, H. (2020). A content-based literature recommendation system for datasets to improve data reusability – A case study on Gene Expression Omnibus (GEO) datasets. *Journal of Biomedical Informatics, 104,* 103399. https://doi.org/10.1016/j.jbi.2020.103399

Pawełoszek, I. (2021). Customer segmentation based on activity monitoring applications for the recommendation system. *Procedia Computer Science, 192,* 4751–4761. https://doi.org/10.1016/j.procs.2021.09.253

Puglisi, S., Parra-Arnau, J., Forné, J., & Rebollo-Monedero, D. (2015). On content-based recommendation and user privacy in social-tagging systems. *Computer Standards and Interfaces, 41,* 17-27. https://doi.org/10.1016/j.csi.2015.01.004

Rastin, N., & Zolghadri Jahromi, M. (2014). *Using content features to enhance performance of user-based collaborative filtering.* arXiv. https://arxiv.org/abs/1402.2145

Rees, G. H., & MacDonell, S. (2017). Data gathering for actor analyses: A research note on the collection and aggregation of individual respondent data for MACTOR. *Future Studies Research Journal: Trends and Strategies, 9*(1), 115-137. https://doi.org/10.24023/FutureJournal/2175-5825/2017.v9i1.256

Ristoski, P., Mencía, E. L., & Paulheim, H. (2014). A hybrid multi-strategy recommender system using linked open data. In M. Stankovic, E. Cambria, I. Cantador, A. Di Iorio, T. Di Noia, C. Lange, D. R. Recupero, & A. Tordai (Eds.), *Semantic web evaluation challenge* (pp. 150-156). Springer. https://doi.org/10.1007/978-3-319-12024-9_19

Roy, D. (2020). Recommending curated content using implicit feedback. *Asian Journal of Research in Computer Science, 5*(2), 10-16. https://doi.org/10.9734/ajrcos/2020/v5i230130

Sandholm, T., & Ung, H. M. (2011). Real-time, location-aware collaborative filtering of web content. *Proceedings of the Workshop on Context-awareness in Retrieval and Recommendation* (pp. 14-18). Association for Computing Machinery. https://doi.org/10.1145/1961634.1961638

Shah, K. R., Salunke, A., Dongare, S., & Antala, K. (2017). Recommender systems: An overview of different approaches to recommendations. *Proceedings of the International Conference on Innovations in Information, Embedded and Communication Systems, Coimbatore, India,* 1-4. https://doi.org/10.1109/ICIIECS.2017.8276172

Son, J., & Kim, S. (2017). Content-based filtering for recommendation systems using multi-attribute networks. *Expert Systems with Applications, 89,* 404-412. https://doi.org/10.1016/j.eswa.2017.08.008

Tahir, Z., & Ali, K. B. (2023). Movies recommendation system using machine learning algorithms. In *2023 International Conference on Advances in Computation, Communication and Information Technology (ICAICCIT)* (pp. 1324-1328). IEEE. https://doi.org/10.1109/ICAICCIT60255.2023.10465879

Thannimalai, V., & Zhang, L. (2021, December). A content-based and collaborative filtering recommender system. *2021 International Conference on Machine Learning and Cybernetics, Adelaide, Australia,* 1-7. https://doi.org/10.1109/ICMLC54886.2021.9737238

Trabelsi, F. Z., Khtira, A., & Asri, B. E. (2021). Hybrid recommendation systems: A state of art. *Proceedings of the 16th International Conference on Evaluation of Novel Approaches to Software Engineering* (pp. 281-288). SciTePress. https://doi.org/10.5220/0010452202810288

Udokwu, C., Zimmermann, R., Darbanian, F., Obinwanne, T., & Brandtner, P. (2023). Design and implementation of a product recommendation system with association and clustering algorithms. *Procedia Computer Science, 219,* 512-520. https://doi.org/10.1016/j.procs.2023.01.319

Vivek Arvind, B., Swaminathan, J., & Viswanathan, K. R. (2012, December). An improvised filtering-based intelligent recommendation technique for web personalization. *Proceedings of the Annual IEEE India Conference, Kochi, India,* 1194-1199. https://doi.org/10.1109/INDCON.2012.6420799

Wadud, M., Ahmed, H. J. A., & Tang, X. (2020). Factors affecting delinquency of household credit in the US: Does consumer sentiment play a role?. *The North American Journal of Economics and Finance*, *52*, 101132. https://doi.org/10.1016/j.najef.2019.101132

Wang, J., Zhu, Z., & Caverlee, J. (2020). User recommendation in content curation platforms. *Proceedings of the 13th International Conference on Web Search and Data Mining* (pp. 627-635). Association for Computing Machinery. https://doi.org/10.1145/3336191.3371822

Wang, P., Hou, H., & Guo, X. (2019). Collaborative filtering algorithm based on user characteristic and time weight. *Proceedings of the 8th International Conference on Software and Computer Applications* (pp. 109-114). Association for Computing Machinery. https://doi.org/10.1145/3316615.3316681

Wang, S., Hu, L., Wang, Y., Cao, L., Sheng, Q. Z., & Orgun, M. A. (2019). Sequential recommender systems: Challenges, progress, and prospects. *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence,* 6332-6338. https://doi.org/10.24963/ijcai.2019/883

Wang, Z., Yu, X., Feng, N., & Wang, Z. (2014). An improved collaborative movie recommendation system using computational intelligence. *Journal of Visual Languages and Computing, 25*(6), 667-675. https://doi.org/10.1016/j.jvlc.2014.09.011

Widiyaningtyas, T., Hidayah, I., & Adji, T. B. (2021). User profile correlation-based similarity (UP-CSim) algorithm in movie recommendation system. *Journal of Big Data, 8*, Article 52. https://doi.org/10.1186/s40537-021-00425-x

Wijaya, I. W. R., & Mudjahidin. (2021). Development of conceptual model to increase customer interest using recommendation system in e-commerce. *Procedia Computer Science, 197,* 727-733. https://doi.org/10.1016/j.procs.2021.12.194

Yang, Y., Yao, H., Li, R., & Wang, S. (2021). A collaborative filtering recommendation algorithm based on user clustering with preference types. *Journal of Physics: Conference Series, 1848,* 12043. https://doi.org/10.1088/1742-6596/1848/1/012043

Yao, Y., Tong, H., Yan, G., Xu, F., Zhang, X., Szymański, B. K., & Lu, J. (2014). Dual-regularized one-class collaborative filtering. *Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management* (pp. 759-768). Association for Computing Machinery. https://doi.org/10.1145/2661829.2662042

Yin, C. C., Chiu, H. C., Hsieh, Y. C., & Kuo, C. Y. (2022). How to retain customers in omnichannel retailing: Considering the roles of brand experience and purchase behavior. *Journal of Retailing and Consumer Services, 69,* 103070. https://doi.org/10.1016/j.jretconser.2022.103070

Yoshida, T., Irie, G., Satou, T., Kojima, A., & Higashino, S. (2012). Improving item recommendation based on social tag ranking. In K. Schoeffmann, B. Merialdo, A. G. Hauptmann, C. W. Ngo, Y. Andreopoulos, & C. Breiteneder (Eds.), *Advances in multimedia modeling* (pp. 161-172). Springer. https://doi.org/10.1007/978-3-642-27355-1_17

Yu, X., Ren, X., Sun, Y., Sturt, B., Khandelwal, U., Gu, Q., Norick, B., & Han, J. (2013). Recommendation in heterogeneous information networks with implicit user feedback. *Proceedings of the 7th ACM Conference on Recommender Systems* (pp. 347-350). Association for Computing Machinery. https://doi.org/10.1145/2507157.2507230

Zhang, J., Peng, Q., Sun, S., & Liu, C. (2014). Collaborative filtering recommendation algorithm based on user preference derived from item domain features. *Physica A: Statistical Mechanics and its Applications, 396,* 66-76. https://doi.org/10.1016/j.physa.2013.11.013

Zhang, W., & Wu, Z. (2024). E-commerce recommender system based on improved K-means commodity information management model. *Heliyon, 10*(3), E29045. https://doi.org/10.1016/j.heliyon.2024.e29045

Zhao, F., Yan, F., Jin, H., Yang, L. T., & Yu, C. (2017). Personalized mobile searching approach based on combining content-based filtering and collaborative filtering. *IEEE Systems Journal, 11*(1), 324-332. https://doi.org/10.1109/JSYST.2015.2472996

Zhao, W., Tian, H., & Wu, Y. (2022). A new item-based collaborative filtering algorithm to improve the accuracy of prediction in sparse data. *International Journal of Computational Intelligence Systems, 15*, Article 15. https://doi.org/10.1007/s44196-022-00068-7

Zheng, Y., Liu, C., Tang, B., & Zhou, H. (2016). Neural autoregressive collaborative filtering for implicit feedback. *Proceedings of the 1st Workshop on Deep Learning for Recommender Systems* (pp. 2-6). Association for Computing Machinery. https://doi.org/10.1145/2988450.2988453

Zhou, H., Feng, B., Lv, L., Wang, Z., & Wang, Z. (2005). A new integrated personalized recommendation algorithm. In Y. Hao, J. Liu, Y. Wang, Y. Cheung, H. Yin, L. Jiao, J. Ma, & Y.-C. Jiao (Eds.), *Computational Intelligence and Security* (pp. 747-751). Springer. https://doi.org/10.1007/11596448_110

Zhou, P., Qi, Z., Zheng, S., Xu, J., Bao, H., & Xu, B. (2016, December). Text classification improved by integrating bidirectional LSTM with two-dimensional max pooling. *Proceedings of the 26th International Conference on Computational Linguistics, Osaka, Japan*, 3485-3495.

AUTHORS

Wiwin Suwarningsih graduated with a degree in Informatics in 2000 and obtained her doctoral degree in 2017 from the School of Electrical and Informatics Engineering at the Bandung Institute of Technology. Currently, she is affiliated with the Research Center for Data and Information Sciences at the National Agency of Research and Innovation (BRIN, Indonesia). Her research interests encompass artificial intelligence, computational linguistics, image processing, data mining, information retrieval, and visual question-answering systems. For further inquiries, she can be contacted at wiwi005@brin.go.id

Nuryani graduated with her bachelor's degree in computer science, Gadjah Mada University (UGM) in 2003. She received her master's degree in electrical engineering at the Bandung Institute of Technology (ITB) in 2013. Currently, she is a doctoral candidate in the School of Electrical and Informatics Engineering, at Bandung Institute of Technology, and works at the National Agency of Research and Innovation (BRIN, Indonesia). Her research interests are computer networks, deep learning, and natural language processing, especially in sentiment analysis. She can be contacted at nury012@brin.go.id