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Enhancing Marketing Provision through Increased Online Safety That Imbues Consumer Confidence: Coupling AI and ML with the AIDA Model

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Abstract: To enhance the effectiveness of artificial intelligence (AI) and machine learning (ML) in online retail operations and avoid succumbing to digital myopia, marketers need to be aware of the different approaches to utilizing AI/ML in terms of the information they make available to appropriate groups of consumers. This can be viewed as utilizing AI/ML to improve the customer journey experience. Reflecting on this, the main question to be addressed is: how can retailers utilize big data through the implementation of AI/ML to improve the efficiency of their marketing operations so that customers feel safe buying online? To answer this question, we conducted a systematic literature review and posed several subquestions that resulted in insights into why marketers need to pay specific attention to AI/ML capability. We explain how different AI/ML tools/functionalities can be related to different stages of the AIDA (Awareness, Interest, Desire, and Action) model, which in turn helps retailers to recognize potential opportunities as well as increase consumer confidence. We outline how digital myopia can be reduced by focusing on human inputs. Although challenges still exist, it is clear that retailers need to identify the boundaries in terms of AI/ML's ability to enhance the company's business model.

Keywords: AIDA model; analytics; artificial intelligence; digital myopia; machine learning



Citation: Lee, Y.-I.; Trim, P.R.J. Enhancing Marketing Provision through Increased Online Safety That Imbues Consumer Confidence: Coupling AI and ML with the AIDA Model. *Big Data Cogn. Comput.* **2022**, *6*, 78. <https://doi.org/10.3390/bdcc6030078>

Academic Editors: Marco Fisichella and Antonia Russo

Received: 8 June 2022

Accepted: 7 July 2022

Published: 12 July 2022

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1. Introduction

In this new era of online shopping, where goods and services are increasingly being placed online, consumers are expected to become actively engaged in comparing online product information and sharing their knowledge through online customer reviews. In addition to this, they are expected to interact more with a chatbot/avatar (which is a form of artificial intelligence (AI)) that is supported by machine learning (ML). Since the start of the COVID-19 pandemic, new digital business models have transformed retailer–consumer interaction. For example, according to the IMRG Capgemini Online Retail Index, total online retail sales increased by over 36% in 2020 compared with the same period for 2019 [1]. This transformation of the retailing sector, coupled with rapid change in online technology that facilitates buying through the utilization of AI and ML [2,3], has resulted in a number of changes in retailing.

Reflecting on the impact and consequences of COVID-19, brings to the fore a number of issues, one of which is the rise in fake news and the harmful consequences of it (e.g., actual deaths from the disease and additional deaths attributed to fake medicines). The rise in the infodemic [4] (p. 671) is now being given attention, and marketers are required to note that consumers may not be able to distinguish fake news from genuine news. Consequently, they may suffer stress and anxiety when trying to make a distinction between the two, which leads to a re-evaluation of how consumers view information usage. Di Domenico et al. [5]

(p. 334) report that the dissemination of fake news “involves creators who develop and use fake social media profiles to spread fake news online”. This is of concern to marketers. In addition, Di Domenico et al. [5] (p. 335) report that “Firms are increasingly opting for online advertising, so fake news creators are incentivized to deliver greater volumes of fake content to drive more online traffic”. A concern that arises is how can consumers who are not aware of such issues, distinguish fake news from credible information? How can retailers help consumers to recognize the signs and make an informed judgement based on their interpretation of what is genuine news? This requires that marketers pay attention to the process of communication and how consumer behavior is influenced through various forms of interaction.

The type of interaction between consumers and retail companies is changing rapidly, and increased attention is being given to the benefits of implementing new online technology, such as AI/ML, that provides consumers with a better interactive shopping journey experience [6–9]. By taking advantage of AI/ML tools, marketers can deploy different types of AI/ML learning (e.g., mechanical, cognitive, and intuitive) to better understand how changes in consumer perception manifest and how consumers view the usefulness of interactive tools. Although research in AI/ML and marketing has recently been carried out, the focus is more on human–computer interaction or the use of technology in decision making. There is, therefore, a need to undertake further research into the application of AI and ML in a marketing context [10]. Hence, a question that arises is how can marketers evaluate the use of AI/ML so that the most suitable tools are chosen to help retailers interact with online users? Understanding the difference in AI/ML learning capabilities allows marketers to focus business operations and make adjustments in terms of marketing strategy implementation [11]. For example, developing AI–CRM (artificial intelligence–customer relationship management) systems can help marketers utilize customer data and link the findings with new product opportunities [12].

Digital technology, which includes the Internet of Things (IoT), artificial intelligence (AI), machine learning (ML), big data, and cloud computing, is advancing at a rapid pace. It is associated with data gathering and analysis, data storage, and the dissemination of information and is providing retailers with an opportunity to both expand their customer base and get close to customers by requiring marketers to manage the customer journey experience more effectively [13–15]. However, digital technology also presents retailers with a challenge in terms of the investment needed in digital infrastructure and connectivity [16,17]. This is partly due to issues in platform compatibility, for example, which may cause the customer to experience disruptions in communication that affect their search for information. Consequently, the consumer may have negative feelings toward the retailer/brand as they experience a high level of dissatisfaction. The level of dissatisfaction can increase when a data/information breach occurs and is mishandled, as was the case with Yahoo [18] (p. 3).

It can also be noted that there are challenges associated with the use of existing AI/ML learning algorithms [19,20], due to algorithmic biases [21], and different forms of network connectivity, which result in issues relating to interoperability. These challenges are the cause of digital myopia that result in unintended outcomes (e.g., negative word-of-mouth and poor online reviews). Marketers need to deal with these challenges by viewing an online purchase experience through the eyes of the consumer.

To deal with the challenges in a coordinated and planned manner, marketers are focusing on hyperpersonalization and the benefits associated with it. For example, consumers have an array of smart devices that provide a direct link between them and retail companies. These devices allow a consumer to search a company’s website and click on products of interest. Such connectivity is useful because it allows marketers to monitor the actions of customers and build up a picture of their lifestyle and how they shop. Collecting data across a range of customer segments allows marketers to analyze data and produce insights into current and evolving consumer trends. AI/ML aids the process by analyzing data relating to an individual’s buying habits. This helps marketers to devise sales promotions

and loyalty schemes and interpret feedback from consumers, the objective of which is to foster cocreation through digital clienteling [22] (p. 18).

Retailers are now moving toward deploying humanoid AI to produce a better customer shopping experience (e.g., use of an avatar in a virtual shopping environment) [23,24]. However, when retailers adopt a digital technology that is AI/ML-powered, they need to decide whether to standardize or adapt the communication message. They also need to give attention to how the product information is made available (e.g., provide accurate and quality information via AI humanoid avatars or via a search engine for example). Hence, it is useful for marketers to understand how online buying behavior is analyzed through various AI/ML tools and how the results can be interpreted. By viewing the customer shopping journey experience and process as spiral and continuous in nature, marketers can formulate and implement an online marketing policy that makes the customer feel appreciated and willing to buy online. By placing the online marketing activity in a holistic setting, marketers can collaborate with staff in other departments (e.g., sales and finance) and ensure that the after-sales service in place is customized. Please consult Figure 1.

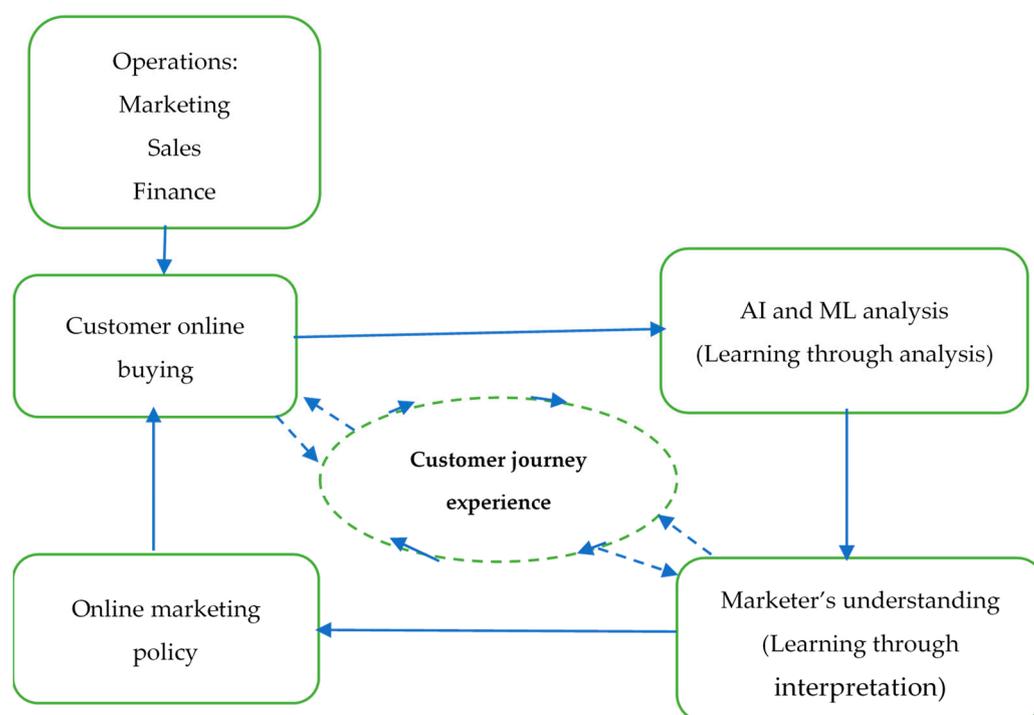


Figure 1. The process of renewing online marketing policy. Source: The authors.

Customization is important as it allows a retailer to meet consumer requirements. This ensures customer expectations are met and increases customer–company engagement that leads to satisfaction and a (re)purchase [25]. In addition to understanding what makes a customer feel safe buying online, it is necessary for retailers to understand the differences associated with various AI/ML tools and how they are used in relation to marketing strategy development and implementation. The AIDA (Awareness, Interest, Desire, and Action) model [26] can be considered relevant in terms of helping marketers to avoid pitfalls associated with digital myopia as it can help them to link the different stages of the customer needs process with appropriate forms of information. This can be viewed as knowledge enhancement. By linking product information with product usage, it is possible to define customer group behavior and meet an individual’s expectations. Hence, the application of the AIDA model in conjunction with the use of appropriate AI/ML tools can help marketers understand the application of marketing theory better. It can also help marketers to develop new perspectives and broaden their knowledge base through

applying an analysis to big data that allows them to interpret the findings in a meaningful way [27,28].

2. Materials and Methods

Reflecting on the transformation of the retailing sector, we formulated the main research question as: how can retailers utilize big data through the implementation of AI/ML to improve the efficiency of their marketing operations so that customers feel safe buying online? We answer the question from two different perspectives: (1) how AI contributes to enhancing consumer engagement with emphasis on the utilization of AI/ML to fine-tune market analysis and (2) how digital myopia can be reduced by linking the AIDA model with AI/ML so a marketer can interpret the results from an AI/ML analysis and formulate an online customer-centric, safety-oriented marketing policy. To the best of our knowledge, no research has been undertaken relating to reducing digital myopia and enhancing online safety through increasing consumer confidence in the context of big data. In this paper, online safety is defined as consumers feeling that they have received relevant and truthful information that gives them confidence to make a purchase. We bear in mind that: “Big data requires technical infrastructure, processing tools, and techniques to cope with the volume, velocity, variety, and generate value out of the data collected” [11] (p. 392). Hence, we pay attention to how different types of AI/ML learning are placed within the context of online marketing provision. Furthermore, we link the separate stages of the AIDA model [26] with different types/functions of AI/ML (e.g., mechanical, analytical, and intuitive) so that marketers can identify different analytical AI/ML tools to analyze big data so that they can assess the appropriateness of the organization’s marketing strategy [14]. This approach is supported by Du et al. [29] and Vollrath and Villegas [28], who highlight the importance of theoretical marketing models/concepts and the use of AI/ML to analyze big data so that digital myopia is avoided.

It is useful to reflect on what digital myopia is. Digital myopia occurs when marketers do not understand (i) the context within which different AI/ML learning occurs and (ii) how they should interpret the results of the data analysis from a customer’s perspective. The aim of which is to improve the organization’s marketing capability and deliver better value to customers [7] through an appropriate marketing strategy. Our contribution is helping marketers to increase the awareness of consumers so that they can distinguish between accurate and erroneous information and feel safe buying online. Understanding and cognizing (unforeseen) challenges, such as negative reactions from customers in relation to their dissatisfaction toward a product/brand, will help retailers to promote their products better.

Considering that we were studying an aspect of the customer journey, it was considered relevant to undertake a systematic literature review that contained an interpretive focus [15] (p. 200) and was composed of four distinct stages [15] (pp. 201–203) and [30] (p. 287). (1) Scoping (the context was digital marketing). (2) Search (e.g., relevant peer-reviewed academic journal articles were identified through Google Scholar and Mendeley) and analysis. The word search included AI/ML, chatbot, digital marketing, online customer journey, and the AIDA model. Filtering was used to screen out less relevant publications based on thematic fit. The papers selected were from top 3- and 4-star rated academic journals. (3) Research gaps were identified [31] (p. 99), and additional reference sources were obtained (e.g., most relevant academic journal articles). (4) Through the process of reading both directly related and indirectly related academic journal articles, the researchers were able to identify additional influential academic papers [30] (p. 287). The most influential academic journals used in the study are listed in Table 1. Each academic paper was read independently by the researchers, and their notes were combined and then reviewed so that only the most relevant material was included in the study. Guidance was taken from Xiao and Watson [31] as regards the steps in the systematic literature review. Please see Figures 2 and 3. It was interesting to note that although the year search was from 1970 to January 2022, Figure 2 portrays the publications dating from 2008.

Table 1. List of most influential academic journals with the key research gaps identified: AI, AIDA, and online shopping journey.

Journals	Topics	Research Gaps
Journal of Marketing	Omnichannel from a manufacturer's perspective.	The data that are needed for retailers and manufacturers that aid the vertical marketing process. Privacy regulation.
	Informational challenges in omnichannel marketing.	How to build incremental data from multiple sources. Privacy concerns.
	Information capturing as fuel for growth.	Identifying the right time to reflect on data captured for panning development. How to identify the right algorithm.
	Agility of marketing and big data.	How to identify gaps in customer expectation.
	Marketing agility: Antecedents and future research.	How to create a suitable environment to match personality traits and the agile marketing environment.
	Capturing data—from a strategic perspective.	How to be aware of the importance of intersections in new data, changes in consumer behavior, and deliverability.
Journal of Retailing	Retailing—from academic to practitioner.	How to facilitate collaboration between academia and practitioners to solve problems. Future growth through data sharing.
	Strategizing retailing in the new technology era.	How a digital display evokes a positive sensory response environment augmented. How virtual retail technology stimulates physical experience.
	Forging a meaningful consumer–brand relationship.	How to connect with individual customers one-to-one in order to provide uniqueness vis-à-vis ability to use one-to-many models.
	The impact of technology in retailing.	How to identify causality of the effect of technology in retailing and the effect of the adoption of technology in retail outcome as well as the retail ecosystem. The effect of the block chain in retail.
	Retail marketing communication—right time, right message.	How to combine different approaches to identify an optimal message for the right person and at the right time.
Journal of Management Information Systems	Advanced customer analytics.	To test Kernel theory in an actual business environment vis-à-vis identifying an appropriate analytical technology/algorithm.
California Management Review	Understanding the role of AI in engagement marketing.	How to manage information sharing between buyer–supplier for efficiency. Storing and processing data vis-à-vis appropriate technology. The issue of trust in personalized engagement.
International Journal of Research in Marketing	ML learning and AI in marketing.	The importance of leveraging rich digital information to address emerging issues in firm–consumer relationships. Challenges in aligning ML learning methods with marketing research challenges.
	Factors affecting the study of marketing issues.	Challenges to recognize the importance of topics instead of relevance. How to trade off in a systematic manner and identify variables to investigate.
	Important issues in evolving marketing.	ICT and its impact on the marketing landscape. Focus on different methodological approaches. Linking marketing theory development with impractical or practical issues in marketing.

Source: The authors.

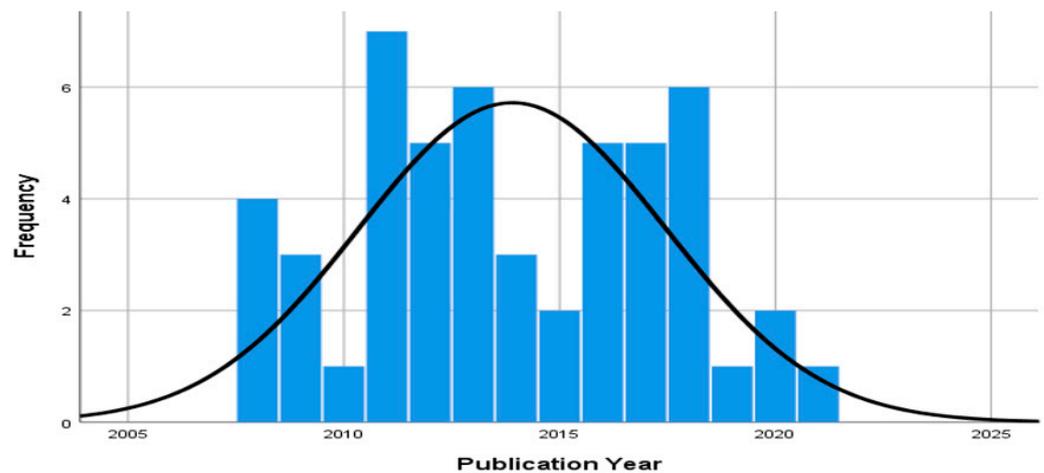


Figure 2. Digital marketing and customer relationship management—Trend analysis of publications 2008 to January 2022. (n = 51). Source: The authors.

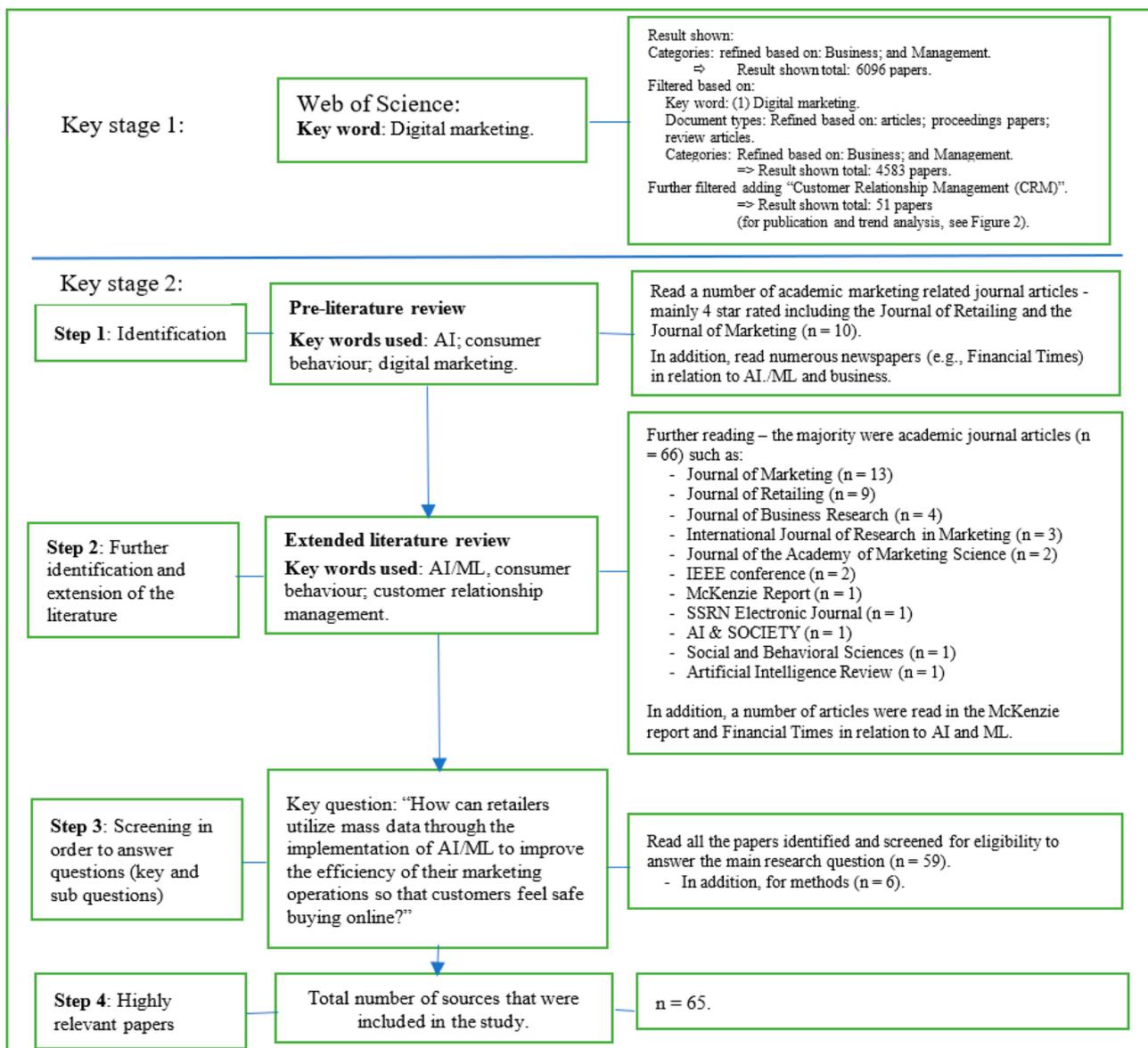


Figure 3. Main steps in the systematic literature review. Source: The authors.

The methodological approach adopted incorporated an integrated component as the researchers focused on an emerging topic and provided a new interpretation of the subject matter [32] (p. 357). Figure 1 can be viewed as the guiding conceptual structure, and the AIDA model can be viewed as the guiding theory. The main objective was to produce a conceptual framework that made reference to a new way of thinking that was derived through critical analysis and synthesis [32] (p. 363). Reflecting on the fact that a systematic literature review would reveal a number of research questions [33] (p. 518), the researchers paid attention to the relevance of the questions and remained mindful not to generate peripheral questions when undertaking the critical analysis. Attention was also paid to how the findings were to be presented [33] (p. 520). Because of the complexity involved, attention was given to conceptualization and visualization through frameworks, as the researchers were able to draw on their knowledge and produce a thematic synthesis.

3. Results

3.1. The ADIA Model and AI/ML

The AIDA (Awareness, Interest, Desire, and Action) model represents a well-utilized hierarchy of effects model [26] that measures the effectiveness of communication of an advertisement and is used by marketers to devise a marketing communications strategy. The hierarchical framework suggests that consumers respond to an advertisement in a sequential way: cognitively—thinking through the mental processes that reflect an individual's own beliefs/thoughts; affectively—general feeling/emotion, which can attribute to a brand; and conatively—consumer behavior of (intention) doing/purchasing [26]. Although the validation of the sequential thinking process is known to be inconclusive [34], it is useful to understand which aspects (emotional or cognitive) consumers are more likely to place emphasis on vis-à-vis the motivation to purchase a product [35].

In relation to the effectiveness in timing of the message, it should be noted that the notion of message receiving to increase an effect in a particular time is no longer linear [28]. Especially in a digital shopping environment, a consumer's decision making evolves with each social exchange of information from various social media sites as well as the company's website, and the consumer no longer buys a brand in isolation but in totality of experience. This places the brand in a social context and includes the purchasing process [36] as well as the motivation for purchase (either hedonic or utilitarian) and how/when it is used. An example of this is Walmart's express delivery service, which allows shoppers to pick what they want, pay for it, and have the product delivered to them in the way they want [6]. Consideration is needed as to how marketers can shape their interaction with consumers vis-à-vis deploying and managing AI appropriately. According to Vollrath and Villegas [28], Google deployed a simple framework of awareness through seeing and evaluation by thinking and action, and this was followed up by providing care through managing postpurchase experience. Through the utilization of digital marketing analytical tools, the issue of creating awareness relates to identifying segmentation groups (e.g., selected products images/messages to specifically defined segments) so that a customer's need can be aligned with the company's offering [37].

Online retailers can use the AIDA model to create awareness for existing products/services through organizing various marketing activities, such as advertisements, promotions, and/or sponsorship through a website, to stimulate consumer interaction and build a positive relationship [35]. In this context, the AIDA model is used as both an indicator of what marketing activities are needed and how these different activities should be integrated. The AIDA model can also be used as an evaluative tool for selecting appropriate AI/ML tools for gathering and analyzing data to support marketing activities. Consumer insights are matched with operational capabilities and allow marketers to create trust through positioning. However, although digital capability is viewed as enabling marketers to analyze various types of data in a short time period, marketers need to understand the level of consumer interpretation in terms of image-product fit and a consumer's motivation to purchase. This is relevant in terms of aligning market data with insights

that allow a personalized relationship with customers to be formed. By implementing a high-level customer service policy, retailers can ensure the customer is valued and their personal data and purchase details are kept secure.

3.2. *The Impact of Artificial Intelligence (AI) and Machine Learning (ML)*

Hamilton et al. [36] suggest that the consumer shopping journey is no longer considered a linear process but a series of interactions with the company through website information searches and machine-aided interaction (e.g., chatbots or Amazon's Alexa or Apple's Siri) as well as social media influence (blogger) interaction, which is proving influential in terms of changing consumer habits [13]. This suggests that marketers need to consider carefully how connectivity facilitates information transfer through appropriate apps and platforms and strengthens customer engagement.

Online searches for products and related information, aided by voice- or text-based interaction with AI, is now mainstream. Retailers, such as Gucci, Burberry, and Louis Vuitton, proactively use a chatbot facility to interact with potential customers, and this enables them to make a purchase 24/7 [38]. The use of the latest technology to assist the consumer's online shopping journey helps marketers make specific product information available in various forms and creates a new shopping experience that is enjoyable and generates dialogue among consumers. This results in additional sales through electronic word of mouth. The benefits of AI and ML, therefore, are known to include price optimization, the identification of certain consumer groups, and recording the reactions of people online, which are learned and acted upon through AI/ML.

AI is machine-based, human-like intelligence, and ML, which is a subset of AI and is algorithm-based [39], allows retailers to uncover insights through data mining from structured (e.g., sales data) and unstructured data (e.g., blogs, documents, video, and images) [27,40]. Furthermore, insights can be established from semistructured data that appear on social networks, such as the Twitter platform [41]. Semistructured data can be assigned internal semantic tags and categorized and analyzed using deep mining tools/models. This can be viewed as helpful as it provides an additional opportunity to utilize big data. There are, however, different types of AI/ML, and it is important for marketers to take cognizance of this. For example, a neural network represents supervised learning and is representative of a human brain as the nodes in the network train data to mimic the connectivity associated with human brain activity [27]. In the case of unsupervised learning, K-means clustering places individuals in groups and monitors their interactions [27], and in the case of reinforcement learning, actor-critic methods help an agent to determine optimal action [42].

There are many forms of AI and ML, such as the recommend system (e.g., user ratings), which enables collaborate filtering and content-based filtering, and a conversational agent/AI chatbot (either voice-based or text-based) to assist different consumers to satisfy their needs during their online shopping journey. What makes consumers engage in online shopping, according to Ashfaq et al. [43], is the quality of the service, which includes accurate information, the ability to navigate the website, and the perceived entertainment associated with the search. In addition to retailers providing accurate information in a timely manner through the deployment of a conversational agent and/or recommend system, for example, retailers also need to consider how they can fulfil a consumer's emotional needs through the deployment of advanced AI. Guha et al. [7] report that in online learning, AI can read the emotions of participants while they interact online, which helps the provider to personalize the interaction by responding to a participant's needs and thus make them feel comfortable. Fulfilling consumer needs can also be considered from the perspective of whether the retailer places emphasis on meeting utilitarian (inexpensive, functional, and requiring minimum effort or accurate product information) needs or hedonic (pleasure, emotional, and psychological) needs [44,45]. A question that arises is: what aspects do marketers need to pay attention to when selecting the most appropriate AI/ML tools so that marketing operations are enhanced and repeat business materializes?

Often AI and ML are used interchangeably as they are related to the harnessing of data and are deployed in data-centered retail technologies [46] as well as the integration of AI and ML in a firm's website design to fit a retailer's specific needs. Hence, the level of data richness and connectivity in terms of the digital ecosystem needs to be considered when establishing the purpose of implementing AI and/or ML to achieve the full effectiveness of AI and ML deployment [47]. For a retailer and channel member organizations to integrate their marketing plans, secure connectivity and data sharing among partner organizations in the supply chain are imperative. However, accessing and/or sharing consumer data among channel partners is not easy due to various reasons. Some partners in the supply chain guard their consumer data very closely for their own improvement [17], and issues of data standardization and unification present challenges also [16]. There are resource limitations regarding interoperability between systems and networks in the context of the supply chain vis-à-vis data accessibility, and attention needs to be given to reducing blindness in capturing consumer data as well as identifying relevant data that are needed for specific tasks that are in line with the firm's strategy [6,28,29,48].

Although there are advantages associated with deploying advanced AI that is intuitive and empathetic in building relationships with consumers through social touch and human-like interaction, it should be noted that there are some risks involved. For example, individuals who are highly sensitive toward privacy might react against a system's autonomy as well as chatbot and humanoid AI [17,43,49] as they feel discomfort due to a lack of trust in the AI's unknown capability [50].

3.3. The Link between the AIDA Model and the Use of AI/ML

The objective of marketers is to deploy digital technology more effectively than those working for the competitors and provide superior value through communication (e.g., accurate and current information) with customers, so that there is a match between the product's visual image and the locally preferred image that is of interest to a specific group/individual through personalization [51]. Roggeveen et al. [25] explain the importance of aligning a retailer's brand identity with a consumer's identity so that customer engagement is increased. This can be done through the retailer utilizing visual aspects online via their website. This highlights the need to create messages/cues that appeal to a particular group of consumers. Hence, marketers need to evaluate the data obtained through analysis and interpret the results in relation to specific marketing activities. Taking this into account, a question arises: how can marketers differentiate the results of the data analysis to gain insights into consumer shopping behavior so that communication with consumer groups is improved? The logic underpinning this view is that by providing accurate information, the company will be viewed as trustworthy, and the (potential) customer's confidence will increase. As a result, potential customers will make a purchase online.

The use of AI for data mining and consumer purchase history provides insightful information that marketers can draw on to plan promotional strategies. In addition, it should be noted that potential blind spots that coincide with the use of AI in relation to its functionality (e.g., based on consumer clicking habits and what appears in the next click) require retailers to link the right product with a specific type of promotion that matches the customer's need [25]. This can be viewed as trustworthiness in the context of a safe website.

To use AI and ML tools more effectively from a marketing and sales perspective, it is useful to reflect on how the AIDA model creates desire by creating stimulus through articulating images and messages that are more relevant and which appeal to a specific target audience. By reflecting on the AIDA model and linking it with different functions of AI and ML, marketers can better organize and frame messages and create product images in relation to a specific marketing objective (e.g., create awareness of a product/brand or desire) and in relation to groups of customers and also produce realistic marketing strategies.

As can be seen in Table 2, the subconcepts in the ADIA model are not linear in a digital marketing environment. Nevertheless, the subconcepts are helpful as they allow marketers to understand why different types of data are needed and to focus their analysis

on a particular target group/segment that has been identified for the product offering. For example, awareness in a traditional marketing context depends on where, when, and how an intended message reaches out among the potential target audience. In a digital marketing environment, the effort of identifying a potential target audience depends on the quality, size, type, and source of data and its analysis. At the awareness stage, the cognitive thinking process in a traditional marketing context focuses on the consumer and how an individual responds to the message a firm has created. In a digital marketing environment, staff place emphasis on how the firm can identify the potential target audience through mining the data and analyzing various data sources. The psychology of the cyclical firm–consumer relationship, in traditional marketing, places the emphasis on a firm trying to lead the consumer to act/purchase a product by influencing the consumer and getting them to identify with and respond to the message in the advertisement. However, in digital marketing, the emphasis is more on how a firm can push a consumer to act/purchase a product through them identifying with a group, and this involves undertaking customization and personalization of the message using social influence (e.g., through social media). Retailers use various AI/ML tools to convince the potential consumer that the product is right for them, and the message portrayed is reinforced by an influencer, who may in fact be a well-known celebrity.

Table 2. How AI contributes to enhancing consumer engagement.

Traditional Thinking		Current Thinking—Digital Marketing with the Use of AI		
Consumer Shopping Funnel	Online Marketing Efforts	Thinking Process: Use of/Function of AI/ML	AI/ML Contribution to Increase Effectiveness	Opportunity to Create Awareness
<p>Awareness: Through advertisements. Sending promotional message. Support identified sponsor.</p>	<p>Web advertisements. Social media presence. Supports opinion leader. Affiliated with other brands/firms.</p>	<p>Cognitive. Mechanical and/or analytical.</p>	<p>Social media. Affiliated marketing. Blogger. Audio and video. Social listening. Use of ML (supervised learning) to identify (potential) segments.</p>	<p>Exploring and acquiring customers via mining data (structured, semistructured, and unstructured).</p>
<p>Interest: Create brand personality/characteristics. Band attributes: colour, taste, smell, and texture. Information about products. Brand image.</p>	<p>Content creation: Creating and posting video clips on a regular basis. Blogging. (Re-)sharing of branded content. Advertise games. Ingame interaction.</p>	<p>Cognitive and/or Affective. Analytical and/or Intuitive.</p>	<p>Social media. Affiliated marketing. Blogger/microblogs. Gamification. Content marketing. Live chat. Search engine (e.g., Adthena, Coveo, and Salesfire); SEO. Live-language translation. Personalized message. Personalized e-mail messenger. Mezi (travel planning). Pandora (music). Alexa, Siri, and Cortana. Replica, etc. Use of ML (supervised and unsupervised learning); redefining consumer interests and forming groups based on segmentation.</p>	<p>Developing (potential) customer groups based on initial clustering and data analysis. Big data.</p>

Table 2. Cont.

Traditional Thinking		Current Thinking—Digital Marketing with the Use of AI		
Consumer Shopping Funnel	Online Marketing Efforts	Thinking Process: Use of/Function of AI/ML	AI/ML Contribution to Increase Effectiveness	Opportunity to Create Awareness
<p>Desire: Produce a unique aspiration that causes mental change in the consumer’s mind and makes them think differently. (Consumer comprehends message and conviction).</p>	<p>Community groups. Special promotion for particular groups (e.g., price sensitive group versus latest trend). Special product information for a particular group (e.g., L’Oréal, Ogilvy in Nestlé).</p>	<p>Affective. Analytical and/or Intuitive and/or Empathy.</p>	<p>Content marketing. Blogger/microblogs. Sharing (pictures and videos). Ria (track health eating level/pattern). Search console (by Google analytical tool for tracking). Expert system to integrate customer characteristics with other data to send a message, etc. Recommend system for personalization. Use of ML (supervised learning, unsupervised learning, and reinforcement learning); provides further personalized information; allows an individual to interact and gain an answer to a particular question. AI learning.</p>	<p>Defining customer groups and leverage through ability to send customized and/or personalized messages based on the result of combining various data sets and interpreting market and consumer intelligence.</p>
<p>Action: Consumer takes action to purchase.</p>	<p>Buy. Become a referee for a brand.</p>	<p>Conative. Analytical/Mechanical.</p>	<p>Chatbot (e.g., Totango, Voyado AI that prevents customer churn or increases upsell opportunity). PayPal. AI learning.</p>	<p>Initial customer retention strategy through establishing trustworthy and easy payment system.</p>
<p>After care (in digital)</p>	<p>Managerial business analysis.</p>		<p>Various supervised and unsupervised learning (e.g., Zaius). Data exploitation.</p>	<p>Customer retention and loyalty based on follow-up survey of customer experience of purchase; third-party service delivery; social listening and observation of customer churn. Structured, semistructured, and unstructured data.</p>

Source: The authors.

A unique aspect of the use of AI/ML in digital marketing is that it provides an analytical function during the various stages of the consumer’s journey (from the retailer’s effort to reach out to the consumer, interact with the consumer, encourage the consumer to interact, and influence the consumer into purchasing the product) [27,46,52,53]. Table 2 shows examples of different AI/ML applications that help to create awareness and at the same time help to generate interest as AI/ML can be implemented for social media listening vis-a-vis the ability to send personalized messages to specific individuals and groups of people.

One of the advantages of the AIDA model is that it helps retailers to deliver continuous customization through AI/ML that considers current and evolving needs that are based

on future forecasts. This is done by combining various datasets for analysis (e.g., media mining, sentence analysis, and record of customer churn) [27]. This allows marketers to map current trends against expected trends and plan sales promotions. AI and ML have the advantage of linking the marketing planning process with customer service delivery as it allows marketers to consider seasonal trends, peaks, and unexpected demand.

AI and ML can understand, interpret, and tailor offers to specific customers based on customer needs through the process of an automation/recommend system that ensures that customers receive the best deal [27]. In addition, in relation to the online consumer shopping experience, the interaction with an avatar in a virtual shopping environment provides customers with accurate information about the product and its availability, and consumers find the interaction with an avatar to be fun and enjoyable as it enhances the virtual shopping experience [23]. The use of an avatar, coupled with a voice-activated personal assistant [52], enriches the virtual shopping experience of the shoppers as they are able to relate to the information, giving them a higher level of satisfaction.

The deployment of technology assists the functional aspects of the business process and helps fashion the business model and resulting marketing strategy. Prepurchase and postpurchase consumer behavior is becoming increasingly influenced by automation [27]. Well-known business models, such as Amazon with Alexa in support, are providing a means to establish engagement in terms of customer–technology relations that encourage consumers to spend more time searching for products that they are looking for. Hence, AI and ML allow consumers and potential consumers to find various alternative options among similar product categories and, at the same time, help marketers to adopt a hyperpersonalization approach. What does surface, however, is the standardization versus personalization debate vis-à-vis utilitarian and hedonic needs. The question that arises is: what aspects do marketers need to consider when setting an online marketing policy? Marketers need to consider how the deployment of technologies (e.g., AI, ML, Internet of Things (IoT), big data, and cloud computing) in the retail sector allows the company to become more customer-centered. Hence, marketers need to rethink their company’s online marketing policy in terms of how the consumer-centered approach in relation to the product mix takes into account issues relating to cost, closeness to local consumer groups, establishment of a relationship with customers through a communication-oriented rapport, and fulfillment of customer expectations through a unique service.

In relation to deploying AI/ML and increasing operational effectiveness, the degree of personalization and the required sophistication of AI/ML may differ depending on the type of retailer and how the retailer is positioned in the market. For example, a high-fashion retailer might deploy a humanoid AI with augmented reality and a search engine. A fast-fashion retailer may only deploy a search engine that has system connectivity with partner organizations in their supply chain. One of the key aspects that needs attention is how retailers integrate AI so that the interface with consumers (front end) is deemed appropriate and how AI is used to support and provide relevant information in real-time (back end). Referring to the ADIA model stages in Table 2, “after care” is a follow-up action. Marketers should undertake a customer satisfaction survey (post purchase) so that they gain insights into buyer experience (including delivery of the product purchased and use of the product) and additional information about possible new products. Such information is useful in terms of preventing customer churn and providing a high-level, continuous, online customer journey experience, which is aimed at customer retention.

3.4. Challenges in the Use of AI and ML in Retailing

The deployment of various AI/ML technologies helps retailers to either decrease their overall costs by enhancing engagement through service provision from various stages in the online shopping journey or utilize inventory so that the service is improved through automatic checking [46]. One of the key challenges of AI/ML is that the learning capability is determined by the algorithms that are designed based on different requirements [27]. Hence, attention is needed to the interconnectivity between different networks (e.g., net-

work data derived from search engines and advertising platforms) and identifying the boundaries vis-à-vis AI/ML's ability in the context of a retailer's business model. This suggests that when marketers choose AI/ML tools, they need to reflect on the positioning strategy in the industry. For example, Amazon's strength is that it focuses on utilizing the deep learning capability of AI for social listening and developing the profiles of web surfers to deliver optimal effects by identifying and grouping consumers into distinguishable segments. Amazon has integrated a voice-based search engine [27] so that consumers can find information about the product easily, which is perceived as convenient and enjoyable and helps them to expedite their purchase decision. One of the key aspects as to why Amazon is able to use various AI tools is due to management's ability to utilize market-level information, which includes the use of third-party data and data relating to competitors [46], which Amazon is able to refine continually based on various criteria so that a personalized service is delivered continuously [27].

To enhance consumer engagement, marketers should consider four key questions. First, is the data captured through various methods (e.g., social listening or data sharing with partner organizations) sufficient for analysis in terms of assessing a specific target audience's need(s)? A firm's accessibility to various social media networks takes it beyond the firm's social media platform, and not all the potential customers are active on social media. In addition, regulations regarding privacy issues and GDPR (General Data Protection Regulation) are not the same worldwide because different countries have different laws, and there are different rating systems in terms of how data are standardized. Second, can marketers establish how the analysis is conducted (e.g., supervised learning versus unsupervised learning)? What needs to be borne in mind here is the original source of the data and how the data are combined (e.g., user-generated content, third-party profile data, or scanned data). Understanding the original source of the data can have implications for evaluating and identifying the uniqueness of the data in terms of segmentation strategy. Third, how can marketers ensure that the AI/ML tools associated with a company's website are familiar to the target audience? Marketers need to attach a search engine to the company's website that is easy to use and which allows consumers to filter and/or personalize their search-ability for a product that they are interested in purchasing. Attention should be given to how end users can become familiar with the different technology available. The search engine also needs to be supported by an inventory system once the consumer reaches the purchase stage. Fourth, is the type of payment system viewed as safe and trustworthy by consumers? Attention also needs to be given to various types of check out system (e.g., Apple Pay, Samsung Pay, or PayPal) as well as consumer perception toward using a payment platform to make payments online. Some companies allow a customer to make a payment online, and there is no extra charge, but some companies charge for a customer to make a payment online, which customers may consider unreasonable and which reduces their level of confidence.

In terms of prediction and personalization, it should be noted that although AI and ML allow marketers to predict future trends/demand, AI/ML learning that is based on patterns, characteristics, and structures, for example, is already in existence and is based on the existing algorithms, which can result in unintended social discrimination as well as misunderstanding [19,20,54]. Hagendorff and Wezel [19] explain the challenges that are compounded within algorithms due to software engineers being trained in computer science and not in sociology, psychology, or ethical or political science. Hence, they follow the "I-methodology" (p. 357) to generalize matters based on their own personality traits and experiences and transfer these to others, which leads to a blind spot for misunderstanding or misinterpretation. This is a crucial point to pay attention to in relation to the categorization of personality and clustering consumer groups vis-à-vis expected consumer responses. Rai [21] points out the importance of recognizing "algorithmic biases" (p. 137) (bias associated with the algorithm itself). Rai [21] explains that the AI system for supporting two-way automated interaction between a retailer and its customers through a personalized recommend system for products and services involves different types of AI models that

need to trade off between accurate predictions and explanations for different choices versus deploying a trustworthy AI system for fairness. What needs to be borne in mind is how marketers influence consumers through various social networks and provide explanations that influence behavior. Notwithstanding the challenges, the AIDA model can be utilized in terms of AI/ML as can be noted in Table 3. The reader will gauge from Table 3 that the challenges bring with them certain risks, and during the desire stage, AI/ML is used to customize and personalize messages. Marketers are expected to interpret how an online marketing policy will result in retaliatory action(s) from competitors and how in the action stage, customer churn can be avoided. The main question to be addressed is: how can marketers devise an online marketing policy that allows them to counteract the actions of competitors? A secondary question can be posed: how can marketers devise an online marketing policy that allows them to counteract the actions of counterfeiters? As regards the latter, marketers can think in terms of devising a ‘safety critical system’ that offers some form of safety assurance [55]. Safety can be viewed as AI and ML combining in the form of the AIDA model to put the consumer at ease and to ensure that marketers create truthful messages that are delivered to the appropriate group of consumers. Another point that surfaces is what is referred to as ‘AI safety’ [56], and we reflect on this by suggesting that a model and the modeling process itself can be reinforced by and through objectivity.

Table 3. Usefulness and challenges in relation to deploying AI/ML through the AIDA lens.

AIDA Model	AI/ML Usefulness	Challenges
Awareness	- To explore structured, semistructured, and unstructured data.	- Issue of the full accessibility of the data. - Knowledge of origin of the data. - Data standardization and unification.
Interest	- To develop a customer base.	- Use of appropriate threshold/criteria for clustering consumer groups. - Ability to track how AI/ML creates new categories for identifying new groups and their behavior patterns.
Desire	- Able to customize. - Able to personalize.	- Ability to check how new customer changes are identified and integrated. - Ability to check how market information (e.g., competitor’s actions) are integrated in short-term/longer-term strategies. - Issue of how to comply with GDPR.
Action	- Provide a convenient payment mechanism.	- Ability to identify factors that affect customer churn vis-à-vis an acceptable cost threshold.

Source: The authors.

3.5. Reducing Digital Myopia

Reflecting on the above, it can be argued that for marketers to effectively utilize AI/ML and expand their online business operations through increased interaction with customers, they need to combine the capabilities of AI/ML with human capabilities [7]. This is because there are challenges associated with algorithmic biases and relevance and fullness of the data from different networks, for example. In addition, to avoid confusion and enhance the use of AI/ML and to support online marketing operations, it is necessary to use marketing theory as a cornerstone to assess data relevance against set criteria for the purpose of analysis and interpretation. This has significant implications for marketing strategy development [11,29] with regards to reducing digital myopia [28]. Figure 4 is illustrative of how digital myopia can be reduced. The reader can take cognizance of the fact that retailers can link the different stages of the AIDA model with the different functions of AI/ML (e.g., mechanical, analytical, and intuitive) and apply relevant theory (e.g., customer journey) in relation to a firm’s specific marketing strategy. Such an approach will allow marketing strategists to deal better with unforeseen challenges associated with the incompleteness of data and implement contingency plans based on their understanding of the level of service provision required to satisfy specific customer groups. It will also

force them to think in terms of delivering promotional campaigns that are viewed as trustworthy and provide the customer with confidence to inquire further and then make an online purchase.

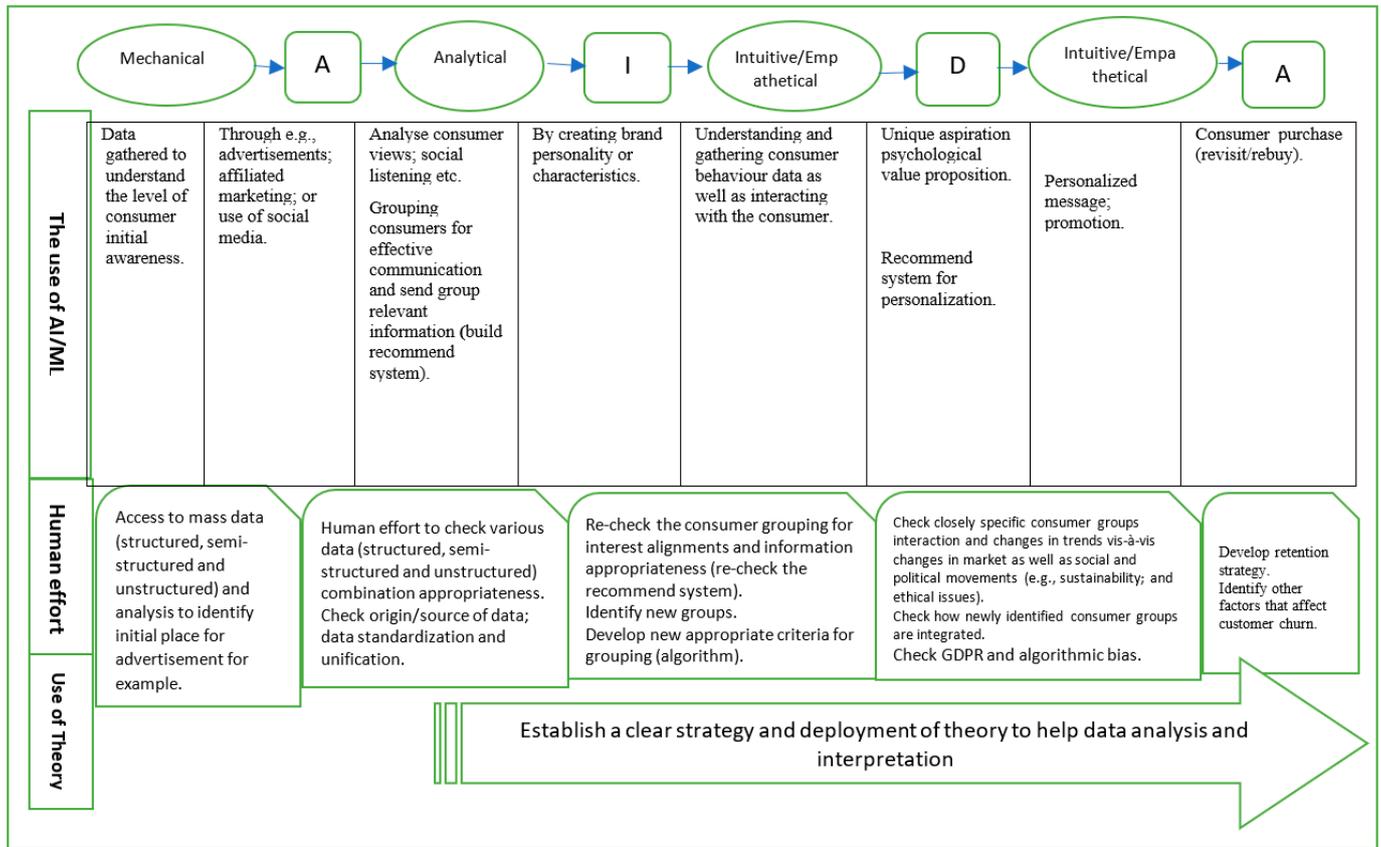


Figure 4. Reducing digital myopia—the link between the AIDA model and AI/ML. Source: The authors.

Marketers who are more focused on utilitarian and standardized products, may place greater emphasis on supervised and unsupervised learning. This is because AI can help consumers navigate a retailer’s website and find what they are searching for. For example, online fast-fashion retailers, such as Oasis, Asos, Boden, and Boohoo, appear to place much emphasis on the image of a product and display the apparel items in a pleasant environment being worn by an actor/actress who portrays the clothes well. By ensuring that the background against which the product is portrayed is both welcoming and appealing, the aspirations of consumers in terms of fit and style should be met. The experience provided to the consumer will evoke an immediate emotional response, and by providing an easy-to-navigate website, it will be easy to find the item of interest, click on it, and then authorize the payment. With regards to the Ted Baker website, consumers can click on various types of products that they are interested in and feel comforted by a chatbot that helps the consumer to receive appropriate advice about the product, styling, availability in store, store location, and the customer service provided. Department stores, such as John Lewis and the House of Fraser, and other luxury fashion retailers, such as Net-A-Porter, are focused on using filtering tools. Amazon provides consumers with the option, if they require it, to have personalized recommendations.

Some fashion retailers, such as M&S, utilize an integrated online fitting room, Texel 3D scanning technology, that allows consumers to create an avatar to represent their size, and they gain in confidence and select the right style of garment. Although the intention of introducing an avatar aid and a 3D fitting room is to reduce the return rate of clothes due to a misfit in size [1], it also creates a new and positive experience for the consumer.

During the interaction with the avatar in the fitting room, consumers find it enjoyable and are possibly willing to share their experience with friends, which creates more interest and the possibility of increased sales through word of mouth. Hence, marketers need to pose the question: how can AI be used to help create a better online shopping experience that increases engagement with consumers? Part of the answer suggests that retailers need to personalize their product range and devise additional customer-focused services [57]. The additional services include the scanning of data that allow the retailer to plan and thus reduce the cycle time as the design team can easily utilize the data to find a fit between the style of designs and type of garments [58] and seasonal variance, which is important in terms of reducing inventory and unsold stock at the end of a season.

4. Discussion

It can be noted that through big data analysis and identifying appropriate consumer groups based on click history in relation to different consumer motivation (utilitarian versus hedonic), an unexpected blind spot can emerge. For example, if consumers spend more time and effort on filtering video and other content of a brand/company either for entertainment or learning about the product without making a purchase, it suggests that consumers are engaged with a brand for hedonic reasons [44,45,59]. This may challenge marketers in terms of turning engagement into sales, as retailers need to understand how the click relates to a product's/brand's attributes, the influence of technology and its functionality (related to navigation of a website, for example), and a customer's personal traits [60]. The key point to emerge is whether a marketer should focus their effort more on the service element or incentives/promotions on offer [61] or provide more appropriate messages and offers [62]. Answering this requires marketers to revisit the cocreation concept and to establish how to design and deploy a technology-based service model. This may mean, however, that marketers need to adopt a wider perspective than they do at present and link AI more firmly with hyperpersonalization and digital clienteling [22]. The advantage of this approach would be to understand better how AI links two bodies of knowledge, such as marketing and psychology [10]. Should this be the case, marketers will be able to embrace more fully what Følstad and Kvale [15] call customer journey mapping and develop new knowledge.

Marketers also need to consider how individuals are influenced by their social network vis-à-vis product purchase decisions. In relation to information sharing about a product and its influence, Park et al. [63] found that consumers are more influenced by social networks when they purchase hedonic products than utilitarian products. What marketers need to consider is that cyberattacks on individuals and organizations are becoming more intense, and because of this, they need to think more carefully about the messages and images they provide on the organization's website. Marketers should, therefore, adopt a proactive approach to cyber security because a data breach will have an effect on the trust-based relationships that are in place [18]. It is for this reason that more attention should be given to the various stages associated with the AIDA model and how security-and confidence-building messages can be built in to awareness provision and reinforced continually.

It can be noted that the use of an avatar and an online 3D fitting room helps fashion retailers to both attract consumers who have a strong technology-related curiosity and enjoy online shopping and attract those who are sensitive to environmental issues, such as pollution and reducing waste (issues that have now been associated with fast-fashion and unsaleable items) [25]. This suggests that by utilizing various types of AI/ML, marketers can also identify new consumer groups and respond to their emerging needs appropriately vis-à-vis matching an individual's motivation and behavior with the use of a product in a social context. In terms of a retailer delivering unique value to customers, marketers need to consider how staff in partner organizations integrate data bases and share data by integrating partner organizations more fully into the firm's marketing planning process. Such an approach can be viewed as beneficial as it allows marketers to better utilize AI/ML for personalization.

In relation to the implementation of humanoid AI in a consumer context, the uncertainty associated with AI's performance is known to affect the choice that consumers make and the decision outcome [8,9]. For AI/ML to be effective or increase the effectiveness of the interface between a company and individual consumers in the digital environment, marketers need to pay greater attention to the prepurchase stage(s) and how consumers search for information and share their experience with friends (e.g., via electronic word of mouth) as well as their propensity to embrace technology for shopping. This relates to how a retailer attracts consumers through confidence building relating to the relevance of information in a social context (popularity of topics vis-à-vis a brand's personality and reputation among social groups) and reinforcing technology usage through online shopping that provides safety.

It should be noted that AI is developing through time, and AI/ML capability is to be viewed as several interlocking AI/ML capabilities. By progressing from supervised to unsupervised learning and beyond, AI/ML is assuming a high level of decision making. Hence, it can be suggested that the utilization of AI/ML fosters the strategic capability of the company [30]. This is achieved through the development of marketing plans and policies and also by helping senior managers to formulate a more market-focused business model. Therefore, to understand how AI/ML is to be implemented requires strategic vision and a commitment to investing in a range of platforms (business platforms, enterprise platforms, and enabling platforms) [64] that provide the company with a sustainable competitive advantage through relationship building.

It can be suggested that successful AI/ML integration throughout a business model is to some degree dependent upon the insights and understanding of senior managers in partner organizations. We acknowledge that AI is influential in terms of helping managers devise and put in place an appropriate business model and agree with the view of Di Vaio et al. [30] that a gap to be researched is how sustainable business models can aid sustainable development goals through the aid of AI. There are several reasons why issues such as this are worthy of future study. First, senior managers in partner organizations are aware of how AI/ML can be utilized from their company's own industry perspective and have already established business relationships with their suppliers that incorporate connectivity and data accessibility vis-à-vis GDPR and compliance [7,17]. Second, by putting in place a website that incorporates AI and ML, their interaction with customers is known to yield market data that can be utilized further, and the intelligence can be shared with suppliers, and if appropriate, government representatives. An example of the latter is a government department concerned with economic development and the role played by small and medium-sized enterprises. Sharing data with supplier organizations and external stakeholders is sensitive, but this represents an opportunity to provide appropriate information at the right time with the right content that is perceived to be of value to the customer/investor. In the case of the consumer, this should make them feel that they have been understood and are perceived as a relevant information source, which can increase an individual's sense of confidence and worth.

Taking cognizance of the work of Gupta et al. [4], it is possible to suggest that AI can be used to develop mitigation strategies for dealing with fake news. The approach outlined in this paper whereby the AIDA model is used to harness AI/ML, can be considered proactive in terms of getting consumers to understand what the truth is or indeed to look for the truth. Identifying fake news and the source of it should help consumers deal with misinformation from various sources, which is spread quickly via social media networks. By understanding how and why fake news is created, it should be possible for marketers to evaluate the motivations of those producing fake news [5] (p. 337) and help consumers identify and relate to genuine news. The AIDA model can help provide awareness and influence attitudinal change so that people are not misled or defrauded into buying counterfeit products via fake websites, for example. In addition, other security awareness approaches can be drawn on to link AI/ML more with cyber security provision and security awareness [65].

5. Conclusions and Future Research

The systematic literature review highlighted how marketers can comprehend the changing requirements of consumers through the application of AI and establish how the use of AI contributes to enhancing consumer engagement. The objective is to reduce digital myopia and establish firmly the link between the AIDA model and AI/ML usage. Marketers can ensure that the various types of data (structured, semistructured, and unstructured) are analyzed and together with other forms of market and industry intelligence are used to position the company in the industry within which it competes. In addition to developing a reputation for tailoring products and services to specific customer groups, actual and potential customers will develop the confidence to engage with the company and purchase products online.

It is clear from the study that the literature reviewed has offered a number of insights into how the development and implementation of AI will both help retailers to adapt to changes in the marketplace and streamline the company's business model. The post-COVID-19 era is likely to see continual rapid change and adaptation as companies move increasingly to online sales. What marketers need to take into consideration is that increased digitalization will require new and additional skills, and although AI appears to be capable of undertaking analysis and forecasting, designated staff will be required to exercise judgement and formulate and implement online marketing campaigns and strategies.

What emerges from the study is how marketers can reduce digital myopia by drawing on marketing theory in the form of the AIDA model and work with the developers of AI/ML to ensure that there is a full understanding of the types of AI/ML learning (e.g., mechanical, cognitive, and intuitive). The approach undertaken in this study represented a critical appreciation of the literature and the resulting synthesis, represented by a conceptual framework [32] (p. 362), and can be deemed a useful contribution to the existing body of knowledge. As well as focusing attention on how marketing theory can be developed in the context of digital marketing, the findings bode well for marketing practitioners as the guidance offered provides insights into how they can devise an appropriate digital marketing strategy.

Future research can be undertaken to establish how retailers can increase positively the customer online shopping experience. First, a study can be undertaken to establish how retailers can identify appropriate AI/ML tools that can enhance a customer's digital shopping experience from the stance of an individual's self-esteem. It is possible that not all types of products will be bought online. Second, research can be undertaken that establishes how retailers devise an AI/ML usage plan with partner organizations so that AI/ML is integrated throughout the supply chain. Third, a study can be undertaken that establishes how retail managers ensure that staff keep pace with government regulations and adhere to compliance so that the company operates an affective digital strategy.

Author Contributions: Conceptualization, Y.-I.L.; writing—original draft preparation, Y.-I.L. and P.R.J.T.; writing—review and editing, Y.-I.L. and P.R.J.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors are grateful to the reviewers for providing advice and guidance as to how to improve the paper.

Conflicts of Interest: The authors declare no conflict of interest.

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