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SUSTAINABLE ARTIFICIAL INTELLIGENCE TOOL STRATEGY AND CUSTOMER EXPERIENCE IN EYE WEAR RETAIL CHAIN STORES

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ABSTRACT
Artificial intelligence tools and processes have hugely impacted the retail industry and the satisfaction of online customers. With technology largely pervading all facets of our lives, people want meaningful experiences. Artificial intelligence has the ability to deliver positive experiences for customers that help build brand trust and customer satisfaction. Whether you are using your smartphone, laptop, or voice assistants such as Alexa or Siri, service on the internet is gaining new ground. This paper does a literature review of the various technological advances that optimize the customer experience to evoke e-satisfaction (i.e., satisfaction while shopping online). E-satisfaction as a construct will be reviewed with its impact on customer purchase intention. The main results of the documentation were used to substantiate the conceptual framework introduced by the paper. The research revealed a variety of advanced solutions, benefits, but also risks that AI generates in retail, in different segments of the value chain, abbreviated CECoR, from improving the customer experience (*Customer Experience*, CE) with the help of virtual agents (chatbots, virtual assistants, etc.), to cost reductions (*Cost*, Co) by using smart shelves, and to increasing revenues (*Revenue*, R) due to product recommendations and personalized offers or discounts. The proposed conceptual framework is focused on customer profiles and includes recommendations on AI implementations in a retail company, from the perspective of CECoR drivers. The results of the research can be capitalized by practitioners and researchers in the field, who are presented with concrete examples of benefits, challenges, and risks generated by AI technologies. The CECoR framework could be a useful tool for both retail and AI specialists, providing common and clear guidelines for initiating and overseeing projects for integrating AI in a company's information systems. This review will provide businesses and other researchers a frame of reference to conduct empirical studies in the area of AI and technology-enabled retail.

KEYWORDS: Customer Experience, E-Satisfaction, NLP (Natural Language Processing), Online Customer Experience (OCE), CECoR framework

INTRODUCTION

In today's dynamic, super-connected business environment, organizations are forced to use systems, mechanisms and tools that allow them to obtain a significant to a significant competitive advantage. With a wide variety of applications, artificial intelligence (AI) is considered disruptive and revolutionary

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because it allows “the simulation of human intelligence, which replaces human beings in complex tasks” (Yang, 2020). Research effortstarget aspects such as natural language recognition and processing, image recognition, objectmanipulation, and there are various categories of AI tools: analytical, human-inspired, and humanized (Kaplan and Haenlein, 2019). Today artificial intelligence has come out of the realm of science fiction and has entered our homes.There are several web technologies used today in everyday life especially in the ecommerce world. AI (Artificial Intelligence) is viewed mostly as robotics but it has much larger technology range such asmachine learning, natural language processing (NLP), learning systems, gaming systems and objectdetection (Greenberg, 2017). Today AI is touching us in all areas such as online shopping, health careand fraud detection. AI has the power to attract customers with personalization and interaction. This can then enhance the revenue of e-retailers. Today, marketers need to understand the huge potentialimpact of AI tools on online customer experience (OCE) and e-satisfaction. Several big e-commerce companies such as Amazon, Flipkart and Walmart have realized that mere web presence is not enough to retain their customers. AI enables machines to achieve difficult and repetitive tasks so that humans can utilize their time and energy for more thinking tasks. AI has enhanced the entire ecommerce shopping experience by adding a touch and feel experience. Slowly AI is bridging the advantage gap between brick and motor stores and online stores. With the integration of AI technologies such as machine learning, deep learning, augmented reality, Virtual try-ons, Avatars and Chabot’s in a website, the e-retailers are achieving the objective of providing convenience to customers and improving their online customer experience. This in turns helps the retailer to bring down returns an increase overall revenue generation. The objective of this article is to outline the different AI based technologies which impact online fashion retail. To ensure a competitive advantage by adopting emerging technologies, retailers must consider three key elements: (1) improving the consumer experience, (2) reducing costs, and (3) increasing revenues and business profitability (Hetu, 2020). The present study aims to identify and highlight the main benefits and challenges of implementing AI technologies in retail along the three mentioned axes. The cognitive acquis thus obtained was capitalized by developing a conceptual framework for integrating AI techniques and algorithms in the information systems of companies in the retail sector. To this end, efforts have been focused on the work areas delimited by the following two research questions: (1) “What are, from the CECoR perspective, the benefits and risks reported by retailers, generated by the AI implementation?”; (2) “How could the initiation and management of an AI technology integration project be supported through this research?”. Artificial intelligence has been around for a long time but has recently shot into prominence with the advent of the internet. In the area of marketing not much research has been conducted relatedto AI. Research in AI till now has dealt with the more technical aspects of AI systems. Not much research is done about the effect AI techniques on customer experience. Artificial intelligence (AI)is the concept of intelligent machines being able to carry out tasks and enhance the tasks by learning from experience on their own Geisel (2018). They provide valuable automated solutions to complexproblems Crittenden, Biel & Lovely (2019). Virtual try-ons like Lenskrafters, Virtual fit applications like NIKE FIT are some of the AI techniques which improve the customer experience in ecommerce.

LITERATURE REVIEW

The paper attempts an analysis of studies which use different types of technologies such as machine learning, recommendation engines, Fit intelligence services, virtual try-ons, personalization servicessuch as chatbots and their impact on online customer satisfaction i.e. e-satisfaction. The literature review has been conducted using keyword searches in pairs in the electronic database of Scopus using the following words: (1) e-satisfaction (2) Artificial Intelligence; (3) online retailing (4) online (Eye Wear) retailing (4) Customer experience (5) virtual try-ons, (6) customer personalizationthrough recommender systems (7) Augmented Reality, (8) Chatbots

The inclusion criteria for these keywords were in different combinations on research studies donein the last ten years. After checking all the abstracts of the articles and complete works, 45 articles that were

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relevant to this topic are chosen. These articles have been discussed and cited in the entirepaper. For the literature review conducted

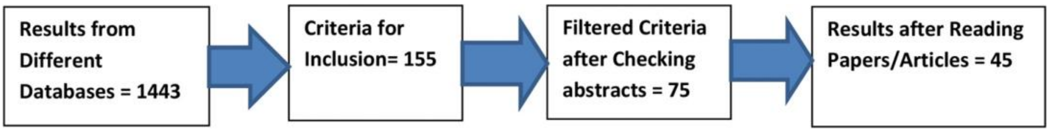

Figure 1. Literature review process used

For more technical topics such as recommendation engines, augmented reality and chatbots separate searches were done on Web of Science with different inclusion criteria. This will allow us to specify the different research gaps and questions emerging from this study (Tranfield & Denyer, 2003). Since the areas of Artificial intelligence and other technologies such as recommendation engines etc. are of highly technical nature we have confined ourselves in our searches to articles in the area of marketing, particularly to their impact on ecommerce and online apparel retail.

Customer Experience

The idea for today's customer is to create memorable experiences rather than physical products (Pine and Gilmore, 1998). Customers in the online world experience products not through physical interaction but with the help of verbal and visual stimuli on the website (Brakus, Schmitt, and Zarantonello 2009; Lemon and Verhoef 2016; Schmitt 1999; Verhoef et al. 2009). The entire customer journey over a period of time is an integral part of the customer experience. Bhandari et al. (2017) have reiterated that customers don't like to feel that they are being forced to buy the products that they do. Instead, they want the influence to be subtler, i.e. they want engagement and to be convinced to buy because the products offered are superior. Online customer experience consists of four dimensions: in formativeness (cognitive), entertainment (affective), social presence (social), and sensory appeal (sensory) (Anderson 1985; Pinker 1997). This has a great influence on e-satisfaction. Today, different artificial intelligence tools can help provide this "customer engagement". "Cyber Atmospherics" is the new term that has been coined which specifies the impact of virtual ambience of the website and its effect on online customer experience (OCE).

E-satisfaction

E-satisfaction, according to one definition is the customers' judgement of their online retail experience in comparison with the brick and mortar stores Szymanski and Hise (2000). A new construct called "customer information satisfaction" (CIS) was proposed for Web sites Wang et al. (2001) which describes the satisfaction with respect to the ecommerce site. As we know, *informativeness* is the primary cognitive dimension of the online customer experience (Lim and Ting 2012). This helps the customer to make the purchase decisions by going through the entire customer decision making process. Research suggests that e-satisfaction is the outcome of online shopping convenience, merchandising (product information and product offerings) and site design Azam, Qiang and Abdullah (2012). Customer satisfaction is a culmination of two factors: Firstly, it is the satisfaction that they experience with their most recent online purchase and secondly it is the cumulative satisfaction and online customer experience (OCE) garnered over a period of time with a specific website or e-retailer Chen and Dubinsky (2003). This is determined by the usefulness of the website. Usefulness can be defined as the extent to which online store provides helpful information to their customers and howit an ease their transactions (Chen & Ching, 2013). Over the last decade most of these features are powered increasingly by artificial intelligence technologies such as chatbots, products lists driven by AI powered recommendation lists and virtual try-on systems. Researchers have used the American Customer Satisfaction Index (ACSI) to measure the satisfaction of customers over a period of time (Chintagunta et al., 2012; Luo and Bhattacharya, 2006). Based on these instances or encounters, customers will compare their online and offline shopping experiences and make judgments about e-satisfaction (Cao

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and Li, 2015). According to Burke (2002), Ryding et.al (2016), customer satisfaction stems from convenience, product quality, value provided, and product selection providedin the e-store.

Customer Personalization

Researchers have tried to understand the customer experience all along the purchase process from awareness to evaluation of the product to the post-purchase phase. The experience at each stage of the purchase process is evaluated and an explicit feedback is provided. Personalized recommendations can increase customer satisfaction, and customer loyalty Rustagi (2012),Bauer et al. (2014); Yang et al., 2017; Jannach & Ludewig, 2017; Kaci, Patel & Pkacirince; 2014). Pricing also plays a key role in purchase decisions. Zhao et al. 2015 have researched this aspect of a customer's willingness to pay and personalized price promotions and their role in customer decisions. Machine learning algorithmsprovide personalization that simplifies the consumer decision making process and reduces customer effort (Ruchika et al., 2017; Seshadri et al., 2017). An algorithm called "Consumer Behaviour DNA", that uses pattern mining can help companies in identifying various types of customer behavior Takahashi (2019). Technology reviewed below allows e-commerce players to deliver personalization, superior product cataloging and product visualization to provide enhance customer experience and satisfaction in their e-stores.

Artificial Intelligence in Online (Eye Wear) Retailing

The Indian e-commerce and particularly the fashion e-retailing is booming. India is one of the countries where the growth rate on e-commerce is phenomenal mostly because of the increase in use of smartphones. The increase in number of online shoppers, particularly in the current situation of the pandemic is forcing a lot of e-retailers to focus on technology to increase sales. According to India Brand Equity Foundation data, the online apparel industry in India holds 29 percent of share which is second only to electronics which has a 45% market share. Hence marketers need to focus on technologies such as recommendation engines, Natural language processing, chatbots, Neural Networks, Genetic algorithms, and other AI tools to enhance customer experience and e-satisfaction. For example, Wang (2014) analyzes AI applications in the online apparel segment. Innovative technologies cause market disruption and this can be traced in history of new products. Thanks to AI, consumers can appreciate better products availability, faster and accurate deliveries (Kati 2018). Thispaper reviews such innovative technologies which are currently being used. AI does not only changethe way online retailing is conducted. It also has an effect on the way customers shop. Marketers haveto map out which tools to use to their advantage in order to optimize the customer experience as theybrowse the website. Johnson, Tara (2019) explains why Artificial Intelligence is an integral technology of the online apparel industry today. AI can help in improving the several service features such as tailoring fits with mix and match, 24 hours of customer assistance and personalization services withchatbots. This improves the efficiency, reduces returns and improves repeat purchases. Defined as the ability of a system to acquire and interpret data, learn, and then apply the new knowledge to achieve certain results or execute a task through adaptive behavior, AI includes many subdomains. Among them we can mention Machine Learning (ML), with supervised, unsupervised, and semi-supervised algorithms for training a software agent, and Deep Learning (DL), based on artificial neural network techniques that can perform complex learning tasks (Lee and Shin, 2020; Madurai Elavarasan and Pugazhendhi, 2020). Learning algorithms (artificial neural networks, Bayesian networks, genetic algorithms, nearest k neighbors, vector support machines, etc.) use advanced processing capabilities to make associations, classifications, groupings, and regressions, by analyzing large volumes of data. (Kartal, et al., 2016). Deep Neural Networks (DNNs) combine many machine learning tasks and leverage other advanced technologies, such as cloud computing, the Internet of Things, or big data, enabling general purpose machine learning algorithms (GPML) to manage various data (video, audio, text) and to improve the accuracy of product demand forecasting by analyzing customer behavior. Moreover, by capitalizing on GPML technologies and other digital platform features, small retail firms have managed to increase their visibility and expand their business globally (Meltzer, 2018).

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Cost-driven savings

Complementary to the other two business drivers, customer experience improvement and revenue increase, cost reduction should be carefully considered when assessing the impact of emerging technologies for retail companies. There are some generators for AI-driven cost savings: effectively reaching the target consumers (Grewal, Roggeveen and Nordfält, 2017), human workforce reduction (Holmqvist, Van Vaerenbergh and Gronroos, 2017; Inman and Nikolova, 2017; van Doorn, et al., 2017), and inventory optimization.

Reaching targeted consumers with lower costs. Timing is crucial in retail: delivering the right message for the right customer, at the right time, could determine a significant increase in sales. Applying big data technologies, such as predictive analytics, retailers are able to "estimate" the consumers' behavior and adjust their offerings accordingly. According to Bradlow et al. (2017), the five dimensions of big data for retail are time, customer, product, location (geo-spatial), and sales channel. Terabytes of new data (e.g., in case of Walmart or Amazon) are integrated with historical data about millions of customers and billions of *journeys* of sold products. AI-backed tools can process this ever-increasing volume of data with fewer technical requirements, incomparably less time and money than humans or pre-existing computer systems, while running without errors or interruption, consequently generating significant cost savings. *Human workforce reduction.* Sensors, mobile, and AI technologies provide new possibilities for cutting down on in-store staff accomplishing "algorithmic" task execution (Olsen and Tomlin, 2020). Smart shelves, encapsulating meshes of strain sensors, photodetectors, microphones, and spillage sensor, collect data on product status and send notifications to the store staff when product quantities on the shelves is below a predefined value; additionally, real-time inventory AI-based management enables grocery stores to apply multiple automated price updates for all products that expire on the current date (Quante, Meyr and Fleischmann, 2009; Inman and Nikolova, 2017). Hence, as smart shelves are self-managed, there is no need for the store staff to periodically check the stock of products on shelves, and then to summarize collected data and send it to the person in charge.

Inventory optimization. Minimizing the inventory costs – direct costs, represented by storage cost, and indirect costs, generated by lost sales – is one of the most critical optimization problems for the retail sector. The quantities of ordered products and the time of ordering for stock replenishment are highly sensitive decisions to make, as they have a direct impact on inventory costs and, consequently, on profit maximization (Miller and John,2010; Mousavi, et al., 2016). This is why inventory optimization emerges as a major use casefor AI implementation by retail companies; for example, machine learning algorithms for classification (Bayes classifiers, artificial neural networks, and support vector machines) canbe used to predict the ABC classification of inventory (where A is the class with the most, and C with the least frequently sold items), with high accuracy (Kartal, et al., 2016). Using machine learning algorithms, Priyadarshi, et al. (2019) also attained the best forecasting models of the weekly seasonality trend, with least possible errors. In practical terms,predictive analytics helps retailers determine the optimum daily amount of fresh products to be supplied, reduce the inventory of perishable food items, minimize the waste by optimally defining the appropriate amount of produce at required locations and intelligently synchronize downstream and upstream supply levels.

AI-enhanced revenue growth

Technological trends have led the rapid diffusion of AI applications across the retail field, with positive results for business revenues, profitability, and efficiency. In this section, we analyses the impact on revenue drivers of various retailing activities that integrate AItechnologies. Discussing the integration of AI and ML tools in the sales process specific to the ongoing fourth industrial revolution, Syam and Sharma (2018) labelled this retail reshaping as "salesrenaissance". They reported many use cases of AI and ML in *sales reinforcement*. Among them, a Harley-Davidson dealership in New York have attained 40 instead of 1 qualified lead per day and an increase of 2930% in its total number of qualified leads, through AI-based lead generation algorithms applied for three months. With the help of a ML solution that leverages dashboards containing pricing variables, qualified leads, IP addresses and other customers' data, sales representatives have determined, in real time, *the best price* for different segments

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of their customer base; also, in the post-order stage, a Gain sight system integrated sales features, customer service and questionnaire results, alerting sales teams when to invoice and *to suggest upsell and cross-sell products* etc. AI technologies may help retailers to *consolidate the sales strategy* by leveraging existing stores features (Feng and Fay, 2020). Prices optimization and sales maximization objectives have led to an increasing use of AI-enhanced big data technologies, detecting correlations between independent variables such as promoted price, display location, assortment expansions, and dependent variables like store sales and profitability, brand switching, etc. (Grewal, Roggeveen and Nordfält, 2017). It was demonstrated that survey-based indicators like purchase intentions or positive evaluations must be considered to *stimulate customers' engagement and increase revenues*. Kumar, Anand and Song (2017) cited by (Grewal, Roggeveen and Nordfält, 2017) also highlighted the strong relationship between analytics and retail profitability.

Recommendation Engines

Recommendation engines are machine learning algorithms that provide product recommendations for a specific customer based on their personalized history, so that it matches their needs accurately(Zhao, Pan & Yang, 2017; Yang, Ou & Zhou, 2017). Recommendation systems predict user preferences with the help of data mining algorithms and customer data from past purchases (Ruchika, Singh & Sharma, 2017). According to data analysts and researchers "Collaborative Filtering" is a popular recommendation technique used for product searches (Zhao, et al., 2017; Bauer & Nanopoulos, 2014).Collaborative filtering gives recommendations on products to customers based on their own past purchase behaviors. The intelligent part in this machine learning technique is that the recommender system is continuously learning and making the required changes based on the search results. Ahmedaet al. (2015) used machine learning and other mining techniques to study and understand customer buying behavior patterns and provide recommendations. Personalized recommendations are known to positively influence customer loyalty. 'Behavioral Analytics' can be a tool to understand the behavior of online customers (Even, 2019). He explained how machine learning algorithms are used to model customer's behavior before purchase. This will save company time and money and one should understand this process in order to improve personalization and overall customer experience. Ecommerce today, through technology, provides immense opportunity to retailers to access global markets, even if they are a small player.

Product Reviews

Products reviews are the singularly, the most important feature of online commerce, since this provides customers opportunity to access and read about the product features and compare them withcompetitors' products. They can do all this without stepping into a store, sitting in front of a laptop or using a smartphone (Wetzlinger, 2017). Good product reviews are a tool for customer engagement. Product variety is another area which can give an e-retailer competitive advantage. Chintagunta et al. (2012) and Luo and Bhattacharya (2006) argue that, the success of a retailer depends on their product variety. With respect to book reviews, research shows that, user contributed reviews have more credibility (Dimitrov, Zamal, Piper & Ruths (2015). Reviews are a way to elicit feedback, both explicit and implicit. Explicit ratings and reviews tell you the performance of products while implicitfeedback is received via the sales and search history of a product (Bauer et al., 2014; Ruchika et al.,2017). An online retailer today offers as much product variety or more than offline retailers. The wide variety adds to the enhanced e-satisfaction levels (Gounaris and Dimitriadis 2003; Szymanski and Hise, 2000). Also, the price comparisons that can be done online allow a customer buy a product atthe best possible price. This is very emotionally satisfying experience and can contribute enhancede-satisfaction (Klaus, 2013). "Digital Nudging" is the term used Djurica & Figl, 2017 to describe the technology used on websites which allow customers to make fast decisions.

Virtual Try-Ons

Another technology that is making a mark is Virtual Try-on's. This has received a lot of attention because it can be used to reduce merchandize returns. This technology uses 3D visualization and helps customers assess the size and styles better. With a virtual try on technology, the users get the in-store

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experience of being able to assess the fit, size and look of the product. There are many apps and fit-intelligence services available now in the fashion industry. These systems can help users to decide on their likes and dislikes of a product. Virtual experience as studied by Klien (1998) talks about product attributes which can easily accessed on the internet. Virtual try on system reduce the perceived risk by providing an experience which is close to the in-store experience of an actual trial. For example, how the shade of the lipstick looks on you when you view it on the internet versus trying it on virtually using this technology. This format of information presentation can alter the weightage consumers give to these different attributes. Virtual try-on technology has the ability to convert the search attributes of a product to experience attributes, reducing the risk of purchase (Klien 1998). In India, the try-on technology has been popularized by Lenkart eyewear brand. Lenskart allows its users to try glasses on using realistic 3D models of themselves just by clicking a selfie with their cameras (Teresa Simon, 2016). Other researchers have explored Artificial Intelligence technology in the fashion industry and believe that AI tools stimulate consumers to purchase online (Liang et.al, 2019)

Augmented Reality

Augmented reality is a market disruptive technology that has emerged out of artificial intelligence which is taking the online business by a storm. In augmented reality there is an integration of the real world and virtual information (Lamantia, 2009) wherein the elements of the live view of a real-world environment are augmented by computer-generated sensory input such as sound, video, graphics data. AR can provide meaningful experiences for online shoppers thus reducing the purchase risk (MacIntyre et al., 2001). The aim of AR is to provide tools which reduce the lack of touch and feel in online shopping and by providing sufficient product information that enables them to evaluate the available products (Lu and Smith, 2007). Research has shown that AR enabled products, enable customers to make product choices easily. AR technology includes head gear like googles and visual equipment for the eyes. The retinal display allows visualization of the product as though you are standing in front of it. Augmented Reality uses QR Code system (Quick Response Code) which has become very popular and can even be used on your smart phone. In QR code, information is encoded and it has a much larger capacity than a traditional UPC barcode. When the QR code is scanned using a code reader, it takes the customer directly to the product's location on the website and get more detailed information on the product. So a QR Code can also be used a promotional tool. Today, the camera on your smartphone can be used to scan QR codes for any product. In India today, a lot of payment applications use this QR code for payments of merchandise. Overall augmented reality can improve people's experiences and improve user confidence by enhancing the shopping experience (Lu and Smith, 2007). Today digital marketing campaigns using AR are becoming increasingly popular and enterprise applications with AR elements account for a large portion of e-retailer revenues.

Chatbots

With the increase in "conversations commerce", chatbots are becoming very popular for rendering customer service. Personal assistance no longer is dependent on physical people but has been takenover by dialog systems and virtual assistants like Alexa and Siri. Chatbots plays an important role in customer communication. Chung et.al (2018) studied the e-services of chatbots and how it influences customer satisfaction. A "chatbots" is a natural language processing (NLP) intelligent agent which can imitate a human conversation (Bala et al., 2017). It uses AI techniques to communicate through software such as instant messaging, websites or mobile apps. Lommatzsch (2018) has shown that chatbots can answer specific questions related to specific scenarios. This is based on previous behaviour of the customer. They guide the customer to ask the right questions and lead them like a human customer service representative in a polite and patience manner. Marwade et al. (2017) say that chat bots provide conversation to the customer which enhances customer experience. Research shows that chatbots are supposed to interact and provide solutions to problems based on the context and since they use machine learning and deep learning algorithms, they are continuously learning. However, the news is not all positive with chatbots. Consumers report a feeling of frustration with chatbots because they cannot understand or misinterpret the questions and hence give incorrect answers and some repeat the same

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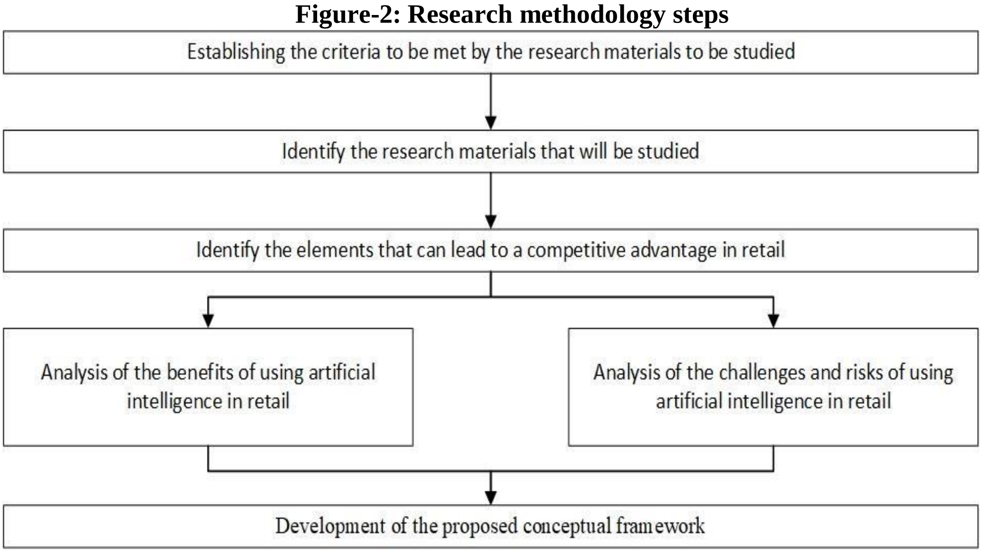
answers in a loop. Johnson & Shumanov (2021) have explored the possibility of a matching customer (human) personality with the corresponding machine personalityusing language, so the future may hold more humane and empathetic bots. Speed up the information search process by asking the right questions. They provide personalized interaction and communication using past behavior and can be used as a feedbackmechanism to gauge customer satisfaction. They provide real time information and responses when communicating with the customer. Reinartz, Weignand & Imschloss(2019) have come up with new sources of value creation in this digital age. These sources include a combination of automation and personalization while giving thecustomers enough control. This paper analyses some of the AI applications and their impact of customer experience in online retail. It can be a framework for future researchers to conduct empirical research.

OBJECTIVES & METHODOLOGY

The aim of this study is to identify practical benefits and associated risks generated by the implementation of artificial intelligence (AI) in retail and capitalize on the results by developing a conceptual framework for integrating AI technologies with the information systems of retail companies. In the first step, the eligibility conditions of the sources to be studied were defined. The inclusion criteria set were represented by the year of publication of the research materials (after 2010), the language of publication (English or French) and the field: artificial intelligence or retail. Another criterion was represented by the international databases were the selected papers were indexed: Web of Science, Scopus, Scientific Information Database or Econ Lit. Also, to capture the concrete results of the implementation of AI solutions in retail, the research area included case studies and reports published by representative actors in this field. Each of the authors independently analyzed the identified sources to establish their eligibility as credible and relevant references.

After selecting the research materials, they were studied to identify a set of elements that could generate a competitive advantage for retail organizations. The benefits and challenges of projects for the integration of artificial intelligence in retail have been analyzed from the perspective of this set of elements, considered as pillars of the proposed conceptual framework. A flowchart of the steps of the research methodology is depicted in Figure-2.

Figure-2: Research methodology steps



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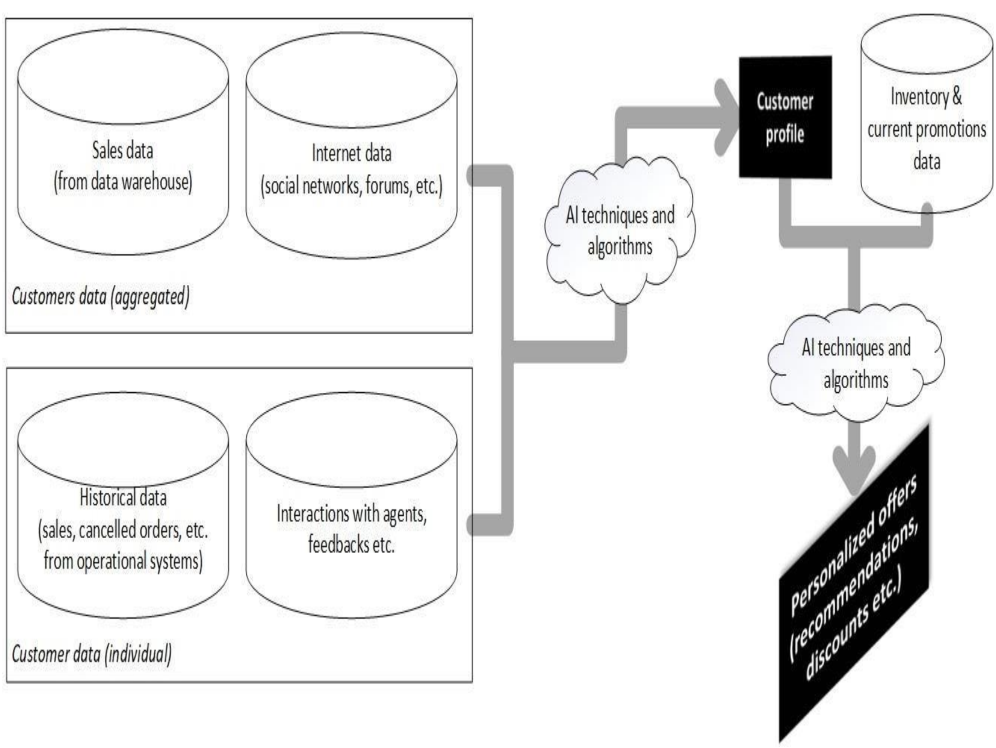
RESULTS AND DISCUSSIONS

The current section of the paper introduces a conceptual, customer profile-centered framework, which could be used by retail organizations, to integrate AI techniques and algorithms with their information systems. The goal of this approach to AI adoption consists in generating highly and accurately personalized offers for each customer. On a primary level, the analysis of the advantages enabled by this conceptual framework must take into account the same business drivers that were used to investigate AI benefits and risks specific to the retail sector: improved customer experience (CE), cost reduction (Co), and increase insales and revenues (R). The main components of the CECoR framework are described below.

General AI integration architecture. The main structural and functional aspects of this integration architecture that should be managed by the AI implementation team of the retailerare briefly described in the paragraphs below, starting with the key subsystems. Aggregated customer data subsystem manages sales data and internet data. The sales data issupplied by a data warehouse collecting and organizing data on analysis dimensions which are typical for retail (e.g. time, customer, product, and location). The internet data isaggregated from external sources such as social networks and public forums, using web mining technologies, or it is acquired from various providers; this data must be further integrated with internet data coming from the organization's own forum. Individual customer data subsystem manages historical detailed transactional data on each customer (completed sales, cancelled orders, updated orders, etc.). This subsystem also integrates "intelligently" gathered and rapidly processed customer data, resulting frominteractions with agents (chatbots, virtual assistants, digital assistants, conversational agents)or from feedback and forum opinions. The third subsystem of the CECoR integration architecture manages inventory data and information on current promotions for the products on sale. Figure-3 offers a schematic representation of a high-level architecture supporting the AIintegration framework.

Figure-3: CECoR framework: high-level AI-based integration architecture



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AI-enabled customer profile management. The processing logic of the integration architecture introduced here relies on the customer profile construct, with the following specializations: generic customer profile, individual customer profile, and contextual customer profile. This section elaborates on the rationale of this profile typology and its rolein an AI-enabled retail information system.
Generic customer profiles. Despite the aspects that individualize each client, there are certain transactional and behavioral patterns that, when identified and combined with different descriptive elements (gender, age, location, etc.), allow segmentation of company's customers into relatively homogeneous groups. Each of the resulting clusters corresponds to a generic profile that covers the defining elements for a subset of customers, allowing a uniform treatment of interactions with them.
Individual customer profiles. While generic profiles abstract common features of a certain cluster of a company's customers, individual profiles are the result of the reverse process, allowing a generic profile to be adapted to each customer's particularities. Individual profiles define preferences and buying patterns that cannot be adequately managed in general terms,so they are directed at distinct treatment of interactions with customers sharing the same generic profile. Therefore, an individual profile is obtained by refining and extending the transactional and behavioral attributes of a generic profile, with elements determined by each customer's identity and transactions.
Contextual customer profiles. They represent particular views on individual profiles, conveying the perception of a specific customer relative to certain elements that the company is planningto use in order to influence the current operational context. For example, contextual profiles could be used to identify the customers most likely to be interested in a new product to be offered for sale, or the customers interested in out of stock or understocked products, to be presented with alternative options. The resulting profiles are temporary, as their relevance is limited to a particular business context, with a specific time frame (e.g. a certain inventory situation, new product launches, social media campaigns for brand support, etc.).
Figure-4 shows the AI-enabled sequence of profiles as a gradual transition from generic to particular in relation to a company's customers, i.e. the derivation of fine-grained profiles out of coarse-grained profiles. The key functions of an AI-enabled customer profile management include: (1) automatic update or reconfiguration of generic and individual profiles, enabled by a continuous flow of new data from internal and external sources; (2) generation of contextual profiles well adapted to situations that justify their use (for example,better configured and targeted promotional campaigns).

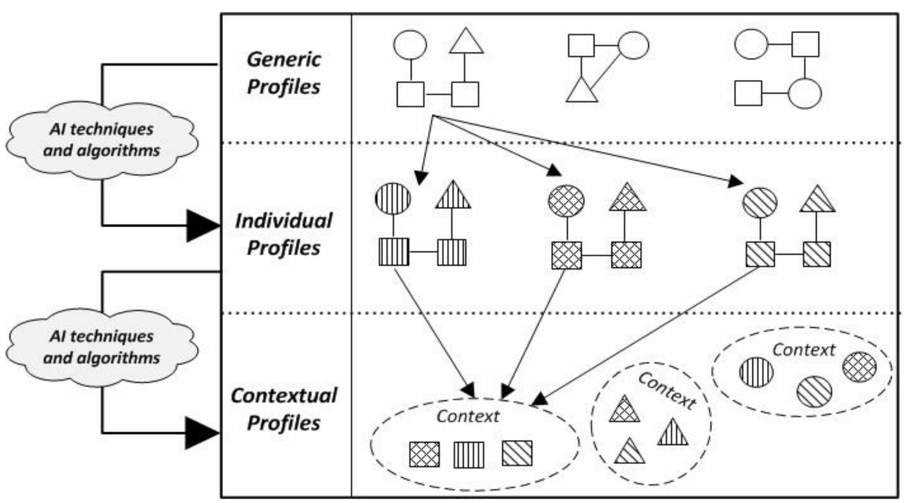

Figure-4: Customer profile layers

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Main expected AI integration outcomes, by stages and CECoR business drivers. The integration logic involving the subsystems described above and the corresponding data flows could be represented as a three-step process. In the first step, AI learning algorithms are used on sales data, adjusted with internet data, to produce generic customer profiles. Subsequently, individual customer data is used to fine tune the profile of a specific person. Once available, the individual profile of a customer is used by the offers' subsystem to matchit with data on inventory and current promotions; in this final phase, AI techniques and algorithms are used, once more, to generate contextual *customer profiles* and corresponding *personalized offers* (e.g., product recommendations, discounts, etc.) for each customer.

The business case for the AI integration solution using a layered approach to customer profile derives from positive effects that could be easily mapped to the same business drivers that were used to investigate AI impact on the retail: improved customer experience – each customer feels important and valued, as offers are tailored specifically for his/her needs and tastes, which are being continuously monitored thanks to dynamically generated customer data; increased sales revenues – this is a direct consequence of personalized product offeringsand enhanced customer experience; reduced costs – offers rely on real-time inventory data, which supports cost reduction for both expired products and lost sales.

Practical and technical issues. The proposed CECoR AI integration model introducedby this paper is a highly generic solution that could be used in multiple business contexts. Naturally, this means that the architecture described here must be further developed to accommodate the information systems currently in use and the IA technologies of a specific retail company. For example, in case of traditional physical stores, the customer needs to "register" using the phone when he enters the store; alternatively, he could be automatically registered by the system, provided that face recognition technology is available in the store. Moreover, the system must be able to "associate" distinct customers: when a couple goes shopping, it is necessary that the persons in question are treated as a single customer entity, with specific characteristics.

Implementation of AI-enriched solutions and the adoption of the CECoR integration framework presented here and pose multiple technical challenges, as this involves a technology mix which is not easily accessible to all retail companies: cloud computing, big data, deep learning, machine learning, neuro-linguistic programming, etc. However, continuous progress in AI research and development, as well as already proven business benefits of AI adoption are likely to pave the way for more affordable AI technologies in theyears to come, with significant impact in all industries, including retail.

A brief review of risks. As AI implementations have implications that move beyond thetechnical realm of learning algorithms and big data processing, the CECoR conceptual framework also involves consistent risk management. This requires a top-down view on the AI context specific to each retailer in order to decide on key principles relative to IT, but alsoto business and ethical issues, e.g. what is acceptable or not in terms of use of learning algorithms for customer profiling, customer privacy, etc. In fact, all ethical concerns that were reviewed in section 1.2 are of immediate interest for any retail system using AI-driven customer profiling. As companies collect, track and analyse so much about their customers, they also have the means to use the profiles to exploit customers' likes and dislikes and to manipulate their buying decisions to the extreme extents allowed by formal regulation. Though apparently justifiable from a business perspective, such practices pose a significant reputational risk that could jeopardize the very business benefits promised by AI technologies. In fact, the key business drivers of AI integration investigated by this paper – improved customer experience, increased sales revenues, cost reduction – could also be perceived as indicators of effective (or ineffective) AI risk management.

FUTURE RESEARCH

Not only is it important for businesses to use the latest AI technologies but they should enhance their technological tools periodically to keep up with their competitors. Also, it is advised that online retailers should communicate with their customers regularly about their shopping experience on the website and offer high quality after-sales service (Yen and Lu, 2008). This literature review brings out some of the artificial intelligence technologies and the research gaps which exist in the impact of these

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technologies on online customer experience (OCE). Some of the research questions which emerge from this review are: RQ1: What are the factors which influence customers to adapt to technology in the online space? RQ2: Which AI techniques have most impact on customer personalization and customer experience?

CONCLUSION

Not only should companies apply advanced AI technologies in their business but they should understand their relevance and whether they are sustainable in the long run. They have to assess the impact of a specific tool in relation to their business and then choose the right technology to provide a cost effective solution to their customers. These technologies are sources of value creation and future research can be conducted to understand how the customer experience is influenced by technology adoption. In conclusion below a summary of the value creation of these technologies: **Recommender Systems:** Simplifies decision making and reduces information overload. They also integrate the product reviews and collate the behavior of other consumers. They use past purchase behavior to provide personalization and display content which the consumer might like to view. **Augmented Reality, Interactive Image and Virtual Try-On's:** They provide a means of product assessment and provide a product presence in the online world which reduces perceived risk.

While the fourth industrial revolution is in full swing, the huge wave of technological changes is pushing companies to adapt quickly to remain competitive. The current research contributes to the support of retail organizations nowadays when artificial intelligence seems to become a pervasive and slowly inserted enhancement in almost every commercial activity. The authors took a cross-disciplinary approach, bringing into the research field a triadic contribution. Firstly, in order to help retail specialists looking to adopt AI in their organizations have real insights, an analysis of AI benefits identified in current practice was performed, structured on the business drivers provided by Hetu (2020): customer experience (CE) enhancement, cost (Co) decrease and revenue (R) growth. Among other findings, we have observed that there are many AI emerging tools with positive influences on not only one, but two or even all three CECoR drivers. For example, the query-based AI systems, like Macy's On Call, Alexa on Amazon's Echo, Cortana on Microsoft, or Siri on the Apple phone, in both online and physical stores, answer customers' questions about specific goods, provide suggestions on possible combination with complementary products, or offer directions about where to find the goods within a store (Grewal, Roggeveen and Nordfält, 2017), Thus, the business impact of those AI systems is significant, manifesting itself simultaneously on all three CECoR levels: customer experience improvement, sales volume increase and to labor costs cut. On smart shelves with integrated digital tags, it was noted it can perform remote price updates almost instantly (Inman and Nikolova, 2017), not needing human intervention; as a result, both staff and stock keeping costs savings and increased customer satisfaction are possible.

Secondly, in relation to the CECoR pillars, the risks that practitioners associate with the AI implementation in retail were revealed. Based on the performed analysis, it can be stated that the positive impact of AI implementation depends on an efficient management of risks associated with this type of technologies. Particular attention should be paid to ethical issues, such as the possibility of manipulating customers through AI. The abusive exploitation of data can cause contrary effects to those initially expected, at the time of implementation of AI solutions for capturing and processing this data. For example, one of the risks that can cause major negative effects is reputational risk, especially important in the context of the specific way the CECoR framework approached customer profiles definition.

The third contribution of the paper is the CECoR conceptual framework, designed to enable implementation teams to align AI initiatives with business priorities aiming at fully leveraging these improvement opportunities and obtaining a meaningful impact and significant competitive advantages for their companies. The elaborated framework was substantiated by capitalizing on the CECoR cognitive acquis, its application having two important purposes: refining customer profiles and

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optimizing the personalization of offers. This dichotomous vision – CECoR oriented and customer profiles-focused – differentiates this article from previous studies in the same area of research. Though it could be seen a research limitation, confining the set of analyzed resources by using methodological criteria to filter scientifically validated and recent papers makes this study relevant and up-to-date, while guiding the research efforts towards the conceptual framework introduced here. The pragmatic analysis of the digital change generated by AI in retail and the elaborated conceptual framework can be documentary resources for futures studies on possible sustainable implementations of AI in retail. Further developments in this research could also aim at deepening and expanding the application scenarios of the CECoR framework, as wellas analyzing trends in the maturation of artificial intelligence technologies and the effects onretail and other areas of activity.

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