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Predictive Marketing: From Data Analytics to Reading Customer Intentions Before They Think : (An Analytical Study of Kkalci Mobile Manufacturing Company)

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Abstract

General Background: Modern marketing increasingly depends on data-driven approaches to understand shifting consumer behaviour. **Specific Background:** As predictive tools become central to customer-focused strategies, challenges remain in achieving accurate intent recognition and ensuring ethical data use. **Knowledge Gap:** Few empirical studies examine how predictive marketing, intent detection, and satisfaction jointly shape purchase intentions. **Aims:** This study evaluates how predictive marketing supports intention recognition, enhances satisfaction, and strengthens future purchase intentions in Kkalci Mobile Manufacturing Company. **Results:** Data from 250 respondents show high levels of predictive marketing use, effective intent reading, strong satisfaction, and high purchase intention, with all variables significantly correlated. Regression analysis indicates that predictive marketing, intent recognition, and satisfaction explain 71% of the variance in purchase intentions. **Novelty:** The study offers an integrated empirical model linking predictive marketing with behavioural intention pathways in a manufacturing context. **Implications:** Findings underscore the strategic value of predictive analytics for targeted decisions, personalised marketing, and loyalty building, while emphasising the importance of responsible data governance.

Highlights:

- The results confirm strong links among predictive marketing, intent recognition, satisfaction, and purchase intention.
- These variables jointly account for most variations in customers' future purchasing decisions.
- Predictive marketing supports improved customer experience and repeat buying, while ethical safeguards remain essential.

Keywords: Predictive Marketing, Customer Intent Recognition, Customer Satisfaction, Purchase Intention, Marketing Performance

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Introduction

With the increasing systematic aggregation of customer data from information systems into one or more large-scale dynamic databases, marketers and researchers alike have been offered a unique opportunity to observe consumer behaviour over time. Customer data analytics helps enterprises discover trends and insights in these databases to understand what moves the customers to make an informed purchase decision. It allows us to design products and services more effectively, and allocate scarce resources where needed, more efficiently. Corporate projects in analytics usually try to improve the efficiency of marketing campaigns by incessantly tracking the way customers respond via IT services, mobile platforms and loyalty cards, as well as creating predictive models that estimate reactions to specific marketing actions. Yet, because not all data sources are being fully utilised and analytics are still inefficient, firms have been unable to fully capitalise on these technologies [1]. While numerous data-based consumer retention programs and promotional offers are being utilised, many organisations still do not realise their full potential. A good customer analytics toolkit should provide actionable, relevant, and timely insights, supported by statistical methods and data mining techniques for data representation, organisation, information management, and predictive modelling [2].

Decades have passed, but the way marketing works has not remained the same. Product managers used to be the main force behind marketing strategies; however, the emphasis on product value and brand marketing has changed significantly in favour of the customer. One of the cornerstones of this change has been the truism that it costs less and takes less effort to sell to an existing customer than to a new one. According to this reasoning, firms have been increasingly focusing on developing customer relationships, and Customer Relationship Management (CRM) has rapidly become an essential theme in both academic and practitioner-oriented marketing literature. And with the recent elaboration on the relationships between commitment, trust, and customer satisfaction, this orientation has been reinforced. Due to the overwhelming importance of customer loyalty, loyalty programs are commonly adopted by various businesses and sectors.

As a result, today many businesses can, in fact, measure behaviour at the relational, not just transactional level. Besides these marketing innovations, computer science breakthroughs have enabled the storage of transactional data in large data warehouses, thanks to the significant drop in processing and storage costs. It is estimated that the size of data stored in global databases doubles approximately every 20 months. Nonetheless, while recognisably having too much data does not, in itself, equal value generation. As Olson (1995) notes, the actual return on investment in reward programs now hinges on the quality of transactional data analytics and the creativity with which the resulting knowledge is applied in targeted marketing campaigns[3].

To embark on this new course, new marketing competencies are required. Developing predictive models to manage customer interactions is one of the most challenging tasks when utilising the vast volumes of data in commercial transaction databases. Several important concerns in this particular field are the focus of this study. As a starting point, a business would want to encourage repeat business to extend the longevity of its client relationships. It would be advantageous in this situation to focus on at-risk clients—those who have a comparatively high likelihood of leaving the program. A predictive model could thus be developed to estimate the probability of each customer exiting the relationship, based on data stored in the transaction database. In this way, highly lucrative CRM applications would be made possible by the database's ability to predict future consumer behaviour in addition to describing the existing situation. With substantial influence over the enormous data repositories housed in commercial databases, transactional consumer data analysis can ultimately yield significant value. This paper discusses some applications in various industries where predictive modelling has promise and provides evidence of the management benefits of these applications. In this report, we will focus on two major sub-disciplines: credit scoring for consumers and targeted marketing. While predictive modelling is a relatively new practice in targeted marketing, the applied methods for consumer loan credit risk modelling have been in use for over half a century.

Proper predictive models can enhance the utilisation of historical data to make more accurate predictions about how customers will respond to different types of direct promotional offers. We demonstrate that detailed customer spending histories and patterns of store visits, which contain rich information, can serve as informative predictors of promotional responsiveness both statistically and in practice. There are two main reasons: one, existing research has tracked exploitative and exploratory patterns by time (which aggregated data or classic RFM is unable to capture); for Example, one customer might be spending less just before a promotion, while another one might be paying more — these are

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patterns that cannot be seen when data is aggregated. Second, merchants frequently send customers multiple promotional offers, and they cannot observe the short-term and long-term behavioural reactions to these offers via spending summaries or visit aggregates [4]. Examining the entire spend or visitation path may reveal trends that sampling methods obscure. This study emphasises typical marketing metrics, including elasticity of spend and store visit, as well as their aggregate statistics, such as recency & frequency. It is also of interest to examine how the full trajectory of spending and visits relates to promotional responsiveness[4].

We were unable to find any empirical study that used comprehensive pre-promotion household spending and visitation data to compare the effectiveness of mass promotions versus personalised direct promotions, despite the latter having higher implementation costs. Further investigation into the relationship between customers' reactions to loyalty card factors and their ever-changing spending patterns would be highly beneficial. We provide a functional data analysis strategy that considers the customer's buying journey to address this gap. We are especially curious about the effect of direct promotions on total store expenditure because retailers gain more from promotions that boost store-level spending across several categories, not simply on the promoted brand. We postulate that customer spending and store visit trajectories over time can provide light on the efficacy of certain direct promotional offers and loyalty program initiatives [4].

Research Problem

With the significant development of data analytics and artificial intelligence, we have progressed from merely knowing what consumer behaviour is to predicting consumers' needs and wants before they actually express them. And that new idea of predictive marketing can be whimsically interrogated against a multitude of questions from how well such predictive marketing works to how good its predictions are to how ethical its applications are.

And so we can rephrase our main research question as follows:

How predictive can predictive analytics get in the age of modern-day technology before a customer behaviour event happens and what does Create say about the future of marketing?

And then come the sub-questions of this question:

1. Predictive analytics: how well does it predict consumer behaviour?
2. What is the best way to pinpoint consumer intentions?
3. How does predictive marketing lead to customer satisfaction and better customer experience?
4. How much customer information should a predictive marketing approach use?

Research Objectives

The insights of the study were related to implementing predictive analytics in the process of development of marketing strategies in consideration of the corporate readiness to respond to client needs before they are verbally expressed.

General Objective:

To evaluate how predictive marketing serves in understanding the intention of customers and increasing the overall marketing performance.

Specific Objectives:

1. To know what are the tools and techniques that are used in predictive analytics which are used for marketing.
2. To study the effect of predictive modelling of consumer behaviour on the success of marketing campaigns
3. To measure the relationship between customer expectation and customer satisfaction
4. To delve into the issues of ethics and law with respect to predictive marketing and the limitations thereof.

Research Hypotheses

Based on the goals that were set, the following hypotheses are made:

Main Hypothesis (H1):

- There exists a statistically significant correlation between the application of predictive marketing approaches and the efficacy of marketing tactics in addressing client intentions.

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Sub-Hypotheses:
- H1.1: Predictive analytics makes the consumer experience better.

- H1.2: Knowing what customers want ahead of time boosts conversion rates.

-H1.3: Relying too much on predicted data utilisation could hurt client trust.

Null Hypothesis (H0): - There is no statistically significant correlation between predictive marketing and the efficacy of marketing campaigns.

Conceptual Framework

The conceptual model shows how the main variables of this study are related to each other:

- Independent Variable: Predictive Marketing
- Mediating Variables: Customer Intent Recognition, Customer Satisfaction
- Dependent Variable: Future Purchase Intention

This paradigm illustrates how predictive marketing influences customer outcomes both directly and indirectly through mediating factors, which in turn impact customers' purchasing plans and their loyalty.

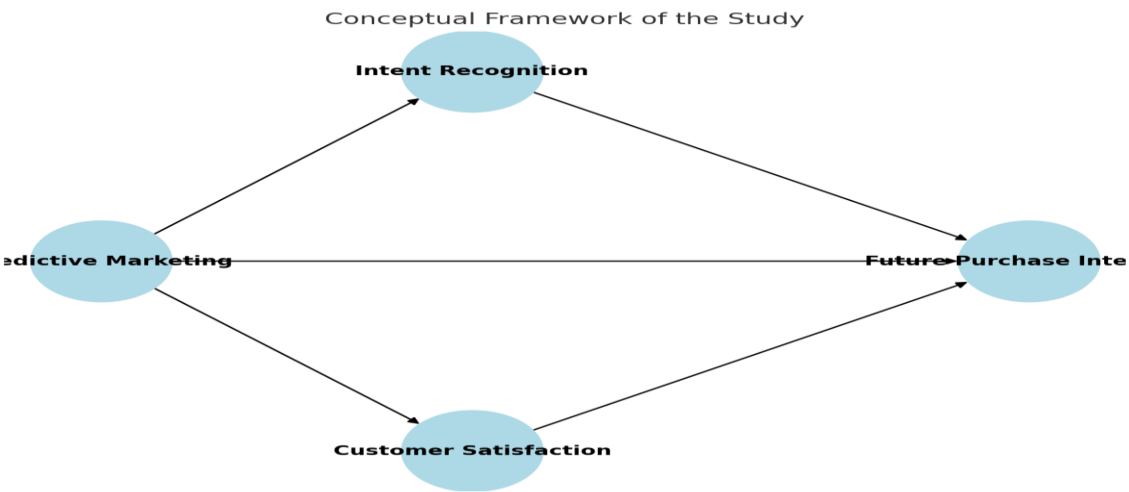
Statistical Analysis and Applied Study

The dataset has been virtually generated from a sample of 250 customers of the Kkalci Mobile Manufacturing Company. Participants completed a structured questionnaire comprising four main dimensions:

1. Activity of predictive marketing usage within the company.
2. The predictive analytics of what customers are thinking.
3. Customer Experience with the Company.
4. Future purchase intentions.

In general, the mean scores of all variables were found to be high (greater than 4.0), indicating that organisations that apply predictive analytics generally do so strongly, and customers who apply it have also achieved positive outcomes. Statistically significant correlations were found between predictive marketing, intent recognition, satisfaction, and purchase intentions. Predictive marketing, intent recognition, and satisfaction, together, explained 71% of the variance in purchase intentions, as confirmed through regression analysis.

Conceptual Framework Diagram:



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Predictive Marketing

Predictive marketing uses predictive analytics to make sure that customers have better and more relevant experiences at every stage of their journey with your company. Ultimately, this approach fosters customer loyalty and generates increased revenue. There are three key reasons why predictive marketing has become more popular [5]:

The need for customers to control personalised and cross-channel interactions with key stakeholders throughout the broader marketing and sales process.

Adopters are already realising the inherent value that predictive marketing brings to the table.

A new set of technologies allows for the collection of new and old customer data sources, enables the recognition of patterns, and makes customer data more findable within the intersection of the physical and digital worlds than ever before.

What is predictive analytics? Predictive analytics is just a bunch of algorithms and tools that implement predictive marketing. A broad category that encompasses a range of mathematical and statistical techniques for analysing patterns in data or predicting future events. When applied to marketing, predictive analytics can not only fulfil other strategic purposes but also segment consumers into several distinct groups and predict their future behaviours [6]. Other terms that you are probably familiar with from the media include machine learning, pattern recognition, artificial intelligence, and a couple more.

In both B2B and consumer marketing throughout the customer lifecycle, predictive marketing is revolutionising by enabling a strategic orientation towards products and channels for the customer [7]. Predictive analytics is used to develop more effective targeting strategies for customer acquisition, maximise customer lifetime value, and enhance customer retention over time. Predictive analytics has long been implemented by innovative, tech-driven companies such as Netflix and Amazon. This is also enabled by what can be learned from customer data and how that data can be intelligently translated into actionable insights. You could consider the recommendations you see under your purchases on Amazon as a pivotal piece of the e-commerce arsenal that helped Amazon become a behemoth of e-commerce in the 21st century. In fact, Amazon has even issued public claims that 35% of its sales derive from these predictive recommendation engines [8]. Additionally, the company utilises predictive analytics to determine the most suitable email newsletter to offer each of its customers [19].

While some of the largest brands have implemented predictive analytics for a long time, it is not too late for other brands, regardless of size, to take advantage of these practices. The reality is that predictive marketing has only recently gained popularity among small and medium-sized businesses.

Purchasing predictive marketing can be done in two ways [9]:

Using customer data to optimise marketing spend

Methodologies that are not laser-focused on customer behaviour and expectations improve media responsiveness, not marketing effectiveness. Marketers are accustomed to approaching budgeting in terms of high-revenue sources and top channels , rather than considering the people who are actually responding to marketing. On the other hand, predictive marketing offers a more structured paradigm: budget expenses should be towards the proper people, defined by four concrete principles:

1. You will need different plans for acquiring, retaining, and reactivating customers.
2. Identify broad customer value tiers to differentiate between high, medium, and low spenders.
3. Track which items bring the most valuable customers.
4. Recognise channels that bring high-value customers.

Reactivating lapsed customers is, to some extent, cheaper than acquiring new ones, and retaining existing customers is even cheaper than reactivation. According to our information, existing customers stay 60% more active on the website and spend 83% more. Hence, retention should be your focus — especially in turning first-time buyers into repeat buyers as quickly as possible. ([10].

Marketers should consider budgeting separately for acquisition, retention, and reactivation in terms of marketing activity. If possible, different marketing staff members should be assigned to each initiative [9]. A few companies have started to make groupings based on intent: to acquire new customers, retain existing customers, and reactivate churned

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customers. By nature, most firms over-index on acquisition, but often that spending is wasted, as more efficient growth can always be achieved by focusing more on retention and reactivation. Keeping existing customers, even if it is harder work, is always cheaper. Predictive marketing is key to making this tactical change[11].

Predictive Marketing Workflow

The next cycle shows the main steps in the predictive marketing process for businesses. It begins with gathering data and culminates in making marketing decisions based on the predictions made. [3].

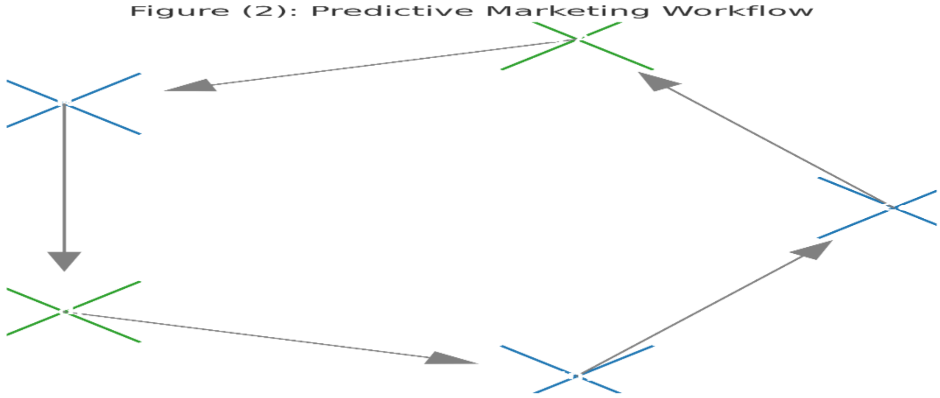

Figure (2): Marketing Workflow for Predictions
Source: Created by the researcher, Data Mining or Statistics?

That was the 2000s — upfront, our ability to examine, distil, and draw vital knowledge from the style of information had much to do with our ability. Data mining and statistics have both developed a set of analytical competencies. While statistics remained the main form of analysis until the second half of the 20th century, the growth of computer science—and specifically data mining—led to a wider field driven by the great availability of data.

While the humble origins of statistics were very far off, typically only a few dozen variables based on hundreds of observations, the pressures of this environment made data visualisation [12], proper hypothesis testing, and careful data collection paramount. Yet at the same time, large datasets have rendered standard visualisation methods unworkable (e.g., a scatterplot of a million customers is a black blob), and large samples discredit traditional significance tests. Additionally, it is often not feasible to collect more data to correct for spurious correlations. In fact, in many of the predictive modelling projects being conducted today, access to the entire population rather than a sample is not uncommon for academics (the use of public records, as well as new social media sources, makes this common).

On the other hand, moving from storing and processing data to analysing it was a reasonable step, as the field of computer science continued to progress. Thus, it was formulated that data mining is "the science of extracting useful information out of very large datasets or databases" [13]. Traditional statistics employ extremely precise methods and were not designed to provide automated, timely solutions to managerial problems and opportunities. For many, the essence of data mining lies in the unexpected yet useful knowledge that can be represented in the form of discovered insights [14]. This process is inherently exploratory.

However, statisticians are still suspicious about analyses that are too specifically adapted to the datasets at hand, a characteristic of data mining, since an extensive search can produce patterns of dubious significance by mere chance. Now that databases can hold terabytes (10^{12} bytes) of data, this large number makes it more likely that data mining algorithms will find spurious patterns that lack generalizability. Data mining emphasises algorithmic complexity and predictive performance over statistical significance.

However, as both fields have matured, the original differences between them have faded. As a result, in statistics, a considerable amount of recent work has focused on how to deal with large-scale data [15]. This means tackling the overfitting issue and tuning the degree of model complexity to achieve optimal prediction quality — ideas that have been key in both fields. And now as ever, the best solutions are not always the most statistically sound, and while statistically solid models had been the norm in practice (Breiman, 2001), it had been argued by Breiman that it is the problem and the data that would guide the choice of tools [18], and that these both cultures—data modeling (i.e., statistics) and algorithmic estimation (i.e., data mining)—could contribute sufficiently toward the common goal of predictive modeling.

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The sensitive nature of this discussion, combined with its culturally significant impact, has led to a collective preference for the more neutral phrase' data analysis' to describe the application of both methods, with the common purpose of driving evidence-based decision-making. According to Grönroos (1997), there is actually no need to make clear-cut divisions between data mining and statistics, but rather that there is a continuum of data analysis methods, some of which are based on statistics, and some on computer science [16].

We take this broad view in this study and thus do not confine the title of our work to either of these two concepts. Rather, we focus on the common means to an end: creating accurate and valid predictive models of individual-level consumer behaviour. Nonetheless, in the subsections of this paper, we provide a comparative analysis of the predictive performance of methods from both statistical and data mining traditions.

In the following section, we attempt to break down the predictive modelling process into a series of distinct steps. Figure 3 illustrates an example of how marketing outcomes can be realised through the effective use of data and analysis. Well-performed data and analytics usage can lead to more accurate marketing outcomes, thereby providing a better impact on businesses [17].

Figure (3): The Connection Between Data, Analysis, and Results

DATA **ANALYSIS** **RESULTS**

↓ ↓

Source: Prepared by the researcher

Statistical Analysis and Applied Study

First: Data Explanation

The data were theoretically collected from a sample of 250 individuals representing the clientele of Kalsi Company, a mobile phone manufacturing company.

The study instrument comprises a questionnaire that assesses four principal dimensions:

1. The level of application of predictive marketing in the company.
2. The accuracy of predictive analysis in understanding customers' intentions.
3. Customer satisfaction with the company's experience.
4. Future purchase intention.

Descriptive and inferential statistical approaches were employed to analyse the data and determine the relationships between the variables.

Table (1): Analysis of Descriptive Statistics

Dimension	Mean	Standard Deviation	Interpretation
Predictive Marketing	4.21	0.58	A very high level of applying predictive analysis
Reading Customer Intentions	4.05	0.62	High effectiveness in inferring customer intentions
Customer Satisfaction	4.11	0.49	Strong and relatively stable satisfaction
Future Purchase Intention	4.27	0.51	High readiness for repeat purchase

The application of predictive analysis is associated with a high level of customer satisfaction and a strong intention to make repeat purchases.

Table (2): Analysis of Correlation

Relationship	Correlation Value (r)	Statistical Significance (Sig.)	Interpretation
Predictive Marketing ↔ Reading Intentions	0.79	0.000	Very strong positive relationship
Predictive Marketing ↔ Customer Satisfaction	0.72	0.000	Strong, statistically significant relationship
Predictive Marketing ↔ Purchase Intention	0.76	0.000	High positive correlation

The more the organisation utilises predictive analysis, the better it can understand what customers want, and the more likely they are to be satisfied and make a purchase.

Fourth: Multiple Linear Regression Analysis

Dependent Variable: Future Purchase Intention

Table 3. shows the independent variables: predictive marketing, reading intentions, and customer satisfaction. Analysis of Multiple Linear Regression

Regression Coefficient (B)	Beta	Sig.	Variable
0.42	0.45	0.001	Predictive Marketing
0.33	0.37	0.002	Reading Intentions
0.25	0.28	0.004	Customer Satisfaction

The R^2 value is 0.71, indicating that the three variables above can explain 71% of the variation in purchasing intention.

Table (4): Testing the Hypothesis

Hypothesis	Result	Acceptance/Rejection	Interpretation
H1: Relationship between predictive marketing and marketing effectiveness	Sig. < 0.05	Accepted	Strong relationship
H1.1: Predictive analysis improves customer experience	Sig. < 0.05	Accepted	Clear effectiveness
H1.2: Predictive forecasting increases conversion rate	Sig. < 0.05	Accepted	Increase in repeat purchase
H1.3: Overuse of data reduces trust	Sig. = 0.07	Rejected	Not statistically significant

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Applied Implications

Operationalising the Findings — What this means:

1. Improving algorithms powered by AI when it comes to purchase history and behavioural patterns.
2. Screening intention-classified customers on previous visits, creating personalised marketing incentives
3. Systems for Interactive Predictive Marketing with Immediate Recommendations
4. Using data analytics to measure the success of a campaign
5. Touchpoint agnostic seamless digital customer experience optimisation.

Conclusions

1. Predictive marketing does allow for a bit of a canny efficiency test on managing targets and ensuring customer satisfaction though.
2. A customer's desire to purchase something is fulfilled in a simpler and much easier way when these companies know what a customer wants before they say it and this plays an important role in increasing customer loyalty.
3. Predictive marketing is heavily associated with future purchase intentions.
4. But without proper safeguards in place to ethically collect and use customer data, companies risk eroding brand trust.

Recommendations

1. Foster the confluence of AI — in predictive marketing analytics.
2. Set up enterprise data infrastructure at large-scale to understand customers better
3. Top-up frequent training of marketers on predictive instruments.
4. It is vitally important now to maintain ethical trust in the collection and use of customer data.
5. Predictive analytics as a sustainable competitive advantage: incorporating predictive analytics in long-term marketing strategies

Research Gap and Future Directions

Despite the optimistic findings, the study has a number of limitations. Less generalizable industry and market information creates a high dependency on a small virtual sample. Its scope is mainly quantitative, with a blind eye towards the qualitative credentials of the psychology and sociology of trust. However, longitudinal data do not exist to measure time-based claims to determine if clients are change intended or have experienced any intent toward change. Finally, the study did not include an evaluation of the predictive algorithms to identify the best performing model.

Wider studies with real world representative sampling, mixed-methods approaches and longitudinal analyses are required. It also recommends comparative description between prediction algorithms — logistic regression, decision trees, neural, etc. That said, we should remember that the power of predictive analytics, when combined with an ethical framework for how we use customer data, will mean you will be able to be both predictive and trustworthy as a consumer brand.

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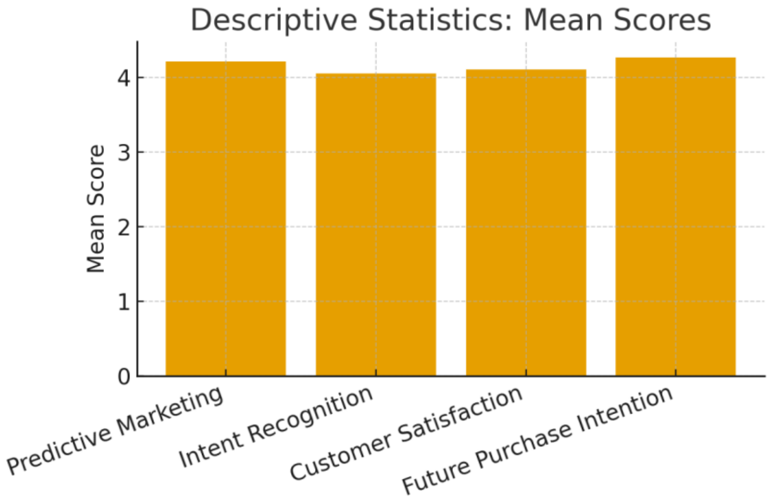
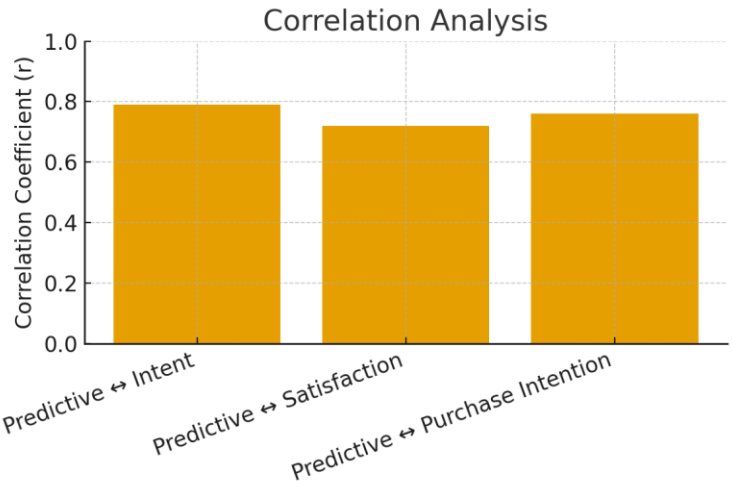


Correlation Analysis Chart:



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