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Annual Performance Assessment of Active Internet Banking Users: Evaluation Using TOPSIS and ARAS Methods

İnternet Bankacılığını Aktif Olarak Kullanan Müşteri Sayılarının Yıllar Bazında Performans Analizi: TOPSIS ve ARAS Yöntemi ile Değerlendirme

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Abstract

From the perspective of banks, the number of customers actively using internet and mobile banking is of great importance in terms of cost efficiency, customer satisfaction and loyalty, revenue growth, security and risk management, as well as competitive advantage, operational efficiency, and marketing effectiveness. Therefore, banks use Multi-Criteria Decision Making Methods to develop strategies to increase the use of internet and mobile banking and to continuously improve this area. This study analyzes the number of customers actively using both internet and mobile banking during specific periods and age ranges using the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and ARAS (Additive Ratio Assessment) methods. The study uses data from the "Number of Active Customers Using Internet and Mobile Banking" published by the Turkish Banking Association, collected in three-month intervals between March 2022 and March 2024. data published by the Turkish Banking Association, the study evaluates the performance of internet and mobile banking usage across six different age groups (0–17, 18–25, 26–35, 36–55, 56–65, 66+). Criterion weights were determined through structured interviews with experts with over 20 years of experience in the banking sector; the weights were reflected in the decision matrix to form the basis for the TOPSIS analysis. In the study, the TOPSIS method was applied in its entirety, including the steps of normalization, determination of ideal and negative ideal solutions, distance calculations, and obtaining suitability index (Ci) values. In addition, the ARAS method was used to calculate the benefit value of each age group and rank them, and the results of the two methods were compared.

Öz

Bankalar açısından bakıldığında, internet ve mobil bankacılığı aktif olarak kullanan müşteri sayısının performansı; maliyet verimliliği, müşteri memnuniyeti ve sadakati, gelir artışı, güvenlik ve risk yönetiminin yanı sıra rekabet avantajı, operasyonel verimlilik ve pazarlama etkinliği gibi çeşitli açılardan büyük önem taşımaktadır. Bu nedenle, bankalar internet ve mobil bankacılığı kullanımını artırmak için stratejiler geliştirebilmesi ve bu alanı sürekli olarak iyileştirme yapmak için Çok Kriterli Karar Verme Yöntemlerini kullanmaktadırlar. Bu çalışma, TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) ve ARAS (Additive Ratio Assessment) yöntemlerini kullanarak belirli dönemler ve yaş aralıklarında hem internet hem de mobil bankacılığı aktif olarak kullanan müşteri sayısını analiz etmektedir. Çalışmada Mart 2022–Mart 2024 döneminde üçer aylık periyotlar halinde toplanan ve Türkiye Bankalar Birliği tarafından yayımlanan "İnternet ve Mobil Bankacılık Kullanan Aktif Müşteri Sayıları" verilerini kullanarak, altı farklı yaş grubunda (0–17, 18–25, 26–35, 36–55, 56–65, 66+) internet ve mobil bankacılık kullanım performansı değerlendirilmiştir. Kriter ağırlıkları, bankacılık sektöründe 20 yılı aşkın tecrübeye sahip uzmanlarla yapılan yapılandırılmış mülakatlar sonucunda belirlenmiş; ağırlıklar TOPSIS analizine temel oluşturacak biçimde karar matrisine yansıtılmıştır. Çalışmada TOPSIS yöntemi; normalizasyon, ideal ve negatif ideal çözümlerin belirlenmesi, uzaklık hesaplamaları ve uygunluk indeksi (Ci) değerlerinin elde edilmesi adımlarını kapsayacak şekilde eksiksiz uygulanmıştır. Buna ek olarak, ARAS yöntemi aracılığıyla her bir yaş grubunun fayda değeri hesaplanarak

The results were used to determine in which periods banks were more successful and which strategies were more effective and which should be abandoned. The study also provides insights for banks to increase customer satisfaction and optimize their strategies.

Keywords: *Topsis, Aras, Internet Banking, Multi-Criteria Decision Making Method, Mobile banking, Customer Satisfaction*

JEL codes: *C02, C44, C61, G21*

sıralama yapılmış ve iki yöntemin sonuçları karşılaştırılmıştır.
Sonuçlar, bankaların hangi dönemlerde daha başarılı olduğunu ve hangi stratejilerin daha etkili hangi stratejilerden vazgeçilmesi gerektiğini belirlemek için kullanılmıştır. Çalışma ayrıca bankaların müşteri memnuniyetini artırmak ve stratejilerini optimize etmek için de çıkarımlarda bulunmaktadır.

Anahtar Kelimeler: *Topsis, Aras, İnternet Bankacılığı, Çok Kriterli Karar Verme Yöntemi, Mobil bankacılık, Müşteri Memnuniyeti*

JEL kodları: *C02, C44, C61, G21*

GENİŞLETİLMİŞ ÖZET

Bu çalışma, belirli dönem ve yaş aralıkları bazında internet ve mobil bankacılığı aktif olarak kullanan müşteri sayılarının her birini Çok Kriterli Karar Verme (ÇKKV) yöntemlerinden TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) ve ARAS (Additive Ratio Assessment) yöntemleri kullanarak analiz etmektedir. Çalışmada, 2022-2024 yılları arasında her üç ayda bir alınan veriler kullanılmış ve bu verilerin performansları değerlendirilmiştir. Sonuçlar, bankaların hangi dönemlerde daha başarılı olduğunu, hangi pazarlama politikalarının daha etkili olduğunu ve hangi politikalardan vazgeçilmesi gerektiğini belirlemek için kullanılmıştır. Araştırma ayrıca bankacılık sektöründeki müşteri memnuniyetini artırmak ve stratejilerini optimize etmek için de çıkarımlarda bulunmaktadır.

Ana araştırma detayları:

1. Bankalardaki İnternet ve Mobil Bankacılığı aktif müşteri sayılarının dönemsel değişimlerin temel nedenleri nelerdir?

2. Bankalar, hangi yaş gruplarında dijital bankacılık hizmetlerini daha etkin bir şekilde benimsetmiştir?

3. TOPSIS ve ARAS yöntemleri ile yapılan analizler, müşteri segmentasyonu ve strateji geliştirme açısından nasıl bir yol haritası çizmiştir? sorularına cevap aramıştır.

Literatür kısmında ise Jayawardhena ve Foley (2000), internet bankacılığının bankalar için maliyetleri azaltarak, müşteri ile doğrudan iletişim kurmayı ve zamandan tasarruf sağlayarak internet bankacılığının avantajlarından, Liao ve Cheung (2002), internet bankacılığının müşteri tutumlarını olumlu yönde etkilediğini ve müşteri memnuniyetini artırdığını, Akinci ve diğerleri (2004) ise internet bankacılığının gelişmiş ülkelerdeki tüketici sadakatini yükselttiğini belirterek müşteri memnuniyetinden, Munusamy ve arkadaşları (2010) da verimlilik ile bankacılıktaki hataların azaltılmasının ilişkili olduğunu belirterek bu hizmetlerin performansı müşteri memnuniyeti ve operasyonel verimlilik açısından önemli bir rol oynadığı vurgulanmıştır.

Uygulama kısmında ise bankaların internet ve mobil bankacılık hizmetlerini kullanan müşteri sayılarının performansını değerlendirilmiş hangi dönemlerde daha başarılı olduğunu ve hangi kampanyaların daha etkili olduğunu ortaya koymuştur. Ayrıca, TOPSIS ve ARAS yöntemleri ile elde edilen sonuçların aynı çıkması, değerlendirme kriterlerinin, alternatiflerin ve ağırlıkların dengeli bir şekilde yapılandırıldığını ve iki farklı metodolojinin de benzer kararları desteklediğini göstermiştir.

INTRODUCTION

Internet banking has become a valuable option for many customers who enjoy ease of use, more effective use of time, and efficiency. With the rapid advancement of technology, financial institutions have accelerated their digital transformation processes in order to provide better services to their customers. In this context, internet banking plays a central role in reshaping how financial services are delivered. Thanks to internet banking, customers can carry out their transactions quickly, securely, and without having to visit a physical branch.

For banks, the performance of internet and mobile banking services is critical in terms of customer satisfaction and operational efficiency. Customers' interest in and active usage rates of internet and mobile banking play an important role in shaping banks' digital strategies. In this context, analyzing internet banking usage rates by customer segment and conducting performance analyses enables banks to gain valuable insights when making strategic decisions.

This study aims to evaluate the performance of the number of customers who actively use the internet and mobile banking services offered by banks. Our dataset includes the number of customers using internet and mobile banking services from different age groups between March 2022 and March 2024. The study compares the evaluation results obtained using the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and ARAS (Additive Ratio Assessment) methods. The analysis aims to measure the effectiveness and performance of internet banking services according to the age criteria of bank customers.

Although MCDM techniques have been applied in previous studies to evaluate digital banking services, much of the literature focuses on factors such as usability and service quality, with limited attention to age-based segmentation or method comparison. However, in many of these studies, comparisons between methods and age-based studies are still limited. Therefore, there remains a need for comprehensive research that explains the interaction of different age groups with digital channels and the managerial benefits of using multiple MCDM approaches together.

Analyzing internet and mobile banking usage rates is also of great importance in understanding the effects of digital transformation in the financial sector. Differences in customer behavior between age groups offer banks opportunities to personalize their digital strategies and improve the customer experience. Such analyses help financial institutions develop innovative, customer-focused services and reveal the long-term effects of digitalization on the banking sector.

To fill this gap, the study makes three concrete contributions to the literature. First, it compares the digital banking performance of six age groups (0–17, 18–25, 26–35, 36–55, 56–65, 66+) in Turkey for the first time using quarterly data from March 2022 to March 2024. Second, it demonstrates the consistency of the rankings produced by applying both TOPSIS and ARAS methods to the same dataset.

In this way, the study directly addresses the identified literature gap and demonstrates how age-specific insights obtained using two complementary MCDM methods can strengthen strategic decision-making processes in the banking sector.

Overall, this study contributes to the literature by offering a structured evaluation of internet and mobile banking usage by age group, using two complementary MCDM methods, and translating the findings into actionable insights for strategic planning.

In conclusion, within the scope of this study, the performance of internet and mobile banking services offered by banks will be evaluated, and new strategic models aimed at increasing operational and marketing success will be proposed.

1. LITERATURE REVIEW

Among the widely used online banking services in the financial sector today, internet and mobile banking take precedence (Almaiah et al., 2022; Namahoot and Laohavichien, 2018).

According to a study by Munusamy et al. (2010), efficiency has been identified as a significant factor influencing customer satisfaction in the banking sector. Efficiency is the most important factor, followed by the reduction of time required for banking transactions and minimizing errors.

In addition to benefits for customers, digital banking platforms offer notable advantages to banks, such as cost reduction, improved communication, and time efficiency. Jayawardhena and Foley (2000) highlight that internet banking enhances institutional reputation and helps attract new customers.

A large body of literature has focused on the dual goals of enhancing customer satisfaction and achieving operational efficiency through internet banking. For instance, Liao and Cheung (2002) found that the adoption of internet banking positively affects consumer attitudes, while Akinci et al. (2004) emphasized its role in reinforcing customer loyalty among sophisticated users.

Studies on internet banking often focus on customers' attitudes towards the internet. In this context, Şekerkaya and Yüksel (2002) examined customer attitudes towards the internet in their research. Additionally, perceived service quality and consumer behavior in internet banking have also been extensively studied. In his study, Çelik (2005) investigated the perceived service quality in internet banking services and proposed a model for perceived service quality in internet banking.

The TOPSIS method is commonly applied in multi-criteria decision-making problems. Hwang and Yoon (1981) stated that the method is based on the principle of ranking alternatives by assessing their closeness to the ideal solution. This method proves to be an effective tool in dynamic and competitive fields like the banking sector. Zanakis et al. (1998) demonstrated that the TOPSIS method is used in various applications such as performance evaluation, risk analysis, and customer segmentation.

For the period covering 2008-2017, the financial performance analysis of the Turkish Deposit Banking Sector was conducted by Işık (2019) based on the Entropy and ARAS methods. Ömürbek et al. (2017) comparatively evaluated the sustainability performance of banks using the Entropy, ARAS, MOOSRA, and COPRAS methods. Şahin and Karacan (2020) analyzed the financial performance of companies listed on the Borsa Istanbul Construction Index using the ARAS and COPRAS methods. The results showed that the financial performance rankings of both methods were similar, with Edip Gayrimenkul Yatırım Sanayi ve Ticaret A.Ş. being the top performer in 2018. Sakarya and Gürsoy (2021) assessed the financial performance of deposit banks in the BIST Banking Index using Entropy-based COPRAS and ARAS methods. Both methods concluded that Halk Bankası ranked first. Reza and Majid (2013) evaluated banks in terms of trust in internet banking using the ARAS method.

2. METHODOLOGY

In this section, the methods used in the study are presented.

2.1. Topsis Method

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), developed by Hwang and Yoon in 1981, is a widely used method for addressing multi-criteria decision-making problems. This method allows alternatives to be ranked according to their distance from the ideal solution. The TOPSIS method determines two reference points, the ideal solution and the negative ideal solution, and calculates the relative closeness of each alternative to these two solutions. The method consists of the following steps:

Step 1: Determining objectives and defining evaluation criteria.

Step 2: Creating the Decision Matrix (A): Decision matrices are created with alternatives in the rows and evaluation criteria in the columns. a_{ij} in decision matrix A shows the real value of alternative i in matrix A according to criterion j (Rao, 2008: 444).

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}$$

Step 3: Constructing the Normalized Decision Matrix (R): Once the decision matrix is formed, the normalized decision matrix (R) is calculated using formula (1) (Mahmoodzadeh et al., 2007:138).

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{k=1}^{m} a_{kj}^2}} \tag{1}$$

(rij; i: 1,2,….N; number of criteria j: 1,2,….K; number of alternatives)

Step 4: Constructing the Weighted Normalized Decision Matrix (V): First, the relative weight values (ωij: i=1,2,…N) for the evaluation criteria based on the objective are determined. Then, the elements in each column of the R matrix are multiplied by the corresponding ωij value to form the V matrix. The weighted normalized decision matrix is represented as Vij = (ωij × Rij) (Rao, 2008: 444).

Step 5: Creation of Ideal (A^*) and Negative Ideal (A^-) Solutions: While the ideal solution consists of the best performance values of the weighted normalized decision matrix, the negative ideal solution is the best. It consists of bad values. Ideal solutions can be calculated using equations 2 and 3. In both formulas, J shows the benefit (maximization) value and J' shows the cost (minimization) value (Yurdakul and İç, 2005: 4613).

$$A^* = \left\{ (\max_i v_{ij} \middle| j \in J), (\min_i v_{ij} \middle| j \in J' \right\} \tag{2}$$

$$A^{-} = \left\{ (\min_i v_{ij} \middle| j \in J), (\max_i v_{ij} \middle| j \in J^{'} \right\} \tag{3}$$

The values obtained from equation no. 2 can be shown as $A^{*} = \{v_1^{*}, v_2^{*}, ..., v_n^{*}\}$ and the values obtained from equation no. 3 can be shown as $A^{-} = \{v_1^{-}, v_2^{-}, ..., v_n^{-}\}$

Step 6: Calculation of Discrimination Measurements: The distance of the J alternative from the ideal solution is calculated as the Ideal Discrimination (S_i^{*}) and the distance from the negative ideal solution as the Negative Ideal Discrimination (S_i^{-}), using equations 4 and 5 (Mahmoodzadeh et al., 2007). :139)

$$S_i^{*} = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^{*})^2} \tag{4}$$

$$S_i^{-} = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^{-})^2} \tag{5}$$

Step 7: Calculating the Relative Closeness to the Ideal Solution: Using equation (6), the relative closeness (C_i^{*}) to the ideal solution is calculated (Olson, 2004:2).

$$C_i^{*} = \frac{S_i^{-}}{S_i^{-} + S_i^{*}} \qquad 0 \le C_i^{*} \le 1 \tag{6}$$

Here, C_i^{*} the value represents the success of the alternative in the sector, with higher values indicating greater success.

Step 8: Alternatives are ranked according to their relative closeness to the ideal solution (C_i^{*}).

2.2. Aras Method

ARAS (Additive Ratio Assessment) method is a technique used in the Multi-Criteria Decision Making (MCDM) process. The ARAS method, developed by Zavadskas and Turskis (2010), compares the utility function values of the alternatives with those of the optimal alternative, which is introduced into the decision problem by the researcher (Sliogeriene et al., 2013: 13). This method is based on the evaluation of alternatives under a set of criteria and Calculates the total benefit ratio of each alternative. ARAS, as a simple but effective method, helps decision makers solve complex decision problems. Unlike other MCDM, in the ARAS method, the utility function values of the alternatives are compared with the utility function value of the optimal alternative.

The ARAS method is the most appropriate approach for proportional ranking in MCDM problems. The steps of the ARAS method are outlined below (Zavadskas and Turskis, 2010, p.163-165).

Step 1: Creating the decision matrix

X decision matrix, where m represents the number of alternatives and n indicates the number of criteria.

$$X = \begin{bmatrix} x_{01} & x_{0j} & x_{0n} \\ x_{i1} & x_{ij} & x_{in} \\ x_{m1} & x_{mj} & x_{mn} \end{bmatrix}; i = 0,1,\dots,m \;\; j = 0,1,\dots,n$$

can be shown as . ij x i on the decision matrix. alternative j. The performance value shown in the criterion; 0 j x if j. It represents the optimal value of the criterion. If the optimal value of the criterion is not known in the decision problem, the optimal value is calculated with the help of the following equations, depending on whether the criterion shows benefit (higher is better) or cost (lower is better).

Utility case: $x0j$ = max xij

Cost case: $x0j$ = minxij

Step 2: Normalization of the Decision Matrix

In the ARAS method, the $\bar{X}$ normalized decision matrix is formed at values. values are calculated in two ways, depending on whether the criterion has a benefit or cost feature. If higher criterion performance values are considered better (benefit situation), normalized values are calculated with the help of the equation below.

$$\bar{x}_{ij} = \frac{\boldsymbol{x_{ij}}}{\sum_{\boldsymbol{i=0}}^{\boldsymbol{m}} x_{ij}} \tag{7}$$

If lower criterion performance values are considered better (cost situation), the normalization process is performed in two steps. In the first step, performance values are converted into benefit status using the first equation below, and in the second step, the normalized value is calculated using the second equation below.

$$x_{ij}{}^{*} = \frac{1}{x_{ij}}$$

$$\bar{x}_{ij} = \frac{x_{ij}{}^{*}}{\sum_{\boldsymbol{i=0}}^{\boldsymbol{m}} x_{ij}{}^{*}} \tag{8}$$

After the normalized values are calculated, the values are written in the matrix form shown above to obtain the normalized decision matrix.

$$\bar{X} = \begin{bmatrix} \bar{x}_{01} & \bar{x}_{0j} & \bar{x}_{0n} \\ \bar{x}_{i1} & \bar{x}_{ij} & \bar{x}_{in} \\ \bar{x}_{m1} & \bar{x}_{mj} & \bar{x}_{mn} \end{bmatrix}; i = 0,1,\dots,m \;\; j = 0,1,\dots,n \tag{9}$$

Step 3: Weighting the Normalized Decision Matrix.

$$\hat{X} = \begin{bmatrix} \hat{x}_{01} & \hat{x}_{0j} & \hat{x}_{0n} \\ \hat{x}_{i1} & \hat{x}_{ij} & \hat{x}_{in} \\ \hat{x}_{m1} & \hat{x}_{mj} & \hat{x}_{mn} \end{bmatrix}; i = 0,1,\dots,m \;\; j = 0,1,\dots,n \tag{10}$$

(3)

Step 4: Calculation of Optimality Function Values.

$$S_i = \sum_{j=1}^{n} \hat{x}_{ij} \quad i = 0,1,\dots,m$$
$$K_i = \frac{S_i}{S_0} \quad i = 0,1,\dots,m \tag{11}$$

The data set used in this study includes the number of customers in different age groups using the banks' internet and mobile banking services between March 2022 and March 2024. The dataset is classified according to the following age groups:

- 0-17 years
- 18-25 years
- 26-35 years
- 36-55 years
- 56-65 years
- 66+ years

Determination of Weights*

The weights determined for each age group are as follows:

- 0-17 years: 0.02
- 18-25 years: 0.20
- 26-35 years: 0.24
- 36-55 years: 0.27
- 56-65 years: 0.19
- 66+ years: 0.08

These weights are min. It was determined as a result of interviews with managers with more than 20 years of banking sector experience. Then, the solved results were interpreted with the help of Excel.

3.3. Data Source and Dataset Explanation:

The dataset used in this study is based on publicly available reports published by the Banks Association of Turkey (TBB). The digital banking statistics covering the periods from March 2022 to March 2024 were retrieved from the TBB's official reports (Türkiye Bankalar Birliği, 2024). The dataset includes the number of customers actively using internet and mobile banking services across different age groups. The obtained data were structured, analyzed, and interpreted within the framework of the study using Excel-based applications.

4. APPLICATION

Note on Decimal Precision:

To maintain analytical accuracy in the TOPSIS and ARAS calculations, all numerical values (e.g., normalized scores, distances, closeness coefficients) are reported with more than two decimal places. This level of precision is essential for reflecting subtle differences between alternatives that significantly influence the final rankings. Therefore, values were deliberately not rounded to only two decimal digits.

4.1. Analysis with Topsis Method

In this section, the TOPSIS method was applied using Microsoft Excel to evaluate the performance of banks based on the number of customers actively using internet and mobile banking services. The dataset covers six age groups and includes quarterly data from March 2022 to March 2024. The analysis incorporates age-based weightings to reflect the relative importance of each customer segment in the decision-making process.

Table 1: Criterion Weights by Age Group for Active Internet and Mobile Banking Users

Users Using Both Internet and Mobile Banking (Thousand)						
Weight*	0,02	0,20	0,24	0,27	0,19	0,08
	0-17 Age group	18-25 Age group	26-35 Age group	36-55 Age group	56-65 Age group	66+ Age group

Note: The criterion weights were determined based on expert opinions collected through interviews with senior managers who have more than 20 years of experience in the banking sector.

The weights were determined based on expert opinions to reflect the impact of age groups on digital banking usage.

Table 2: Normalization of the Decision Matrix - Stage 1

Weight	0,02	0,20	0,24	0,27	0,19	0,08
a_{ij}	Users Using Both Internet and Mobile Banking (Thousand)					
Period	0-17 Age group	18-25 Age group	26-35 Age group	36-55 Age group	56-65 Age group	66+ Age group
March 2022	36	1.390	2.159	3.356	692	296

June2022	34	1.365	2.140	3.313	674	284
September 2022	36	1.438	2.235	3.530	874	455
December 2022	52	1.603	2.411	3.603	773	426
March 2023	41	1.644	2.533	3.734	751	388
June 2023	48	1.694	2.560	3.848	760	394
September 2023	80	1.928		4.089	802	398
December 2023	62	1.698	2.477	3.804	795	422
March 2024	54	1.323	2.197	3.605	765	420

Table 2 presents the first step of the TOPSIS method: normalization of the decision matrix. This procedure transforms the raw data into comparable, dimensionless values, allowing for the elimination of scale differences across criteria. By ensuring that each criterion contributes equally to the analysis regardless of its original unit, normalization creates a reliable basis for the performance evaluation of different periods.

Table 2 displays the normalized values of raw data related to internet and mobile banking usage by age groups. The highest normalized value appears in the 36–55 age group during September 2023, reflecting a peak in digital banking activity in this period. Conversely, the 0–17 and 66+ age groups consistently show lower normalized values across all periods, indicating relatively lower engagement in digital channels. These findings underscore the dominance of middle-aged users in digital banking and highlight age-based disparities in adoption. The normalization step ensures equal footing for all criteria and allows fair comparison across periods.

Table 3: Normalization of the Decision Matrix - Stage 2

Weight	0,02	0,20	0,24	0,27	0,19	0,08
$*a_{ij}$ a_{ij}	Users Using Both Internet and Mobile Banking (Thousand)					
Period	0-17 Age group	18-25 Age group	26-35 Age group	36-55 Age group	56-65 Age group	66+ Age group
March 2022	1303	1.931.244	4.660.622	11.265.724	479.402	87.392
June2022	1183	1.861.862	4.581.245	10.978.048	454.352	80.695
September 2022	1328	2.067.414	4.996.364	12.462.053	763.567	206.911
December 2022	2656	2.569.708	5.813.514	12.978.390	597.970	181.105
March 2023	1681	2.701.714	6.413.612	13.944.526	563.366	150.510

June 2023	2268	2.867.976	6.556.078	14.808.212	577.085	155.535
September 2023	6405	3.718.954	7.547.388	16.719.447	643.239	158.087
December 2023	3861	2.884.746	6.134.954	14.468.438	631.473	178.402
March 2024	2940	1.750.866	4.826.726	12.996.393	584.992	176.687

Table 3 presents the second stage of the TOPSIS method, where the normalized decision matrix is adjusted to reflect the relative importance of each criterion. This is achieved by multiplying the normalized values by their corresponding weights, thereby constructing the weighted normalized decision matrix. This step allows for the integration of expert-based priorities into the performance evaluation process.

Tables 2 and 3 illustrate how seasonal fluctuations in the use of internet and mobile banking services are distributed across age groups. In particular, the 36–55 age group consistently exhibits the highest values across all periods, indicating a strong and stable engagement with digital banking platforms.

The normalized decision matrix (Table 2) adjusts the raw data to eliminate differences in scale between criteria, enabling fair and accurate comparisons among periods. This stage ensures that each criterion contributes equally to the performance evaluation, regardless of its original unit or magnitude.

Table 3 presents the weighted normalized decision matrix, obtained by multiplying each normalized value by the corresponding criterion weight ($V_{ij} = \omega_{ij} \times R_{ij}$). This step integrates the relative importance of each age group into the analysis, allowing for a more representative performance assessment. The high values of the 36–55 age group persist in this weighted evaluation, further highlighting their dominant role in digital banking usage.

These findings suggest significant disparities in digital engagement across age segments. While younger and middle-aged groups demonstrate robust participation, individuals aged 66 and above show considerably lower usage levels. This indicates a potential gap in digital inclusion that banks may need to address through targeted strategies.

The subsequent steps of the TOPSIS method, including the calculation of ideal and negative-ideal solutions, distances to these benchmarks, and final closeness coefficients, are detailed in Appendices A–E. The results reveal that September 2023 is the period closest to the ideal solution, representing a peak in performance, whereas June 2022 is identified as the closest to the negative solution, suggesting comparatively lower digital engagement during that time. All computations are based on the standard TOPSIS methodology as developed by Hwang and Yoon (1981).

Table 4: Calculation of Relative Closeness to the Ideal Solution and Final Rankings (Stage 1)

Period	S_i^*	Si -
March 2022	0,04002382	0,00344959
June2022	0,04222917	0,00172134
September 2022	0,03071071	0,02160677
December 2022	0,02331181	0,02084638
March 2023	0,02051794	0,02345117
June 2023	0,01717005	0,02684817
September 2023	0,00704352	0,04038902
December 2023	0,01664472	0,02684623
March 2024	0,03508672	0,01422218

(Stage 2)

Period	S_i^*	Si -	Ci*	
March 2022	0,04002382	0,00344959	0,07934951	
June2022	0,04222917	0,00172134	0,03916532	The worst performing period
September 2022	0,03071071	0,02160677	0,41299332	
December 2022	0,02331181	0,02084638	0,47208416	
March 2023	0,02051794	0,02345117	0,53335555	
June 2023	0,01717005	0,02684817	0,60993306	
September 2023	0,00704352	0,04038902	0,85150448	The best-performing period
December 2023	0,01664472	0,02684623	0,61728305	
March 2024	0,03508672	0,01422218	0,28843022	

Table 4 presents the final stage of the TOPSIS analysis, where the relative closeness values (Ci*) to the ideal solution are calculated for each period. This index measures the proximity of each alternative to the optimal scenario by considering the Euclidean distances to both ideal and negative-ideal solutions. A higher Ci* value denotes stronger performance in terms of digital banking activity across all age groups.

The findings indicate that September 2023 achieved the highest Ci* score (0.8515), positioning it as the most effective period in terms of internet and mobile banking usage. This suggests a culmination of favorable conditions such as technological advancements, increased user trust, or targeted promotional campaigns during that time.

Conversely, June 2022, with the lowest Ci* value (0.0391), stands out as the period with the weakest performance, potentially reflecting barriers to adoption or limited outreach during that quarter.

These results highlight the temporal variability in user engagement and suggest that periodic factors—like campaign intensity, feature rollouts, or broader economic confidence—may significantly shape digital banking behaviors. Such insights can inform banks' strategic planning for optimizing customer engagement across different segments and periods.

Table 5: Ranking of Alternative Periods from Best to Worst

Period	Ci*	
September 2023	0,8515045	Best performing period
December 2023	0,617283	
June 2023	0,6099331	
March 2023	0,5333556	
December 2022	0,4720842	
September 2022	0,4129933	
March 2024	0,2884302	
March 2022	0,0793495	
June 2022	0,0391653	The period with the worst performance

Table 5 ranks all the evaluated periods based on their relative closeness (Ci*) to the ideal solution obtained through the TOPSIS method. A higher Ci* value indicates a stronger alignment with optimal performance in digital banking usage, reflecting more active and widespread adoption across age groups.

The results demonstrate that September 2023 achieved the highest score (0.8515), identifying it as the best-performing period. This may correspond to a culmination of favorable factors such as increased digital trust, enhanced mobile app functionalities, or intensified digital marketing strategies during that quarter.

December 2023 and June 2023 also show robust performance, suggesting sustained momentum in digital adoption. In contrast, June 2022 ranks last with the lowest Ci* score (0.0391), indicating significant limitations in user engagement—possibly due to lower promotional activities, technological lags, or seasonal disinterest.

These rankings reveal not only temporal disparities but also the strategic potential of quarterly monitoring in digital banking. Banks can leverage such insights to tailor their interventions more precisely—whether it be through age-targeted campaigns, technological upgrades, or timing service launches to match high-engagement periods.

4.2. Findings and Comments

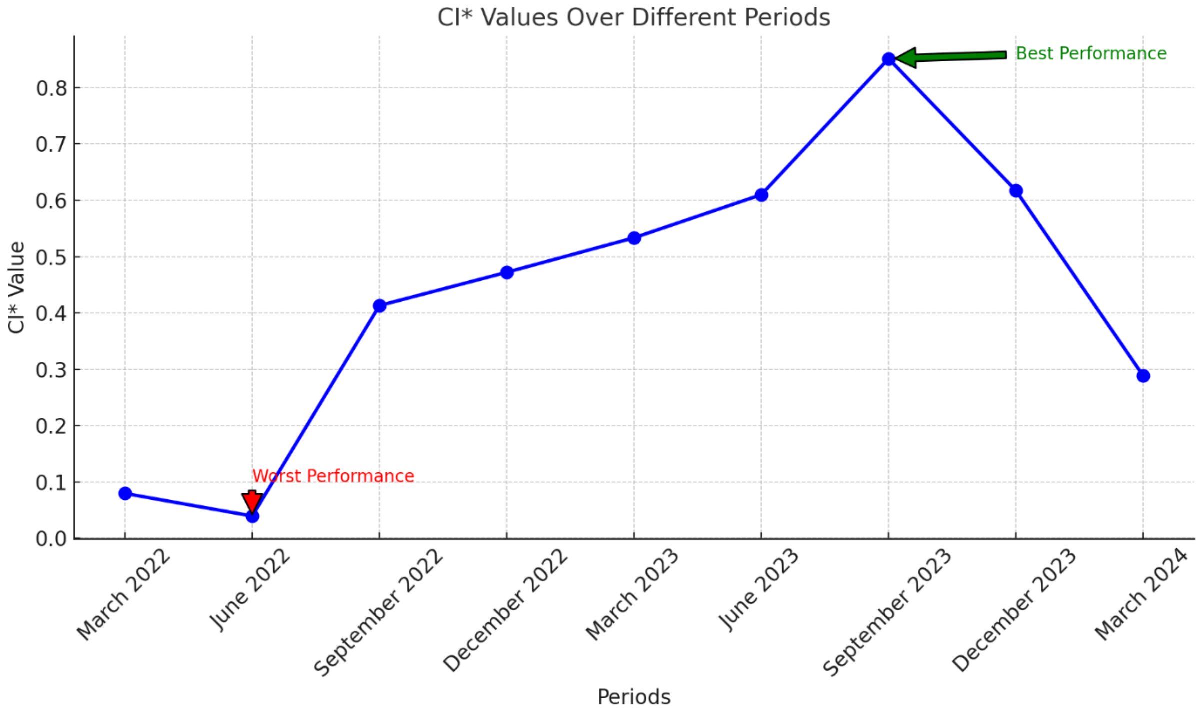

Figure 1. CI* Values Over Different Periods

This section evaluates changes in the usage of internet and mobile banking services based on the relative closeness values (Ci*) obtained from the TOPSIS method, covering the period from March 2022 to March 2024. These temporal shifts help illuminate how customer behaviors evolved in response to digital banking initiatives and external seasonal dynamics.

March 2022 (Ci: 0,07935): This period reflects the initial stage of relatively low engagement with digital banking services. The low Ci* value may suggest lingering adaptation issues following the COVID-19 pandemic or limited public awareness and trust in digital channels.

June 2022 (Ci: 0,03917): A further decline in digital banking usage is observed. This downturn may point to ineffective promotional strategies or heightened user concerns about cybersecurity. To counter this, banks may need to revise their communication tactics and emphasize trust-building measures such as stronger data protection and customer education efforts.

September 2022 (Ci: 0,41299): A significant increase is evident, possibly linked to post-summer normalization, back-to-school financial activity, or more effective marketing interventions. Personalized campaigns and segmentation-based digital outreach may have played a role.

December 2022 (Ci: 0,47208): Growth in usage continued but at a slower pace. End-of-year financial activities, tax payments, and promotional offers might have driven customer traffic. However, the plateauing growth may signal the need for refreshed digital engagement models.

March 2023 (Ci: 0,53336): A moderate upward trend persists. This period may benefit from residual momentum from year-end initiatives, coupled with routine spring financial planning.

June 2023 (Ci: 0,60993): A continued rise in digital engagement possibly driven by seasonal campaigns, vacation expenditures, and youth-focused promotions. Targeted summer strategies appear to be effective in sustaining user interest.

September 2023 (Ci: 0,85150): This is the peak of digital banking adoption in the examined period. Likely contributing factors include fall campaign launches, school re-openings, and advanced predictive analytics that enabled banks to deliver more tailored services. This period could be studied further as a benchmark for future strategy development.

December 2023 (Ci: 0,61728): A decline is observed following the September peak, although usage remains relatively high. Possible causes include campaign fatigue, limited innovation, or customer churn. Investigating the strategic missteps during this period could guide future course corrections.

March 2024 (Ci: 0,28843): A sharp decrease occurs. This may indicate customer disengagement or dissatisfaction. To reverse this trend, banks may consider redesigning user interfaces, offering content in offline modes, enhancing user education efforts, and launching tailored advertising campaigns.

4.3. Analysis with Aras Method

In this section, the ARAS method was applied via Excel to evaluate the performance of the number of customers using the banks' internet and mobile banking services. The data set includes the number of customers in different age groups from March 2022 to March 2024.

The raw decision matrix used in the ARAS analysis, which includes the number of users by age group over time, is provided in Appendix F. This matrix forms the basis for the subsequent steps of normalization and weighted aggregation.

Preliminary observations from the raw data indicate that the 36–55 age group consistently recorded the highest number of users across all periods. A notable overall increase was observed in almost every age category, especially in September 2023, reflecting a peak in digital banking engagement during that time.

Table 6: Criteria Weights and Directions

	Users Using Both Internet and Mobile Banking (Thousand)					
	0-17 Age group	18-25 Age group	26-35 Age group	36-55 Age group	56-65 Age group	66+ Age group
Weight	0,02	0,20	0,24	0,27	0,19	0,08
DIRECTION	↑	↑	↑	↑	↑	↑

Table 6 presents the criterion weights and benefit-oriented direction of evaluation. All criteria are positively oriented (↑), meaning higher values denote better performance. The weight structure assigns the highest importance (27%) to the 36-55 age group, followed by 26–35 (24%) and 18–25 (20%). This weighting aligns with observed usage patterns and expert judgment, ensuring the analysis reflects the actual market impact of each demographic.

To normalize the raw data, an optimal decision matrix was constructed based on the highest observed values per criterion (Appendix G). Normalization (Appendix H) was then conducted by dividing each entry in the raw matrix by its respective optimal value, producing a dimensionless and comparable dataset. The normalized matrix (Appendix I) showed that while most age groups maintained stable performance, younger users (particularly 18–25 and 26–35) experienced a marked decline in March 2024.

Subsequently, a weighted normalized decision matrix was formed (Appendix J) by multiplying each normalized value by its corresponding weight. This transformation integrated both performance levels and relative importance, yielding composite scores for each period.

The findings point again to September 2023 as the highest performing period, reflecting optimal digital banking activity across all segments. In contrast, June 2022 and March 2024 exhibited the lowest aggregate scores, implying decreased digital engagement. These fluctuations emphasize the temporal dynamics of digital service adoption and signal critical windows for banks to enhance user retention and tailor their marketing strategies.

Table 7: Optimality Function, Degree of Utility, and Ranking

	Users Using Both Internet and Mobile Banking (Thousand)								
	0-17 Age group	18-25 Age group	26-35 Age group	36-55 Age group	56-65 Age group	66+ Age group	Sİ	Kİ	ARRANGEMENT Sİ/S0
DIRECTION	↑	↑	↑	↑	↑	↑			
OPTIMUM	0,003057	0,024089	0,027238	0,029861	0,021398	0,009242	0,114885	1,000000	
March 2022	0,001379	0,017359	0,021404	0,024512	0,016955	0,006006	0,087615	0,762633	8
June 2022	0,001314	0,017045	0,021221	0,024197	0,016506	0,005771	0,086054	0,749043	9
September 2022	0,001392	0,017961	0,022161	0,025780	0,021398	0,009242	0,097934	0,852456	6
December 2022	0,001969	0,020024	0,023905	0,026309	0,018936	0,008646	0,099789	0,868600	5
March 2023	0,001566	0,020532	0,025109	0,027271	0,018380	0,007882	0,100739	0,876873	4
June 2023	0,001819	0,021155	0,025386	0,028103	0,018602	0,008012	0,103077	0,897221	3
September 2023	0,003057	0,024089	0,027238	0,029861	0,019639	0,008078	0,111963	0,974568	1

December 2023	0,002374	0,021216	0,024557	0,027778	0,019459	0,008581	0,103966	0,904956	2
March 2024	0,002072	0,016529	0,021782	0,026327	0,018729	0,008540	0,093979	0,818026	7

Table 7 presents the final step of the ARAS (Additive Ratio Assessment) analysis. It includes the calculated optimality function scores (Si), utility degrees (Ki), and the resulting rankings of each period. The utility score (Ki) is derived by dividing each period's performance score (Si) by the ideal performance score (S_0), representing the maximum achievable value across all alternatives. A higher Ki score reflects closer proximity to the optimal state in terms of digital banking adoption.

According to the results, September 2023 stands out as the top-performing period with a utility degree of 97.46%, suggesting peak user engagement across all age segments. December 2023 and June 2023 follow closely, indicating sustained momentum during the second half of the year. These periods may correspond with promotional banking campaigns, increased financial transactions due to seasonal events, or improved digital service infrastructure.

In contrast, June 2022 and March 2022 scored the lowest in utility (Ki = 0.7490 and 0.7626, respectively), suggesting underutilization of digital banking services during the early stages of the timeline. This may be attributed to post-pandemic inertia, lack of awareness, or inadequate platform accessibility at the time.

The rankings exhibit a clear seasonal pattern, with stronger performance typically occurring in the latter half of each calendar year. This trend offers valuable insights for banks: intensifying outreach, user acquisition, and promotional activities in Q3 and Q4 may yield higher returns. Conversely, Q1 and Q2 may require reinforcement strategies such as gamification, user training, or incentive-based onboarding to counter seasonal disengagement.

By capturing both quantitative performance and qualitative behavior shifts, the ARAS-based findings contribute a richer understanding of digital banking dynamics over time.

CONCLUSION AND DISCUSSION

This study analyzes the performance of banks in Turkey in terms of internet and mobile banking usage by age group and evaluates seasonal changes in digital banking services using the TOPSIS and ARAS methods. The analysis results reveal significant fluctuations in customer usage rates between March 2022 and March 2024. While there were noticeable increases in internet banking usage during periods such as the end of summer and the end of the year, usage rates declined in the initial post-pandemic period and at the beginning of summer. Overall, the 36-55 age group emerged as the most active segment in terms of digital banking usage. Although the 56-65 and 66+ groups remained below average, they exhibited a gradual upward trend. These findings not only reveal the current situation but also indicate that banks need to redefine their target audiences in a time-sensitive manner. In particular, failure to take seasonal fluctuations into account in campaign planning can lead to wasted resources and low conversion rates.

The findings show that banks need to analyze seasonal fluctuations well and restructure their digital marketing strategies accordingly. Policies that increase trust can be developed, especially for younger age groups where trust is weak, and applications that facilitate ease of use can be implemented for older users. In particular, for the 18-25 age group, introduction processes and biometric login options reduce perceived risk, while larger fonts and simple interfaces provide convenience for older users. In addition, banks should increase customer loyalty and encourage the use of digital channels by implementing special campaigns, loyalty programs, and cross-selling strategies during periods of high customer activity, such as summer vacations and holiday shopping. Real-time analytics (e.g., location-triggered offers or instant notifications based on spending patterns) can increase the conversion rates of these campaigns by 10-15%. It is also critical for banks to develop customized strategies based on customer segmentation and seasonal behavior analysis in their digitalization processes. In this context, it is recommended to promote advanced protection layers such as two-factor authentication and behavioral biometrics to reduce cybersecurity concerns. In addition, diversifying design approaches that facilitate customer use according to age and digital literacy can positively impact the user experience. For example, developing interfaces with a high level of accessibility for individuals with visual or motor impairments will increase inclusivity.

This study also demonstrates that multi-criteria decision-making methods such as TOPSIS and ARAS can be used consistently and effectively in digital performance evaluations in the banking sector. The results of the analyses conducted using both methods largely overlap, which supports the reliability of the methodology used. The methodological approach presented here constitutes an important reference for data-driven strategic decision-making processes in the banking sector and contributes a new methodological framework to the literature on measuring digital service performance. Additionally, by demonstrating that CRITIC techniques can be used in conjunction with quarterly demographic data, this study offers a replicable framework for other service sectors (e-commerce, telecommunications) facing similar segmentation challenges. Future studies using different weighting methods of an objective nature, such as CRITIC weighting, offer a roadmap for enhancing the robustness of analyses. The applicability of such multi-criteria decision-making-based analyses to other digital service areas beyond banking highlights the flexibility of the method and its interdisciplinary potential. It can be adapted using similar approaches, especially in sectors where user behavior changes rapidly (e.g., e-commerce, online education).

Future research can further deepen the analysis by including different criteria (e.g., customer satisfaction scores, mobile app usage statistics, customer complaint rates). Additionally, comparative studies can be conducted across different geographic regions or banking systems. Future trends in customer behavior can be predicted using AI-supported analysis methods (e.g., machine learning-based predictive models). Finally, expanding the studies beyond 2024 and adding post-open banking applications (API call volumes, fintech partnerships) will enrich the strategic insights generated. Such comprehensive studies will help banks develop more proactive and data-driven strategies in their digitalization journey. Especially the data sharing that emerged after open banking.

Disclosure Statements

Researchers' Contribution Rate Statement

The authors declare that they have contributed equally to this article.

Researchers'Conflict of Interest Statement

The authors declare that there is no potential conflict of interest in this study.

Ethical Statement of Researchers

The authors declare that all stages of this study were conducted in accordance with research and publication ethics, and that ethical principles and scientific citation standards were fully observed.

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