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Android-based decision support system using MAGIQ-MARCOS for digital bank selection

Gede Surya Mahendra [1]*, I Nyoman Indhi Wiradika [2], Kadek Yota Ernanda Aryanto [3]

[1] *Information System Study Program, Universitas Pendidikan Ganesha, Indonesia*
[2] *Education of Informatics Engineering Study Program, Universitas Pendidikan Ganesha, Indonesia*
[3] *Computer Science Study Program, Universitas Pendidikan Ganesha, Indonesia*

*Corresponding Author: *gmahendra@undiksha.ac.id*

Abstract: Choosing a digital bank is a challenge for anyone, especially due to cognitive biases that influence decision making. This study aims to develop an Android-based Decision Support System (DSS) using the MAGIQ MARCOS method to provide recommendations for digital banks that suit users' preferences. The MAGIQ method is used to weight the main criteria, namely Application Performance (C1), Financial Reports (C2), and User Experience (C3), while MARCOS is used to rank digital banking alternatives. This study includes data collection through surveys and interviews, data processing using MAGIQ for weighting, and ranking alternatives using MARCOS. The results indicate that Jenius ranked first with a preference value of 0.7632 followed by Seabank with 0.7164 and Krom Digital Bank with 0.6983. These findings show that the system is able to differentiate alternatives based on user priorities. The system achieved an accuracy of 80.39 percent compared with students' manual selections confirming that the recommendations align with actual user preferences. The recommendations generated by the system are consistent with the priorities of decision makers who value application quality and user experience. Use case testing also shows that all test scenarios function as expected. This research contributes to the development of technology based DSS to help students make more rational and data driven decisions in choosing a digital bank. Future work may integrate real time data updates and predictive analysis to improve recommendation accuracy and expand the MAGIQ-MARCOS method to other sectors that require multi criteria decision making.

Keywords: android, digital banking, DSS, MAGIQ, MARCOS

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Introduction

In today's digital age, digital banks have become the main alternative for the public, especially students, to conduct banking transactions efficiently and practically [1]. Digital banks, which operate entirely through electronic platforms such as mobile applications or websites, allow customers to access various banking services without having to visit a physical branch office [2]. The main advantages of digital banks are ease of access, lower administrative costs, and the convenience of conducting transactions anytime and anywhere [3]. However, despite the many options available, students often find it difficult to choose a digital bank that suits their needs and preferences.

The main problem students face in choosing a digital bank is cognitive bias, which influences their decision-making process. Cognitive biases, such as confirmation bias or bandwagon bias, often lead students to choose banks that are already popular or the most accessible, without carefully considering whether the services provided suit their needs [4]. Factors such as hidden costs, service quality, and additional features are often not considered in depth, leading to suboptimal decisions. Therefore, to help students make more rational decisions that suit their needs, a system is needed that can provide objective, data-driven recommendations.

One solution that can be implemented is to use a Decision Support System [5]. A Decision Support System (DSS) is a technology-based solution designed to assist decision makers in addressing complex situations that involve multiple criteria [6]. It provides structured analytical support by processing diverse data inputs and transforming them into meaningful information for evaluation [7], [8]. Through this capability, a DSS enables users to make more objective, consistent, and informed decisions in environments where manual judgment alone may be insufficient [9], [10]. In the context of choosing a digital bank, a DSS can provide recommendations based on several important criteria, such as administrative costs, transaction security, ease of use of the application, and customer service quality. A DSS allows users to make more objective decisions by simplifying the complex decision-making process [11], [12]. Through structured evaluation and systematic weighting of relevant criteria, the system helps users arrive at decisions that are more consistent, transparent, and aligned with their actual preferences [13], [14]. A DSS is an interactive computer-based system that helps decision makers utilize data and models to solve unstructured and semi-structured problems [15], [16], [17].

This study aims to develop an Android-based Decision Support System that uses the MAGIQ-MARCOS method to provide recommendations for digital banks that best suit student preferences. MAGIQ (Multi-Attribute Global Inference of Quality) is a method used to weight various criteria based on the order of priority set by the user [18], [19], [20], [21]. This method converts comparison attributes into normalized numerical weights, enabling faster and easier evaluation of alternatives. MARCOS (Measurement Alternatives and Ranking according to Compromise Solution) is used to rank alternatives based on their proximity to the ideal solution and how far they are from the worst solution [22], [23], [24], [25]. The combination of these two methods enables the system to provide recommendations for digital banks that more accurately match students' needs and preferences.

In the initial stage of this research, an analysis was conducted on the problems faced by students in choosing a digital bank. The results of the preliminary study showed that students often choose a digital bank based on factors such as ease of access or popularity, without carefully considering the more technical and specific features of each bank. Some students also tend to be influenced by social or emotional factors, such as choosing a bank used by their friends, which means that the decisions they make are not always rational. In addition, students often find it difficult to compare the various digital banking alternatives available due to their limited knowledge of the features and services offered by each bank.

From the results of this problem identification, it can be concluded that students need a system that can provide objective and data-driven recommendations. A technology-based Decision Support System can be an effective solution to help students overcome this decision-making problem. Using the MAGIQ-MARCOS method, the DSS can provide recommendations for digital banks that suit students' preferences, based on criteria they consider important, such as transaction security, administrative costs, and ease of use of the application.

This study also aims to test the effectiveness of the developed Android-based DSS. This test will be conducted by comparing the recommendations provided by the system with the choices selected manually by students. This aims to ensure that the developed system is capable of providing accurate recommendations that are relevant to user preferences. In addition, this study will also test the performance of the application, including its speed and accuracy in providing recommendations for digital banks that match user criteria.

With the Android-based DSS that integrates the MAGIQ-MARCOS method, students are expected to be able to make better and faster decisions in choosing a digital bank. This system will simplify the complex decision-making process and help students focus more on the criteria that are truly important to them. Thus, this research has the potential to make a significant contribution to improving the quality of students' decision-making in choosing a digital bank that suits their needs and preferences.

Methodology

This study aims to develop and implement an Android-based Decision Support System (DSS) using the MAGIQ-MARCOS method in selecting a digital bank that suits the preferences and needs of students. The method used in this study consists of several integrated stages, ranging from preliminary studies, field studies, to system implementation and testing stages. The stages of the research methodology that were carried out are shown in Figure 1.

Preliminary Study Phase

This initial phase aims to understand the overall context and challenges faced by students in choosing a digital bank. An analysis of various digital bank alternatives available in Indonesia is conducted to map common issues experienced by potential users. Factors influencing decision making such as administrative fees, accessibility, service features, and social influence are examined. The output of this phase is a foundational understanding of the decision-making difficulties that students encounter when selecting a bank that fits their needs.

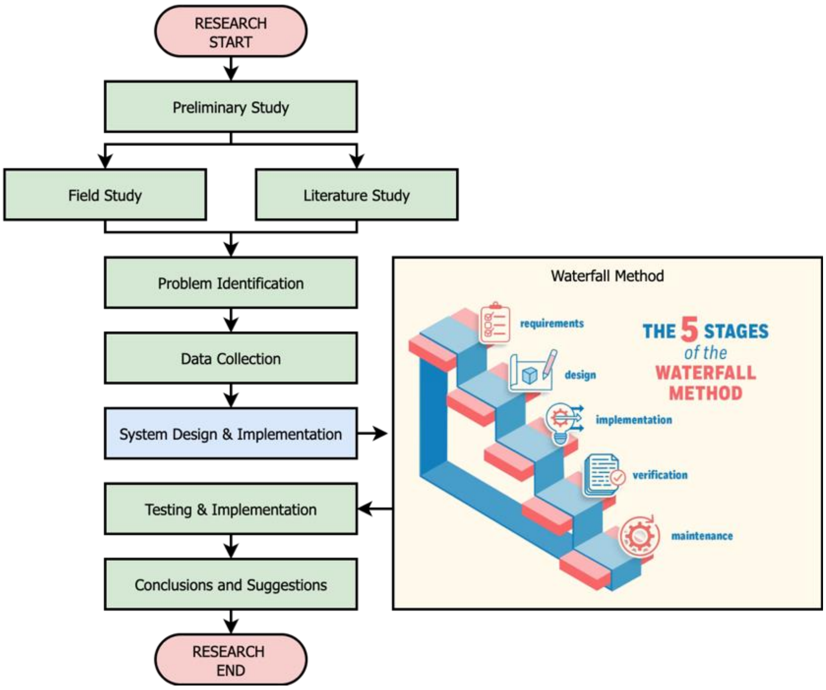

Figure 1. Research methodology

Field and Literature Study Phase

The field study is carried out to gather in-depth insights into student preferences. A total of ten student participants were involved in a Focus Group Discussion (FGD). Participants were selected using purposive sampling with eligibility requirements that included being active undergraduate students aged 18 to 25 years and having used at least one digital banking application within the past six months. Interviews, observations, and FGDs are used to explore preferred criteria, decision priorities, and experiences with digital banking services. To ensure rigor, data validation procedures include triangulation through cross-verification of FGD results, interview data, and observation notes.

The literature study supports the field findings by reviewing academic publications on Decision Support Systems, Multi-Criteria Decision-Making (MCDM), and the implementation of MAGIQ and MARCOS. This phase ensures that the system design is grounded in established theoretical frameworks.

Problem Identification Phase

In this phase, findings from the preliminary study, field study, and literature review are synthesized to formulate the core problem addressed by the DSS. The analysis reveals that students often experience cognitive biases, such as choosing digital banks based on popularity or peer influence rather than evaluating objective criteria. Students also demonstrate a limited understanding of technical indicators, including application performance metrics, financial stability indicators, and user experience variables, due to the complexity and lack of accessible information. Furthermore, the field study results, which involved eight students selected through purposive sampling, show that participants struggle to systematically compare digital banking alternatives because available information is scattered across different platforms.

These issues collectively hinder rational decision-making and highlight the need for a system capable of presenting structured, validated, and multi-criteria information. The insights from interviews, observations, and FGD sessions were validated using methodological triangulation, ensuring consistency across data sources. Based on this synthesis, the functional needs of the DSS are determined, it must objectively evaluate multiple criteria, eliminate cognitive bias, simplify comparison of alternatives, and produce data-driven recommendations tailored to user-defined preferences.

Data Collection Phase

The data collection phase consists of two primary components: user preference data and technical digital banking data. This phase also includes methodological details required by the reviewer, such as sampling, eligibility criteria, and validation procedures.

User preference data is obtained from interviews and FGDs involving eight eligible student participants, with selection based on the following criteria: active undergraduate status, age range 18–25 years, and experience using at least one digital bank within the past six months. Purposive sampling is used to ensure that participants possess relevant experience in digital banking. Through FGDs, participants describe their decision priorities, such as ease of navigation, security, and transaction cost, and identify factors contributing to their satisfaction or dissatisfaction with digital banks. The data is analyzed using thematic categorization and validated by cross-referencing interview narratives, field observations, and participant feedback to maintain reliability.

Technical data encompasses operational, financial, and experiential indicators that serve as quantifiable input for multi-criteria analysis. This includes app store metrics, installation counts, user ratings, financial report components, and user engagement indicators. Data is collected from publicly verifiable sources, including financial disclosures, Google Play Store analytics, and secondary research repositories. Data validation is performed using source triangulation to ensure consistency across databases.

Criteria and Sub-Criteria Data

Three main criteria are used to evaluate digital banks such as Application Performance (C1), Financial Reports (C2), and User Experience (C3). Each criterion is further divided into more detailed sub-criteria. For example, the Application Performance criterion includes sub-criteria such as application file size (C1-A), application rating (C1-B), user rated (C1-C), Total installations (C1-D), and release date (C1-E). Meanwhile, the Financial Reports criterion uses data on current accounts (C2-A), savings accounts (C2-B), deposits (C2-C), and net profit(C2-D), which indicate the financial stability of digital banks. The User Experience criterion assesses the level of user happiness (C3A), engagement (C3B), adoption (C3C), retention (C3D), and task success (C3E) in using the application.

Alternative Data

There are 17 digital banks as alternative data used in this study. These alternatives include banks such as Line Bank, Jenius, Bank Jago/Jago Syariah, Aladin, UOB TMRW Indonesia, Seabank, and others. Data related to the criteria and sub-criteria of each digital bank was collected through surveys, observations, and relevant field data. Each bank was assessed based on predetermined factors, and the results were used to calculate the ranking of each digital bank.

Data Processing

The collected data was then processed using the MAGIQ method to assign weights to each criterion and sub-criterion. These weights were adjusted according to the priorities set by the decision makers involved in this study. These weights are very important to provide an overview of how much each criterion influences the final decision in choosing a digital bank. The decision-maker provided the criteria data, which were subsequently analyzed using the MAGIQ method. The results of this analysis are presented in Figure 2.

The MAGIQ-MARCOS method combination consists of 3 main stages, namely alternative normalization calculation, weighted alternative normalization calculation, and utility function value calculation. Since this study is a 2-level hierarchy, the calculation is performed from the bottom level upwards. The following shows the calculation process at the bottom level in MAGIQ-MARCOS, focusing on the Application Performance Criteria (C1) section, with a sample calculation for the Line Bank Alternative. Alternative data for the Application Performance criterion (C1) are presented in Table 1.

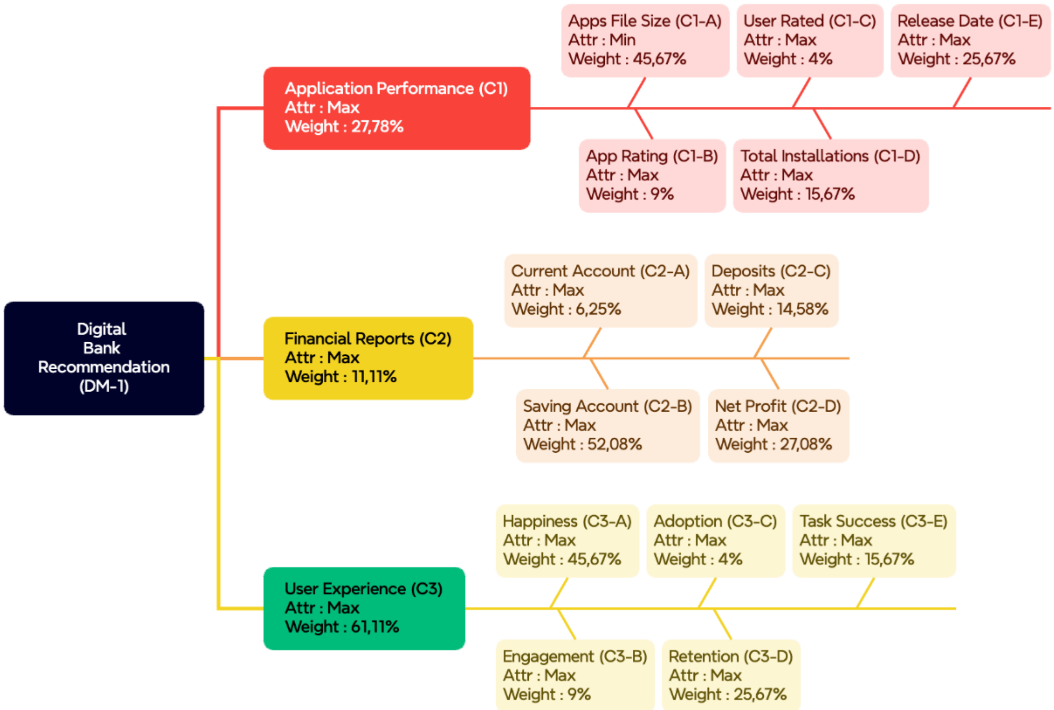

Figure 2. Criteria Weight using MAGIQ

Table 1. Alternative data for application performance criteria (C1)

Alternative ID	Alternative	C1-A	C1-B	C1-C	C1-D	C1-E
Bank01	Line Bank	51	3.12	26,482	4,127,684	1474
Bank02	Bank Jago/Jago Syariah	72	4.50	195,249	14,224,225	1524
Bank03	Aladin: Bank Syariah Digital	26	4.22	40,223	5,204,447	1203
Bank04	UOB TMRW Indonesia	116	4.37	51,456	2,968,246	1988
Bank05	Seabank	88	4.87	1,937,756	25,478,632	1574
Bank06	Jenius	66	3.31	202,007	12,784,553	3235
Bank07	Blu by BCA Digital	129	4.53	108,244	4,268,444	1424
Bank08	Raya - Digital Bank	59	4.38	9,954	1,408,317	970
Bank09	MotionBank	27	3.57	11,683	1,219,611	1771
Bank10	Neobank by BNC Digital	49	3.36	279,555	30,989,349	1555
Bank11	Capital Flex	30	3.79	179	33,512	490
Bank12	Digibank by DBS Indonesia	81	4.42	90,576	3,227,431	3109
Bank13	Krom - Bank Digital	14	4.82	20,358	913,111	613
Bank14	Superbank	23	4.40	26,446	3,355,124	531
Bank15	Bank Saqu	93	4.70	57,681	4,407,612	587
Bank16	Allo Bank	51	3.98	52,904	9,939,041	1204
Bank17	HiBank	46	4.91	1,813	104,742	118

Alternative normalization stage

$$n_{C1-A;Bank-01} = \frac{\min(51;72;\cdots;51;46)}{51} = \frac{14}{51} = 0.275$$
$$n_{C1-B;Bank-01} = \frac{3.12}{\max(3.12;4.5;\cdots;3.98;4.91)} = \frac{3.12}{4.91} = 0.653$$
$$n_{C1-C;Bank-01} = \frac{26482}{\max(26482;195249;\cdots;52904;1813)} = \frac{26482}{1937756} = 0.014$$
$$n_{C1-D;Bank-01} = \frac{4127684}{\max(4127684;14224225;\cdots;9939041;104742)} = \frac{4127684}{30989349} = 0.133$$
$$n_{C1-E;Bank-01} = \frac{1474}{\max(1474;1524;\cdots;1204;118)} = \frac{1474}{3235} = 0.456$$

Weighted alternative normalization stage

$$v_{C1-A;Bank-01} = 0.275 \times 45.7\% = 0.125$$
$$v_{C1-B;Bank-01} = 0.635 \times 9.0\% = 0.057$$
$$v_{C1-C;Bank-01} = 0.014 \times 4.0\% = 0.001$$
$$v_{C1-D;Bank-01} = 0.133 \times 15.7\% = 0.021$$
$$v_{C1-E;Bank-01} = 0.456 \times 25.7\% = 0.117$$

The outcomes of the normalization stage and the subsequent weighted normalization for the Application Performance criteria (C1) are summarized in Table 2, which provides a structured representation of how each digital banking alternative is standardized based on MAGIQ-derived weights. This table demonstrates the conversion of raw attribute values into normalized scores, followed by the application of criterion weights to produce weighted normalization values. These values serve as the foundation for the utility function calculations in the MARCOS method, ensuring that each alternative is evaluated consistently and in accordance with user-defined priorities.

Table 2. Alternative normalization and weighted alternative normalization data for application performance criteria (C1)

Alternative	Alternative Normalization					Weighted Alternative Normalization				
ID	C1-A	C1-B	C1-C	C1-D	C1-E	C1-A	C1-B	C1-C	C1-D	C1-E
Bank01	0.2745	0.6354	0.0137	0.1332	0.4556	0.1254	0.0572	0.0005	0.0209	0.1169
Bank02	0.1944	0.9165	0.1008	0.4590	0.4711	0.0888	0.0825	0.0040	0.0719	0.1209
Bank03	0.5385	0.8595	0.0208	0.1679	0.3719	0.2459	0.0774	0.0008	0.0263	0.0954
Bank04	0.1207	0.8900	0.0266	0.0958	0.6145	0.0551	0.0801	0.0011	0.0150	0.1577
Bank05	0.1591	0.9919	1.0000	0.8222	0.4866	0.0727	0.0893	0.0400	0.1288	0.1249
Bank06	0.2121	0.6741	0.1042	0.4125	1.0000	0.0969	0.0607	0.0042	0.0646	0.2567
Bank07	0.1085	0.9226	0.0559	0.1377	0.4402	0.0496	0.0830	0.0022	0.0216	0.1130
Bank08	0.2373	0.8921	0.0051	0.0454	0.2998	0.1084	0.0803	0.0002	0.0071	0.0770
Bank09	0.5185	0.7271	0.0060	0.0394	0.5474	0.2368	0.0654	0.0002	0.0062	0.1405
Bank10	0.2857	0.6843	0.1443	1.0000	0.4807	0.1305	0.0616	0.0058	0.1567	0.1234
Bank11	0.4667	0.7719	0.0001	0.0011	0.1515	0.2131	0.0695	0.0000	0.0002	0.0389
Bank12	0.1728	0.9002	0.0467	0.1041	0.9611	0.0789	0.0810	0.0019	0.0163	0.2467
Bank13	1.0000	0.9817	0.0105	0.0295	0.1895	0.4567	0.0884	0.0004	0.0046	0.0486
Bank14	0.6087	0.8961	0.0136	0.1083	0.1641	0.2780	0.0807	0.0005	0.0170	0.0421
Bank15	0.1505	0.9572	0.0298	0.1422	0.1815	0.0687	0.0862	0.0012	0.0223	0.0466
Bank16	0.2745	0.8106	0.0273	0.3207	0.3722	0.1254	0.0730	0.0011	0.0502	0.0955
Bank17	0.3043	1.0000	0.0009	0.0034	0.0365	0.1390	0.0900	0.0000	0.0005	0.0094

Utility function value calculation stage

$$K_{(K1;Bank-01)}{}^{-} = \frac{0.1254+0.0572+0.0005+0.0209+0.1169}{\min(0.1254;\cdots;0.1390)+\cdots+\min(0.1169;\cdots;0.0094)} = \frac{0.3209}{0.0496+0.0572+0.0000+0.0002+0.0094} = \frac{0.3209}{0.1163} = 2.7597$$

$$K_{(K1;Bank-01)}{}^{+} = \frac{0.1254+0.0572+0.0005+0.0209+0.1169}{\max(0.1254;\cdots;0.1390)+\cdots+\max(0.1169;\cdots;0.0094)} = \frac{0.3209}{0.4567+0.0900+0.0400+0.1567+.02567} = \frac{0.3209}{1.0000} = 0.3209$$

$$f\left(K_{(K1;Bank-01)}{}^{-}\right) = \frac{0.3209}{0.3209+2.7597} = 0.1042$$

$$f\left(K_{(K1;Bank-01)}{}^{+}\right) = \frac{2.7597}{0.3209+2.7597} = 0.8958$$

$$f\left(K_{(K1;Bank-01)}\right) = \frac{0.3209+2.7597}{1+\frac{1-0.8958}{0.8958}+\frac{1-0.1042}{0.1042}} = 0.3171$$

The complete dataset for the Financial Reports criteria (C2) and the User Experience criteria (C3) is provided in Table 3, which presents the operational, financial, and experiential attributes for all digital banking alternatives considered in this study. These values form a crucial input for the evaluation process, as they represent the quantitative measures used to assess financial soundness (such as current accounts, savings, deposits, and profit) and user interaction performance (including happiness, engagement, adoption, retention, and task success). The structured presentation of this information in Table 3 ensures consistency and transparency in subsequent normalization, weighting, and ranking procedures within the MAGIQ MARCOS framework.

Table 3. Alternative data for application financial reports (C2), and user experience (C3)

Alternative ID	C2-A	C2-B	C2-C	C2-D	C3-A	C3-B	C3-C	C3-D	C3-E
Bank01	9,108,419	1,619,459	16,201,040	519,430	3.63	3.40	3.60	3.20	3.71
Bank02	990,303	1,087,125	4,629,116	128,518	4.33	4.16	4.35	4.12	4.00
Bank03	678	665,213	4,744,140	(73,727)	3.46	3.80	3.63	3.40	3.93
Bank04	32,135	35,076	49,701	406,240	3.43	3.40	3.75	3.40	3.83
Bank05	7,646,091	10,658,970	8,348,328	378,769	4.23	3.92	4.15	3.84	4.37
Bank06	25,586,525	16,909,498	67,926,531	2,230,270	3.97	4.00	4.15	3.80	4.17
Bank07	4,680	5,542,457	6,182,903	107,972	3.43	4.04	3.85	3.96	3.94
Bank08	9,160	39,341	359,965	39,084	3.83	3.80	3.88	3.45	3.93
Bank09	1,123,635	1,855,261	11,451,750	74,850	3.97	3.68	3.95	3.76	3.89
Bank10	514,834	3,095,982	9,452,976	37,483	3.88	3.95	4.00	3.90	4.21
Bank11	2,012,703	3,508,919	7,050,639	220,838	3.08	3.35	3.31	3.10	3.64
Bank12	16,237,212	5,055,926	29,382,955	1,488,080	3.83	3.55	3.75	3.85	3.82
Bank13	12,176	496,140	2,650,460	124,060	3.87	3.48	3.85	3.72	3.91
Bank14	113,672	1,258,347	3,570,807	(384,957)	3.40	3.56	3.60	3.28	3.63
Bank15	561,701	634,614	5,211,170	(334,719)	3.93	3.72	3.95	3.56	3.66
Bank16	85,336	693,272	5,316,510	467,106	3.87	3.80	4.05	3.84	3.91
Bank17	4,426,221	839,852	7,377,070	131,797	3.00	3.10	3.06	2.95	3.36

The results of the utility value computation for the three main criteria, namely Application Performance (C1), Financial Reports (C2), and User Experience (C3), are detailed in Table 4, providing a quantitative representation of each alternative's performance relative to the ideal and anti-ideal benchmarks. These utility values are subsequently integrated into the Level 1 preference calculation, as illustrated in Table 5, which consolidates the weighted utility function outputs along with the final ranking outcomes for DM1. Together, these tables present the complete analytical progression from criterion-level evaluation to the final decision recommendation, thereby demonstrating the effectiveness of the MAGIQ MARCOS framework in identifying the most suitable digital bank alternative.

Table 4. Utility value for C1, C2, C3

Alternative	C1		C2		C3	
ID	K_i^-	K_i^+	K_i^-	K_i^+	K_i^-	K_i^+
Bank01	2.7597	0.3209	-3.7312	0.1700	1.1489	0.8220
Bank02	3.1658	0.3681	-1.3488	0.0614	1.3791	0.9867
Bank03	3.8340	0.4458	-0.4768	0.0217	1.1637	0.8326
Bank04	2.6574	0.3090	-1.1106	0.0506	1.1445	0.8189
Bank05	3.9180	0.4556	-9.0193	0.4109	1.3487	0.9650
Bank06	4.1537	0.4830	-21.9498	1.0000	1.2984	0.9290
Bank07	2.3166	0.2694	-4.3266	0.1971	1.2197	0.8726
Bank08	2.3471	0.2729	-0.1482	0.0068	1.2265	0.8775
Bank09	3.8625	0.4491	-2.0537	0.0936	1.2683	0.9075
Bank10	4.1095	0.4779	-2.6661	0.1215	1.2923	0.9246
Bank11	2.7659	0.3216	-3.4011	0.1550	1.0504	0.7516
Bank12	3.6531	0.4248	-9.6399	0.4392	1.2468	0.8921
Bank13	5.1484	0.5987	-0.7917	0.0361	1.2442	0.8902
Bank14	3.5968	0.4183	0.0010	0.0000	1.1221	0.8028
Bank15	1.9344	0.2249	0.1874	-0.0085	1.2358	0.8842
Bank16	2.9684	0.3452	-1.9689	0.0897	1.2669	0.9064
Bank17	2.0546	0.2389	-1.5041	0.0685	1.0000	0.7155

Table 5. Alternative data level 1, utility function (preference value) and rank for digital banking recommendation for DM1

Alternative ID	Alternative	C1	C2	C3	$f(K)$	Rank
Bank01	Line Bank	0.3171	0.1696	0.6331	0.5673	Rank 12
Bank02	Bank Jago/Jago Syariah	0.3637	0.0613	0.7599	0.6611	Rank 6
Bank03	Aladin: Bank Syariah Digital	0.4405	0.0217	0.6413	0.6076	Rank 9
Bank04	UOB TMRW Indonesia	0.3053	0.0505	0.6307	0.5500	Rank 14
Bank05	Seabank	0.4502	0.4100	0.7432	0.7164	Rank 2
Bank06	Jenius	0.4772	0.9978	0.7155	0.7632	Rank 1
Bank07	Blu by BCA Digital	0.2662	0.1967	0.6721	0.5761	Rank 11
Bank08	Raya - Digital Bank	0.2697	0.0067	0.6759	0.5623	Rank 13
Bank09	MotionBank	0.4438	0.0934	0.6989	0.6544	Rank 7
Bank10	Neobank by BNC Digital	0.4722	0.1212	0.7121	0.6771	Rank 4
Bank11	Capital Flex	0.3178	0.1546	0.5788	0.5296	Rank 16
Bank12	Digibank by DBS Indonesia	0.4197	0.4382	0.6870	0.6692	Rank 5
Bank13	Krom - Bank Digital	0.5915	0.0360	0.6856	0.6983	Rank 3
Bank14	Superbank	0.4133	0.0000	0.6183	0.5794	Rank 10
Bank15	Bank Saqu	0.2223	-0.0085	0.6810	0.5456	Rank 15
Bank16	Allo Bank	0.3410	0.0895	0.6981	0.6131	Rank 8
Bank17	HiBank	0.2361	0.0684	0.5510	0.4707	Rank 17

System Design and Implementation Phase

The design phase focuses on developing the system architecture capable of integrating the MAGIQ MARCOS workflow. The user interface is designed to allow users to input their preference priorities, initiate computations, and receive ranked recommendations. The database schema is structured to store criteria, sub-criteria, weights, and alternative values. During implementation, the Android application is built using Java and XML, and the multi-criteria decision-making algorithms are embedded into the application's backend logic. This ensures a seamless computational flow from user input to recommendation output.

Testing Phase

Testing is undertaken to ensure the reliability, accuracy, and usability of the application. Black-box testing is first conducted to assess whether all features operate according to specifications, such as preference input, weight assignment, and recommendation generation. User acceptance testing (UAT) is conducted with student participants to evaluate the clarity, responsiveness, and overall usability of the application interface. Additionally, accuracy testing is performed to measure the degree to which DSS-generated recommendations align with the participants' manually chosen alternatives. The system demonstrates high reliability, with all test scenarios producing valid outcomes and the ranking results showing consistency with stated user priorities.

Conclusion and Suggestion Phase

In the final phase, conclusions are drawn regarding the effectiveness of the DSS, particularly its ability to provide objective, preference-based recommendations for selecting digital banks. Suggestions for future work include integrating real-time financial data, implementing predictive analytics to improve recommendation accuracy, and adapting the MAGIQ MARCOS methodology to other decision-making contexts, such as insurance or investment product selection.

Results and Discussions

System Design and Implementation

After the data is prepared, the next step is to design and implement a system that integrates the collected data with the MAGIQ-MARCOS method. The developed system is Android-based and requires users to select their preferences based on existing criteria.

System Design

The system design includes an intuitive user interface, allowing students to easily enter their preferences for the specified criteria. The main page of the application displays options for selecting criteria and user preferences, while the weighting page allows users to assign weights to each criterion. The recommendation results are displayed in the form of graphs and tables to facilitate user understanding.

The structural overview of the developed Decision Support System is presented in Figure 3, which illustrates the integration of key components including the user interface module, the database management layer, and the computational engine responsible for executing the MAGIQ MARCOS procedures. This design framework clarifies how user inputs are processed, transformed through multi-criteria decision-making algorithms, and subsequently returned as ranked digital bank recommendations. The figure provides a comprehensive visualization of the system’s workflow, ensuring transparency in the functional relationships and data pathways implemented within the Android application.

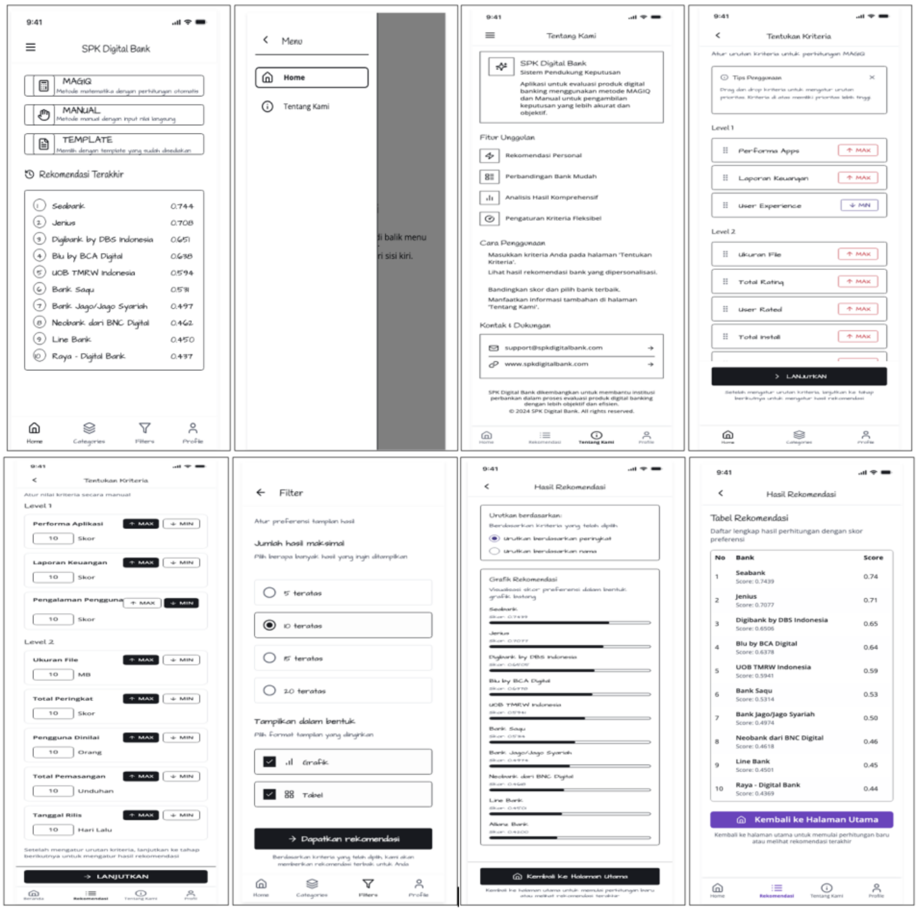

Figure 3. System design

System Implementation

The system implementation is carried out by developing an Android-based application using Java and XML for the user interface. The MAGIQ method is used for weighting criteria, while

MARCOS is used for ranking digital banks. Users are asked to enter their preferences, and the application then calculates the ranking of digital banks based on the weights given by users.

This application also allows users to choose manual weighting, giving them more flexibility in determining criteria priorities. After that, the application provides digital bank recommendations based on the preferences entered by the user.

The operational form of the developed Decision Support System is depicted in Figure 4, which presents the implemented Android application reflecting the system design and computational framework previously outlined. This figure demonstrates how the user interface, preference input modules, and recommendation output features have been translated into a fully functioning mobile application. It also highlights the integration of MAGIQ MARCOS algorithms within the backend processes, ensuring that user selections are accurately converted into structured decision outputs. The visualization provided in this figure affirms the alignment between the conceptual design and its practical deployment on the Android platform.

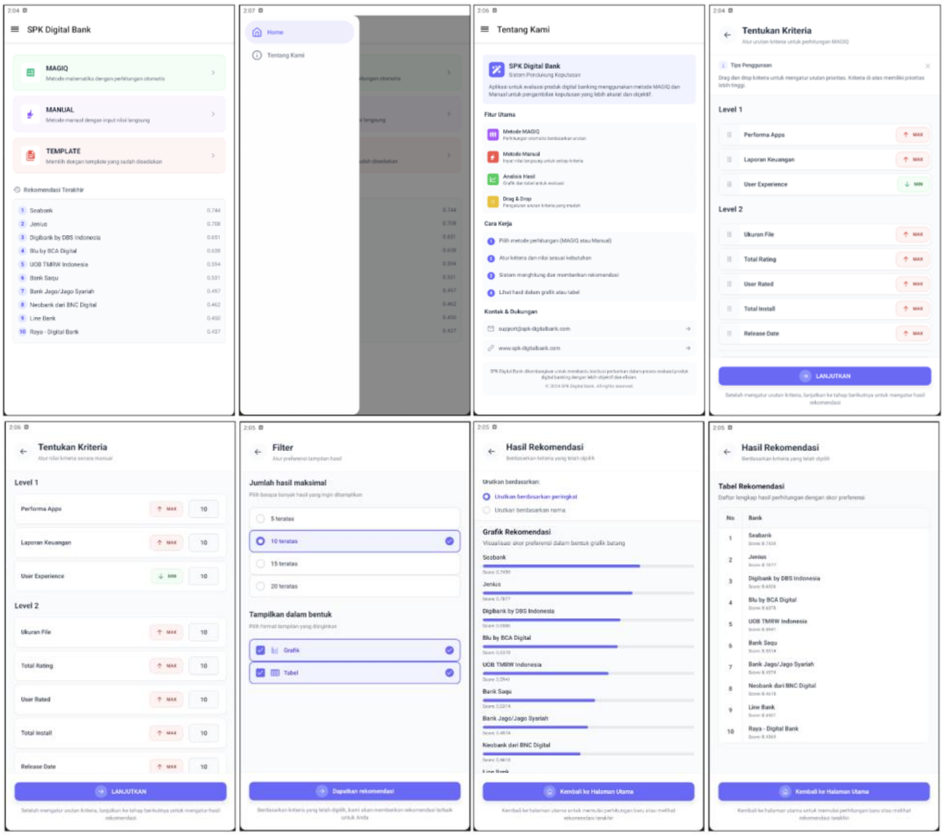

Figure 4. System implementation

Testing and Evaluation

After the system has been implemented, the next step is testing and evaluation to ensure that the application functions as expected and provides accurate recommendations. The testing conducted in this study used use case testing.

This testing ensures that every feature in the application functions properly in real-world situations. The test results show that all features, including manual preference weighting, preference storage, and recommendation results presentation, work as expected. No significant problems were found in the navigation and use of the application. As shown in Table 6, the use case testing results confirm that all system functionalities operate as expected, with each scenario validated successfully.

Table 6. Use case testing result

No	Testing Scenario	Expected Result	Obtained Result	Validation
1	Access the main page of the application, both on the web and mobile	The main page opens and displays a list of options for selecting digital bank preferences using MAGIQ or performing manual weighting	The main page opens and is in accordance with the design, displaying the expected options	Valid
2	The user selects one of the criteria on the "Select Criteria" page	The system displays a list of digital banks based on the criteria selected by the user	The system successfully displays a list of digital banks according to the criteria selected by the user	Valid
3	The user attempts to perform manual weighting to determine preferences	The system allows the user to enter preference weights for the available criteria	Manual weighting is successfully performed and the system accepts the input as desired by the user	Valid
4	Saving the preference weights entered on the manual weighting page	The system saves the user's preference weight data and displays a successful save notification	The preference weight data is successfully saved and a notification appears as expected	Valid
5	The user requests recommendations based on the preference weights that have been set	The system generates a list of digital bank recommendations according to the preference weights that have been entered and displays the ranking results	Digital bank recommendations appear according to the weights entered, with a ranking display	Valid
6	Accessing the recommendation results page with ranking and name display options	The system displays recommendation results in two display options: by ranking and by name	Recommendation results appear according to the display settings selected by the user	Valid
7	The user presses the "Back" button on the recommendation results page to return to the weighting page	The system returns the user to the manual preference weighting page or district selection page	The user successfully returns to the previous page as expected	Valid
8	Loading the application on various mobile devices with different resolutions	The application adapts responsively and displays a neat interface on various screen resolutions	The application appears responsive and neat on various tested devices	Valid
9	Closing the application or returning to the main menu while on the recommendation results page	The system allows users to return to the main page without losing data or settings that have been configured	Users return to the main page with settings intact	Valid

Discussions

This study successfully developed an Android-based decision support system (DSS) using the MAGIQ-MARCOS method to provide recommendations for digital banks that suit student preferences. In this study, three main criteria were used to assess digital bank alternatives, namely Application Performance, Financial Reports, and User Experience. These criteria were each divided into more detailed sub-criteria, which measured technical aspects such as application ratings, number of installations, bank financial stability, and user experience in using the application. From the data processing results, Jenius ranked first based on the system's recommendation results for DM1, followed by Seabank in second place, and Krom - Bank Digital in third place. These recommendations are in line with the preferences expected by DM1, which tends to choose digital banks with high application performance and a better user experience. These results demonstrate the effectiveness of the MAGIQ-MARCOS method in providing relevant and objective recommendations based on the criteria priorities determined by users.

Use-case testing shows that all application features function as expected. The application can accommodate user needs in selecting a digital bank through manual weighting and generate recommendations that match the preferences entered. These results emphasize the importance of implementing technology-based DSS systems to simplify complex decision-making, such as selecting a digital bank. This research provides significant benefits for students who have difficulty choosing a digital bank, as this system can provide data-driven and objective recommendations. In addition, this research opens up opportunities for further development in creating similar systems in other sectors that require multi-criteria decision making, such as insurance or investment selection. Future work could include improving the system by introducing real-time data updates and predictive analysis features, which could improve the accuracy of recommendations as market dynamics and user preferences change.

Conclusion

This study successfully developed an Android-based Decision Support System (DSS) using the MAGIQ MARCOS method to provide recommendations for digital banks that suit student preferences. Based on three main criteria, namely Application Performance, Financial Reports, and User Experience, the system was able to generate objective recommendations, with Jenius ranking first, followed by Seabank and Krom Digital Bank. These findings confirm the effectiveness of the MAGIQ MARCOS approach in simplifying complex decision-making and producing accurate results that reflect user-defined priorities.

Despite its successful implementation, the developed system has several limitations. First, the data used for evaluation is static and does not incorporate real-time financial or application performance updates, which may reduce accuracy when market conditions change rapidly. Second, the system relies on a relatively small number of respondents in the weighting process, particularly the eight FGD participants, which may limit the generalizability of the preference model. Third, only three main criteria were included, and certain qualitative aspects such as customer support responsiveness or long-term reliability were not assessed due to data availability constraints. Finally, the system currently supports a single decision maker at a time and does not yet include collaborative or group decision-making features.

In the future, this research can be expanded through the integration of real-time data updates, predictive analytics, and automated data scraping mechanisms to improve recommendation accuracy over time. Additional user studies with more diverse respondents could also be conducted to enhance the robustness of the weighting process. This system additionally holds potential for application in other sectors, such as investment or insurance selection, that require multi-criteria decision-making. Thus, this research contributes to the advancement of DSS for digital banking while opening opportunities for broader application in other data-driven decision analysis domains.

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