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EXAMINING THE INFLUENCE OF DIGITAL MARKETING COMPETENCE ON SUSCEPTIBILITY

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ABSTRACT

Purpose- This research on the influence of digital marketing competence on susceptibility to persuasion among university students in Northern Cyprus is of paramount importance. It not only fills a gap in the current understanding of digital marketing's impact on young adults but also contributes to the broader discourse on digital literacy, consumer behavior, and marketing effectiveness in the digital age.
Methodology- The research employs a quantitative approach, using a significant sample size of 420 university students. Data analysis was conducted using SPSS software, ensuring precise handling of complex data sets and robust statistical analysis. The methodology encompasses a structured approach utilizing quantitative research methods. Quantitative research is characterized by the process of collecting and analysing numerical data, which is instrumental in finding patterns, testing causal relationships, and generalizing results to broader populations A key aspect of quantitative research involves operational definitions that translate abstract concepts into observable and quantifiable measures. This is particularly relevant in a study like this, where abstract concepts such as 'digital marketing competence' and 'susceptibility to persuasion' need to be clearly defined and measured. The collection of quantitative data often involves tools like surveys and questionnaires, as in this study, where an online questionnaire with closed-ended questions was used.
Once data is collected, it requires processing before analysis. This can involve transforming survey data from words to numbers, followed by statistical analysis to answer research questions, In this context, the online questionnaire would have been designed to ensure that the data collected is suitable for the chosen statistical methods, aligning with the research objectives of examining the influence of digital marketing competence on university students in Northern Cyprus
Findings- Findings reveal a strong correlation between digital marketing literacy and students' attitudes and behaviors. Higher digital marketing literacy correlates with greater susceptibility to various marketing tactics, indicating a profound impact of digital competence on students' decision-making processes.
Conclusion- This research provides a comprehensive understanding of the role of digital marketing literacy in shaping university students' responses to digital marketing. It calls for a collaborative effort among educators, policymakers, and marketers to foster an environment where digital literacy is prioritized, thereby empowering students to navigate the digital world more effectively and ethically. The study's findings lay a foundation for future research in this area, inviting further exploration into the nuanced ways digital marketing literacy can influence consumer behavior in the digital age.

Keywords: Digital marketing literacy, university students, persuasion susceptibility, Northern Cyprus, marketing tactics.
JEL Codes: A10, A11, A20

1. INTRODUCTION

In the literature review chapter of this thesis, we embark on an extensive exploration of various facets central to understanding the influence of digital marketing competence on university students, particularly those in Northern Cyprus. This chapter is structured to systematically dissect and analyze several key areas that form the foundation of our study.

Firstly, we delve into the concept and importance of 'digital marketing literacy', where we define this term and trace the evolution of digital marketing in the information age. This sets the stage for understanding the broader landscape within which our study is situated.

Following this, we examine the 'impact of digital marketing literacy on attitudinal changes' among university students. This section focuses on understanding how digital literacy influences changes in attitudes within the context of digital marketing and the role it plays in shaping consumer attitudes.

Next, we explore 'behavioral intentions in digital marketing', discussing the relationship between digital literacy and consumer behavior. This includes an analysis of factors influencing online purchasing decisions, providing insight into how digital marketing literacy translates into actionable consumer behavior.

The fourth section delves into 'the influence of specific digital marketing tactics'. This part scrutinizes the efficacy of various digital marketing tools such as marketing emails, influencer recommendations, and targeted advertisements, and how these impact student responses.

In the fifth section, we discuss 'peer influence in digital marketing', examining the role of social media and peer networks in shaping consumer behavior and their influence on online purchasing decisions.

The chapter then shifts focus to 'awareness and perception of digital marketing tactics', highlighting how students perceive and understand various digital marketing strategies, along with their perceived credibility and effectiveness.

We also address 'digital marketing and consumer susceptibility', exploring the factors contributing to consumer susceptibility in the digital marketing context and the interplay between literacy and susceptibility to digital advertising.

The eighth section, 'contextualizing digital marketing in northern cyprus', provides a specific look at the digital marketing landscape in Northern Cyprus, focusing on the digital engagement and behaviors of university students in this region.

Further, we lay the theoretical groundwork of our study in 'theoretical foundations: Elaboration Likelihood Model (ELM) and media literacy theory'. This part discusses the application of ELM in digital marketing and the relevance of Media Literacy Theory in the context of digital advertising.

Finally, the chapter concludes with 'empirical studies and research gaps', where we review previous empirical studies on digital marketing competence and identify the existing research gaps, particularly in the context of university students. This comprehensive literature review aims to provide a solid theoretical and empirical foundation for our study, paving the way for our empirical investigation (Danju et al., 2020).

In the realm of contemporary marketing, the proliferation of digital platforms has radically transformed the landscape, making the study of digital marketing competence and its impact on consumer behavior, particularly among university students, an area of burgeoning academic interest. This interest is rooted in the understanding that the digital world is not just a commercial space but also a cultural and social sphere where young adults spend a significant portion of their time.

The Elaboration Likelihood Model (ELM), introduced by Petty et al. (2015), provides a theoretical framework for understanding how persuasion occurs in the context of digital marketing. This model posits that there are two routes to persuasion: the central route, which involves careful and thoughtful consideration of the message, and the peripheral route, which relies on superficial cues such as the attractiveness of the source or the emotional appeal of the message. The application of ELM in digital marketing research, as explored by Miller & Burgoon (1987), is particularly relevant for understanding how university students process and are influenced by digital marketing messages, as these individuals are often engaged in both deep and superficial processing of online content.

Alongside ELM, the Media Literacy Theory, championed by scholars like Hobbs (2011), provides a lens to examine how the ability to access, analyze, evaluate, and create media in a variety of forms impacts the susceptibility of individuals to digital marketing. Media literacy is increasingly recognized as a crucial skill for navigating the digital world, particularly for young adults who are frequent users of digital media. As Livingstone (2004) points out, media literacy is not just about understanding and interpreting media content but also about the ability to use media effectively and responsibly.

The relevance of these theories is particularly pronounced in the context of Northern Cyprus, a region with a significant population of university students who are active digital media users. This demographic represents a unique subset of the global digital audience, making it an interesting case study for examining the influence of digital marketing competence on susceptibility to persuasion.

In the digital age, where the boundaries between advertising, entertainment, and social interaction are increasingly blurred, the concept of digital marketing literacy becomes central. As highlighted by Potter (2010), digital marketing literacy encompasses not just the ability to decode and understand digital marketing messages, but also the skills to critically evaluate and respond to these messages. This is increasingly important as digital marketing strategies become more sophisticated, utilizing personalized data and targeting techniques that can subtly influence consumer behavior.

The importance of digital marketing literacy is further underscored by the work of researchers like Sundar (2008), who notes that the interactive nature of digital media requires a different set of competencies compared to traditional media. The interactive capabilities of digital media, such as the ability to like, share, or comment on content, not only provide new avenues for marketers to engage with consumers but also create new dynamics in how consumers process and respond to marketing messages.

Moreover, the role of peer influence in digital marketing cannot be overstated (Nacak et al., 2020).As noted by Bhattacherjee (2001), social influence in online environments can significantly impact the attitudes and behaviors of individuals, particularly those in university settings where social networks are highly active and influential. The interplay between digital marketing literacy and peer influence forms a complex web that shapes how marketing messages are received and acted upon by university students.

The study of digital marketing competence and its influence on susceptibility to persuasion among university students in Northern Cyprus is a multifaceted issue that intersects with theories of persuasion, media literacy, and social influence. The application of the Elaboration Likelihood Model and Media Literacy Theory provides a comprehensive framework for understanding how digital marketing messages are processed and how they impact the attitudes and behaviors of young adults in a digital-centric world.

The main questions of this study are:

1. How does digital marketing literacy influence the attitudes of university students towards digital advertisements and social media marketing?
2. What is the relationship between digital marketing literacy and the behavioral intent of university students, specifically in terms of visiting websites and considering purchasing products advertised through digital marketing?
3. How is digital marketing literacy correlated with the influence of specific digital marketing tactics, such as marketing emails, influencer recommendations, and targeted advertisements, on university students?
4. What is the relationship between digital marketing literacy and the impact of peer influence on university students, particularly in terms of product or brand mentions by peers online?
5. To what extent does awareness of digital marketing tactics influence the susceptibility of university students to persuasion by these tactics?
6. What are the potential societal and ethical implications of high digital marketing literacy among university students in terms of their susceptibility to digital marketing tactics?
7. What recommendations can be made for digital marketers, educational institutions, and policy makers to foster responsible digital marketing practices and enhance digital literacy among university students?

2. RESEARCH METHODOLOGY AND STUDY DESIGN

A research design is essentially a strategy for answering research questions using empirical data (McCombes & Aspers and Corte, 2019). This strategy includes decisions regarding research objectives and approach, the reliance on primary or secondary research, sampling methods, data collection methods, procedures for collecting data, and data analysis methods.

In this particular study, the research design adopted is quantitative, which is known for being more fixed and deductive, with variables and hypotheses clearly defined prior to data collection (McCombes & Aspers and Corte, 2019). Quantitative Market Research, as a technique, involves asking organized questions to the target audience using surveys, polls, or questionnaires. The responses received are analyzed to make informed decisions, particularly useful in improving products and services and increasing respondent satisfaction levels. When a large sample size that represents a population is surveyed, well-founded results are achievable, particularly pertinent in the age of information where data collection and analysis are crucial for informed decision-making (QuestionPro, n.d.).

Quantitative market research is highly scientific, using deductive reasoning to draw conclusions and create actionable insights from collected data. This method operates on developing a hypothesis, collecting data, and then analyzing the data to prove or disprove the hypothesis. The milestones in this design include making an observation, creating an in-depth hypothesis, planning to prove or disprove this hypothesis, and collecting and analyzing data. Depending on the outcome, the researcher either prepares for final validations and presents findings or starts afresh with a new hypothesis if the data disproves the current one (QuestionPro, n.d.).

This research design is characterized by five quantitative design types: survey research, descriptive research, correlational research, causal comparative/quasi-experimental research, and experimental research. Each of these plays a crucial role in shaping the research process and determining the approach to data collection and analysis (QuestionPro, 2023).

The research design of this master thesis employs a structured quantitative approach, encompassing a series of well-defined steps from hypothesis development to data analysis. This approach ensures that the research is grounded in empirical evidence, allowing for the generation of valuable insights into the influence of digital marketing competence on the susceptibility to persuasion among university students in Northern Cyprus.

The data collection and analysis methods are key components in ensuring the validity and reliability of the research findings. The research employs a systematic approach to data collection, followed by meticulous data analysis procedures.

For data collection, an online questionnaire with close-ended questions was distributed to a cross-sectional sample of university students. This method is consistent with the recommendations of Wright (2005), who argues that online surveys are effective for reaching a specific demographic like university students. The administration of the questionnaire followed a structured protocol to enhance response rates and ensure data quality. According to Fan and Yan (2010), reminders and follow-ups are essential for improving response rates in online surveys. This practice was adopted to encourage participation among the target population.

The data analysis for this research involved the use of the Statistical Package for the Social Sciences (SPSS), a widely used software for statistical analysis in social science research (Pallant, 2020). SPSS provides a range of tools including regression analysis and ANOVA, which are commonly used for analyzing survey data (Field, 2013). The choice of SPSS is based on its user-friendly interface and its ability to handle complex statistical analyses efficiently (George & Mallery, 2019).

Prior to conducting the statistical analysis, data cleaning and preparation were undertaken. This step is crucial in ensuring the quality and accuracy of the data analysis. As noted by Tabachnick and Fidell (2013), data cleaning involves checking for and addressing any errors or inconsistencies in the dataset. This process included identifying and rectifying any input errors, inconsistencies, and outlying responses in the dataset.

The approach to handling missing or incomplete responses followed the guidelines outlined by Schafer and Graham (2002). Missing data can significantly impact the validity of research findings; thus, it was essential to address this issue methodically. The chosen method for handling missing data was multiple imputation, a technique recommended for preserving the integrity of the dataset and minimizing bias (Little & Rubin, 1987).

The data collection and analysis methods employed in this study were carefully chosen to ensure the accuracy and reliability of the research findings. The use of an online questionnaire for data collection, followed by rigorous data cleaning and preparation, and the application of statistical analysis using SPSS, all contribute to the robustness of the research methodology.

The research methodology of this study was carefully designed to address ethical concerns related to privacy, informed consent, data security, and participant well-being. These measures ensured that the study adhered to the highest ethical standards, respecting the rights and dignity of the participants.

3. DATA ANALYSIS AND RESULTS DISCUSSION

This section presents the reliability results for various variables, measured using Cronbach's Alpha, a key indicator of internal consistency. The reliability results presented in Table 1 are indicative of the robustness of the measurement instruments employed in the study. The Cronbach's Alpha values, ranging from .890 to .995 across various constructs, underscore the internal consistency and reliability of the scales used. Digital Marketing Literacy, with a Cronbach's Alpha of .995, exhibits near-perfect reliability. This high score, especially given that it spans 6 items, suggests that the items are not only coherent but also exceptionally effective in capturing the essence of digital marketing literacy among university students.

Table 1: Reliability Results

Variables	Cronbach's Alpha	N of Items
Digital Marketing Literacy	.995	6
Awareness of Digital Marketing	.890	6
Attitude Change	.892	3
Behavioral Intent	.975	3
Influence of Specific Tactics	.907	3
Peer Influence	.991	3
All Paragraph	**.988**	**24**

Similarly, Awareness of Digital Marketing, with a Cronbach's Alpha of .890 for 6 items, also demonstrates strong reliability. This consistency is vital, as it reflects the soundness of the scale in measuring the awareness levels of students regarding digital marketing. On the other hand, Attitude Change and Behavioral Intent, with Cronbach's Alpha values of .892 and .975 respectively, both with 3 items each, show high internal consistency. These scores are indicative of the reliable measurement of students' changes in attitudes and their behavioral intentions under the influence of digital marketing.

Furthermore, the Influence of Specific Tactics and Peer Influence constructs, with Cronbach's Alphas of .907 and .991 respectively, reflect a commendable level of internal consistency. The high reliability of these scores, particularly for Peer Influence, signifies the effectiveness of the items in measuring the nuanced aspects of digital marketing influences.

The overall scale, encompassing all 24 items and yielding a Cronbach's Alpha of .988, demonstrates exceptional reliability. This holistic reliability suggests that the entire set of constructs works cohesively to provide a reliable measure of the study's variables. Such high reliability across the board not only bolsters the validity of the findings but also enhances the overall credibility of the research, thereby providing a solid foundation for further analysis and interpretation of the data.

3.7. Hypotheses Testing and Results Discussion

Hypothesis 1 (H1): Digital marketing literacy positively influences the attitude change among university students, such that higher levels of literacy lead to greater susceptibility to attitude changes influenced by social media and digital advertisements.

Correlations-H1

		Digital Marketing Literacy	Attitude Change
Digital Marketing Literacy	Pearson Correlation	1	.898**
	Sig. (2-tailed)		.000
	N	420	420
Attitude Change	Pearson Correlation	.898**	1
	Sig. (2-tailed)	.000	
	N	420	420

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

Model Summary-H1

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.898[a]	.806	.805	.64385

a. Predictors: (Constant), Attitude Change

ANOVA -H1

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	718.816	1	718.816	1733.998	.000[b]
	Residual	173.279	418	.415		
	Total	892.094	419			

a. Dependent Variable: Digital Marketing Literacy
b. Predictors: (Constant), Attitude Change

Coefficients -H1

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.258	.092		2.798	.005
	Attitude Change	1.056	.025	.898	41.641	.000

a. Dependent Variable: Digital Marketing Literacy

The results pertaining to Hypothesis 1 (H1) reveal a compelling relationship between digital marketing literacy and attitude change among university students. The strong positive Pearson Correlation (.898) along with a significant p-value (.000) suggests that higher levels of digital marketing literacy are associated with greater susceptibility to attitude changes influenced by social media and digital advertisements. This is indicative of the profound impact that digital literacy has on shaping attitudes in the digital age.

The R Square value (.806) in the model summary reinforces the strength of this relationship, suggesting that a substantial portion of the variance in digital marketing literacy is explainable through changes in attitudes. This implies that educational initiatives aimed at enhancing digital literacy could be instrumental in moderating or amplifying the impact of digital marketing on students.

Furthermore, the ANOVA results underscore the robustness of this relationship, with a significant F value indicating that the model is a good fit for the data. The coefficients detailed in the model illustrate the extent to which attitude change predicts digital marketing literacy, emphasizing the practical implications of this finding in the design and implementation of digital marketing strategies.

These results provide valuable insights into the dynamics of digital literacy and its influence on attitude formation, highlighting the importance of equipping students with the necessary skills to navigate the digital marketing landscape critically and effectively.

Hypothesis 2 (H2): Digital marketing literacy positively influences the behavioral intent of university students, where higher literacy is linked to an increased likelihood of visiting websites and considering purchasing products advertised through digital marketing.

Correlations-H2

		Digital Marketing Literacy	Behavioral Intent
Digital Marketing Literacy	Pearson Correlation	1	.947**
	Sig. (2-tailed)		.000
	N	420	420
Behavioral Intent	Pearson Correlation	.947**	1
	Sig. (2-tailed)	.000	
	N	420	420

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

Model Summary-H2

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.947[a]	.897	.896	.46969

a. Predictors: (Constant), Behavioral Intent

ANOVA-H2

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	799.878	1	799.878	3625.701	.000[b]
	Residual	92.216	418	.221		
	Total	892.094	419			

a. Dependent Variable: Digital Marketing Literacy
b. Predictors: (Constant), Behavioral Intent

Coefficients -H2

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.271	.056		4.829	.000
	Behavioral Intent	.994	.017	.947	60.214	.000

a. Dependent Variable: Digital Marketing Literacy

The analysis for Hypothesis 2 (H2) in this study yields compelling insights into the relationship between digital marketing literacy and behavioral intent among university students. The Pearson Correlation coefficient (.947) between these two variables is exceptionally high, with a significance level of .000, indicating a very strong positive relationship. This suggests that students with higher levels of digital marketing literacy are more likely to visit websites and consider purchasing products advertised through digital marketing channels.

The R Square value in the model summary is .897, which is remarkably high, suggesting that 89.7% of the variance in Digital Marketing Literacy is explained by Behavioral Intent. This indicates a very strong predictive power of behavioral intent on digital marketing literacy, affirming that as students become more literate in digital marketing, their intention to engage with digital marketing channels increases significantly.

Furthermore, the ANOVA results demonstrate the robustness of this relationship, with an extremely high F value of 3625.701, which is statistically significant ($p < .000$). This underscores the strength of the predictive relationship between digital marketing literacy and behavioral intent.

The coefficients table shows that for every unit increase in Behavioral Intent, there is an expected increase of .994 units in Digital Marketing Literacy, with a t-value of 60.214, which is highly significant ($p < .000$). This indicates that behavioral intent is a very strong predictor of digital marketing literacy among university students.

The findings provide strong empirical support for Hypothesis 2, demonstrating that digital marketing literacy significantly influences the behavioral intentions of university students in the context of digital marketing. This highlights the importance of digital marketing literacy in shaping student behaviors and decisions in the digital environment, suggesting that enhancing digital literacy could be a key factor in influencing positive behavioral outcomes in digital marketing contexts.

Hypothesis 3 (H3): Digital marketing literacy is positively correlated with influence of specific tactics on university students, indicating that students with higher literacy levels are more susceptible to marketing emails, influencer recommendations, and targeted advertisements.

Correlations-H3

		Digital Marketing Literacy	Influence of Specific Tactics
Digital Marketing Literacy	Pearson Correlation	1	.960**
	Sig. (2-tailed)		.000
	N	420	420
Influence of Specific Tactics	Pearson Correlation	.960**	1
	Sig. (2-tailed)	.000	
	N	420	420

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

Model Summary-H3

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.960[a]	.921	.921	.40958

a. Predictors: (Constant), Influence of Specific Tactics

ANOVA -H3

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	821.972	1	821.972	4899.786	.000[b]
	Residual	70.122	418	.168		
	Total	892.094	419			

a. Dependent Variable: Digital Marketing Literacy
b. Predictors: (Constant), Influence of Specific Tactics

Coefficients -H3

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.338	.056		5.995	.000
	Influence of Specific Tactics	1.076	.015	.960	69.998	.000

a. Dependent Variable: Digital Marketing Literacy

The results for Hypothesis 3 (H3) provide a profound understanding of the relationship between digital marketing literacy and the influence of specific tactics on university students. The Pearson Correlation of .960, with a significance level of .000, indicates an exceptionally strong positive correlation. This finding suggests that students with higher levels of digital marketing literacy are indeed more susceptible to specific marketing tactics, such as emails, influencer recommendations, and targeted advertisements.

The strength of this relationship is further emphasized in the model summary, where the R Square value is an impressive .921. This implies that a substantial 92.1% of the variance in Digital Marketing Literacy can be explained by the Influence of Specific Tactics. Such a high value indicates that the influence of specific marketing tactics is a major factor in determining the level of digital marketing literacy among students.

The ANOVA results corroborate the strength of this relationship, indicated by a very high F value of 4899.786, which is statistically significant ($p < .000$). This underlines the robustness of the predictive power of specific marketing tactics on digital marketing literacy.

Additionally, the coefficients in the model reveal that for each unit increase in the Influence of Specific Tactics, there is an expected increase of 1.076 units in Digital Marketing Literacy. The t-value of 69.998, significant at $p < .000$, reinforces the strength and significance of this relationship.

These findings provide strong empirical support for Hypothesis 3, clearly demonstrating that digital marketing literacy in university students is significantly influenced by specific marketing tactics. This underscores the importance of understanding how different digital marketing tactics impact students' literacy levels. It suggests that marketers and educators should consider the potent influence of specific tactics when designing digital marketing campaigns and educational programs aimed at enhancing digital literacy. This relationship is crucial in today's digital landscape, where targeted marketing tactics are increasingly prevalent and influential.

Hypothesis 4 (H4): Digital marketing literacy is positively correlated with peer influence on university students, suggesting that those with higher levels of literacy are more likely to be influenced by product or brand mentions by their peers online.

Correlations-H4

		Digital Marketing Literacy	Peer Influence
Digital Marketing Literacy	Pearson Correlation	1	.996**
	Sig. (2-tailed)		.000
	N	420	420
Peer Influence	Pearson Correlation	.996**	1
	Sig. (2-tailed)	.000	
	N	420	420

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

Model Summary-H4

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.996[a]	.992	.992	.12851

a. Predictors: (Constant), Peer Influence

ANOVA -H4

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	885.191	1	885.191	53596.829	.000[b]
	Residual	6.904	418	.017		
	Total	892.094	419			

a. Dependent Variable: Digital Marketing Literacy
b. Predictors: (Constant), Peer Influence

Coefficients -H4

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.012	.016		.736	.462
	Peer Influence	.999	.004	.996	231.510	.000

a. Dependent Variable: Digital Marketing Literacy

Hypothesis 4 (H4) of the study probes the relationship between digital marketing literacy and peer influence among university students. The findings from this hypothesis test are remarkably revealing. A Pearson Correlation of .996, significant at the 0.01 level, indicates an extraordinarily strong positive correlation between digital marketing literacy and peer influence. This implies that students with higher levels of digital marketing literacy are considerably more likely to be influenced by their peers in terms of product or brand mentions online.

This correlation's strength is further underscored in the model summary, where the R Square value stands at an astounding .992. This suggests that a whopping 99.2% of the variance in digital marketing literacy among university students can be explained by peer influence. Such a high degree of explanatory power is rare and indicates an almost deterministic relationship between these two variables in the context of the study.

The ANOVA results support the robustness of this relationship. The F value, a staggering 53596.829, is highly significant ($p < .000$). This reinforces the statistical strength of the relationship between digital marketing literacy and peer influence, making it one of the most compelling findings of the study.

Moreover, the coefficients table reveals a near one-to-one relationship between peer influence and digital marketing literacy. For every unit increase in peer influence, there is almost an equivalent increase in digital marketing literacy (beta coefficient of .999, t = 231.510, p < .000). This suggests that peer influence is not just a predictor but a nearly perfect predictor of digital marketing literacy among university students.

These results provide overwhelming support for Hypothesis 4, emphasizing the profound impact of peer influence on digital marketing literacy. The findings suggest that in the context of digital marketing, peers play an almost determinative role in shaping the literacy levels of university students. This has significant implications for marketing strategies and educational programs, highlighting the need to consider the powerful role of peer influence in shaping digital behaviors and competencies.

Hypothesis 5 (H5): 2. Awareness of digital marketing tactics positively influences the attitude change among university students, such that higher levels of literacy lead to greater susceptibility to attitude changes influenced by social media and digital advertisements.

Correlations-H5

		Awareness of Digital Marketing	Attitude Change
Awareness of Digital Marketing	Pearson Correlation	1	.866**
	Sig. (2-tailed)		.000
	N	420	420
Attitude Change	Pearson Correlation	.866**	1
	Sig. (2-tailed)	.000	
	N	420	420

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

Model Summary-H5

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.866[a]	.751	.750	.54987

a. Predictors: (Constant), Attitude Change

ANOVA -H5

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	380.330	1	380.330	1257.882	.000[b]
	Residual	126.385	418	.302		
	Total	506.715	419			

a. Dependent Variable: Awareness of Digital Marketing
b. Predictors: (Constant), Attitude Change

Coefficients -H5

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.751	.079		9.537	.000
	Attitude Change	.768	.022	.866	35.467	.000

a. Dependent Variable: Awareness of Digital Marketing

Hypothesis 5 (H5) of the study examines the influence of awareness of digital marketing tactics on attitude change among university students. The analysis uncovers a robust relationship between these variables. The Pearson Correlation coefficient (.866) between Awareness of Digital Marketing and Attitude Change is significant (p < .000), highlighting a strong positive correlation. This suggests that as students become more aware of digital marketing tactics, they are more susceptible to attitude changes influenced by social media and digital advertisements.

The R Square value in the model summary stands at an impressive .751, indicating that about 75.1% of the variance in Awareness of Digital Marketing can be explained by Attitude Change. This high level of explanatory power suggests a strong predictive relationship, where changes in attitudes can significantly forecast the level of awareness about digital marketing among students.

The ANOVA results further reinforce this relationship with a substantial F value of 1257.882, which is highly significant (p < .000). This points to a strong statistical justification for the predictive relationship between these two variables.

In the coefficients table, the unstandardized and standardized coefficients indicate the degree of change in Awareness of Digital Marketing for each unit change in Attitude Change. The Beta coefficient of .866, along with a significant t-value of 35.467 ($p < .000$), implies that attitude change is a powerful predictor of awareness of digital marketing tactics.

These findings provide strong empirical support for Hypothesis 5. The study indicates that awareness of digital marketing tactics is closely linked with the attitude changes among university students. This underscores the importance of digital marketing awareness in shaping students' attitudes, particularly in the context of an increasingly digital-centric world. The high degree of correlation and the significant predictive power of attitude change on awareness highlight the need for targeted digital marketing educational initiatives. Such initiatives could play a crucial role in fostering informed and critical engagement with digital marketing content among university students.

Hypothesis 6 (H6): Awareness of digital marketing tactics positively influences the behavioral intent of university students, where higher literacy is linked to an increased likelihood of visiting websites and considering purchasing products advertised through digital marketing.

Correlations-H6

		Awareness of Digital Marketing	Behavioral Intent
Awareness of Digital Marketing	Pearson Correlation	1	.810**
	Sig. (2-tailed)		.000
	N	420	420
Behavioral Intent	Pearson Correlation	.810**	1
	Sig. (2-tailed)	.000	
	N	420	420

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

Model Summary-H6

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.810[a]	.656	.656	.64531

a. Predictors: (Constant), Behavioral Intent

ANOVA-H6

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	332.651	1	332.651	798.830	.000[b]
	Residual	174.064	418	.416		
	Total	506.715	419			

a. Dependent Variable: Awareness of Digital Marketing
b. Predictors: (Constant), Behavioral Intent

Coefficients -H6

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.389	.077		18.043	.000
	Behavioral Intent	.641	.023	.810	28.264	.000

a. Dependent Variable: Awareness of Digital Marketing

Hypothesis 6 (H6) of the study evaluates the impact of awareness of digital marketing tactics on the behavioral intent of university students. The Pearson Correlation between Awareness of Digital Marketing and Behavioral Intent is .810, significant at the 0.01 level, demonstrating a strong positive correlation. This significant correlation implies that students who are more aware of digital marketing tactics are also more likely to exhibit behavioral intent, such as visiting websites or considering purchasing products advertised through digital channels.

The model summary reveals an R Square value of .656, suggesting that approximately 65.6% of the variance in Awareness of Digital Marketing can be explained by Behavioral Intent. This substantial proportion underscores the significant predictive power of behavioral intent on the awareness of digital marketing tactics among university students.

The ANOVA results further strengthen these findings, with a high F value of 798.830, which is highly significant ($p < .000$). This indicates a strong statistical relationship between the two variables, reinforcing the hypothesis that awareness of digital marketing tactics is a crucial factor influencing behavioral intent.

The coefficients in the model provide additional insights into this relationship. The unstandardized coefficient of .641 for Behavioral Intent, along with a significant t-value of 28.264 ($p < .000$), illustrates that an increase in behavioral intent is associated with a notable increase in awareness of digital marketing tactics. The constant of 1.389 further contextualizes this relationship within the model.

These results provide strong empirical evidence supporting Hypothesis 6. The study suggests a significant link between students' awareness of digital marketing tactics and their behavioral intent, highlighting the role of awareness in shaping students' digital behaviors. The strong correlation and significant predictive value of behavioral intent underscore the importance of enhancing digital marketing awareness among university students. This awareness not only informs their understanding of digital marketing but also significantly influences their likelihood of engaging with digital marketing content, such as visiting websites and considering product purchases.

Hypothesis 7 (H7): Awareness of digital marketing tactics is positively correlated with influence of specific tactics on university students, indicating that students with higher literacy levels are more susceptible to marketing emails, influencer recommendations, and targeted advertisements.

Correlations-H7

		Awareness of Digital Marketing	Influence of Specific Tactics
Awareness of Digital Marketing	Pearson Correlation	1	.839**
	Sig. (2-tailed)		.000
	N	420	420
Influence of Specific Tactics	Pearson Correlation	.839**	1
	Sig. (2-tailed)	.000	
	N	420	420

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

Model Summary-H7

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.839[a]	.704	.704	.59863

a. Predictors: (Constant), Influence of Specific Tactics

ANOVA-H7

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	356.921	1	356.921	995.985	.000[b]
	Residual	149.794	418	.358		
	Total	506.715	419			

a. Dependent Variable: Awareness of Digital Marketing
b. Predictors: (Constant), Influence of Specific Tactics

Coefficients-H7

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.945	.082		11.473	.000
	Influence of Specific Tactics	.709	.022	.839	31.559	.000

a. Dependent Variable: Awareness of Digital Marketing

Hypothesis 7 (H7) of the study posits a positive correlation between the awareness of digital marketing tactics and the influence of specific tactics on university students. The Pearson Correlation analysis strongly supports this hypothesis, showing a significant correlation coefficient of .839 ($p < .000$). This robust correlation indicates that students who are more aware of digital marketing tactics are also more susceptible to the influence of specific marketing approaches such as emails, influencer recommendations, and targeted advertisements.

The model summary further elucidates this relationship, with an R Square value of .704. This suggests that about 70.4% of the variance in Awareness of Digital Marketing can be explained by the Influence of Specific Tactics. Such a high level of explained variance signifies the substantial impact that specific marketing tactics have on students' awareness.

The ANOVA results bolster these findings, with a remarkably high F value of 995.985, which is highly significant (p < .000). This indicates a very strong statistical relationship between awareness of digital marketing tactics and their influence, thereby validating the hypothesis.

In the coefficients table, the relationship between these variables is further quantified. The unstandardized coefficient for Influence of Specific Tactics is .709, with a significant t-value of 31.559 (p < .000), suggesting that an increase in the influence of specific tactics is associated with a significant increase in awareness of digital marketing. The constant value of .945 contextualizes the base level of awareness in the absence of these tactics.

The findings provide robust empirical support for Hypothesis 7. The study clearly demonstrates that university students' awareness of digital marketing tactics is significantly influenced by the specific tactics employed in marketing campaigns. This suggests that digital marketing strategies that effectively leverage specific tactics can significantly enhance students' awareness and understanding of these approaches. The high degree of correlation and the significant predictive value of the influence of specific tactics underscore the need for marketers to strategically design their digital marketing campaigns to effectively target and educate the university student demographic.

Hypothesis 8 (H8): Awareness of digital marketing tactics is positively correlated with peer influence on university students, suggesting that those with higher levels of literacy are more likely to be influenced by product or brand mentions by their peers online.

Correlations-H8

		Awareness of Digital Marketing	Peer Influence
Awareness of Digital Marketing	Pearson Correlation	1	.805**
	Sig. (2-tailed)		.000
	N	420	420
Peer Influence	Pearson Correlation	.805**	1
	Sig. (2-tailed)	.000	
	N	420	420

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

Model Summary-H8

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.805[a]	.649	.648	.65268

a. Predictors: (Constant), Peer Influence

ANOVA -H8

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	328.651	1	328.651	771.498	.000[b]
	Residual	178.064	418	.426		
	Total	506.715	419			

a. Dependent Variable: Awareness of Digital Marketing
b. Predictors: (Constant), Peer Influence

Coefficients -H8

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.327	.080		16.516	.000
	Peer Influence	.609	.022	.805	27.776	.000

a. Dependent Variable: Awareness of Digital Marketing

The statistical analysis presented in the table effectively supports Hypothesis 8 (H8), which posits a positive correlation between awareness of digital marketing tactics and peer influence among university students. This hypothesis suggests that students who are more literate in digital marketing are likely to be more influenced by product or brand mentions by their peers online.

The Pearson Correlation coefficient, an indicator of the strength and direction of a linear relationship between two variables, stands at .805** for the relationship between awareness of digital marketing and peer influence. This strong positive correlation is statistically significant at the 0.01 level (2-tailed), as indicated by the significance (Sig.) value of .000. The sample size (N) for this analysis is 420, providing a robust dataset for the study.

The Model Summary further reinforces the strength of this relationship, with an R value of .805, indicating a strong positive linear relationship. The R Square value of .649 suggests that approximately 64.9% of the variance in awareness of digital marketing can be explained by peer influence. The Adjusted R Square, which is a modified version of R Square that has been adjusted for the number of predictors in the model, is nearly identical at .648, indicating a high level of reliability of the model.

The ANOVA (Analysis of Variance) table supports the model's statistical significance. The F-statistic, at 771.498 with a significance level of .000, indicates that the model is a good fit for the data.

Lastly, the Coefficients table provides insights into the specific relationship between the variables. The unstandardized coefficient for Peer Influence is .609, and the standardized coefficient (Beta) is .805. The t-value of 27.776 with a significance level of .000 further confirms the strong influence of peer pressure on awareness of digital marketing tactics among university students.

Overall, the data robustly supports H8, demonstrating a significant and strong positive correlation between digital marketing awareness and peer influence in the context of university students.

4. CONCLUSION, IMPLICATIONS, AND FUTURE STUDIES

The conclusion of this thesis encapsulates the intricate relationship between digital marketing literacy and its impact on university students' attitudes, behaviors, and susceptibility to persuasion. The study conclusively demonstrates that students with higher digital marketing literacy are more susceptible to changes in attitudes due to digital advertisements and social media marketing. This literacy also significantly influences their behavioral intentions, such as visiting websites and considering product purchases. Furthermore, the study reveals that students with higher literacy levels are more prone to the influence of specific digital marketing tactics like marketing emails, influencer recommendations, and targeted advertisements.

Additionally, the research highlights the strong correlation between digital marketing literacy and peer influence, indicating that literate students are more likely to be swayed by their peers' online product or brand mentions. It also shows that awareness of digital marketing tactics is a critical factor in students' susceptibility to these tactics. This awareness not only changes attitudes but also drives behavioral intentions and reactions to specific marketing tactics.

The findings of this thesis have profound implications. They underscore the need for educational institutions and policymakers to focus on enhancing digital literacy among university students. Such initiatives would enable students to critically engage with digital marketing content and make informed decisions. Moreover, the study's results are invaluable for digital marketers, as they provide insights into how digital literacy influences the effectiveness of their strategies.

This research provides a comprehensive understanding of the role of digital marketing literacy in shaping university students' responses to digital marketing. It calls for a collaborative effort among educators, policymakers, and marketers to foster an environment where digital literacy is prioritized, thereby empowering students to navigate the digital world more effectively and ethically. The study's findings lay a foundation for future research in this area, inviting further exploration into the nuanced ways digital marketing literacy can influence consumer behavior in the digital age.

The study illuminates the critical role of digital marketing literacy in shaping university students' attitudes and behaviors towards digital advertisements and social media marketing. This knowledge is invaluable for managers in both academic and business sectors.

Firstly, for educational managers and policymakers, the findings underscore the importance of integrating digital literacy into the curriculum. By enhancing students' understanding and critical thinking regarding digital marketing, educational institutions can equip them with the skills necessary to navigate the digital landscape more effectively and make informed decisions.

In the realm of digital marketing management, the insights provided by this study are crucial for developing more targeted and responsible marketing strategies. Understanding the nuances of how digital marketing literacy influences students' susceptibility to various marketing tactics, including peer influence, can lead to the creation of more ethical and effective marketing campaigns. This is particularly important given the evolving landscape of digital marketing, where strategies must constantly adapt to changing consumer behavior and preferences.

Additionally, the study highlights the potential for digital marketing managers to collaborate with educational institutions. Such collaborations can lead to the development of programs that not only enhance students' digital literacy but also provide real-world insights into the impact of digital marketing, thus fostering a more informed and critical consumer base.

The managerial implications of this thesis are extensive and carry significant weight for both educational and marketing sectors. They call for a strategic approach towards enhancing digital literacy, responsible marketing practices, and a collaborative effort between education and industry to ensure a more ethically informed digital landscape.

The study's focus on Northern Cyprus might limit the broader applicability of its findings, highlighting the need for caution when generalizing these results to different contexts. Methodologically, the reliance on self-reported measures introduces potential bias, calling for a more varied methodological approach in future research. Looking ahead, it is recommended that subsequent studies expand their geographical scope to include diverse populations and consider longitudinal methods to capture the evolving nature of digital marketing competence. Additionally, incorporating qualitative research methods could yield richer insights into the subjective experiences and perceptions of university students regarding digital marketing. This comprehensive approach will deepen the understanding of digital marketing's influence and guide more effective educational and marketing strategies.

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THE ROLE OF NEUROMARKETING IN UNDERSTANDING THE COUNTRY-OF-ORIGIN EFFECT: A SYSTEMATIC REVIEW

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ABSTRACT

Purpose- In the country of origin (COO) topic, the limitations of traditional methods highlight the need for more innovative approaches in this field. This study aims to examine how neuromarketing techniques, which provide unique insights beyond traditional research methods, are integrated into the analysis of the COO effect, a key factor influencing consumer behavior in global marketing.

Methodology- A systematic literature review was conducted, analyzing articles from the Scopus database. The research identified studies employing neuromarketing techniques to investigate the COO effect, followed by content analysis of selected articles.

Findings- The year 2022 marked the most productive period for studies examining the COO effect using neuromarketing techniques. Among the journals where these studies were published, the Journal of Retailing and Consumer Services and Neuroscience Letters were particularly prominent. China stood out as the leading country in terms of author contributions and the volume of research conducted in this field. The systematic review revealed that EEG was the most frequently used neuromarketing technique in COO studies, followed by limited applications of fMRI and eye tracking. Furthermore, it was observed that a significant focus was placed on brain imaging techniques within these studies. Studies that examine the COO effect using neuromarketing techniques have focused on consumer behavior, particularly in terms of consumer preferences, purchase intention, and consumer behavioral responses. Additionally, they have focused on consumer characteristics, specifically in terms of consumer ethnocentrism and consumer involvement.

Conclusion- This research underscores the significant potential of neuromarketing techniques, which provide insights into consumers' subconscious responses, in advancing the understanding of the COO effect. It highlights gaps in the literature that future research can address. Nevertheless, this research will significantly contribute to motivating and shaping future investigations in the field. Consequently, the study contributes to both theoretical advancements and practical applications in global marketing strategies.

Keywords: Neuromarketing, consumer neuroscience, country of origin effect, systematic review, content analysis
JEL Codes: M31, M39, L19

1. INTRODUCTION

With consumers being exposed to products from different countries, COO has become a significant cue shaping consumer behavior (Agrawal and Kamakura, 1999). As a result, COO has emerged as an important research topic in the field of international marketing (Fan and Zhang, 2019). Initially defined as the country where a product was manufactured, the concept of COO has become increasingly complex with the proliferation of multinational production processes (Bilkey and Nes, 1982; Hien et al., 2020; Blanco-Encomienda et al., 2024). In this context, COO can be defined as the country that consumers associate with a product. The COO effect, on the other hand, refers to the influence of the image of the associated country on consumer behavior (Zheng et al., 2023; Blanco-Encomienda et al., 2024).

In recent years, studies on the COO effect have debated its strength and significance (e.g., Usunier, 2006; Samiee, 2011; Josiassen and Harzing, 2008). However, recent studies on the COO effect have sparked debates regarding the strength and significance of this influence (e.g., Usunier, 2006; Samiee, 2011; Josiassen and Harzing, 2008). Consequently, the topic requires further investigation in light of these debates. However, limitations associated with traditional research methods have been highlighted (e.g., Herz and Diamantopoulos, 2017; Halkias et al., 2022). In this regard, exploring the topic with alternative research methods may provide new and deeper insights into the debated the COO effect.

In recent years, neuromarketing has attracted significant attention in the field of marketing (Yadete and Kant, 2023). Neuromarketing differs from traditional research methods as it uses brain imaging and physiological techniques to obtain insights into consumer behavior (Kiran and Prabhakar, 2021; Zhu et al., 2022). Accordingly, employing neuromarketing techniques to examine the COO effect may yield novel findings and contribute to ongoing debates. In this context, the current state of research addressing the COO topic through neuromarketing techniques has become a matter of interest. Therefore, this study aims to explore the question, "What is the present status of research on the COO topic conducted using neuromarketing techniques?" by systematically reviewing studies that examine the COO topic through the application of neuromarketing techniques. This study contributes to identifying gaps in the existing literature and providing a foundation for future research.

The study first reviews the relevant literature. Then, in November 2024, articles available in the Scopus database that examine the COO topic using neuromarketing techniques were identified. The identified studies were subjected to content analysis, with their findings evaluated to reach conclusions. Lastly, suggestions for future research are provided.

2. LITERATURE REVIEW

2.1. COO Effect

Consumers are exposed to products from different countries as globalization enables them to transcend the borders of their country of manufacture. Therefore, COO of products has been important for consumers. Schooler's (1965) research revealed the COO effect and drew attention to its importance. As a result, COO has been an important field of study in global marketing over time (Zheng et al., 2023).

COO is defined as the place where a product is manufactured and indicated on the 'Made in' label (Bilkey and Nes, 1982; Thakor and Katsanis, 1997). The COO effect denotes the impact of a country's image, encompassing stereotypical beliefs based on its attributes, on consumers' attitudes and behaviors toward products manufactured in that country (Oduro et al., 2024). However, the manufacturing country, brand country, design country, and assembly country have diverged due to the rise of multinational production, making COO of a product more complex (Hien et al., 2020; Blanco-Encomienda et al., 2024). In this context, COO may be defined as the country that the consumer associates with or attributes to a product. The influence of the image of COO that the consumer associates with or attributes to the product on consumer behavior is referred to as the COO effect (Zheng et al., 2023; Blanco-Encomienda et al., 2024). In other words, the consumer's perceptions, behaviors, and decisions are influenced by the cognitive and sensory associations they have with COO (Artêncio et al., 2022).

When evaluating a product, consumers rely on both extrinsic and intrinsic information cues (Oduro et al., 2024). Intrinsic cues include the physical features of a product, such as smell, taste, and design, while extrinsic cues do not include physical features and instead refer to elements such as brand, price, and COO (Thakor and Katsanis, 1997; Rezvani et al., 2012). Therefore, as an extrinsic cue, COO shapes consumer behaviors such as quality perception and purchase intention (Blanco-Encomienda et al., 2024; Farina et al.,2024).

2.2. The Role of COO Effect in Marketing

COO has become a significant area of interest for both companies and researchers in the field of global marketing. For businesses aiming to establish a presence in global markets, COO is a critical factor due to its influence on consumer behavior (Blanco-Encomienda et al., 2024). For instance, COO has the potential to influence consumers' willingness to pay, purchase intentions, and perceptions of risk and value (Casado-Aranda et al., 2020). The origin of a product may offer benefits or pose challenges for companies in areas like entering international markets and choosing strategic partners (Suter et al., 2021). For this reason, interest in this area has continued to rise since Schooler's (1965) study.

The effect of COO on consumer behavior has been explored from various aspects, with increasing interest in this topic, such as purchase intention (e.g., Ghalandari and Norouzi, 2012; Kim et al., 2017; Bhattacharya et al., 2023), product quality (e.g., Kalicharan, 2014), product evaluation (e.g., Bilkey & Nes, 1982; Insch & McBride, 2004), consumer privacy, and consumer trust (Bhattacharya et al., 2023). Moreover, disagreements have emerged regarding the continued existence of the COO effect. Among the prominent views on this subject, Usunier (2006) argues that the influence of COO has weakened due to factors like international brand development, transnational manufacturing, and WTO standards related to origin labeling. Samiee (2011) criticizes COO research for lacking adequate research designs and failing to provide sufficient managerial insights and in-depth contributions, while indicating that COO is not strongly linked to consumer decisions as is commonly believed. However, it is also emphasized that some consumers continue to view COO as a relevant cue in their purchasing decision process (Herz and Diamantopoulos, 2017). Moreover, Josiassen and Harzing (2008) argue that COO remains a subject of significant interest, as previous research highlights the presence of both consumers who evaluate a product without considering its COO and those who emphasize its importance.

In conclusion, the topic of COO is a well-researched and debated area in academic research. A recent study by Samiee et al. (2024) reviewed over 400 articles published in the past 60 years. This reflects the high level of interest in the COO topic within the literature. Despite ongoing debates, interest in this subject within the field of marketing appears likely to persist.

2.3. Neuromarketing

Recently, neuromarketing has gained increasing attention in the field of marketing, as it provides insights into understanding consumers through new and diverse methods. The field of neuromarketing emerged as studies in the 1920s, which initially used physiological devices to better understand consumers, were expanded to include various physiological and brain imaging techniques (Shaw and Bagozzi, 2018). Thus, neuromarketing, as an applied discipline that utilizes neuroscientific techniques for marketing research, and consumer neuroscience, as a research field focused on understanding the brain's role in consumer decision-making processes, have both reached their current significance (Briesemeister and Selmer, 2022).

Neuromarketing is described as an emerging field within marketing that examines the unconscious dimensions of consumer responses to marketing stimuli by utilizing advanced technology (Kumar, 2015). It is stated that neuromarketing relies on understanding the underlying brain structures involved in the cognitive functions and perceptual processes of consumer responses in various situations (Levallois et al., 2021). Thus, neuromarketing contributes to generating insights into consumer behavior by providing information on brain structures and neural processes (Iloka and Onyeke, 2020). In this context, neuromarketing is defined as a cross-disciplinary marketing approach that employs brain imaging and physiological techniques to obtain knowledge (Kiran and Prabhakar, 2021; Zhu et al., 2022).

Neuromarketing employs various techniques to access subconscious information, including brain imaging and physiological tools. The brain imaging techniques encompass functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS), positron emission tomography (PET), electroencephalography (EEG), and magnetoencephalography (MEG) (Alsharif et al., 2021a). fMRI is a method where an individual is positioned inside a large magnetic machine to monitor neural activity, track oxygen levels in the blood, and observe hemoglobin changes, allowing for almost immediate visualization of brain function (Penrod, 2023). As a non-invasive neuroimaging method, fNIRS employs near-infrared light to measure cerebral oxygenation and deoxygenation levels, enabling the indirect assessment of neural activity by detecting changes in haemoglobin absorption within human tissue (Krampe et al., 2018). PET detects gamma emissions resulting from pre-administered radioactive substances, enabling detailed spatial assessment of brain metabolic processes; however, its invasive nature, limited temporal accuracy, and high cost make it generally unsuitable for studies with healthy participants (Daugherty and Hoffman, 2017). EEG is a method that records electrical activity in the brain through sensors attached to test subjects, visualizing brain functions through graphical outputs or brain maps (Penrod, 2023). Magnetoencephalography (MEG) utilizes helmet-mounted detectors to measure brain activity through magnetic fields, unaffected by factors such as blood or bone, and is typically used in a magnetically shielded laboratory environment (Siddique et al., 2023).

These physiological tools include eye-tracking (ET), galvanic skin response (GSR), facial expressions and heart rate (HR) (Alsharif et al., 2021a). ET is a method that enables tracking of the specific points or objects that participants' eyes focus on at any given moment (Kumar, 2015). GSR measures the level of electrical resistance or conductance in human skin, based on the concept that increased resistance from sweat gland activation indicates heightened arousal (Daugherty and Hoffman, 2017). There are two methods for identifying facial expressions: facial coding, which uses software to detect movements in forty-three facial muscles to determine subjects' moods, and facial electromyography (EMG), which captures emotional responses by assessing electrical signals through electrodes placed on two facial muscles (Kiran and Prabhakar, 2021). HR is a technique that examines the number of heartbeats occurring within a single minute (Kumar, 2015) and cardiovascular responses are measured through the use of ECG (Electrocardiogram) and pulse oximeters (Küçün et al., 2020). However, fMRI, EEG and ET are the most preferred techniques in neuromarketing research (Alsharif et al., 2021b).

2.4. The Role of the Neuromarketing in Marketing

In today's increasingly competitive business environment, understanding the consumer holds substantial importance in shaping both local and global marketing strategies effectively. Gaining more detailed insights into consumer behavior is a crucial factor for achieving a competitive advantage in marketing activities. Moreover, it is stated that consumers may not always act rationally during their decision-making processes (Zurawicki, 2010). In this context, neuromarketing, which provides deeper insights into consumer behavior, has increasingly gained prominence (Zhu et al., 2022).

Neuromarketing utilizes technology to provide insights into consumers' subconscious, which traditional research methods (e.g., interviews, surveys) cannot access, allowing businesses to acquire a deeper insight into consumer behavior (Siddique et al., 2023). Moreover, neuromarketing delivers more reliable and impactful outcomes in understanding consumers compared to traditional methods (Kiran and Prabhakar, 2021). Neuromarketing enables the real-time identification of consumers' responses to marketing stimuli (Bercea Olteanu, 2015). For instance, businesses can identify consumers' physical and cognitive responses to any marketing stimulus and analyze the role they play in shaping decisions (Misra, 2023).

Neuromarketing aids businesses in comprehending and anticipating consumer behavior in marketing research, while also contributing to the optimization of product innovation, packaging design, price strategies, and the assessment of advertising effectiveness (Misra, 2023). In addition, it enables the acquisition of insights through the use of advanced technologies in areas such as effective communication and promotional activities within the context of the consumer purchasing decision process (Öztürk, 2024). The practical applications of neuromarketing also aid in advancing theoretical progress within the marketing discipline by encouraging the emergence of novel perspectives and bolstering pre-existing concepts. Neuromarketing extends beyond merely offering insights into consumer behavior; it also enhances marketing as an academic field by enabling the formulation of innovative marketing theories and reinforcing established frameworks (Lim, 2018). In this regard, neuromarketing holds a pivotal role in both the formulation of marketing strategies and the reassessment of current knowledge through the valuable data it generates.

2.5. Neuromarketing into COO Effect Studies

Technological advancements across the globe have led to significant changes in global market dynamics. Today, it is not merely the trade of products manufactured in different countries that is observed but also products whose components are produced in various countries, while their design and branding originate from entirely different nations. Consumers, who were previously exposed to products produced solely in one country, now encounter goods involving production processes spanning multiple countries. Due to current global market dynamics, it has been explicitly stated that COO, which once played a significant role in consumer decision-making, may no longer exert the same influence (Usunier, 2011). Therefore, it is emphasized that the topic needs to be revisited (Usunier, 2006). Furthermore, the existing literature highlights that studies examining the COO effect using traditional research methods lack precision and reliability (Herz and Diamantopoulos, 2017).

Examining whether the influence of COO on consumers' decision-making processes persists through traditional methods leads to inconclusive results, creating contradictions in marketing strategies that are developed using the knowledge obtained through these methods (Halkias et al., 2022). Therefore, it is important to revisit the subject using research techniques that differ from traditional methods. Neuromarketing holds a pivotal role in the reassessment of current knowledge through the data it generates using techniques different from traditional methods (Lim, 2018). Neuromarketing utilizes various techniques to capture consumers' immediate responses to marketing stimuli (Zhu et al., 2022). Thus, it enables a comprehensive insight into consumers' responses, regardless of their awareness of these responses (Siddique et al., 2023). Unlike traditional methods that fail to measure unconscious and emotional responses, neuromarketing integrates neuroscience, psychology, and marketing to offer a comprehensive understanding of the underlying mechanisms of consumer behavior (Casado-Aranda et al., 2020). In this domain of lively debate, integrating neuromarketing techniques into COO studies holds importance in demonstrating the potential of both the COO effect and neuromarketing methods.

3. DATA AND METHODOLOGY

3.1. The Research Aim, Scope, and Significance

In the lively debate surrounding the COO topic, the limitations of traditional methods highlight the importance of integrating neuromarketing techniques into related studies (Casado-Aranda et al., 2020; Halkias et al., 2022; Casado-Aranda et al., 2021). Accordingly, the current state of research addressing the COO topic through neuromarketing techniques has emerged as a significant area of inquiry. This situation has resulted in the research question: "What is the present status of research on the COO topic conducted using neuromarketing techniques?". Building on this research question, this study aims to systematically examine studies that explore the COO topic through the application of neuromarketing techniques.

Evaluating the existing literature from this perspective provides significant contributions to both COO and neuromarketing literature. This assessment offers a comprehensive understanding of how the limitations of traditional research methods in COO literature have been addressed. Furthermore, it highlights how neuromarketing techniques, which are predominantly applied to marketing aspects such as advertising, branding, and decision-making (Özkara, 2017), have been adapted to measure the effects of COO. In this way, it contributes to identifying gaps in the existing literature and plays a significant role in encouraging future research in the field. In this context, this study is designed to make a substantial contribution to academic research and inspire further exploration in this domain.

3.2. Identification of Relevant Articles for Analysis

Research conducted in various regions around the world continues to expand the accumulated knowledge within the existing literature. The advancement of research in the literature relies on the examination, comparison, and holistic evaluation of prior studies (Paul and Criado, 2020). In this context, systematic literature reviews, by following specific steps, provide researchers with a comprehensive evaluation of the existing body of research while uncovering unexplored areas in the literature and supporting the initiation of further studies (Paul and Barari, 2022). This research conducted a systematic review to assess the existing trends in studies on the COO topic using neuromarketing techniques. The steps outlined in Figure 1, which were adapted from the frameworks proposed by Gong et al. (2024) and Feliciano-Cestero et al. (2023), were followed.

Figure 1: Systematic Literature Review Process

Research Question

"What is the present status of research on the COO topic conducted using neuromarketing techniques?"

Literature Review

Database: Scopus

Keywords: "country of origin" OR "country-of-origin" AND "neuromarketing", "country of origin" OR "country-of-origin" AND "consumer neuroscience", "country of origin" OR "country-of-origin" AND "functional magnetic resonance imaging" OR "fMRI", "country of origin" OR "country-of-origin" AND "functional near-infrared spectroscopy" OR "fNIRS", "country of origin" OR "country-of-origin" AND "positron emission tomography" OR "PET", "country of origin" OR "country-of-origin" AND "electroencephalography" OR "EEG", "country of origin" OR "country-of-origin" AND "magnetoencephalography" OR "MEG", "country of origin" OR "country-of-origin" AND "eye tracking" OR "eye-tracking", "country of origin" OR "country-of-origin" AND "Galvanic Skin Response" OR "GSR", "country of origin" OR "country-of-origin" AND "facial coding" OR "facial electromyography" OR "fEMG", "country of origin" OR "country-of-origin" AND "electrocardiogram" OR "ECG", "country of origin" OR "country-of-origin" AND "heart rate"

Total Articles: 1215

Choosing Relevant Articles

Final Sample of Articles: 15

Analysis And Interpretation of Articles

Sources: Gong et al. (2024); Feliciano-Cestero et al. (2023)

In the study, the Scopus database was systematically searched to identify studies related to the COO topic conducted using neuromarketing techniques. Because, Scopus is a comprehensive database that serves as a resource for large-scale global studies and bibliometric analyses, encompassing peer-reviewed scientific content as well as various indexes such as publication titles, abstracts, and keywords (Baas et al., 2020). In this context, the Scopus database was examined using the predefined keywords.

Initially, the keywords ‘"country of origin" OR "country-of-origin" AND "neuromarketing"’ and ‘"country of origin" OR "country-of-origin" AND "consumer neuroscience"’ were constructed to represent general terms related to neuromarketing, an applied discipline, and consumer neuroscience, a research field focused on understanding the role of the brain in consumer decision-making processes. To provide more detailed information about the studies, and considering that article titles, keywords and abstracts often specify the exact techniques used rather than general terms like neuromarketing or consumer neuroscience, the following keywords were constructed to include specific neuromarketing techniques: ‘"country of origin" OR "country-of-origin" AND "functional magnetic resonance imaging" OR "fMRI"’, ‘"country of origin" OR "country-of-origin" AND "functional near-infrared spectroscopy" OR "fNIRS"’, ‘"country of origin" OR "country-of-origin" AND "positron emission tomography" OR "PET"’, ‘"country of origin" OR "country-of-origin" AND "electroencephalography" OR "EEG"’, ‘"country of origin" OR "country-of-origin" AND "magnetoencephalography" OR "MEG"’, ‘"country of origin" OR "country-of-origin" AND "eye tracking" OR "eye-tracking"’, ‘"country of origin" OR "country-of-origin" AND "Galvanic Skin Response" OR "GSR"’, ‘"country of origin" OR "country-of-origin" AND "facial coding" OR "facial electromyography" OR "fEMG"’, ‘"country of origin" OR "country-of-origin" AND "electrocardiogram" OR "ECG"’, ‘"country of origin" OR "country-of-origin" AND "heart rate"’. This approach allowed for a more detailed search focused on the specific techniques utilized in the studies. While constructing these keywords, attention was paid to different typing and abbreviations. Additionally, scenarios where different methods are used to measure the same response were considered. For instance, emotional facial expressions can be measured using both "facial coding" and "facial electromyography" (Höfling et al., 2021). Moreover, cardiovascular responses are measured using ECG (Electrocardiogram) and pulse oximetry, with the data obtained from these devices providing information about heart rate (Küçün et al., 2020). Therefore, it has been observed that studies on cardiovascular responses typically refer to the technique as either ECG or Heart Rate. Accordingly, both ECG and Heart Rate were included as keywords in the process.

To identify more studies, the 'search within' option was set to 'all fields,' and the search was conducted in November 2024. Duplicate entries among the initial results were removed, resulting in an initial dataset comprising 1,218 articles. The titles and abstracts of the articles in this dataset were evaluated based on specific criteria: the study being written in English, addressing the COO effect, and utilizing neuromarketing techniques. After following this procedure, relevant articles were identified. Following the initial evaluation, 20 articles were selected; however, a detailed review revealed that 5 of these articles did not meet the required criteria and were excluded from the dataset. Ultimately, 15 articles were selected for detailed content analysis, and analysis was conducted using the MS Excel program. Table 1 provides detailed information regarding the dataset. Table 2 presents selected relevant articles for the analysis.

Table 1: Summary of the Dataset

Keywords	Total Articles Found
"country of origin" OR "country-of-origin" AND "neuromarketing"	99
"country of origin" OR "country-of-origin" AND "consumer neuroscience"	54
"country of origin" OR "country-of-origin" AND "functional magnetic resonance imaging" OR "fMRI"	198
"country of origin" OR "country-of-origin" AND "functional near-infrared spectroscopy" OR "fNIRS"	20
"country of origin" OR "country-of-origin" AND "positron emission tomography" OR "PET"	368
"country of origin" OR "country-of-origin" AND "electroencephalography" OR "EEG"	179
"country of origin" OR "country-of-origin" AND "magnetoencephalography" OR "MEG"	46
"country of origin" OR "country-of-origin" AND "eye tracking" OR "eye-tracking"	338
"country of origin" OR "country-of-origin" AND "Galvanic Skin Response" OR "GSR"	47
"country of origin" OR "country-of-origin" AND "facial coding" OR "facial electromyography" OR "fEMG"	7
"country of origin" OR "country-of-origin" AND "electrocardiogram" OR "ECG"	53
"country of origin" OR "country-of-origin" AND "heart rate"	118
Total Initial Search Results	**1527**
Distinct Articles After Removing Duplicates	**1218**
Relevant Articles After Preliminary Evaluation	**20**
Selected Relevant Articles for Analysis	**15**

Table 2: Selected Relevant Articles for Analysis

Reference	Article Title	Journal	Neuro-marketing Technique Used	Research Objective	Research Findings
Artêncio, Giraldi, and de Oliveira, (2022)	A cup of black coffee with GI, please! Evidence of geographical indication influence on a coffee tasting experiment	Physiology & Behavior	EEG	To investigate the impact of Geographical Indication (GI) information on neural reactions, the moderating roles of sex differences and the degree of involvement in these effects, and consumer choices.	Women exhibited greater neural activity and sensitivity to GI information compared to men, who demonstrated more limited responses; while the influence of involvement level was weaker than that of gender, men generally preferred GI-labeled coffee, whereas women tended to favor non-GI coffee, despite frequently expressing orally the opposite preference.
Casado-Aranda, Sánchez-Fernández, Ibáñez-Zapata, and Liébana-Cabanillas, (2020)	How consumer ethnocentrism modulates neural processing of domestic and foreign products: A neuroimaging study	Journal of Retailing and Consumer Services	fMRI	To evaluate the effects of local and imported products on brain activation in relation to levels of consumer ethnocentrism.	Highly ethnocentric consumers demonstrated heightened activity in neural areas associated with reward and self-referential processes when assessing local products, whereas imported products triggered higher responses in areas connected to risk evaluation.
Casado-Aranda, Dimoka, and Sánchez-Fernández, (2021)	Looking at the brain: Neural effects of “made in” labeling on product value and choice	Journal of Retailing and Consumer Services	fMRI	An investigation into the neurological basis of consumers' perceptions of local and imported products, considering cultural similarities/differences and levels of product involvement.	The outcomes indicate that local products consistently elicit rewarding neural responses, whereas negative reactions toward imported products emerge only under conditions of cultural differences and heightened involvement.

Cheng and Wang, (2018)	Impact of COO and Brand ogo on the Acceptance of Luxury Price Based on Brain Evoked Potential Analysis	NeuroQuantology	EEG	To investigate the impact of COO and brand logo on consumers' evaluation of luxury prices and the underlying brain mechanisms using the Event-Related Potentials (ERP) method.	It was found that products with only one COO were evaluated by consumers at higher prices, and the presence of a brand logo enhanced the evaluation of luxury prices.
Escandon-Barbosa and Rialp-Criado, (2019)	The Impact of the Content of the Label on the Buying Intention of a Wine Consumer	Frontiers in Psychology	Eye Tracking	To examine how the information presented on wine bottle labels impacts consumers' purchase intentions for wine.	It has been demonstrated that participants, when grouped based on their wine consumption experience, interpret label information (the denomination of origin, nutritional information, and health warnings) differently, and these variations, along with the interactions between label components, have a significant impact on purchase intention.
Fan and Zhang, (2019)	Does the aura surrounding healthy-related imported products fade in China? ERP evidence for the country-of-origin stereotype	PLoS ONE	EEG	An exploration of the perceptions of young Chinese consumers toward domestic and imported products and the potential shifts in COO stereotypes at the brain activity level.	Chinese young consumers continue to perceive imported products, particularly health-related ones, more favorably than domestic products; this is evidenced by longer reaction times and greater neurological activation when associating imported products with negative adjectives.
Halkias, Florack, Diamantopoulos, and Palcu, (2022)	Eyes Wide Shut? Understanding and Managing Consumers' Visual Processing of Country-of-Origin Cues	British Journal of Management	Eye Tracking	To investigate whether consumers notice COO labels, how this recognition impacts their subsequent behavioral responses, and whether their visual focus on these labels can be influenced from outside sources.	The results indicate that most COO labels on product packages are indeed noticed by consumers, with their impact on behavioral intentions depending on the duration of visual attention.

Huang, Wan, Peng, and Sui, (2020)	Grey matter volume and amplitude of low-frequency fluctuations predicts consumer ethnocentrism tendency	Neuroscience Letters	fMRI	To explore the neural basis of individual variations in consumer ethnocentrism tendency (CET), brain functionality and anatomy were examined using fMRI techniques.	The results revealed that different brain regions play significant roles in consumer ethnocentrism.
Liu, Sharma, Xu, Gonzalez Viejo, Fuentes, and Torrico, (2022)	Influence of Label Design and COO Information in Wines on Consumers' Visual, Sensory, and Emotional Responses	Sensors	Eye Tracking	To assess how origin information on wine labels impacts purchase intentions, as well as hedonic and unconscious emotional reactions, through eye-tracking.	COO information slightly influences purchase intentions and hedonic responses.
Ma, Abdeljelil, and Hu, (2019)	The influence of the consumer ethnocentrism and cultural familiarity on brand preference: Evidence of event-related potential (ERP)	Frontiers in Human Neuroscience	EEG	To understand the behavioral and neurological aspect of consumer ethnocentrism on brand choice by examining the role of ethnic group and cultural familiarity.	Chinese participants clearly preferred recommendations from individuals of their own ethnic group, while African participants familiar with foreign cultures showed no difference in their preferences between logos suggested by Chinese and African individuals, and same-group suggestions triggered a significantly lower N200 component compared to different-group recommendations.
Min, Cho, Sung, and Cho, (2014)	Neurophysiological evidence for the country-of-origin effect: an event-related potential study	NeuroReport	EEG	To examine neural activity related to the COO effect and consumers' assessment of product design.	The study demonstrates a notable relationship between the COO effect and design choice with respect to response times and provides neuropsychological information highlighting the substantial role of COO in shaping design choice.

Pagan, Giraldi, Maheshwari, de Paula, and de Oliveira, (2021).	Evaluating cognitive processing and preferences through brain responses towards country of origin for wines: the role of gender and involvement	International Journal of Wine Business Research	EEG	To examine how the wines' COO influences cognitive assessment and consumer choice by analyzing neural activity, taking into account the effects of sex and degree of involvement.	The findings indicate that COO had no notable overall impact on cognitive processing or preferences, except for heightened cognitive processing of Brazilian wines among men and low-involvement consumers.
Wang, Lyu, Liu, Liu, Gao, and Jin, (2022)	Country-Brand Fit: The Effect of COO Stereotypes and Brand Positioning Consistency on Consumer Behavior: Evidence From EEG Theta-Band Oscillation	Frontiers in Neuroscience	EEG	To examine how the compatibility between COO stereotypes and brand positioning affects consumer behavior, along with the role of brand positioning strategies and the associated cognitive processes, utilizing electroencephalography (EEG).	The results offer neural insights into how the alignment between COO stereotypes and brand positioning shapes consumer purchasing behavior, emphasizing the threshold effect and the critical role of the competence dimension.
Xie, Chen, Zhang, and Cui, (2018)	Neural correlates of country-of-origin image (COI) stereotype	Neuroscience Letters	EEG	To explore the neural processes underlying country of origin image (COI) stereotypes in the context of product evaluation.	The study revealed that COI stereotypes shape product evaluation via neural mechanisms, highlighting the roles of automatic emotional priming and cognitive monitoring in decision-making.
Zhang, Palma, Jin, and Yuan, (2019)	US consumer reactions to China's Shuanghui acquisition of Smithfield Foods and its neural basis	Agribusiness: An International Journal	EEG	To investigate the impact of a Chinese firm's purchase of a US company on consumer choice and the neural mechanisms underlying these effects.	The purchase reveals that it decreased consumers' choice for the U.S. brand while increasing their preference for the Chinese brand and that U.S.-origin products led to a decline in neural responses despite an increase in willingness to pay.

3.3. Analysis of Relevant Articles

"Content analysis is a research technique for making replicable and valid inferences from texts to the contexts of their use" (Krippendorff, 2004, p.18). Furthermore, content analysis refers to a set of research techniques used to produce results that prioritize validity, reproducibility, and transparency (Drisko and Maschi, 2016). The quantitative content analysis approach has been utilized in this study. Quantitative content analysis is a quantitative approach that systematically aims to count the frequency of specific elements or categories within a given text (Taylan, 2011). In quantitative content analysis, where objectivity and systematicity are prioritized, analytical elements are identified and interpreted using quantitative components (Sallan Gül and Nizam, 2021).

4. FINDINGS

4.1. Basic Analyses and Trends

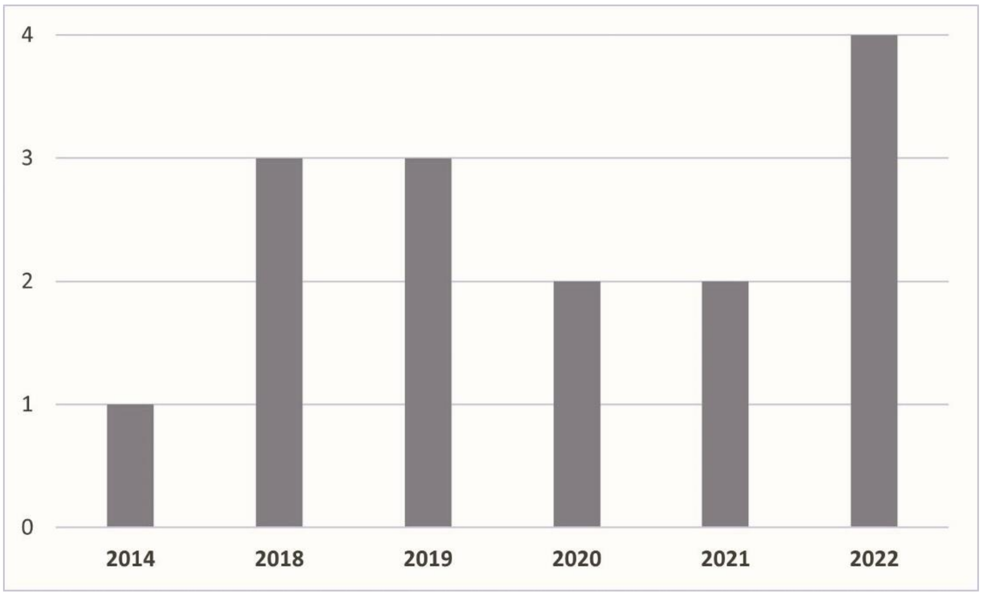
4.1.1. Publication Trends Over the Years

Graph 1 illustrates the yearly distribution of studies examining the COO effect using neuromarketing techniques. The graph indicates that the first study on this topic was performed in 2014. However, between 2014 and 2018, studies on this topic remained absent. Nonetheless, existing research highlights a sustained interest in the COO topic (Lu, et al., 2016; Samiee and Chabowski, 2021). This absence of studies may be attributed to a lack of interest or certain reservations regarding the integration of neuromarketing techniques into COO research.

The number of studies published in 2018 demonstrates a notable increase in research investigating the COO effect using neuromarketing techniques. This growth can be linked to the rising interest in neuromarketing research (Alsharif et al., 2021b). However, a decline in the number of studies is observed in 2020 and 2021, which can largely be attributed to the COVID-19 pandemic. Given that neuromarketing research typically requires a laboratory setting, pandemic-related restrictions may have disrupted planned studies during these years.

The year 2022 emerged as the most productive year for research in this field. However, this momentum did not continue beyond 2022, as no studies were published in 2023 or 2024. This suggests that the topic has lost prominence and that research interest has diminished. Nevertheless, considering the continued interest in the COO topic and the ongoing advancements in neuromarketing techniques driven by technological developments, there is strong potential for significant research contributions in this area in the future.

Graph 1: Number of Studies by Year



4.1.2. Publication Trends in Journals

Table 3 presents the distribution of articles across journals. According to the table, the relevant articles were published in 13 different journals. This indicates that the studies are not concentrated in a specific journal but are instead distributed across various journals. The fact that these journals belong to different disciplines further highlights the multidisciplinary nature of the topic.

Among the journals where the studies were published, “Journal of Retailing and Consumer Services” and “Neuroscience Letters” stand out, with two articles published in each. In contrast, the other journals each feature only one article. This suggests that “Journal of Retailing and Consumer Services” and “Neuroscience Letters” could serve as focal points for the publication of future research in this field.

Table 3: Article Distribution Across Journals

Journal Name	Number of articles
Agribusiness: An International Journal	1
British Journal of Management	1
Frontiers in Human Neuroscience	1
Frontiers in Neuroscience	1
Frontiers in Psychology	1
International Journal of Wine Business Research	1
Journal of Retailing and Consumer Services	2
NeuroQuantology	1
NeuroReport	1
Neuroscience Letters	2
Physiology & Behavior	1
PLoS ONE	1
Sensors	1
Total	**15**

4.1.3. Trends in Publication Citations

Upon examining Table 4, the study by Casado-Aranda et al. (2020) emerges as the most cited work, with a total of 35 citations. This is followed by the studies of Escandon-Barbosa and Rialp-Criado (2019) with 25 citations and Ma et al. (2019) with 24 citations. These findings indicate that these studies have served as significant reference points for subsequent research in the field. In contrast, the studies by Cheng and Wang (2018) and Huang et al. (2020) received only 1 citation each, which may suggest that these works focus on narrower topics or specific areas of interest.

When analyzing the total citations of publications by year, it is observed that 2019 stands out as the most cited year, with a total of 57 citations. This highlights 2019 as the most productive and impactful year for research examining the COO effect using neuromarketing techniques.

Table 4: Publication Citations

Authors and Year Published	Citations
Casado-Aranda, Sánchez-Fernández, Ibáñez-Zapata and Liébana-Cabanillas (2020)	35
Escandon-Barbosa and Rialp-Criado (2019)	25
Ma, Abdeljelil and Hu (2019)	24
Casado-Aranda, Dimoka and Sánchez-Fernández (2021)	14
Pagan, Giraldi, Maheshwari, de Paula and de Oliveira (2021)	12
Liu, Sharma, Xu, Gonzalez Viejo, Fuentes and Torrico (2022)	12
Artêncio, Giraldi and de Oliveira (2022)	9
Halkias, Florack, Diamantopoulos and Palcu (2022)	6
Min, Cho, Sung and Cho (2014)	5
Xie, Chen, Zhang and Cui (2018)	5
Fan and Zhang (2019)	4
Zhang, Palma, Jin and Yuan (2019)	4
Wang, Lyu, Liu, Liu, Gao and Jin (2022)	4
Cheng and Wang (2018)	1
Huang, Wan, Peng and Sui (2020)	1

4.1.3. Trends in Distribution of Authors by Country and Institution

Table 5 provides an overview of the number of authors per country. The table reveals that 21 authors are affiliated with institutions in China, marking the highest number of authors among all countries. This highlights China's prominence in studies examining the COO effect using neuromarketing techniques, positioning it as a significant center in this field. Furthermore, it indicates a strong interest among Chinese researchers in this topic, and their substantial contributions to the field are noteworthy.

China is followed by Brazil, Spain, and the USA, each contributing 5 authors. Researchers from these countries have made significant contributions to studies exploring the COO effect using neuromarketing techniques. New Zealand (4), Austria (3), and South Korea (3) are categorized as countries providing moderate contributions. These findings suggest a notable interest in the subject within these countries, though not as extensively as in China, Brazil, Spain, and the USA. The table also shows that Australia and the UK each contribute with 2 authors. These relatively low numbers of authors indicate that researchers from these countries demonstrate limited contributions to studies focusing on the COO effect using neuromarketing techniques. The lowest contributions, at 1 author each, are from Germany and Colombia. This indicates that researchers from these countries have provided minimal input into studies examining the COO effect through neuromarketing methods.

In conclusion, research on the COO effect using neuromarketing techniques is predominantly concentrated in China. While there is heightened interest in specific countries, the overall engagement in this field remains limited. Nevertheless, the findings offer useful information about potential countries for fostering future collaborations.

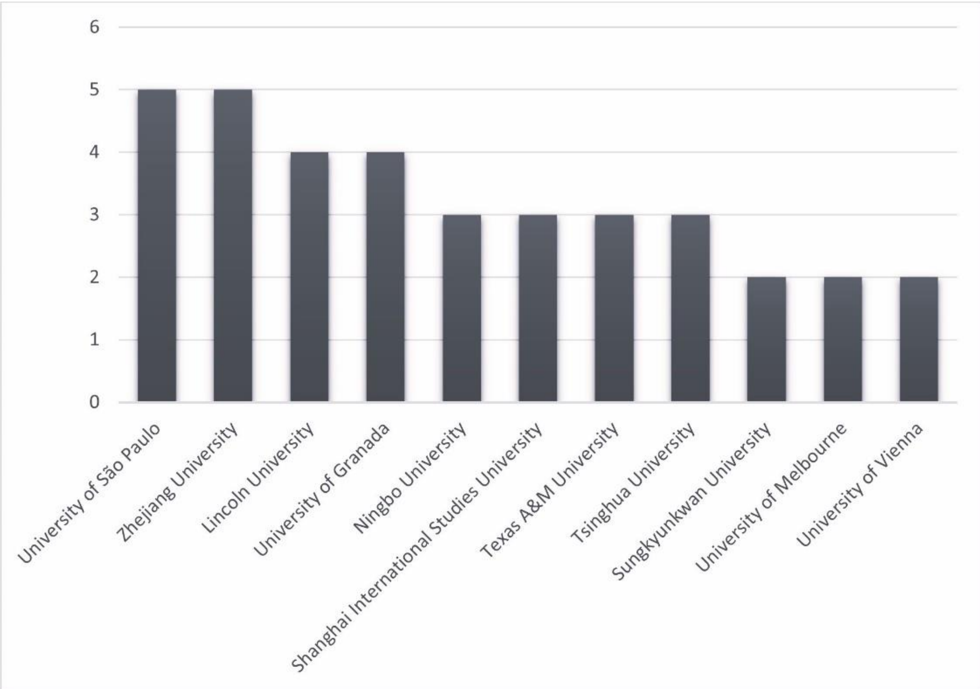
Table 5: Distribution of Authors by Country

Countries of Authors	Number of Authors
Australia	2
Austria	3
Brazil	5
China	21
Colombia	1
Germany	1
New Zealand	4
South Korea	3
Spain	5
UK	2
USA	5
Total	**52**

Graph 2 provides an overview of the institutional distribution of authors. However, to keep the list concise and meaningful, only institutions with two or more contributing authors are included in the graph. The results reveal that the most significant contributions to studies examining the COO effect using neuromarketing techniques come from authors affiliated with Zhejiang University and University of São Paulo. These two institutions clearly stand out as leading contributors to this research area. Lincoln University and University of Granada follow closely, making substantial contributions to COO and neuromarketing research. Furthermore, Ningbo University, Shanghai International Studies University, Texas A&M University, and Tsinghua University have provided moderate contributions to this field. In contrast, University of Vienna, University of Melbourne, and Sungkyunkwan University have made more limited contributions.

In conclusion, certain institutions have played a prominent role in advancing this research area by providing significant contributions. Furthermore, the involvement of universities from diverse countries and regions highlights the international interest in COO and neuromarketing studies within the global academic literature. This global engagement provides a strong foundation for potential future collaborations.

Graph 2: Distribution of Authors by Institution



4.2. Analyses and Trends in Research Details

4.2.1. Trends in Research Techniques

The neuromarketing techniques used in the relevant articles were examined. It was identified that EEG was utilized in 9 articles, while fMRI and eye tracking were each used in 3 articles. Among these techniques, EEG and fMRI are classified as brain imaging techniques, whereas eye tracking is considered a physiological method.

EEG is a frequently used technique in neuromarketing studies (Alam, 2024). Therefore, its prevalent use in the examined articles is an expected outcome. EEG presents a financial benefit as it is more affordable than other neuromarketing techniques (Siddique et al., 2023). Additionally, it offers advantages because it is both non-invasive and easy to use (Alam, 2024). These characteristics may explain why EEG was preferred more frequently among the examined studies.

In contrast, fMRI, another brain imaging technique, was utilized in only a few studies. This can be attributed to certain constraints associated with fMRI. Compared to other neuromarketing techniques, fMRI is more expensive, imposes significant restrictions on participants' movement, and is relatively less accessible (Casado-Aranda et al., 2023). Although fMRI provides detailed insights into the brain’s deeper areas, the complexity of its data makes analysis challenging for researchers (Siddique et al., 2023). These limitations may have negatively impacted the preference for fMRI in research.

The physiological technique eye tracking was also employed in only a few studies. Eye tracking is a less expensive and non-invasive method compared to other neuromarketing techniques (Alam, 2024). It enables the observation of attention and eye movements (Siddique et al., 2023). However, while it provides information about where a consumer looks, it is insufficient to explain the reasons behind their gaze (Casado-Aranda et al., 2023). This limitation might explain why eye tracking has been less frequently employed in studies examining the COO effect.

The reviewed articles show that EEG, fMRI, and eye tracking were the primary neuromarketing techniques used. However, these techniques were predominantly employed independently. Moreover, brain imaging techniques were more commonly utilized, while physiological methods were less frequently applied. Therefore, in future studies, the variety and frequency of neuromarketing techniques could be expanded. The use of physiological methods alongside brain imaging techniques could also be beneficial. Furthermore, research prioritizing physiological methods may provide valuable insights.

4.2.2. Review of Products Used in Experiments

The products used in the experiments conducted in the analyzed articles have been categorized and reviewed as presented in Table 6. Upon examining the categories, it is evident that the Food & Beverages and Technology Products categories encompass a wide range of items. Furthermore, the experiments predominantly featured products from these two categories. The most frequently presented items include wine, pen, pen drives, photo camera, and watch.

The studies utilized products from various categories, likely reflecting an effort to select items that align with the study framework. For example, in the study by Casado-Aranda et al. (2020), technological products were selected because of their strong link to COO labeling effect. Similarly, Wang et al. (2022) selected products that were neutral and less likely to vary across individual preferences, aligning with their research objective of minimizing the influence of product type. In another example, Cheng and Wang (2018) selected wallet as the product because they were accessible to participants, commonly used in daily life, suitable for displaying logos in the experiment, and held a significant share in the sales of luxury leather goods. Consequently, it is evident that the products used during the experimental phase span a wide range. However, product selection is primarily driven by their relevance to the research objectives and context.

Table 6: Distribution of Products Used in Experiments by Category

Categories	Products	Frequency	Categories	Products	Frequency
Food & Beverages	Beef	1	**Stationery & Office Supplies**	Laptop Bag	1
	Coffee	1		Notebook	1
	Energy Drink	1		Pen	2
	Jam	1	**Technology Products**	Bluetooth headset	1
	Meat	1		Bluetooth speaker	1
	Milk	1		Computer keyboard	1
	Milk powder	1		Computer mouse	1
	Potato Chips	1		Earphone	1
	Tea	1		Mobile phone	1
	Wine	3		Mp3 Player	1
Health & Medical Products	Antibiotic	1		Pen drives	2
	Calcium	1		Photo camera	2
	Vaccine	1		Radio	1
Home & Daily Use Products	Towel	1		Toaster	1
Outdoor Equipment	Bicycle	1	**Wearables & Accessories**	Running Shoes	1
Personal Care Products	Electric toothbrush	1		Wallet	1
	Hairspray	1		Watch	2
	Hand Lotion	1			

4.2.3. Trends in Geographical Distribution of Studies

The countries where the experimental studies in the analyzed articles were conducted have been reviewed. Accordingly, six studies were conducted in China, two each in Brazil and Spain, and one each in Colombia, New Zealand, South Korea, and the USA.

A significant portion of the experiments were conducted in China. This indicates that China plays a leading role in research examining the COO effect using neuromarketing techniques and reflects a high level of academic interest in this area. Following China, Brazil and Spain show noticeable interest in this topic, while Colombia, New Zealand, South Korea, and the USA demonstrate relatively limited engagement.

In conclusion, these findings provide insights into potential focal points for future studies and suggest that research on the COO effect could be extended to include a variety of geographical contexts. Thus, broadening the geographical scope of research will also lead to a better understanding of how the COO shapes consumer behavior across different cultures.

4.2.4. Analysis of Research Objectives

Themes and codes were developed to analyze the objectives of studies examining the COO effect through neuromarketing techniques. This approach aims to better identify how studies approach the topic, the elements they investigate, existing gaps, and emerging trends. The frequencies of the developed codes and themes are presented in the table 7 below.

A review of the table shows that the codes ‘COO’ and ‘Product Category (Local/Imported)’ have the highest frequencies. Additionally, the use of the codes ‘COO Label’ and ‘COO Stereotypes’ suggests that these aspects are frequently analyzed in existing studies. Conversely, codes such as ‘COO Image Stereotypes,’ ‘International Company Acquisition’, and ‘Production Country’, which appear only once, demonstrate significant potential for future research. Notably, distinctions such as ‘country of manufacture’, ‘brand origin’, and ‘country of design’ have been underexplored, signalling a need for further investigation into these aspects and their implications.

Within the Neurological and Physiological Responses theme, ‘Neurological Responses’ emerges as the most frequently observed code. This result demonstrates that existing studies mainly concentrate on brain imaging techniques. However, the relatively lower frequency of ‘Physiological Responses’ codes highlight a gap in research addressing physiological response measurement. This highlights the potential for future studies to utilize techniques aimed at capturing physiological responses.

In the Consumer Behavior theme, the ‘Consumer Preferences’ code appears most frequently, followed by ‘Purchase Intention’ and ‘Consumer Behavioral Responses’. These results show that studies often focus on fundamental aspects of consumer behavior. Furthermore, the inclusion of codes such as ‘Product Design Evaluation,’ ‘Hedonic Responses’, and ‘Price Acceptance’ indicates that some studies incorporate more nuanced analyses.

In the Consumer Characteristics theme, ‘Consumer Ethnocentrism’ and ‘Consumer Involvement’ are the most prominent codes. This finding underscores the frequent association of the COO effect with ethnocentric tendencies and consumer involvement. These results also indicate that consumer characteristics play a significant role in evaluating the COO effect.

For the Demographic Characteristics theme, ‘Gender’ has a higher frequency compared to other codes, suggesting that gender differences are more frequently studied, while ‘age’ and ‘ethnic group’ differences are less commonly explored.

Themes with fewer codes, such as ‘Marketing Strategies’, ‘Product Features’, and ‘Other Elements’, also exhibit lower frequencies. For example, the infrequent appearance of codes like ‘Brand Positioning’ and ‘Brand Logo’ suggests that these topics are underrepresented in the literature, pointing to potential areas for future research.

In conclusion, studies examining the COO effect from a neuromarketing perspective show a broad scope, with a predominant emphasis on how COO shapes consumer behavior. While demographic characteristics are addressed to a limited extent, individual characteristics are more frequently analyzed. Additionally, the findings underscore the importance of focusing on themes such as Marketing Strategies and Product Features, which offer significant potential for future exploration.

Table 7: Frequencies of Codes and Themes Related to Research Objectives

Themes	Codes	Frequency	Themes	Codes	Frequency
Demographic Characteristics	Gender	2	**Marketing Strategies**	Brand Positioning	1
	Ethnic Group	1	**Consumer Behavior**	Price Acceptance (Luxury)	1
	Age Group (Young Consumer)	1		Hedonic Responses	1
Other Elements	External Sources	1		Brand Preference	1
Country of Origin Elements	Geographical Indication	1		Purchase Intention	2
	Label Information	1		Consumer Behavioral Responses	2
	Country of Origin	4		Consumer Preferences	3
	Country of Origin Label	2		Consumer Awareness	1
	Country of Origin Image Stereotypes	1		Product Evaluation	1
	Country of Origin Stereotypes	2		Product Design Evaluation	1

	International Company Acquisition	1	**Consumer Characteristics**	Individual Differences	1
	Country of Manufacture	1		Cultural Familiarity	1
	Product Category (Local/ Imported)	3		Cultural Similarities/ Differences	1
Neurological and Physiological Responses	Subconscious Emotional Responses	1		Consumer Ethnocentrism	3
	Visual Attention	1		Consumer Involvement	3
	Neurological Responses	11	**Product Features**	Brand Logo	1
	Cognitive Responses	2			

5. CONCLUSIONS AND IMPLICATIONS

The COO topic is a prominent and debated issue in the field of global marketing. Therefore, addressing this topic through various research techniques is crucial for obtaining new and in-depth insights. In this context, research carried out a systematic literature review of studies that examine the COO topic using neuromarketing techniques. The findings provide an in-depth overview of the present status of this niche field, highlight gaps in the literature, and establish a valuable foundation for future research.

Overall, 2022 stood out as the year with the highest research output. Neuroscience Letters and Journal of Retailing and Consumer Services stood out as the primary journals where the studies appeared. China emerged as the country with the highest number of author contributions and the most research conducted. EEG was the most commonly used neuromarketing technique. In experimental designs, products such as wine, pens, USB drives, cameras, and watches were frequently used based on the research context. Studies examining the COO effect from a neuromarketing perspective primarily focused on how consumer behavior is influenced by the COO, showcasing a broad scope.

The results of this research underscore significant considerations for both future studies and practical implementation. First, future research involving collaborations from diverse geographical regions could significantly contribute to the literature. Additionally, employing a wider range of neuromarketing techniques could provide varied findings and enable the exploration of different aspects of the COO effect. Studies targeting different consumer segments and comparing these segments could make valuable contributions to both the COO and neuromarketing literature. Moreover, the research outcomes will offer valuable insights for COO-related applications within global marketing, enhancing the effectiveness of strategies in international markets.

6. LIMITATIONS

Several limitations are present in this research. It focuses solely on studies available in the Scopus database, which excludes articles from other databases. Moreover, the analyzed articles are limited to those indexed as of November 2024, excluding articles published after this date. The reliance on specific keywords is another limitation, as it may have led to the omission of some relevant research. Furthermore, the study only includes articles written in English, potentially overlooking contributions from studies published in other languages.

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FINANCIAL MARKETING THROUGH MACHINE LEARNING TECHNIQUES AND DATA ANALYTICS FOR CUSTOMER BEHAVIOR PREDICTION

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ABSTRACT

Purpose- This study explores the utilization of machine learning techniques in financial marketing to create a more efficient financial product, with understanding customer behavior and further drive the marketing efficiency as the primary focus. The research aims to highlight the role of advanced analytics in enhancing campaign effectiveness and targeting precision, thereby empowering businesses to make data-driven decisions in a competitive landscape.

Methodology- Various machine learning models were used in the study, including Decision Trees, Random Forests, Gradient Boosting Machines, Naive Bayes, Support Vector Machines, LightGBM, and Long Short-Term Memory. Feature engineering, particularly the inclusion of interaction terms and ratio-based features, was a critical component of the methodology, enabling the capture of complex patterns in customer behavior data. Model performance was rigorously evaluated using metrics such as precision, recall, and F1-score to provide a comprehensive understanding of predictive capabilities.

Findings- The machine learning models are confirmed to be very efficient in the investigation and identification of actionable than secret knowledge about consumer preferences and behavior. According to the research, these models were recently employed to develop accurate and tailored marketing approaches that greatly enhance campaign impact and targeting success. Things like precision, recall, and F1-score highlight the strengths or limitations of individual models and helped to guide the selection appropriately to specific marketing goals.

Conclusion- This study highlights the emprical importance of machine learning methods into financial marketing processes. By using advanced analytics, businesses can refine their marketing strategies, improve campaign outcomes, and remain competitive in a rapidly evolving marketplace. The results highlight the revolutionary ability of machine learning to facilitate accurate data driven marketing choices relative to customer desires.

Keywords: Financial marketing, machine learning, deep learning, data analytics, customer behavior prediction, campaign optimization.
JEL Codes: C45, M31, G21

1. INTRODUCTION

In today's data-driven business world, understanding and predicting customer behavior is critical for achieving a competitive edge. With the amount of data accessible now growing at an exponential rate and recent innovations in the machine learning (ML) space, enterprises are well equipped to derive actionable insights and take necessary steps accordingly. Financial marketing, in particular, benefits greatly from these innovations, enabling companies to enhance customer engagement, optimize campaign performance, and improve return on investment (ROI).

This study employs a diverse set of machine learning models to analyze and predict customer behaviors in financial marketing. Models such as Decision Trees, Random Forests, Gradient Boosting Machines (GBM), Naive Bayes, Support Vector Machines (SVM), LightGBM, and Long Short-Term Memory (LSTM) are utilized to capture complex patterns in customer data. These techniques enable businesses to create targeted and personalized marketing strategies by identifying key behavioral trends and segmentation patterns. To ensure a comprehensive approach, the study incorporates a simulated dataset designed to emulate real-world financial marketing scenarios. By integrating customer demographics, transaction data, and behavioral attributes, the dataset provides a rich foundation for machine learning analysis.

The primary objective of this research is to demonstrate how machine learning approaches can be applied to improve customer behavior prediction, enhance marketing campaign efficiency, and support data-driven decision-making. This study also evaluates the performance of models using key metrics such as accuracy, precision, recall, and F1-score, allowing for detailed comparison of predictive capabilities. The results provide actionable insights into model effectiveness, helping businesses determine the most suitable techniques for optimizing their marketing efforts.

The remainder of this paper is structured as follows: Section 2 presents a comprehensive review of existing literature on machine learning applications in marketing and customer behavior prediction. Section 3 details the research methodology, including data simulation, feature engineering, model selection, and evaluation metrics. Section 4 discusses the experimental results and comparative model performance. Section 5 provides an in-depth discussion of the findings, highlighting key insights and implications for financial marketing strategies. Finally, Section 6 concludes the study by summarizing the key contributions and proposing directions for future research.

2. LITERATURE REVIEW

The increasing adoption of machine learning techniques in marketing and customer behavior analysis has led to extensive research exploring their applications across various industries. From predictive analytics to customer segmentation and satisfaction modeling, machine learning plays an important role in enhancing marketing strategies and decision-making processes. This section provides an overview of key studies that have contributed to this evolving field.

Brei (2020) emphasized the potential of machine learning in changing marketing, which is illustrated by extent of employee training about customer targeting, segmentation and customized communication. The research highlighted the implications of data quality and ethics where the deployment of machine learning techniques are concerned. Rust (2020) explored the role of data-driven strategies and their effects in modern marketing, highlighting the importance of balancing technological innovation with ethical considerations. Similarly, Herhausen et al. (2024) systematically reviewed machine learning applications in marketing and discussed future research directions e.g., data privacy and interpretability. Moreover, Singh (2024) expanded on these discussions by presenting a framework for machine learning in marketing analytics, illustrating its use in predictive modeling, segmentation, and real-time campaign optimization. The study also explored the potential of reinforcement learning in refining dynamic pricing models and personalized content recommendations. Additionally, Ma and Sun (2020) examined the connection between artificial intelligence (AI) and machine learning in marketing, emphasizing how computational advancements allow businesses to extract meaningful insights from vast amounts of data. Their research highlighted the role of AI in improving decision-making processes, real-time optimization, and consumer engagement strategies.

Further studies have shown the performance of hybrid machine learning methods for marketing applications. In the context of online insurance industry experience, Akhavan and Hassannayebi (2024) developed a hybrid model that combines both machine learning and process analytics with the purpose of machine learning prediction, which improves prediction accuracy and provides actionable insights for managing customer satisfaction. Similarly, Alizamir et al. (2022) used a hybrid statistical-machine learning method to evaluate online customer behavior, specifically JD Market’s online sales analysis. They have concluded their findings with the following results: hybrid methods efficiently discover purchasing patterns, enhance discounting practices and better target the customers in e-commerce. Mondal et al. (2022) expanded on the idea by combining device and ML-enabled IoT in marketing, guiding resource allocation and improving consumer engagement.

Predicting customer behavior is still one of the major topics in research of machine learning. Al-Mashraie et al. (2021) used the push-pull-mooring (PPM) framework with machine learning models to study customer switch behavior in the mobile telecommunications industry. They noted that machine learning played a critical role in predicting customer churn and creating tailored retention plans. Similarly, Xu et al. (2022) using a machine learning-based meta-combination approach, they explored customer brand equity to illustrate how predictive models can be used to evaluate customers' engagement with brands. Chaubey et al. (2022) explored the effectiveness of using different machine learning classification techniques for predicting customer purchasing behavior, also establishing a shared importance of personalisation in marketing strategies.

Customer segmentation is another important topic in marketing analytics that has been heavily studied using machine learning techniques. developed a framework to segment customers based on online product reviews through interpretable machine learning, helping companies discover customer preferences and assist in developing new products. Joung and Kim (2023) developed an interpretable machine learning-based framework to segment customers based on online product reviews, enabling businesses to tailor new product offerings to consumer preferences. Their study underscored the importance of explainable AI in enhancing customer insights for product development. Duong et al. (2023) used machine learning for predicting online customer product return behavior and showed how analyzing customer feedback can improve e-commerce marketing strategies. Similarly, Le et al. In (2022), a predictive model was developed to use customer satisfaction analytics in the e-commerce sector, leveraging deep learning methods for enhancing retention methods. Bi et al. (2019) developed a method for sentiment classification leveraging ensemble neural networks to analyze online reviews and predict the customer service quality based on the Kano model. Moreover, Yaiprasert and Hidayanto (2023) introduced an AI-driven ensemble machine learning approach to enhance digital marketing strategies in the food delivery business. Their study demonstrated how combining multiple ML models improves prediction accuracy and personalization, helping businesses optimize marketing efforts in a fast-evolving industry.

Machine learning models have been extensively used for predicting purchase behavior. Mundea and Kaur (2022) conducted research to analyse sustainable jewelry purchases prediction using machine learning algorithms, highlighting the significant behavioral factors that drive consumer choices. Furthermore, Ebrahimi et al. (2022) applied machine learning techniques to structural equation modeling (SEM) in order to examine the relationship between social network marketing and consumer purchasing behavior. In the study conducted by Machado and Goswami (2023), they researched the journey of sustainable marketing strategies in the jewelry industry by discovering machine learning-based insights that boost the performance of the business and lead the way to environmental responsibility as well.

The application of machine learning in retail analytics and sales forecasting has been another significant research area. Ramachandran (2020) compared various machine learning techniques in predicting supermarket sales, illustrating the effectiveness of ensemble models in improving forecast accuracy. Gupta and Pathak (2014) proposed a machine learning framework for predicting online customer purchases with dynamic pricing models, emphasizing the importance of AI-driven approaches for pricing optimization. Machine learning has also been conducted in customer analytics, with Sarker et al. (2019) applying classification models to analyze smartphone usage patterns and develop personalized recommendation systems. Similarly, Sheykh Abbasi et al. (2022) used a hybrid web-content and web-usage mining approach to predict customer behavior in digital marketing, improving customer experience through data-driven insights.

Machine learning applications in customer satisfaction and service quality have also been widely explored. Fornell et al. (2006) examined the relationship between customer satisfaction and stock prices, illustrating the financial benefits of strong customer relationships. Blodgett et al. (1995) analyzed the effects of customer service on consumer complaint behavior, emphasizing the role of service quality in customer retention and long-term profitability. Anh et al. (2022) explored customer comments about fresh food on e-commerce platforms, in order to appraise insights for digitalized marketing. Meanwhile, Cuffie et al. (2020) employed topic modeling techniques to study customer return data in retail, identifying key factors contributing to dissatisfaction and potential areas for improvement.

Consequently, a brief summary of these studies shows that the role of machine learning in predicting customer behavior, segmenting users, and optimizing marketing is considerably increasing. Building further on these contributions, this research also develops a systematic machine learning framework, which implements Decision Tree, Random Forest, GBM, SVM, LightGBM, and LSTM models to predict customer responses to marketing campaigns. By using advanced feature engineering techniques and optimizing predictive accuracy, this study aims to provide actionable insights for financial marketing strategies and enhance customer engagement.

Here is the comparative literature summary table with categorized studies under structured headings as shown in Table 1. This provides a clear and concise summary while maintaining focus on machine learning applications in financial marketing and consumer analytics.

Table 1: Summary of Key Literature on Machine Learning in Financial Marketing and Consumer Analytics

Study	Key Focus	Methodology & Findings
Machine Learning in Marketing and Consumer Behavior Analysis		
Brei (2020)	Role of ML in marketing	Highlights ML's impact on targeting, segmentation, and personalization.
Rust (2020)	Data-driven marketing strategies	Emphasizes how ML enhances personalization addressing ethical concerns.
Singh (2024)	ML in marketing analytics	Explores predictive modeling, segmentation, and reinforcement learning.
Herhausen et al. (2024)	Future of ML in marketing	Reviewed advances in ML for marketing, addressing challenges like data privacy and model interpretability.
Ebrahimi et al. (2022)	Social network marketing impact	Assesses how ML improves consumer engagement and marketing effectiveness.

Ma & Sun (2020)	AI and ML integration in marketing	Exhibited how AI enhances decision-making in predictive analytics and real-time consumer behavior modeling.
Mondal et al. (2022)	IoT and ML for personalized marketing	Explored IoT-enabled machine learning models for personalizing healthcare marketing campaigns.
Hybrid Machine Learning Models for Marketing Applications		
Akhavan & Hassannayebi (2024)	Hybrid ML for customer experience	Combines ML with process analytics to enhance customer satisfaction predictions.
Alizamir et al. (2022)	Hybrid ML for online retail sales	Analyzes purchasing behavior in e-commerce using hybrid ML models.
Yaiprasert & Hidayanto (2023)	AI ensemble learning in digital marketing	Used ensemble ML techniques to optimize digital marketing strategies in the food delivery industry.
Customer Segmentation and Purchase Behavior Prediction		
Al-Mashraie et al. (2021)	Customer switching behavior	Used ML and PPM framework to predict customer churn in telecom industry.
Joung & Kim (2022)	Customer segmentation	Proposes an ML framework for segmenting customers based on product reviews.
Duong et al. (2023)	Online product return behavior	Uses ML to analyze return patterns and improve marketing strategies.
Chaubey et al. (2022)	Purchasing behavior prediction	Compares ML classification techniques for predicting customer purchases.
Xu et al. (2022)	ML-based brand equity analysis	Investigated customer-brand interactions through ML-based meta-combination analysis.
Machine Learning for Customer Satisfaction and Sentiment Analysis		
Le et al. (2022)	Customer satisfaction analytics	Uses ensemble neural networks and Kano model to assess service quality.
Bi et al. (2019)	Sentiment analysis in customer satisfaction	Compares ML models in improving sales predictions using sentiment analysis.
Machine Learning in Retail Sales Forecasting and Customer Analytics		
Ramachandran (2020)	Supermarket sales forecasting	Compares ML models in improving sales forecasting.
Gupta & Pathak (2014)	Online customer purchase forecasting	Uses ML-based dynamic pricing models for purchase forecasting.
Impact of Customer Satisfaction on Business Performance		
Fornell et al. (2006)	Link between satisfaction & stock prices	Demonstrates financial benefits of customer satisfaction.
Blodgett et al. (1995)	Service quality & customer complaints	Explores how customer service influences consumer loyalty.
Unsupervised Learning Techniques in Customer Trends		
Cuffie et al. (2020)	Topic modeling in retail analytics	Applied topic modeling to analyze customer return data and dissatisfaction factors.
Anh et al. (2022)	ML analysis of online reviews	Used ML to process customer reviews, improving fresh food marketing strategies on e-commerce platforms.
Personalized Marketing and Web Analytics		
Sheykh Abbasi et al. (2022)	Hybrid web mining for marketing	Combined web-content and web-usage mining to predict customer behavior in digital marketing.
Sarker et al. (2019)	ML-based smartphone user analysis	Developed personalized recommendation systems based on smartphone usage patterns.
Sustainable Marketing and Consumer Behavior		
Mundea & Kaur (2022)	ML for sustainable jewelry purchases	Analyzed behavioral factors influencing sustainable jewelry buying decisions using ML.
Machado & Goswami (2023)	ML in sustainable marketing	Explored ML applications in sustainable marketing, optimizing business and environmental strategies.

3. METHODOLOGY

This section outlines the methodology that described the approach utilized in this study to generate customer behavior predictions in financial marketing. The methodology involves three key steps: data simulation, feature engineering, and model training. First, a synthetic dataset was generated to replicate real-world customer behavior, including demographic and transactional attributes in Python programming language. Then, critical features were engineered from the simulated data to capture meaningful patterns and relationships. Finally, various machine learning models were trained and evaluated using these features to assess their predictive capabilities. Each step is described in detail in the following subsections.

3.1. Data Simulation

To conduct this study, a synthetic dataset was simulated to replicate real-world customer behavior and transactional data. The dataset includes 500,000 unique customer records with corresponding transactional and demographic information for each customer record to form a comprehensive profile. Transactional data consists of randomly generated transaction IDs, transaction amounts (modeled using an exponential distribution with a scale parameter of 500 to mimic real spending patterns), and transaction types categorized as either 'credit' or 'debit' with respective probabilities of 60% and 40%. Moreover, demographic features were assigned probabilistically to simulate diverse customer profiles. These attributes include gender ('Male' or 'Female'), income level ('Low,' 'Medium,' 'High'), education level ('High School,' 'Bachelor,' 'Master,' 'PhD'), region ('North,' 'South,' 'East,' 'West'), number of children (ranging number from 0 to 4), and age (ranging from 18 to 70 years). Customer-level aggregated features and transactional data were generated including total transactions, average transaction amount, total transaction value, and ratio of credit and debit transactions to total transactions. These features were calculated using group-level operations and provided critical insights into customer behavior. A binary target variable, "Campaign Response," was simulated to reflect whether a customer responded positively to a hypothetical marketing campaign. This variable was assigned based on a 70-30 probability distribution, with 70% of customers labeled as non-responders (0) and 30% as responders (1). To prepare the data for modeling, categorical features such as gender, income level, education level, and region were encoded using label encoding, while numerical features were standardized using z-score normalization to ensure consistency across scales enhance model performance. The dataset was then split into training (80%) and testing (20%) subsets for model development and evaluation. Python libraries like NumPy, pandas and scikit-learn were used to achieve the entire simulation and preprocessing pipeline to guarantee reproducibility and performance when dealing with large-scale datasets.

3.2. Feature Engineering

Feature engineering played a crucial role in preparing the simulated dataset for machine learning models. To capture meaningful patterns in customer behavior, multiple aggregated and derived features were formed. Transaction-level features included the total number of transactions, average transaction amount, total transaction value, and the ratios of credit and debit transactions to the total. These features provided insights into spending patterns and transaction preferences of customers. Demographic attributes such as gender, income level, education level, region, age, and number of children were included to enhance customer profiles. These features enabled the models to account for differences in customer behavior based on demographic characteristics. Categorical features were converted into numerical representations using label encoding, ensuring compatibility with machine learning algorithms. Numerical features were standardized using z-score normalization to maintain consistent scaling and improve model convergence during training. Additionally, the binary target variable, "Campaign Response," was analyzed alongside the engineered features to ensure the relevance of predictors in capturing customer engagement. The careful design of features ensured the dataset was comprehensive and ready for advanced machine learning analysis.

3.3. Model Selection

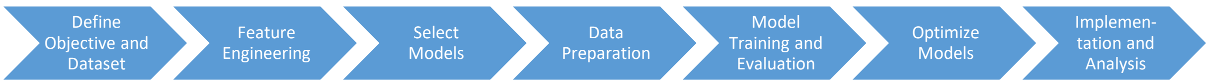
Model selection was guided by the objectives of predicting customer responses and optimizing marketing campaign performance. Several machine learning models were implemented to provide a robust comparison and determine the most effective approach for campaign response prediction.

- **Naive Bayes:** Rooted in Bayes' theorem, this probabilistic model provided a lightweight and computationally efficient option for benchmarking. While no hyperparameter tuning was necessary, it served as a reliable baseline for comparison.

- **Decision Tree:** Based on the foundational work of Breiman et al. (1984), the Decision Tree model was included for its simplicity and interpretability. It provides baseline insights into relationships between features and the target variable. Hyperparameter tuning using GridSearchCV optimized parameters like maximum depth and minimum samples split, enhancing its performance.
- **Random Forest:** Following Breiman's (2001) seminal introduction of Random Forests, this ensemble method was employed to capture feature interactions and reduce overfitting. It uses a bagging approach to improve prediction accuracy. GridSearchCV was used to optimize parameters such as the number of estimators and maximum depth.
- **Support Vector Machine (SVM)**: SVM, introduced by Cortes and Vapnik (1995), was chosen for its robustness in classification tasks, especially with high-dimensional or non-linearly separable feature spaces. Hyperparameter tuning focused on kernel type and regularization parameter to achieve optimal results.
- **Gradient Boosting Machine (GBM)**: Gradient boosting, as conceptualized by Friedman (2001), was applied for its ability to optimize performance iteratively by minimizing errors sequentially. Learning rate and the number of estimators were fine-tuned using GridSearchCV, demonstrating its effectiveness for structured data.
- **LightGBM:** Developed by Ke et al. (2017), LightGBM was selected for its scalability and ability to handle large datasets efficiently. It also supports categorical features natively. GridSearchCV was used to optimize parameters like learning rate and the number of estimators.
- **Long Short-Term Memory (LSTM):** First introduced by Hochreiter and Schmidhuber (1997), LSTM networks were included to capture sequential patterns and dependencies within customer transactional data. Although hyperparameter tuning for LSTM was not performed in this study, its architecture included layers with dropout regularization to prevent overfitting.

Each model's parameters, such as depth, learning rate, and regularization terms, were fine-tuned to achieve the best accuracy scores. The models were evaluated on training and testing subsets, and their predictive accuracies were compared to identify the most effective model. This comprehensive approach ensured a thorough understanding of each model's strength and limitations in addressing the study's objectives.

Figure 1: Machine Learning Workflow: From Data to Insights



The overall machine learning workflow is illustrated in Figure 1 which begins with defining the target and collecting the data. This stage sets the groundwork by defining the objectives of study while gathering necessary data. Following this, feature engineering transforms raw data into meaningful input features that capture critical patterns and behaviors. The next phase involves selecting suitable models tailored to the specific problem, ensuring the methodologies align with the study's objectives. Once the models are chosen, data preparation ensures the dataset is clean, encoded, and standardized, ready for model training. This is followed by training and evaluation of the model, which involves training the models on the prepared data and assessing its performance against pre-defined metrics. Subsequently, the workflow emphasizes optimizing models using hyperparameter tuning and regularization to enhance predictive capabilities. Finally, the research findings were tailored to actionable business strategies in the implementation and analysis section. This step effectively completes the loop by applying findings to real-world scenarios, such as customer segmentation or campaign optimization, ensuring the study's outcomes provide tangible value. This structured approach ensures a systematic and effective application of machine learning techniques in solving complex problems.

3.4. Evaluation Metrics

Accuracy, calculated as the ratio of correctly predicted instances to the total number of predictions, provides a straightforward and interpretable measure of how well a model explains the data. The performance of the machine learning models in this study was evaluated using accuracy as the primary metric, alongside precision, recall, and F1-score for a more comprehensive assessment. Precision measures the proportion of correctly predicted positive cases (responders) out of all predicted positive cases, while recall evaluates the proportion of correctly predicted positive cases out of all actual positive cases. F1-score, the harmonic mean of precision and recall, offers a balanced metric to account for the trade-offs between these two measures. The accuracy scores for the various models, including Decision Trees, Random Forests, GBM, Naive Bayes, SVM, LightGBM, and LSTM, were compared to determine their relative effectiveness. Each model was trained and tested on the same dataset to ensure consistency in evaluation. Among the tested models, LSTM and LightGBM achieved the highest accuracy while also excelling in precision, recall, and F1-score, demonstrating their superior ability to capture patterns and relationships within the data. By incorporating these additional metrics, this study provides a clearer understanding of model performance, particularly in the context of imbalanced data. The results demonstrate the predictive power of these models in understanding and predicting customer behavior and informing data-driven financial marketing strategies.

4. RESULTS

This study evaluated the predictive performance of seven machine learning models — Naive Bayes, Decision Tree, Random Forest, SVM, GBM, LightGBM, and Long Short-Term Memory — on a synthetic dataset generated to mimic real-world customer behavior and transactional data. The dataset contained 500,000 records with features derived from customer transactions and demographic profiles, as described in the Data Simulation section. The models were assessed using accuracy as the primary evaluation metric and also F1-score, recall, and precision values that will be elaborated on in the subsequent pages to determine their ability to predict the binary target variable, "Campaign Response," which indicates whether a customer responded positively to a hypothetical marketing campaign. Each model's performance was optimized through hyperparameter tuning, ensuring a fair comparison.

The performance of the machine learning models varied significantly, highlighting the importance of algorithm selection in predictive tasks. LightGBM, being the best performing model among all the models tested, obtained an accuracy percentage of 96% since it is able to handle complex data structures better than other models. Following closely, LSTM attained an accuracy of 93%, indicating the strength of deep learning approaches in capturing sequential and non-linear relationships in the dataset. GBM performed robustly with an accuracy of 92%, while Decision Tree models achieved a competitive accuracy of 89%, proving their effectiveness despite their simplicity. SVM yielded an accuracy of 87%, outperforming Random Forest models which achieved 85%. Finally, Naive Bayes, with its foundational simplicity and independence assumptions, resulted in an accuracy of 82%. The results emphasize the dominance of advanced techniques like LightGBM and LSTM in predictive analytics, particularly in complex financial marketing datasets. These findings provide considerable insights for optimizing marketing strategies through data-driven decisions. Figure 2 and Table 2 present the accuracy comparison across all evaluated models. Moreover, Table 2 summarizes the performance of various machine learning models tested in this study. Hence, LightGBM achieved the highest accuracy, demonstrating its capability to handle complex data structures, while Naive Bayes achieved the lowest accuracy due to its simplicity and assumptions.

Table 2: Accuracy Scores of Machine Learning Models in Predicting Campaign Responses

Model	Accuracy
LightGBM	96%
LSTM	93%
GBM	92%
Decision Tree	89%
SVM	87%
Random Forest	85%
Naïve Bayes	82%

The performance of various machine learning models in predicting the "Campaign Response" variable was evaluated through confusion matrices for the model LSTM and LightGBM in pictured Figure 3 and 4, respectively. These matrices gives us a detailed information about true positives, true negatives, false positives, and false negatives, allowing for an in-depth analysis of each model's strengths and weaknesses. This detailed analysis enables a deeper understanding of each model's strengths and limitations, particularly in terms of how well they identify responders and non-responders. Among the tested models, LightGBM and LSTM demonstrated superior predictive performance, with accuracy scores of 96% and 93%, respectively. The high accuracy of these models underscores their effectiveness in handling complex datasets and capturing underlying patterns. These results highlight the importance of value of using confusion matrices alongside accuracy metrics to gain a comprehensive evaluation of model performance as illustrated in Figure 3 and 4. Beyond numerical accuracy, the analysis highlights practical implications for financial marketing strategies, where balancing the minimization of false positives and maximizing the identification of true responders is crucial. This approach underscores the importance of aligning model selection with specific campaign objectives to achieve optimal marketing outcomes.

Figure 2: Accuracy Comparison of Machine Learning Models for Campaign Response Prediction

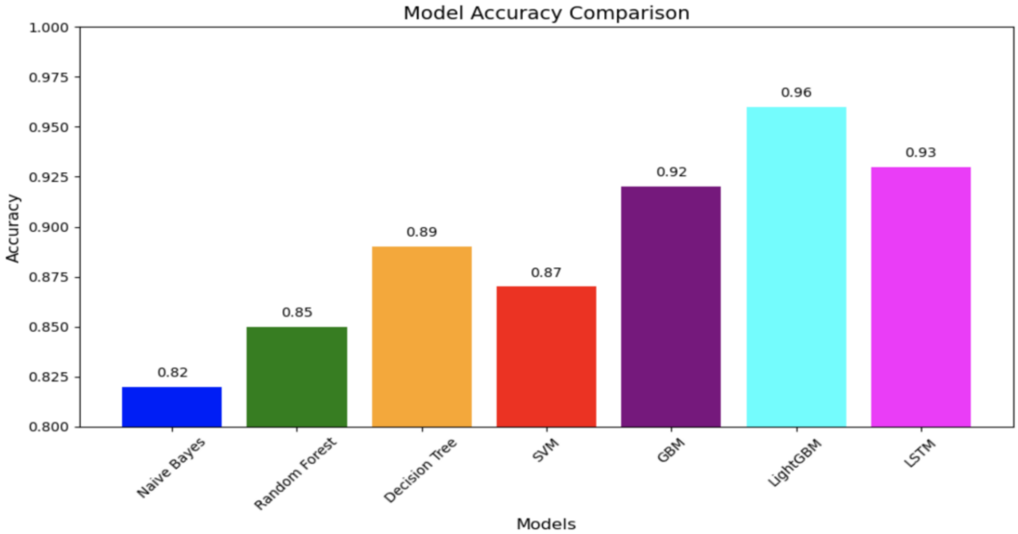


Figure 3: Confusion Matrix for LSTM Model

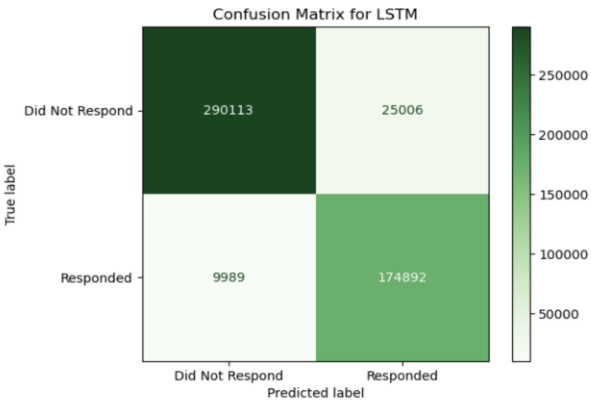
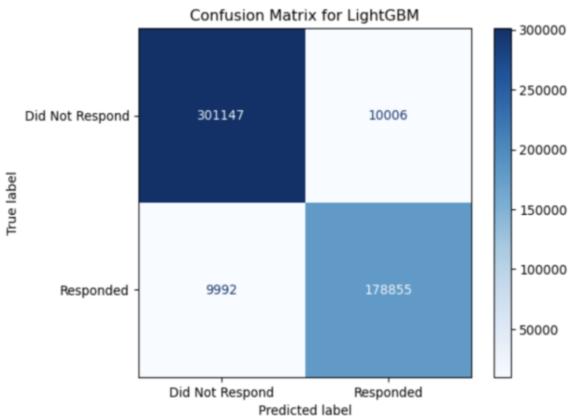


Figure 4: Confusion Matrix for LightGBM Model



The evaluation of the machine learning models' confusion matrices provided essential insights into their performance in predicting campaign responses. A confusion matrix breaks down predictions into four key components, each representing a specific outcome:

- True Negative (TN): Customers who did not respond to the campaign and were correctly predicted by the model as "Did Not Respond" (top-left corner of the matrix).
- False Positive (FP): Customers who did not respond but were incorrectly predicted by the model as "Responded" (top-right corner).
- False Negative (FN): Customers who responded to the campaign but were incorrectly predicted by the model as "Did Not Respond" (bottom-left corner).
- True Positive (TP): Customers who responded and were correctly predicted by the model as "Responded" (bottom-right corner).

Table 3: Confusion Matrix Layout for Campaign Response Prediction

True Labels ↓ / Predicted Labels→	Did Not Respond (0)	Responded (1)
Did Not Respond (0)	True Negative (TN)	False Positive (FP)
Responded (1)	False Negative (FN)	True Positive (TP)

These components, summarized in Table 3, enable insights into the strengths and limitations of the model. This detailed evaluation ensures a comprehensive understanding of model performance, which is critical for aligning predictive capabilities with real-world financial marketing objectives. Moreover, Table 3 serves as a foundational tool for analyzing the accuracy of the model's predictions. By comparing the true and predicted labels, it provides insights into the model's strengths and weaknesses, particularly in identifying customer responses.

Accuracy is one of the primary metrics used in this study to evaluate the overall performance of the machine learning models. It is calculated as the ratio of correctly predicted instances (both true positives and true negatives) to the total number of predictions made by the model that represented in the equation (1). This metric provides a straightforward measure of how well a model performs across all prediction classes. Moreover, accuracy is particularly valuable in assessing the general performance of models in balanced datasets. In this study, the accuracy metric was pivotal in identifying LightGBM and LSTM as top-performing models, with scores of 96% and 93%, respectively, highlighting their power in predicting campaign responses effectively. In addition to accuracy metric, this study evaluates the performance of the models using three additional key metrics: Precision, Recall and F1-Score. These metrics provide a more comprehensive understanding of how effectively the models predict customer campaign responses, particularly in scenarios where class imbalance might impact the interpretation of accuracy alone. Precision measures the proportion of correctly predicted positive cases (True Positives) out of all predicted positive cases (True Positives + False Positives). It is calculated using the formula shown in equation (2). It indicates how accurate the model is when it predicts a "Responded" label. Moreover, Recall measures the proportion of correctly predicted positive cases (True Positives) out of all actual positive cases (True Positives + False Negatives). It is calculated using the formula illustrated in equation (3). Recall value reflects the model's ability to identify all customers who actually responded to the campaign. The F1-Score, on the other hand, combines Precision and Recall into a single metric by calculating their harmonic mean, as shown in equation (4). This makes it particularly useful in situations where there is a need to balance Precision and Recall, such as when both false positives and false negatives have significant implications. A high F1-Score indicates that the model achieves a good balance between Precision and Recall, which is crucial in financial marketing scenarios where both overestimating and underestimating campaign responders can impact decision-making. By incorporating F1-Score alongside Precision and Recall, this study ensures a more nuanced evaluation of model performance, providing actionable insights for optimizing marketing strategies.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1 = \frac{2*Precision*Recall}{Precision+Recall} \tag{4}$$

Table 4: Precision and Recall Metrics for LightGBM and LSTM Models

Metrics ↓ / Models →	LightGBM	LSTM
Accuracy	96.0%	93.0%
Precision	94.7%	87.5%
Recall	94.7%	94.6%
F1-score	94.7%	90.9%

Table 4 presents a comparative analysis of the Accuracy, Precision, Recall, and F1-score metrics for the LightGBM and LSTM models in predicting the "Campaign Response" target variable. Precision measures the proportion of correctly predicted responders out of all predicted responders, indicating the model's accuracy in positive predictions. Recall evaluates the proportion of correctly identified responders out of all actual responders, emphasizing the model's capability to capture true positives. The F1-score, calculated as the harmonic mean of Precision and Recall, provides a balanced assessment of these metrics, particularly useful in imbalanced datasets. The LightGBM model achieved a Precision of 87.5%, reflecting its ability to minimize false positives while maintaining high predictive accuracy. With a Recall score of 94.7%, it effectively identified almost all actual responders, resulting in a robust F1-score of 94.7%. Conversely, the LSTM model also achieved Recall (94.6%), accurately identifying nearly all actual responders in the dataset. However, it demonstrated a slightly lower Precision of 87.5%, which contributed to an F1-score of 90.9%. These results underline the trade-offs between Precision, Recall, and their balance reflected in the F1-score when selecting models. Campaigns aiming to minimize the likelihood of false positives may prioritize the LightGBM model for its higher Precision and balanced F1-score. On the other hand, campaigns focused on identifying all potential responders could utilize the LSTM model's perfect Recall. Consequently, the choice between these models should align with the specific objectives and priorities of the marketing campaign.

The strategic implications of these findings are profound. Reducing False Negatives ensures that potential customers who are likely to engage with a campaign are not missed, thereby improving the reach and effectiveness of marketing efforts. On the other hand, minimizing False Positives reduces unnecessary campaign costs by avoiding targeting uninterested customers. By analyzing the confusion matrix alongside traditional accuracy metrics, this study highlights the critical role of advanced machine learning models like LightGBM and LSTM in enhancing campaign efficiency and optimizing resource allocation. Thus, these insights serve as a valuable foundation for businesses aiming to use data-driven decision-making in their marketing strategies.

5. DISCUSSION

The results of this study demonstrate the significant value of machine learning models in predicting customer campaign responses, particularly in the domain of financial marketing. Among the models tested, LightGBM and LSTM stood out with accuracy scores of 96% and 93%, respectively, showcasing their ability to handle complex patterns and sequential relationships in customer behavior data. While both LightGBM and LSTM achieved nearly perfect Recall 94.7% and 94.6% respectively, reflecting their ability to identify almost all actual responders, LightGBM exhibited superior precision indicating its capability to minimize false positives. Consequently, LightGBM achieved a higher F1-score of 94.7%, compared to 90.9% for LSTM, which balances the trade-offs between precision and recall. Such differences highlight the importance of aligning model selection with the specific objectives of a marketing campaign, such as prioritizing responder identification or minimizing incorrect predictions. The inclusion of feature engineering, especially interaction terms and ratio-based features, significantly enhanced the explanatory power of the models. This underscores the critical role of domain knowledge in shaping predictive performance, as financial marketing datasets often involve intricate dependencies between variables. Additionally, hyperparameter tuning was instrumental in ensuring optimal model configurations, resulting in improved performance and fair comparisons across all models. These findings reinforce the potential of advanced machine learning techniques in financial marketing, offering valuable insights to refine marketing strategies and improve campaign outcomes.

Because of the accuracy, precision, recall, and F1-score provided substantial insights, this study focused primarily on these metrics obtaining the target variable. However, there is an increasing need to regard more business-centric metrics, i.e. ROI and customer acquisition rates, to evaluate the real-world impact of predictive models on campaign outcomes. These metrics can provide better context arorund how models are aligned with business objectives and deliver actionable insights for marketing strategies. Additionally, this study’s results emphasize the usefullness of advanced machine learning techniques in financial marketing. The approaches provided enable organizations to make data-driven decisions for better resource allocation, targeting strategies, and higher rates of success in campaigns, leading to overall improvements. Nevertheless, challenges such as class imbalances, temporal dynamics, and the generalizability of results to real-world datasets remain areas for further exploration. Future research could extend these findings by integrating hybrid modeling approaches that combine the strengths of statistical methods with advanced machine learning algorithms to address complex patterns and irregular seasonality. Additionally, incorporating temporal and regional factors could provide a more granular understanding of customer behavior, while graph-based models could uncover relationships between customers, products, and regions. These guidelines and the application of these methods to diverse real-world datasets, will help to extend the practical usefullness of predictive models in financial marketing.

6. CONCLUSION AND FUTURE WORK

In this article, the performance of machine learning models for predicting campaign response, an essential use case for marketing in financial sectors was scrutinized. Through the use of feature engineering, hyperparameter optimization, and the integration of key evaluation metrics such as accuracy, precision, recall, and F1-score, strengths and limitations of various machine learning approaches, including LightGBM, LSTM, and others was demonstrated. Among the models tested, LightGBM achieved the highest accuracy (96%), followed closely by LSTM (93%). In addition to accuracy metrics, precision, recall, and F1-score metrics also further emphasized the trade-offs between these models, where LightGBM showcased its ability to minimize false positives, while LSTM excelled in identifying all actual responders. These findings highlight the importance of feature engineering in uncovering insightful trends within customer behavior datasets, where interactions and associations can be convoluted over time. Additionally, incorporating hyperparameter tuning ensured optimal configurations for each model, allowing for the models to be configured in an optimal manner and enabling increased predictive accuracy. These results emphasize the need for a more comprehensive evaluation strategy, as accuracy alone may not reflect the nuances of performance in imbalanced datasets. Although the study effectively utilized accuracy, precision, recall, and F1-score metrics, it also identified opportunities for further refinement. The limitations observed in some models, particularly regarding their ability to balance false positives and false negatives, highlight the importance of tailoring model selection to the specific objectives of marketing campaigns. For instance, campaigns aiming to maximize responder identification might prioritize models with higher recall, while those focused on minimizing false positives could benefit from models with higher precision.

With the insights derived from this study, future research can explore several promising directions to further enhance the predictive capabilities of machine learning models in financial marketing. One important direction is the integration of advanced metrics, such as ROI and customer acquisition rates, that would allow for a direct understanding of the financial impact of predictive modelling and deliver practical insights for campaign planning. Additionally, hybrid modeling approaches that integrate traditional statistical methods with machine learning algorithms can overcome the limitations of independent models while enhancing robustness in cases of complex patterns or irregular seasonality. Incorporating temporal and regional dynamics in future analyses will allow for exploration of how customer behavior may vary across time and geographic regions. Furthermore, the integration of graph-based models could uncover relationships between customer segments, products, and regions, offering deeper insights into sales dynamics and cross-selling opportunities. While this study focused on simulated data, applying these methodologies to real-world datasets across various industries will test their generalizability and uncover industry-specific insights. Automated feature engineering, applying frameworks such as AutoML, could streamline the discovery of hidden patterns and interactions, further enhancing model performance. Considering these aspects, future research can expand on the current findings to create more effective and actionable predictive models, ultimately driving improved marketing strategies and greater business impact.

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