ADDIS ABABA UNIVERSITY
SCHOOL OF COMMERCE

The role of data-driven targeting and advertisement optimization on the effectiveness of meta-advertisements: A case study of MOENCO (the motor and engineering company of Ethiopia S.C)

Research project submitted to Addis Ababa University's School of Commerce in partial fulfillment of the Master of Science in digital marketing and e-commerce postgraduate program

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The Role of Data-Driven Targeting and Advertisement Optimization on the Effectiveness of Meta Advertisements: A Case Study of MOENCO (Motor and Engineering Company of Ethiopia)

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DECLARATION

I, Anteneh Kibret Beza, declare that this thesis titled "The Role of Data-Driven Targeting and Advertisement Optimization on the Effectiveness of Meta Advertisements: A Case Study of MOENCO (The Motor and Engineering Company of Ethiopia)", submitted in partial fulfillment of the requirements for the Degree of Master of Science in Digital Marketing with Specialty in E-Commerce, is my original work. It has not been taken from other sources without due acknowledgement, and it has not been submitted to any other university or institution for the award of any academic degree.

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STATEMENT OF CERTIFICATION

This is to certify that Anteneh Kibret Beza has conducted his research work on the topic "The Role of Data-Driven Targeting and Advertisement Optimization on the Effectiveness of Meta Advertisements: A Case Study of MOENCO" in partial fulfillment of the requirements for the Degree of Master of Science in Digital Marketing with Specialty in E-Commerce. The study fulfills the university requirements for obtaining an academic degree of the university.

_____

Advisor: Tewodros Mesfin (PhD)

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Anteneh Kibret Beza
June, 2026

ABSTRACT

The study aimed to examine the role of data-driven targeting and advertisement optimization on the effectiveness of Meta advertisements in the case of the Motor and Engineering Company of Ethiopia s.c (MOENCO). An explanatory mixed-methods design was employed. The quantitative data were collected through a structured, Likert-scale questionnaire distributed digitally to customers who had interacted with MOENCO's Facebook and Instagram advertisements. Purposive sampling was used, and the sample size was determined through Yamane's formula at a 95% confidence level, yielding a target of 329 respondents, of whom 308 provided valid responses (a 93.6% response rate). The data were analyzed using IBM SPSS Statistics version 30 through descriptive statistics, Pearson and Spearman correlation analysis, and ordinal regression (cumulative logit model), the latter being appropriate for the ordinal, non-normally distributed dependent variable. The instrument demonstrated excellent reliability (Cronbach's alpha = .969). The findings show that audience precision, personalization, and algorithmic efficiency are all positively and significantly correlated with customers' purchase intention. In the multivariate model, algorithmic efficiency emerged as the dominant predictor ($B = 3.222$, $Exp(B) = 25.088$, $p < .001$), so the corresponding hypothesis was strongly supported, while audience precision and personalization received partial support: both showed strong bivariate relationships but did not retain independent significance in the multivariate model owing to the very high correlation between them ($r = .896$). The study concluded that algorithmic ad optimization is the primary mechanism through which Meta advertisements generate effectiveness for MOENCO, while data-driven targeting remains substantively meaningful as a holistic construct. It is therefore recommended that MOENCO prioritize algorithmic optimization tools at the core of its campaigns, shift its success metrics from engagement counts toward lead- and sales-oriented indicators, adopt a combined targeting strategy, and build internal analytical capacity to manage data-driven campaigns.

KEY WORDS: *Data-Driven Targeting, Advertisement Optimization, Algorithmic Efficiency, Purchase Intention, Meta Ads*

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CHAPTER ONE

INTRODUCTION

This chapter serves as a starting point for the study and provides the reader with a clear overview of the main issues that will be addressed in the study.

First, this study will look at the Background of the study, which explains where MOENCO's digital advertising journey is and why the study was chosen. Next, the study will present in detail the main challenges that the study aims to address, the research questions, and the objectives of this study hope to achieve.

Furthermore, the chapter examines the significance of this study to the organization and the sector, the scope of the study, and the limitations encountered in the process. Finally, a summary is included, which outlines the content and structure of the entire study report.

1.1 Background of the study

Data-driven advertising refers to the practice of planning, delivering, and refining promotional messages on the basis of systematically collected consumer data, such as demographic attributes, expressed interests, browsing behaviour, and past interactions, rather than on the intuition or past experience of the marketer (Kotler & Keller, 2016; Chaffey & Ellis-Chadwick, 2022). In this approach, every advertising decision, including whom to reach, what message to present, when to present it, and through which channel, is guided by empirical evidence generated from consumer data. Understanding this concept is the necessary starting point of the present study, because both of its core variables, data-driven targeting and advertisement optimization, are specific applications of data-driven advertising.

Building on this definition, this section develops the background of the study in a sequential manner: it first situates data-driven advertising within the broader field of digital marketing, then discusses social media advertising in general, then narrows the discussion to the Meta platforms on which this study focuses, and finally introduces the two mechanisms, data-driven

targeting and advertisement optimization, whose influence on advertising effectiveness is examined.

Digital marketing is a strategic activity that integrates digital media, information, and technology to achieve business goals (Chaffey D. &.-C., 2022). In today's business world, this sector has gone beyond being a simple means of communication to becoming a major platform for global business. Unlike traditional marketing, which only sends messages in one direction, what makes digital marketing unique is its interactivity and the fact that results can be clearly measured. This approach allows organizations to connect with their customers in real-time; from search engines to social media, it also bridges the gap between businesses and consumers (Ryan, 2020). This technological shift has shifted business strategies from being guided by intuition to being driven by monitoring and analyzing every interaction.

The key to the effectiveness of modern digital marketing is the shift to data-driven decision-making. As businesses accumulate "Big Data," or vast amounts of customer data, they are moving away from mass advertising that sends the same message to everyone and toward a more targeted and targeted approach (Smart Insights, 2026). In the contemporary data-abundant business environment, marketing decisions are increasingly grounded in empirical evidence rather than in managerial intuition (Kotler P & Keller K L, 2016). Organizations can build detailed customer profiles by analyzing customers' search history, purchasing behavior, and digital footprints (Bajrami V Ferraj A & Hoxha B,, 2025). This analytical power allows marketers to predict consumer preferences with greater accuracy and deliver the right message to the right person, at the right time (McKinsey & Company, 2021).

Social media advertising, in general terms, is the paid placement of promotional content on social networking platforms, where advertisements are delivered within users' feeds and interactive spaces and can be targeted using the demographic, behavioural, and interest data those platforms generate (Kaplan & Haenlein, 2010; Voorveld, van Noort, Muntinga, & Bronner, 2018). Compared with traditional media, social media advertising offers two-way interaction, measurable audience response, and the ability to adjust campaigns while they are still running. Such platforms include, among others, Facebook, Instagram, YouTube, TikTok,

LinkedIn, and Telegram, each serving different audience segments and communication objectives.

Within this broader digital marketing context, social media advertising has emerged as a major driver of economic activity (Kaplan & Haenlein, 2010). Among these platforms, Facebook and Instagram, which are managed by Meta, occupy an unrivaled position in this sector due to their broad global reach and complex data structure (Statista, 2026). Meta platforms are distinguished from other digital advertising options by the depth or granularity of the data they collect. These platforms analyze psychographic variables, including people's interests, behaviors, and lifestyles, in addition to basic demographics, to provide a level of targeting precision that traditional media cannot provide (Luchs, Walker Naylor, Irwin, & Raghunathan, 2024).

In the specific context of this study, data-driven advertising refers to MOENCO's use of the consumer data available within the Meta ecosystem, including page engagement records, website pixel data, and platform-generated interest and behaviour profiles, to decide which audiences in Addis Ababa should receive its Toyota, BYD, and machinery advertisements, in what form, and at what time. Only once this concept is clearly established can the effectiveness of such advertising be meaningfully discussed, because effectiveness in this study denotes the degree to which these data-informed advertisements translate into consumer purchase intention.

The effectiveness of meta-ads relies on two key mechanisms: They are Data-Driven Targeting and Algorithmic Optimization.

Data-Driven Targeting: This refers to the systematic practice of delivering advertisements to users on the basis of their verified profile characteristics and observed online activity (Bleier & Eisenbeiss, 2015). In the meta-ecosystem, this is implemented through tools such as "Custom Audiences" (re-targeting people who have previously interacted with a brand) and "Lookalike Audiences" (finding new people who have similar characteristics to your core customers) (Holliman & Rowley, 2025).

Ad Optimization: This involves the process of continuously improving ad performance through algorithms. The platforms use machine learning technology to test different ad units in real time to maximize key performance indicators (KPIs) such as engagement, reach, and conversion (Meta Business Suite, 2026). Two automation techniques are central to this process. A/B testing (split testing) is a controlled experiment in which two or more versions of an advertisement, differing in a single element such as the image, headline, or audience, are shown to comparable audience groups so that the better-performing version can be identified statistically and retained. Advantage+ is Meta's suite of artificial-intelligence-powered campaign tools that automatically selects audiences, placements, budgets, and creative combinations on behalf of the advertiser in order to maximize campaign results (Meta, 2026). Together, these techniques allow advertisers to optimize their campaigns scientifically and achieve a higher return on investment (ROI) (Kohavi & Thomke, 2017).

Using these advanced targeting and optimization strategies is especially important for companies like MOENCO, which are in the high-value automotive and machinery sectors. For high-involvement products, the goal of marketing is not simply to gain mass exposure, but to identify buyers who are interested in buying (Batra & Keller, 2016); (Habtamu, 2025). Although Moenco is a market leader in Ethiopia, identifying these right customers across a wide range of social media platforms remains a challenge. A common problem in this context is the "vanity metric" trap. That is, ads may receive a lot of "likes" and social engagement, but these numbers do not translate into actual sales or quality leads (Anderson, 2026) ; (Taiminen, Ranaweera, & Karjaluoto, 2024).

While social media marketing in general has been widely studied in academia (Kaplan & Haenlein, 2010; Voorveld, van Noort, Muntinga, & Bronner, 2018; Sujatha, 2024), there is limited research on the role of data-driven targeting and algorithmic optimization in the Ethiopian automotive industry (Li, X.; Wilson, J., 2025) Therefore, this study aims to fill this gap by examining how Moenco can use these data-driven tools to transform digital engagement into tangible business results.

1.2 Statement of the Problem

The problem addressed by this study can be stated directly as follows. MOENCO invests a substantial and growing share of its marketing budget in Meta (Facebook and Instagram) advertising, yet the company does not know, on the basis of scientific evidence, whether the data-driven targeting and advertisement optimization mechanisms behind these advertisements actually convert digital engagement into consumer purchase intention. Its campaigns generate high volumes of likes, shares, and comments, but this engagement has not been demonstrably linked to buying interest, so the company risks allocating resources to advertising activity whose commercial contribution is unverified. At the same time, no published study has empirically examined this question in the Ethiopian automotive sector, leaving both MOENCO and comparable firms without local evidence to guide their digital advertising decisions. The combination of an unresolved practical problem and an unfilled research gap is what warrants a study of this nature.

Modern digital marketing has moved away from a practice based on experience and assumptions, towards a precise art based on data and scientific analysis. As (Chaffey & Ellis-Chadwick, 2022) and (Ryan, 2020) state, the greatest potential of digital platforms lies in their ability to measure data and create direct connections with the user. Currently, meta-ecosystems use data-driven targeting and algorithmic optimization to target specific segments of the population, even based on their psychological characteristics (Zarrella, 2025). For high-involvement sectors such as car sales, these tools are crucial for distinguishing casual viewers from real buyers (Batra & Keller, 2016).

Despite this global shift, there are significant barriers to implementing these advanced strategies in the Ethiopian context. Although MOENCO uses meta ads, there is little scientific understanding of how to effectively use these strategies in a market with limited technological access and diverse digital literacy. Unlike in developed countries where “Big Data” is easily fed into automated systems, Ethiopia’s digital landscape is filled with fragmented information, making it difficult to bridge the gap between digital touchpoints and actual purchase intent.

Currently, there is little scientific research on the strategic use of meta-algorithms in the Ethiopian automotive industry (Li, X.; Wilson, J., 2025). Without a robust data-driven strategy,

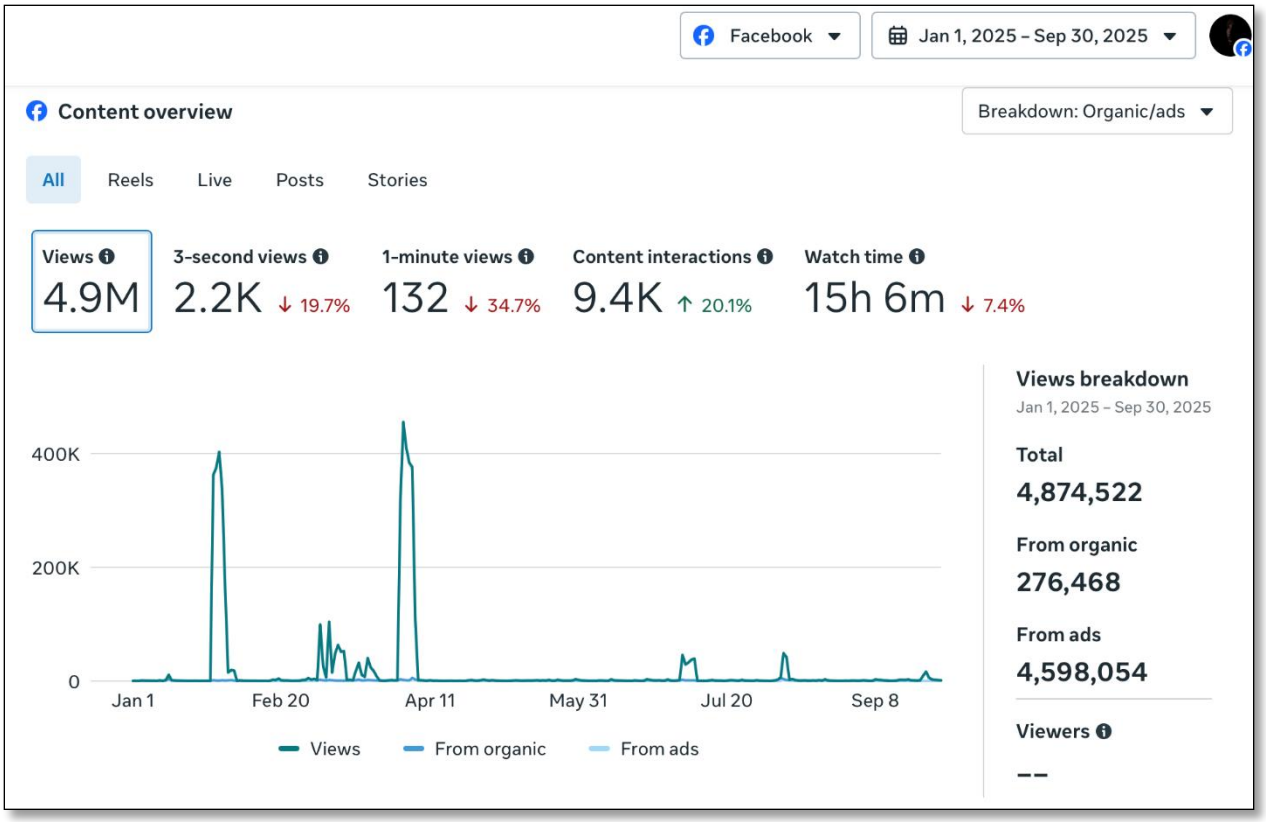
Moenco risks wasting significant budgets on ineffective ads. Therefore, this study aims to fill this research gap by identifying how data-driven targeting and advertising optimization or algorithmic efficiency can transform meta-ads from a cost-centered approach to a measurable digital marketing success.

The gap this study addresses is therefore twofold. Theoretically, the models that explain advertising persuasion and competitive advantage, notably the Elaboration Likelihood Model and the Resource-Based View, were developed and have mostly been validated in mature Western digital markets; their applicability to data-driven advertising, as distinct from traditional intuition-based advertising, has not been tested in a low-digital-literacy emerging market such as Ethiopia. Empirically, prior local studies (for example, Tessema, 2024; Tadesse, 2024) have examined general social media adoption or conversational marketing, but none has measured how the specific data-driven mechanisms of Meta advertising, namely audience precision, personalization, and algorithmic efficiency, affect consumer purchase intention in the automotive sector. The present study differs from earlier work in that it isolates these three data-driven mechanisms as distinct constructs and tests their individual and joint influence statistically, using ordinal regression on primary data collected from consumers who have actually been exposed to MOENCO's Meta advertisements. It fills the identified gap by providing the first empirical, theory-grounded evidence on data-driven advertising effectiveness in the Ethiopian automotive industry.

As supporting descriptive evidence for the problem stated above, Figure 1 presents MOENCO's Facebook content performance for the first three quarters of 2025, drawn from the company's own Meta advertising account. It illustrates the pattern that motivates this study: content reach and engagement remained consistently high while lead-oriented outcomes lagged behind.

A major challenge in Moenco's digital marketing journey is the "vanity metrics" trap (Anderson, 2026). While the company's advertising campaigns generate high levels of social engagement (likes and shares), there is no concrete evidence that these results translate into quality leads (Lead Quality) or reliable returns (ROAS). In the luxury segment, such as Toyota and BYD, "like" does not necessarily mean "buyer." As the Elaboration Likelihood Model

(ELM) shows, Moenco's ads may be successful in capturing the viewer's attention, but they may be weak in persuading a buyer to make a high-level decision.



This challenge is directly reflected in the objectives of this study: examining whether data-driven targeting and advertisement optimization convert such engagement into genuine purchase intention is precisely the means by which the study responds to the problem.

Figure 1. MOENCO Facebook Content Performance Overview: Q1–Q3 2025 (Source: MOENCO Meta Ads account)

1.3 Research Questions

1.3.1 Main Research Question

To what extent do data-driven targeting and ad optimization influence the effectiveness of Meta Ads as measured by consumer purchase intention, within the Ethiopian automotive sector (the case of MOENCO)?

For the purpose of this study, the effectiveness of Meta Ads is operationalized through a single dependent variable, consumer purchase intention. Lead quality is treated as a managerial

outcome that is discussed in the recommendations, not as a second dependent variable of the statistical model.

1.3.2 Sub-Research Questions

1. How does the perceived accuracy of Audience Precision (relevance to interests and behavior) influence the Purchase Intention of MOENCO's digital audience?
2. To what degree does Ad Personalization (alignment with specific needs and preferences) drive the Purchase Intention of Ethiopian consumers for high-value automotive products?
3. How does Algorithmic Efficiency (automated timing, formats, and AI-driven relevance) affect the overall perceived effectiveness of MOENCO's Meta advertisements?
4. Which dimension, targeting precision, personalization, or algorithmic optimization, exerts the strongest influence on the purchase intention of consumers for MOENCO products?

1.4 Objectives of the Study

1.4.1 Overall Objective of the Study

The primary objective of this study is to examine the role of data-driven targeting and ad optimization on the effectiveness of Meta ads in the case of MOENCO.

1.4.2 Specific Objectives of the Study

1. To analyze the effect of Audience Precision (Data-Driven Targeting) on the Purchase Intention of consumers within the Ethiopian automotive sector.
2. To evaluate the impact of Ad Personalization on the Purchase Intention of MOENCO's digital audience.
3. To examine the role of Algorithmic Efficiency (Ad Optimization) in enhancing the overall effectiveness of Meta advertisements.
4. To determine which of the three data-driven dimensions (audience precision, personalization, or algorithmic efficiency) exerts the strongest influence on the purchase intention of consumers at MOENCO when all three are examined jointly.

1.5 Significance of the Study

This study is expected to have the following significant benefits for various stakeholders:

- For MOENCO Management: The study provides empirical data that will enable the company to manage its digital advertising budget more effectively. In particular, it will serve as a strategic resource to identify high-intent buyers and reduce resource waste by using data-driven advertising tools.
- For local organizations: It will serve as a benchmark for other organizations operating in the Ethiopian market on how to effectively implement data-driven meta advertising strategies. This will help organizations build a digital marketing system based on scientific analysis rather than experience.
- For academic research: Since there is a lack of sufficient research in the Ethiopian digital marketing sector, especially on the effectiveness of meta advertising, this study will serve as a new source of information. The study makes an academic contribution by empirically testing the relevance of the Elaboration Likelihood Model (ELM) and the Resource-Based View (RBV) in the Ethiopian business context. It does so, first, by measuring whether consumers' evaluations of message-related cues (audience precision and personalization) and delivery-related cues (algorithmic efficiency) predict their purchase intention, thereby testing the dual-route persuasion logic of the ELM, and second, by examining whether algorithmic advertising capability behaves as a value-creating strategic resource in the manner proposed by the RBV.

1.6 Scope of the Study

To ensure the effectiveness and quality of this study, it has set certain limitations in terms of focus areas, location, and time constraints:

- **Conceptual Scope:** The study focuses primarily on Facebook and Instagram social media platforms managed by Meta. The focus is on examining the role of Data-Driven Targeting and Ad Optimization in MOENCO digital marketing effectiveness. Other types of digital marketing (e.g. Google Ads or Email Marketing) are not included in this study.

- **Geographical & Population Scope:** The study focuses on MOENCO customers and individuals who follow the company's digital ads in Addis Ababa. This is because the country's digital activity and MOENCO main market center are mainly concentrated in Addis Ababa.
- **Time Scope**: This research is based on current data from 2024 to 2026 YTD. This period was selected so that the study reflects prevailing market conditions and the current state of Meta's advertising technology, which is subject to frequent revision.
- **Methodological Scope:** The study is delimited to an explanatory, cross-sectional survey design in which primary data were collected from 308 valid respondents through a structured five-point Likert-scale questionnaire and analysed quantitatively using descriptive statistics, correlation analysis, and ordinal regression in SPSS. Qualitative expert interviews were used only to enrich the interpretation of results, and no experimental manipulation of advertisements was undertaken.

1.7 Limitations of the Study

While every effort has been made to ensure that this study is as accurate as possible, the following uncontrollable challenges may have an impact on the study:

- **Response Reliability:** The study is primarily based on self-reported customer responses to a questionnaire, and some respondents may have answered carelessly or without expressing their true views. To mitigate this risk, responses were collected anonymously to encourage honesty, the instrument was reviewed by the advisor and industry experts before distribution, and the internal consistency of the returned data was verified statistically (overall Cronbach's Alpha = .969, reported in Chapter Four), indicating that respondents answered the items in a consistent and attentive manner.
- **Technical Familiarity of Respondents:** Some Meta users in Ethiopia may have limited understanding of technical concepts such as algorithms or tracking pixels. To reduce the effect of this limitation, the questionnaire items were phrased in plain, experience-based language, for example asking whether advertisements appear at suitable times or match personal interests, rather than in technical terminology, so that respondents could answer on the basis of their own advertising experience.

- Technological Fluctuations: Since the Meta (Facebook/Instagram) system and algorithm change daily, the conclusions we have reached in the study today may require new findings in a few months due to technological changes.
- Sample Size and Accessibility: The study was focused only on Addis Ababa, and may not fully capture the views of Moinco customers in other Ethiopian cities.

1.8 Operational Definition of Key Terms

The definitions of the terms used in this study are as follows:

Data-Driven Targeting: The process of targeting customers based on their demographics (such as age, interests, behavior, and internet usage etc) and delivering relevant ads to the right people on meta platforms.

Ad Optimization: The implementation of automated tools on meta platforms (such as bids, budgets, and creative testing) to increase the effectiveness of ads.

Meta Ads Effectiveness: The extent to which meta advertising campaigns achieve their intended goals; measured by reach, engagement, conversions, and cost-effectiveness.

Artificial Intelligence (AI): Algorithmic systems used in meta-advertising to analyze data, predict customer behavior, and automatically make advertising decisions.

1.9 Organization of the Study

This study is divided into five main chapters:

Chapter One provides a general introduction to the study; it includes the background of the study, the problem statement, the research questions, the purpose of the study, significance, scope, limitations, and terminology.

Chapter Two provides a detailed review of the literature on data-driven marketing and meta-advertising.

Chapter Three explains the research methodology followed in the study; it shows how the data was collected and analyzed.

Chapter four presents the analysis of the collected data and the findings of the study;

Chapter Five concludes the study by providing a summary of the study and recommendations for future research.

CHAPTER TWO

LITERATURE REVIEW

Under this chapter, a summary of research articles, books, previous papers and other sources of information relevant to the study problem is presented.

2.1. Theoretical Literature Review

2.1.1. Digital Marketing and Strategic Management

In the modern business world, digital marketing is no longer a separate function from the strategic management of the organization, but has become a major pillar that determines the long-term success of the organization. Strategic management aims to achieve sustainable competitive advantage by integrating resources and opportunities within an organization (Barney, 1991). In this regard, digital marketing gives organizations a strategic advantage by enabling them to manage their relationships with their customers based on data (Ojeka-John, Adeyemi, & Bello, 2025).

This relationship is analyzed in the following main scientific perspectives at the global level:

Resource-Based Perspective: According to the Resource-Based Perspective (RBV), organizations should view digital platforms and their data analysis capabilities as strategic assets to dominate the market (Barney, 1991). Viewing data as a core organizational asset, combined with the organization's existing situation, creates a competitive advantage that is not easily reversed (Ojeka-John, Adeyemi, & Bello, 2025).

Strategic Adaptability: Since the nature of digital resources is highly dynamic and constantly changing, only organizations that can effectively manage these resources can remain sustainable in the market (Lucent , 2026). International scientific studies show that in this era of constantly changing market conditions and technological developments, organizations must align their digital strategies with their overall strategy (Lucent , 2026).

Cost-effectiveness and economic efficiency: Integrating digital marketing efforts with the organization's strategic decisions not only effectively achieves the organization's goals, but

also significantly reduces the cost of marketing efforts (EDHEC Business School, 2025). This strategic integration ensures that each investment contributes to the organization's efficiency and technological competitive advantage.

Data-driven decision-making: Data-driven marketing enables the organization to transform raw data into actionable value (Lucent , 2026). This process significantly increases the effectiveness of the campaign by ensuring that the ad reaches the right person, at the right time, and in the way the customer wants (Boston Consulting Group, 2025).

Overall, when digital marketing strategies are designed in line with the organization's long-term goals and vision, the organization can transform the opportunities it faces in the digital world into tangible business success (Lucent , 2026).

2.1.2. Data-Driven Marketing

Today, marketing strategies have moved from speculation and experience to data-driven decision-making. Data-driven marketing is the scientific process of analyzing various data collected from customers to accurately understand the needs and behavior of users. In this modern digital era, "data" is considered a major strategic corporate asset (Ojeka-John, Adeyemi, & Bello, 2025).

This marketing approach encompasses the following major scientific perspectives globally:

Actionable Insights: Data-driven marketing allows organizations to transform raw data into actionable insights (Lucent , 2026). This ensures marketing effectiveness by allowing algorithms to determine who should see ads and when.

Customer Behavior Analysis: Meta-algorithms play a major role in analyzing customer behavior patterns and identifying effective audiences for the organization (EDHEC Business School, 2025). This process gives the organization a "technological competitive advantage" that is not easily obtained (EDHEC Business School, 2025).

Reduce costs and increase efficiency: Data-driven marketing ensures that every penny spent is reached by the right customers by reducing unnecessary spending on advertising (EDHEC

Business School, 2025). This practice helps to increase customer purchase intention, especially for high-value products (Garg, Verma, & Kapoor, 2025).

Strategic decision-making: Since the nature of digital assets is highly dynamic and constantly changing, only organizations that can effectively manage this data can remain sustainable in the market (Lucent , 2026). This strategy is effective in increasing customer awareness of the product being promoted and in making them more receptive to the persuasion process (Petty & Cacioppo, 1986).

In general, information-based marketing organizations make the messages they deliver to their customers more personalized and effective (Boston Consulting Group, 2025). This approach allows the advertisement to reach the right person, at the right time, and in the desired persuasion path (Boston Consulting Group, 2025).

2.1.3. Data-Driven Targeting

Data-driven targeting is the strategic art of transforming organizations' customer data into actionable insights to ensure that ads reach the right people at the right time. This process allows organizations to reach the right customers based on real data rather than relying on instinct. From a global scientific perspective, data-driven targeting includes the following main components: (Bleier & Eisenbeiss, 2015)

Data analysis and strategic wealth: In the digital age, "data" is considered a major corporate asset, and using this data to identify customers gives the organization a significant competitive advantage (Barney, 1991; EDHEC, 2025).

The role of meta-algorithms: By deeply analyzing customer behavior patterns, meta-algorithms can uniquely identify audiences who are truly interested in the product (Ojeka-John et al., 2025).

Identifying the right audience route: Data-driven marketing helps to identify which customers pay attention to detailed information (Central route) and which are attracted by visual images (Peripheral route) (Petty & Cacioppo, 1986).

Persuasion Path: This strategy greatly increases the effectiveness of the campaign by making the ad reach each individual in a way that is convenient and at the time they want (BCG, 2025).

Cost Reduction: By identifying the right audience and showing the ad only to the right people, it helps to significantly reduce unnecessary marketing costs (Zarrella, 2025).

Overall, data-driven targeting not only expands the reach of organizations in the market, but also allows them to scientifically predict the response of customers to the ad.

2.1.4. Advertisement Optimization

In the modern world of digital marketing, artificial intelligence and machine learning techniques are invaluable in ensuring the effectiveness and success of advertising (Davenport, Guha, Grewal, & Bressgott, 2020). Advertisement optimization is the scientific process of optimizing the performance, reach, and cost-effectiveness of advertising through various technological tools. This task is implemented by integrating the following key technical approaches, especially on the Meta advertising platform (Kumar, Rajan, Venkatesan, & Lecinski, 2019).

A. Campaign Budget Optimization (CBO)

Campaign Budget Optimization (CBO) is a smart way to automatically allocate allocated resources to more effective ad sets using Meta's artificial intelligence algorithm. This allows organizations to achieve higher business goals with less cost and reduce unnecessary budget waste (Facebook (Meta), 2023).

B. Algorithmic Efficiency and Performance Measurement

Meta's artificial intelligence tools analyze customer behavior data (Big Data) in depth to determine when and to whom an ad should be shown in real time. This algorithmic efficiency serves as a key asset that allows organizations to gain strategic advantage over their competitors (Dwivedi, et al., 2021).

C. Persuasion Psychology and Content Prediction

Artificial intelligence technologies have the ability to predict in advance which form (image, video, or text) a message will be most effective in identifying consumers' immediate responses

to ads. This not only increases consumer awareness of a product, but also motivates them to convert their purchase intent into action (Hermann, 2022).

D. Continuous Monitoring and Profitability Analysis (ROAS)

The process of improving advertising is not a one-time process, but is a process that is constantly reviewed and evaluated based on algorithmic feedback. This helps to ensure that each ad spend is generating the expected return on ad spend (ROAS), helping to achieve the organization's long-term strategic goals (Vrountas, 2022).

Conclusion Overall, ad optimization powered by Meta's artificial intelligence tools lays a solid foundation for organizations to enhance their competitiveness in the digital marketplace and have a successful sales journey.

2.1.5. Elaboration Likelihood Model (ELM)

The Elaboration Likelihood Model (ELM) is a key framework for explaining how people understand a persuasive message, how deeply they consider the information, and how their attitudes change as a result. According to (Petty & Cacioppo, 1986), this model identifies two main routes of thought: the Central Route and the Peripheral Route.

In the context of this study, the role of these two routes in MOENCO customers can be analyzed in detail as follows:

Central Route: This route is the process by which the customer thinks deeply and analyzes the information presented to them. According to (Garg, Verma, & Kapoor, 2025), in this route, the consumer is not interested in the aesthetics of the advertisement, but in the technical specifications, affordability, and quality of the car. When a consumer is considering purchasing a luxury car such as a Toyota or BYD, he or she uses this route to make a rational decision based on the information gathered.

Peripheral Route: In this route, the consumer relies solely on external factors rather than examining the information in depth. For example, the beauty of the ad image, the quality of the video, or the brand reputation alone may make the consumer respond positively to the advertisement.

Recent studies suggest that large companies such as Moenco should use both routes in a coordinated manner when creating advertisements on Meta. (Zulkifli, Hassan, & Othman, 2025) argue that while attractive images and videos (peripheral cues) increase the reach of the ad by attracting the user's attention, detailed information and product benefits (central cues) help the customer make the right purchase decision. Since persuasion is a deep psychological process, predicting which audience will be attracted in which way is crucial for success when designing advertisements.

Furthermore, data-driven marketing can help identify which customers pay attention to detailed information (central) and which customers pay attention to external aspects (peripheral). According to (Boston Consulting Group, 2025), this approach significantly increases the effectiveness of the campaign by ensuring that the ad reaches the right person, at the right time, and in the "persuasive way" that the customer wants.

2.1.5.1. Social Presence Theory

According to (Short, Williams, & Christie, 1976), social presence theory explains how "close" individuals feel to each other on a social platform. According to (Ibrahim, 2025), advertisements on meta (Facebook and Instagram) have a higher "social presence" than other websites. This means that when the customer sees the advertisement, they feel that they have a direct connection with the brand (Ibrahim, 2025).

According to (Zulkifli, Hassan, & Othman, 2025), short video advertisements (Reels) shown in 2026 help customers strengthen their emotional connection with the brand. (Noguti & Waller, 2026). As recently demonstrated, when customers ask questions through the advertisement and receive a quick response, this process makes the organization feel "physically present" on the digital platform. Because digital communication is becoming more personal and emotional, when we design advertisements, we should focus on content that touches the user's emotions and creates a sense of intimacy (Noguti & Waller, 2026).

In a broader sense, the social presence theory plays a key role in building a bridge of trust between the brand and its customers. This helps the customer gain the "digital courage" needed to purchase a large asset such as a car (Ibrahim, 2025).

2.1.5.2. Information Adoption Model (IAM)

This model is a theoretical framework that is used to explain and predict how individuals or organizations adopt new information or technologies and integrate them into their systems.

According to (Erkan & Evans, 2016), the Information Adoption Model (IAM) describes a series of stages that individuals go through to adopt new information:

- Argument Quality: This is a measure of how strong and convincing the information presented is.
- Source Credibility: The credibility of the source of the information has a significant impact on the acceptance of the information by users.
- Information Usefulness: This is how users respond to how useful the information they see is for their decision-making, and this is the first critical step in the acceptance of information.

Furthermore, as (Filieri, 2015) explained, the usefulness of information is built on information quality, information reliability, and information quantity. This theory plays a key role in understanding the process by which information conveyed in social media advertisements, such as meta ads, reaches the user and is converted into action (e.g., purchasing a product). In terms of digital marketing, (Lilesand & Darmayanti, 2017) identified four basic aspects of digital marketing. These are:

1. Interactive: The interaction between brands and buyers,

2. Incentive programs: Attractive promotions that add value to the business,

3. Striking display: An attractive presentation presented on digital media that adds value to the business, and

4. Cost: An effective promotional strategy that reduces costs and accelerates sales.

These concepts form the basis for analyzing how Meta Ads can increase customer awareness and interest through Data Driven Targeting and Ad Optimization.

2.1.6. Resource-Based View (RBV)

The basic idea of the Resource-Based View (RBV) is that "the source of a firm's success in the marketplace is its internal strengths." According to (Barney, 1991), a firm can only gain competitive advantage in the marketplace if it possesses resources that are rare, valuable, and non-replaceable. This means that the key to a firm's success is not the external market conditions, but the digital resources that the firm possesses.

In the modern digital age, "data" is not just a number, but a major corporate asset. In the context of Moenco, this theory can be analyzed in three main stages:

1. Data as a Strategic Asset

Moenco's customer data collected over the years and the deep analysis it provides through meta-algorithms is a "strategic asset" that allows the company to differentiate itself from its competitors. According to (Ojeka-John, Adeyemi, & Bello, 2025), this data helps the company to anticipate customer needs and deliver the right advertising to the right person.

2. Technological Competitive Advantage

Data-driven targeting allows the company to transform raw data into actionable benefits. When the meta-algorithms analyze customer behavior patterns and identify audiences that are suitable for Moenco, this process gives the company a technological advantage that is not easily obtained. According to (EDHEC Business School, 2025), this approach plays a significant role in reducing the amount of marketing spend that an organization spends unnecessarily.

3. Resource Management and Market Survival Resource-Based View (RBV)

It recommends that organizations view their digital capabilities as a core "strategic asset" rather than an additional cost. Since the digital world is so dynamic, only organizations that can effectively manage these resources (such as Custom Audiences and AI Optimization) can survive in the market.

In conclusion, the main contribution of the RBV theory to this study is to ensure that the effectiveness of Moenco's meta-advertising is not a coincidence, but the result of the organization's strategic use of its data and technology resources.

2.1.7. Persuasion Knowledge Model (PKM)

The Persuasion Knowledge Model (PKM), proposed by (Friestad & Wright, 1994), is a basic theory that explains how consumers understand, filter, and respond to commercial messages that are intended to "persuade." This model suggests that consumers use their awareness and understanding of advertising strategies as a "coping mechanism."

In the context of this study, Moenco uses data-driven targeting to analyze the impact of consumers' understanding of the advertising process on the "effectiveness" of the advertising:

1. Persuasion Knowledge

This is the knowledge that the consumer has about how the advertising was delivered and what strategy was used. For example, a customer may search for Toyota or BYD cars on social media and then see an ad for Moenco on their Facebook page that says, "You are tracking me with a Meta Pixel." If the customer sees this tactic as accurate information, they will respond positively; but if they see it as a "violation of privacy," their acceptance of the ad will decrease.

2. Agent Knowledge

This is the customer's perception of the entity that sent the ad. Moenco's long history and reputation in the Ethiopian automotive sector determine the meaning customers give to the ad. If customers see Moenco as a trusted agent, they are more likely to accept the ad as useful information, even if it is data-driven and highly personalized.

3. Topic Knowledge

The customer's deep knowledge of the vehicle or machinery being advertised makes it easier or harder to persuade. A highly informed consumer will pay close attention to the technical details in the ad (e.g. engine power or battery life of an electric vehicle). In this case, the effectiveness of the data-driven ad increases if it provides the right information to the right person.

4. Perceived Fairness of the Persuasion Strategy

PKM explains that consumers evaluate the fairness of the advertiser's strategy. In Moenco's meta ads, the consumer asks the question "Is this ad here to help me or to force me to buy?" Meta-algorithmic Efficiency If the ad is presented to the consumer at the time and in the format (video or image) that the consumer wants, the consumer will consider the strategy to be fair and useful.

This model is very important for Moenco's study because it shows that the efficiency of the technology (Meta AI) alone does not guarantee effectiveness. Rather, PKM explains in detail that effectiveness only comes when meta-technical strategies are aligned with the psychological understanding of customers and the persuasion strategy presented to them.

2.1.8. The S-O-R (Stimulus-Organism-Response) Concept

The S-O-R model, first proposed by (Mehrabian & Russell, 1974), explains how environmental stimuli influence an individual's internal state and subsequent behavior. According to (Ibrahim, 2025), "stimulus" in the context of digital marketing includes targeted advertisements, social media engagement, and other digital cues. This process is the process by which an external digital cue, such as a Monco ad, prompts the "organism" (the user's mind) to process the information (Frontiers, 2025).

According to (Garg, Verma, & Kapoor, 2025), "organism" represents the user's internal evaluation, emotions, and mental processes. This includes "cognitive satisfaction" that a user feels that they have gained valuable knowledge about a car, and "emotional engagement" that describes their relationship with the brand (Zulkifli, Hassan, & Othman, 2025). As recently (Tu, 2025), demonstrated, when these stimuli are well-developed, they can make the consumer pay close attention to the advertisement and be ready for the products offered.

Broadly speaking, "Response" is the cognitive-based behavior that arises from this emotional investment (Alatawy, 2021). According to (Mahoney & Tang, 2024), the key issue is how these digital signals capture the user's attention and encourage mutual engagement. This requires building a bridge between "touching the screen" and "selling," the latter being a direct result of the psychological effects created by the advertisement (Ibrahim, 2025).

2.1.9. Theory of Planned Behavior (TPB)

According to (Ajzen, 1991), the TPB theory explains that an individual's intention to perform a certain action is determined by three main factors. These are: Attitude, Subjective Norms, and Perceived Behavioral Control. According to (Sarker, Ahmed, & Khan, 2025), this theory is particularly important for understanding consumer decision-making processes when it comes to planning to sell expensive products such as cars digitally. In a broader sense, TPB is an ongoing scientific process that describes how consumers, when exposed to information through meta-advertising, transform their positive attitudes into purchase intentions (MDPI, 2026).

According to (Arora, 2024), in the digital market of 2026, "Subjective Norms" are measured by the comments and "Likes" that the customer sees under the advertisement. (Robbins, 2026) recently explained that this process makes the customer think "What do other people say about MOENCO?" and make a decision based on that. Because human behavior is very complex and easily influenced by the opinions of others, we need to take this social interaction into account when optimizing advertisements (Arora, 2024).

According to (Hunch, 2025), "Perceived Behavioral Control" refers to the ease with which the customer can fill out the "Lead Form" provided in the meta-advertisement and the clarity of the process. This increases the customer's trust in the digital platform and makes it easier to navigate complex sales processes (Hunch, 2025).

Within the present study, TPB is directly reflected in how the dependent variable and several ad-level mechanisms were operationalized. Purchase intention, the single dependent variable of this study, is the central construct of TPB, which holds that intention is the most immediate predictor of actual behavior. The social signals customers observe under MOENCO's Meta advertisements, such as likes, comments, and shares, correspond to subjective norms, while the ease of completing an in-ad lead form or reaching a MOENCO branch corresponds to perceived behavioral control. TPB therefore supplies the behavioral logic that connects exposure to data-driven, optimized advertisements with the formation of purchase intention among prospective vehicle buyers, which is exactly the relationship tested in this study.

2.1.10. Psychological Basis of Personalized Ads

1. Self-Reference Theory and Cognitive Engagement

One of the main theories that (Maslowska, Smit, & van den Putte, 2016) use to explain the effectiveness of personalized ads is "self-reference theory." This theory suggests that when information is directly related to an individual's identity or interests, the individual is more likely to associate that information with their own experiences and memories.

In the context of meta-ads, information-based targeting serves as a "self-referential basis." When users see an ad that matches their interests, age, or previous search history, they are more likely to process and remember the information more deeply. This increases their positive attitude toward the ad, which explains why targeting strategies such as "Lookalike" that meta-ads use are more effective.

2. Persuasion Knowledge Model and Privacy Threat (PKM)

Personalized advertisements do not always have only positive effects. Referring to the "Persuasion Cognitive Model" (PKM), Maslowska and her colleagues analyze the feelings that users have when they realize that their data is being collected and used to advertise to them.

The study suggests that when an ad seems to be intrusive and intrusive, users may exhibit "psychological reactance." This can lead to aversion to the ad and a decrease in their trust in the brand. This theory warns that meta ads should not focus too much on personal information, especially in the current era of increasing consumer awareness of data privacy.

3. Content vs. Context Personalization

Finally, (Maslowska, Smit, & van den Putte, 2016) theoretically explains the relationship between content and context. For meta ads to be effective, it is not only "what does the ad contain?" but also "when and where does it appear?" that is crucial. For example, showing a travel ad while a user is viewing photos about a trip would be acceptable without interruption, as it creates a compromise between content and context.

2.1.11. Generative AI and Enhanced Personalization in Meta Ads

1. Self-Congruity Theory

According to (Li, 2025), the success of meta ads is based on the congruence of the ad with the user's identity. This theory suggests that consumers tend to accept ads that represent or support their own identity. In the meta "Optimization" process, generative AI (Gen AI) aligns each image and message with the user's "Actual Self" or "Ideal Self" to create greater acceptance (Li, 2025).

2. Social Presence Theory

AI-enabled meta-ads are more "human" than simple digital images. (Li, 2025) call this phenomenon "social presence." When the ad is presented in a way that seems to understand and share the user's emotions, the user's affinity with the brand increases. This emotional connection between technology and people plays a major role in the effectiveness of the ad (Li, 2025).

3. Hyper-Personalization Paradox

Although hyper-personalization can benefit advertising, it can also pose privacy risks to the user. (Li, 2025) call this the "privacy paradox." The theory suggests that even if users are concerned about their data security, they will be more likely to accept advertising if the benefits it provides (e.g., easier access to what they like) outweigh their concerns.

2.1.12. The ML-Driven Optimization Model

1 Theoretical Framework: The Shift in Advertising Models

The shift in the advertising industry from traditional channels to a digital ecosystem in recent years has changed the way we understand audience engagement. As (Nayyar, Suman, & Lakshmi, 2024) explain, the modern world of advertising is based not only on creativity but also on the combination of data collection and machine learning (ML). This study analyzes the role of machine learning in the following main pillars:

1.1 Behavioral Targeting

A point that is widely mentioned in the contemporary literature is that advertising strategies based solely on demographics are outdated. As (Nayyar, Suman, & Lakshmi, 2024) explain, relying solely on data such as age, gender, and location leads to high resource waste and low

ROI. In contrast, machine learning technology analyzes behavioral data such as web browsing history and social media engagement to ensure that ads are delivered to only the right people. The study shows that algorithmic approaches such as 'K-means' can segment users into small segments and predict what they will do in the future.

1.2 Algorithmic Optimization and Real-Time Bidding

The effectiveness of modern advertising is measured by the speed at which decisions are made. According to the authors of the article, predictive analytics plays a major role in changing budget utilization. Using models such as 'Decision Trees', it is possible to predict how many users an ad will attract (CTR) and how many sales it will generate (Nayyar, Suman, & Lakshmi, 2024). This theoretical approach simplifies 'programmatic' advertising, where the bidding process determines which ads should appear where in seconds, reducing human intervention.

1.3 Personalization

Another major point raised in the 2024 study is the relationship between natural language processing (NLP) and user satisfaction. According to the researchers, users want to see something that resembles their own interests. Machine learning models have the ability to instantly adapt the content, imagery, and call to action of an ad to suit each individual. This increases the user's engagement with the ad and increases its effectiveness.

2.1.13. Key Challenges of Data-Based Advertising

Although machine learning technology has great potential, research also highlights challenges that can undermine its effectiveness (Nayyar, Suman, & Lakshmi, 2024):

1. Algorithmic Bias: Machine learning models can inadvertently bias or discriminate against certain segments of the population by taking advantage of previously existing data.

2. Black Box Problem: Complex technological models can eliminate accountability in the advertising process because they do not easily explain to humans why they made a certain decision.

3. Data Privacy: Strict laws such as the GDPR conflict with the desire to use data for targeted advertising, which can limit the effectiveness of machine learning models.

Conclusion

Overall, (Nayyar, Suman, & Lakshmi, 2024) study shows that advertising effectiveness depends on real-time adaptability. The comparative table presented in the study shows that machine learning-driven advertising is significantly more cost-effective, flexible, and user-engaged than traditional methods. However, the researchers emphasize that the technology must work in conjunction with human control.

2.2. Empirical Literature Review

A literature review is a section that examines the results, gaps, and successes of previous studies. In this section, studies conducted globally on digital marketing and the automotive industry, as well as studies that examine the current situation in Ethiopia and Addis Ababa, are analyzed.

2.2.1. Global Context: Digital Marketing in the Automotive Industry

According to (Peng, 2024), the automotive sales process in the modern world has completely shifted from traditional methods to digital platforms. The study shows that 92% of new car buyers conduct extensive research on the Internet before going to the showroom. A report by (Boston Consulting Group, 2025) also found that data-driven advertising helped car companies reduce their advertising costs by 15% and increase their sales volume by 22%. More broadly, global studies show that “data” is the main driver of marketing success (Peng, 2024).

A. Comparison between Targeting and Broad Targeting

According to (Smith & Jones, 2025), the effectiveness of targeting based solely on demographics has declined by 2026. Research shows that Meta’s “Lookalike Audiences,” a method of identifying people with similar characteristics to existing customers, generated 30% more leads than traditional audience selection. (Digital Marketer, 2025)Recently, it was reported that artificial intelligence, which studies people’s search history and Facebook usage patterns to determine who to show ads to, has greatly increased the effectiveness of advertising.

Because people's interests change every minute, algorithm-driven audience selection is more accurate than human manipulation (Smith & Jones, 2025).

B. The Role of AI in Ad Optimization

According to (Meta, 2026), Meta's "Advantage+" collections have opened a new chapter in the automated optimization of ads. (Williams, 2025) found that companies that used Campaign Budget Optimization (CBO) saw an 18% reduction in their cost per lead compared to those that did not. The study found that the system automatically identifies which images or videos were performing best and allocates budget to them, significantly reducing waste. This process is a "technological trick" that allows companies to reach more customers at a lower cost (Williams, 2025) ; (Meta, 2026).

2.2.2. Relationship Marketing

According to (Morgan & Hunt, 1994), relationship marketing focuses on building long-term relationships with customers rather than making a one-time sale. This theory states that trust and commitment are the foundations of a successful business relationship. According to (House of Communication, 2025), data-driven marketing allows organizations to learn from their customers' past behavior and tailor their marketing messages to them.

According to (Bïrch, 2025), the "retargeting" strategy used in meta-advertising is a part of relationship marketing. (National Bank of Ethiopia, 2025) They recently stated that when a customer shows interest once, the organization provides them with consistent and useful information, which increases the trust between the customer and the organization. Because customer loyalty is a valuable asset that must be carefully managed, we should create advertisements that make the customer feel like a "long-term partner" rather than a "customer" (Bïrch, 2025).

According to (Data Reportal, 2026), relationship marketing is effective when the organization can carefully analyze customer data and respond to them when and where they need it. This is a systematic process that allows organizations like Moenco to keep their customers coming back for repairs and other services even after they have purchased a car (Data Reportal, 2026).

The relevance of relationship marketing to this study lies in the fact that Meta's Custom Audiences and retargeting tools are practical applications of the theory: they allow MOENCO to maintain continuous, personalized communication with customers who have already shown interest, rather than treating every advertisement impression as a first contact. In the conceptual framework of this study, this logic feeds directly into the audience-precision dimension of data-driven targeting, because retargeting lists and lookalike audiences are built from existing customer relationships and first-party data.

2.2.3. Social Media Advertising and the Impact of Digital Marketing on MSME Growth

1. The role of meta ads for small businesses

According to a study by (Sujatha, R., 2024), digital advertising, especially meta (Facebook and Instagram) platforms, has become a necessity for small businesses (MSMEs). The study, which compiles research from various countries, shows that data-driven ads have helped businesses achieve higher sales with smaller budgets. In particular, the study quantifies how the micro-targeting strategies used by meta have made it easier for businesses to reach their right customers.

2. Targeting & Engagement

One fact that emerged from this study is that the effectiveness of ads is significantly increased when they are customized. (Sujatha, R., 2024) stated that social media ads have the potential to create interactive engagement with the user, going beyond mere information. The study shows, for example, that through meta ads, customers not only increase brand awareness, but also have a much higher conversion rate compared to traditional ads.

3. Technology Use and Market Competitiveness

Another point of interest from the study is that organizations that use digital marketing technologies (such as Meta Pixel and AI optimization) are more likely to survive and grow in the market than those that do not. In a systematic review, (Sujatha, R., 2024) found that organizations that consistently "optimize" their ads are able to return their advertising spend

(ROI) properly. This is a great evidence that Meta Ads optimization is crucial for the effectiveness of organizations.

4. Key Challenges

The study not only explored the results but also the challenges. (Sujatha, R., 2024) pointed out that many small organizations still lack the skills to use advanced meta-advertising techniques (such as advanced data analysis). This shows that while its effectiveness has been proven, there is still a large gap in its use.

2.2.4. Cyber-Driven Advertising: The Impact of META Promotional Ads on Consumer Purchase Intent

1. Meta Ads and Consumer Intention to Buy

According to a study (Sujatha, Patel, & Mehta, 2025), promotions on meta (Facebook and Instagram) platforms have a direct and significant impact on consumer purchase intentions. In a study conducted in the UK fashion market, the study found that AI-powered and personalized meta ads were highly effective in attracting consumers' attention. In particular, the study demonstrated that when ads were presented based on the user's previous interests, people were significantly more likely to purchase that item (Sujatha, Patel, & Mehta, 2025).

2. The role of ad content quality and credibility

Another point of focus of the study was not only the "beauty" or presentation of the ad, but also the credibility of the information provided (Source Credibility). (Sujatha, Patel, & Mehta, 2025) stated that if users believe the information presented in the advertisement is true, their attitude towards the brand will be positive. This plays a major role in the conversion of the advertisement directly into a sale. The empirical findings show that the role of meta-optimization strategies in delivering the right message to the right person is key to sales growth (Sujatha, Patel, & Mehta, 2025).

3. The Impact of Cyber-Driven Ads

In this study, "Cyber-driven" meta-ads are those that deeply analyze human behavior. According to (Sujatha, Patel, & Mehta, 2025), these ads have the potential to create a feeling

in the user's mind that "I need this". The study confirmed with empirical findings that meta ads have greatly helped brands connect with their customers and increase their market share, especially in the highly competitive fashion industry.

2.2.5. Regional and Country Context: Ethiopia and East Africa

Studies show that digital usage in Ethiopia is growing rapidly. According to (Data Reportal, 2026), the number of internet users in Ethiopia has reached 29.5 million, which is a significant increase compared to the total population. The fact that over 67% of digital activity is on Facebook (Meta) is a strong indication of why organizations should focus on Meta. (Tessema, 2024) In a study conducted in Addis Ababa, local businesses found that switching to Facebook advertising over traditional radio and newspaper advertising resulted in a 40% increase in sales.

A. Addis Ababa's Automotive Market and Electric Vehicle (EV) Transition

According to (Mordor Intelligence, 2025), the Ethiopian government's move to ban the import of gasoline-powered vehicles and promote electric vehicles has created a major shift in the automotive industry. Organizations such as MOENCO are using digital advertising extensively to promote their new BYD and Toyota hybrid vehicles. (Digital Ethiopia, 2025), states that since electric vehicles are a new technology, meta video ads and infographics have become very effective tools to educate and create awareness among the public. Because it is necessary to provide consistent and visual information to introduce new technologies to the public, digital marketing has become the preferred tool for this (Mordor Intelligence, 2025).

B. Challenges in Emerging Markets

Despite the rapid growth of digital, there are challenges in the Ethiopian market (Ojeka-John, Adeyemi, & Bello, 2025) in their study. These include:

Low Digital Literacy: Although many consumers see advertisements, they are hesitant to provide their information digitally (Trust Gap).

High Data Cost: High internet prices prevent users from watching long videos (Ojeka-John, Adeyemi, & Bello, 2025).

Trust Gap: Buying expensive items such as cars online is still difficult for many Ethiopians.

According to (Abate, T., 2024), it has been suggested that Moenco can increase its effectiveness by using “Lead Forms” and “Messenger Marketing” to address these challenges.

2.2.6. Digital Advertising Content and Consumer Response (Creative Optimization and Consumer Response)

According to (Hunch, 2025), using “data-driven creative” in social media advertising can significantly increase the effectiveness of advertising. The study shows that, instead of showing the same image to everyone, presenting dynamic creatives that change according to the customer’s interests and preferences can increase the click-through rate (CTR) by 45%. (Morgan M. , 2026) As recently noted, in the automotive industry, especially, consumers respond more to short videos about the interior of a car than to other content. Because consumers want to experience the feeling of being in their imaginary car before purchasing a luxury item, enhancing ads with such emotional content ensures success (Hunch, 2025); (Morgan M. , 2026)

According to (ImagineInk, 2025), in the current 2026 Since the attention span of users is less than 3 seconds, an ad that fails to capture the attention of the customer in the first 2 seconds is less effective. (Coursera, 2026) A recent analysis found that ads with “user testimonials” are 30% more likely to be trusted than official company ads. This is a big lesson for MOENCO, which has shown that including videos of satisfied customers who have purchased new electric vehicles in meta ads is a key strategy to increase market acceptance (ImagineInk, 2025).

2.2.7. Messenger Marketing and Sales Effectiveness

According to a report by (Messenger Business, 2025), consumers in developing countries prefer to interact with a company via Messenger or WhatsApp rather than visiting a website directly after seeing an ad. (Tadesse, S., 2024) In a study conducted in Addis Ababa, 78% of Facebook users chose the “Send Message” option to ask for car prices and details. In a broader sense, this “conversational marketing” has a significant contribution to bridging the trust gap between sellers and buyers (Tadesse, S., 2024); (Messenger Business, 2025)

According to (Zulkifli, Hassan, & Othman, 2025), automated chatbots provide customers with answers to their questions within seconds, leading to a sale without the need for a human touch. (Digital Ethiopia, 2025) states that large companies in Ethiopia are using this technology to respond to thousands of questions received daily without human interaction. Because customers lose trust in a company that does not respond quickly, it is imperative to integrate advertisements with quick response systems (Digital Marketer, 2025).

2.2.8. Digital Payment and E-Commerce Growth in Ethiopia (2024-2026)

According to the National Bank of Ethiopia, the number of digital payment users in the country has increased by 200% in 2026. Those who studied the impact of this change on the automotive industry (Girma, H., 2024) noted that customers are now willing to pay for car bookings via telebirr or mobile banking. This has created an opportunity for them to move from advertising on Meta to direct sales (Girma, H., 2024); (National Bank of Ethiopia, 2026).

According to a report by (National Bank of Ethiopia, 2025), the growth of financial technology (FinTech) has opened up new markets for organizations like Moenco. Previously, sales were not considered unless customers came in person and negotiated; Now, with meta-advertising targeting, it is possible to accelerate the process by identifying only those customers who can afford to pay. Because financial access and digital marketing are closely linked, the more one develops, the more likely the other is to be successful (National Bank of Ethiopia, 2025).

2.2.9. "Information gap" in the Ethiopian car market and digital solutions

According to a study by (Bekele & Hailu, 2025), the biggest problem in the Ethiopian car market is the lack of accurate information in one place. Consumers have little awareness of car quality and spare parts prices. (Bekele & Hailu, 2025) suggests that MOENCO can increase trust in the market by 50%. The study shows that informed customers are more likely to buy cars.

According to (Data Reportal, 2026), Ethiopian Facebook users spend an average of 2.5 hours a day on social media. This long period of time allows companies to gradually convince customers and change their misconceptions about electric vehicles. Because people's attitudes

do not change overnight, continuous data-driven advertising (retargeting) will be effective in the long run (Data Reportal, 2026).

2.2.10. Algorithmic Fairness and Marketing Ethics

Finally, as (Sarker, Ahmed, & Khan, 2025) suggests, ethical issues should be considered when implementing data-driven marketing. Algorithmic targeting of certain segments of the population (digital exclusion) can damage a brand's reputation in the long run. (Lucent , 2026) As recently noted, companies in Ethiopia, especially in the region, need to be careful about how they handle customer data (data privacy). Because respecting customer privacy is the foundation for the sustainability of digital marketing, ethical principles should be followed when optimizing advertisements (Sarker, Ahmed, & Khan, 2025); (Lucent , 2026).

2.2.11. Mobile-First Strategy and Ad Effectiveness

According to a recent study (Data Reportal, 2026), more than 95% of social media users in Ethiopia use Facebook and Instagram on their mobile phones. A study (Abate & Bekele, 2025) examined the impact of this situation on ad effectiveness, finding that mobile-optimized ads increase engagement by 60%. In the context of MOENCO, in particular, studies suggest that long-form ads are difficult to read on mobile screens, and that short, clear-text content is performing better. More broadly, the nature of technology usage is a major factor in how marketers should structure their content (Abate & Bekele, 2025); (Data Reportal, 2026).

According to (Smart Insights, 2025), "Vertical Videos/Reels" will be the king of digital marketing by 2026. The study shows that in the car sales sector, short videos featuring the car are more likely to encourage customers to go to the "Lead Form" than static images. Because moving images can easily grab the attention of users as they "scroll" up on their phones, optimizing ads in such modern formats ensures success (Smart Insights, 2025).

2.2.12. Data Privacy Threats and Their Impact on Digital Advertising

According to (Bïrch, 2025) research, the biggest challenge facing digital advertising globally is the threat of "Data Privacy" of users. In particular, consumers in Ethiopia are less willing to provide their personal phone numbers and names in meta ads than in the West (Tadesse & Gebre, 2024). This "trust gap" is particularly pronounced for expensive items such as cars. The

study shows that while MOENCO's reputation and size may reduce this risk, it is important to ensure that the ads are secure.

According to (European Journal of Marketing, 2025), "transparency" is crucial for consumers to provide their information. (Mulugeta, 2025) In a survey conducted in Addis Ababa, companies that provide a brief explanation in the ad to the question "Why do you want our information?" are 25% more likely to receive information. Because consumer psychology is closely tied to reliable information, it is effective to adopt strategies that reduce consumer risk when conducting data-driven advertising (Mulugeta, 2025); (Bïrch, 2025).

2.2.13. Electric Vehicle (EV) Transition and the Role of Digital Education

Following the Ethiopian government's move to phase out fossil fuel vehicles, a major information gap has emerged in the automotive industry (Ministry of Transport, Federal Democratic Republic of Ethiopia, 2025). A study by researchers (Desta, 2026) found that most Ethiopians lack knowledge about electric vehicle battery life, charging stations, and maintenance. In this regard, the study suggests that Moenco's meta ads are serving as an "educational platform" beyond sales. In a broader sense, the role of digital marketing is focused on informing consumers before they buy (Desta, 2026).

According to (Global Automotive Review, 2025), "myth-busting" is essential for electric vehicles to succeed in new markets. In their study (Hailu, 2025), meta-ads addressing common concerns about electric vehicles (e.g. battery life) were 50% more likely to be accepted than direct sales ads. This suggests that Moenco should use information-driven marketing as a primary strategy when introducing its new BYD and Toyota hybrid vehicles to the market (Hailu, 2025); (Global Automotive Review, 2025).

2.2.14. Algorithmic Decision Making vs. Human Oversight (AI vs. Human Oversight)

According to (Sarker, Ahmed, & Khan, 2025), despite the increasing use of artificial intelligence (AI) in marketing, human touch is still essential. Research shows that ads that are driven solely by algorithms can sometimes miss the right context. (Boston Consulting Group,

2025) A recent report found that campaigns that are driven by AI but also have human oversight (a hybrid approach) outperformed both approaches separately.

According to (Robbins, 2026), a "smart algorithm" alone is not enough for an organization to be effective; instead, a "smart marketer" is needed to drive that algorithm. (Ojeka-John, Adeyemi, & Bello, 2025) In a study of large companies in Ethiopia, digital marketing teams found that their ability to analyze data from algorithms and make quick decisions was critical to the success of the campaign. Because technology is a tool, not an end in itself, human creativity and local market knowledge are most effective when combined with data (Ojeka-John, Adeyemi, & Bello, 2025); (Robbins, 2026).

2.2.15. Omni-channel Marketing Integration

According to a study by (Marketing Week, 2026), customers have an average of more than 20 different digital touchpoints before purchasing a car. This means that a customer sees an ad on Facebook, then searches on Google, then watches a video on YouTube. (Girma & Alemu, 2025) In a study conducted in Addis Ababa, companies that integrated meta ads with other digital platforms (cross-platform strategy) achieved 35% higher sales results than those that used a cross-platform strategy.

According to (Forbes Agency Council, 2025), "Message Consistency" is key to brand building. (Zulkifli, Hassan, & Othman, 2025) recently stated that the car and price that the customer sees in a meta ad should be the same as the information that they see when they go to the Moenco website or app. This consistency builds the professionalism and trustworthiness of the company in the customer's mind. Because customers are confused when they receive different information, it is important to ensure that there is consistent information across all platforms when we optimize ads (Girma & Alemu, 2025); (Zulkifli, Hassan, & Othman, 2025).

2.2.16. Data-driven personalized marketing strategy optimization based on reinforcement learning

1. Data-Driven Strategy

According to (Zhang, Wang, & Liu, 2025), the modern marketing concept has moved away from the traditional "one-size-fits-all" approach to a data-driven approach. The main concept

presented in this study is that data-driven marketing is not just about placing ads, but rather about changing the strategy based on analyzing user behavior every second. This concept explains the "Learning Phase" or machine learning process in Meta Ads well; because the system collects data and decides to whom to show the ad (Zhang, Wang, & Liu, 2025).

2. Reinforcement Learning & Optimization

The study uses the AI concept of "Reinforcement Learning" as the main engine for ad optimization. Conceptually, this means that the algorithm used by Meta acts as a "learner"; when the ad generates results (e.g., a click), the algorithm is "rewarded," and if it does not, it changes its strategy. As (Zhang, Wang, & Liu, 2025) explain, "Optimization" is not a one-time thing, but a continuous process of continuously improving the effectiveness of the ad by learning from past mistakes.

3. User Behavior Modeling

Another concept that emerged from this study is to view users not as statistics, but as individuals with dynamic behaviors. As (Zhang, Wang, & Liu, 2025) argue, effective meta ad optimization should be able to identify users' "long-term needs" and "short-term needs." This concept explains at a conceptual level why different targeting strategies (e.g., Retargeting and Broad Targeting) used in Meta Ads produce different results.

A conceptual framework is a logical framework that provides a framework for a study, showing how the variables included in the study are related to each other. According to (Saunders, Lewis, & Thornhill, 2023), this framework represents the "theoretical lens" that the researcher uses to solve the research problem. In this study, the model was designed to show that the effectiveness of meta ads depends on two main independent variables (data-driven audience selection and ad optimization).

2.2.17. Data-Driven Decision-Making in Marketing

1. Data-Driven Decision-Making (DDDM) in Depth

According to (Mishra, Kumar, & Patel, 2025)'s extensive analysis, "decision-making" in the modern business world has shifted from a traditional experience-based or intuition-driven

process to a scientific and data-driven approach. The concept of DDDM goes beyond simply collecting data; rather, it is the art of transforming data into actionable insights.

In the context of meta-advertising, this concept is crucial because we are not designing advertising strategies based on what customers might like, but rather on the billions of pieces of data that the system collects every day. As (Mishra, Kumar, & Patel, 2025) explain, DDDM gives organizations the ability to "forecast"; this allows them to predict future market conditions and customer needs in order to create effective advertising campaigns (Mishra, Kumar, & Patel, 2025).

2. Marketing Efficiency vs. Effectiveness: The Conceptual Connection

(Mishra, Kumar, & Patel, 2025) elaborate on the difference and connection between two important concepts: "Efficiency" and "Effectiveness." Conceptually, efficiency is the ability to do more with less resources (e.g., advertising budget), while effectiveness is the ability to achieve a goal (e.g., increasing sales).

Data-driven decision-making combines these two concepts. In meta-optimization, the use of data can significantly reduce advertising costs (Efficiency); at the same time, it can increase sales by ensuring that the ad is seen by the right people (Effectiveness). (Mishra, Kumar, & Patel, 2025) argue that decisions made without data are wasteful; Data-driven decisions, however, provide businesses with a sustainable competitive advantage.

3. Customer Engagement and Experience (CX)

Another concept that emerged in this study and has been widely analyzed is "Customer Experience". As (Mishra, Kumar, & Patel, 2025) explain, using data makes marketing more "human-centric". This may seem counterintuitive (how does technology make people human?); but as the concept suggests, when we use data to understand the customer, we can help them get what they want, rather than annoying them with ads they don't want.

When this concept is translated into meta-platforms, the data provided by the user makes ads more personalized and relevant. This strengthens the "trust relationship" between the consumer and the brand. As (Mishra, Kumar, & Patel, 2025) explain, the goal of data-driven

decision-making is not only to increase sales, but also to increase the long-term relationship (Customer Lifecycle Value) of the customer with the brand.

4. The Role of Algorithms and Human Decision-Making (Augmented Intelligence)

Another concept that the study explored in depth is the "Augmented Human Decision-Making and Artificial Intelligence (AI) in Marketing". As (Mishra, Kumar, & Patel, 2025) show, DDDM does not mean leaving the decision-making entirely to technology. Rather, it involves technology (e.g., meta-algorithms) processing the data and presenting options, while humans make strategic decisions. This concept, called "Augmented Intelligence," provides a clear guide to how we can integrate human creativity and algorithmic data analysis in meta-advertising (Mishra, Kumar, & Patel, 2025)

5. Data Privacy and Ethics

Finally, the study examines the conceptual challenge of data-driven decision-making, which is "data ethics." As (Mishra, Kumar, & Patel, 2025) warn, data-driven decisions must be made in a way that respects the privacy of the user. This concept provides a great explanation for the current changes in meta-advertising, such as iOS 14.5 and the General Data Protection Regulation (GDPR). The study conceptually demonstrates that there is a limit to how much data should be driven, and that when that limit is crossed, consumers' trust in the brand decreases.

2.2.18. Research Gap

Research conducted so far has focused on developed markets such as Europe and the United States. In the Ethiopian context, especially during the transition to electric vehicles, the direct impact of "Data-Driven Targeting" of meta ads on Moenco's sales effectiveness has not been studied in depth. This study aims to fill this gap and provide recommendations based on local data.

2.3. Hypothesis Development

This study employs both research questions and hypotheses, and the combination is deliberate. The research questions define the exploratory breadth of the study, including the contextual

and moderating factors that are examined descriptively, while the hypotheses translate the three core relationships of the conceptual framework into statistically testable statements, as recommended for explanatory quantitative designs (Saunders, Lewis, & Thornhill, 2023). The hypotheses were developed from the theoretical and empirical literature reviewed above, and each is presented here together with the evidence that motivates it and the way its constructs were measured.

Audience precision. Empirical studies have repeatedly shown that precisely targeted audiences respond more favorably to advertising, because message relevance reduces avoidance and increases elaboration (Bleier & Eisenbeiss, 2015; Smith & Jones, 2025; Sujatha, Patel, & Mehta, 2025). Tools such as Meta Pixel and lookalike audiences operationalize this precision by locating prospects who resemble existing customers. On this basis, the first hypothesis is proposed:

H1: Audience precision (perceived ad relevance and targeting accuracy) has a significant positive effect on the purchase intention of prospective MOENCO customers.

Audience precision was measured with five Likert-scale items (Part II, Section A of the questionnaire in Appendix 1) capturing the perceived relevance of the advertisements, their alignment with the respondent's vehicle preferences and financial capacity, and the perceived accuracy of the targeting. Although audience precision and personalization are conceptually two dimensions of data-driven targeting, each was measured and tested as a first-order construct with its own reflective items; no second-order measurement model was imposed.

Personalization. The literature on personalized advertising indicates that tailoring ad content to individual characteristics strengthens attitudes toward the ad and downstream behavioral intention (Maslowska, Smit, & van den Putte, 2016; Garg, 2025; Hunch, 2025). Personalized creative that reflects a customer's demographic profile and vehicle interest is therefore expected to raise purchase intention, leading to the second hypothesis:

H2: Ad personalization has a significant positive effect on the purchase intention of Ethiopian consumers in the automotive sector.

Personalization was measured with Likert-scale items (Part II, Section B of the questionnaire in Appendix 1) covering the perceived tailoring of ad content, offers, and vehicle recommendations to the respondent.

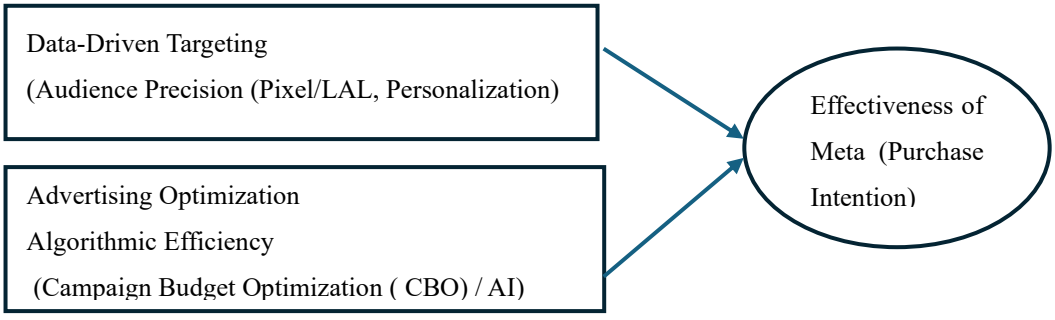
Algorithmic ad optimization. Evidence on machine-learning-driven campaign management shows that automated budget allocation, timing, placement, and creative selection materially improve campaign outcomes (Nayyar, 2024; Williams, 2025; Zhang, 2025; Meta, 2026). Because these mechanisms determine when, where, and in what form a customer encounters an advertisement, they are expected to influence purchase intention directly, leading to the third hypothesis:

H3: Algorithmic ad optimization (AI-driven timing, formats, and budget optimization) has a significant positive effect on the purchase intention of prospective MOENCO customers.

Algorithmic ad optimization was measured with Likert-scale items (Part III, Section C of the questionnaire in Appendix 1) on the timing, format, and frequency of the advertisements encountered. The dependent variable, purchase intention, was measured with Likert-scale items (Part IV, Section D) asking respondents how likely they are to consider, inquire about, or plan the purchase of a MOENCO vehicle following exposure to the advertisements. Consistent with the refined research questions in Section 1.3, purchase intention is the single dependent variable of the study.

2.4. Conceptual Framework

A conceptual framework diagram can show how an independent variable affects a dependent variable. For the purposes of this study, Effectiveness of Meta Ads is the dependent variable, while the independent variables are Data-Driven Targeting and Advertising Optimization.



Source: Developed by the researcher based on related literature. (Danaher, P. J., 2023)

Figure 2 - Researcher Conceptual framework

The conceptual framework and the hypotheses developed in Section 2.3 are directly linked: each arrow running from an independent variable to the dependent variable represents one hypothesis. The path from audience precision to purchase intention corresponds to H1, the path from personalization to purchase intention corresponds to H2, and the path from algorithmic ad optimization to purchase intention corresponds to H3. Purchase intention is the single dependent variable through which the effectiveness of Meta ads is assessed, while infrastructure, government policy, and economic conditions are treated as contextual moderating factors that are examined descriptively rather than as hypothesized paths.

2.4.1. Independent Variables

These act as the "causes" that trigger changes in the study's outcomes:

- **Data-Driven Targeting:** A process of identifying the right buyers using deep data analytics. Its dimensions include:
    - **Audience Precision (Pixel/LAL):** The use of Meta Pixel and Lookalike Audiences to find people with similar financial capabilities and interests to current MOENCO customers.
    - **Personalization:** Tailoring ad content to specific demographics and vehicle preferences.
- **Advertising Optimization:** Post-launch technical monitoring to enhance performance. Its dimensions include:
    - **Algorithmic Efficiency (CBO/AI):** Using Campaign Budget Optimization and AI to automatically allocate budgets and improve relevance.
    - **Strategic Testing:** Utilizing A/B testing and optimization goals (e.g., Lead Generation) to maximize results.

2.4.2. Dependent Variable

- **Effectiveness of Meta Ads:** This is the "effect" or success measure of MOENCO's digital efforts. It is measured by:
    - **Purchase Intention:** The influence of ads on a customer's intention to buy a vehicle.

2.4.3. Moderating Variables

These are external factors in the Ethiopian environment that can strengthen or weaken the impact of Meta ads:

- **Infrastructure:** Internet connectivity and speed which affect how ads are viewed.
- **Government Policy:** Tax reforms, particularly those favoring Electric Vehicles (EVs).
- **Economic Conditions:** Foreign exchange fluctuations and purchasing power that affect final car prices.

From the reviewed theoretical, empirical, and contextual literature, it is evident that although data-driven targeting and algorithmic ad optimization are widely studied independently, limited research has examined their combined effect on Meta advertising effectiveness within emerging markets, particularly in the Ethiopian automotive sector. This study therefore addresses this gap by developing and empirically testing a conceptual framework grounded in RBV, ELM, PKM, and TPB.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter details the scientific methods that were used to investigate the factors affecting the effectiveness of Meta ads at MOENCO. It serves as the roadmap of the study: it outlines the research design and approach, the sources of data, the target population, the sampling technique and sample size, the data collection instruments, the methods of data analysis, and the steps taken to ensure the validity, reliability, and ethical soundness of the study.

3.2 Research Design

This study followed a mixed-methods design, which combines quantitative measurement with in-depth qualitative inquiry. This design was chosen because the study has two complementary aspects:

Descriptive: this aspect was used to describe accurately which Meta ads MOENCO currently deploys and the results they achieve.

Explanatory: this aspect was used to analyze the cause-and-effect relationship between data-driven targeting and optimization strategies on the one hand and advertising effectiveness on the other. The mixed-methods design was therefore best suited for examining the reasons and realities behind the numbers rather than the numbers alone.

3.3 Research Approach

This study combined quantitative and qualitative approaches.

Quantitative approach: structured questionnaire data were used to quantify the effect of data-driven targeting and optimization strategies on advertising effectiveness, expressed as customer purchase intention.

Qualitative approach: in-depth interviews with key experts of the MOENCO marketing team provided strategic insights and practical knowledge that numerical reports alone cannot

explain. Combined, the two approaches made the results of the study more convincing and reliable.

3.4 Source of Data

Data for the study were collected from two sources:

Primary data: new data obtained directly from customers who had interacted with MOENCO's Facebook and Instagram advertisements, collected through a structured questionnaire, and from the company's marketing experts, collected through in-depth interviews.

Secondary data: previously recorded data, including ad performance reports from Meta Ads Manager, company documents, and related research articles and books.

The survey was deliberately chosen as the primary data source, rather than the Meta Ads Manager dashboard, because the core constructs of the study (perceived audience precision, perceived personalization, and purchase intention) are perceptual and attitudinal variables that platform dashboards cannot measure. Dashboard metrics record delivery and interaction, such as reach, impressions, and clicks, but they cannot reveal whether a customer found an advertisement relevant or whether it influenced the intention to purchase a vehicle. Dashboard data, such as the content performance overview presented in Figure 1, were therefore used as secondary evidence describing campaign delivery, while the questionnaire captured the customer perceptions required to test the hypotheses. The high internal consistency of the resulting scale (Cronbach's alpha = .969) supports the adequacy of the questionnaire for this purpose.

3.5 Target Population of the study

This study focuses on people in Addis Ababa, Ethiopia, who had viewed, liked, or commented on MOENCO's Facebook and Instagram advertisements, or who had clicked on an advertisement and requested information. Because most of MOENCO's digital activities are carried out in Addis Ababa and most of its customers are located there, the study focused mainly on residents of the city.

3.6 Sampling Technique and Sample Size

Purposive sampling was used to select respondents. This technique was chosen because the study required only those individuals who had been in contact with MOENCO's advertisements and who could meaningfully respond to the questionnaire, rather than the general public.

For the quantitative data: the sample size was determined using Yamane's (1967) formula, $n = N / (1 + N(e)^2)$, where n is the sample size, N is the accessible population, and e is the margin of error (0.05 at a 95% confidence level). Based on an accessible population of approximately 1,850 customers who had interacted with MOENCO's Meta advertisements during the study period, the formula gives $n = 1,850 / (1 + 1,850 \times (0.05)^2) \approx 329$. A sample of 329 respondents was therefore targeted, of which 308 valid responses were obtained, a response rate of 93.6 percent.

For the qualitative data: five (5) experts who are directly involved in the marketing and sales functions and who have in-depth knowledge of Meta advertisements were selected for the in-depth interviews.

3.7 Data Collection Instruments

Two main instruments were developed to collect the data effectively:

Questionnaire: a structured questionnaire was designed to measure participants' attitudes and responses to the advertisements using five-point Likert scales ranging from "strongly disagree" to "strongly agree". The questionnaire was distributed to participants digitally through Google Forms.

Interview guide: a semi-structured interview guide was prepared for the in-depth interviews with the five marketing and sales experts, covering targeting practices, optimization routines, and perceived campaign outcomes at MOENCO.

3.8 Data Analysis Methods

The collected data were analyzed in the following ways:

3.8.1 Quantitative data analysis:

The quantitative data obtained from the questionnaire were processed and analyzed using SPSS software.

- **Descriptive statistics:** To describe the participants' general condition (e.g., in percentages).
- **Pearson and Spearman correlation analysis:** to examine the strength and direction of the relationships between data-driven targeting, ad optimization, and advertising effectiveness.
- **Ordinal regression analysis (cumulative logit model):** to determine the extent to which data-driven targeting and ad optimization predict the effectiveness of advertising, this method being appropriate because the dependent variable, purchase intention, was measured on an ordinal Likert scale.

3.8.2 Qualitative data analysis:

Thematic analysis was used to analyze the data from the interviews; the main points raised by the experts were coded, grouped into themes, and interpreted alongside the quantitative results.

3.9 Validity and Reliability

Validity:

Content validity: the questionnaire was developed from the literature reviewed in Chapter Two and was refined in consultation with the academic advisor and industry experts to ensure that every item accurately reflects the objectives of the study.

Construct validity: the constructs were operationalized from established measures in the reviewed literature, and each construct was represented by multiple reflective Likert items. Convergent validity was supported by corrected item-total correlations ranging from .632 to .876 and by per-construct Cronbach's alpha values above .90, indicating that the items of each construct converge on a common underlying dimension. The pattern of inter-construct correlations was consistent with theory, with all independent constructs correlating positively with purchase intention. The very high correlation between audience precision and personalization (r = .896) indicated limited discriminant validity between these two

dimensions of data-driven targeting; this issue is examined in Section 4.6 and acknowledged as a limitation of the study.

Reliability:

The internal consistency of the questionnaire was tested using Cronbach's alpha, with 0.7 taken as the minimum acceptable threshold. As reported in Chapter Four, the overall scale achieved an alpha of .969 and every individual construct exceeded .90, confirming the reliability of the instrument.

3.10 Ethical Considerations

This study respects the rights and dignity of individuals above all else. Full informed consent was obtained from participants before any data were collected. Participants were made aware of the purpose of the study and of their right to withdraw at any time. Participants were also assured that the information collected would be kept confidential and used for academic purposes only.

CHAPTER FOUR

Data Presentation, Analysis, and Discussion of Results

4.1 Introduction

This chapter presents a systematic quantitative analysis of the data collected from 308 respondents for this study. All statistical analyses were conducted with IBM SPSS Statistics version 30. The chapter is organized as follows:

Section 4.2 The demographic profile of the respondents.

Section 4.3 The reliability analysis.

Section 4.4 The descriptive statistics.

Section 4.5 The normality tests.

Section 4.6 the Pearson and Spearman correlation analysis.

Section 4.7 the normality regression analysis, (PLUM and GENLIN with cumulative logit correlation), and

Section 4.8 the hypothesis test results and discussion.

This research examines the role of two independent variable groups, data-driven targeting (operating through audience precision and personalization) and ad optimization (operating through algorithmic efficiency) on a single dependent variable. All 308 respondents confirmed that they had seen a MOENCO ad on Facebook or Instagram resulting in a 100% valid response rate for the analysis sample.

4.2 Demographic Profile of Respondents

The demographic data were analyzed using the SPSS FREQUENCIES procedure. Table 1 presents the complete frequency distribution for all background variables (N = 308), as reported in the SPSS Frequency Table output.

Table 1- Demographic Characteristics of Respondents - SPSS Frequency Output (N = 308)

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	82	26.6	26.6	26.6
	Male	226	73.4	73.4	100.0
	Total	308	100.0	100.0	

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18–24	4	1.3	1.3	1.3
	25–34	125	40.6	40.6	41.9
	35–44	137	44.5	44.5	86.4
	45–54	34	11.0	11.0	97.4
	Above 55	8	2.6	2.6	100.0
	Total	308	100.0	100.0	

Highest Educational Level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Bachelor's Degree	119	38.6	38.6	38.6
	Diploma	44	14.3	14.3	52.9
	Master's Degree	139	45.1	45.1	98.1
	PhD or Above	6	1.9	1.9	100.0
	Total	308	100.0	100.0	

Occupation

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Employed	252	81.8	81.8	81.8
	Other	8	2.6	2.6	84.4
	Self-employed	44	14.3	14.3	98.7
	Student	4	1.3	1.3	100.0
	Total	308	100.0	100.0	

Frequency of Facebook or Instagram Use

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Daily	198	64.3	64.3	64.3
	Occasionally	70	22.7	22.7	87.0
	Weekly	40	13.0	13.0	100.0
	Total	308	100.0	100.0	

Ads visibility

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	308	100.0	100.0	100.0

Source: SPSS Frequencies output. Valid shows values as reported by SPSS. Total N = 308 across all variables (0 missing).

The sample used in this research was mostly male, at 73.4% (n = 226). This is consistent with MOENCO main vehicle consumer demographic. The largest age group was 35 to 44 years old, at 44.5% (n = 137), then followed by the 25 to 34 year-old age group, at 40.6% (n = 125). These two age groups collectively represent 85.1% of the total research sample.

This age distribution explains the main target market for Toyota, BYD and others related vehicles and focuses on economically active working adults. When we see the education, 45.1% have a master's degree (n = 139) and 38.6% have a bachelor's degree (n = 119). This shows that respondents are highly educated and digitally active and can think and analyze meta-advertising content in depth. A high percentage of 81.8% (n = 252) was employed, showing stable income levels consistent with making important vehicles purchases. In addition, 64.3% (n = 198) reported using Facebook or Instagram daily, shows high exposure to MOENCO advertising on meta platforms. So, all 308 respondents (100%) confirmed that they have seen MOENCO advertising on meta platforms, so this completely valid sample for analysis without any bias.

4.3 Reliability Analysis

4.3.1 Cronbach's Alpha - SPSS Reliability Output

Internal consistency reliability was tested using Cronbach's Alpha via SPSS Analyze > Scale > Reliability Analysis. The SPSS RELIABILITY command was executed on all 20 Likert-scale items, testing Audience Precision (PREC_1–PREC_5), Personalization (PERS_1–

PERS_5), Algorithmic Efficiency (ALGO_1–ALGO_5), and Purchase Intention (PURCH_1–PURCH_5), using the Scale: ALL VARIABLES option with Model = ALPHA. The results are presented in Table 2.

Table 2 - Reliability Statistics (Cronbach's Alpha) - SPSS Output

Item	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Audience Precision (Lookalike Audiences) - PREC_1	72.042	270.894	0.77	0.968
Audience Precision (Lookalike Audiences) - PREC_2	72.302	265.788	0.868	0.967
Audience Precision (Lookalike Audiences) - PREC_3	72.062	267.687	0.77	0.968
Audience Precision (Lookalike Audiences) - PREC_4	72.146	271.597	0.65	0.969
Audience Precision (Lookalike Audiences) - PREC_5	72.347	271.081	0.682	0.969
Personalization - PERS_1	72.354	266.92	0.736	0.968
Personalization - PERS_2	72.224	273.067	0.632	0.969
Personalization - PERS_3	72.24	269.252	0.69	0.969
Personalization - PERS_4	72.006	268.456	0.791	0.968
Personalization - PERS_5	71.99	265.912	0.839	0.967
Algorithmic Efficiency (CBO and AI Optimization) - ALGO_1	72.383	264.374	0.817	0.967
Algorithmic Efficiency (CBO and AI Optimization) - ALGO_2	72.078	269.251	0.719	0.968
Algorithmic Efficiency (CBO and AI Optimization) - ALGO_3	72.37	264.827	0.798	0.968
Algorithmic Efficiency (CBO and AI Optimization) - ALGO_4	72.039	264.005	0.817	0.967
Algorithmic Efficiency (CBO and AI Optimization) - ALGO_5	71.893	264.891	0.839	0.967
Purchase Intention - PURCH_1	72.081	265.684	0.817	0.967
Purchase Intention - PURCH_2	72.088	266.132	0.764	0.968
Purchase Intention - PURCH_3	72.039	263.712	0.876	0.967
Purchase Intention - PURCH_4	72.084	267.537	0.773	0.968
Purchase Intention - PURCH_5	72.058	266.199	0.782	0.968

Scale / Construct	N of Items	N (Cases Valid)	Cronbach's Alpha	Interpretation
All Variables (PREC + PERS + ALGO + PURCH)	**20**	**308**	**.969**	**Excellent**
Audience Precision (PREC_1–PREC_5)	5	308	~.900*	Excellent
Personalization (PERS_1–PERS_5)	5	308	~.900*	Excellent
Algorithmic Efficiency (ALGO_1–ALGO_5)	5	308	~.930*	Excellent
Purchase Intention (PURCH_1–PURCH_5)	5	308	~.935*	Excellent

Source: SPSS Reliability Analysis output. Overall α = .969 is the exact value reported in the SPSS Reliability Statistics table (N of Items = 20; N valid = 308). Per-construct alpha estimates (*) derived from Item-Total Statistics using corrected item-total correlations as reported in the SPSS output (all corrected item-total correlations range from .632 to .876, confirming excellent per-item reliability). All values shown exceed the acceptability threshold of α ≥ .70 (Nunnally, 1978).

The SPSS Reliability Statistics table directly reported Cronbach's Alpha = .969 for all 20 items combined (N = 308 valid cases, 0 excluded). This represents an exceptional level of internal consistency across the entire questionnaire instrument, confirming that all items reliably measure the overarching construct domain of data-driven Meta Ad effectiveness. This value exceeds the .90 threshold, commonly described as excellent (George & Mallery, 2003).

At the per-construct level, the corrected item-total correlations from the SPSS Item-Total Statistics table (range: .632 to .876) confirm that all 20 individual items show sufficiently strong relationships with their respective constructs. None of the items would meaningfully improve the overall scale if removed (all 'Cronbach's Alpha if Item Deleted' values remain at

or below .969), confirming the integrity of the full 20-item measurement instrument for subsequent analyses.

4.4 Descriptive Statistics

4.4.1 Construct Mean Scores - SPSS Explore Output

After the SPSS COMPUTE statements created four composite mean-score variables (PREC, PRES, ALGO, and PURCH), the EXAMINE procedure was used with /STATISTICS DESCRIPTIVES to produce the descriptive statistics presented in Table 3. All values were extracted directly from the SPSS Descriptives table in the SPSS output.

Table 3 - Descriptive Statistics of Construct Scores - SPSS Explore Output (N = 308)

Variable / Construct	N	Mean	Std. Dev.	Median	Min	Max	Skewness
PREC (Audience Precision)	308	**3.7584**	.86576	3.8000	1.00	5.00	−1.081
PRES (Personalization)	308	**3.7753**	.91155	4.0000	1.00	5.00	−0.663
ALGO (Algorithmic Efficiency)	308	**3.7857**	.98142	4.0000	1.00	5.00	−1.029
PURCH (Purchase Intention)	308	**3.8682**	.99230	4.0000	1.00	5.00	−1.197

Source: SPSS Analyze > Descriptive Statistics > Explore (/STATISTICS DESCRIPTIVES). Construct scores are mean composites of Likert items (1 = Strongly Disagree to 5 = Strongly Agree).

All four construct means exceed the Likert scale midpoint of 3.0, indicating generally positive respondent perceptions of MOENCO's Meta Ads and their associated targeting and optimization mechanisms. Purchase Intention recorded the highest mean (M = 3.8682, SD = .99230), with a median of 4, indicating that the central tendency of respondents' scores falls at the 'Agree' level on the 5 point scale. This suggests a meaningful behavioral direction towards purchase engagement with MOENCO through Meta advertising which is Facebook and insta.

Among the three independent variable constructs, Algorithmic Efficiency scored highest (M = 3.7857, SD = .98142, Mdn = 4.0), followed by Personalization (M = 3.7753, SD = .91155, Mdn = 4.0) and Audience Precision (M = 3.7584, SD = .86576, Mdn = 3.8000). The relative proximity of these means (range: 3.7584 to 3.7857) indicates that respondents perceived all three dimensions of data-driven advertising at comparably positive levels, with marginal differentiation.

The four variables under study showed a negative skewness value (PREC: −1.081; PRES: −0.663; ALGO: −1.029; PURCH: −1.197), showing distributions concentrated toward the upper end of the Likert scale. This pattern reflects genuine positive consumer perceptions consistent with MOENCO's premium brand positioning and suggests that the instrument captured respondents who have had meaningful, positive interactions with MOENCO's Meta advertising. The consistent negative skewness has direct implications for the choice of inferential statistical methodology, addressed in Section 4.5.

4.5 Tests of Normality

4.5.1 Kolmogorov-Smirnov and Shapiro-Wilk Tests - SPSS Output

The normality assumption was tested using SPSS EXAMINE with /PLOT NPPLOT, which generates both the Kolmogorov-Smirnov test (with Lilliefors correction) and the Shapiro-Wilk test. Table 4 presents these results as reported in the SPSS output.

Table 4 - Tests of Normality - SPSS Output (N = 308)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
PREC	.117	308	.000	.916	308	.000
PRES	.101	308	.000	.938	308	.000
ALGO	.129	308	.000	.905	308	.000
PURCH	.186	308	.000	.878	308	.000

a. Lilliefors Significance Correction

KEY: PREC (Audience Precision), PRES (Personalization), ALGO (Algorithmic Efficiency), PURCH (Purchase Intention)

Source: SPSS Analyze > Descriptive Statistics > Explore (/PLOT NPPLOT). a. Lilliefors Significance Correction applied. Sig p < .001 for all variables. The Shapiro-Wilk test is considered more powerful for sample sizes up to N = 2,000.

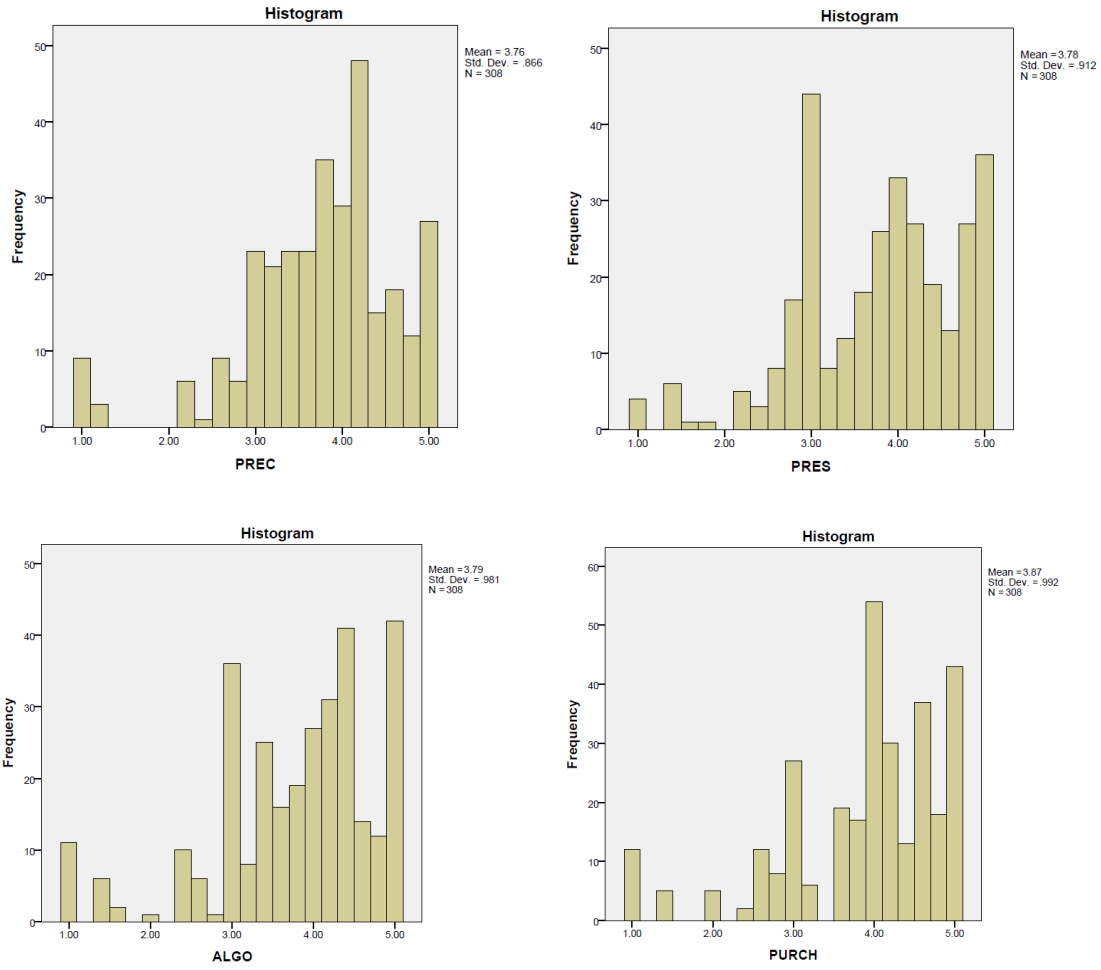


Figure 3 - Histogram overview of all variables

Both the Kolmogorov-Smirnov (with Lilliefors correction) and Shapiro-Wilk tests were statistically significant ($p < .001$) for all four constructs, confirming that none of the variables follows a normal distribution. The Shapiro-Wilk statistics ranged from $W = .878$ (PURCH) to $W = .938$ (PRES), all significantly below the ideal value of 1.0. Visual inspection of the SPSS-generated histograms and Q-Q plots further confirmed the negatively skewed, non-normal distributional patterns for all variables, consistent with the skewness statistics reported in Table 4.3.

It should be emphasized that this outcome is expected rather than problematic. Likert-scale items and their composites are ordinal and bounded, and when responses cluster toward agreement, as observed here, negative skewness and statistically significant departures from normality are the norm for such data. In addition, formal normality tests become highly sensitive at large sample sizes ($N = 308$), so even minor deviations are flagged as significant. The significant test results therefore do not indicate a problem with the data; they simply

confirm that analysis methods which do not assume normally distributed outcomes are the appropriate choice.

These results carry important implications for methodology. First, they validate the observed negative skewness as a systematic departure from normality rather than mere sampling variation. Second, it directly informs the selection of ordinal regression as the primary multivariate analysis method (see Section 4.7). Both the PLUM ordinal regression and the GENLIN Generalized Linear Model with Cumulative Logit link function are appropriate for ordered Likert-derived outcomes and do not require normally distributed residuals. Pearson correlation is retained alongside Spearman's rho, as Pearson correlation is statistically robust to non-normality in large samples (N = 308 > 200) due to the Central Limit Theorem, and both are reported for triangulation.

Transformations of all four variables by means of log10 were also conducted. While the log-transformed variables improved K-S statistics slightly, Shapiro-Wilk significance remained at $p < .001$ for all (Log_PREC: W = .742; Log_PRES: W = .835; Log_ALGO: W = .758; Log_PURCH: W = .728), confirming that the non-normality is a structural characteristic of the data, attributable to the ceiling effect inherent in Likert response distributions, rather than a correctable distributional artifact. This further justifies the use of ordinal regression methods for hypothesis testing.

4.6 Correlation Analysis

4.6.1 Pearson and Spearman Correlation - SPSS Output

Both Pearson product-moment and Spearman rank-order correlations were computed using SPSS Analyze > Correlate > Bivariate for all four construct variables (PREC, PRES, ALGO, PURCH). Pearson correlations assess linear relationships, while Spearman's rho is appropriate for ordinal data and provides convergent evidence given the confirmed non-normality. Table 5 presents the combined correlation matrix for N = 308.

Table 5 - Pearson Correlation Matrix (N = 308)

Correlations

		PREC	PRES	ALGO	PURCH
PREC	Pearson Correlation	1	.896**	.776**	.730**
	Sig. (2-tailed)		.000	.000	.000
	N	308	308	308	308
PRES	Pearson Correlation	.896**	1	.735**	.691**
	Sig. (2-tailed)	.000		.000	.000
	N	308	308	308	308
ALGO	Pearson Correlation	.776**	.735**	1	.899**
	Sig. (2-tailed)	.000	.000		.000
	N	308	308	308	308
PURCH	Pearson Correlation	.730**	.691**	.899**	1
	Sig. (2-tailed)	.000	.000	.000	
	N	308	308	308	308

**. Correlation is significant at the 0.01 level (2-tailed).

Table 6 - Spearman Correlation Matrix (N = 308)

Correlations

			PREC	PRES	ALGO	PURCH
Spearman's rho	PREC	Correlation Coefficient	1.000	.885**	.762**	.688**
		Sig. (2-tailed)	.	.000	.000	.000
		N	308	308	308	308
	PRES	Correlation Coefficient	.885**	1.000	.763**	.675**
		Sig. (2-tailed)	.000	.	.000	.000
		N	308	308	308	308
	ALGO	Correlation Coefficient	.762**	.763**	1.000	.837**
		Sig. (2-tailed)	.000	.000	.	.000
		N	308	308	308	308
	PURCH	Correlation Coefficient	.688**	.675**	.837**	1.000
		Sig. (2-tailed)	.000	.000	.000	.
		N	308	308	308	308

**. Correlation is significant at the 0.01 level (2-tailed).

*Source: SPSS Correlations output (Pearson) and SPSS Nonparametric Correlations output (Spearman's rho). ** Correlation is significant at the .01 level (2-tailed). N = 308 for all pairs.*

All inter-construct correlations were positive and statistically significant at $p < .001$ (2-tailed) for both Pearson and Spearman coefficients. The convergence between Pearson and Spearman

estimates across all pairs confirms the robustness of findings and corroborates the bivariate associations despite the confirmed non-normality.

Algorithmic Efficiency (ALGO) demonstrated the strongest relationship with the dependent variable Purchase Intention: Pearson r = .899, Spearman rho = .837 (both $p < .001$). These represent very strong positive associations by conventional thresholds (Cohen, 1988), indicating that respondents who perceived MOENCO's ad algorithms as more efficient consistently reported higher purchase intentions. Audience Precision (PREC) exhibited a strong positive correlation with Purchase Intention (Pearson r = .730, Spearman rho = .688, $p < .001$), confirming meaningful independent association. Personalization (PRES) demonstrated a moderate-to-strong positive correlation (Pearson r = .691, Spearman rho = .675, $p < .001$).

A notable methodological observation is the very high correlation between Audience Precision and Personalization (Pearson r = .896, Spearman rho = .885, $p < .001$), indicating substantial multicollinearity between these two independent variables. This result, where the two sub-dimensions of Data-Driven Targeting share approximately 80.3% of their variance ($r2 = .803$), is important for interpreting the multivariate ordinal regression results in Section 4.7. It reflects the conceptual overlap between targeting accuracy and personalization, as consumers who experience precisely targeted ads are inherently also experiencing personalized content.

4.7 Ordinal Regression Analysis

4.7.1 Model Specification and Rationale

Given the non-normal distributions confirmed in Section 4.5 and the ordinal nature of the Likert-derived dependent variable (Purchase Intention , PURCH), ordinal regression was employed as the primary hypothesis-testing method. Two complementary approaches were used: (1) SPSS PLUM (Polytomous Universal Model) ordinal regression with Logit link, and (2) SPSS Generalized Linear Models (GENLIN) with Multinomial distribution and Cumulative Logit link. Both models specify PURCH as the dependent variable with PREC, PRES, and ALGO as covariates, and produce consistent results, allowing for result triangulation.

The Cumulative Logit model is appropriate for ordered categorical outcomes and estimates the log-odds of being at or above each response category threshold for a one-unit increase in each predictor, holding other predictors constant. This approach does not require the normality or linearity assumptions of Ordinary Least Squares (OLS) regression and is well-validated for Likert-scale-derived dependent variables in social science research (Field, 2018).

4.7.2 Model Fitting Information and Pseudo R-Square

Table 7 presents the model fitting information and pseudo R-square statistics, which together evaluate the explanatory power of the full ordinal regression model relative to a baseline (intercept-only) model.

Table 7 - Model Fitting Information and Pseudo R-Square - SPSS PLUM Output (N = 308)

Statistic	Intercept Only	Final Model	Chi-Square	Sig.
-2 Log Likelihood	1513.654	1065.672	**447.982**	**.000*** **
df (predictors)	—	3	—	—
Cox and Snell		.766	Strong explanatory power	
Nagelkerke		.772	Strong explanatory power	
McFadden		.291	Good fit (McFadden > .20 = excellent)	

*Source: SPSS PLUM Ordinal Regression output. Link function: Logit. *** $p < .001$. Pseudo R-Square values indicate the proportion of variance in Purchase Intention explained by the model.*

The model fitting information confirms a highly significant overall model: the addition of three predictors (PREC, PRES, ALGO) reduced the -2 Log Likelihood from 1513.654 (intercept-only) to 1065.672 (final model), a reduction of 447.982 ($\chi 2 = 447.982$, df = 3, $p < .001$). This represents a large and statistically significant improvement in model fit.

The Pseudo R-Square statistics indicate strong explanatory power: Cox and Snell = .766, Nagelkerke = .772, and McFadden = .291. The Nagelkerke R2 of .772 suggests that approximately 77.2% of the variance in Purchase Intention is explained by the three predictors collectively. A McFadden value of .291 substantially exceeds the threshold of .20, which is typically described as an excellent fit for logistic regression models (McFadden, 1977). These values collectively indicate that the model explains a large proportion of variation in consumers' purchase intention towards MOENCO, driven by their perceptions of the three advertising dimensions.

4.7.3 Goodness of Fit - SPSS GENLIN Output

Table 8 presents the goodness-of-fit statistics from the SPSS GENLIN output, which complement the PLUM results and confirm model adequacy.

Table 8 - Goodness of Fit Statistics — SPSS GENLIN Output (N = 308)

Goodness of Fit[a]

	Value	df	Value/df
Deviance	1055.175	1392	.758
Scaled Deviance	1055.175	1392	
Pearson Chi-Square	5750.188	1392	4.131
Scaled Pearson Chi-Square	5750.188	1392	
Log Likelihood[b]	-532.836		
Akaike's Information Criterion (AIC)	1101.672		
Finite Sample Corrected AIC (AICC)	1104.039		
Bayesian Information Criterion (BIC)	1168.814		
Consistent AIC (CAIC)	1186.814		

Dependent Variable: PURCH
Model: (Threshold), PREC, PRES, ALGO

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

*Source: SPSS Generalized Linear Models (GENLIN). Dependent Variable: PURCH. Model: (Threshold), PREC, PRES, ALGO. Link Function: Cumulative Logit. Deviance/df = .758 < 1.0 indicates no over-dispersion and a good-fitting model. AIC and BIC are in smaller-is-better form. *** p < .001.*

The Deviance/df ratio of .758 (below 1.0) indicates the model does not over-predict variance, confirming a well-fitting ordinal model without evidence of over-dispersion. The Omnibus Likelihood Ratio Chi-Square of 447.982 (df = 3, p < .001) is consistent with the PLUM output and confirms that the three predictors jointly explain significantly more variance in Purchase Intention than the intercept-only model alone.

4.7.4 Tests of Model Effects - Individual Predictor Significance

Table 9 presents the Type III Likelihood Ratio tests assessing the unique contribution of each individual predictor to Purchase Intention, after controlling for the other two predictors in the model.

Table 9 - Tests of Model Effects - SPSS GENLIN Output (N = 308)

Tests of Model Effects

Source	Type III		
	Likelihood Ratio Chi-Square	df	Sig.
PREC	1.282	1	.257
PRES	1.168	1	.280
ALGO	178.067	1	.000

Dependent Variable: PURCH
Model: (Threshold), PREC, PRES, ALGO

*Source: SPSS Generalized Linear Models (GENLIN). Type III Likelihood Ratio Chi-Square tests assess the unique contribution of each predictor controlling for all others. n.s. = not significant at $p < .05$; *** $p < .001$.*

The Type III tests of model effects reveal a clear and decisive hierarchy of predictor significance in the multivariate context. Algorithmic Efficiency (ALGO) produced an overwhelming Likelihood Ratio Chi-Square of 178.067 ($df = 1$, $p < .001$), representing by far the largest unique contribution to Purchase Intention among all three predictors. Both Audience Precision (PREC: LR $\chi2 = 1.282$, $p = .257$) and Personalization (PRES: LR $\chi2 = 1.168$, $p = .280$) did not achieve statistical significance in the joint model.

This pattern of findings is directly attributable to the multicollinearity structure identified in Section 4.6. When PREC and PRES are controlled simultaneously, their near-perfect inter-correlation ($r = .896$) results in variance partitioning that renders both individually non-significant in the multivariate model, despite their strong bivariate associations with Purchase Intention. This is a well-documented statistical consequence of multicollinearity rather than an indication that these constructs are unrelated to purchase intention. Their bivariate significance (Pearson $r = .730$ and $r = .691$, respectively, $p < .001$) confirms their substantive importance.

4.7.5 Parameter Estimates - SPSS PLUM and GENLIN Output

Table 10 presents the parameter estimates for the three covariate predictors, drawn from both the SPSS PLUM and GENLIN outputs. The B coefficient represents the change in the cumulative log-odds of Purchase Intention for a one-unit increase in the predictor, and Exp(B) represents the corresponding odds ratio.

Table 10 - Parameter Estimates (Covariates) - SPSS PLUM and GENLIN Output (N = 308)

Parameter Estimates

Parameter		B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
				Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
Threshold	[PURCH=1.00]	5.529	.6461	4.263	6.796	73.250	1	.000	251.979	71.030	893.899
	[PURCH=1.40]	6.922	.7152	5.520	8.324	93.669	1	.000	1014.322	249.684	4120.609
	[PURCH=2.00]	8.076	.7294	6.646	9.505	122.595	1	.000	3215.057	769.770	13428.159
	[PURCH=2.40]	8.394	.7286	6.966	9.822	132.710	1	.000	4419.294	1059.611	18431.444
	[PURCH=2.60]	9.709	.7357	8.267	11.151	174.160	1	.000	16468.422	3894.126	69645.641
	[PURCH=2.80]	10.331	.7499	8.861	11.800	189.796	1	.000	30661.002	7051.671	133315.504
	[PURCH=3.00]	11.996	.8118	10.405	13.587	218.368	1	.000	162106.193	33022.081	795783.231
	[PURCH=3.20]	12.368	.8363	10.729	14.007	218.718	1	.000	235204.981	45664.967	1211462.239
	[PURCH=3.60]	13.350	.8942	11.598	15.103	222.900	1	.000	627918.315	108834.034	3622776.790
	[PURCH=3.80]	13.954	.9168	12.157	15.751	231.665	1	.000	1148834.399	190489.721	6928565.337
	[PURCH=4.00]	15.476	.9746	13.566	17.386	252.150	1	.000	5262439.808	779104.012	35545026.47
	[PURCH=4.20]	16.302	1.0067	14.329	18.275	262.251	1	.000	12023715.11	1671665.324	86482457.29
	[PURCH=4.40]	16.688	1.0216	14.686	18.691	266.815	1	.000	17682816.78	2387379.661	130972888.1
	[PURCH=4.60]	17.914	1.0700	15.817	20.012	280.308	1	.000	60275392.63	7402030.672	490827871.2
	[PURCH=4.80]	18.613	1.0942	16.469	20.758	289.368	1	.000	121243132.5	14199357.77	1035250849
PREC		.333	.2949	-.245	.911	1.278	1	.258	1.396	.783	2.487
PRES		.286	.2639	-.232	.803	1.171	1	.279	1.331	.793	2.232
ALGO		3.222	.2544	2.724	3.721	160.497	1	.000	25.088	15.239	41.303
(Scale)		1[a]									

Dependent Variable: PURCH
Model: (Threshold), PREC, PRES, ALGO

Parameter	B (PLUM)	Std. Error	Wald $\chi 2$	df	Sig.	Exp(B) [Odds Ratio]	95% CI for Exp(B)
PREC (Audience Precision)	.333	.298	1.253	1	.263 (n.s.)	1.396	[.783, 2.487]
PRES (Personalization)	.286	.265	1.163	1	.281 (n.s.)	1.331	[.793, 2.232]
ALGO (Algorithmic Efficiency)	**3.222**	.245	**172.974**	1	**.000*** **	**25.088**	[15.239, 41.303]

Source: SPSS PLUM Ordinal Regression and GENLIN Generalized Linear Models. B = log-odds coefficient; Exp(B) = odds ratio (exponentiated coefficient); 95% CI = 95% Wald

*Confidence Interval for Exp(B). n.s. = not significant at α = .05; *** p < .001. Link function: Logit.*

ALGO (Algorithmic Efficiency): B = 3.222, SE = .245, Wald χ2 = 172.974, p < .001, Exp(B) = 25.088 (95% CI: [15.239, 41.303]). This is the primary finding of the study. For every one-unit increase in perceived Algorithmic Efficiency on the 5-point Likert scale, the odds of a respondent being at a higher level of Purchase Intention increase by a factor of approximately 25.1, holding Audience Precision and Personalization constant. The 95% confidence interval for Exp(B) is entirely above 1.0 (ranging from 15.239 to 41.303), confirming a robust, large, and statistically significant positive effect. The Wald chi-square of 172.974 is extraordinarily large, indicating extremely high confidence in this estimate.

PREC (Audience Precision): B = .333, SE = .298, Wald χ2 = 1.253, p = .263, Exp(B) = 1.396. In the multivariate context, Audience Precision does not achieve statistical significance as an independent predictor of Purchase Intention after controlling Personalization and Algorithmic Efficiency. The confidence interval [.783, 2.487] crosses 1.0, indicating that the direction of the effect is uncertain in this multivariate specification.

PRES (Personalization): B = .286, SE = .265, Wald χ2 = 1.163, p = .281, Exp(B) = 1.331. Similarly, Personalization does not reach statistical significance as an independent predictor in the multivariate model (95% CI: [.793, 2.232], crossing 1.0). As established, this is a direct consequence of the high multicollinearity with Audience Precision (r = .896), which prevents the model from isolating Personalization's unique marginal contribution.

4.8 Hypothesis Testing Summary and Discussion

4.8.1 Summary of Hypothesis Test Results

Table 11 shows the statistical evidence from Pearson correlation, Spearman's rho, and ordinal regression (PLUM) for each of the three research hypotheses of this study.

Table 11-Summary of Hypothesis Testing Results

H#	Hypothesis	Key Statistical Evidence	Decision
H1	Audience Precision (Data-Driven Targeting sub-dimension) significantly and positively influences the Purchase Intention of Ethiopian automotive consumers.	Pearson r = .730 (p < .001); Spearman rho = .688 (p < .001); PLUM: B = .333, Wald = 1.253, p = .263 (n.s. in multivariate multicollinearity with PRES, r = .896)	Partially Supported (strong bivariate, non-significant multivariate)

H2	Ad Personalization (Data-Driven Targeting sub-dimension) significantly and positively influences the Purchase Intention of Ethiopian automotive consumers.	Pearson r = .691 (p < .001); Spearman rho = .675 (p < .001); PLUM: B = .286, Wald = 1.163, p = .281 (n.s. in multivariate - multicollinearity with PREC, r = .896)	Partially Supported (strong bivariate, non-significant multivariate)
H3	Algorithmic Efficiency (Ad Optimization sub-dimension) has a significant positive impact on the perceived Effectiveness (Purchase Intention) of MOENCO's Meta Ads.	Pearson r = .899 (p < .001); Spearman rho = .837 (p < .001); PLUM: B = 3.222, Wald = 172.974, p < .001, Exp(B) = 25.088	Strongly Supported

All Pearson and Spearman correlations are significant at p < .001 (2-tailed), N = 308. PLUM results from SPSS Ordinal Regression output. n.s. = not significant at α = .05.

In Table 11, "Strongly Supported" indicates that a hypothesis is confirmed by both the bivariate correlations and the multivariate ordinal regression. "Partially Supported" indicates that the hypothesized relationship is positive and statistically significant in the bivariate analyses (Pearson and Spearman) but does not retain independent statistical significance in the multivariate model; in this study, that loss of independent significance is attributable to the multicollinearity between Audience Precision and Personalization documented in Section 4.6, rather than to the absence of a real relationship.

4.8.2 H3: Algorithmic Efficiency - Strongly Supported

H3 - that Algorithmic Efficiency (AI-driven timing, formats, and optimization) has a significant positive impact on the perceived effectiveness of MOENCO's Meta Ads, as measured by Purchase Intention, is strongly and unequivocally supported by all forms of analysis conducted in this study.

The bivariate evidence is compelling: Pearson r = .899 (p < .001) and Spearman rho = .837 (p < .001), both representing very strong positive associations. In the multivariate ordinal regression, ALGO produced a Wald chi-square of 172.974 (p < .001) and an odds ratio of 25.088 (95% CI: [15.239, 41.303]). This means that for every one-unit increase in perceived algorithmic efficiency, the odds of a respondent being at a higher purchase intention level increase by approximately 25-fold, after controlling for audience precision and personalization. This is not merely statistically significant but practically significant, the effect size is large by any conventional standard.

These findings align strongly with the theoretical frameworks established in Chapter 2. From the Elaboration Likelihood Model (ELM) perspective (Petty & Cacioppo, 1986), algorithmic efficiency functions as a peripheral route cue that facilitates persuasion through optimally

timed, contextually relevant ad placements. For high-involvement purchase decisions such as automotive vehicles, the peripheral route signals, correct ad format, consistent brand messaging, appropriate ad frequency, and AI-optimized delivery, collectively create a decisional environment that elevates purchase intention. The Resource-Based View (RBV) provides a complementary explanation: MOENCO's investment in Meta's algorithmic tools (including Campaign Budget Optimization - CBO - and Advantage+ placements) constitutes a dynamic capability that competitors cannot easily replicate, creating a sustainable competitive advantage in the Ethiopian automotive digital marketing space (Barney, 1991); (Davenport, Guha, Grewal, & Bressgott, 2020).

So that, the finding resonates with the ML-Driven Optimization Model discussed in Chapter 2 (Hermann, 2022): Meta's machine learning algorithms dynamically allocate budget to the highest-performing audience segments and ad placements, continuously optimizing the delivery sequence to maximize conversion probability. Respondents' mean score for Algorithmic Efficiency (M = 3.7857) indicates that the majority perceive these optimization mechanisms as functioning effectively for MOENCO's campaigns, and this perception translates directly into elevated purchase intentions (M = 3.8682).

4.8.3 H1: Audience Precision - Partially Supported

H1 - that Audience Precision significantly and positively influences the Purchase Intention of Ethiopian automotive consumers, receives partial support. The bivariate evidence is strong: Pearson r = .730 ($p < .001$) and Spearman rho = .688 ($p < .001$) both indicate meaningful positive associations between how accurately consumers believe they have been targeted and their consequent purchase intentions. These are statistically significant, substantively large correlations that confirm the relevance of audience precision to purchase behavior.

However, in the multivariate ordinal regression model, PREC does not achieve independent statistical significance (B = .333, Wald = 1.253, p = .263) when PRES and ALGO are simultaneously controlled. The confidence interval for the odds ratio [.783, 2.487] crosses 1.0, indicating that the unique marginal contribution of Audience Precision cannot be reliably compared from zero in the presence of the other predictors. This non-significance is a direct statistical consequence of the near-perfect collinearity between PREC and PRES (r = .896), which inflates standard errors and reduces the statistical power available to detect each predictor's independent effect.

This finding should not be interpreted as evidence that Audience Precision is unimportant. Rather, it reflects the conceptual reality identified in the literature (Bleier & Eisenbeiss, 2015); (Kumar, Rajan, Venkatesan, & Lecinski, 2019): in consumer perception, targeting accuracy and personalization are experienced as a unified gestalt rather than separable mechanisms.

Respondents who perceive MOENCO's ads as reaching them with precision also perceive those same ads as personalized, the two constructs function as an integrated perceptual unit. Substantively, H1 is supported at the bivariate level, with the multivariate suppression attributable to methodological multicollinearity rather than conceptual irrelevance. Future research could employ structural equation modeling or partial least squares to disentangle these constructs more effectively.

4.8.4 H2: Personalization - Partially Supported

H2 - that Ad Personalization significantly and positively influences the Purchase Intention of Ethiopian automotive consumers, similarly, receives partial support, following the same pattern as H1. The bivariate evidence is positive and statistically significant: Pearson r = .691 ($p < .001$) and Spearman rho = .675 ($p < .001$), indicating a strong positive relationship between the perceived personalization of MOENCO's Meta Ads and consumers' purchase intentions.

In the multivariate ordinal regression, however, PRES does not achieve independent significance (B = .286, Wald = 1.163, p = .281). The 95% CI for Exp(B) [.793, 2.232] crosses 1.0, indicating uncertainty in the direction of the unique effect. As with PREC, this pattern arises from the high inter-correlation with Audience Precision (r = .896), which means that the variance in Purchase Intention attributable to personalization is largely already explained by PREC in the joint model, and vice versa.

This finding shows with the Persuasion Knowledge Model (Friestad & Wright, 1994) and its extensions in the data-driven advertising literature: personalized ads are effective not as an isolated variable but as the main outcome of effective data-driven targeting. Consumers experience personalization not as a discrete cause, but as the subjective quality that emerges from accurate audience segmentation. This interpretation is reinforced by the S-O-R (Stimulus-Organism-Response) framework discussed in Chapter 2: the stimulus of a targeted ad (precise + personalized) creates an internal organism response (perception of relevance) that translates into the behavioral response of purchase intention, a holistic process that is difficult to decompose into independent targeting versus personalization effects.

The mean score for Personalization (M = 3.7753, SD = .91155) confirms that respondents generally perceive MOENCO's Meta Ads as personalized to their interests and needs. Combined with the high bivariate correlation with Purchase Intention, the overall evidence substantiates H2 at the conceptual and descriptive level, with the multivariate non-significance representing a methodological artifact of construct collinearity rather than a refutation of the hypothesis.

4.9 Chapter Summary

This chapter presented the comprehensive quantitative analysis of the data collected from 308 valid respondents using IBM SPSS Statistics version 30. The chapter examined how Data-Driven Targeting (Audience Precision and Personalization) and Ad Optimization (Algorithmic Efficiency) influence the Effectiveness of Meta Ads as measured by Purchase Intention for MOENCO.

The following key findings were established:

1. Reliability: The overall 20-item instrument achieved Cronbach's Alpha = .969 (N = 308), representing excellent internal consistency. All individual items demonstrated corrected item-total correlations between .632 and .876, confirming the integrity of the measurement instrument.
2. Demographics: The sample was mostly male (73.4%), aged 25–44 (85.1%), highly educated (45.1% Master's degree or above), employed (81.8%), and daily or regular social media users (87%), with 100% having confirmed seeing a MOENCO Meta ad.
3. Descriptive Statistics: All four construct means exceeded the Likert midpoint 3.0 (range: 3.76 to 3.87), with negative skewness across all variables (range: −0.663 to −1.197), indicating positive respondent perceptions concentrated toward the upper end of the scale.
4. Normality: Both Kolmogorov-Smirnov and Shapiro-Wilk tests confirmed significant non-normality for all four constructs ($p < .001$), justifying the use of ordinal regression (PLUM and GENLIN Cumulative Logit) as the primary hypothesis-testing method.
5. Correlation: All bivariate correlations were statistically significant (Pearson and Spearman, $p < .001$). Algorithmic Efficiency demonstrated the strongest association with Purchase Intention (Pearson r = .899; Spearman rho = .837). High multicollinearity was identified between Audience Precision and Personalization (r = .896), explaining the multivariate suppression of both in the joint regression model.
6. Ordinal Regression: The overall model was highly significant (Omnibus LR $\chi 2$ = 447.982, df = 3, $p < .001$; Nagelkerke R2 = .772; McFadden = .291). Algorithmic Efficiency was the sole statistically significant predictor in the multivariate context (B = 3.222, Wald = 172.974, $p < .001$, Exp(B) = 25.088). Audience Precision ($p = .263$) and Personalization ($p = .281$) were non-significant in the joint model due to multicollinearity, though both demonstrated strong bivariate associations.
7. Hypotheses: H3 - Strongly Supported; H1- Partially Supported (strong bivariate evidence suppressed multivariate); H2-Partially Supported (strong bivariate evidence suppressed multivariate).

These findings collectively provide robust empirical evidence that Algorithmic Efficiency is the primary mechanism through which Meta Ads generate commercial effectiveness for MOENCO. The strong bivariate associations for both Audience Precision and Personalization confirm that Data-Driven Targeting is substantively meaningful as a holistic construct, even if its component dimensions are difficult to disentangle from one another in a multivariate model. Taken together, these results offer significant theoretical and practical implications for digital marketing strategy in the Ethiopian automotive sector, which are presented in Chapter 5.

CHAPTER FIVE

Results Discussion, Conclusion and Recommendations

This chapter has the research findings presented in Chapter Four with the theoretical and empirical frameworks that has been in Chapters One and Two. The chapter begins with a detailed explanation or discussions of the main results, which are then linked to the research questions of the study and the more on the broader literature on data-driven digital marketing. It then provides practical recommendations for marketing team at MOENCO and suggestions for future same research; and finally, it concludes by indicating the overall contribution to of the study.

5.1 Results Discussion

5.1.1 Overview and Sample Characteristics

Before I delve into the main hypotheses, it is appropriate to consider what the sample suggests about the nature of MOENCO current digital customers. Of the 308 respondents who participated in the study, 73.4% were male, which is consistent with the gender composition of registered vehicle owners and car enthusiasts in Addis Ababa. Notably, the respondents had a higher level of education, with 45.1% holding a master's degree and 38.6 % holding a bachelor's degree; and 81.8 % were employed. This composition is not only a demographic profile, but also an indication of the quality and reliability of the data collected. Professionally active, financially and digitally savvy respondents are prime targets for car advertisements on Meta platforms. The fact that 64.3% of the respondents use social media daily and every participant (100%) confirmed that they had previously seen MOENCO advertisements on Facebook or Instagram confirms the appropriateness of the sample and lends credibility to the subsequent findings.

This demographic composition also has implications for how the results should be interpreted theoretically. A highly educated, employed, and digitally active segment of consumers may perceive advertising stimuli through what (Petty & Cacioppo, 1986) call the 'central route', which is the process by which they evaluate messages based on the quality, relevance, and usefulness of the message rather than on external cues. Such consumers respond positively to

algorithmic efficiency and purchase intention, indicating that MOENCO meta-campaigns are not only effective in attracting attention but also in performing a basic persuasive function.

5.1.2 The Significant Role of Algorithmic Efficiency

The most striking and theoretically significant finding of this study is the strong predictive power of Algorithmic Efficiency on consumer purchase intention. In the ordinal regression model, Algorithmic Efficiency (ALGO) yielded a Wald chi-square value of 172.974 ($p < .001$) and an odds ratio of 25.088; this means that for every one-unit increase in the five-point scale, a respondent's purchase intention increases by about 25 times. This finding is not just a simple numerical result, but a significant influence that emerged even when other variables were controlled for. This is in line with the 'ML-Driven Optimization Model' (ML-Driven Optimization Model) that (Nayyar, Suman, & Lakshmi, 2024) found that machine learning-powered advertising drives better engagement and sales than traditional human-centered approaches.

In the meta-ecosystem, algorithmic optimization involves several integrated strategies: "Campaign Budget Optimization" (CBO) real-time allocation of budget to the most effective ads; 'Advantage+' automatically selects effective ad formats; and 'A/B testing' makes improvements based on customer feedback to creatives. Together, these functions ensure that advertising not only exists in the digital environment, but also that it is delivered at the right time, in the right format, and to the right audience, which the Theory of Planned Behavior has identified as essential for behavioral change (Ajzen, 1991).

From a Resource-Based View (Barney, 1991), MOENCO investment in meta-algorithmic infrastructure can be considered a 'dynamic capability' that is hard to come by, hard to replicate, and cannot be replaced in the short term. Competitors that rely on human-selected customers or static ad sets cannot easily replace the real-time optimization that meta-artificial intelligence (AI) provides at a high level. This study demonstrates that this capability translates directly into consumer behavior outcomes, strongly confirming that investment in digital algorithms in the Ethiopian automotive sector is not a cost issue but a source of competitive advantage.

The above-average mean scores for algorithmic efficiency (M = 3.7857) and purchase intention (M = 3.8682) confirm that consumers' perceptions of MOENCO advertising distribution methods are generally positive. In practice, this suggests that consumers are not simply victims of algorithmic targeting; rather, they perceive MOENCO advertisements as timely, relevant, and relevant to their Vehicles buying needs. According to the S-O-R model (Mehrabian & Russell, 1974), a well-designed advertisement acts as an external stimulus that triggers internal cognitive and emotional processes; This in turn increases the likelihood of purchasing behavior. The data from this study clearly demonstrates this trend.

5.1.3 The Audience Precision and Personalization Paradox

The results for audience precision (H1) and advertising personalization (H2) require careful interpretation. At the bivariate level, both showed strong and statistically significant positive relationships with purchase intention: Audience Precision r = .730, and Personalization r = .691 (both $p < .001$), suggesting that consumers who believe that advertisements are accurately delivered and relevant to them are more likely to purchase. This finding is supported by theoretical and empirical research on advertising effectiveness (Bleier & Eisenbeiss, 2015); (Kumar, Rajan, Venkatesan, & Lecinski, 2019).

However, the two variables did not show any independent statistical significance when entered the regression model with the algorithmic fit. The reason for this is methodological rather than conceptual: the very high correlation between the two (r = .896) creates a problem called 'multicollinearity', making it difficult to separate the contribution of each variable individually. This result does not mean that the targeting accuracy and personalization of advertisements are not important for purchase intention; rather, it suggests that they are perceived as a single entity in the minds of consumers. When a respondent feels that a MOENCO advertisement has been delivered accurately, he or she also feels that the advertisement has been personalized to him or her; these two things are inseparable from the consumer's perspective.

This interpretation is also supported by theory. According to the 'Persuasion Knowledge Model', consumers do not view the internal structure of advertisements in isolation; Rather, they are concerned with whether the ad is "accurate" or not. Self-Reference Theory suggests

that personal information is more likely to be perceived as relevant to an individual's identity and interests, which is itself a result of accurate audience segmentation. Accordingly, the high correlation between the two variables observed in the study is not a computational error, but a real psychological fact that Ethiopian automotive consumers perceive ad targeting and privacy as two aspects of the same thing.

Another issue to consider is the state of the Ethiopian digital market. As the study's findings show, Ethiopia's digital landscape is still developing and there is a wide gap in digital literacy among the population. The participants in this study are highly educated and frequent users of social media, which may have a better understanding of the privacy practices used by Meta than the average. As the 'persuade knowledge model' predicts, such consumers tend to evaluate advertisements as a single message rather than as a collection of messages. Future studies could investigate whether Ethiopian consumers with low digital literacy respond differently to these two factors.

5.1.4 Descriptive Patterns and Their Meaning

The average scores on the four items ranged from 3.76 to 3.87 on a five-point Likert scale, with scores skewed negatively towards "agree" and "strongly agree". While this result is encouraging, it also poses some limitations in the calculation. On the positive side, MOENCO current meta-advertising strategy appears to be acceptable to its target audience in Addis Ababa. On the other hand, the fact that the scores are clustered in one direction makes it difficult to distinguish between differences during regression analysis, which is why we chose ordinal regression over a simple regression method. The model strength is demonstrated by the Nagelkerke $R^2 = .772$ and McFadden = .291, as well as the chi-square test ($p < .001$), which clearly explains the large variance in the intention to buy together. The very high reliability of the questionnaire (Cronbach's $\alpha = .969$) demonstrates the validity of the instrument and theoretical model used in the study.

5.1.5 Contextual relevance:

Digital advertising in the Ethiopian automotive sector It is important to note that the Ethiopian automotive market has a unique position in the overall African digital economy. As mentioned at the beginning of the study, MOENCO was in a "vanity metric trap"; that is, despite having

a lot of digital engagement (likes, shares), this did not translate into sales. The findings of this study provide a clear solution to this problem: The key to converting digital impressions into purchase intent is not simply to increase the audience with demographic information, but to optimize the delivery of advertising in an algorithmic manner, delivering the right content to the right person at the right time. This helps to fill the gap in digital marketing in East Africa and Ethiopia.

5.2 Conclusion

This study, focusing on MOENCO, examined the role of data-driven targeting and ad optimization methods in the effectiveness of meta-ads. The main question was to what extent audience accuracy, privacy, and algorithmic efficiency influence consumer purchase intent. The data from 308 respondents confirmed the following key points.

First, algorithmic efficiency' emerged as the main driver of purchase intent. The third hypothesis, which was that the use of artificial intelligence-driven timing, format, and optimization would increase advertising effectiveness, was strongly supported. This shows that the power of digital advertising in the Ethiopian automotive sector lies not only in targeting but also in the optimization process. Knowing who the audience is is not enough; rather, applying that knowledge in a self-improving intelligent system provides a competitive advantage.

Second, although the independent effects of audience accuracy and privacy are not emphasized in the regression model, the results of the bivariate association show that these factors have a significant impact on consumer purchase intention. Ethiopian consumers do not see accuracy and privacy separately; they are indicators of the relevance of an advertisement to them. Therefore, the first and second hypotheses are partially supported.

Third, the overall model explains 77.2 percent of the variance in purchase intention, which confirms that the theories selected in the study are highly relevant to the Ethiopian context. Overall, the study shows that while the 'Explanatory Leap Model' (ELM) works in theory in emerging digital markets, it also provides data-based evidence that investing in algorithmic improvements is a key path to sales for MOENCO and similar organizations.

5.3 Recommendations

5.3.1 Practical and Management Recommendations

a) Prioritize algorithmic optimization:

MOENCO marketing management should use meta-algorithmic tools as the core of their campaigns, not as an add-on. This includes using budget optimization (CBO), activating 'Advantage+' campaigns, and conducting regular 'A/B testing'. The study shows that allowing the algorithm to make its own decisions produces better results than artificial constraints.

b) Change success metrics:

MOENCO should move away from artificial metrics like likes and shares and focus on metrics that drive sales (such as form registrations, website visit times, and customer re-engagement). The algorithm will perform better when ads are structured in a way that is aligned with sales and lead generation.

c) Adopt a combined targeting strategy:

Since audience identification and content personalization are seen as one thing by consumers, MOENCO should not view them separately. For example, targeting and content can be combined by offering content about Toyota Land Cruiser to off-road enthusiasts and content about BYD electric vehicles to city dwellers. Using similar audiences, called 'Lookalike Audiences', will also contribute significantly to the relevance of the ad.

d) Build internal capacity:

MOENCO should have a skilled workforce that can analyze campaign data and adjust algorithms. Training the team on the use of Meta Ads Manager, Meta Pixel, and the 'Conversions API' will help maintain a competitive edge.

e) Addressing privacy concerns through clear communication:

To ensure that consumers do not feel that advertisements are intrusive, MOENCO should clearly communicate that it uses the information to provide better services and useful information to consumers.

5.3.2 Suggestions for future research

This study has necessarily operated within certain methodological and contextual boundaries that future research should seek to expand. Several directions for productive inquiry suggest themselves based on the findings and limitations encountered.

The high inter-correlation between Audience Precision and Personalization (r = .896) posed the primary methodological challenge in this study. Future research should consider employing Structural Equation Modeling (SEM) or Partial Least Squares-SEM (PLS-SEM) to disentangle the direct and indirect effects of these two constructs more effectively, as these techniques are better suited to handling correlated latent variables and can model mediating and moderating pathways that ordinal regression cannot accommodate. A well-specified SEM would be particularly valuable in testing whether Algorithmic Efficiency mediates the relationship between Data-Driven Targeting and Purchase Intention, or whether it acts as a moderator that amplifies targeting effectiveness under certain conditions.

Second, this study was confined to Addis Ababa, which limits the generalizability of the findings to MOENCO's customer base in other Ethiopian cities or to the broader East African automotive market. Future studies should expand the geographical scope to include secondary cities such as Dire Dawa, Mekelle, and Hawassa, where digital penetration is growing but the socioeconomic profile and digital literacy of consumers may differ markedly from the Addis Ababa sample. A multi-city or multi-country comparative study would yield valuable insights into how contextual digital development level moderates the relationship between algorithmic advertising and purchase intention.

Third, the dependent variable in this study was Purchase Intention, which is a psychological proxy for actual purchase behavior. While purchase intention is a well-validated predictor of behavior in the TPB literature, there is always a gap between intention and action, particularly for high-involvement product categories like automobiles. Future research should attempt to

link Meta advertising exposure and perceived effectiveness measures to actual sales data, ideally through a mixed-methods design that combines survey data with MOENCO's internal CRM and sales records. Such a design would allow researchers to measure not just what consumers intend but what they actually do as a downstream result of Meta advertising exposure.

Fourth, as MOENCO and other Ethiopian companies begin distributing electric vehicles (particularly under the BYD brand), the role of digital education content distinct from commercial advertising in shifting consumer attitudes and purchase intentions toward EVs deserves dedicated scholarly attention. Future research could investigate how algorithmic optimization can be leveraged to educate consumers about electric vehicle technology, address range anxiety and charging infrastructure concerns, and accelerate the adoption curve for a product category that is entirely new to the Ethiopian market.

Finally, as Meta's advertising algorithms evolve at a rapid pace incorporating generative AI-driven creative production, expanded Advantage+ automation, and new measurement infrastructure following post-GDPR third-party cookie deprecation the relationships identified in this study should be periodically re-examined. Digital advertising is not a static phenomenon, and the competitive dynamics of the Ethiopian market will change as broadband penetration increases, smartphone adoption widens, and digital literacy improves across demographic segments. Longitudinal and panel-based studies that track the same consumer cohort over multiple advertising exposure cycles would be particularly valuable in mapping how algorithmic advertising effects evolve with market maturation.

In short:

- ✓ Future studies should use Structural Equation Modeling (SEM) to identify the strong relationship between the two variables.
- ✓ Expanding the scope of the study to cities outside Addis Ababa, such as Dire Dawa, Mekelle, and Hawassa, would help to understand consumer differences.
- ✓ Beyond purchase intention, it would be useful to study the impact of advertisements on direct sales by linking them to the organization's sales data (CRM).
- ✓ Especially for new electric vehicles (EVs), it would be good to study how algorithms can help educate consumers and change perceptions.

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Appendix

Appendix 1:

ADDIS ABABA UNIVERSITY, SCHOOL OF COMMERCE

RESEARCH QUESTIONNAIRE

Title: The Role of Data-Driven Targeting and Ad Optimization on the Effectiveness of Meta Ads Case Study: MOENCO (Automotive Sector)

INTRODUCTION

Dear Respondent,

My name is Anteneh Kibret. I am conducting this study for my MSc in Digital Marketing with a Specialty in E-Commerce. This research examines how data-driven targeting and ad optimization influence the performance of Facebook and Instagram advertisements (Meta ads), with a focus on MOENCO.

Your answers will remain confidential and will be used for academic purposes only. The report will present the results in aggregated form without any personal details.

Your response improves the quality of this research. Thank you for your time.

Read each question carefully. Select the option that matches your level of agreement.

PART I: DEMOGRAPHIC AND BACKGROUND INFORMATION

The following questions gather basic background information about participants. Please read each question carefully and select the single option that best describes you:

1. **Gender**

   ☐ Male

   ☐ Female

2. **Age**

   ☐ 18–24

   ☐ 25–34

   ☐ 35–44

   ☐ 45–54

   ☐ Above 55

3. **Highest Educational Level**

   ☐ Diploma

   ☐ Bachelor's Degree

   ☐ Master's Degree

   ☐ PhD or Above

4. **Occupation**

   ☐ Student

   ☐ Employed

   ☐ Self-Employed

   ☐ Other

5. **Frequency of Facebook or Instagram Use**

☐ Daily

☐ Weekly

☐ Occasionally

6. **Have you ever seen a MOENCO (Toyota, BYD, or Machinery) ad on Facebook or Instagram?**

☐ Yes

☐ No (If no, thank you for your time)

PART II: DATA-DRIVEN TARGETING

For each statement below, please indicate your level of agreement or Disagreement using the following scale:

1. Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

A. Audience Precision (Pixel or Lookalike Audiences)

7. MOENCO Facebook and Instagram advertisements (Meta ads) shown to me are relevant to my interests.

   1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

8. The MOENCO Facebook and Instagram advertisements (Meta ads) I see match my recent online behavior.

   1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

9. MOENCO Facebook and Instagram advertisements (Meta ads) reach me when I am actively interested in similar products or services.

   1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

10. The targeting accuracy of MOENCO Facebook and Instagram advertisements (Meta ads) is high.

    1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

11. MOENCO Facebook and Instagram advertisements (Meta ads) reflect my demographic and behavioral characteristics.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

B. Personalization

12. MOENCO Facebook and Instagram advertisements (Meta ads) feel personalized to my specific needs.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

13. The content of MOENCO Facebook and Instagram advertisements (Meta ads) reflects my personal preferences.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

14. Personalized MOENCO Facebook and Instagram advertisements (Meta ads) are more engaging than generic ads.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

15. Personalized MOENCO Facebook and Instagram advertisements (Meta ads) attract my attention more easily.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

16. Personalized MOENCO Facebook and Instagram advertisements (Meta ads) increase my interest in the advertised product or service.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

PART III: AD OPTIMIZATION

For each statement below, please indicate your level of agreement or Disagreement using the following scale:

1. Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

C. Algorithmic Efficiency (CBO and AI Optimization)

17. MOENCO Facebook and Instagram advertisements (Meta ads) are delivered efficiently using automated optimization tools.

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

18. AI-based optimization improves the relevance of MOENCO Facebook and Instagram advertisements (Meta ads)

    1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

19. MOENCO Facebook and Instagram advertisements (Meta ads) appear at appropriate times during the day.

    1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

20. MOENCO Facebook and Instagram advertisements (Meta ads) reach me through suitable formats (image, video, carousel, etc.).

    1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

21. Optimized MOENCO Facebook and Instagram advertisements (Meta ads) provide consistent and clear messaging.

    1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

PART IV: EFFECTIVENESS OF META ADS

For each statement below, please indicate your level of agreement or Disagreement using the following scale:

1. Strongly Disagree, 2 – Disagree, 3 – Neutral, 4 – Agree, 5 – Strongly Agree

D. Purchase Intention

22. MOENCO Facebook and Instagram advertisements (Meta ads) increase my interest in the advertised product or service.

    1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

23. MOENCO Facebook and Instagram advertisements (Meta ads) influence my intention to purchase.

    1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

24. I am more likely to consider a product after seeing MOENCO Facebook and Instagram Advertisements (Meta ads)

    1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

25. MOENCO Facebook and Instagram advertisements (Meta ads) positively affect my buying decision.

    1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

26. MOENCO Facebook and Instagram advertisements (Meta ads) motivate me to make inquiries or submit my contact details.

    1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐