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Review

Artificial Intelligence in Business-to-Customer Fashion Retail: A Literature Review

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Abstract: Many industries, including healthcare, banking, the auto industry, education, and retail, have already undergone significant changes because of artificial intelligence (AI). Business-to-Customer (B2C) e-commerce has considerably increased the use of AI in recent years. The purpose of this research is to examine the significance and impact of AI in the realm of fashion e-commerce. To that end, a systematic review of the literature is carried out, in which data from the Web Of Science and Scopus databases were used to analyze 219 publications on the subject. The articles were first categorized using AI techniques. In the realm of fashion e-commerce, they were divided into two categories. These categorizations allowed for the identification of research gaps in the use of AI. These gaps offer potential and possibilities for further research.

Keywords: AI; fashion; business-to-customer; retail

MSC: 68T07; 68T01

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1. Introduction

E-commerce has grown significantly in recent years, both in terms of the number of users and the number of commercial websites. eMarketer [1] estimated that the growth of e-commerce sales in 2020 over the previous year would be 27.6%, for a total of USD 4.28 trillion. Statista [2] projected that e-retail sales would increase to USD 5.4 trillion by 2022. Despite the fact that the past few years have been difficult for retail, the COVID-19 pandemic is significantly affecting e-commerce due in major part to a shift in consumer behavior [3]. Merchants of non-essential items, such as clothing and footwear, are experiencing a decline in sales, while retailers of vital goods, such as food, consumables, and healthcare, have seen an increase in online shopping [4]. The COVID-19 pandemic has fundamentally altered international trends and compelled quick reforms in several industries. Despite the challenges the industry is facing, Statista [5] reports that the fashion industry is the largest Business-to-Customer (B2C) e-commerce market segment. By the end of 2025, the industry is projected to have a total market value of USD 1003.5 billion.

Artificial intelligence (AI) has altered numerous industries over the past few decades, including healthcare [6,7], manufacturing [8,9], transportation [10,11] and retail [12,13], The application of AI is also on the rise in e-commerce strategies [14–17]. Many merchants are already utilizing artificial intelligence (AI) technologies as a driving force for the development of e-commerce in a competitive environment where consumers are becoming more demanding. As an example, consider how e-commerce behemoths like Amazon, Alibaba, and eBay invest in research and development to integrate visual recognition techniques, develop algorithms to meet user content preferences, or adjust pricing based on in-the-moment comparisons of rival products. E-commerce makes more information available to both consumers and rival businesses. E-commerce retailers are compelled to take on new AI techniques due to fierce online market rivalry.

Within this context, the goals of this investigation can be listed as follows: First, to analyze the current trend of AI in the fashion e-commerce sector and the future of AI technology. Second, to understand how the sector's use of AI technology enhances firm profitability. Third, to identify knowledge gaps that might be investigated by future scholars. In order to accomplish these objectives, the following research approach is presented.

2. Research Approach

The research questions (RQs) plus the methodology to respond to them and, consequently, deal correctly with the previously detailed objectives are presented herein.

The following research issues are addressed in this study:

- RQ1: What are the uses of AI technology in the e-commerce world of fashion?
- RQ2: How can the fashion sector use AI to its fullest potential in order to increase customer satisfaction and financial success?
- RQ3: What are the hot topics and upcoming research directions in the field of AI for the e-commerce industry of fashion?

A narrative literature review (NLR) method was employed in this research as, compared to others such as the ones mentioned in Ref. [18], the (a) systematic, (b) scoping, (c) argumentative, (d) integrative, or (e) theoretical literature reviews, the NLR is better oriented to identify gaps in the existing knowledge base [19]. The narrative literature review methodology employed in this evaluation follows the suggestions of Green, Johnson, and Adams [20] and Ferrari [21] for the narrative overview variant. These narrative overviews are recognized as great, up-to-date papers [21]. Several research studies in the literature reviews of information systems, technological applications, and management science have effectively used this methodology [22,23], and that is the reason this methodology has been chosen. Thus, the main steps of a narrative document review approach are as follows:

1. Determine the research questions;
2. Develop inclusion and exclusion criteria;
3. Conduct a thorough search of relevant databases and other sources;
4. Review and select studies based on inclusion and exclusion criteria;
5. Extract data from selected studies, and analyze and synthesize data extracted from studies.

It is important to note that the methodology may vary slightly depending on the specific research question or topic and the type of research being conducted. In our case, we have incorporated a sixth step, which is:

6. Validation of results.

Thus, this manuscript's contribution is an analysis of the current trend of AI in the fashion e-commerce sector, the future of AI technology, and how the sector's use of AI technology enhances firm profitability, by applying an NLR process to identify and analyze research literature in the field of AI for the e-commerce industry of fashion. The NLR method is commonly used in research studies to provide an unbiased, comprehensive, and rigorous analysis of the existing literature. For that reason, the authors have not discussed the pros and cons of each of the techniques, in order to reduce the possibility of biasing the study, as the reasons for using one or another technique can be extremely varied.

Based on the research initiative that uses the NLR as a core, Figure 1 explains the flow this work has followed to respond to the three RQs.

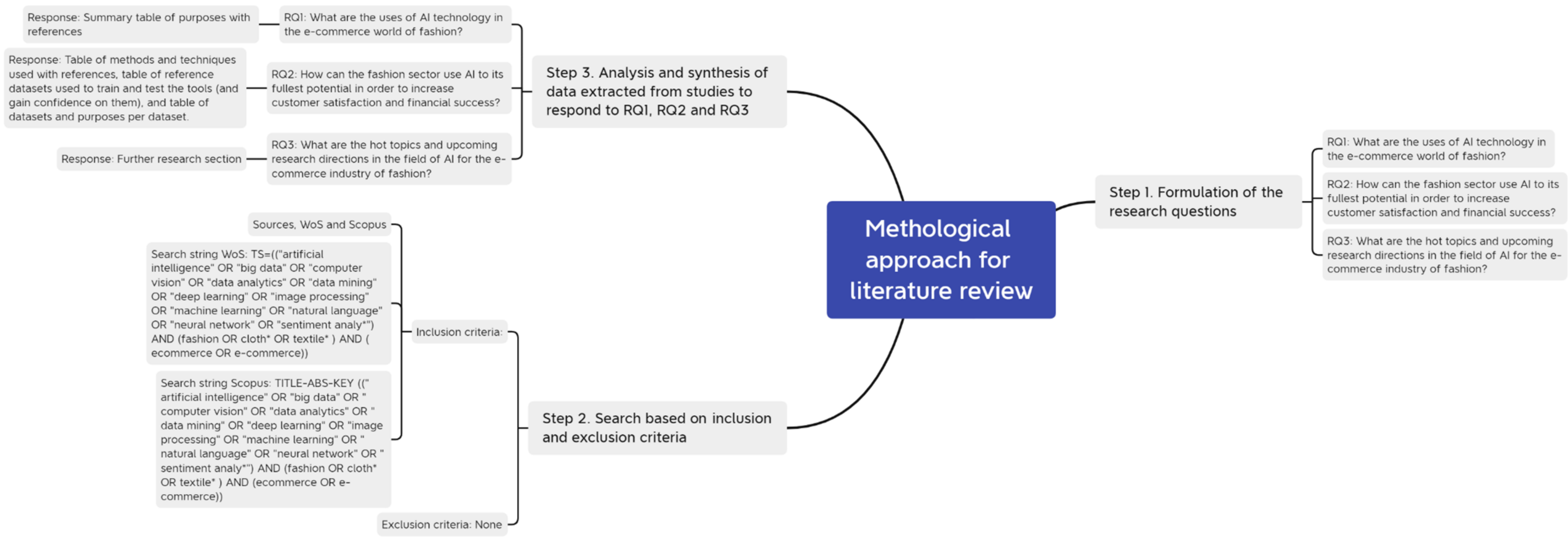

Figure 1. Review methodology. The character * denotes a wildcard.

As indicated in Figure 1, this research starts from the formulation of the three research questions shown at the beginning of Section 2. Afterwards, it defines the scope (inclusion and exclusion criteria concerning sources and keywords) and performs the search based on it. Lastly, as a third step, analysis and synthesis of data extracted from studies to respond to RQ1, RQ2, and RQ3 are performed, resulting in responses to each of the questions as follows:

- RQ1: What are the uses of AI technology in the e-commerce world of fashion? Response: Summary table of purposes with references.
- RQ2: How can the fashion sector use AI to its fullest potential in order to increase customer satisfaction and financial success? Response: Table of methods and techniques used with references, table of reference datasets used to train and test the tools (and gain confidence on them), and table of datasets and purposes per dataset.
- RQ3: What are the hot topics and upcoming research directions in the field of AI for the e-commerce industry of fashion? Response: Further research section.

Thus, the rest of the paper is structured as follows. The criteria for inclusion and exclusion of items are described in Section 3. Section 4 discusses the uses of the techniques in the scope of the article. Section 5 addresses the second research question and describes the AI approaches used to increase consumer satisfaction along with the main fashion databases used in the articles included in the review. The third research question and the validation of the results are addressed in Sections 6–8, looking at forecasting future trends, as they present the research gaps that have been found.

Analysis and synthesis of data extracted from studies to respond to RQ1, RQ2, and RQ3 are as follows:

- RQ1: What are the uses of AI technology in the e-commerce world of fashion? Response: Summary table of purposes with references (Section 3).
- RQ2: How can the fashion sector use AI to its fullest potential in order to increase customer satisfaction and financial success? Response: Table of methods and techniques used with references, table of reference datasets used to train and test the tools (and gain confidence about them), and table of datasets and purposes per dataset (Section 4).
- RQ3: What are the hot topics and upcoming research directions in the field of AI for the e-commerce industry of fashion? Response: Hot topics and conclusions sections (Sections 5 and 6, respectively).

3. Article Inclusion and Exclusion Criteria and Overall Results

Article selection was made using scientific databases, specifically Web of Science and Scopus, two of the most important repositories for publications. To examine all relevant studies in the field and complete RQ1's aim, no time restrictions were imposed during the search procedure. The search terms include 60 fashion e-commerce synonyms as well as AI synonyms. The final search terms utilized for the investigation are shown in Table 1.

Table 1. Final query implemented for filtering the repositories for publications. The * is used as a wildcard character.

Scientific Database	Search String
Web of Science	TS=(((“artificial intelligence” OR “big data” OR “computer vision” OR “data analytics” OR “data mining” OR “deep learning” OR “image processing” OR “machine learning” OR “natural language” OR “neural network” OR “sentiment analy*”) AND (fashion OR cloth* OR textile*) AND (ecommerce OR e-commerce)))
Scopus	TITLE-ABS-KEY ((“artificial intelligence” OR “big data” OR “computer vision” OR “data analytics” OR “data mining” OR “deep learning” OR “image processing” OR “machine learning” OR “natural language” OR “neural network” OR “sentiment analy*”) AND (fashion OR cloth* OR textile*) AND (ecommerce OR e-commerce))

A total of 392 references were discovered using these search terms, including 108 duplicates between the two sources; 124 were in Web of Science and 268 in Scopus.

Ultimately, 252 references were examined. Due to the ambiguity of the word fashion and the lack of association with the issue under study, 65 articles were discarded after reading them. Many of these articles refer to fashion trends in the context of AI used in e-commerce rather than specifically in the fashion business. For the literature review, 245 research articles were read. The distribution of documents over the years is shown in Figure 2, and it has been observed that the number of papers published in the previous three years has significantly increased.

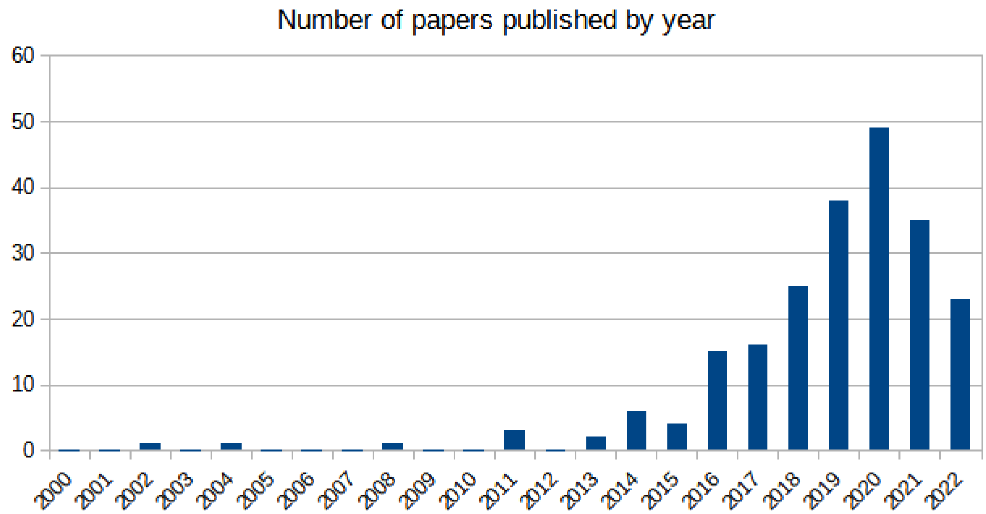

Figure 2. Number of papers published by year.

4. RQ1: Uses of AI Technology in the e-Commerce World of Fashion

The information extraction process used to answer research questions RQ1, RQ2, and RQ3 is detailed in this section. Based on Ref. [24], this study divides artificial intelligence (AI) into three major categories: computer vision (CV), natural language processing (NLP), and other machine learning (ML) applications. The reasoning behind this division is that, when dealing with garment data, most authors process the images of the garments, their text description, or other data, with the first two being the more prevalent ones. This process has been carried out by taking into account recent research on AI in fashion e-commerce. Figure 3 shows the classification of the number of manuscripts by topic and subtopic in accordance with the study objectives. In the same figure, the number of articles linked to each topic is displayed in brackets.

It is important to note that certain research publications are featured in more than one classification section because they either use a variety of AI methodologies or provide answers to many research questions.

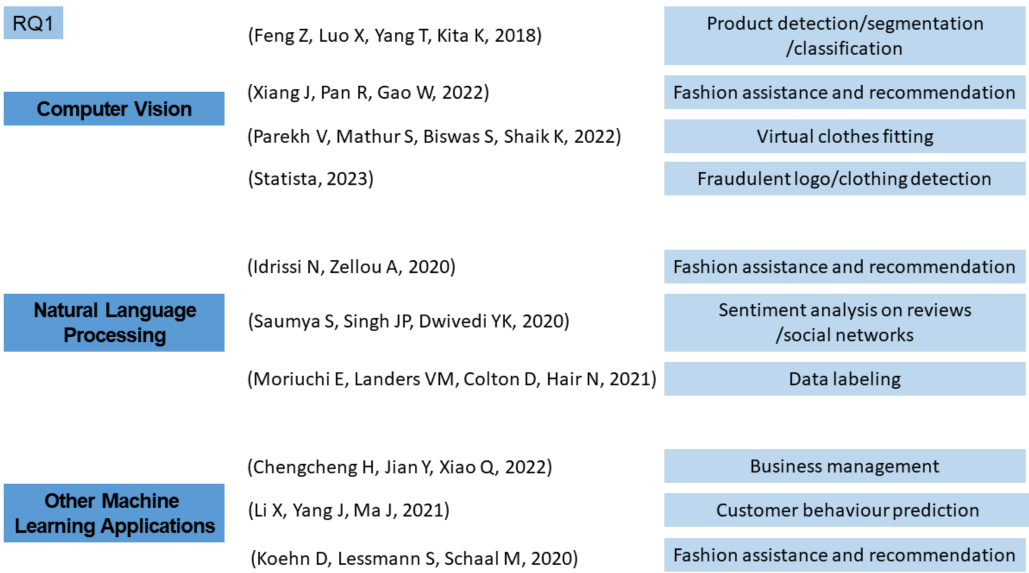

Figure 3. Number of articles per topic and subtopic found in the literature review.

5. RQ2: How the Fashion Sector Can Use AI to Its Fullest Potential in Order to Increase Customer Satisfaction and Financial Success

In order to correctly apply the potential of AI to the B2C fashion retail sector, it is necessary to identify both where it can be utilized and how it can be applied. The wideness of the 'how' term involves approaching the question from different angles.

If the articles read are approached in a more specific manner, additional sorting information regarding the databases used by the studied articles can be offered, as well as the techniques they apply and the specific purpose they have. Thus, these sections respond to how the sector can use AI, identifying:

- Most of the common algorithms used in the sector (Section 5.1);
- The purposes pursued when using each of the datasets (Section 5.2);
- The databases used to train and test the algorithms used (Section 5.3); and
- Actual examples of the way AI can be applied to customer satisfaction and lucrativeness (Section 5.4).

We respond to the four bullets in the list with several tables and figures. These tables and or figures show the amount of times each database, technique, purpose, etc., appears in the literature review. In all cases, the specific purposes, techniques, or databases appearing just once have been merged onto a single 'Others' group, to make feasible a clean and clear visualization of the charts (see e.g., Table 2).

Table 2. Databases used.

Database	Frequency
Retailshop	41
Collected	37
CollectedfromtheInternet	31
DeepFashion	21
Collectedfromreviewsofretailshops	19
Collectedfromsocialmedia	10
Fashion-MNIST	10
Collectedfromscanner	4
ImageNet	4

Table 2. *Cont.*

Database	Frequency
Polyvore	4
Virtualfitting	4
Amazon	3
Kaggle	3
MPV	3
VITON	3
Amazon5-core	2
AmazonDresses	2
DeepFashion3D	2
LookBook	2
Taobao	2
CzechRetailshop	2
Others	30

5.1. Families of Algorithms Used in the B2C Fashion Retail Sector

As can be seen in Table 3, a plethora of AI techniques are used to process garment information for classification. They have been grouped by traditional machine learning techniques and deep learning techniques. Multiple authors use different techniques to solve the problems efficiently, with all of them being suitable in the right situation. In the following subsections, some of the AI algorithms used in the articles in this review are described (Table 4).

Table 3. Techniques applied.

Technique/Method	Frequency
CNN	59
BigData	18
DCNN	16
ML	14
NN	12
Survey	11
GAN	9
DL	8
Imageprocessing	7
kNN	7
randomforest	7
Review	6
DNN	5
LSTM	5
NaiveBayes	5
Siamesenetwork	5
Decisiontree	4
k-means	4
LAC	4
SVM	4
Word2vec	4
Collaborativefiltering	3
CorrelationalNN	3
Fuzzylogic	3
GraphCNN	3
BERT	2
Classificationalgorithms	2
CNNLSTM	2
DART	2
GaussianMixtureModels	2
H-CNN	2
Kneser–Ney	2
LR	2
RBFSVM	2
Regressionmodels	2
SSD	2
Others	56

Table 4. Specific purpose.

Technique/Method	Frequency
CNN	59
BigData	18
DCNN	16
ML	14
NN	12
Survey	11
GAN	9
DL	8
Imageprocessing	7
kNN	7
randomforest	7
Review	6
DNN	5
LSTM	5
NaiveBayes	5
Siamesenetwork	5
Decisiontree	4
k-means	4
LAC	4
SVM	4
Word2vec	4
Collaborativefiltering	3
CorrelationalNN	3
Fuzzylogic	3
GraphCNN	3
BERT	2
Classificationalgorithms	2
CNNLSTM	2
DART	2
GaussianMixtureModels	2
H-CNN	2
Kneser–Ney	2
LR	2
RBFSVM	2
Regressionmodels	2
SSD	2
Others	56

5.1.1. Traditional Machine Learning Techniques

Several traditional (not deep learning) algorithms have been applied to this task. One of the simplest sorting algorithms used in machine learning is the KNN algorithm. This classification approach uses space analysis to analyze the k-nearest neighbors [25]. Two other commonly used algorithms for fashion article classification are decision trees and random forests [26]. The naive Bayes utilizes a series of simplification operations based on the Bayes theorem and is based on the theory's streamlining processes. The notion is that the classifier may be used to categorize the number of independent variables if there are too many of them. It is useless to apply probability tables when the number of independent variables is too big, which leads to the reductions that simplify the sample and give it the moniker "naive Bayes" [27]. A hyperplane that separates an n-dimensional representation of the data into two distinct areas serves as the foundation for support vector machines (SVM) classifiers. The area between two classes, also known as spatial regions, that maximizes the margin m between them is referred to as the hyperplane. This margin is computed from the distance of the specimens that are closest to the hyperplane and is defined as the longest distance between the specimens of the classes [28]. K-means is a vector quantization technique that was first used in signal processing to divide n observations into k clusters, with each observation belonging to the cluster that has the closest mean (also known as the cluster centroid or cluster center), which serves as a prototype for the cluster [29]. Recommender systems employ a method called collaborative filtering. By gathering preferences or taste data from several users, collaborative filtering is a technique for automatically predicting (filtering) a user's interests (collaborating) [30].

A probabilistic model called a Gaussian mixing model posits that all of the data points are produced by combining a limited number of Gaussian distributions with unknown parameters [31]. Finally, fuzzy logic is an approach to computing based on degrees of truth that imitates human reasoning rather than Boolean logic [32]. The DART algorithm is an iterative improvement on multiple additive regression trees (MART), which is more robust towards class imbalances [33]. The Kneser–Ney algorithm calculates the probability of a word following a particular context by computing the raw probability of the word following the context and subtracting a discounting amount [34]. Finally, DDS is a single-shot detector algorithm that predicts the boundary boxes and the classes directly from feature maps in one single pass [35].

5.1.2. Deep Learning Techniques

Deep learning, commonly referred to as deep structured learning, is one of several machine learning techniques built on representation learning and artificial neural networks. Unsupervised, semi-supervised, and supervised learning are all possible [36]. Multiple deep learning algorithms have been used for this task in the literature.

Convolutional neural networks (CNN, or ConvNet) are a form of artificial neural network (ANN) that is often used to assess visual pictures. CNNs, also known as shift-invariant or space-invariant artificial neural networks, are based on the shared-weight architecture of the convolution kernels or filters that slide along input features and create translation-equivariant outputs known as feature maps (SIANN). Contrary to common perception, most convolutional neural networks downsample the input, which prevents them from translating invariantly. They are used in financial time series, natural language processing, brain–computer interfaces, image and video analysis, segmentation, classification, recommender systems, medical image analysis, and image and video recognition [37]. Multiple neural network layers make a deep convolutional neural network (DCNN). Convolutional and pooling layers, two different kinds, are often alternated. From left to right in the network, each filter's depth rises. Usually, the final level consists of one or more completely linked layers [38]. Multiple variations of CNNs have been used, such as application of hierarchical classification, which takes advantage of the hierarchical structure of categories by embedding CNNs into a category hierarchy [39], or graph convolutional neural networks, which represent similarities using a graph architecture and perform CNN, multiplying the input neurons by a set of weights [40].

Long short-term memory (LSTM) networks have been also employed in this task [41], both as standalones or as a combination with CNNs. Convolutional neural network long short-term memory is an architecture that uses CNN layers for feature extraction and LSTM to support sequence prediction, usually used for images and video inputs [42].

The natural language processing (NLP) tool Word2vec was introduced in 2013. With the help of a huge text corpus, the Word2vec technique employs a neural network model to learn word connections. Once trained, a model like this may identify terms that are similar or propose new words to complete a phrase. As the name suggests, Word2vec uses a specific set of integers called a vector to represent each unique word. Given vectors that are properly selected to capture the semantic and syntactic characteristics of words, the degree of semantic similarity between the words represented by those vectors can be determined using a straightforward mathematical function (cosine similarity) [43]. Another NLP processing model commonly used is BERT, or bidirectional encoder representations from transformers. Its innovation is applying the bidirectional training of transformers to language modeling [44].

A Siamese neural network, also known as a twin neural network, is a type of artificial neural network that uses the same weights to calculate equivalent output vectors from two distinct input vectors simultaneously. A precomputed version of one of the output vectors frequently serves as a benchmark for comparison with the other output vector. Despite being more precisely referred to as a distance function for locality-sensitive hashing, this is comparable to comparing fingerprints [45].

5.2. AI in B2C Retail and Application Areas of the Techniques

RQ1 is centered on the general AI trend in the fashion e-commerce sector. Figure 3's summary of the literature review illustrates numerous subtopics employing various AI methods.

Numerous papers on computer vision (CV) focus on the early stage of exploitation and interpretation of the data offered by the photographs. These studies aim to enhance the annotation process's object identification, segmentation, and classification algorithms [34,35,39,40,46–120]. Another group of studies develops techniques for advising and helping customers by pairing products or examining the textures of garments [78–81,84,121–128]. Additionally, some authors [32,129–152] are developing virtual reality technology to help customers with clothing fitting. Finally, CV can be used to spot fake logos and clothes [153,154]. Several techniques, including image processing and deep learning using convolutional neural network designs, are employed for all of these applications.

In order to transition the traditional buying experience to e-commerce, NLP is mostly utilized for fashion advice and recommendations [34,78,79,124,126,155–168]. Another significant area of study focuses on gathering data from consumers using sentiment analysis techniques, such as via reviews or social media[42,44,169–180]. Finally, studies on picture tagging using textual content analysis have been conducted [55,61,73,89,94,95,98,104,107,113,116,118,181–184].

A number of publications concentrate on using ML and data analytics together to enhance the administration of e-commerce businesses. Some authors have researched subjects like budget management, inventory issues, and sales and demand forecasting [177,185–209]. Other authors [33,210–236] aim to forecast product return or purchase intention by predicting consumer behavior. Several studies investigate personalized recommendation systems using ML approaches in relation to consumer behavior [230,231,237–249].

5.2.1. Fashion e-Commerce and Research Problems

This section provides an overview of the key research issues that have been raised in studies that have analyzed and applied AI approaches. The goal of each task determines how it is divided.

Garment Representation

A considerable number of articles concentrate on how clothing is represented in fashion accessories. It is the earliest stage of information exploration and interpretation, with the goal of being accurate so that it may be used in particular applications. The majority of fashion studies begin with a precise detection task. Classification, landmark recognition, and item retrieval are the three sub-tasks that make up fashion detection.

Data labeling. The quality of the data used directly affects the accuracy levels of the AI models. When data are unlabeled, the process of adding tags to the data enables machine learning models to learn and recognize those things. Machine-based annotation is a revolutionary method of labeling that allows data annotation to be done more quickly without sacrificing quality [183].

Clothes classification. An image is used as the input for the image classification job, which then generates the classification label using metrics like probability or precision. The number of distinct tags from the labeled data determines how many classes the model can categorize. Some classifications are distinct in the fashion industry, based on the problem to be approached, such as classifying apparel by category (such as t-shirt or frock) and by attribute (such as white or round neck). The convolutional neural network (CNN) is the most frequently used algorithm for classifying clothing [58]. Deep convolutional neural networks (DCNNs) [63], also known as these networks' deep architectures, are used in a number of studies. Examples include VGG16 [57,62] and VGG19 [60].

Detection of landmarks. Fashion landmark identification anticipates where functional clothing keypoints like the neckline and cuff will be located. Because of the nature of the clothing, this is a more complicated challenge than pose estimation. A number of states, such as wrinkles or sags, can be found in clothing. In this review, two papers [35,66] that used DCNNs to improve this task are discussed.

Product retrieval. Finding comparable or identical objects in databases is the purpose of item retrieval tasks. The AI community has paid a lot of attention to fashion retrieval, mostly because it can be challenging to describe clothing in words and users typically find it simpler to search by image. The majority of research focuses on identifying identical or nearly identical clothing or even detecting plagiarism. The use of DCNN algorithms to resolve retrieval tasks has become popular due to deep learning advancements [54,86]. For this objective, generative adversarial networks (GAN) are also helpful [71,75]. In these networks, two neural networks compete to make predictions with greater accuracy. Finally, several studies employ support vector machines (SVMs) [64,87] during the classification phase of the item retrieval task.

Customer Satisfaction

There are two primary categories of customer-centered applications in this review. By using these programs, you can attempt to recreate the offline buying experience online.

Recommender systems. The goal of recommender systems is to provide users with useful suggestions. There are two main types of approaches for this task: content-based methods and collaborative filtering methods. Content-based approaches solely rely on past client information, such as purchases, browsing patterns, and search queries. The recommender system creates a model with the user's characteristics using these data and looks for profiles with attributes that are comparable to the user's. The interactions between users and objects constitute the foundation of collaborative approaches. These techniques do not need users to provide any information. Recommender systems connect users based on how they engage with the product.

There are additional recommender systems that are concerned with fashion and trends. These models typically use text and visual data to derive brand-new traits pertaining to style. The consumer is then given recommendations for related clothing, fashionable clothing, or clothing that goes well together.

The creation of fashion recommendation systems uses a range of AI models. To improve the prediction's accuracy, researchers also change the algorithms and tweak the parameters. One of the most popular models is CNN, which consists of many layers, with the number of layers being tailored to the results of the recommendation system [81,123,128,163]. Numerous studies using deep neural networks (DNN) for recommendation tasks have been conducted [84,159].

Virtual fitting systems. Virtual fitting solutions are bridging one of the biggest gaps between e-commerce and physical stores: the inability to try on clothing. The ability to take body measurements and determine clothing size and fit are the two key topics discussed. Studies that employ 2D photographs and the ones that use 3D reconstructions are two distinct sorts of research cases.

The fit of virtual clothing is frequently evaluated using neural networks [144], including CNN [140] and GAN variations [141]. The employment of alternative algorithms, such as the naive Bayes (NB) algorithm for classification [149], the Viola–Jones (VJ) algorithm for body tracking [148], or the fuzzy neural network (FNN) [32], has also been the subject of some research.

Customer Behavior Forecasting

Many clients and items can be managed by businesses thanks to AI, which also makes it simple for them to understand every aspect of each product's storage, distribution, and sale. Simple and real-time control and management are possible. Although many studies use historical data to build their forecasting models, social media is becoming a larger and more common source of information in recent years. Social media platforms provide insight into how consumers feel about things, making it possible to forecast future sales or alter products to better meet customer needs.

Sentiment analysis. An analysis of the mood on social media reveals how consumers feel online about a product or brand. It is an examination of feelings and opinions, not just a basic tally of mentions or comments. This kind of study enables businesses to understand their target market, spot trends, enhance customer experience, and spot crises in their earliest phases [174]. Many studies [42,169] use CNN for sentiment analysis, and occasionally [44] a final fine-tuning algorithm like BERT is constructed. The studies employ both SVM [172] and NB [179] for classifying opinions [179].

Business administration. The main focus of artificial intelligence in company management is on creating prediction models based on past data in order to improve management and uncover new customer-facing opportunities. Profit maximization, sales forecasting, shipping logistics, inventory management, and fraud detection are some of the key duties in this study problem. The majority of recent studies have an ML method focus [185–187,209].

Multimodal Systems

Combining various approaches is a very active topic of AI research. Since many of the works included in this review use a combination of CV and NLP techniques to achieve the goal, it was simple to see this effect [34,55,94,95,102,107,116,126,156,157]. When information from many modalities is included in a research problem, such as text–image, video–audio, or another combination, it is referred to as multimodal research. Compared to multimodal systems, a crossmodal system is a model that only receives data from a separate modality, such as when requesting an image response via text. A model produced by a multimodal system may have the same modality as the input or a different modality. In other words, multimodal systems can integrate several modalities together, such as text and visual. In particular, a crossmodal system, shown in Figure 4, is the process of using one modality to gain information in another modality.

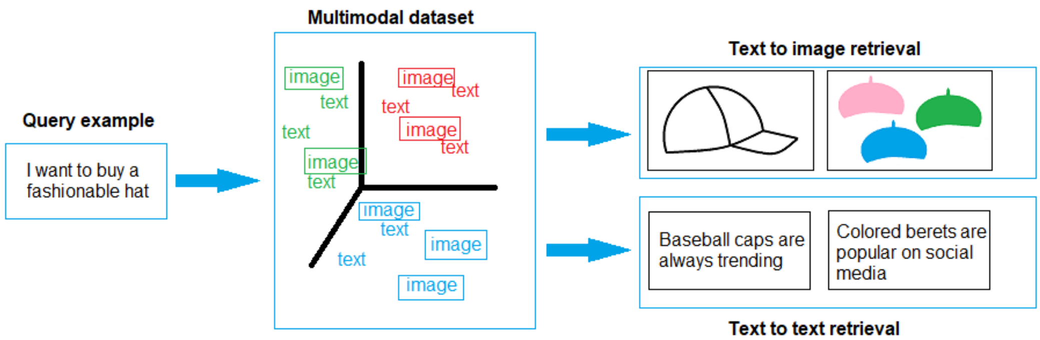

Figure 4. Example scheme of a multimodal and crossmodal system.

Twenty-two publications on multimodal systems for item retrieval, classification, and apparel recommendation have been found in this study. The percentage of completed work for the various jobs may be seen in Figure 5.

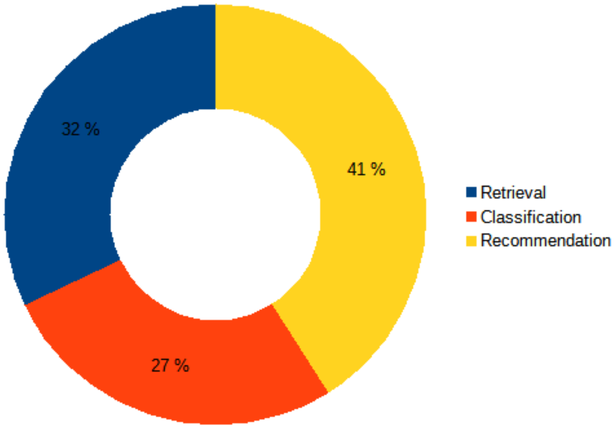

Figure 5. Fraction of multimodal manuscripts per task type.

5.2.2. Summary

The papers examined are summarized in this section. Tables 5–7 present the research's techniques, objectives, and dataset.

Table 5. Summary of methods with references.

Methods	Citations
ALS	[235]
associationrules	[247]
AttentionCNN	[163]
AttentionDeepLearning	[161]
Bayesiannetworks	[227]
BEAM	[167]
BERT	[44,78]
BigData	[177,189,192–194,198–200,205,206,212,214,216,225–227,241]
BPR	[235]
CF	[247]
Classificationalgorithms	[217]
CNN	[46–49,52,57,58,60–62,66,68–70,72,74,76,78,81–83,91,93,96–98,100–102,104,105,112,123,128,137,140,145,154,156,158,166,250–253]
CNNLSTM	[42,169]
Collaborativefiltering	[238,240,249]
CollaborativefilteringCNN	[243]
CorrelationalNN	[73,95]
DART	[33]
DCNN	[54,55,63,86,88,90,103,108,111,159,170,254]
Decisiontree	[42,131,179,220]
Deformationalgorithm	[151]
DL	[50,134,135,195,211,241,245]
DNN	[84,183,187,246]
Domaindictionary	[178]
DPM	[110]
ELR	[201]

Table 5. *Cont.*

Methods	Citations
FastkNN	[152]
FCNN	[56]
FNN	[32]
Fuzzylogic	[106,113]
GAN	[71,75,99,129,134,141,155,251]
GA-RF	[65]
GaussianMixtureModels	[109,118]
gradientboostingdecisiontree	[42]
GraphCNN	[40,122]
GraphDCNN	[89]
GRU	[230]
GSN	[87]
H-CNN	[39,157]
HOG	[153]
HypergraphNN	[80]
Imageprocessing	[119,120,130,132,135,136,147]
k-center	[117]
k-means	[114,203,232,244]
k-medoids	[115]
Kneser–Ney	[34]
kNN	[54,137,222,235,237,250]
LAC	[107,116]
Lassoregression	[222]
LDA	[160]
LightGBM	[173]
LinearSVC	[182]
logisticregression	[42]
LR	[179,220]
LSTM	[85,126,163,171,176]
MDNN	[77]
ML	[130,132,133,136,185,197,209,223,224,228,229,234,236,244]
Modularontology	[184]
MT-GAN	[67]
MultimodalNN	[124]
NaiveBayes	[149,165,176,179,220]
NN	[94,144,164,168,174,195,202,208,213,218]
OLS	[222]
Pareto	[209]
Pareto/NBD	[207]
PCA-SVD	[125]
randomforest	[33,42,186,215,220,231]
RBFSVM	[175,220]
RCNN	[51]

Table 5. *Cont.*

Methods	Citations
R-CNN	[59]
Recommender	[201]
Regressionmodels	[142,174]
RepTree	[203]
review	[121,138,188,190,204,248]
RFM	[207]
R-GCN	[242]
RNN	[80]
Robotandpressuremeasurements	[146]
SEM	[239]
siamesenetwork	[46,75,79,156]
SSD	[35,92]
Survey	[53,127,143,150,162,181,191,196,210,219,221]
Survey:kanomodel	[139]
SVM	[64,87,153,179]
SVM.REPTree	[172]
SVP	[222]
UCB	[233]
VAR	[207]
VGG-IE	[65]
Viola–Jones	[148]
word2vec	[98,102,167]
word2vecSVMperf	[180]
XGBoost	[176]

Table 6. Summary of purposes with references.

Purpose	Citations
Clothesclassification	[34,39,46–49,52,56–58,60–63,65,67–69,74,76,82–84,89–93,96,101,105,107,110,111,114,116,118]
Customerbehavior	[33,210–215,217–249]
Datalabeling	[55,61,94,95,98,104,107,111,113,116,181–184]
Itemretrieval	[40,50,51,53–55,59,62,64,70,71,73,75,77,81,84–88,94,95,98–104,106,112,113,115,117,119,120,153,154]
Landmarkdetection	[35,66,72,97,108,109]
Management	[33,177,185–200,202–209,216,217]
Recommender	[34,78–81,121–128,155–168,201,202,250–254]
Sentimentanalysis	[42,44,169–180]
Virtualfitting	[32,129–136,138–146,149–152]

Table 7. Summary of databases with references.

Databases	Citations
ACS	[83]
AdidasAG	[82]
Amazon	[34]
amazon.com	[158]

Table 7. *Cont.*

Databases	Citations
Amazon5-core	[163]
AmazonDresses	[94]
AmazonFashion	[122]
Amazonfashiondataset	[73]
ane-commerceplatform	[50]
ASOS	[124]
CCP	[97]
Clothing1M	[70]
Collar-6	[49]
Collected	[76,91–93,96,98,100,110,112,114,136,137,145,149,151,152,201,223, 224,227,230,231,235,236,245,247,251]
Collectedfromreviewsofretailshops	[42,44,160,165,169,170,174,178–180,183]
Collectedfromscanner	[46,132]
Collectedfromsocialmedia	[107,116,172,175,222]
CollectedfromtheInternet	[81,95,102,104,117,128,153,155,167,168,176,177,192,203,225,226, 228,234,238,252]
CollectedfromtheInternetandsocialmedia	[206]
Colorful-Fashion	[35]
CzechretailshopsfromtheInternet	[54]
DARN	[103]
DeepFashion	[48,52,55,62,64,67,69,77,79,84,89,101,103,123,154,250]
DeepFashion2	[154]
DeepFashion3D	[135]
DeepFashion-C	[57]
DressCode	[129]
FashionAI2018	[72]
FashionDNA	[88]
Fashionista	[108]
FashionLandmarkdetection	[57]
FashionMNIST	[39,74,87]
Fashion-MNIST	[58,62,65,68]
FashionVC	[166]
Feidegger	[123]
FindFashion	[40]
GoogleAnalytics	[212]
ImageNet	[47,56,63]
Image-Net	[157]
iPER	[141]
Kaggle	[60,125,173]
LookBook	[75]
MovingFashion	[51]
MPV	[134,140]
POG	[159]

Table 7. *Cont.*

Databases	Citations
Polyvore	[78,126]
PolyvoreMayland	[166]
retailshop	[33,156,185–187,195,196,198,199,202,207,208,211,214–216,229,232,246,254]
RetailshopfromtheInternet	[218,237]
RetailshopsfromtheInternet	[71,99,105,109,111,144,182,189,209]
Street2Shop	[79]
Taobao	[80]
TaobaoiFashion	[122]
ThePraguetexturesegmentationdata-generatorandbenchmark	[118]
Tianchi	[159]
Virtualfitting	[137,147,148]
VITON	[134,140]
WFID	[86]

5.3. Fashion Datasets

A quality dataset is essential for an AI-based model to produce the results that are expected. The fashion-related datasets that were found in the examined publications are summarized in this section. Table 8 presents the datasets and lists the name of each dataset, the publication year, the problem to be solved, some features, and the data source. It is significant to note that many authors choose to modify and produce datasets based on those shown below, or even to collect data from the internet, in order to address particular research issues.

Table 8. Summary of datasets in the reviewed articles.

Dataset	Year	Task	Key Features	Source
Fashionista	2012	garment labeling	158k images, annotated with tags, comments, links	chitopia.com, accessed on 1 June 2023
ACS	2013	clothes classification	80,000 images, 15 types of clothes	shopping websites
CCP	2014	garment labeling	2k high-resolution street fashion photos	shopping websites
Colorful-Fashion	2014	garment labeling	2k 600 × 400 images, annotated with 13 colors	chitopia.com, accessed on 1 June 2023
DARN	2015	clothes retrieval	545k images, annotated upper clothing image pair	shopping websites
DeepFashion	2016	landmark detection	800k images (categories, attributes, landmarks)	Forever21, Mogujie
DeepFashion-C	2016	landmark detection	289k images, annotated with bounding box pose variation, category, and attributes	shopping websites and Google
FLD	2016	landmark detection	123k images annotated, clothing type and pose variation type	Deep Fashion
LookBook	2016	clothes retrieval	84k images; 75k images are associated with 10k top product images	Bongjashop, Jogunshop, Stylenanda, SmallMan, WonderPlace
Clothing1M	2017	clothes classification	1 million images in 14 classes	shopping websites

Table 8. *Cont.*

Dataset	Year	Task	Key Features	Source
Fashion-MNIST	2017	clothes classification	70k images, 28 × 28 greyscale images, 10 classes	Zalando
Amazon 5-core	2018	sentiment analysis	41 million reviews, in which all users and items have at least 5 reviews	amazon.com, accesed on 1 June 2023
Feidegger	2018	text–image retrieval	8k images of dresses, each image with 5 textual annotations in German	Zalando
ExpFashion	2018	clothes recommendation	853k outfits; outfits consist of: one top and one bottom piece	polyvore.com, accesed on 1 June 2023
Polyvore68K	2018	clothes recommendation	Polyvore68K-ND and Polyvore68K-D, 175k items	polyvore.com, accesed on 1 June 2023
VITON	2018	virtual try on	32k pairs of frontal view women and top clothing images	
Womens e-commerce clothing reviews	2018	sentiment analysis	23k customer reviews and ratings	
DeepFashion2	2019	parsing, landmark detection, retrieval, pose estimation	491k images	DeepFashion, shopping websites
FindFashion	2019	clothes retrieval	565k images, merges two existing datasets	Steet2Shop, DeepFashion
iPER	2019	virtual try on	206 video sequences, 30 subjects in random actions, 103 clothes	
Amazon Fashion	2020	clothes retrieval	53k images with text description	amazon.com, accesed on 1 June 2023
MPV	2020	virtual try on	37k/14k people/clothes images; person with different poses	
Tianchi	2020	recommendation	28k user profiles and 2.8 million records of purchase behavior	Alypay

5.4. AI Applied to Customer Satisfaction and Lucrativeness

The application of AI technologies to increase customer satisfaction and business profitability is documented in RQ2. Retailers are categorized as B2C since end users are their main clients [255]. Customer happiness benefits the company in a number of ways, such as through increasing future sales or lowering product returns. In this examination of the literature, a number of studies that aim to please the customer and encourage online apparel shopping have been discovered. A chatbot for buying assistance is still being researched [164,210], and there are also cutting-edge studies to anticipate how clothing will fit [137,149,211] and personalization of recommendations based on style or purchase histories [126,237–239]. When examining the sample of chosen articles from a business standpoint, it is important to draw attention to specific studies on demand forecasting, customer purchase intent, and inventory management.

Decathlon, a sports products company with more than 1000 locations globally, was a successful case study. Decathlon launched its online store in the Netherlands, where machine learning technology is being used to analyze and monitor customer behavior in real time and recommend products. As a result, in 2018, their income increased by 10.7%, while the average order value rose by 5.2%. The international jewelry company Pandora is an additional and more recent case study. Virtual Try-On, a web-based augmented reality tool, has been made available across the full inventory as of January 2021. While browsing on their mobile devices, customers can try on a piece of jewelry that is perfectly proportioned [19,256].

6. RQ3: Hot Topics and Upcoming Research Directions in the Field of AI for the e-Commerce Industry of Fashion

After responding to how AI can be actually applied to B2C fashion retail, RQ3 seeks to identify potential future research topics related to e-commerce and artificial intelligence. This analysis identifies four expanding areas where research is anticipated to make progress using the NLR approach.

6.1. Smart City (SC) Oriented e-Commerce

There are several research issues associated with e-commerce of fashion in smart cities that could be explored. AI is a key enabling technology to realize smarter cities and address their challenges [257]. Even though e-commerce was not the primary focus of the smart city paradigm's initial approach, there are currently several studies that show its significance [258–261]. Next, we list some research challenges that could be addressed by bringing together the AI and smart city paradigms and the fashion domain:

- Supply chain optimization [262]: Smart cities offer new opportunities for optimizing the fashion supply chain, from sourcing materials to manufacturing and distribution. Indeed, AI and other complementary technologies, e.g., IoT, could be used to improve supply chain efficiency, reduce waste, and improve sustainability.
- Personalization of fashion e-commerce [194]: As smart cities become more connected and data-rich, there is an opportunity to provide more personalized fashion e-commerce experiences. There is a need to keep exploring how AI and machine learning algorithms can be used to recommend products that are tailored to individual consumers based on their preferences, shopping behavior, and location data.
- Customer behavior and preferences [263]: Smart cities generate vast amounts of data about consumer behavior and preferences that can be used to inform fashion e-commerce strategies. Further research should explore how these data can be leveraged to understand consumer trends, predict future demand, and create more targeted marketing campaigns.

6.2. Omnichannel Shopping Experience for Customers

Omnichannel provides consumers with a buying experience that incorporates the benefits of numerous channels into a single customer journey [264,265]. The variety of consumer gadgets makes this task increasingly challenging for retailers. By using the internet and new purchasing technology, many consumers want easier yet richer shopping experiences [266]. For a true omnichannel experience, data must be gathered and analyzed from all channels. For retailers looking to reimagine their businesses using various technologies, such as augmented reality, virtual reality, and mobile applications, SC has some cutting-edge options [267].

6.3. Social Network Information for e-Commerce Marketing

As data sources for the creation of artificial intelligence solutions, social networks are becoming increasingly significant. Social networks are the sources that transmit the perspective of society in real time and have a big impact on how individuals engage with one another. Businesses can now manage information that would normally be impossible to manage or require an excessive amount of time and resources to gather. Social networks have a significant impact on the fashion industry. Networks enable direct communication with customers wherever they are in the retail industry. On the other hand, data analysis enables trend forecasting and the creation of fresh marketing approaches [268,269].

6.4. Matching of Fashion Products

E-commerce has compelled businesses to alter their pricing strategies, ensuring uniform pricing and competitor discounts [270]. Through the use of AI techniques, items that appear to be different but actually refer to the same entity can be automatically identified from various web sources. However, the fashion sector still faces a lot of obstacles for further improvement. Numerous merchants may sell the same clothing items in several markets and languages. Fashion items may have several names, graphics, and descriptions, making their identification more difficult than with other types of items. The categorizing of clothing remains a difficult task. The subjective nature of the perception of garments causes different classes to share many characteristics, making classification a challenging task. A future line of research is suggested to enhance fashion categorization performance due to the nature of the product, using a hybrid approach comparing photos and textual metadata.

7. Validation of Results

Two subject matter experts in the field have reviewed and validated the results obtained in this research. Specifically, an academic expert in the field with experience in the retail B2C sector and an ex-director of a high-end brand that provides athletic clothing with experience in research and development in the retail sector (see Refs. [271–273] for further details) were selected for this study. After reviewing this research, they agreed on the results proposed herein, thus validating the developed work.

8. Concluding Remarks

Rapid change is a hallmark of the fashion industry. E-commerce behemoths (such as the aforementioned Decathlon, Pandora, or Amazon) are currently using AI technology to optimize their own e-commerce platforms and boost their level of competition. New AI technologies and methodologies connected to the e-commerce fashion business are promising and are supported by ongoing research advances.

The study's objective was to carry out an NLR to see what the uses of AI technology in the e-commerce world of fashion are (RQ1), how the fashion sector can use AI to its fullest potential in order to increase customer satisfaction and financial success (RQ2), and what the hot topics and upcoming research directions in the field of AI for the e-commerce industry of fashion are (RQ3). After searching the academic databases Web of Science and Scopus, we found and analyzed 219 articles to answer these questions.

Finding AI applications for the fashion e-commerce industry is the aim of RQ1. A classification taking into account AI techniques was suggested to answer this question: CV, NLP, and other ML applications. The primary applications of CV center on the retrieval of apparel and virtual fitting environments. NLP is mostly utilized for consumer sentiment analysis and recommender system development. Other ML applications, such as profit maximization and sales forecasting, are targeted towards company management control. RQ2 aims at answering how AI could improve business profitability. According to this study, AI is utilized to enhance business management and fulfill consumer experience, which both contribute to increased advantages. Lastly, RQ3 indicates potential future research topics in this area. This analysis identified four expanding areas where new discoveries are anticipated in the future. On the one hand, the effects of e-commerce in SC and users' omnichannel experiences enable them to easily purchase both online and offline. On the other hand, social media data mining and fashion product matching appear to be some of the most significant issues for the near future. Thus, for scholars drawn to this issue, this research paper offers potential research subjects.

Further research will be oriented to offer a more detailed comparison between different categories of specific techniques: it is clear that all the techniques have their application areas, but it is necessary to go deeper into detail regarding when it is best to apply one or the other considering different criteria. As in all AI disciplines, some techniques are easier to use/implement, some are fast-converging, others are more accurate, etc. Thus, it is essential to analyze their advantages, disadvantages, and applicability limits.

In line with these future orientations, it is worth noting that this study has its limitations. The main restriction this research deals with is how rapid AI itself is changing. These days, all disciplines are changing due to the invasion of open AI. Nevertheless, it was not possible to dedicate a specific section to it because there is a discrepancy about evaluating whether or not a specific AI technology is 'open'. As this a limitation of the research, even though there are already references in the literature approaching the topic (e.g., Ref. [274]), future work will be oriented to study the potential of open AI as a tool applied to B2C fashion retail. Another limitation of the study is the aforementioned comparison of methods. In this vein, it is necessary to provide statistical analysis that studies how they evolve over time and why some methods seem better than others for a particular class of cases, etc. Regarding the development of the applicability of these methods over time, it is worth noting that most of the references are less than 10 years old (see Figure 2 for details). Therefore, it may be too soon to analyze the temporal evolution of the applied techniques.

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