UNIVERSITA' DEGLI STUDI DI PADOVA
DIPARTIMENTO DI SCIENZE ECONOMICHE ED AZIENDALI
"M.FANNO"

CORSO DI LAUREA MAGISTRALE IN

Entrepreneurship and Innovation

TESI DI LAUREA

Implementing AI technologies for enhanced e-commerce strategies

Relatore: Eleonora Di Maria
Dipartimento Sc. Economiche e Aziendali "M. Fanno"

Laureanda: Alina Shishkova
Matricola N. 2070974

Anna Accademico 2023 – 2024

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Shishkova A.

Abstract

The emergence growth of the electronic commerce (e-commerce) industry during recent decades transformed business processes. It, firstly, involves the need and capability to collect and process huge amounts of data on consumer behaviour and internal company operations to reach a performance increase. To achieve it effectively, e-commerce industry is implementing AI technologies for various functions including price maintaining, recommendation systems, personalized and voice assistance, supply chain optimization and many more. AI empowered such e-commerce tools as personalized systems, improved A/B testing, immediate customer support that evidently led to data-driven strategies adoption and structural business changes. This study aimed to analyze how AI algorithms such as Machine Learning, Natural Language Producing (NLP), etc. are used for e-commerce tools in order to boost performance metrics. Through the deep literature review the integrative map of AI technologies in various e-commerce processes was created. Additionally, the article explored case studies from e-commerce companies and firms providing AI solutions for businesses. Nowadays, the rapid development of both AI and e-commerce creates not only more opportunities but also challenges, making the integration of AI essential for businesses aiming to have a competitive position in the market.

Keywords: E-commerce, AI technologies, Data-Driven Strategy, Digitalization

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Introduction

With the rapid growth of the e-commerce market during recent years many business processes have also transformed dramatically. Firstly, such evolution involves the need to collect and process a huge amount of data on consumer behavior and customer journey steps. Data-driven decisions are crucially empowering business performance by optimizing advertising budgets, customer targeting and segmenting, supply chain management and customer support services.

The expansion of e-commerce has revolutionized retail structure moving it to the adoption of omnichannel strategy that involves both offline and online channels. Longer customer journeys with more interconnected stages force brands to adopt more complex marketing strategies. Customers are easily shifting between offline and online channels comparing prices, offers and other products features. To stay relevant companies are implementing technological tools to provide both better customer experience and deeper understanding of customer needs.

At the beginning of the research we will discuss the existing and evolving e-commerce business models that differ by their distribution strategies. Further we are highlighting main e-commerce trends that will be actual during the next years and empower online shopping experience. Current trends in the e-commerce market include the adoption of new technologies such as mobile commerce, electronic marketing and automated supply chain management with a shift towards sustainability. These advancements enable businesses to improve customer experience increasing their retention and loyalty.

Along with advantages, the e-commerce industry is facing some serious challenges that slow its expansion. The most significant one is represented by trust issues towards online transactions security and personal data storage.

The second chapter of this study highlights the importance of data maintenance and usage for the enhanced customer journey. Global digital transformation that accelerated e-commerce industry growth has fundamentally changed some business operations. During the last decade such digital tools as chatbots, targeting advertising and virtual assistants have been normalized and commonly used. Along with increasing customer expectations from the shopping experience nowadays businesses aim to provide continuous and personalized communication. In their turn these processes are enabled by developing data maintenance and analysis methods which capture valuable insights about customer behaviour and preferences.

The ability to analyze and utilize large datasets empowers companies to respond to market changes and consumer demands ensuring growth and competitive advantage.

Lately artificial intelligence and machine learning technologies have become integral into e-commerce processes. They are offering advanced tools for data analysis, customer behaviour prediction and automated personalization. Particular applications that are discussed in the third chapter of this paper are personalized recommendation systems, chatbots and voice assistants for quality customer support and AI-driven tools for optimized marketing budgets allocation. Additionally, technologies for real-time A/B testing process, dynamic pricing strategies and customer reviews analysis are discussed.

In summary, the research aims to structure the variety of implementation of AI and ML tools into different e-commerce processes and describe how each of them is able to increase business performance. The integration of AI and ML in e-commerce not only improves performance metrics but also drives data-driven strategies and structural business changes. As the e-commerce industry continues to evolve the adoption of these advanced technologies is essential for businesses to maintain a competitive and long-term market position.

Chapter 1

E-commerce Market Dynamics

1.1 Overview and Structure of E-commerce market

In this chapter we are aiming to overview the e-commerce market (EC) evolution, current trends happening in the industry and challenges it is facing. Moreover, we will provide a comprehensive outline of the e-commerce business model and its difference with offline business.

Worldwide e-commerce market is showing a graduate growth in the last decade reaching 5,784 billion US dollars in 2023 and forecasting a 39% increase by 2027. (*E-Commerce Worldwide*, 2023) Globally the e-commerce market is growing annually by almost 10% attracting new customers and increasing the frequency of its usage. Total retail e-commerce revenue is led by the Asian market that reached 1,664 billion dollars in 2023 which is more than the sum of revenues of EC markets in Americas and Europe that counts 889,1 and 533 billion dollars subsequently. *(Statista, 2024, 3)*

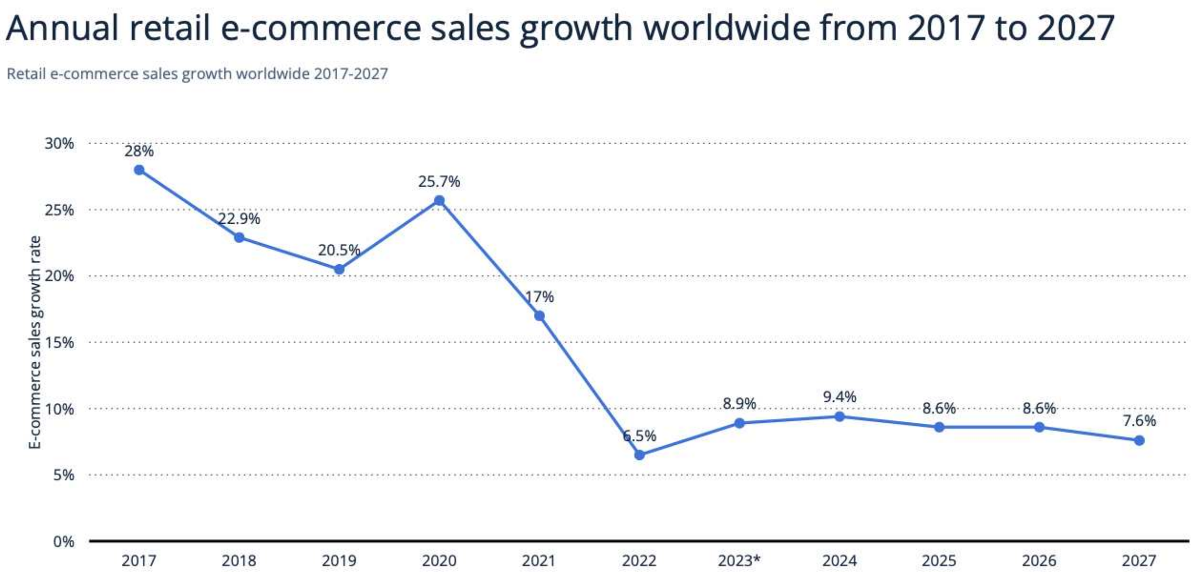

Figure 1. Annual retail e-commerce sales growth worldwide from 2017 to 2027 (E-Commerce Worldwide, 2023)

Nowadays around a quarter of global sales are made online. The highest picks of e-commerce market growth were noticed in 2017 and 2020 years with the average growth rate of 27%. This dramatic growth was sponsored by rapid digital adoption and covid-19 pandemic. Rapid growth in most of the cases requires new solutions from the business to handle the market expansion and stay on the top of it. Due to the specificity of the e-commerce market its main growth hacking tool is new technology enabling processing higher amounts of data for such operations as supply chain, production, logistics, safety and building more precise forecasting models.

In this paper we will use the definition of E-commerce used by Rosário and Raimundo who describe e-commerce as the sale and purchase of goods and services through the internet, involving the transfer of money and data to complete transactions. (Rosário, 2021) In other research the dependence on new technologies of the e-commerce market is discussed as crucial for defining the e-commerce market. Among them are M-Commerce, E-Marketing, E-SCM (Supply Chain Management), EDI (Electronic Data Interchange), and EFT (Electronic Funds Transfer). (Attar et al., 2022) We will discuss technologies that enable the steady growth of the e-commerce market in the following parts.

Firstly, to have a better understanding of the e-commerce market we will provide an analysis of its structure and processes.

There are three main distribution strategies for firms not depending whether it operates online or offline: direct, indirect and hybrid. The direct type is defined by channels exclusively owned by the company. Among these channels are local retail shops, their own contact center or company website. Direct distribution model in e-commerce enables firms new opportunities to have real-time customer feedback and, consequently, better understanding of their needs and ability to improve customer experience and product much faster. (Belvedere et al., 2021) Indirect type through 3rd party channels includes a stage between producer and customers. Adopting that model companies are selling their products through offline or online distributors, partners and franchises. In this case a product's producer gives more ownership on defining prices, promotions and location of distribution to the distributor that changes its cost structure model. The last hybrid model is integrating both direct and indirect channels for product or services distribution.

Furthermore, the identification of main distribution strategies is tightly connected to the e-commerce business models. There is the main proposed categorization of e-commerce business model types that is important to be mentioned: Business-To-Consumer (B2C), Business-To-Business (B2B), Consumer-To-Business (C2B), Consumer-To-Consumer (C2C), Business-To-Government (B2G) and Consumer-To-Government (C2G). All these models could both exist in online and offline markets with some functional differences. In this work we will not consider B2G and C2G business models that are characterized by providing services or goods directly to government and administrative states.

There is a direct connection between two proposed theories of distribution and e-commerce business model adopted. The direct model of distribution is identified by B2C or C2C structures as they are defined by direct selling of products to the customers. On the other hand, B2B and C2B structures could both belong to the indirect and direct distribution model depending on the statement if business that is being the product is its final customer or not.

The most adopted business model in EC is B2C that includes marketplaces and D2C shops. According to the Gartner report that sector is forecasted to grow up to 26% of total retail sales in 2026. (*Digital Commerce — 20 Quick Fixes to Increase Revenue and Reduce Costs*, 2023) Moreover, the B2B sector is also showing a steady growth with a compound annual growth rate of around 11% between 2012 and 2027. However, businesses still are getting most of their sales through channels other than their first-party e-commerce website like marketplaces, other partners and social media. And only 5% of their sales are getting from their own e-commerce. (*B2B E-Commerce Market — Industry Dynamics, Market Size and Opportunity Forecast to 2027*, 2021)

Another rapidly developing e-commerce business model is C2C that is characterized by transfer of goods and services among customers without a traditional business – concentrated on consumer relationships. C2C E-commerce platforms enable users to sell, buy and deliver goods and services between each other. In this case, business is providing an online platform to enable customer communication and focus on creating a high quality user experience. Moreover, online platforms might offer other technological advantages to attract users: secure personal data storage, internal communication tools, orders status tracking and safe payment provider. EBay and AirBnb companies are examples of C2C e-commerce business models as they are connecting those who have a product or flat to offer and those who are looking for it. To grow these companies are working on a two-sided network effect expanding both sides of the business – those who offer and those who want to buy.

The definition of C2B EC model could be still considered as developing, as there is no unified understanding of that concept yet. Some researchers consider that business model as a part of the B2C model, while others as an independent model. An outstanding feature of C2B model is a consumer-driven decision making where the decision to buy a product comes primarily from its production and stimulates companies to create a product that meets individual needs. (Wu et al., 2020)

In that work we will mostly concentrate on B2C, B2B and partly C2C businesses and how they can implement new advanced technologies into their business processes.

There is another proposed categorization of e-commerce business model types that enrich our understanding of online distribution models. One of the classification that is actual for our work is the one analyzed by Lin Tian and based on the revenue share model. (Tian et al., 2018) Based on their work e-commerce models are divided into marketplaces, resellers and hybrid models. Resellers model is an online version of traditional retailer, while marketplace model is directly connecting sellers or producers with their customers. As examples of the marketplaces models we can name Amazon, Ebay, Shopee, AliExpress which enter the top-10 global marketplaces worldwide. A distinct feature of that model is a lack of pricing control as sellers are determining prices by itself. Moreover, logistics and order-fulfillment costs might be divided between sellers and marketplace platforms based on the seller preferences. In most of the cases, the marketplace provides logistics and fulfillment services with a fee for each product. Additionally, it charges for the advertising costs and every order. Consequently, marketplaces are providing online platforms and supply chain management for sellers and become more attractive for customers with growing numbers of sellers and assortment. On the other hand, online resellers are using a traditional retail model providing a fixed variety of products with a determined price. Many researches comparing these two models are highlighting that the marketplace model is more profitable for both marketplace and sellers. (Tian et al., 2018) It is additionally illustrated by the 35% of online purchases worldwide made through marketplaces channel, while 13% of purchases are made through resellers. (Statista, 2024, 22)

In contrast to the reseller and marketplace models there is a Direct To Consumer (DTC) e-commerce business model that is characterized by direct sales of products or services to the customer by the brand or producer. That channel share reached 14% of online purchases worldwide in 2023. (Statista, 2024, 22) To fulfill these purposes brands are using their own online stores via websites or even social media. By adopting this business model, the producer becomes in charge of all the processes involved in the customer journey – from the customer retention and order placement to the delivery and post-delivery services. Some of the advantages of this model are gaining more control over the customer experience and also collecting first-party data from the customers. (McKee et al., 2023) On the other hand, handling your own online shop requires higher resources, financial investments to customer acquisition and supply chain maintenance. Moreover, due to the growing number of DTC retailers during the covid-19 pandemic and after that has shown a 45% increase, the differentiation problem became more relevant for small and medium enterprises. (The Rise of Direct-To-Consumer - KPMG Global, 2022) Depending on the product category and business performance forecast, business might choose between marketplace platforms such as Amazon or create its own online shop adoption DTC business model. Further we will discuss which technologies enable a better maintenance of operations for marketplaces and DTC e-commerce shops.

Besides these three models, there are some others that exist only online and show a steady growth: subscription-based model followed by freemium model and on-demand services such as Uber and other taxi companies.

Even though the subscription model was first established many centuries ago and mostly used for delivering newspapers on a regular basis, now this model is experiencing a new wave. According to market research by UnivDatos Market Insights “subscription e-commerce market is expected to grow at a CAGR of 68% from 2019-2025 to reach US$ 478.2 million by 2025”. (UnivDatos Market Insights, 2020) Now it is estimated that around 15% of online shoppers are subscribed to any kind of e-commerce products or services.

There are different types of subscription-based business models that can be viewed. First two types are product subscriptions and services subscriptions. Product subscriptions are characterized by regular delivery of products that were primarily set by the customer – among these products are groceries, household supplies etc. Service subscriptions allow customers to get a particular service subscribed for a particular period of time – mostly, one month, few months or a year. This can be applied to such services as gym memberships or marketing or financial agency advisory. Therefore, there is a Software-as-a-Service (SAAS) subscription that offers businesses access to the advanced software by paying a fee. An example of this model is a Stripe company that offers small and medium businesses a software for providing payments operations. Moreover, there is a content subscription that might be one of the most used among customers as it includes subscriptions for exclusive content such as music, films, courses etc. Bright examples of those are Netflix and Spotify platforms. Besides these models there are access subscriptions for VIP offers and hybrid models. (Ecommerce Subscriptions: Definition, Types, and Best Tools (2024), 2024)

Another trend of subscription based models in e-commerce is the one for tangible goods. Based on the market research in 2018 there were already 15% or online shoppers who have subscribed for at least one service to regularly receive goods. There are two types of subscriptions in this market. (Trends and Opportunities in the Subscription E-Commerce Market, 2018) First one is a subscription for replenishment that is aiming to deliver primary products such as lenses, groceries, vitamins, food for pets etc. on a regular pre-planned basis. That subscription is seen to answer one crucial need of modern customers – saving their time. Customers are ready to pay more for a convenient regular solution that will free them from ordinary routine. One of the company examples is using this business model if Dollar Shave Club – company offers monthly tools for shaving for 12$ with a monthly delivery. Second type of the subscription model is a subscription for curation. This model is an answer to another customer's need for getting new experience and being surprised. In that business model the customer is getting a subscription to the particular category or type of the product but oftenly doesn't know exactly which product they will receive. Adopting a subscription based model to the tangible products business has to provide a superior experience to satisfy the customer. It is conditioned by a high cost of acquisition of new customers and a high focus on the retention rate. A research by Van den Poel and Lariviere is highlighting that retention rate has a greater influence on the revenues growth than acquisition while reduction of churn rate by 5% could increase profitability by 75%. (Van den Poel & Lariviere, 2004)

There are two dominant recent trends that are enhancing the growth of subscription-based businesses. Firstly, covid-10 restrictions increased the adoption of digital technologies and fast logistics by both consumers and businesses that had to adapt to the new realities. Secondly, customers tend to search for more convenient and hassle-free shopping experiences. In the era of 'time poverty' when people are struggling more than ever in managing their time for work, leisure and themselves, services and products that are meant to save their time create an additional value. Consequently, the subscription-based model frees customers from managing their products' stock or renewing services, increasing the quality of customer experience. In further chapters we will discuss which AI technologies are enhancing businesses to provide subscription-based products or services.

Technologies are enabling various opportunities for businesses and customers to get the most convenient solutions. One of the business models that appeared thanks to advanced data maintenance is an on-demand model. The on-demand model can be compared to the marketplace model where the marketplace is matching suppliers with their buyers. (UltroNeous Technologies, 2023) The on-demand model is characterized as a marketplace that operates in real-time and provides fast and convenient solutions to their users. Traditional marketplaces such as Amazon are also adopting the on-demand model as the fast delivery service. Distinguishing features of the on-demand model are usage of on-demand distribution model and scalability due to two-sided network effect. (Pazour & Unnu, 2018) Two-sided network effect is a growth factor for the on-demand business as each user either on the side of suppliers or users is increasing the value of the platform by growing its demand by one of the sides. On-demand distribution model designed to provide dynamic supply chain processes to optimize resources and capabilities of the company and to balance them with the demand from customers. That's why the on-demand model needs a tremendous amount of data to analyze orders, locations and customers. In the following chapters we will discuss more on how machine learning and artificial intelligence is implemented into the supply chain maintenance.

Furthermore, on-demand distribution model is used for the last-mile delivery that is a common concept for the e-commerce market. Last-mile concept is defined as the last period of delivery of a product to the final user – for instance, from the moment the product reaches the urban area of the delivery address till the preferred destination point. (Boysen et al., 2020) This period is considered to be crucial for customer relationship management and complex for maintenance by the company. Last-mile delivery becomes more challenging for companies because of the urban traffic, high demand and increasing customer expectations. To meet them businesses are integrating new technologies that provide automatic optimisation of delivery date, time and route and moreover, forecast the demand of the services.

Last-mile delivery is used commonly for grocery and ready to eat meals delivery companies such as UberEats, Glovo. This market is characterized by the fast delivery that makes it more challenging for companies. That business model can be also called q-commerce which is the e-commerce segment enhanced by quick delivery up to one hour from the moment of order. (Rau1 et al., 2023, p. 79) Q-commerce companies provide their services in the urban areas to be able to reach them in the shortest period of time. Moreover, despite the traditional e-commerce, q-commerce is utilizing dark-stores networks in the neighborhoods to stay closer to the customers and cover larger territories. Dark stores are small distribution centers that are organized like a grocery shop and are used only by the company workers to collect ordered items into one bag. Furthermore, another differentiating feature of q-commerce is a smaller product assortment. Due to its mobility, the q-commerce model has to sacrifice part of a wide grocery shop assortment to guarantee high product quality and speed. The last difference from the traditional e-commerce is a choice of delivery means of transportation – q-commerce companies are using electric or traditional scooters and bikes to provide a faster delivery service that is not influenced by traffic. Q-commerce business model is based on the concept of maximizing customer convenience by fast delivery that requires a maximized operational efficiency in the supply chain. That turns q-commerce to the implementation of new advanced technologies to their operation maintenance.

1.2 E-commerce Market Trends

The adoption of new technologies and the development of e-commerce changed the shape of traditional customer journeys and, therefore, led to the change of customer relationship management. During the last decades numerous new channels appeared – social media, websites, mobile applications and marketplaces. Simultaneously with the growing number of channels, companies get more opportunities to touch and communicate to customers. Hence, digital transformation forced companies to implement omnichannel strategy integrating both online and offline channels into customer relationship management. The access to more information about companies and products or services variety increase customer expectations and requirements to the shopping experience. Likewise, omnichannel strategy provides a seamless shopping experience and offers different convenient shopping options. (Iglesias-Pradas & Acquila-Natale, 2023, 656) Moreover, customer behaviour has changed dramatically with the growing usage of mobile. During the last decade customers became used to collecting information on products or services online before and after visiting a physical store that definitely prolonged the decision making process to the acquisition. (Belvedere et al., 2021) Implementation of omnichannel strategy gives firms benefits by increasing customer satisfaction and their retention and improving the efficiency of channel combinations. Furthermore, omnichannel strategy enables companies to collect more differentiated data about their customers that can be utilized for predicting customer behaviour, sales and building a more accurate and personalized strategy for existing and future consumers.

M-commerce that means mobile-commerce can be defined as one of several subsets and developing trends of e-commerce. Mobile-commerce is a particular segment of e-commerce that is used to describe online purchase processes through the mobile instead of desktop. This subset was additionally defined with the tremendous growth of mobile commerce worldwide – in 2023 50% of all e-commerce purchases were made with the usage of digital wallet, that includes mobile money. Moreover, almost 80% of retail website visits are reached by smartphone. (Statista, 2024, 25) Also for instance, Zalando, Berlin-based online fashion company, had reported around 89% of all traffic through the mobile application in 2021. (Chevalier, 2022)

The development of m-commerce and social media created a near form of e-commerce – social commerce. More and more people are starting to explore and buy products and services right in social media like Instagram and TikTok. Utilizing live streams, influencers and dynamic content brands are creating a more engaging atmosphere within the company and customers. Furthermore, the new distribution channel for the company opens new opportunities and also shortens the customer journey as previously social media accounts led customer traffic to the website or marketplace to make a purchase. In 2025 social commerce is already forecasted to reach more than 5% of overall e-commerce sales in the US. (Social Commerce Market: US Brands' Strategies for Growth, 2022)

Analyzing the e-commerce market: online traveling market, marketplaces in various fields from taxi and scooters to food from restaurants, large e-commerce shops as Amazon, Alibaba and eBay are the most growing industries worldwide from 2022. Every year the e-commerce market is becoming more and more competitive, introducing new players. Nevertheless, the undisputed leader of retail EC worldwide is Amazon company which reached 1,338 billion dollars by the end of 2023. It is followed by Alibaba company, that has Chinese origin, and Prosus, a company that is investing and controlling online services firms like Delivery Hero, iFood etc. operation on all continents. However, the most growing online services industry with 52% CAGR between 2022 and 2024 year is online travel with such leaders as Booking, Expedia and Airbnb. After that with the CAGR of 11-13% go companies from marketplaces, classifieds and large cap e-commerce industries. (Statista, 2024, 11-12)

Moreover, the shopping behavior online differs a lot from the one offline. Current marketplaces have become some kind of inspirational and autonomous browsing search resource that customers use even when they don’t have a need for a particular product and prefer to use the marketplace to look for a product instead of traditional browsers. (*E-Commerce Worldwide*, 2023) In 2023 35% of online shoppers agreed that marketplaces have become their leading sources of inspiration for purchases. (Statista, 2024, 30)

The variety of digital payments methods has introduced another trend in online shopping: the buy now, pay later (BNPL) business payment model that allows customers to postpone their payments. The leading country that adopted that model is China, counting more than 78 millions of users of the BNPL model in 2022. China is followed by the US, Brazil and India with around 65, 40 and 26 millions of BNPL users respectively. (Statista, 2024, 37)

According to McKinsey Research the next wave of e-commerce is going beyond traditional e-commerce. (*Becoming Indispensable: Moving Past E-Commerce to NeXT Commerce*, 2022) It means that e-commerce is not only aiming to sell the product but it also tries to solve other issues of the customer connected to the product. As an example the researchers had provided a runner experience that wants to buy new sneakers. New wave of e-commerce will not only accompany customers with comparing, purchasing and receiving shoes, but also integrate a person into a 360-degree immersion in the running communities, training and meal plan applications and recommendations. According to the online shoppers survey in 2022, 88% of them consider the experience that companies provide as important as its products or services. (Statista, 2023, 25) Consequently, the e-commerce industry is able to create new opportunities and channels for touching their customers that therefore provide various data about the customer and build more loyal relationships.

1.3 E-commerce Challenges

It is essential to understand which issues the e-commerce industry is facing now, because these issues are becoming business priorities on their way to exponential growth.

It is seen that nowadays the e-commerce market still consists of big corporations. Joana Costa and Rafael Castro summarize two main groups of factors that limit SME to adopt e-commerce business model: internal and external. Technological adoption is seen as one of the biggest barriers due to high cost processes especially on the initial stages, and the need for particular skills. That obstacle is especially correlated with the company size, as small and medium enterprises tend not to have enough resources to adopt complex AI and Machine learning technologies. Nevertheless, they are able to overcome that difficulty by implementing an external ML tool for particular operations that is not personalized for the company but might help to optimize processes and profits.

Another internal barrier is unclear policy measures and regulations which are fast-changing due to the newly developed industry. (Costa, 2021) That obstacle is bigger than implementing AI in e-commerce, because it is connected to the issue of using artificial intelligence in general.

From the marketing perspective, on one hand, e-commerce enables usage of more channels and touchpoints with customers. On the other hand, the cost of customer retention is growing dramatically, changing the approach businesses have to implement. During the past 5 years customer acquisition costs increased by 60% making it more challenging for businesses to expand. (*Brands Losing a Record $29 for Each New Customer Acquired*, 2022) Newly announced limitations of sharing third-party cookies have led to the growing expenses as many companies do not collect data about their customers or do not have enough capabilities to transform it into valuable insights. That trend is pushing the industry to involve more into creating viral content and building more trusted relationships with customers to have access to their data.

Moreover, during the rapid e-commerce growth due to the covid-19, it became visible that turnover growth doesn't necessarily lead to proportional revenue growth. According to the McKinsey research of 100 large online retailers, they have experienced a dramatic decline in margin during the covid-19 growth. (*A Path Toward Healthy, Sustainable Growth in E-Commerce*, 2021) It happened due to the unexpected increase of variable costs to fulfillment, delivery and marketing. Logistics operations are seen to be a challenge for the e-commerce industry with the growing expectations of customers for quick and convenient delivery and growing costs for its realization. Several researchers show that logistics processes are crucial for efficiency of online distribution business. The promised service level to customers, delivery data security, geographical cover, customer density and delivery windows are defined to influence the most on the logistics performance. (Belvedere et al., 2021) Therefore, supply chain optimization based on the data is required. Logistic operations optimizations are needed both for SME and corporations. The first type of companies might suffer from high costs of deliveries with few orders – that trend might decrease the margin dramatically. On the other hand, corporations have to optimize their logistics operations providing maximization in delivery direction optimization that should both keep the high level of delivery service and decrease the delivery cost per each product.

Following the rapid growth of fast delivery services it can cause environmental and urban problems due to the increasing number of parcels and as a consequence their fumes. Therefore, sustainability is one of the main challenges and trends for the modern e-commerce market. Among such environment-friendly solutions are increased usage of electric vehicles and bikes, drones and delivery robots. Moreover, there are countries implementing government policies encouraging businesses including e-commerce to become more sustainable. According to the current forecasts, the 2019-2030 period is expected to show the highest level of CO2 emissions from global international shipping on the level of around 680 million metric tons with the following annual reduction to 120 in the 2070. (Statista, 2024, 3) Nowadays most of the emissions are caused by passenger cars and it is expected to be the industry that needs to implement sustainability the most. Among the sustainable strategies that are currently being implemented by companies are usage of right-size packaging, recyclable or reusable shipping boxes and products packages.

Furthermore, the issue of trust is also one of the main ones in the e-commerce industry. It is becoming more crucial compared to offline retail due to absence or lack of physical interaction with goods or services, postponed receival of them and usage of personal and payment data. Therefore, customers have to assess more risks than in offline purchase. In the context of trust in e-commerce researchers are using theory of reasoned action (TRA) framework to explain customer behaviour. This framework consists of three phases: trust and perceived benefit, purchase intention, purchase behaviour. Purchase intention is customer readiness and willingness to consume product or service. In turn it is influenced by trust and perceived benefit concepts. Perceived Benefit refers to the functional or emotional value expected by the usage of purchased product or service. (Kim et al., 2008) Trust Concept is explained as customer evaluation of risks and possible consequences connected to the purchase. In the e-commerce industry trust concept is defining purchase intention and behaviour – if risks are too high, customers will not proceed to the purchase. In online shopping risks and possible negative consequences are wider compared to the traditional offline trade. According to that, building trustful relationships with customers is a special emphasis for online businesses. Shukuan Zhao et al. tested TRA framework for C2C E-commerce businesses in China and proved that trust and perceived benefit have a significant positive effect of purchase intention. (Zhao et al., 2020) It is valuable to notice that perceived benefit has a stronger influence on purchase compared to trust. Despite that, Shukuan Zhao studied how customers perceive various kinds of risks and found out that Perceived Security Protection is the most crucial. This risk is based on providing personal information of ID cards and credit cards for the payment process as their loss can be followed by fraudulent activities. Additionally, inaccurate description of product or services, any product imperfections, ability to return and refund, providing personal information as name, address also influence on the level of trust and, furthermore, purchase intention. (Zhao et al., 2020)

In the following sections we aim to discuss how all above mentioned challenges could be overcome by using the strength of data analysis and particularly new artificial intelligence and machine learning technologies.

Chapter 2

Data-Driven Decisions in Digital Transformation Era

2.1 Data Maintenance in the era of Digital Transformation

Technological development is encouraging businesses to adapt and change many of their traditional processes. Such new technologies as targeting advertising, chatbots, virtual and voice assistance and many more are revolutionizing consumer journey and approaches in customer relationship management. The decision making process is turning to be data-driven, based on collected information and extracted insights about the customers. Still with the variety of instruments and continuous technological changes companies are struggling to apply collected data to their usual operations because frequently it requires structural changes and timely and financial investments.

Marketing industry experienced dramatic changes within its digital transformation and adoption of digital instruments. Digital orientation of the marketing industry implemented more channels and improved the customer experience and customer-brand relationships. Moreover, the communication between companies and customers became more regular and closer as it became a new norm to 'touch' your customer every day using various instruments. Transformation of customer behaviour patterns and increasing expectations from customer experience forces organizations to implement more marketing analytics instruments. The researches are showing that marketing analytics usage positively affects customer relationship management (CRM) and brand management capability (BMC) by effectively extracting and transforming insights from the data. In turn, CRM and BMC influence marketing performance. Furthermore, marketing analytics is used for the customer linking process that is defined by aggregating customer data from various channels to identify customer characteristics. (Cao & Tian, 2020, 1295-1296)

Nowadays the usage of targeting advertising, advanced social media engagement seems not enough and the industry aims to adopt new technologies to increase brand value and customer experience. Moreover, the marketing online spending tended to get higher due to increasing competitiveness and became less conversional and profitable in a short-time period due to the changing customer behaviour. Also the banner blindness is staying to be an issue for modern marketers as customers do not notice advertising on traditional advertising places. For instance, online shoppers tend to skip part of the online search where there is usually an advertising placement. (Nielsen Norman Group, 2018) Nowadays brands have to fight for the customers attention by using unique offers, messages and visual content. That issue is being overcomed by adopting new technologies that create a new level of interaction with a customer.

The main purpose of extracting more valuable information from collected data in marketing is forecasting product or service demand and therefore sales and customer behaviour. Moreover, over 50% of the companies in the Americas and EU that are using artificial intelligence, utilize it for product development because data could provide a real-time feedback loop and opportunities for products or service beta-testing. (Statista, 2024, 25) Instead of using only historical data for predicting future trends, new technologies enable organizations to collect, reorganize and analyze real-time data generated from different channels. (Liu et al., 2016, 365) The process that would take days or weeks for humans to do could now be automated and used by employers for faster extracting and implementing insights.

Data could be considered as an input and output of the e-commerce operations. For instance, all e-commerce transactions are made digitally that gives it an opportunity to gather and analyze a bigger amount of data. Moreover, the more data the business has processed - better insights and actions it is able to undertake to increase its performance. New technologies enable companies to collect such information as individual data, browsing history, IP address, data from connected devices and even live location.

Due to the current EU General Data Protection Regulation (GDPR) (European Parliament and Council of the European Union., 2016) on the protection of personal information people get more ownership on the data shared with the companies. Therefore, businesses have to gather insights on customer behaviour with incomplete data. (Abraham et al., 2019, 424) In the article observing customer signals that are made digitally Schweidel with other authors (Schweidel et al., 2022) proposed three categories of consumer signals based on their visibility: anonymous, privately observable and publicly observable. As customers have more ownership on their personal data they have an opportunity to decide which information they want to share with which websites or applications. According to it, companies can collect various types of data on different levels. Further we will explore the concept of consumer digital signals as all consumer online actions.

So, anonymous consumer signals refer to consumers actions that can be detected but are not tied to any particular individual and its other data. For instance, a company is able to detect the fact of a specific activity by one person without having any other information about it. Another type of signals is privately observable signals that are privately provided by consumers to the company, for example, by leaving personal email or phone number on the website to get notifications. Due to the law, the company cannot share that private information with any other external parties but is able to use it for personal purposes. The third type of the signal is publicly observable. These customer actions could be observed by a wide audience. Among these actions can be a post in social media with mentioning a particular brand. All types of data can give companies valuable insights on consumer behaviour if they are productively used.

Current technological innovations are making it possible to collect some types of information about consumers that were not available before and, furthermore, upgrade competitiveness. Authors of the above mentioned article (Schweidel et al., 2022) described two developing approaches to capture more data about the consumer. Firstly, a strong business can create an ecosystem that controls different types of consumer data due to its high reliance on company services and is able to match different types of collected data. Secondly, firms tend to partner with technology providers that are able to capture deeper data on consumer behaviour.

Additionally, Sara Quach et al. in their research of appeared due to digital transformation tensions in privacy, proposed three types of customer privacy: information, communication and individual. *(Figure 2.)* Communication and individual types of privacy are considered to be under strong customer protections as they include private information including emotional condition and interpersonal communications like chats with friends or family. Collection of these types of data are raising security and ethical concerns the solutions to which are not founders yet. Information type of privacy includes data that can be shared with companies. (Quach et al., 2022, 1301-1307) Consequently, firm performance is influenced by data with four main components – government privacy regulation, firm way of data maintenance, social tensions considering data privacy and customer actions on its data protection.

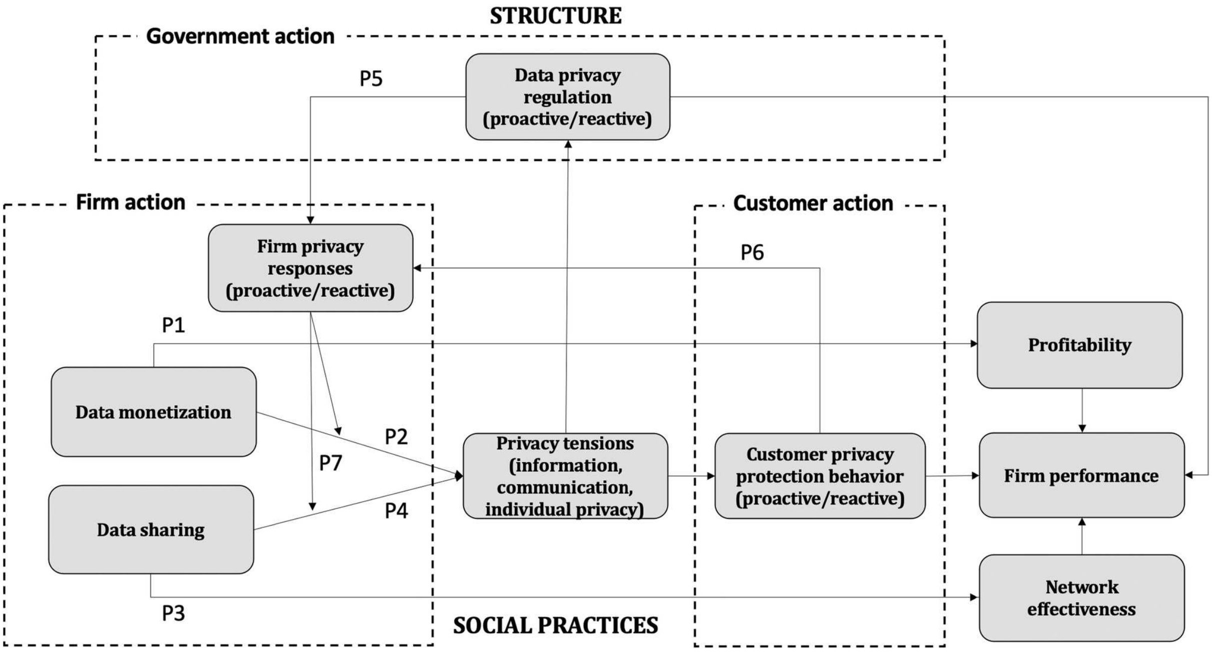

Figure 2. Integrated framework of privacy structuration (Quach et al., 2022, 1302)

Furthermore, there are conditions that might encourage customers to share more personal information with companies. Based on the US online shopping user's survey, personalization in general is one of its drivers. More than 20% of respondents highlighted that they are willing to share more personal data if product characteristics (type, color, style etc.) will be made according to customer preferences and also if a search process will be quicker and closer to the customer needs. (Statista, 2023, 31) For companies it means that higher personalization and better user experience is an exchange currency for the customer loyalty and personal data, that means that company has to provide a measurable value to the customer who is sharing its personal data compared to the one who does not. Moreover, a transparency data approach, user-friendly opt-out mechanism, and feeling of having more control on the data make it easier for customers to share it.

The huge amount of information collected by organizations is called Big Data that in its turn could be characterized in dimensions of volume, velocity and variety. Big Data is measured in huge amounts in petabytes, exabytes and zettabytes and shows a continuous growth. Velocity of Big Data enables access to the real-time data from various channels that is collected simultaneously with data sharing. Finally, there is a phenomenon of a variety of data starting from textual post ending videos, images and audio recordings. (Erevelles et al., 2016, 898) In the era of Big Data business got access to new types of data that differ a lot from the traditional structured data. If in the previous decades, marketing was basing its forecast on surveys and numeric data like sales, nowaday businesses have to learn how to analyze unstructured data. Unstructured data includes video, voice, image and nonverbal data like facial and gestural cues that are difficult to interpret objectively. (Balducci & Marinova, 2018, 558-559) However, unstructured data has some valuable advantages compared to structured data. Unstructured data is more flexible, richer for conceptual insights and enables a more dynamic analysis. (Balducci & Marinova, 2018, 561)

In summary, collecting data and the way it is used by the company enables businesses to perform successfully and generate higher profits. Further in this chapter we will discuss how data and new technologies are enabling new opportunities in customer relationships and provide a scientific approach on marketing decision making process.

2.2 Data-Driven Marketing

As we have mentioned above with the advancement of technology customers dramatically changed their behaviour and became more knowledgeable. That transformation encouraged firms to adopt a customer-centric approach where customer became a company priority. Therefore, customer data creates a basis for companies' transformation to a customer-centric and data-driven approach. (Pascucci et al., 2023, 30) Figure 3. from the above mentioned article depicts how data transformation is influencing the various processes in the company, starting from marketing activities and finishing with organizational structure.

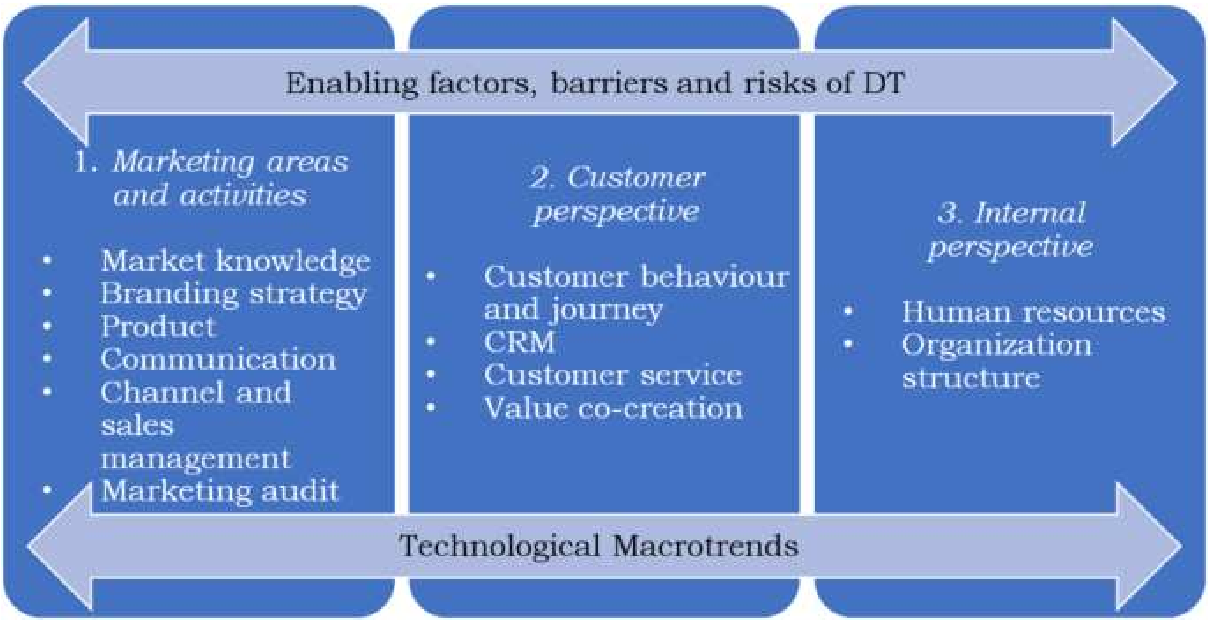

Figure 3. The role of DT within firms (Pascucci et al., 2023, 30)

However, the relevance of the company nowadays is seriously defined by its ability to follow the trends of personalization, accurate advertising targeting and less straightforward communication. Informed data-based decisions are enhancing higher performance of marketing instruments and growth hacking strategies. According to the survey of marketing decision-makers published by Statista, e-mail marketing, customer journey mapping, personalization, paid advertising and products or services development are areas in which data-driven decisions had shown the biggest success. (Statista, 2023, 9)

Moreover, it is noticeable that modern customers are willing to be co-creators of products and services with brands, that is possible only with functioning quick communication and feedback. The replacement of four P' or Marketing Mix to the four C' that includes co-creation, currency, communal activation and conversation was proposed by Philipp Kotler. (Kotler et al., 2016, 45) These fundamental changes in the customer-firms relationships and its technological direction developed a new step in the marketing that is currently named 'Marketing 4.0'.

Nowadays, the customer journey length has increased up to 50-200 touchpoints to be made before the purchase. Moreover, customer's requirements for the consumer-brand experience are growing. Brands that provide a continuous value and product variety are getting customers' loyalty, but at the same time 32% of customers are ready to stop buying products or services from the brand they loved after only one bad experience. (*Customer Experience Is Everything*, 2018) That factor dramatically affects the retention rate and forces companies to improve their customer experience through the whole customer journey. The most valuable factors in any customer experience are efficiency, convenience, friendly and knowledgeable service and easy payment. (*Customer Experience Is Everything*, 2018)

To provide the best customer experience companies are implementing omnichannel strategy that is strongly connected to the data collection. Omnichannel strategy aims to provide a seamless and connected customer-firm communication through all types of channels. For instance, several researches show that multiple-channel buyers are more valuable for firms than single-channel customers as they are characterized by 30% longer lifetime value (LTV). (Kotler et al., 2016, 139-140) However, a connected through channels customer experience is possible to organize when a company is able to identify and connect customer data from different channels. That marketing channel approach is raising the importance of implementing advanced data analytics.

According to the Schweidel et al. new research, the quality of customer-company relationships are determined by the amount of digital signals and, therefore, data which customers are willing to share. (Schweidel et al., 2022) Data about customers received from different channels enable companies to suit their offers for the customer and market changing needs, stay more relevant and provide a better personalization.

Personalization is seen to be a strong trend that could be used more efficiently with the usage of new technologies. Personalized offers increase satisfaction, loyalty of customers and their retention rate that makes it nearly a mandatory tool for organization. 73% of brands in the Asia-Pacific region that used technology for personalization had increased the level of consumer trust. (Statista, 2023, 37) In traditional marketing with lack of consumer data, personalization is realized through the segmentation process that is more based on the assumptions than on the real data. Previously, a segmentation process was aiming to create several customer portraits describing customers characteristics starting from socio-demographic ones to personal interests. Nowadays, technologies enable optimization of personalization process by automatically finding patterns in a bigger amount of data collected. With the more advanced implementation of AI instruments personalization recommendations can stay relevant due to the continuous learning from real-time data and method adaptation. (Raji et al., 2024, 68) Moreover, current technologies push segmentation to the next level by being able to segmentate customers into smaller groups and provide them with more accurately personalized offers. Despite the increasing trend for personalization, it is followed by the risk of breaking trust in the case of proposing irrelevant advertising and offers or ignoring customer preferences at all. (Statista, 2023, 38)

Consequently, data collection always has to be followed by proper analyzes because lack or incorrect usage of personal information can lead to customer's dissatisfaction and growth of churn rate.

2.3 AI in Marketing

Current level of technological advancement pushes organizations to improve their operations in all departments. A few years ago data and new technology were able to optimize such marketing activities as targeting advertising in social media and e-mail and make it easier for marketers to calculate ROI% of marketing initiatives. Now the new generation of technologies is able to take more responsibility for the decision making process by up to 100% automatisation of advertising expenditures. Researching the influence of AI on marketing, Haleem had proposed a framework with main marketing segments that are targeted by AI optimization: pricing, strategy and planning, product management and promotion management. Among the operations implementing AI are targeting and positioning, real-time pricing and fluctuating demand, product design and customer needs maintenance. (Haleem et al., 2022, 121)

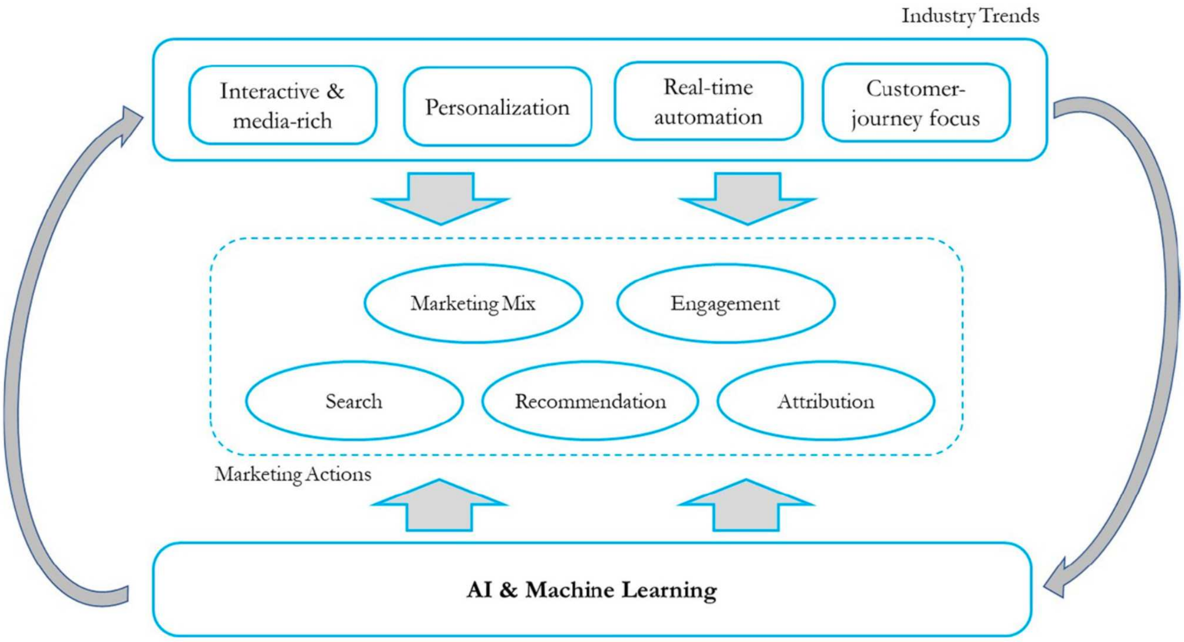

Figure 4. AI-driven marketing landscape. (Ma & Sun, 2020, 489)

Implementation of AI in marketing is believed to strengthen marketing strategies and increase the value proposed by marketing and furthermore promote products and services. Marketing benefits from adopting AI- and ML-driven instruments in different ways. Firstly, they are increasing the performance by providing stable operations 24/7 with the same quality as they reduce the chance of errors caused by human subjective factors. Secondly, AI tools are able to analyze several layers of data simultaneously and determine a faster decision based on data. (Miklosik et al., 2019, 85707-85708) Thirdly, AI instruments are significantly reducing advertising investments. (Mishra et al., 2022) The framework proposed by Kirk Planger et al. is illustrating the applications of AI technologies and their strategic outcomes for businesses which include increasing customer and brand value and changing societal value. (Plangger et al., 2022, 1127)

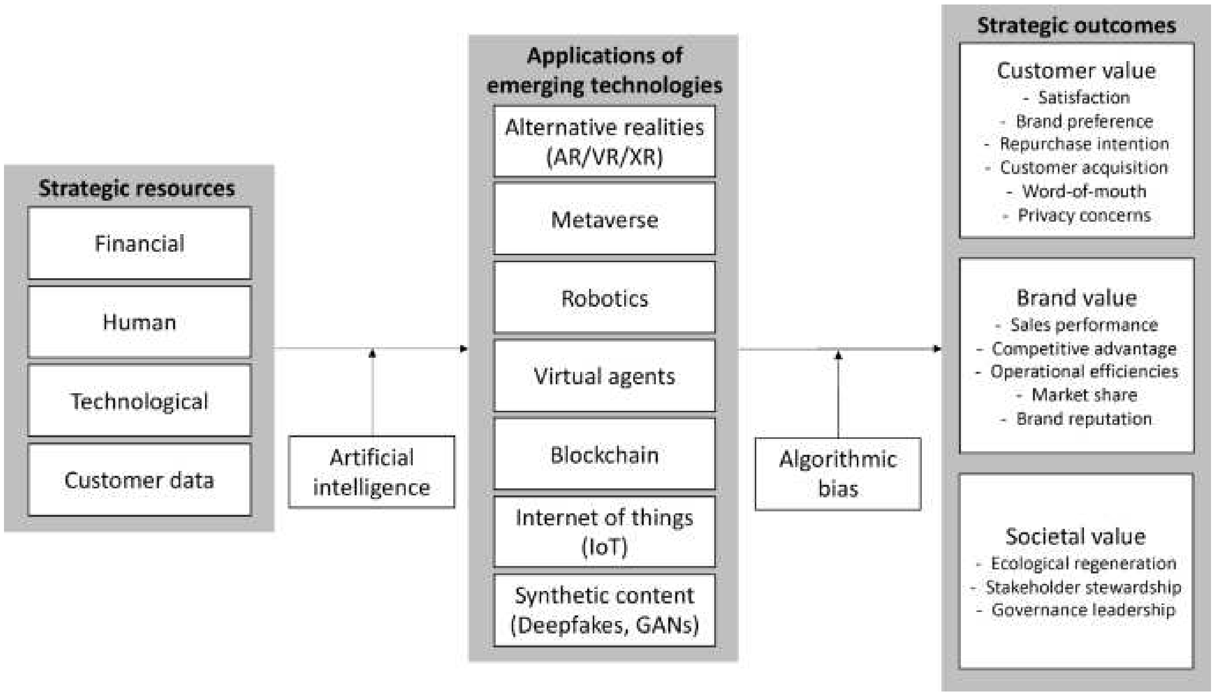

Figure 6. AI technologies application framework (Plangger et al., 2022, 1127)

Beyond increasing the performance of marketing strategies and customer experience, new technologies enable more secure data storage and protection of personal information. (Plangger et al., 2022, 1129-1130) In its turn, it empowers customers to build more trustworthy relationships with brands and share more personal information.

Furthermore, social media accounts of both brands and consumers are extremely valuable channels for gathering personal and behavioral information – sex, age, marital status, location, time, interests and online activity. Machine learning (ML) algorithms assist in detecting customer traces and signals that further can be used by marketers. Moreover, ML usage in social media assures activity security and safety by detecting bots, spammers and other anomalies. (Miklosik & Evans, 2020, 101287)

Providing a bright example of AI implementation to the marketing processes, we would discuss how Uber company is accelerating ML methods on every step of customer in-app journey. UberEats application offers customers fast food delivery from restaurants. During the in-app customer journey, UberEats is using a recommendation system based on the previous orders and similar places, automated search competition, products ranking based on the customer features, upsells system that also considers customer preferences, and dynamic pricing.

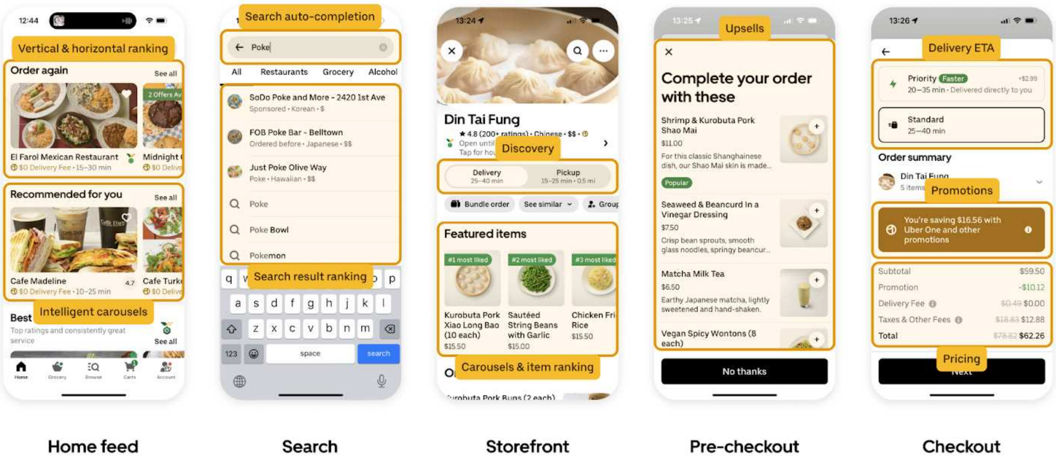

Figure 7. Real-time ML underpins Eater app core user flow. (Uber Blog, 2024)

Personalization trend with usage of AI technologies enables another level of company performance. Mixing collection of data from omnichannel strategy with other AI instruments companies could provide a more personalized experience. As another example, Sephora beauty brand, that was ranked number first in Sailthru's Retail Personalization Index 2022 (*Retail Personalization Index | Top Retail Marketing Campaign*) had provided a new recommendation system suggesting virtual product testing based on the customer purchase history both via mobile and in-store channels. (*Solving the Paradox of Growth and Profitability in E-Commerce*, 2021)

Nowadays the development of AI and ML enables optimization of many marketing operations, but some of them still stay underexplored. So researchers had created a framework of the current stage of ML methods integration into marketing. Ma and Sun ((Ma & Sun, 2020, 497-500) proposed a framework illustrating the types of statistical based ML methods connected with data transparency needed and level of connection to the marketing concepts. According to that framework, the most developed and used implementations of ML are connected to the prediction, feature extraction and optimization operations. It is noticeable to mention that all these processes are characterized by low or medium connection to the marketing theories as they are mostly constructed on the historical data and does not require a deep understanding of customer journey and advertising by itself. However, these applications are dramatically improving marketing performance. Prediction models aim to predict customers' next step in their customer journey that gives brands opportunities to provide relevant communication and increase the customer interest. The main drawback of prediction models lies in their somewhat narrow view on the data as they do not take into account causal connections between variables affecting marketing performance. Furthermore, prediction models do not tell the marketer which action will be the most efficient to take next. Moving forward, the feature extraction process is more connected to the marketing concepts and allows companies to analyze unstructured types of data as it is the one prevailing in marketing data. Extracting valuable insights from unstructured data gives companies a deeper understanding of customer digital interaction. Process that requires the highest data transparency between the above mentioned ones is optimization – it enables the use more advanced methods of estimation to provide large-scale optimization.

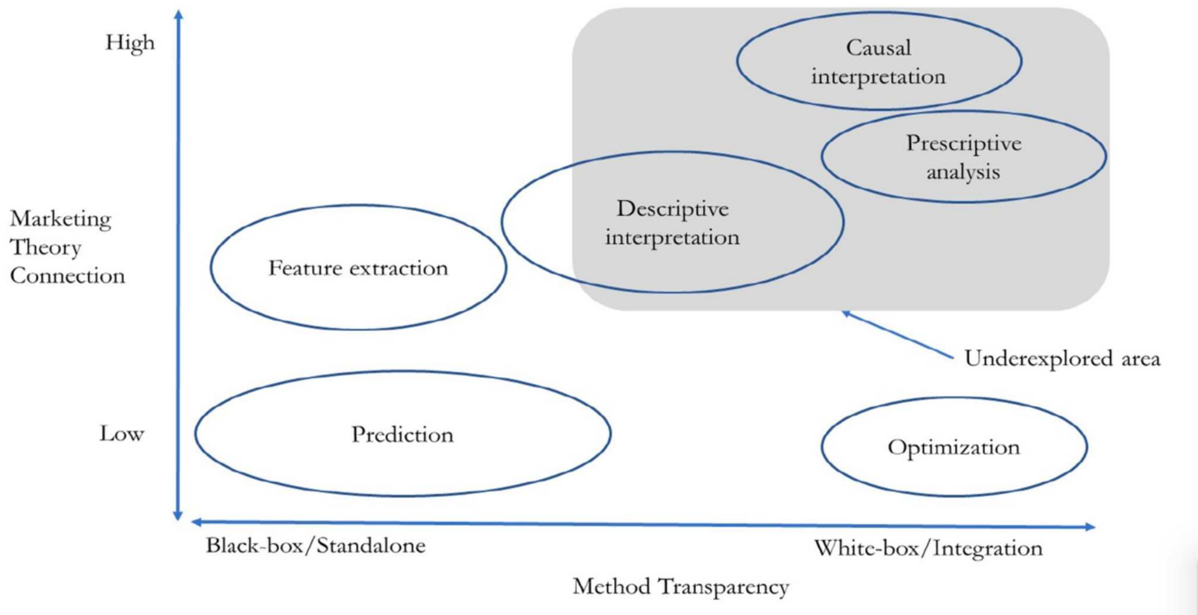

Figure 8: The usage of machine learning methods. (Ma & Sun, 2020, 498)

Going further to the ML methods that are not explored and used enough, we are able to predict how AI implementation is going to empower marketing and e-commerce processes even more in the following years. Among the most prospective ML methods are descriptive interpretation analysis, prescriptive analytics and causal inference interpretation. What differ them from the currently developed AI methods used in e-commerce and online marketing are both high connection with marketing theories that have to be taken into account while engineering the model and high level of data integration and transparency. These methods go further in analyzing deepness and are able not only screen and predict customers behaviour but generate recommendations on the most efficient next action. For instance, ML methods based on causal inference theory aim to gather cause and effect correlation between company actions. In near future it will be more feasible to measure the effect of brand communication, mix of channel usage and create an accurate plan on future actions influence.

It is seen to be a dramatic change and a big step in the development of performance marketing from which e-commerce companies will benefit the most as it has been one of the main challenges to provide a comprehensive analysis of customer journey points and correlation between each of them.

2.4 Challenges of AI in Marketing

Despite the increasing speed of AI and Machine Learning instruments, the business industry faces several barriers to implement these technologies into their routine operations. The main challenge among worldwide e-commerce companies is the implementation costs for business intelligence and analytics.

Furthermore, measuring the efficiency of AI technologies seems challenging for businesses. Currently organizations that have already implemented AI-driven operations are using such performance indicators like accuracy of data, speed of real-time data, customer retention or repeat purchases and time-saving for the business. (Statista, 2023, 16)

Also, the lack of expertise inside the company can postpone new technologies implementation into its processes. With a faster developing industry of AI and ML, companies from other industries may not be aware of new technological solutions. Moreover, other organizational difficulties of implementing AI technologies should be considered. Due to the complexity of technology, the lack of strategy understanding could appear. That's why that type of structural changes should be driven top-bottom and include the organizational culture and management readiness to succeed. (Miklosik et al., 2019, 85715)

Moreover, both from consumer and organization points of view a data-security issue oftenly appears. As we have mentioned in the previous chapter, trust issue is significant for consumers so they share their payment and personal information carefully. From the organization side, usage of advanced technologies and collecting of personal customer data might lead to the reputational risks with customer and revenue loss in the case of fraud and cyber-attacks.

The moral and ethical principles are also hardly affecting the adoption of AI instruments by companies. There is an opinion that the ability of humans to make decisions, express emotions and understand the limits of morals cannot be replaced by AI and ML algorithms. And in the case of such a possible development stage new government regulations will be needed to provide successful implementation of new technologies. (Miklosik et al., 2019, 85708)

Chapter 3

Implementation of AI in E-commerce

3.1 Development of AI Technologies

Investments in artificial intelligence technologies are growing in a lot of industries worldwide. Top industries that implement AI are the medical sector, data management, fintech, cybersecurity and retail. In 2022 investments in these 5 sectors counted more than 26 billion dollars. This trend illustrates how AI is actively implemented in various industries. Already in 2023 73% of retailers in the United States and the EMEA region declared the usage of artificial intelligence, computer vision (CV) or machine vision (MV) in selected operations or even in a wide scale of processes and only 3% of companies are not using these technologies at all. (*Artificial Intelligence (AI) and Extended Reality (XR) in E-Commerce*, 2023)

Nowadays AI technologies are starting to be not an innovation, but a commodity in people's everyday life. With the development of some softwares as ChatGPT, Midjourney and Apple Intelligence (Apple, 2024) artificial intelligence is entering not only a business area, but also domestic operations. For instance, as of mid-2024 ChatGPT is counting more than 180 million users monthly with the dominant users of 43% in the age of 18-29. (NamePepper, 2024) This trend is brightly showing that adopting AI technologies is becoming not a competitive advantage for businesses, but a must for continuous successful performance.

Before going further to the AI usage in the e-commerce industry, the definition and structure of artificial intelligence industry should be established. Firstly, we will use the definition of AI as ‘a technology that enables computers and machines to stimulate human intelligence and problem solving capabilities’. (IBM, 2023) Modern scientific society defines three main stages of AI development called Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI) and artificial super intelligence (ASI). (Kappagantula, 2019) Nowadays most of the AI-driven technologies are using ANI that is characterized by the ability of performing specific pre-learned tasks. For example, even advanced voice chats from Amazon and Apple companies are teached to do only a particular list of operations. AGI and

ASI stages of AI development are not reached yet. These AI stages are defined by equal to human or better intelligence including self-awareness. (IBM, 2023)

Artificial Intelligence has several main branches that differ in algorithm usage and targeting problem solving. Among them are machine learning (ML), Neural Networks, Robotics, Expert Systems, Fuzzy Logic and Natural Language Processing (NLP). Earlier in this work a machine learning algorithm was mentioned. It can be defined as one of the AI algorithms along with deep learning that is modeled to learn from data and make data-driven predictions and decisions. NLP algorithm is operating with textual, visual and vocal information in order to understand it, identify meanings and create these forms of data providing a clear and structured communication. Neural networks, in their turn, are used for identifying patterns and customer segmentation. Consequently, it is used in providing more targeted advertising and creating recommendations. Furthermore, fuzzy logic algorithms can be applied in marketing and e-commerce as it is widely operating within uncertainty.

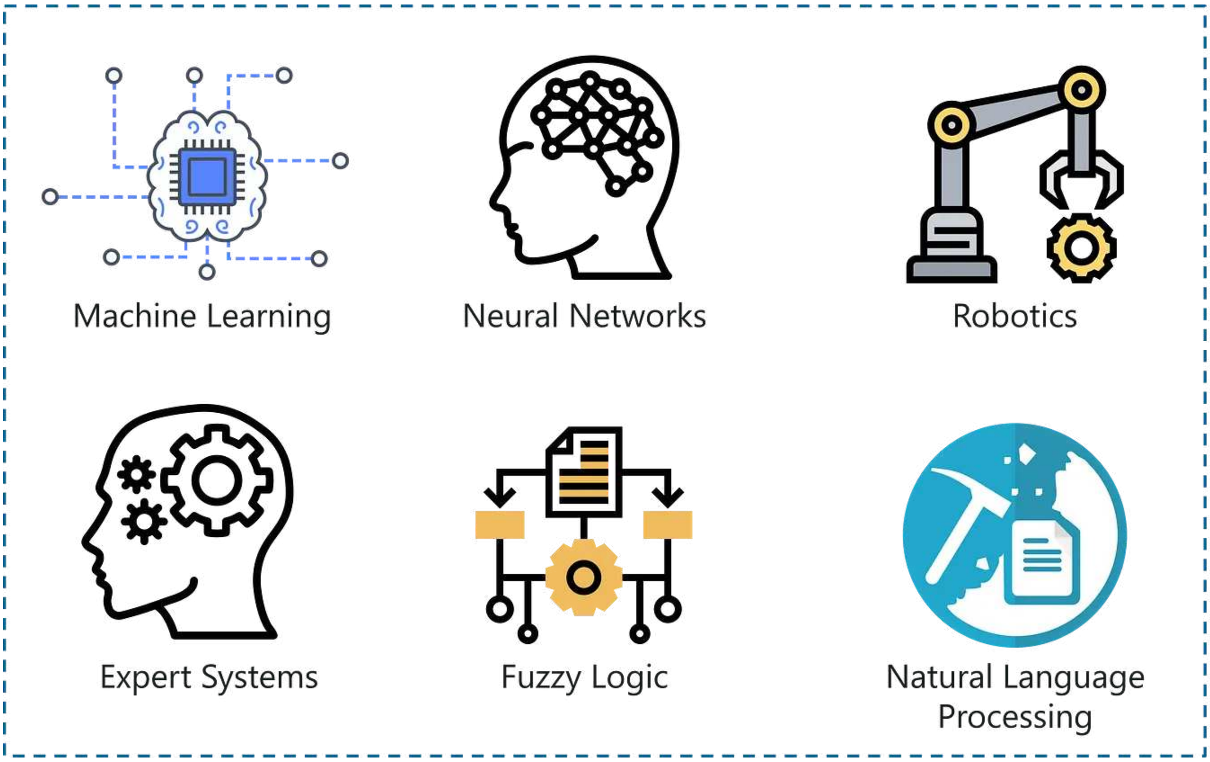

Figure 9. Branches Of Artificial Intelligence (Kappagantula, 2019)

3.2 Implementation of AI in E-commerce

The biggest impact of AI technologies on e-commerce is expected in the next 3 years according to professionals from e-commerce companies. (*Artificial Intelligence (AI) and*

Extended Reality (XR) in E-Commerce, 2023) The impact of AI in E-commerce might be analyzed in two dimensions – internal and external. Into the internal dimension we will include all the processes that are connected to the customer user experience and in which customers can personally interact with the AI-technology services. The most expected improvements and implementations of AI in e-commerce customer experience is expected in the following cases: price comparison, finding deals, relevant offerings, personalized and voice assistance, review, frictionless payments. Nowadays customers are experiencing a need in optimizing the discovery process of new products by better understanding of their needs and convenient search. (*Artificial Intelligence (AI) and Extended Reality (XR) in E-Commerce*, 2023)

Considering the specific operational needs and type of product distribution, every business could benefit from new technologies differently. For instance, marketplaces that differ from traditional retail shops by tremendous amount of product, customer and, therefore, data and processes, benefit the most from optimizing supply chain operations – stock maintenance, logistics route planning etc. On the other hand, Direct-to-Consumer (D2C) brands enhance their business by improving customer experience and implementing automated customer support instruments.

As digital payment is a fundamental operation for e-commerce business, it is crucial to provide it on a high quality level. One of the biggest challenges of the Ai implementation into digital payments is a lack of knowledge and trust. 76% of consumers worldwide are not comfortable or have doubts about using AI-driven payments technology. The rest are already using or ready to try in the next several years when this type of payment is more established and regulated. (*Artificial Intelligence (AI) and Extended Reality (XR) in E-Commerce*, 2023) That statistics illustrates that main barriers that stop AI expanding are lack of trust, regulation and understanding of its background. Nevertheless, AI systems aim to strengthen the security and fraud activities as it has more advanced methods to create strong and self-updating protection systems. (Lingam, 2018, 2283) Therefore, it is seen to be a question of time when AI will become a more trusted tool for storing and operating with personal data and payments.

Nevertheless, younger generations are more convenient and used to consuming ai-driven technologies. For instance, Gen Z is showing almost 95% of interest in regular implementation of AR in their online shopping experience – from choosing furniture to trying beauty products. The wish of using AR technologies is shown by around 30% of consumers buying online in most of the European countries.

Implementation of AI in e-commerce processes in general leads to increase of sustainable performance of the company by optimizing both backend and frontend operations. Artificial Intelligence (AI) can be described and understood in different ways – as an algorithm or paradigm. (He & Liu, 2024, 1) The main purpose of AI is to gather, predict and imitate human behavior patterns. In e-commerce that technology enables a better consumer understanding and provides more suitable solutions. Moreover, the e-commerce industry can be considered as the retail industry that is able to gather more than others from AI adoption due to its direct contact with customers.

Business benefits from AI tools by optimizing decision-making processes basing them on data insights, more accurate understanding of dependencies and predictions. Latest research demonstrates a positive trend of business performance connected to market expansion, new product development and supply chain optimization after implementing AI technologies in e-commerce. (Chen et al., 2022, 3) Additionally, marketing and e-commerce industry benefit from AI for innovative and creative tasks. Even if these types of operations used to be seen as subjective ones, automation tools like A/B testing are making it easier to make a decision on a creative banner or product functionalities based on objective performance metrics.

Moreover, it is significant to mention that a thoughtful interconnection of AI instruments implemented to the business can dramatically increase its performance. For example, based on the communication in chatbots, algorithms are able to collect information based on which it would provide personalized recommendations and pricing from which both sides will benefit the most.

3.3 Personalized Recommendations

According to Xiaorong He and Yan Liu research on evolution of AI implementation in E-commerce, recommendation systems (RSs) development is the main path and focus of current research and e-commerce businesses. E-commerce is characterized by a wide range of offers and their increasing number that makes the customer decision making process more complicated and longer. Nowadays, customers have to choose products or services among a huge number of offers. That is why both sides are interested in reducing time for choosing: customers are looking for easy, personalized and fast solutions, and businesses are aiming to boost purchases and increase loyalty. Additionally, with the growing loyalty brand gets a higher life-time-value (LTV) of customers and improved customer retention due to excellent customer experience.

The RSs are the main e-commerce tools that allow customer satisfaction by advancing user-experience and aim to provide customers with the best solutions based on their data. Customer data on their behavior and product preferences like price segment, type of products, colors and others allow them to make precise predictions on what customers would like or not. Therefore, RSs are dramatically increasing conversion rate (CR%) to the purchase providing a better matching between customer needs and online shop offers. An increasing CR% is consequently decreasing return on advertising spends (ROAS) as recommendations are targeted to the related customer segments.

So, the central issue of e-commerce businesses is how to provide the most relevant products or services to customers. In this chapter we will discuss current technologies used to build recommendation systems in e-commerce businesses.

The mechanism staying behind the recommendation systems is machine learning that is used to find patterns in user behavior and forecast it. Machine learning mechanisms can be based on various models depending on the purpose and context of RS implementation. Moreover, the structure of the recommendation system might differ based on data used for forecasting and method of filtering. (Sharaf et al., 2022). Currently there are two main approaches in building recommendation systems based on methods of model learning: supervised and unsupervised. The principal difference between these approaches lies in the way of predicting future customer behavior.

The most used model of unsupervised method is clustering that aims to find similarities and group items or customers based on provided data.

For instance, Sharaf (Sharaf et al., 2022) in his paper about usage of recommendation systems in the finance sector is discussing three main methods for classification and providing the best solution for customers. There are collaborative filtering that can be based both on user prior behavior and items, content-based recommendation and hybrid one. The hybrid model combines textual matching of customer search phrases patterns with items characteristic and customer grading patterns. (Singh & Kaur, 2021) The main challenge to implement any of them is so called Cold Start of user or item, that means that there is not enough data on the new user preferences and new item characteristics to provide a high convertible recommendation. (Sharaf et al., 2022)

Considering that one of the main purposes of RS in E-commerce is to provide the best recommendation of an item to the customer that leads to an increase of his interest and time in the online shop that by itself might lead to the increase of average order value. Thus the method of building a recommendation system is described in the article by Chaithra et al. (Chaithra et al., 2024) In this article the method of web pages recommendations is described, but the method is also applicable for any other RS. The whole process is divided into 5 steps. Firstly, business needs to collect data on user behaviors and item preferences. The second step is a data processing that includes data unifying by removing special characters, adapting text and images normalizing. In the following step, the model should be trained on the collected data using either classification either regression model. Classification model tries to predict whether the customer will like or not, will buy or not the proposed product. The regression model aims to predict a rating that a customer can potentially give to the product. Chaithra in his work is using a classification model.

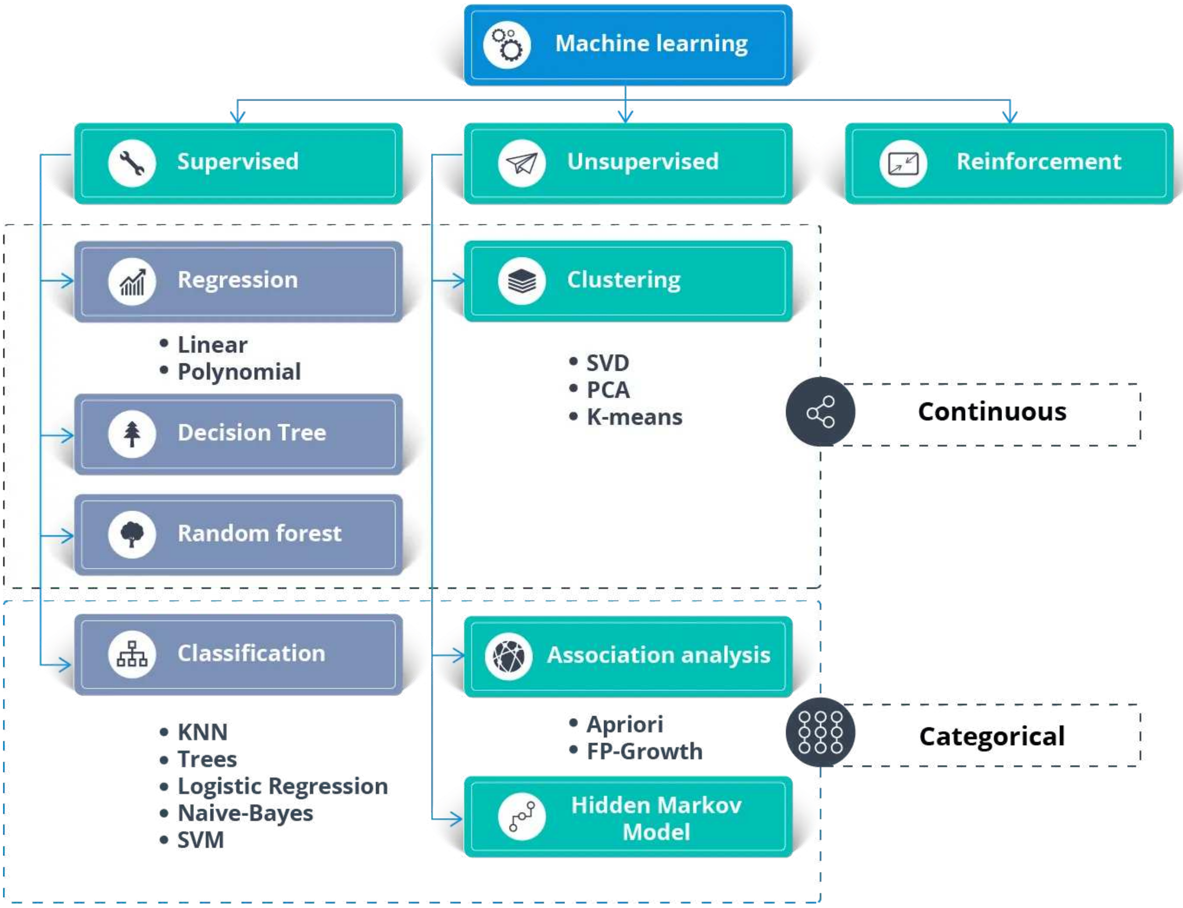

Figure 10. Types of Machine Learning Algorithms (Kappagantula, 2018)

To make a prediction of customer preferences researchers are implementing a Random Forest learning method (Chaithra et al., 2024) that creates a variety of decision making trees to find patterns and unique features of customer behavior. This method is based on model learning on randomly created samples of dataset aiming to find prediction factors of customer purchasing behavior. Furthermore, the model is able to match its prediction on customer behavior based on features it had extracted with real customer behavior. That principle is called supervised learning that provides continuous model improvements until the prediction factor matches real customer behavior. When a model has learned from real historical data of customer behavior it can be used to predict future customer patterns and create more precise recommendations.

Thanks to recommendation systems and data used for them valuable insights on customers behaviour, their preferences and decision-making patterns can be extracted. Informed business decisions oriented to consumers are proven to increase its performance and optimize operations.

3.4 Hypothesis Testing

Digital transformation and an increased amount of data give a tremendous amount of insights on customer behaviour. Furthermore, the specificity and higher flexibility of online platforms enable opportunities in experimenting. So e-commerce companies and advertising platforms are enabled to test various banners, prices, location and sequence of elements on a website, an application or advertising materials. These tests are useful for deeper understanding of customer reactions and attitude towards even slight changes. Moreover, the results of testing different hypotheses on the customer preferences improve customer experience and, therefore, company profits.

The process of testing hypotheses aiming to increase profit is common in numerous processes in e-commerce. By testing hypotheses, businesses try to find the best instrument mix to increase customer conversion rates, sales and other KPIs depending on the process. For instance, the hypothesis testing process is mostly used in content testing. By testing different banners or product cards, companies detect a creative that has a higher click conversion rate. After finding the best solutions from tested ones, companies often leave it as the main one.

That large-scale hypothesis testing process is called A/B testing. Nowadays e-commerce can provide A/B testing with the help of Google Analytics and other analytical platforms by testing images, texts and other visual concepts such as colors, button positioning and others to measure which variant will be more attractive for customers. A/B testing does not rely on AI algorithms but uses statistical methods to show the significance of difference of tested variants. Fundamentally, A/B testing is using two or more variants of visual or textual data, randomly assigning them to customers and providing an evaluation of results showing which variant had a higher rate and interest among customers.

Despite the proven efficiency of the A/B testing, it has some drawbacks that might affect the result. Firstly, A/B testing processes require a proper traffic split for a particular period of time. For example, it means that the selection of testing should be as randomized as possible. Randomized selection provides more relevant to real-market conditions results as it normalizes the amount of customers participating in tests among various socio-demographic groups.

Furthermore, during the testing period other than the testing changes should be minimized as they are likely to affect the final result too. As the causal-effect relationships are more complex to estimate it would not be representative to analyze a/b testing results with several dependent variables. However, hypothesis testing cannot proceed in vacuum market conditions and there are some market circumstances that cannot be influenced by the company – for example competitors' activity. It means that still, the A/B testing process can show biased results.

Depending on the tested feature A/B testing results can be interpreted differently. In most of the cases, the efficiency of banners, prices etc. are measured by customer conversions on every or one particular stage of customer journey. In the first stage when a customer is showing its interest toward the product of service, the company is measuring click-through rate (CTR%) seeing how many customers clicked on the product card, for instance. Further, to compare the quality of product or service description on the marketplace, the company is able to measure conversion rates to order or customer basket. Consequently, traditional A/B testing is measuring CTR% or CR% before and after the tested changes. Therefore, the company leaves the variant with higher performance.

Traditional A/B testing based on statistical evaluation is being steadily replaced by a more advanced method of hypothesis testing based on AI that calls Multi Armed Bandit Models (MAB). (Xiang et al., 2022, 4205) In simple terms, MAB aims to provide a higher reward by implementing any changes to the visual-textual information. These changes are made automatically by using machine learning algorithms that allow the model to observe the context in which it's making a change, choose an action, evaluate the effect of it and teach the model better based on new and past experiences. Consequently, MAB model creates a wide decision tree and tests every variant on the randomized selection. Every decision tested is either successful and increases the performance or shows less efficiency. Steadily, the model is testing and comparing all the available options and provides a result on the most long-term efficient variant.

The principal change of MAB compared to A/B testing lies in the improved context observation. MAB model is able to provide an action with the highest possible result on, for instance, open rate, based on the customer demographic and behavior data and context that contains daytime, location etc. Moreover, MAB model enables testing of a wider variety of changes and controlling the selection principle.

3.5 Dynamic Pricing Algorithms

Price of the product or service is one of the most defining factors for the purchase decision making. Depending on the product type it might have a higher or lower influence. Anyway, pricing strategy alignment with the product type is crucial for successful company performance. Dynamic pricing or personalized pricing concept refers to the differentiation of price paid for the product or service affected by the value attributed to the offer. (Narahari et al., 2005, 233)

Dynamic pricing strategy is taking its roots from the public markets, where price was mostly negotiated between buyer and seller. With the development of retail shops and later on e-commerce, companies had to define pricing tags for each product without adapting it to the customer characteristics. Nowadays, due to the development of machine learning algorithms, dynamic pricing strategy has become more than possible to implement into the online shopping experience. However, in 2024 only 21% of e-commerce companies are somehow implementing dynamic pricing and only 15% of firms are planning to do it in the near future. Other companies still did not evaluate benefits caused by dynamic pricing strategies or decided not to implement it. (Grover, 2024)

Narahari Y. et al. described five interconnected types of models for dynamic pricing: inventory-based model, data-driven optimization model, auction based model, game theoretic model and machine learning based model. They differ by the factors and methods on which the prediction and computation of optimal dynamic prices are based. (Narahari et al., 2005, 237)

Due to the high sensitivity of the price perception and fairness, dynamic pricing strategy has to be implemented with a particular careful consideration of its impact on consumer behaviour. Studies on pricing strategies showed that high magnitude and rapidity of price changes are more likely to drive customer dissatisfaction and significantly reduce brand loyalty. (Victor et al., 2018, 4) As we have previously observed, one negative purchase experience can motivate customers to stop being brand clients.

While implementing dynamic pricing strategies it is crucial to identify which and how factors influence consumer behaviour. Research shows that overall shopping experience, awareness of dynamic pricing usage and its perceived fairness and personal buying strategy affect consumer purchase decisions. (Victor et al., 2018, 11)

Transparency of dynamic pricing strategies is increasing trust and loyalty of the customer, as they become a co-decision-maker and get the understanding of what and why they are paying for. Moreover, the feeling of having some control and understanding how a person can 'trick' the pricing system and get a better deal, increases user satisfaction, while the opposite situation gives frustration.

Compiling insight on the difference of perception of paid amount of money electronically and in cash was explored by Amy Finkeslsteins. She found out that people that pay electronically are less aware of the precise amount of money they have paid than those who paid in cash. (Finkelstein, 2009, 980) It is connected to the fact that during online shopping it is consciously easier to spend money as a person does not have physical contact with it. Consequently, e-commerce businesses benefit from faster and easier decision making processes compared to physical stores. Moreover, the process of price comparison from different producers became more complicated due to the variance of distribution channels, dynamic prices and sales. Even if customers are able to search for products from the same device, it would be more problematic to compare prices with offline channels. Additionally, due to the increasing amount of products and variance in prices and channels, customers are ready to pay more for advanced experience, that includes convenient shopping, awareness of product and brand quality and quick delivery.

All the factors influencing price strategy in the e-commerce industry could be divided into two categories: personal and external factors. Among external factors are weather conditions, level of demand, stock, competition prices, day of the week and time of day. Those characteristics as age, gender, wellness level, type of phone, level of phone battery involve personal factors. Depending on the product, customer journey and target audiences, business could take into consideration different groups of factors influencing price.

There are two main approaches for building an automated dynamic pricing model. First one is a simple optimisation approach that is based on testing different prices and analyzing profits provided with each of them. Further, the model is choosing an optimal price that brings the height revenue. (ELEKS, 2023) The main drawback of that model is seen in the short-term profits, because in many cases it is not enough to analyze the influence of price to the sales.

Moving on to the second model, for providing an AI-driven dynamic pricing strategy, a reinforcement learning (RL) technique can be adopted. That unsupervised technique is built on the behavioral learning model that continuously tests hypotheses, gets feedback and optimizes performance. (Ma & Sun, 2020, 485) Therefore, the RL model learns by continuous trials, errors and successes. In simpler words, ML techniques for dynamic pricing are able to, firstly, collect the information from internal and external resources and structure it for the following analyses. Secondly, the model is identifying factors that influence customer purchase behaviour the most and understanding how these factors are connected with prices. (Symson, 2024) This stage is a crucial development for e-commerce companies and their sales and marketing departments as identifying the connections and causality between all the market features and prices is closely an impossible task for humans. Therefore, with the machine's ability to analyze and test a tremendous amount of data, companies are able to set the most fair price for both sides. On the further stages, ML model is trained and tested on real-time price predictions

One of the most developed and used in marketing methods of reinforcement learning is the Multi-Armed bandit (MAB) method. MAB method creates a tree of possible outputs, which is price in the case of dynamic pricing, tests them and gets either punishment or reward in the form of profit. Algorithm can be set with parameters that create a basement for hypothesis formulations, for instance, demand curve of the product. Moreover, as unsupervised learning methods do not need pre-setted settings about which parameters and how influence demand curve, a MAB model will learn from its experience which factors are affecting the demand curve and consequently to profits.

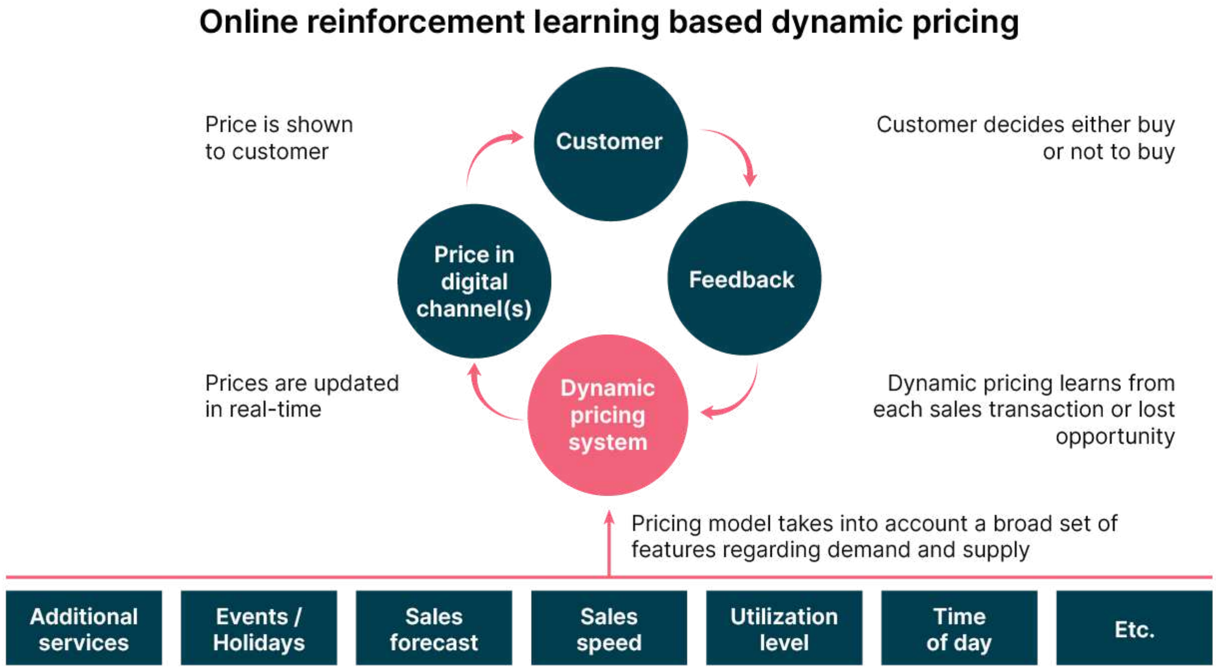

Figure 11. Online reinforcement learning based dynamic pricing (Heiskanen & Friedland, 2023)

A crucial feature of reinforcement learning model for pricing model is learning from natural market realities and aiming to maximize a cumulative long-term reward. Consequently, the RL model is able to learn how price should be defined considering the seasonality factor, competitors activity and many others. (ELEKS, 2023) That analysis makes it possible to create a more accurate forecast for pricing and sales for a longer period of time. Sometimes due to the complexity of market dynamics, a train market model can be created for initial stages of RL model optimizations.

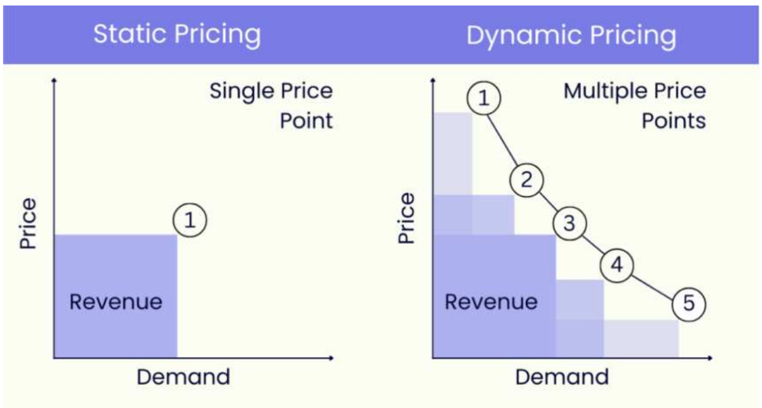

Figure 12. Price point in dynamic pricing (Doe, 2023)

This method gives crucial advantages to the price setting procedure in e-commerce. Firstly, online marketplaces are characterized by a huge amount of products that exceed its amount in the retail shops. Due to that factor, it is much more complicated to manually control levels of product demand and change the price. However, the RL model is enabling receiving more profits by expanding market share and attracting new customers with the price they are ready to pay for a product or service. (*Fig. 12.* (Doe, 2023) It means that dynamic pricing is helping companies to provide a better segmentation and reach customers that were wider than their previous narrow target audience. Secondly, due to the individual specificity of online shopping experience where no fixed price tags are needed, e-commerce businesses are able to continuously change prices and test their performance. Moreover, e-commerce companies have the access to customer data like no other offline retail company has. It is beneficial for online businesses that can more accurately and faster adapt prices to the market and personal conditions. Additionally, pricing strategy is helping businesses to deal with inventory management. AI-driven pricing model is able to take into consideration available stock and forecasted period of sales and adapt price to sell products faster or to escape out-stock by increasing the price. (Doe, 2023)

Furthermore, dynamic pricing strategy might be more relevant for particular product categories and products. For instance, products with a limited sale window (until a particular date) or highly seasonal products with fluctuating demand can benefit from AI-driven dynamic pricing. (Bradley, 2023) That's why the first companies that started active adoption of dynamic pricing strategies were companies with dynamic demand like airline firms, taxi services, house renting websites etc. For instance, Uber taxi service, AirBnb and Ryanair are using dynamic pricing strategies that are influenced by an amount of external and internal factors. Taxi services are globally using that strategy as they have a fluctuating demand during the day that is also connected to a big amount of such factors as weather, amount of drivers on the streets, global events in the region etc that sometimes are difficult to predict. (Phillips, 2024)

Additionally, dynamic pricing contributes a lot when optimizing prices during sales periods – for example, Black Friday. Online retailers are able to optimize the discount price based on the demand, location, stocks etc. several times a day to maximize company profit. So, Amazon marketplace is updating prices every 10 minutes to provide best prices and gather more profit. (Dowling, 2023)

Moreover, Reinartz highlighted several market conditions that increase the efficiency and relevancy of dynamic pricing strategy usage. Firstly, he is basing the existence of dynamic pricing on the variancy in customers willingness to pay for the offer. According to that, dynamic pricing is working in the industry with different levels of WTP. Secondly, dynamic models are relevant in the highly segmented customer audience. (Reinartz, 2002, 58)

3.6 Chatbots and Voicebot technology

Continuous strategic communication between brand and customer is the basement of any customer relationship management (CRM) that promotes clients brand loyalty. With the growing number of small and medium enterprises customers require more personalized, convenient and fast communication. That trend generated a conversational commerce that is defined as 'an interaction between a brand and a consumer that stimulates human dialogue and refers to purchasing products or services through a chatbot'. (Sidlauskiene et al., 2023, 1)

Chat services as a way to communicate with brand customers are widely used in e-commerce retail for obtaining information about the product or services and solving technical, order processing, delivery and other problems. Firstly, intelligent chats on the websites or in social media replaced live chat customer support services, which dramatically reduced human and financial resources. However, at the first stage of customer support development, chats were working in real-time and required people who could promptly answer the new customer request. The significant advantage of that approach is total personalization of communication. Nevertheless, with the continuous technological development and higher demand of 24/7 customer support many companies have changed real-time human chats to chatbots. The most basic version of chatbot is called '*decision-trees chatbots*'. (Ciesla, 2024, 116) That chatbot does not have any intelligence but is based on the branching decision tree with responses that depend on the limited amount of questions customers can ask. Due to the ease of its implementation, many SME companies prefer to use that type of chatbot.

An intelligent stage of chatbot as an AI system can be defined as 'a computer program which responds like an intelligent entity when conversed with.' (Khanna et al., 2015, 277) In other words, 'instead of offering direct touch with a real human agent, a Chatbot is a software application that conducts an online chat conversation via text or text-to-speech'. (Singh et al., 2023, 672)

Chatbots are widely used in the e-commerce retail industry as customers require a permanent online support. Among advantages of chatbot in e-commerce are an increase of retention rate in the conversation, reduction of costs and human resources, high level of objectivity and task-oriented approach. Chatbots are not getting tired and cannot express their emotions which could negatively affect customer perception and satisfaction from conversation. The figure below illustrates the main advantages of using chatbots in the opinion of respondents from the US in 2023.

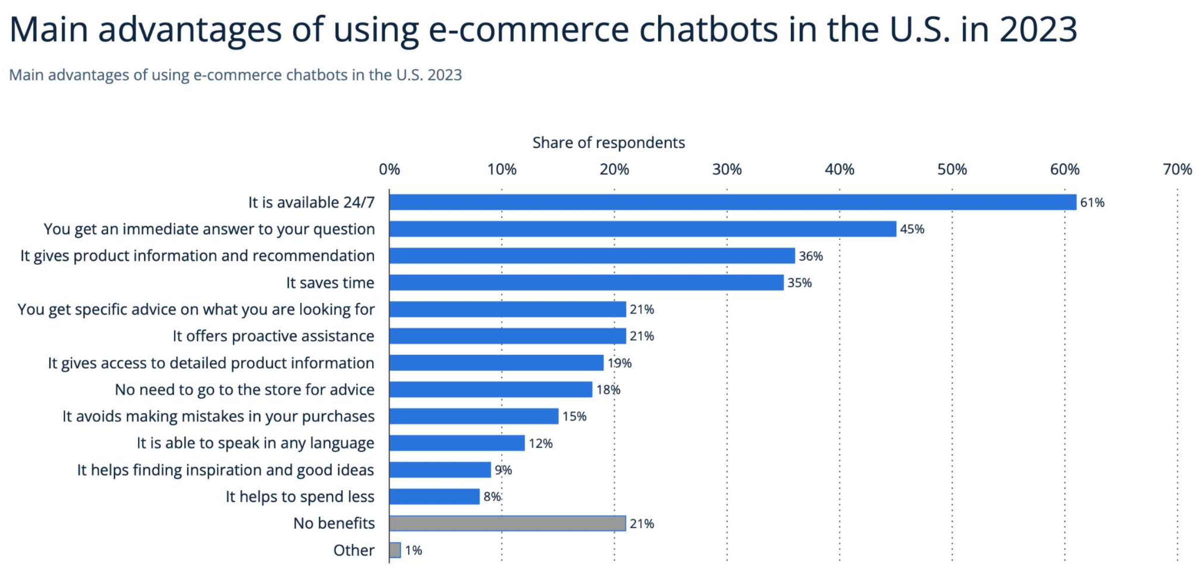

Figure 13. Main advantages of using e-commerce chatbots in the U.S. in 2023 (Statista, 2024, 29)

The basement of any chatbots lay on the algorithm it is built: existing approaches are rule-based and machine learning-based. Rule-based chatbot is easier to build and operate because it creates predefined responses following the rules. Rule-based chatbot is using a pattern recognition algorithm that is teached on the testing data sample and can decode customer messages even with some spelling mistakes. The significant difference of ML-based approach of building a chatbot is based on the fact that these chatbots do not need predefined responses for customer inputs. These chatbots are built with the usage of Natural language Processing (NLP) algorithm that is able to understand the context, meaning and emotion of the customer from the text. ML-based chatbots are continuously learning how to answer customers more informatively. Moreover, chatbots vary depending on the amount of accessible knowledge, service provided, goals and response generation methods. They can be connected to the open or close domain that defines the amount of information chatbot can use to generate a response. Moreover, depending on the chatbot goal it can be task-, information- or conversation- based. Conversation-based chatbots are enabling new business opportunities for companies such as automated translation of text or speech language to the preferred one by customer.

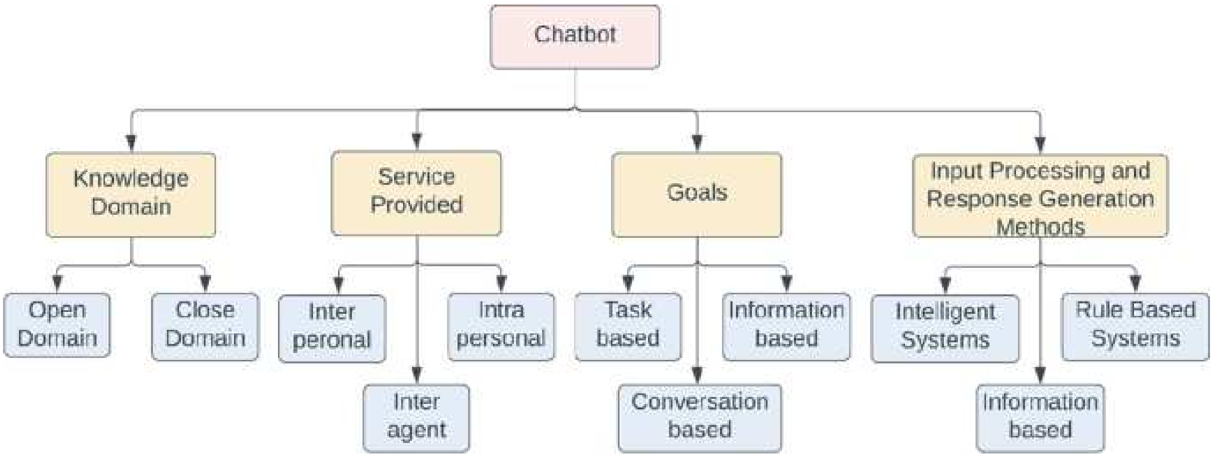

Figure 14. Types of chatbots (Singh et al., 2023, 675)

Usage of chatbots is also followed by e-commerce and marketing industries trends for personalization and omnichannel strategy. Chatbots are able to collect and analyze information on consumer requests and preferences, that could be used both in building relevant recommendations and reaching customers in other channels. Asbjørn Følstad (Følstad et al., 2019, 150-153) had proposed another categorization of chatbots that companies provide based on the locus of control and user- or chatbot-driven nature. The most used type in e-commerce chatbot's type is named 'customer support' and characterized by short-term duration of relation, mostly one-time usage, and user-driven nature, as a user is always initiating the dialog with chatbot. Another two developing trends in chatbot industry are 'personal assistant' and 'coach' that are both characterized by building long-term relationships with users. Personal assistants are user-driven, highly personalized and aim to continuously serve user needs. Coach chatbots are offering a continuous chat-driven communication based on its task – for instance, educational or sport exercise.

As in the whole industry of AI, trust can be an issue for customers while using chatbots. Depending on the sensitivity of the topic, customers may prefer human interaction instead of an intelligent chatbot. Researches are showing that trust for communication in chatbots is built on the usability and empathy factors. (Ltifi, 2023, 5) For business it means that the emotional factor of the chat communication is also significant for user satisfaction, as along with the aim of solving the problem users have the unconscious need of being understood and listened to. Moreover, the ability of chatbots to identify personality of the customer based on the previous user interaction is increasing the perceived empathy to the chat and, consequently, trust. This type of chat is called Other-Personality-Aware Chatbots (OPAC).

(Baha et al., 2023, 4) Furthermore, the comparison between anthropomorphic (= more human-like structure of conversation) and non-anthropomorphic chatbots showed that communication with a more anthropomorphic chatbot gives customers a higher sense of personalization of product or service. However, it is discovered that the perception of a more personalized product or service in the chatbot does not influence the customer's willingness to pay more. (Sidlauskiene et al., 2023, 11-12) Those observations give a business new insights on the structure of chatbot it could construct. Businesses that aim to provide more personalized offers are recommended to adopt more anthropomorphic chatbots that are using NLP and have a conversation-based goal.

To enable personalization in the chatbot, it has to understand not only the literal meaning of the text message, but also customer emotions and undertones. To do it, sentiment analysis, a sub-area of NLP, is implemented in chatbot operations. Sentiment analysis is able to deconstruct user’s messages, extract features based on which it could make decisions and create a classifier model supported by ML to identify whether the message has positive, negative or neutral tone. (El‑Ansari & Beni‑Hssane, 2023, 1628-1629)

However, AI and pattern recognition algorithms went further and enabled voice recognition models that could be implemented into the customer-brand communication in the form of voice-chat. Vocal communication is characterized by more informal sentence structures, flexible syntax and faster pace. All these factors make it more difficult to analyze audio in a synchronous way. Nevertheless, researched that usage of voice-based interfaces impacts on consumer experience of interface flow. Consequently, compared to text-based chatbot, it affects more significantly on customer’s brand perception in terms of its value and behavioral outcomes. (Zierau et al., 2023, 833)

Communication format	Text-mediated communication	Voice-mediated communication
Cue Characteristics	**Textual** - Formal structure and grammar - Precise syntax - Limited symbol set - No prosodic or temporal cues	**Verbal** - Informal structure - Flexible syntax - Extensive symbol set - Prosodic and temporal cues
Channel Characteristics	**Low Synchronicity** - Slower-paced - Asynchronous (sequential processing) **High Revisability** - Possibility to assess, deliberate, and rehearse	**High Synchronicity** - Faster-paced - Synchronous (parallel processing) **Low Revisability** - Little to no possibility to rehearse

Figure 15. Key conceptual properties of text-mediated vs. voice-mediated communication (Zierau et al., 2023, 827)

Moreover, the choice between voice- and text-based chatbot should be defined with the connection to the type of products or services offered by business. With the evolving development of voice recognition and producing technologies, voice-based bots are expected to grow in the following years. A research by David Schindler et al. illustrated that communication through bot could be more effective if types of the product or service matches bot mode. It was discovered that speaking bots drive feeling-based focus and stimulate customers to choose more hedonic products that in its turn increase their satisfaction from the purchase. On the contrary, writing bots fit better products with utilitarian features. (Schindler et al., 2024, 640) However, it is important to mention that the majority of customers still prefer writing method of communication.

To conclude, chatbots market size is expected to grow up to 1.250 million dollars till 2025 showing the growth of more than 500% during the last 10 years. (Artificial Intelligence (AI) and Extended Reality (XR) in E-Commerce, 2023) Current technologies of text and speech recognition are one of the most developed algorithms in AI that perfectly empowers customer-brand relationships within online shopping.

3.7 Marketing Spends Allocation

With the adoption of omnichannel strategy companies have to make a continuous decision on advertising spends allocation to different offline and online channels. The process of measuring effectiveness of one channel and especially several channels without or with influence on each other is still one of the biggest challenges in digital marketing. As customer journey becomes more complex and longer with the high requirements to the products and increasing customer acquisition costs, businesses are motivated to make data-driven decisions on efficiency of each digital and offline channel. In this part of the chapter we will discuss how artificial intelligence algorithms can be implemented on every step of planning a marketing mix.

Personalization trend forced companies to make marketing communication for each customer more unique. For that purpose segmentation and targeting instruments as one of the first steps in marketing campaign planning are applied. Firstly, as an e-commerce type of business gives a variety of information about each customer, it is possible to create groups of people with similar characteristics and purchase history that are expected to behave in a similar way for the same marketing message. That process of extracting groups with similar characteristics is called segmentation. It aims to create as many segments from all customers as possible to provide a higher level of personalization. Segmentation could be based on different types of data, for example on such social-demographic characteristics as age, gender, location or behavioral characteristics as product or categories preferences, frequency of purchase and average cost of purchase basket. That process helps businesses to understand which segments of potential customers will be the most convertible and profitable. Before the digital transformation era, the segmentation process included a lot of 'guesswork' as there was not enough representative data collected about the customers. Digital shift to e-commerce business models or omnipresence gave marketers an opportunity to base their segmentation in more relevant databases. However, the bigger a database is the more challenging it is to create segments of customers by hand. Therefore, AI tools enable a more detailed segmentation based on a higher variety of customer characteristics.

For providing an ai-driven segmentation analysis an unsupervised machine learning model is used. Unsupervised machine learning is helpful to provide an exploratory data analysis and empower marketers decisions. Unsupervised ML is using advanced clustering algorithms to identify patterns in customer characteristics and behaviour. An advantage of that model for segmentation lies in its flexibility to marketers needs as they can program particular features of customers on which they want to base a segmentation and also to define the level of its detailing (for example, create 5 or 200 segments). Moreover, ai-driven tools enable dynamic segmentation based on the real-time data and provide predicted behavioral modeling based on the current data. (*AI Customer Segmentation Strategies*, 2024)

After the segmentation process is done every group of customers should be programmed to receive relevant messages with personalized recommendations, discounts updates etc. The process of sending various messages to different audience segments is called targeting as it aims to target particular narrow groups of people.

Nowadays the adopted omni-channel strategy that includes both online and offline channels of communication with customers provide huge amounts of customer data and requires a more data-driven approach of targeting and marketing spends allocation.

A Marketing Mix Model driven by ML algorithm has been developed to measure efficiency of advertising through various channels and forecast the most profitable spends allocation in each of them. (Vincent, 2021) Traditional statistical methods assume the linear relationship between advertising budget and profits that follow the approach 'the more the business spends on marketing – the more profits and new customers it will attract'. In reality that assumption faces an obstacle that the effect of advertising spends on the customer acquisition is not linear. It means that from some point on the spend - new customers graph the function becomes plain, meaning that increase in budget gives a slighter and none effect on the customer acquisition efficiency. The main goal of marketer and MMM is to identify that point and grade of budget effect on the channel performance (Figure 16).

Therefore, the Marketing Mix Model is based on the Bayesian Statistics Approach that takes into account both marketer assumptions on each channel efficiency and their historical data. It means that the Media Mix Model is built at first place on the marketer's understanding and historical data of channels division and their influence on the company profits. Further, that model is tested on real-time data for accurate modifications.

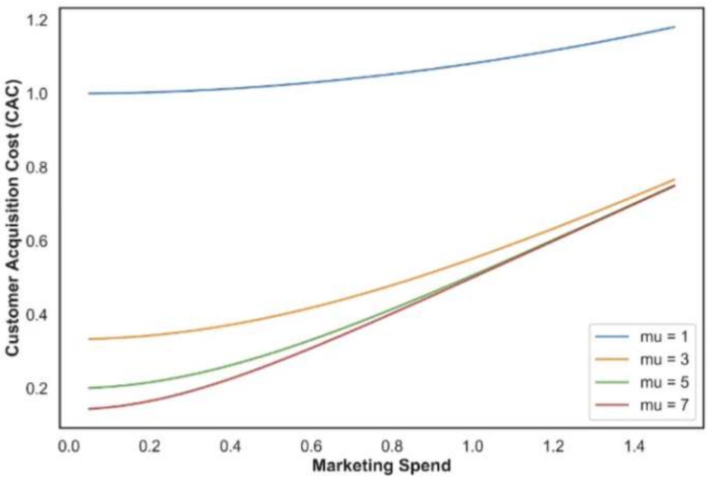

Figure 16. CAC function for marketing budget (Fiaschi, 2020)

Moreover, that model allows businesses to improve a fundamental issue of choosing an attribution model for measuring channel performance. Attribution models are methods to measure the efficiency of marketing channels by assigning ‘credits’ or ‘importance rate’ to some of them. Traditionally there are several main models: single-touch models (first-click, last-click, last non-direct) and multiple-touch models (linear, position-based, time-decay). Every attribution model is based on the pre-setted assumption on how every touch-point with the marketing communication through the whole customer journey affected customer purchase. Each of these attribution models has disadvantages as they do not provide high flexibility and accuracy. That problem is overcome by implementing the MMM model in marketing spending decision allocation.

Bayesian based model is taking into account traditional marketing funnels that divide all the channels considering their purpose. For instance, such top-funnel channels like TV are increasing brand awareness and usually have a slighter effect on purchase decisions. Further, there are middle and bottom funnel channels which aim to increase people’s interest to the brand, convert them into customers and keep their loyalty. (Fiaschi, 2020) Every customer's touch to the brand marketing activity somehow affects its brand awareness, willingness to buy and actual purchase behaviour but to calculate these effects is a statistical challenge.

As the period of every advertising campaign influences the customer behaviour in different unknown duration – from immediate purchase to increased willingness-to-buy and purchase in half of the year, measurements of channel efficiency should be accomplished taking it into account. That concept of delaying influence is called carryover effect. (Jin et al., 2017, 3) Forecasting model of advertising effectiveness enables marketers to plan long-term campaigns and base their inventory plan on forecasting sales that dramatically optimize business operations and prevent over- and out- stocks.

Therefore, Bayesian statistical model empowers marketer with the tool for marketing spends allocation by providing measurements on the forecasted effect of investment in every channel. Moreover, as every channel has its volume and maximized effect point after which the higher investment will lead to the increase of ROI% (return on investments), MMM helps to identify the most efficient mix of channels and their effect duration. (Fiaschi, 2020) That model is innovative for the marketing industry in general and primarily applicable for online businesses adopting omnichannel strategy. The variety of online and offline communication channels is increasing the complexity of marketing planning that could be optimized by implementing Media Mix Modeling. That model empowers e-commerce businesses that are aiming to expand their digital presence and increase the variety of channels used for product or services distribution. We consider that similarly marketplaces, direct-to-customers and subscription models are able to optimize their marketing strategy by MMM. Moreover, it is significant that the higher are the budgets and the richer is the variety of channels – more useful and beneficial the MMM adoption is.

Furthermore, the planning marketing campaigns process and targeting settings has to account for the variety of customer's reaction to brand communication activity. It is assumed that any communication can have positive, neutral and negative effects on a campaign objective (Figure 17, (Mosca, 2023)). However, there are four groups of customers depending on their behaviour to the advertising campaign: 1. who buy after marketing communication, 2. who do not buy after marketing

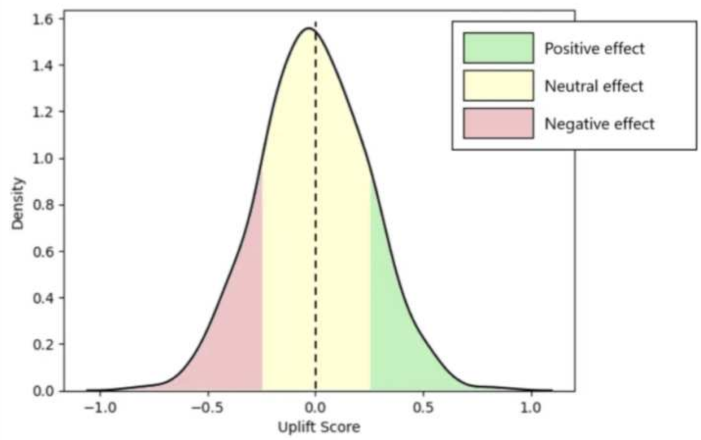

Figure 17. Uplift Score Distribution (Mosca, 2023)

communication, 3. who buy not depending on the advertising, 4. who do not buy not depending on the advertising.

A relevant communication frequency with each of these customer's groups leads to improved customer retention and ROI%. But the challenge of predicting customer behaviour lies on the issue of predicting the causal effect of marketing activity on every single customer. To overcome it a model needs to analyze two different scenarios of customers reaction – it predicts the reaction and behaviour of each customer in the case of receiving the message and in the case of not receiving it. Therefore, for that purpose the uplift score can be estimated. (Mosca, 2023) That score aims to predict the difference in CR% to purchase between customers who received a marketing message and those who did not. From the algorithm point of view those who received a message are 'treated' and those who did not are 'non-treated' groups. Calculation of uplift score is showing if the effect of marketing activity will show a positive impact on purchase behaviour, negative impact following by decreasing loyalty and interest to the brand or neutral impact defining that marketing message did not affect customers. That concept is improving targeting settings by identifying if investments in targeting a particular customer will increase profit, will not influence it or will decrease it. The type of e-commerce businesses that might benefit the most from implementing Uplift Score is a subscription based model business. As one of the main issues of that model are increasing customer lifetime value (CLV) and decreasing churn rate (% of unsubscribers), uplift score empowers subscription businesses to communicate with every customer or not on a predicted base. Furthermore, marketplaces and direct-to-customers businesses are as well able to increase their marketing performance by adopting that approach.

For evaluating Uplift Score a causal effect framework is adopted meaning that the model tries to identify the reaction of each customer in the scenario if it receives marketing communication or if it does not receive it. (Mosca, 2023) Therefore, calculating an uplift score empowers companies with a budget optimization tool by measuring the outcome of every single communication. Combining two data-driven algorithms MMM and Uplift Score, the company is able to dramatically improve customer experience and optimize advertising investments receiving maximized profit from them. Both MMM and Uplift Score are implemented before the start of a marketing campaign and therefore are improved on the real data. Models are, firstly, identifying, which channels mix will be the most effective with the available budget and therefore optimize targeting settings in each of the channels to maximize the positive effect of brand communication.

These two predictive models are able to significantly transform online marketing campaigns in the following years. It is still notable that the main key for enabling this opportunity lies in the accurate data collection.

3.8 Customer's Reviews Usage

One of the significant parts of any e-commerce business is customer reviews that are mostly automatically published on the website or application. Customer reviews are another instrument that can be used to make business decisions data-driven. Reviews create a continuous feedback loop between the customer and the brand from which both sides can benefit. For customers it is a way to express their impression of the experience, communicate with the brand they like or to prevent other customers from purchasing if the experience was negative. Customer reviews is a strong tool for e-commerce companies that can help to grow business if used correctly. For companies reviews are customers real-time opinion on the product that continuously aims to meet consumer and market expectations. If there is a digital product like an application, then its product or service can be modified in a short period of time and, therefore, attract more customers. If a company provides physical products or services, it is also able to see changes in customer satisfaction by regularly analyzing customer reviews.

Moreover, if a company receives negative reviews, it might notice dramatic drawbacks of their product or transform a disappointed customer into a loyal one by providing personal communication and solving the issue. Additionally to that, customer reviews can be used as a basis for customer segmentation and, furthermore, recommendation system. (Aarthi et al., 2023, 826)

Consequently, it is clear that e-commerce businesses have a significant advantage over offline companies as they have a self-updating database on their products by their direct customers. This is another feature illustrating the closeness of customers and companies in the digital transformation era. Further, for better understanding of customer needs the company has to adopt an approach of customer reviews analysis. For small companies with rare reviews it is feasible to read every review by themselves and make conclusions on further products or services improvements. With the company growth it becomes more challenging to critically evaluate every review and group them by topics and emotions. On that step the adoption of various technological tools can crucially simplify the process of extracting insights from customer reviews. That technological adoption is primarily beneficial for marketplace businesses where both the range of products categories and products along with the amount of sales and reviews are increasing. Analysis of customer reviews gathers understanding of customer satisfaction of marketplace usage and enables predictions of products rating dynamic. It empowers marketplaces to build more complex prediction models including a wide range of products and their future ranking changes. Additionally, sentiment analysis provides continuous real-time data on customer satisfaction level that could empower business with fast product improvements and during emergency situations. Moreover, with the company growth ML model is easily scalable to the larger amount of data which is beneficial in comparison to human capability.

Another valuable e-commerce operation that requires customer reviews is identification of fake reviews. (Alsubari et al., 2023, 259-260) That process is relevant only for the marketplace business model as it is characterized by internal competition of sellers. Surveys illustrate that around 90% of customers buying online are considering other customer’s reviews and product range during the decision making process. Moreover, not only the mark of the product but also the amount of reviews increase product quality from customer point of view. Therefore, it motivates sellers to buy fake reviews published by third parties. As frauders are also improving their skills in publishing reviews - they use the same language constructions and highlight product features like real customers - it becomes more and more challenging to analyze and detect them. Marketplaces aim to provide a fair competition on the market and to do so they need to provide a fair system of product evaluation. For now there is no unified solution for that problem that would accurately carry out fake opinions. Depending on the approach adopted, researchers proposed consideration of the following review attitudes different from text for extracting fake reviews: evaluation duration, emotions, clarity, the difference of customer review from current product rating and average rating mark appointed by customer. (Alsubari et al., 2023, 259)

To use customer reviews for its own purposes business has to proceed with an analysis classifying each review from negative to positive and extracting main subjective insights about the product. Marketplaces leading the technological adoption of AI instruments among e-commerce companies are using ML methods like sentiment analysis and emotion detection to identify subjective information from reviews. One of the most challenging parts is data classification due to the deeply unstructured nature of information. (Büschken & Allenby, 2016, 2)

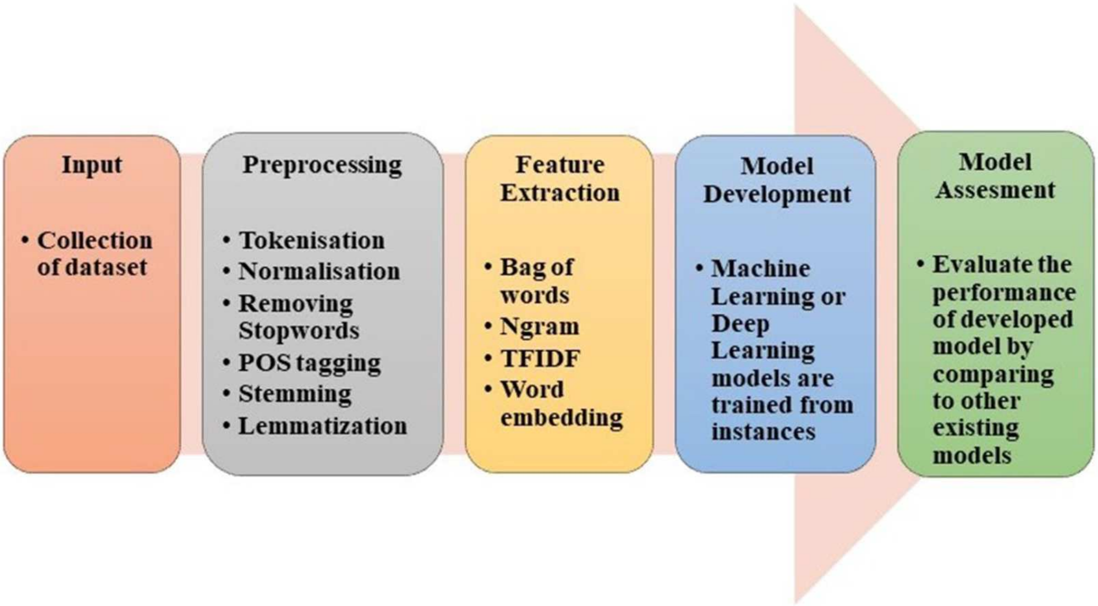

Figure 18. Basic steps to perform sentiment analysis and emotion detection (Nandwani & Verma, 2021, 6)

Sentiment analysis and emotion detection are areas of Natural Language Processing (NLP) which is processing and generating text, visual and audio content. Sentiment analysis perfectly fits the aim of reviews classification as it is used to group data with positive, negative and neutral attitudes. (Nandwani & Verma, 2021, 2) Besides applying Machine Learning models to categorize reviews, the data preparation process has to be carried on. Several techniques of data preprocessing are illustrated on the figure 18. Firstly, during the tokenization all the textual information is broken down into separate words. Furthermore, for easier analysis and data unifying the model is changing word forms to its base form. The next step of the lemmatization technique model is creating groups of words with similar meaning. These processes of data preparation are crucial as the initial stage of the database is highly unstructured. Furthermore, the usage of unstructured data is increasing the probability of mistake and meaning misunderstanding by the model. On the feature extraction stage prepared textual information is transformed into numerical values.

Sentiment analysis is still a complex procedure due to the reliance on the unstructured textual data. As customers reviews are written with plenty of abbreviation, slang, emoji and emotional connotations, it is challenging to understand the precise meaning. For model improvement it has to be trained on the huge training data.

Along with sentiment analysis another type of ML technique is used – emotion detection. While sentiment analysis aims to categorize reviews into three groups with negative, positive and neutral connotations, emotion recognition techniques help to identify feelings. The variety of feelings can be setted by a model engineer that gives more flexibility to the analysis.

Together with sentiment analysis emotion recognition techniques, which are both based on the NLP, create a full impression of customers intentions from reviews. In sum, sentiment analysis and emotion recognition techniques can be used to proceed any unstructured textual data and empower e-commerce businesses with better understanding of customer sentiment.

Chapter 4

Conclusions

The integration of artificial intelligence and machine learning technologies has significantly transformed the e-commerce landscape offering new analysis tools for efficient business operations and improved customer experiences. Application of AI in e-commerce is pivotal for implementation of data-driven strategies and advanced metrics optimization.

Increasing customer expectation led to the development of personalization recommendations systems based on the supervised and unsupervised ML methods. Capturing customer behavior patterns and prediction models enable creating tailor-made recommendations which noticeably improve conversion rate and customer satisfaction.

Furthermore, chatbots and evolving voice assistants become valuable for providing a continuous and high quality customer support process during online shopping. Based on the Natural Language Processing and Sentiment analysis, the model is able to capture meanings, intentions and customer emotions from the unstructured textual information. These tools clearly strengthen customer service by efficiently handling a wide range of inquiries and improving response time and overall customer happiness.

Additionally, the e-commerce industry benefits from real-time testing and prediction models which are able to provide automated A/B testing and propose an efficient marketing mix for budget allocation.

Besides that, the e-commerce industry noticeably gains advantage of AI tools for logistic optimization and dynamic pricing strategies that increase the efficiency of investments.

The adoption of AI and ML in e-commerce goes with several serious challenges. Issues such as data privacy, algorithmic transparency, and the ethical use of AI require ongoing attention. However, the benefits of these technologies in enhancing business performance and customer experience are undeniable.

Also, the integration of AI in logistics and supply chain management also presents opportunities for developing sustainability. AI can optimize delivery routes to increase the use of eco-friendly transportation methods.

From the business perspective it is crucial to address ethical challenges of AI usage and develop fair and transparent systems for gaining consumer trust and loyalty.

In conclusion, AI and ML have become essential tools in the e-commerce industry driving efficiency, personalization and forecasting. These technologies are driving digital channels and primarily the e-commerce industry to better understand customers, make data-driven product or services improvements, provide tailor-made offers and communication. As AI and ML technologies continue to advance, their implementation will be a key to achieving sustained competitive advantage in the digital era and meeting the needs of the market.

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