AI Multigrid Marketing Strategy (AIMMS): Proposing a Marketing Framework for Optimizing Marketing Budgets

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[Abstract] This research paper proposes a construct for a strategic framework for leveraging artificial intelligence (AI) in business marketing to optimize return on investment (ROI) and improve client satisfaction. The framework builds upon existing marketing strategies by combining key concepts from contemporary research with insights extracted from a quantitative analysis of secondary data sources, including customer behavior metrics, campaign performance data, and market trends.

The proposed AI-driven framework can utilize AI and machine learning techniques to develop targeted marketing strategies that dynamically adjust to consumer preferences, behaviors, and market conditions. By aligning marketing efforts with data-driven insights, the framework is designed to maximize the efficiency of marketing budgets while enhancing client satisfaction. Additionally, the framework's adaptive and scalable design allows for the incorporation of additional components and variables as AI technology and market dynamics evolve. This paper lays the groundwork for future research and practical applications, offering a flexible use case for AI modeling that businesses can further develop to achieve their specific marketing objectives and optimize outcomes.

[Keywords] AI in marketing, framework for social media marketing, return on investment, client satisfaction, data-driven marketing strategies, marketing optimization**,** use case for AI and big data

Introduction

In the past few years (between 2021 and 2024), research conducted on the topic of social media marketing (SMM) seemed to be focused on developing a better understanding of the SMM phenomenon. Literature published and available in the English language during this time can be divided into themes such as brand loyalty, customer engagement, content type, content design, co-creation of value, customer participation, and intention to purchase. When studied in isolation the research covered by these general themes provides an insight into the dynamics between the social media variables within the context of the social media universe. Nonetheless, when viewed from a business perspective, the findings do not seem to provide a workable guideline for developing an improved marketing strategy that can significantly improve product sales. The following discussion can help further clarify this gap.

SMM as Multi-Generation Awareness Platform

McCarthy, Rowley, and Keegan (2022) posited that effectiveness of social media marketing is noticeable as an awareness creating platform. Although focused on building fan bases for soccer clubs, their findings aligned with a later study on luxury brands (Kyrousi, Koronaki, & Zotou, 2022), which confirmed that SMM effectively strengthens emotional bonds and enhances value perception among customers. Likewise, a similar effect was found to be true for medical services, where SMM was deemed to be a powerful technology (when incorporated with your marketing plan) to create service or product awareness across clients of all generations.

How members of various age groups perceive and interact with social media is also based on the ability of social media to impart awareness. Gen Z has been studied to have a higher rate of engagement based on the content and strength of an influencer's message. Gen X has a lower rate of engagement as their engagement is triggered by the authenticity of the influencers. (Bratina & Faganel, 2024). Furthermore, not only that Gen X and Gen Z SM users indicate a level of awareness about the SMM strategies and the ethnicity of influencers, but they also understand that entertainment and peer approval are the main driving force behind their SM behavior (Aran-Ramspott et al., 2024). This observation brings to light the non-linear nature of social media marketing space, which depicts that social media user engagement can also be generated for reasons other than an intent to purchase.

Establishing the use of SMM as an awareness generation platform is useful, nonetheless, how to use this knowledge to convert customer opinions into a sales transaction remains to be established. Where researchers have found many benefits of using SMM to benefit a brand, sales improvement does not seem to be one of them. Quite on the contrary, when looked in isolation SMM does not seem to have a competitive advantage on boosting sales significantly (Lopes & Oliveira, 2022). However, there is significant evidence that when used as a component of an overall marketing strategy, SMM works as a catalyst to boost overall marketing performance (Venciute, Auruskeviciene, & Reardon, 2023), and higher customer engagement rate (Semenda, Sokolova, Korovina, Bratko, & Polishchuk, 2024).

Customer Engagement

Since customer engagement on social media is dependent on the content that is created for the social media, several recent studies focused on the topic of content generation. Mathur et al. (2022) illustrated how user generated content (UGC) influences online purchase intentions, and purchase decisions. Vieria et. al. (2022) also noted that pull notifications on mobile devices are more effective than push notifications because they require user engagement. These studies validated the concepts of earlier studies that identified a positive correlation between customers' behavior of value co-creation and their purchase intention (Tran & Vu, 2021; Bazrkar et al., 2021).

However, contrary to Mathur et al. (2022), Jeong et al. (2022) reported that a firm's strategy to generate personified brand visuals (FGC) fosters emotional and social connections with consumers. In a later study Tyrväinen et al. (2023) also reported that firm-generated content (FGC) made a more significant impact on brand loyalty than user-generated content (UGC). An explanation of these contradictory findings may exist in a study by Iqbal and Sainudheen (2023) who underscored the mediating (rather than a moderating) role of customer engagement in the relationship between SMM and brand loyalty.

User Behavior

Owing to the non-linear nature of the interaction between marketing strategies and customer engagement, more recent studies have seemed to shift their focus on understanding this complex environment. Simmons and Durkin (2023) proposed a conceptual model that explained how firms may lose control over brand value creation because of a social media interaction between brand loyalists and brand rebels. Laradi et al. (2023) proposed that regular strategic postings and engaging with users through comments, likes, shares, and direct messages, and tracking and analyzing social media metrics and feedback may regulate brand loyalty and value perception.

In a detailed study Arora, Rana, and Prashar (2023) published some valuable findings. The authors noted that due to the viral behavior on social media, social media marketing should focus on social relationships, use vivid visuals over text, and offer personalized ads. However, intrusive customization negatively affects ad effectiveness and should be avoided. The authors further concluded that marketing professionals should track user behavior over social media to evaluate the effectiveness of their marketing strategies.

A study published by Kočišová & Štarchoň (2023) re-emphasized the crucial role of marketing metrics in social media, emphasizing the need for businesses to effectively measure and analyze their social media efforts. However, Ahmad and Khan (2003) made an important distinction between user behavior and customer behavior. The authors noted that high response rates on social media result in higher purchase intentions than the high response rates on text messages or affiliate marketing channels (Ahmad & Khan, 2023).

Nonetheless, what remains to be understood is the factor that converts a purchase intention to a purchase completed. Although these studies provide a deep understanding of how customer engagement is vital for driving outcomes on social media platforms, they remain SM-centric. They overlook the broader landscape of customer engagement that could also be driven by offline touchpoints or integrated marketing strategies that involve more than just digital engagement. The narrow focus on customer engagement as mediated or moderated by SMM neglects how other marketing efforts outside of social media can contribute to long-term brand loyalty and customer participation.

Frameworks

Some of the frameworks published to understand the phenomenon of SMM since 2021 have made significant contributions to stirring up the scholarly efforts towards grasping the SMM dynamics. In their final framework, Jami-Pour, Hosseinzadeh, and Mahdiraji (2021) proposed strategy, process, technology, content, performance evaluation and the people as the six key success factors for a social media marketing strategy depicting content criterion as the most important success factor. Later, Li, Larimo and Leonidou (2023) attempted to breakdown the social media space into five key functional areas namely, a communication and branding channel, social media as a monitoring and intelligence source, social media as a customer relationship management and value co-creation platform, and social media as a general marketing and strategic tool. In another similar attempt Hung et al. (2023) proposed a social media marketing roadmap based combining Koter's 5As (awareness, appeal, ask, act, and advocate) with the IDEA (identify, develop, engage, and assess) method of problem solving.

Although the studies and frameworks mentioned here contribute tremendously to developing an understanding of the SMM phenomenon, they seem to have maintained a social media centric approach, and lost focus on the factors impacting SMM that may fall outside the locus of typical SMM variables. Contemplating the findings and more so important contradictions between these findings, we attempted to broaden the canvas of variables to paint a broader picture through our AIMMS framework.

The AI Multigrid Marketing Strategy (AIMMS) Framework

The theoretical framework for developing AIMMS is based on the principles of engagement theory and social exchange theory. Engagement theory emphasizes the importance of active and meaningful interaction between individuals and digital content, with a focus on fostering deeper engagement through relevant and personalized experiences. In social media marketing, this approach aims to build stronger relationships and brand loyalty by encouraging users to participate, interact, and co-create rather than passively consume content (Kearsley & Shneiderman, 1998). The social exchange theory proposes that social behavior is driven by a process of exchanging actions aimed at maximizing benefits while minimizing costs (Homans, 1958). Based on these theories we attempted to take into consideration all factors that impact engagement and social exchange not limiting ourselves within the constraints of SMM centric variables. Furthermore, AIMMS is built upon the previous valuable scholarship and is a humble contribution towards furthering the scholarly quest of developing a holistic understanding of the success factors associated with SMM strategies.

The AI factor

The integration of artificial intelligence (AI) with social media marketing is a rapidly unfolding phenomenon that has generated considerable interest within both academic and business communities. With respect to the SMM space, the current and emerging focus of AI application is fixated primarily on content creation, content personalization and product design to improve decision making (Heitmann, M, 2024). As AI continues to evolve, it offers innovative capabilities that have the potential to transform traditional marketing approaches. However, the interplay between established marketing philosophies and the emerging potential of AI-driven strategies has yet to reach its ideal equilibrium.

Recent research has focused on optimizing the use of social media as a marketing channel, but challenges remain in aligning AI capabilities with core marketing objectives such as technology adaptation, brand loyalty, brand value, and strategic decision-making. Additionally, understanding demographic preferences, creating effective frameworks, promoting sales conversions, and engaging customers as collaborators are crucial elements that require further exploration to fully harness AI's potential in this domain.

The purpose of this paper is to provide a holistic view of the dynamic relationship between traditional marketing philosophies, emerging AI capabilities, and the vast amounts of big data generated by social media platforms. By synthesizing insights from existing research and proposing a new framework this study aims to guide businesses in strategically leveraging AI to optimize both client satisfaction and return on investment (ROI). This paper addresses the opportunities associated with AI in marketing, offering a comprehensive approach to maximize its impact on SMM strategy development in an increasingly digital world.

Method

This study employed a quantitative research design utilizing multiple secondary data sets obtained from publicly available online repositories. The data sets selected for this study provided longitudinal data on consumer and engagement behavior of social media users over a significant period. This approach allowed for a comprehensive analysis of various dimensions of user interactions and purchasing patterns across different social media platforms.

The primary objective was to identify correlations between the diverse elements available in these data sets, such as user engagement rates, consumer behavior trends, demographic variables, and purchasing decisions. To achieve this, we systematically analyzed the data using statistical techniques, including correlation analysis and regression modeling. The aim was to uncover patterns and relationships that could inform the development of the AI Multigrid Marketing Strategy (AIMMS), a structured framework for optimizing marketing strategies through AI.

One of the key data sets used in this research provided rich insights into the multidimensional aspects of consumer behavior. This data set was particularly valuable because it contained granular information on user engagement metrics, such as click-through rates, likes, shares, comments, and purchase conversions, segmented by product type and consumer income levels. By analyzing this data, we were able to explore how different types of products and varying income levels influenced consumer behavior and engagement on social media platforms.

Through correlation analysis, we discovered significant patterns that revealed how consumer behavior differs based on product type and income levels. For example, luxury products were more likely to be purchased by higher-income users who also demonstrated a higher engagement rate with AI-driven advertisements. In contrast, essential or low-cost products were more appealing to a broader range of consumers, but their engagement rates varied significantly depending on the content type and platform. These findings provided the foundational basis for the conceptualization of AIMMS as a formal structure to develop marketing strategies that effectively leverage AI technologies.

The insights gained from this data-driven approach led to the formulation of AIMMS, which proposes a multi-layered, AI-driven framework that considers these nuanced correlations to optimize marketing efforts. This framework can be adapted and expanded with additional components to suit various market conditions and consumer segments.

We will address the limitations of this study following the discussion of the patterns and relationships identified in the data. Notably, the use of secondary data presents certain constraints, such as the lack of control over data quality and potential biases inherent in the data collection methods of the original sources. Additionally, the data sets used may not fully capture all variables influencing consumer behavior, and the correlations observed may not necessarily imply causation.

To further substantiate the AIMMS framework, future research could incorporate primary data collection methods, such as surveys or experiments, to validate and refine the identified correlations. Moreover, expanding the analysis to include additional demographic variables and platform-specific behaviors could provide a more comprehensive understanding of AI's role in optimizing social media marketing strategies.

Results

Table 1 highlights spending preferences across different product categories (Beauty, Books, Clothing, Electronics, Food, Home Goods, Sports, and Toys) for four income levels (High, Medium, Low, and Very High). The values represent the deviation of each income level from the mean spent of the entire group in each category. Asterisks (*) indicating the highest deviation for each product category. The dot (˙) represents the highest deviation for each income group.

Table 1

Deviations of Various Income Level Spending Patterns From The Mean Spent of The Population For Various Product Categories

	Beauty	Books	Clothing	Electronics	Food	Home Goods	Sports	Toys
High	-9	-14	-3	7	-17 □	6	15	-14
Low	-3	-29 *□	12 *	-2	-5	-11	20 □	8
Medium	40 *□	23	-9	6	27 *	-1	-6	22 *
Very High	27 □	12	-5	27 *□	22	18 *	27 *□	-10

For **high-income** consumers, do not dominate any product category in their spending pattern. However, within their income level, they spend less than the population mean on Food (-17), Toys (-14), Books (-14), and Beauty (-9) in an online transaction. The highest online product the high-income group spends on is Sports (+15).

Low-income consumers dominate the most deviation from the mean spend of the population in the Books category (-9) and Clothing categories (+12). Within the group, they spend the least on Books and Home Goods (-9), and most on Sports (+20) in an online transaction.

Medium-income consumers lead the deviation chart in the Beauty (+40), Food (+27), and Toys (+22) categories. They also spend the most among the population on Books (+23). The least dollars spent by the medium income level is on Clothing (-9).

Very high-income consumers display the highest deviation from the mean spent of the population on Electronics (+27), Home Goods (+18), and Sports (+27). Within their group, they spend the least on Toys (-10) in online transactions.

This table provides insights into which product categories different income groups prioritize their spending on, helping to tailor marketing strategies and product offerings accordingly.

Table 2

Correlations Between Purchases Made and The Response Rate to Marketing Strategies By Each Income Level For Various Product Categories

	Beauty	Books	Clothing	Electronics	Food	Home Goods	Sports	Toys
High	B	□	En	□	B, Sn	B	□	□
Medium	□	□	□	□	□	□	B	B
Low	S	□	E	S	□	E	S	B
Very High	E	□	B	□	□	Sn, Bn	□	Sn

The table presents correlations between total purchases and different conversion or engagement rates for various product categories (Beauty, Books, Clothing, Electronics, Food, Home Goods, Sports, and Toys) across four income levels (High, Medium, Low, Very High). The values in the table depict the marketing strategies as follows:

B – Web search engine, E – Email marketing, S - Social media marketing

Any letter followed by an "N" depicts a negative correlation between the purchases completed and the marketing strategy.

As an example, for high-income consumers, positive correlations between total purchases and marketing search engine conversion rates (B) were recorded for Beauty, Electronics, and Home Goods, while a negative correlation was recorded between email conversion rates (En) in the Clothing category. Medium-income consumers show no specific trends, as most categories have neutral (€).

As another example, low-income consumers exhibit positive correlations with social media (S) or email (E) conversion rates, indicating these channels may be more effective in driving purchases. For very high-income consumers, positive correlations with email conversion rate (E) are noted for Beauty, and a mix of negative correlations (Sn, Bn) appears across categories like Home Goods and Toys, suggesting these channels may be less effective for this group. Table 2 provides four factor tabulation which includes the products (columns), income level (rows), and the correlations between the purchase amount and the response rate to marketing strategies.

Analysis

The concept of a grid in the given context can be described as a data frame consisting of multiple interrelated variables of a single segment (container). As an example, Product is a single segment with variables such as category, size, color, price range etc. Our current dataset only included one variable (category) with eight subcategories. Likewise, in Figure 1 we displayed four grids, namely, High, Medium, Low, and Extra High-income levels, stacked over the Products base grid to create a relative or comparative view. This presentation serves as a structured framework for examining various interrelated variables pertaining to a single perspective while incorporating multiple interrelated variables. By overlaying multiple grids in alignment with a base grid, more nuanced insights and hidden patterns within a dataset can be discovered.

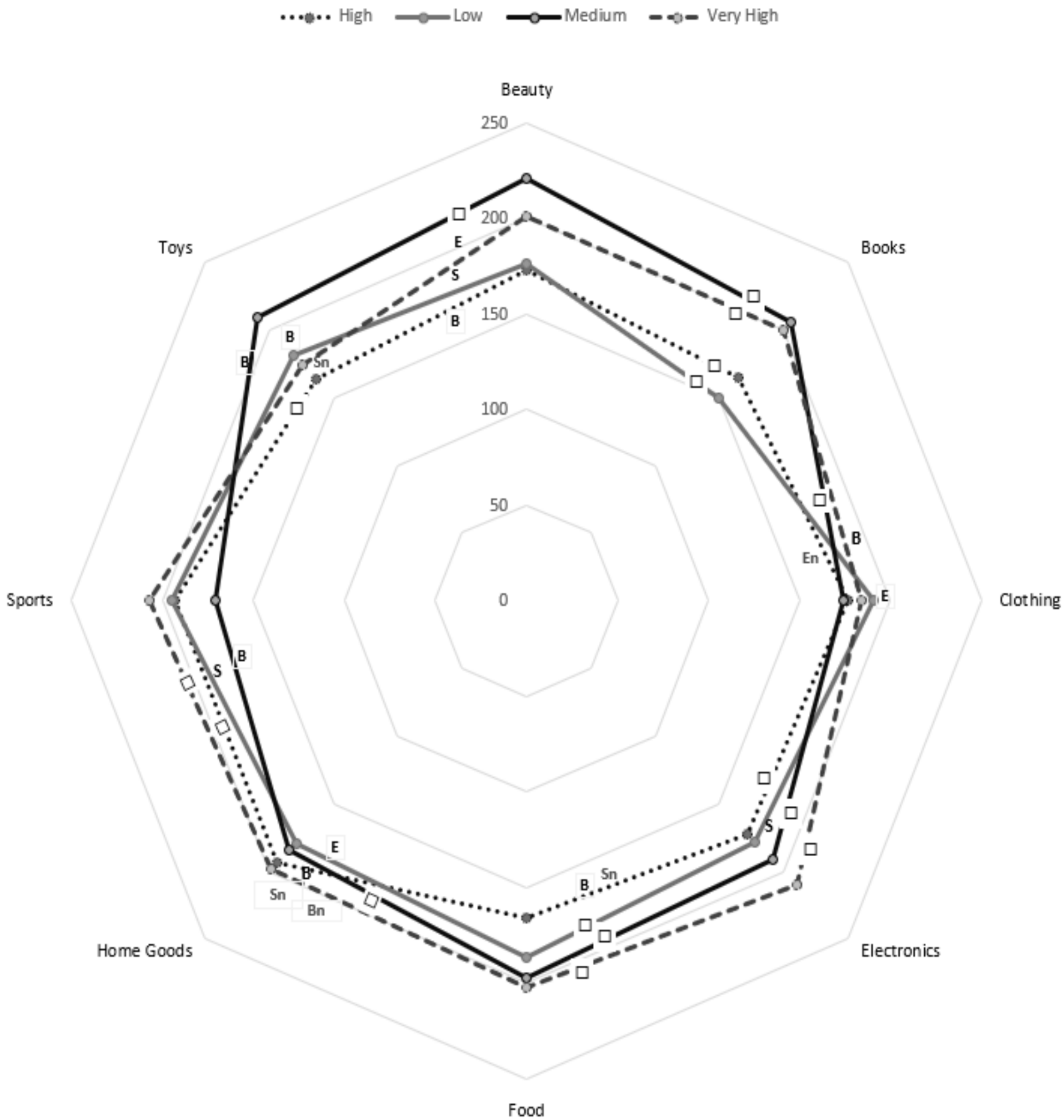
Figure 1 illustrates this approach by using the "Product" grid as the base grid, with four additional grids representing various income levels: high, medium, low, and very high. Each of these grids provides data on expenditure levels for different product categories and reveals the corresponding spending triggers tied to specific marketing strategies. For example, the grid for the "very high" income level indicates the highest spending on "home goods." However, there is a negative correlation with both social media and search engine conversion rates. This may suggest a preference among very high-income consumers for distinctive home décor items or a preference for a concierge-style shopping experience in physical stores. Conversely, the "high" income level grid shows comparable spending on "home goods" but with a positive correlation to search engine conversions. This may reflect a tendency among this group to avoid social media trends and seek unique styles through web searches.

Similarly, the data for the "clothing" category reveals that the highest spending comes from the lowest income group, strongly associated with email marketing conversions. This may be reflective of the presence of certain perceptions within the lowest income level. In contrast, the high-income group shows minimal spending in this category and an aversion to email marketing.

The very high-income level displays a correlation with search engine marketing, while the medium-income group does not show a strong association with any marketing strategy. Interestingly, in the "books" category, there is no discernible correlation between spending patterns and marketing strategies across any income level. Interplay between these grids for all other variables of the product base grid can be read in the same way.

Figure 1

The Multi Grid Data Depiction using the AIMMS Framework



Discussion

In this study, the multi-layered grid analysis provided a comprehensive view of how different income levels engage with various product categories and marketing strategies. This view could offer valuable insights into consumer behavior across diverse demographic segments. The visualization of these data brings to foreground multiple unexplained ubiquitous behavioral patterns as topics of further research that could otherwise stay unnoticed. The following are some use cases of this approach.

Instant Application of the Model

The model presented in figure 1 may be replicated with a similar dataset to get instant insights into a given sales strategy. The results depicted from the resulting visualization may provide guidance for more targeted sales strategies for a given product. As an example, various marketing campaigns can be generated for a product, targeting customers from each income level using the most relevant marketing strategy. This approach may result in optimizing the marketing budget by optimizing the marketing impressions in each category. Furthermore, this approach may also avoid the potential negative marketing, which may occur in cases where a certain income group shows statically significant aversion to a specific marketing strategy.

Role of AI Integration

This multigrid analysis is an ideal use case for AI and big data applications; hence, we coined the name AIMMS. Utilizing big data can facilitate developing any desired number of grids, such as gender, geography, seasonality, and cultural and social orientations etc. Where utilizing artificial intelligence (AI) and machine learning (ML) multiple grids can be overlayed on a base grid of choice to compute or visualize desired insights. These powerful tools can also allow you to change the base grid or reference grid to create multiple contexts.

As an example, in the present study, we could have generated a visualization using total online spending by each income level as our base grid. Such a visualization would render sellers a breakdown of what top products and marketing strategies could be selected to service their target income level. Application into multiple subject areas: the robustness of AIMMS can be applied to multiple fields of study such as media production and voter persuasion (which some would argue to be a branch of marketing).

Future Research

A research application of this grid could also be generated to compute or visualize the what-if analyses for any product (or project) before its launch. Interplay between various grids could help understanding the deeper social, psychological, and cultural (to name a few) rationales behind behavioral patterns. Such an application is also likely to identify unexplained patterns, which would open doors for new research.

Limitations

The limitation of this study is in terms of including all layers of complexities into a single paper, and the fact that this study was conducted using secondary data. If data is purposefully collected for the purposes of developing this model, more accurate results can be obtained. Role of AI and Big Data, provides a guided path for pinpointed development of a platform that can suggest optimal segmented marketing strategies that can be deployed to get the optimal ROI on marketing spend.

With AI based automation, the cost of all sorts of content development and engagement methods have significantly dropped. We can create personalized service perception for the masses.

Conclusions and Suggestions

The AIMMS model offers a versatile, stackable, and modular framework designed to incorporate a wide range of marketing variables, including demographic, social, cultural, ethical, religious, political, and psychological factors that influence customer preferences. Leveraging advanced AI, automation, and big data techniques, this model allows for the addition of unlimited layers or grids, providing a comprehensive means to determine the optimal context and approach for presenting a product to potential customers. Researchers and data scientists can enhance this model by utilizing both existing data sources and customized data collection methods to gather large-scale data. By identifying correlations within each data grid, AIMMS enables a multidimensional understanding of customer preferences and behaviors.

As consumer behavior continues to evolve, particularly with the increasing sophistication of online purchases, the AIMMS model requires continuous data input to remain current and effective. Ongoing data collection is crucial for capturing the dynamic nature of the variables under study and ensuring that the model adapts to changing market conditions and consumer trends. This adaptability makes AIMMS a powerful tool for developing targeted marketing strategies, optimizing return on investment, and enhancing overall customer satisfaction. Furthermore, by integrating new data and insights over time, AIMMS can remain a valuable framework for understanding and anticipating shifts in consumer behavior, allowing businesses to stay competitive in an increasingly digital marketplace.

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