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Modeling a Sustainable Decision Support System for Banking Environments Using Rough Sets: A Case Study of the Egyptian Arab Land Bank

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Abstract: This study addresses the vast amount of information held by the banking sector, especially regarding opportunities in tourism development, production, and large residential projects. With advancements in information technology and databases, data mining has become essential for banks to optimally utilize available data. From January 2023 to July 2024, data from the Egyptian Arab Land Bank (EALB) were analyzed using data mining techniques, including rough set theory and the Weka version 3.0 program. The aim was to identify potential units for targeted marketing, improve customer satisfaction, and contribute to sustainable development goals. By integrating sustainability principles into financing approaches, this research promotes green banking, encouraging environmentally friendly and socially responsible investments. A survey of EALB customers assessed their interest in purchasing homes under the real estate financing program. The results were analyzed with GraphPad Prism version 9.0, with 95% confidence intervals and an R-squared value close to 1, and we identified 13 units (43% of the total units) as having the highest marketing potential. This study highlights data mining's role in enhancing marketing for the EALB's residential projects. Combining sustainable financing with data insights promotes green banking, aligning with customer preferences and boosting satisfaction and profitability.

Keywords: customer satisfaction; data mining; EALB (Egyptian Arab Land Bank); GraphPad Prism analysis; green banking; real estate financing; rough set theory; sustainable development; targeted marketing; Weka program

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1. Introduction

In today's fast-paced business environment, the corporate sector is marked by fierce competition, with each entity striving for financial advancement and heightened company value. Within this context, data mining emerges as a pivotal tool, serving as an interdisciplinary field that leverages sophisticated data analysis methodologies from machine learning, statistics, artificial intelligence, and database systems. Data mining involves the extraction of meaningful patterns, trends, and relationships from large datasets, which are not easily discernible through conventional manual methods.

Data mining is often associated with several key concepts and processes. Data preprocessing, for instance, involves cleaning and transforming raw data into a suitable format for

analysis. Techniques such as data cleaning, normalization, transformation, and reduction are employed to handle noisy, inconsistent, and high-dimensional data (Kumar et al., 2022). Pattern discovery is at the core of data mining and includes techniques like clustering, classification, association rule mining, and anomaly detection (Song & Hua, 2022). Each method has its own strengths and applications, depending on the nature of the data and the specific business goals.

Predictive modeling, using historical data to forecast future trends and behaviors, employs machine learning algorithms such as decision trees, random forests, support vector machines, and neural networks. These models assist in making informed decisions (Augusto et al., 2017). The results obtained from data mining need to be evaluated for their validity and usefulness. Statistical measures, such as precision, recall, F-score, and ROC curves, are employed to assess model performance. Additionally, interpreting the findings in a business context is crucial for deriving actionable insights (Aghayan & Khafajeh, 2018).

Moreover, data mining plays a significant role in enhancing business intelligence. By integrating data mining techniques with business intelligence tools, organizations can create a robust framework for analyzing market trends, customer preferences, and operational efficiencies. This integration enables companies to make data-driven decisions that drive strategic initiatives and foster innovation (Western Governors University, 2020; Markovate, 2024).

The structure of this research paper is meticulously organized to deliver a comprehensive analysis of the study. Section 2 unveils the results of the research, providing a detailed account of the findings. Section 3 embarks on a thorough discussion of these results, offering insightful interpretations and contextual understanding. Section 4 delves into the research methods, commencing with the formulation of a decision system. This section includes an in-depth explanation of the proposed rough set model, elaborating on the steps involved in generating the reducts and core of attributes. Additionally, this section emphasizes the significance of data collection and analysis, detailing the methodologies employed for data gathering and subsequent analysis. Furthermore, the section on extracting rule models delineates the techniques utilized to derive meaningful rules from the data, thereby facilitating a deeper understanding of the underlying patterns. The paper culminates in the Conclusions Section, summarizing the key takeaways of the study and discussing their broader implications for the banking sector.

2. Literature Review

Many researchers have addressed this topic from different points of view and using different techniques. The study by Miyan (2017) delves into the applications of data mining within the banking industry. It begins with a broad overview of data mining, including definitions, basic methods, and key domains of application. The study highlights the sectors of retail and insurance banking, which stand to benefit significantly from the implementation of data mining solutions. It also examines the principal features of commercially available data mining tools and outlines key components of a data mining solution that enhances customer experiences and decision making in banking systems. These components include customer segmentation, banking profitability, marketing, risk management, customer relationship management, and fraud detection.

In the banking and finance industries, data mining addresses corporate problem solving by uncovering trends, causes, and correlations in market pricing and business data that may not be immediately apparent due to the vast and rapidly generated volume of data. Bank managers strive to recognize patterns, occurrences, and regularities in their clients' transactional behaviors. This information can facilitate more effective customer segmentation, targeting, acquisition, retention, and maintenance. Additionally, intelligence

and data mining techniques enable businesses to identify various consumer classes and develop class-based approaches to pricing and product development, potentially leading to enhanced revenue management (Dass, 2006).

Ahmed (2024) explores the impact of big data analytics on technological advancement within the central banking financial system. By integrating the contributions of monetary policy, big data analytics, pollutant emissions, and aggregate demand within a modified extensive growth theory framework, a digital technological progress model is developed to analyze the economy's aggregate supply. This model calculates productivity indicators and total factor productivity (TFP) by incorporating both the positive and negative externalities of data analytics, including cybersecurity issues and pollution emissions. This comprehensive framework addresses sustainable development and long-term economic growth by considering the broader implications of digital technology in the banking sector.

Evaluating a bank's sustainability is a complex process that relies on expert judgment. Research by Karimi et al. (2022) introduces a decision support system (DSS) based on banks' self-reported sustainability indexes. The DSS predicts a bank's sustainability level using self-declared data, helping assessment teams prepare for the extensive and costly process of sustainability auditing. The system was developed by analyzing the sustainability auditing procedures of eight banks, identifying 29 condition characteristics and one decision attribute. Rules generated by the naive/genetic/object-related model serve as the DSS inference engine with a high accuracy of 91.5%.

The transition to a low-carbon economy, driven by China's "double carbon" target, underscores the role of commercial banks in green financial development. Li et al. (2022) constructed a green finance evaluation system using data mining and game theory to optimize weights based on green economy index data from eight commercial banks between 2016 and 2020. The evaluation model provides an objective, scientific, and comprehensive assessment of green finance development, which is essential for measuring the current state of green finance.

Further, the study by Gunawan et al. (2022) assesses the sustainability and green banking performance of Indonesian banks over nine years, based on sustainability reports. The findings indicate that sustainability and green banking disclosures vary dynamically each year, with economic disclosures being the most prevalent and environmental disclosures the least. Using the Global Reporting Initiative (GRI) and Measuring Green Banking Practices guidelines, this study aims to contribute to the literature on green banking by developing a comprehensive disclosure list to guide sustainability measurement and reporting.

Manuylenko et al. (2021) address innovation risk in banks as part of their financial and innovative strategies. By identifying hierarchical concepts and their order, such as "banking innovation", "economic effects of innovative activities", "financial and innovative strategy", and "innovation risk", the study highlights the importance of forecasting and assessing potential innovation risks.

In the digital economy, customer relationship management (CRM) has emerged as the cornerstone of sustainable marketing performance and the lifeblood of banking (Chuang & Fan, 2020). The transition from an industrial to a digital economy, driven by the advent of computers and the Internet, has led to numerous benefits, including a surge in research publications and collaborations. To support sustainable marketing performance in banks through innovations such as customer acquisition, segmentation, customization, loyalty, and profitability, marketers have developed a CRM system that melds digital infrastructure with human digital capabilities. This research aims to analyze the scientific landscape surrounding CRM and sustainable marketing performance in the digital economy by extracting 1485 documents from the Scopus database, with 248 documents filtered for detailed analysis.

The filtered documents were exported to VOSviewer version 1.6.20_for visualization mapping, including co-occurrence and co-authorship analysis, which illustrates the relationships between keywords. The findings reveal an increase in research publications since 2003, growing interest from countries and institutions in sponsorship and collaboration, and correlations among the terms. The emergence of financial crises has fueled research in this domain. Moreover, the integration of CRM into digital technology fosters cooperation and innovation, leading to the development of banking software applications that enhance customer acquisition, loyalty, retention, profitability, and sustainability. The study created an integrated framework for sustainable banking performance, highlighting the importance of CRM during global crises such as COVID-19 and financial downturns (Acheampong et al., 2023). Research and the integration of green banking remain crucial, laying the foundation for future studies and policy development by bankers.

Prediction is a pivotal topic in data science, especially in achieving accurate forecasts to build confidence in outcomes. Predicting customer revenue is vital across industries, enabling strategic development. Traditionally, profits and losses were assessed post event, but data science principles now allow future earnings predictions. Various data mining techniques, each with different accuracy levels, can forecast future revenue. The study by Acheampong et al. (2023) analyzes the revenue predictions of bank clients using several forecasting methods, including regression, decision trees, random forests, and clustering, to determine the best strategy for estimating client income.

Data mining concepts have numerous applications in banking today, such as evaluating security issues and finding better security solutions for online banking. Information from surveys was used to create a dataset for this research, employing clustering techniques and Student's *t*-test with SPSS V30.0 software to identify statistically significant differences between bank and e-banking customers' perceptions of e-banking security (Jafari et al., 2024).

Recent studies have also highlighted the role of data mining in enhancing the efficiency of marketing strategies in the banking sector. One such study by Patel et al. (2021) demonstrated how machine learning algorithms could be utilized to predict customer churn, thereby allowing banks to implement timely interventions to retain customers. This approach not only improves customer satisfaction but also enhances the overall profitability of the bank.

Additionally, Zhang et al. (2022) explored the application of big data analytics in identifying fraudulent activities within the banking sector. By leveraging advanced data mining techniques, banks can detect unusual patterns in transactions, thereby preventing potential fraud and ensuring the security of customer data.

The Egyptian Arab Land Bank (EALB) aims to fulfill customers' desires for owning registered units of a certain quality, ensuring the reliability of title deeds and documents (Jones & Smith, 2023). The challenges are balancing customer desires with successful marketing operations and achieving set goals for marketing and real estate financing sectors. This research study focuses on data mining for financing products.

Furthermore, a study by Kumar (2023) emphasized the importance of integrating environmental, social, and governance (ESG) factors into banking operations. By applying data mining techniques to assess ESG performance, banks can make informed decisions that promote sustainable development and enhance their reputation among stakeholders.

The reviewed literature emphasizes the pivotal role of data mining in transforming the banking sector. Through the application of advanced analytical techniques, data mining has significantly improved customer relationship management, sustainability practices, fraud detection, and overall operational efficiency. By uncovering intricate patterns within expansive datasets, data mining facilitates informed decision making and strategic devel-

opment. Research indicates its efficacy in tackling challenges such as risk management and customer segmentation while also highlighting the integration of big data analytics in green finance evaluations. Collectively, these studies illustrate the indispensable nature of data mining in optimizing banking operations, driving innovation, and fostering sustainable growth in the dynamic digital economy.

3. Materials and Methods

The research methodology for this study involves a series of systematic steps using data mining tools, specifically the rough set theory, to analyze data from the marketing sector of a bank related to a residential project. The subject of the study focuses on data collected in terms of unit areas, floors, building numbers, the price per square meter for each unit, and the total price of each unit based on its area. These data were compiled into (Table A1 in Appendix A) to construct the information table for the rough set theory, which is used in data mining for a residential project related to real estate financing and the Waikato Environment for Knowledge Analysis (Weka version 3.0). Furthermore, GraphPad Prism 9.0 was utilized in the analysis process.

The key steps are as follows:

1. Theoretical Model and Information Table Construction:
    - Using rough set theory, a theoretical model and information table were constructed.
    - Equations were prepared to process the data collected from the bank's marketing sector using the Weka version 3.0 program.
2. Data Processing and Analysis:
    - The data were processed to extract relevant information and generate curves.
    - This step includes preparing data clearly and concisely for use.
3. Questionnaire Design and Data Collection:
    - A questionnaire comprising 10 closed-type questions was designed.
    - The questionnaire was administered to 86 bank customers to identify their desires for owning and purchasing a residential unit.
    - This step aimed to align customer desires with the bank's goals, policies, and sustainability initiatives.
4. Data Analysis and Statistical Evaluation:
    - The results from the questionnaire were extracted and analyzed using the GraphPad Prism version 9.0program. The analysis involved the following steps:
    - Creating a decision system.
    - Preprocessing the data.
    - Generating reducts and cores of attributes.
    - Extracting rule models.
    - Evaluating the accuracy of the rule models.
5. Visual Representation and Interpretation:
    - The results were then presented and statistically analyzed to extract the final insights.

This methodology ensures a comprehensive approach to understanding customer preferences and aligning them with the bank's strategic goals and sustainability efforts. Through this systematic process, this study aims to provide actionable insights for enhancing customer satisfaction and achieving sustainable marketing performance in the banking sector.

Figure 1 provides a simplified explanation of the research methodology, including the design of a decision support system. It outlines the data mining process, the extraction of useful results and patterns, and the conducting of a customer desire questionnaire to achieve the bank's sustainability objectives.

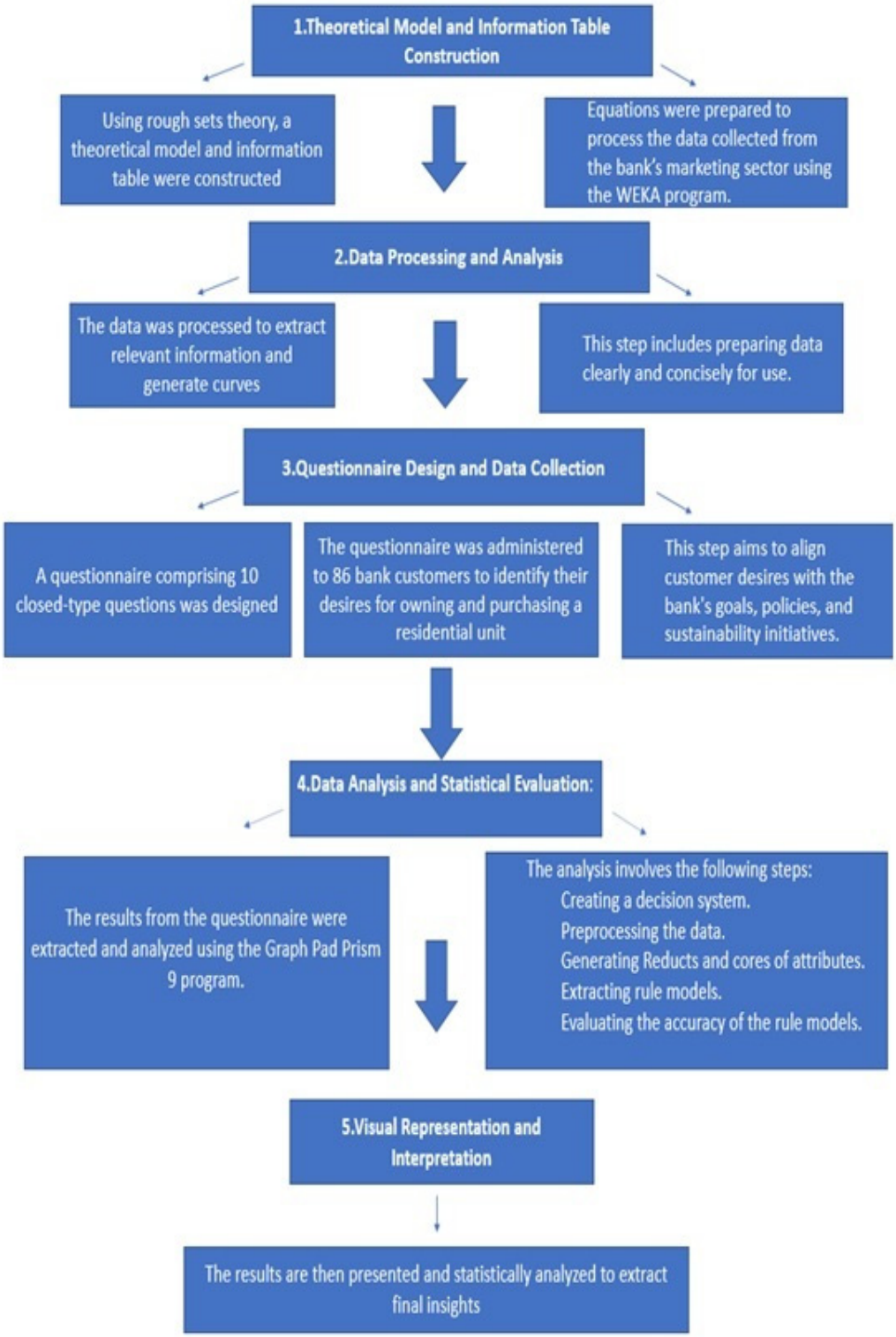


Figure 1. The framework of our research methodology.

A sample was taken from a residential project for the marketing sector of the Real Estate Bank for a group of mixed units in more than one building with a number of (30) units.

The study in this research paper is based on the use of rough set theory. Table A1 in Appendix A contains the information used to build a theoretical model for extracting equations for the variables, which can then be coded to perform the necessary analysis and classification through the Weka version 3.0 program. Consequently, Table A1 in Appendix A includes all the variables under study and is organized to construct a theoretical model to achieve the desired results.

The second part of this research paper involves a closed-type questionnaire administered to 86 of the bank's clients to understand their preferences for owning housing units with the real estate financing system, considering the banks' focus on customer satisfaction and sustainability. The questionnaire results were extracted, and statistical analysis was performed using GraphPad Prism version 9.0, resulting in statistical data and curves generated by the program.

3.1. Creating a Decision System

- The Proposed Rough Set Model

After creating the information table for the rough set theory, the variables and values of the object are determined, which is the group of residential units in the real estate financing project, as follows:

- U equals the number of units starting from unit number 1 to unit number 30 and a equals the variables (Apart. No, Description, Type, District Name, Space, Floor, Price Apart., Unit Price, Building No, Finishing Status, and Buying Rate).
- Va is a set of values for attribute a; Va include (V Apart. No, V Description, V Type, V District Name, V Space, V Floor, V Price Apart., V Unit Price, V Finishing Status, and V Buying Rate.
- V Apart. No includes unit numbers in the project (30 units), V Description includes the type of units, which is apartments, V Type includes the type of units, which is residential, V District Name includes the name of the project, V Space includes unit areas in meters, and V Floor includes the roles of the units in the project from the first floor to the eleventh floor.
- V Price Apartment includes the price of each unit in the project, V Unit Price includes the price of each unit of the project, V Building No includes project building numbers, V Finishing Status includes the finishing condition of the units in the project, and V Buying Rate includes purchase rates for units in the project.
- U is the set of objects.
- U is a group of residential units, the number of which is in units, starting from X1 to X30.
- A set of attributes U-to Va is A.
- The set of variables that control the set of units is A.
- Va is a set of values for attribute a.
- U = {X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11, X12, X13, X14, X15, X16, X17, X18, X19, X20, X21. . .X30}.
- A = {Apartment No, Description, Type, District Name, Space, Floor, Price Apartment, Unit Price, Building No, Finishing Status, Buying Rate}.
- V Apartment No = {11, 23, 24, 34, 41, 42, 52, 54, 62, 63, 71, 72, 73, 81, 83, 84, 91, 92, 93, 102, 103, 104, 111, 114, 13, 14, 21, 23, 24, 33, 34}.
- V Description = {Apartment}.
- V Type = {Residential}.
- V District Name = {Nasr City}.
- V Space = {181, 192, 188, 193, 189, 192, 171, 155}.

- V Floor = {first, second, third, fourth, fifth, sixth, seventh, eighth, ninth, tenth, eleventh}.
- V Price Apartment = {2900, 2950, 3050, 2750, 2800, 2600, 2650}.
- V Unit Price = {2900, 2950, 3050, 2750, 2800, 2600, 2650}.
- V Building No = {Building 1, Building 4}.
- V Finishing Status = {half-finished}.
- V Buying Rate = {high, medium, low}.

3.2. Preprocessing the Data

Figures 2–5 illustrate the representation of the data and variables pertinent to the residential project under investigation, as depicted by the Weka version 3.0 program. These figures encompass the analysis and classification of the data to derive the results. The graphical representations delineate various aspects of the units, including their number, area, price per square meter, individual unit price, unit types, and the spatial location of each unit within the building (by floor). These visualizations exemplify the data characteristics and relationships. Figure 2 presents a graphical representation depicting the total number of housing units within the residential project under study, which amounts to 30 housing units.

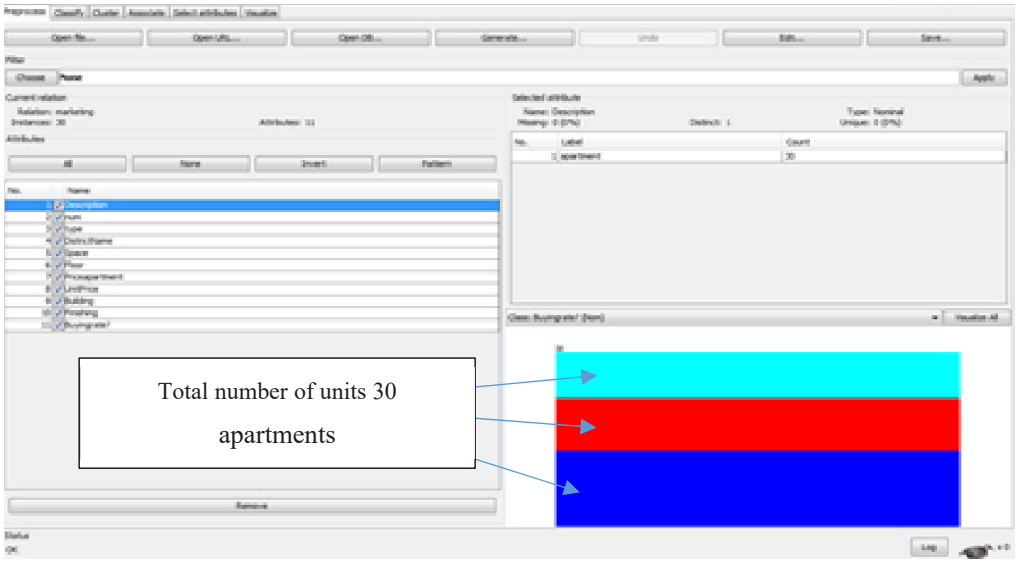


Figure 2. Description of units.

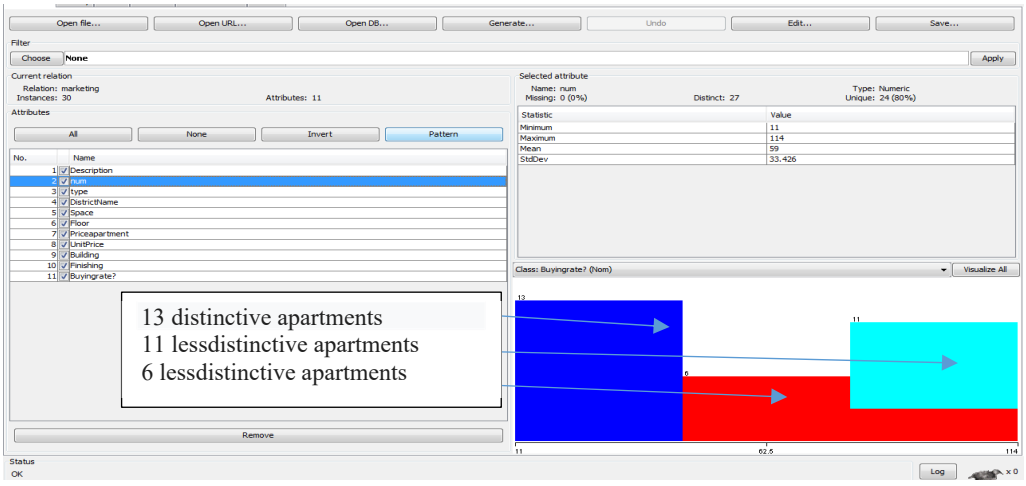


Figure 3. The run of units.

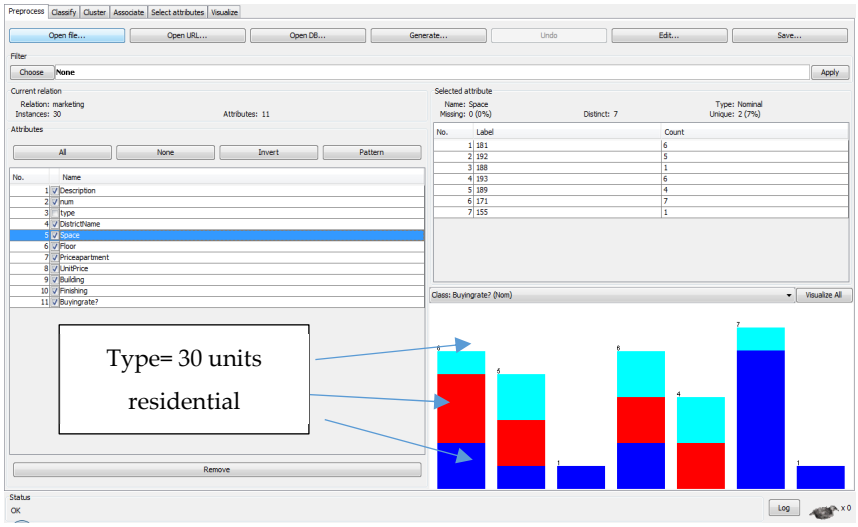


Figure 4. The space of units (6, 5, 1, 6, 4, 7, 1 = units num space = 181, 192, 188, 193, 189, 171, 155).

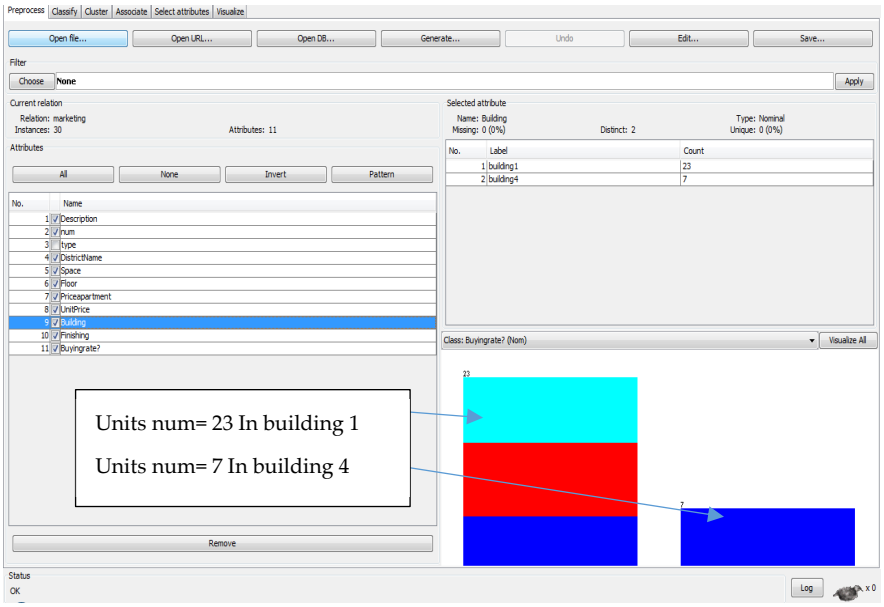


Figure 5. Building number for units.

Figure 3 presents a graphical representation of the distinguished and least distinguished units within the residential project. Specifically, it shows that there are 13 distinguished units, followed by 11 less distinguished units, and finally, 6 units that are categorized as the least distinguished.

Figure 4 presents a graphical representation of the unit numbers within the project buildings alongside the area of each unit. Specifically, it shows that unit numbers 6, 5, 1, 6, 47, and 1 have areas of 181, 192, 188, 193, 189, 171, and 155 square meters, respectively.

Figure 5 presents a graphical representation of the number of buildings within the residential project, alongside the number of units contained within each building. Specifically, Building No. 1 comprises 23 housing units, whereas Building No. 4 comprises 7 housing units.

3.3. Generating the Reducts and Core of Attributes

Data Collection and Analysis

A closed-type electronic questionnaire was developed, consisting of 10 questions to gauge the preferences of the bank's customers regarding housing unit specifications. This

questionnaire was conducted with 86 clients. The questions were chosen based on their scientific relevance (Table A2 in Appendix A).

Question 1: Based on the theory of housing preferences, which explores the relationship between population needs and living choices, this question aims to understand housing trends according to individual lifestyles, a critical aspect of real estate market studies (Brzezicka et al., 2019).

Question 2: Related to the theory of spatial needs and residential behavior, this question focuses on space allocation based on family size and lifestyle, drawing from studies on housing unit design and space distribution (García-Magariño & Lacuesta, 2017).

Question 3: This question pertains to environmental comfort and spatial perception research, examining factors like natural light, ventilation, and views to understand preferences for comfort and privacy (Hui et al., 2016).

Question 4: Inspired by the urban gradation theory, this question studies the relationship between population density and housing patterns, aiming to identify preferred options in terms of size and social organization (Jang-Trettien, 2022).

Question 5: Tied to construction economics, this question measures individuals' willingness to bear additional costs for a completed residence, related to studies on real estate purchasing behavior (Jones, 2022).

Question 6: Based on the concept of luxury consumer behavior, this question examines the demand for high-quality products as part of a lifestyle, identifying demographic groups interested in luxury housing (Khan, 2017).

Question 7: This question relates to the theory of real estate distribution channels, studying preferred purchase methods and their role in facilitating the buying and selling process (Killemsetty et al., 2022).

Question 8: Inspired by the real estate brokerage trust theory, this question examines the role of brokers in enhancing or complicating the buying experience (Mouratidis, 2021).

Question 9: This question relies on the concept of payment preferences in behavioral economics to understand appropriate financial choices for target groups (Olin et al., 2022).

Question 10: Based on personal debt management theory, this question studies individuals' flexibility in managing long-term financial obligations (Park & Lee, 2019).

These questions were chosen over others for the following reasons:

1. Comprehensive Coverage: The questions encompass all aspects of residential preferences, including area, location, finishing, and financing.
2. Ease of Answering: The questions are straightforward and clear, ensuring accurate data collection.
3. Alignment with Objectives: The questions are tailored to fit the real estate market analysis, identifying customer needs and trends.
4. Based on Theories: The questions are grounded in studied scientific concepts, ensuring the quality of the results.
5. Achieving Sustainability Goals: The questions align with the bank's objectives of promoting sustainability.

The Graphpad Prism version 9.0program was used to perform a statistical analysis of the questionnaire and extract the results (Tables 1–4).

Table 1. The results of sample questionnaire for the first, second and third questions.

Apartment	Villa	Large	Medium	Small Area	Lower Roles	Middle Roles	Upper Roles
47	39	35	48	3	11	57	11

Table 2. The results of sample questionnaire for the fourth, fifth and sixth questions.

Large Towers	Medium Buildings	Small Houses	Finished	Semi-Finished	On Brick	Luxe	Super Luxe	Super Luxe Excellent
20	37	29	50	24	12	10	33	43

Table 3. The results of sample questionnaire for the seventh, eighth and ninth questions.

Bank	Company	Individuals	Yes	No	Cash Payment	Installments
26	14	46	4	82	34	52

Table 4. The results of sample questionnaire for the tenth question.

3 Years	5 Years	7 Years	10 Years	15 Years	20 Years	25 Years
26	11	13	15	5	4	12

3.4. Statistical Processing

Statistical analysis was conducted for the closed questionnaire sample of 86 customers according to the questions described in the questionnaire. The results of the analysis are listed in Table 5 below using the *t*-test.

Table 5. Statistical analysis by the GraphPad Prism version 9.0 (in the first, fourth, and tenth questions, there are statistically significant differences according to the *p* value summary, and the remaining questions have no statistically significant differences).

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
Theoretical mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Actual mean	41.50	27.67	27.67	27.67	27.67	27.67	27.67	41.00	40.50	11.43
Number of values	2	3	3	3	3	3	3	2	2	7
t, df	t = 16.60, df = 1	t = 2.160, df = 2	t = 1.943, df = 2	t = 5.281, df = 2	t = 2.467, df = 2	t = 3.005, df = 2	t = 3.029, df = 2	t = 1.108, df = 1	t = 6.231, df = 1	t = 4.322, df = 6
***p* value (two-tailed)**	0.0383	0.1634	0.1915	0.0340	0.1324	0.0952	0.0939	0.4674	0.1013	0.0050
***p* value summary**	*	ns	ns	*	ns	ns	ns	ns	ns	*
Significant (alpha = 0.05)?	Yes	No	No	Yes	No	No	No	No	No	Yes
Discrepancy	41.50	27.67	27.67	27.67	27.67	27.67	27.67	41.00	40.50	11.43
SEM of discrepancy	2.500	12.81	14.24	5.239	11.22	15.95	15.82	52.33	9.192	6.997
95% confidence interval	9.734 to 73.27	−27.45 to 82.79	−33.60 to 88.94	5.126 to 50.21	−20.59 to 75.92	9.207	9.135	37.00	6.500	2.644
R squared (partial eta squared)	0.9964	0.6999	0.6537	0.9331	0.7526	−11.95 to 67.28	−11.64 to 66.97	−429.1 to 511.1	−42.09 to 123.1	4.958 to 17.90

* means that there are statistically significant differences and it is only uniform in 3 questions. ns: means that there are no statistically significant differences, as the *p* value summary is the measure because if its value is less than 0.05 or more, it indicates the presence of statistical differences.

Figures A1–A10 (Appendix B) present the curves generated from the GraphPad Prism version 9.0 program for the questionnaire results. Each figure corresponds to 1 of the 10 questions from the closed questionnaire. Detailed explanations of the results are provided before each figure. Figure A1 (Appendix B) shows that there are 47 customers who prefer to buy residential apartments, while there are 39 customers who prefer to buy villas.

Figure A2 (Appendix B) shows that there are 20 customers who prefer to own a large residential unit, while there are 37 customers who prefer to own a medium-sized residential unit, and 29 customers prefer a small-sized residential unit. Figure A3 (Appendix B) shows that there are 11 customers who prefer to own a residential unit located on the lower floors, while there are 57 customers who prefer to own a residential unit located on the middle floors, and 11 customers prefer to own a residential unit located on the upper floors. Figure A4 (Appendix B) shows that there are 20 customers who prefer to own a residential unit located within large towers, while there are 37 customers who prefer to

own a residential unit located within medium-sized towers, and 29 customers prefer to own a small house. Figure A5 (Appendix B) shows that there are 50 customers who prefer to own a fully finished residential unit, while there are 24 customers who prefer to own a semi-finished residential unit, and 12 customers prefer to own a brick residential unit.

Figure A6 (Appendix B) shows that there are 10 customers who prefer to own a residential unit with a good finishing level, while there are 33 customers who prefer to own a residential unit with a super deluxe finishing level, and 43 customers prefer to own a residential unit with an excellent super deluxe finishing level. Figure A7 (Appendix B) shows that there are 26 customers who prefer to own a residential unit through a bank, while there are 33 customers who prefer to own a residential unit through a specialized real estate company, and 46 customers who prefer to own a residential unit through a person.

Figure A8 (Appendix B) shows that there are 4 clients who prefer to own a residential unit through a broker, while there are 82 clients who do not prefer to own a residential unit through a broker. Figure A9 (Appendix B) shows that there are 34 customers who prefer to own a residential unit by paying in cash, while there are 52 customers who prefer to own a residential unit through the installment system. Figure A10 (Appendix B) shows that 26 customers prefer to own a residential unit by paying in installments over 3 years. There are 11 customers who prefer installments over 5 years, 13 customers over 7 years, 15 customers over 10 years, 5 customers over 15 years, 4 customers over 20 years, and 12 customers over 25 years.

4. Results

The analysis and classification operations were conducted through the Weka version 3.0 program and its algorithms. The results are drawn in Table 6 based on the results extracted from the program, according to the following extracts from the program.

Table 6. Final results after processing with Weka.

Units No.	Building No.	Area Meters	Floors	Classification	Ranking
13	4	171	first	high best	1
21	4	171	second	high best	2
23	4	171	second	high best	3
24	4	171	second	high best	4
33	4	171	third	high best	5
34	4	171	third	high best	6
11	1	181	first	best	7
34	1	181	third	best	8
24	1	188	first	best	9
14	4	155	first	best	10
41	1	193	fourth	best	11
52	1	189	fifth	best	12
54	1	193	fifth	best	13

The analysis revealed that the residential project under study achieved the highest marketing rates for specific units as in Table 6, as detailed below:

1. Building No. 4:
    - Units No. 13, 21, 23, 24, 33, and 34.
    - Area: 171 square meters.
    - Floors: first, second, and third.
2. Building No. 1:
    - Units No. 11 and 34.
    - Area: 181 square meters.
    - Floors: first and third.

3. Buildings No. 1 and 4:
    - Units No. 24, 14, 41, 52, and 54.
    - Areas: 188, 155, 193, and 189 square meters.
    - Floors: first, second, fourth, and fifth.

In total, 13 distinctive units achieved the highest marketing rates, representing 43% of the total units. The remaining units accounted for 57% and were located on the sixth to eleventh floors.

The statistical analysis, conducted using the GraphPad Prism version 9.0 program, involved 86 bank customers who participated in an electronic questionnaire. This questionnaire aimed to identify customer preferences for owning and purchasing residential units. The analysis revealed the following customer preferences:

- Medium-sized units with super-luxe finishing.
- Condominium systems over tower structures.
- Installment plans (real estate financing) with repayment periods ranging from 3 to 25 years.

The analysis demonstrated high statistical confidence, with 95% confidence intervals, an R-squared value close to 1, and no missing values.

5. Discussion

This research has explored various aspects of data mining and its applications in the banking sector, highlighting significant studies conducted in different regions and contexts. Despite the lack of prior studies specifically addressing this research point, several relevant investigations provide a foundational understanding of the subject.

In the Russian Federation, studies have focused on the benefits of data mining and extracting insights from big data within the banking sector. The methodological instruments for applying big data technology in intellectual analysis have proven pivotal in implementing marketing relationship theories in Russian banks. Key actions identified include the growth of marketing relationships in the digital economy, understanding the advantages and prospects of big data mining in the banking industry, and developing digital marketing strategies based on big data processing methods (Bala et al., 2020).

In Indonesia, research on Islamic banks has utilized data mining techniques to predict financial performance through key exogenous factors of profitability. Methods such as LASSO regression, random forest (RF), artificial neural networks (ANNs), and k-nearest neighbor (KNN) have been applied to monthly data from Islamic banks. The study highlighted the effectiveness of these techniques in business and management modeling, providing valuable insights for financial academics and decision makers in the Islamic banking sector (Chen & Cheng, 2013).

Data mining has also found extensive applications in marketing and sales, particularly in predicting customer behavior and loyalty. The banking sector, being an early adopter of machine learning for credit evaluation, has successfully deployed data mining technologies to address issues like customer retention and loyalty. These applications demonstrate the potential of data mining to transform business processes by leveraging vast amounts of documented data (Ledhem, 2022).

The importance of data mining in the banking sector cannot be overstated, especially in the context of globalization and intense competition. Banks have increasingly recognized the need to develop competitive strategies through data mining to capitalize on their expanding databases. This approach has become a strategic tool for building a knowledge base that provides a competitive edge (Al Atif et al., 2022).

Rough set theory has emerged as a valuable tool for data mining and analysis, particularly when dealing with ambiguous or incomplete data. This mathematical approach has been instrumental in extracting meaningful patterns and rules from large datasets, facilitating intelligent data analysis. Studies have demonstrated the efficacy of rough set theory in various applications, including the development of electronic banking services (Bal, 2013).

One such study examined the factors driving the adoption of electronic banking services in the context of technological progress and the transition to digital banking. The research, conducted on Mellat Bank in the province of Kerman, utilized the rough model to analyze variables affecting the uptake of e-banking. The findings indicated that factors like usefulness, user-friendliness, data confidentiality, and the quality of internet connections significantly influence the consumer acceptance of online banking (Ghezelayagh & Davarpanah, 2015).

These studies collectively underscore the transformative potential of data mining in the banking sector. By leveraging advanced analytical techniques and integrating digital technologies, banks can enhance their marketing strategies, improve customer satisfaction, and achieve sustainable growth. The findings provide a robust foundation for future research and policy development, emphasizing the critical role of data mining in the evolving landscape of the banking industry.

5.1. Potential Economic Analyses

- Market Impact:
  - Supply and Demand: Analyzing how the identified high-potential units align with current market demand could provide valuable insights. Discussing trends in the real estate market and how the EALB's offerings meet these demands could be beneficial (Smith, 2022).
  - Price Elasticity: Conducting a price elasticity analysis to predict how changes in pricing strategies might impact sales could offer insights into demand sensitivity (Johnson, 2021).
- Financial Performance:
  - Profitability Analysis: Including detailed profitability metrics such as net present value (NPV), the internal rate of return (IRR), and return on investment (ROI) for the bank could provide a comprehensive financial performance analysis (Lee & Raschke, 2023).
  - Cost–Benefit Analysis: Performing a thorough cost–benefit analysis to assess marketing and selling costs against anticipated financial benefits, including marketing expenses, maintenance costs, and any buyer incentives, could add depth (Williams, 2020).
- Customer Segmentation:
  - Demographic Analysis: Conducting an in-depth demographic analysis of potential buyers, examining factors like income levels, family size, and employment status, could help understand their influence on purchasing decisions (Brown, 2021).
  - Economic Incentives: Exploring the impact of economic incentives such as tax breaks, subsidies, or financing options available to different customer segments could be insightful (Martinez, 2022).
- Macroeconomic Factors:
  - Economic Environment: Analyzing the broader economic environment in Egypt, including GDP growth, inflation rates, and interest rates, could provide

insights into their influence on the real estate market and EALB's marketing strategies (Kim, 2023).
    - Government Policies: Discussing the impact of government policies on real estate financing and sustainable development, such as housing policies, environmental regulations, and incentives for green banking, could be beneficial (Garcia, 2020).
- Risk Analysis:
    - Market Risks: Identifying potential risks in the real estate market, including property price fluctuations, regulatory changes, and economic downturns, and discussing mitigation strategies could add value (Davis, 2021).
    - Sustainability Risks: Evaluating risks associated with sustainability initiatives, such as the cost of implementing green technologies and potential regulatory changes, could be important (Lopez, 2023).
- Comparative Analysis:
    - Benchmarking: Comparing the EALB's performance and strategies with other banks in the region, highlighting best practices and areas for improvement, could offer valuable insights (Thompson, 2022).
    - Case Studies: Including case studies of successful sustainable banking projects from other countries to provide context and insights could be informative (Patel, 2020).

5.2. Limitations of the Study

While this study offers valuable insights, its focus on data from the Egyptian Arab Land Bank (EALB) limits the generalizability of the findings to other banks with different customer bases, operational models, or market conditions. The reliance on rough set theory and self-reported data introduces potential biases and limitations in capturing the full complexity of customer behavior and preferences. Additionally, the sample size of 86 respondents, though sufficient for preliminary insights, may not provide definitive conclusions.

The study's scope is also constrained by its specific period and geographical context, which may affect the applicability of the results to other regions and time periods. Market dynamics, economic conditions, and customer preferences can vary significantly, impacting the generalizability of the findings. Furthermore, this research study does not fully explore the potential challenges and barriers to implementing green banking practices, such as regulatory constraints, financial costs, and institutional resistance.

Despite these limitations, this study underscores the transformative potential of data mining in the banking sector, particularly in enhancing marketing strategies and achieving sustainable growth. Future research should aim to address these limitations by including a broader range of data sources, larger sample sizes, and diverse geographical contexts. Additionally, examining the practical challenges of adopting green banking practices can provide a more comprehensive understanding of their feasibility and effectiveness in promoting sustainable development.

6. Conclusions

This study highlights the essential role of data mining, specifically rough set theory and the Weka version 3.0 program, in refining marketing decisions and boosting customer satisfaction within the banking sector. The focus on large residential projects managed by the Egyptian Arab Land Bank (EALB) showcases how leveraging vast amounts of data can identify the most promising units, facilitating tailored marketing strategies that align with customer preferences and sustainable development goals.

Incorporating data mining techniques with sustainable financing strategies is crucial for advancing green banking practices. This approach not only promotes environmentally friendly and socially responsible investments but also aligns with the EALB's strategic objectives of achieving high customer satisfaction and profitability. The insights from the customer survey, analyzed using GraphPad Prism version 9.0, underscore the importance of understanding customer preferences to design marketing strategies that prioritize eco-friendly housing options.

The study's findings reveal key indicators for both the marketing and real estate finance sectors, enabling the presentation of projects that satisfy customer desires while achieving optimal marketing rates. By aligning these strategies with sustainability principles, banks can attract new customers, enhance customer trust, and secure long-term profitability.

The significance of this research lies in its contribution to the concept of green banking. Green banking emphasizes the role of financial institutions in promoting sustainable economic growth and environmental stewardship. By integrating green banking practices, banks can support sustainable urban development and contribute to the global agenda of mitigating climate change and environmental degradation. The analysis demonstrated high statistical confidence, with 95% confidence intervals, an R-squared value of 1.000, and no missing values in total; 13 distinctive units achieved the highest marketing rates, representing 43% of the total units.

In conclusion, the application of data mining in banking offers transformative potential. Institutions like the EALB can make informed decisions that drive sustainable development, highlighting the importance of adopting innovative technologies and methodologies in a data-driven world. This study emphasizes the critical role of green banking in fostering a more sustainable and customer-centric banking environment, ultimately benefiting both the economy and the planet.

7. Future Directions of Research

Building on the findings of this study, several avenues for future research can be explored to further enhance the role of data mining in banking, particularly in promoting sustainability and green banking practices:

1. Enhanced Data Mining Techniques: Future research could explore more advanced data mining techniques, such as deep learning and machine learning algorithms, to improve the accuracy and efficiency of identifying promising residential units. These techniques could provide deeper insights into customer preferences and market trends, enabling more precise and effective marketing strategies.

2. Integration with Other Financial Sectors: Expanding the scope of data mining applications beyond the residential sector to include other financial sectors such as commercial and industrial real estate. This integration could provide a more comprehensive understanding of the entire financial landscape, supporting holistic sustainable development goals.

3. Longitudinal Studies on Green Banking: Conducting longitudinal studies to assess the long-term impact of green banking initiatives on customer satisfaction, loyalty, and overall bank performance. These studies could provide valuable data on the sustainability of green banking practices and their effectiveness in achieving environmental and social objectives.

4. Customer Behavior Analysis: Analyzing customer behavior in response to green banking products and services. Future work could focus on understanding the factors that influence customer decisions to adopt eco-friendly housing options and sustainable banking products, leading to better-targeted marketing efforts.

5. Policy Development and Implementation: Investigating the role of regulatory frameworks and policies in promoting green banking. Research could explore how dif-

ferent regulatory approaches impact the adoption and success of sustainable banking practices, providing recommendations for policymakers to create conducive environments for green banking.

6. Technological Advancements: Exploring the integration of emerging technologies such as blockchain and the Internet of Things (IoT) with data mining to enhance transparency, security, and efficiency in banking operations. These technologies could support more robust and reliable data analysis, furthering the goals of green banking.

7. Cross-Cultural Comparisons: Conducting cross-cultural comparisons to understand how green banking practices are implemented and perceived in different regions. This research could highlight best practices and challenges in various cultural contexts, providing a global perspective on sustainable banking strategies.

By addressing these areas, future research can build on the current study's findings to advance the banking sector's role in promoting sustainability and environmental stewardship. This ongoing exploration will contribute to the development of more effective and innovative green banking practices, fostering a more sustainable financial ecosystem.

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Data Availability Statement: Data were generated and collected during the study. All data is available in the paper.

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Appendix A

Table A1. The information system (including the required information; areas and floors of the units, unit price, finishing status, and buying rate).

Var.	Apart. No.	Description	Type	District Name	Space	Floor	Price Apart.	Unit Price	Building No.	Finishing Status	Buying Rate
X1	11	Apart.	Residential	Nasr City	181	First	2900	524,900	Building 1	Half-finished	High
X2	23	Apart.	Residential	Nasr City	192	Second	2950	566,400	Building 1	Half-finished	High
X3	24	Apart.	Residential	Nasr City	188	Second	3050	573,400	Building 1	Half-finished	High
X4	34	Apart.	Residential	Nasr City	181	Third	3050	573,400	Building 1	Half-finished	High
X5	41	Apart.	Residential	Nasr City	193	Fourth	2900	524,900	Building 1	Half-finished	High
X6	42	Apart.	Residential	Nasr City	193	Fourth	2750	532,125	Building 1	Half-finished	High

Table A1. *Cont.*

Var.	Apart. No.	Description	Type	District Name	Space	Floor	Price Apart.	Unit Price	Building No.	Finishing Status	Buying Rate
X7	52	Apart.	Residential	Nasr City	189	Fifth	2750	532,125	Building 1	Half-finished	Medum
X8	54	Apart.	Residential	Nasr City	193	Fifth	3050	576,450	Building 1	Half-finished	Medum
X9	62	Apart.	Residential	Nasr City	192	sixth	2750	532,125	Building 1	Half-finished	Medum
X10	63	Apart.	Residential	Nasr City	181	sixth	2950	567,875	Building 1	Half-finished	Medum
X11	71	Apart.	Residential	Nasr City	193	Seventh	2900	524,900	Building 1	Half-finished	Medum
X12	72	Apart.	Residential	Nasr City	192	Seventh	2750	532,125	Building 1	Half-finished	Medum
X13	73	Apart.	Residential	Nasr City	181	Seventh	2950	567,875	Building 1	Half-finished	Medum
X14	81	Apart.	Residential	Nasr City	192	eighth	2900	524,900	Building 1	Half-finished	Medum
X15	83	Apart.	Residential	Nasr City	189	eighth	2950	567,875	Building 1	Half-finished	Medum
X16	84	Apart.	Residential	Nasr City	181	eighth	3050	576,450	Building 1	Half-finished	Medum
X17	91	Apart.	Residential	Nasr City	193	Ninth	2900	524,900	Building 1	Half-finished	Low
X18	92	Apart.	Residential	Nasr City	192	Ninth	2750	532,125	Building 1	Half-finished	Low
X19	93	Apart.	Residential	Nasr City	193	Ninth	2950	567,875	Building 1	Half-finished	Low
X20	102	Apart.	Residential	Nasr City	192	Tenth	2750	532,125	Building 1	Half-finished	Low
X21	103	Apart.	Residential	Nasr City	189	Tenth	2950	567,875	Building 1	Half-finished	Low
X22	104	Apart.	Residential	Nasr City	181	Tenth	3050	576,450	Building 1	Half-finished	Low
X23	111	Apart.	Residential	Nasr City	189	Eleventh	2600	470,600	Building 1	Half-finished	Low
X24	114	Apart.	Residential	Nasr City	171	Eleventh	2800	529,200	Building 1	Half-finished	High
X25	13	Apart.	Residential	Nasr City	171	First	2650	454,475	Building 4	Half-finished	High
X26	14	Apart.	Residential	Nasr City	155	First	2750	471,625	Building 4	Half-finished	High
X27	21	Apart.	Residential	Nasr City	171	Second	2600	403,000	Building 4	Half-finished	High
X28	23	Apart.	Residential	Nasr City	171	Second	2650	454,475	Building 4	Half-finished	High
X29	24	Apart.	Residential	Nasr City	171	Second	2750	471,625	Building 4	Half-finished	High
X30	33	Apart.	Residential	Nasr City	171	Third	2650	454,475	Building 4	Half-finished	High

Table A2. A closed-type electronic questionnaire.

Question	Answer Options	Purpose
Q1: What type of housing do you prefer, an apartment or a villa?	▪ Apartment ▪ Villa	To determine the preferred type of housing based on the respondent's lifestyle and needs.
Q2: Do you prefer a home with a large, medium, or small area?	▪ Large ▪ Medium ▪ Small	To understand the respondent's size preference for living spaces, helping to identify market demand for property sizes.
Q3: Do you prefer lower roles, middle roles, or upper roles?	▪ low floors ▪ middle floors ▪ high floors	To evaluate preferences for specific floor levels, which could guide property developers in designing or marketing buildings accordingly.
Q4: Do you prefer to live in large towers, medium buildings, or small houses?	▪ Large towers ▪ Medium ▪ buildings ▪ Small houses	To assess the preferred type of residential structures to help developers target specific segments.
Q5: Do you prefer the house finished, semi-finished, on brick?	▪ Finished ▪ Semi-finished ▪ On brick	To gauge preferences for construction stages, allowing developers to focus on delivering homes in the desired condition.
Q6: Do you prefer any finishing level?	▪ Luxe ▪ Super Luxe ▪ Excellent	To understand luxury expectations and finishing standards for targeted audience segmentation.
Q7: Do you prefer to buy from one person?	▪ Bank ▪ Company ▪ Individuals	To identify the preferred purchasing channel, aiding stakeholders like banks, real estate companies, or individual sellers to improve services.
Q8: Do you prefer to buy with a broker?	▪ Yes ▪ No	To measure the preference for using real estate brokers, which could indicate trust levels in intermediaries.
Q9: Do you prefer cash payment or installments?	▪ Cash payment ▪ Installments	To identify the payment method preference, helping in structuring financial offerings tailored to the buyer's needs.
Q10: Do you prefer the installment payment period to be short, medium or long?	▪ 3 year ▪ 5 years ▪ 7 years ▪ 10 years ▪ 15 years ▪ 20 years ▪ 25 years	To analyze preferences for installment periods, aiding in designing flexible financial plans for buyers.

Appendix B

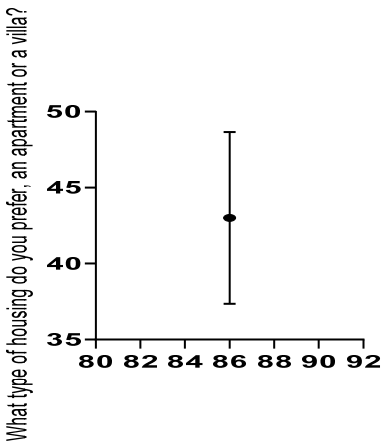


Figure A1. The first question (1 What type of housing do you prefer, an apartment or a villa? 95% confidence intervals, R squared = 1.000, number of X values = 2, number of missing values = 0).

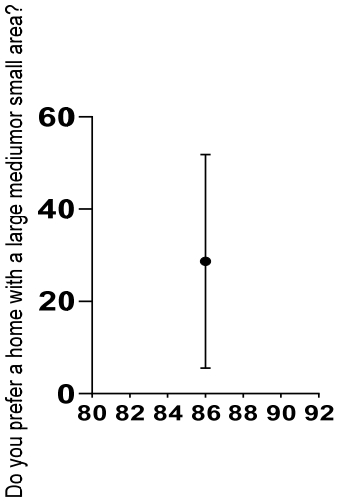


Figure A2. The second question (2. 95% confidence intervals, R squared = 1.000, number of X values = 3, number of missing values = 0).

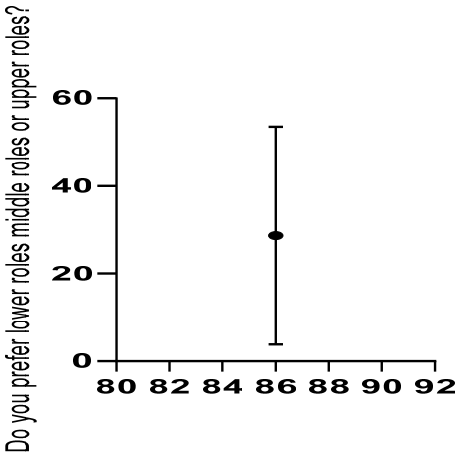


Figure A3. The third question (3: Do you prefer lower roles, middle roles, or upper roles? 95% confidence intervals, R squared = 1.000, number of X, values = 3, number of missing values = 0).

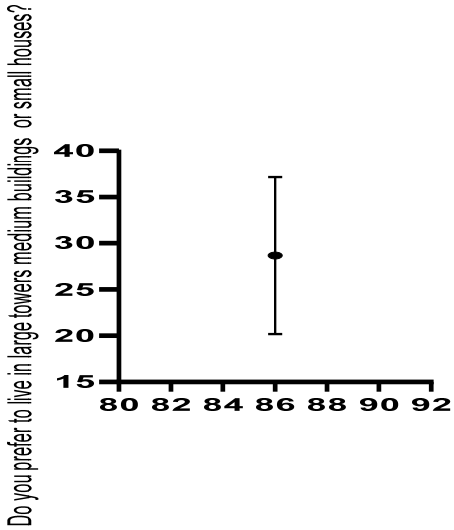


Figure A4. The fourth question (4: Do you prefer to live in large towers, medium buildings, or small houses? 95% confidence intervals, R squared = 1.000, number of X values = 3, number of missing values = 0).

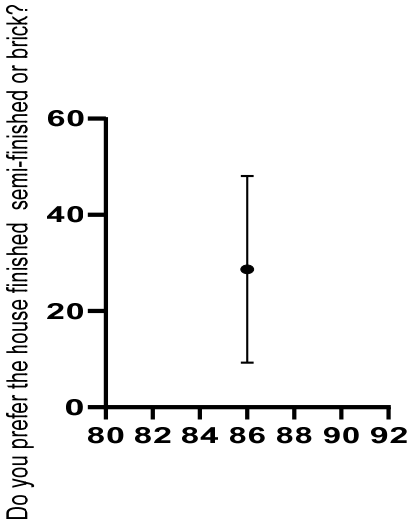


Figure A5. The fifth question (5: Do you prefer the house finished, semi-finished, or brick? 95% confidence intervals, number of X values = 3, R squared = 1.000, number of missing values = 0).

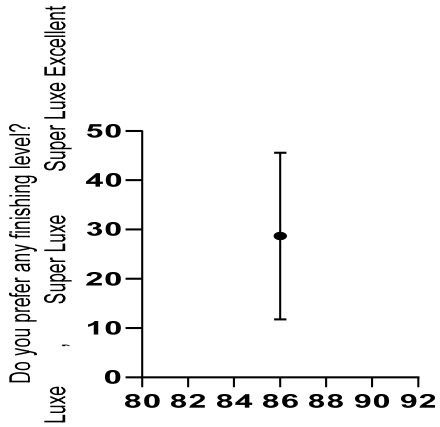


Figure A6. The sixth question (6: Do you prefer any finishing level? 95% confidence intervals, R squared = 1.000, number of X values = 2, number of missing values = 0).

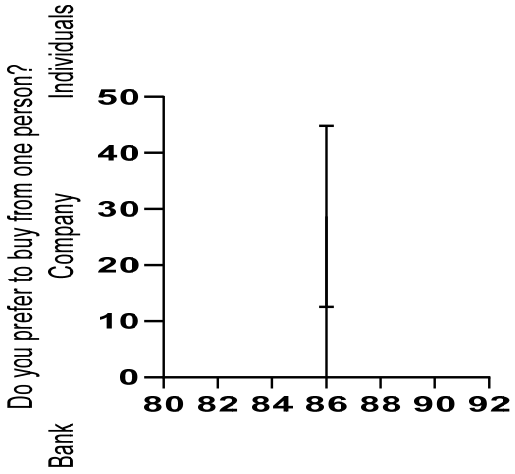


Figure A7. The seventh question (7: Do you prefer to buy from one person? 95% confidence intervals, R squared = 1.000, number of X values = 3, number of missing values = 0).

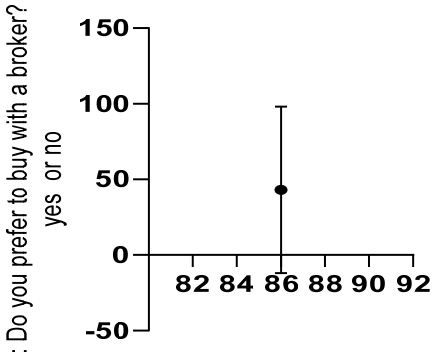


Figure A8. The eighth question (8: Do you prefer to buy with a broker? 95% confidence intervals, R squared = 1.000, number of X values = 2, number of missing values = 0).

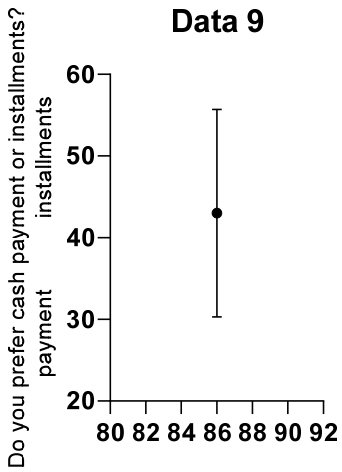


Figure A9. The ninth question (9: Do you prefer cash payment or installments? 95% confidence intervals, R squared = 1.000, number of X values = 2, number of missing values = 0).

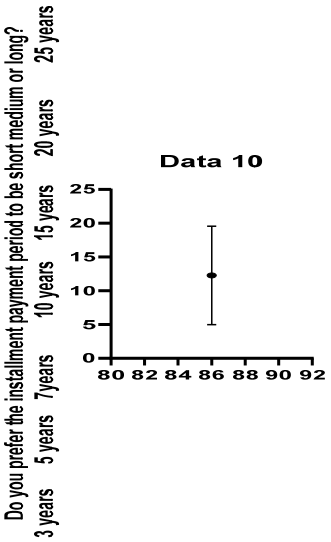


Figure A10. The tenth question (10: Do you prefer the installment payment period to be short, medium or long? 95% confidence intervals, R squared = 1.000, number of X values = 2, number of missing values = 0, 25. Evaluating the accuracy of rule models).

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