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SURVEY

Analysis of Recommender System Using Generative Artificial Intelligence: A Systematic Literature Review

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ABSTRACT Recommender Systems (RSs), which generate personalized content, have become a technological tool with diverse applications for users. While numerous RSs have been proposed and successfully implemented across various domains, traditional AI-based RSs still encounter certain challenges, such as data sparsity, cold start, and diversity. Generative Artificial Intelligence in recommender systems is a recent advancement used by platforms like Netflix, Spotify, and Amazon to recommend items, news, videos, audios, goods, and services to their customers/users or to personalize experiences for their customers/users. The main purpose of this review is to compare traditional AI-based recommender systems with generative AI-based recommender systems. A total of fifty-two (52) papers, published between 2019 and February 2024, were selected from six major online libraries. To get a more comprehensive understanding of the selected study, we reviewed the selected studies techniques, and the models, datasets, and metrics used. Our systematic review reveals that generative AI models, such as generative adversarial networks (GANs), variational autoencoder (VAEs) and autoencoders have been widely used in recommender systems and they perform better than traditional AI techniques. Among the 30 datasets analyzed, MovieLens was the most frequently used, accounting for 33%, while Amazon datasets accounted for 11%, Recall and RSME are the most commonly used metrics. Our literature review offers understandings into the Generative AI techniques used across different recommender systems and provides suggestions for the future research. Finally, we elaborated on open issues and discussed current and future trends in generative AI-based recommendation systems.

INDEX TERMS Recommender system, generative AI, traditional recommender systems.

I. INTRODUCTION

Recommender Systems (RSs) uses data analysis and machine learning techniques to suggest relevant information (items, contents, movies, news, music etc.) to the users. These systems analyze large amounts of data about the users' past behavior, preferences, and interests using machine learning algorithms like clustering, collaborative filtering, and deep neural networks to generate personalized recommendations. Amazon, Netflix, and Spotify are well known examples of robust RSs. Amazon suggests products which are based on the past purchases and browsing history of the users, Netflix recommends personalized movie suggestions to their users/customers, and Spotify provides personalized playlists and music suggestions based on listening history and preferences of the users. The main purpose of using recommender systems is to offer or recommend personalized and significant suggestions to the users which is centered on their past preferences, behavior, and the user's interest [1], [2], [3], [4]. RSs can also be utilized to solve information overloading

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problems in different domains such as e-learning [5], [6], [7], e-commerce [8], [9], [10], entertainment [11], [12], [13], [14], and social networks [15], [16], [17], [18], [19], [20]. Therefore, the major three problems been faced by recommender systems are Cold Start, Sparsity and Diversity, and these needs the collection of past user's feedback [21]. Many authors are currently working on more effective recommender algorithms to solve the problems and to improve the system's accuracy and the satisfaction of the users [22]. Recommender Systems (RSs) is now playing a very significant role in the online lives of the users, it serves as personalized filters for users to discover relevant items, due to their efficiency. RSs have now been widely employed in the e-commerce platforms [23].

Generative AI has become an essential area of study, modernizing different domains, such as creative arts, computer vision, and natural language processing. Our systematic literature review aims to explore into the fundamental aspects of the generative AI, which includes requirements, models, datasets, generative types, and evaluation metrics, to have a comprehensive understanding of this significant discipline [24]. Generative AI focuses on the development of algorithms and models that can generate synthetic data which closely resemble real-world data. Generative AI has been widely used in different domains to promote prosperous opportunities in applied data science, health, education etc. [25]. It can generate novel and realistic data which has vast implications across multiple industries, and this includes entertainment, finance, healthcare, etc. The models of Generative AI have now opened new opportunities for applications such as text generation, image synthesis, music composition, and human-like chatbots [26]. Different studies have been conducted to review the functionality and the significance of Generative Artificial Intelligent [24], [26], [27]. Generative AI is subset of artificial intelligence (AI) and it has impact on online digital content [28].

Generative AI has some models which includes Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), the models have the ability to create new contents and they are more reliable in generating novel, a very high quality data, which can benefit recommender systems by learning from the existing data or samples [29]. According to some Authors, generative AI can improve and bring benefits to education [30], [31], [32]. Generative AI can produce original content on its own, in contrast to traditional AI models that depend on large-labeled datasets for task(s) [29], [33], [34]. Generative Adversarial Networks in recommendation algorithms, has the potential to address data sparsity issues [35] and it can improve users experience and satisfactions [36]. These studies collectively underscore the potential of generative AI in enhancing the performance of recommender systems compared to traditional AI.

The major generative AI models for recommender systems include generative adversarial networks (GAN), variational autoencoders (VAEs), Transformer-based models, and Autoregressive Models. These generative AI models: generative adversarial networks (GANs) and Variational Autoencoders (VAEs) are both powerful abilities to generate new contents, and they have distinct characteristics make them to be better than other traditionally methods utilized in recommendation systems [29]. Earlier research using Generative AI based RSs has compiled and analyzed the best scholarly articles, however, none of them examine the various social network properties that are significant for producing useful suggestions on the advantages of Generative AI over Traditional AI on RSs on recommender systems. To better understand the fundamental advantages and disadvantages of these approaches for helping researchers develop RSs, a thorough analysis of the most recent publications focusing on RSs utilizing Generative AI is urgently needed. Moreover, there are few current literature reviews that incorporate the Generative AI models created in the previous five years.

This paper presents the published papers and articles from 2019 to February 2024 and it equally presents a taxonomy of Generative AI algorithms in recommender systems. This review article intends to provide a detailed systematic literature review in the RSs using Generative AI and traditional AI. For this study, the review process is divided into five (5) research questions. The questions were carefully designed keeping in view the different perceptions of RSs.

Our Research Objectives (RO) are to:

i. Provide an overview of the state-of-the-art, and approaches used in Generative AI-based recommender system domains.
ii. Identify the current models, techniques, and to equally identify the various domains, datasets, and evaluation metrics that have been used in Generative AI-based RSs.
iii. Compare the performance of recommender systems between Traditional AI and Generative AI.
iv. Present current trend and future directions to researchers who are searching for new research opportunities in recommender systems using Generative AI.

To address the objectives, our aim is to contribute to the understanding and progress of Generative AI-based recommender systems by providing an associated and overview of the latest advancement and trends in these rapidly evolving techniques.

The remaining part of this review article is structured as follows:

- **Section II: Related Work** presents a comprehensive review of relevant research, this also include the surveys, present studies, reviews, and summaries and discussions of the key contributions.
- **Section III: Background** provides the necessary competencies, techniques, models, and approaches in recommender systems.
- **Section IV: Research Method** describes the systematic approach undertaken during the review, which includes the formulation of research questions, strategies for searching articles, procedures for screening, evaluations

of quality, and the selection of articles guided by the data extraction form.

- **Section V: Results Interpretation and Discussions** provides the interpretation of results and initiates discussion by presenting the analysis findings derived from the reviewed literature. This includes outlining the classification methods for each category, highlighting key insights, offering a comprehensive summary of discoveries, and identifying research gaps within each type.
- **Section VI: Limitations and Future Work** this section on "limitations and future works" critically assesses the constraints of the study, discusses challenges faced by generative AI recommender systems, and suggests potential areas for future study aimed at addressing these challenges.
- **Finally, Section VII Concludes Review**

The article extensively examines the existing research on recommender systems using Generative AI. It encompasses the introduction, reviews of relevant studies, background context, detailed methodology, findings, and suggestions for potential future research directions.

II. RELATED WORK

In recent times, there has been a notable increase in the utilization of Generative AI techniques in recommender systems. Generative AI can create or generate new content that resembles the original dataset it was trained on [30], [31], and [32]. In their study [23], [37] observed that generative AI has capabilities to enhance RSs by tackling the challenges been faced by the systems. They were selected because they offer a comprehensive overview of related works and to help steer future research endeavors. Similarly, some authors [38] have also recognized these three categories as relevant works.

The existing literature reviews show the contribution of various researchers in the field of recommender systems using generative AI. In their survey [39] presented the use of Collaborative filtering, Matrix factorization, Content-based filtering, Decision trees, Neural networks on recommendations. The survey is on Survey on AI-based job recommendation systems, techniques, challenges, and applications. Also, in their survey [37] on adversarial recommender systems, focusing on attack/defense strategies and GANs. The survey reviewed 76 articles on adversarial machine learning in recommender systems. GANs applied in RS for recommendation models; to improve learning accuracy, model enhances personalized citation recommendation in niche RS domains. Reference [40] provides a systematic survey of autoencoder-based recommender systems, they proposed a classification scheme for organizing and clustering related works. The advantages and disadvantages of different research prototypes are summarized. Statistical analysis identifies the contributions and characteristics of these studies. New trends and future directions in the research field are discussed. In their survey they established that autoencoder improves recommendation quality by understanding user demands and item characteristics.

The literature review paper of [41] discusses the methodologies and techniques in recommender systems. They assert that AI can effectively improve the development and application of recommender systems, the paper also identifies current research issues and new research directions, various AI approaches, such as fuzzy techniques and neural networks improve recommender systems. Reference [42] provides a comprehensive knowledge of AI-based recommender systems for e-commerce. In their systematic literature review they conducted research on recommender systems with emphasis on AI models, to address the present gaps in knowledge related to the most used techniques, the effectiveness of generative AI-based RSs, their benefits and drawbacks, and how they are compared to traditional Recommender Systems.

To the best of our knowledge, systematic literature reviews on recommender systems based on generative AI models are rare, so, our systematic literature review will delve into generative AI models on recommender systems comprehensively. Our aim is to differentiate the distinct research methodologies, models, metrics, and datasets employed by respective categories, enhance comprehension of generative AI-based recommender systems, and to facilitate more efficient searches for related articles by researchers. Through the analysis of this systematic review, researchers can gain a better understanding of the current state-of-the-art and pinpoint future research directions.

A. SUMMARIZED REVIEW OF GENERATIVE AI APPROACHES

We conducted analysis on multiple articles focusing on Generative AI-based recommendation systems, which encompass Generative Adversarial Networks (GANs), Variational Autoencoders (VAES), and Autoencoder-Based Models. This review offers valuable insights into the present-day advancements in the field, thereby aiding in the creation of more efficient recommender systems.

Anelli et al. [43] in their survey discussed the attacks, defense, and generative adversarial networks on recommender systems. The review serves as a reference for the RSs community working on the security of RS or on generative models using GANs to improve their quality. Li et al. [44] presented a review on recommendation method, named STRGAN (Social Trust Relationships Generative Adversarial Network), the model leverages on the advantages of generative adversarial networks (GANs) to tackle the problem of data sparsity, by integrating social relationships and user ratings. Zhou et al. [45] discussed a generative adversarial network-based recommendation framework using a positive-unlabeled sampling strategy. Specifically, they utilized the generator to learn the continuous distribution of user-item tuples and design the discriminator to be a binary classifier that outputs the relevance score between each user and each item. Wang et al. [46] proposed a novel generative recommender paradigm named GeneRec, which adopts an AI generator to personalize content generation and leverages user instructions to acquire users' information needs. Zheng et al. [47] presents an aggregate reciprocal neighbor of users which is based on the fusion of their explicit and implicit information; the aim is to capture user preference information.

Song et al. [48] introduced the independent encoder and generator to learn features representation during adversarial training.They combined VAEs and GANs to enable models to learn features representation during adversarial training, and to improve the learning ability of the model. Bahareh Jahanyar et al. [49] developed a modified GAN architecture for schizophrenia sample augmentation. Enriched GAN evaluation measures using confidence interval and calibration. Generated artificial samples close to the original samples. Chen et al. [50] proposed a deep learning-based poison attack approach, which uses generative adversarial network (GAN) to learn the cloud API QoS data distribution of real users in an adversarial way, so as to generate high-quality fake user attack vectors. Nguyen and Ishigaki [51] in their review paper used D2D-TM model for multi-domain collaborative filtering. The authors used GANs and VAEs to extract features and constrain inter-domain relations. Dipak Mahajan et al [52] in their study presents conditional generative adversarial networks (cGANs), they model used the model to produce more samples from the joint distribution of sparse custom training data. Chae et al. [53] explores the use of deep learning and generative adversarial networks (GANs) in collaborative filtering for accurate recommendation, they aim to exploit the success of GANs and deep learning in various domains and apply them to recommender systems. Hassan et al. [54] devise a novel serendipity-oriented recommender system (Generative Self-constrained Serendipitous Recommender System, GS2-RS) that generates users' preferences to enhance the recommendation performance. Bock and Maewal [55] proposes a conditional, coupled generative adversarial network (*RecommenderGAN*) that learns to produce samples from a joint distribution between view and buy behaviors found in extremely sparse implicit feedback training data. Zhao et al. [56] used a student discriminator to refine the knowledge of the teacher's, and then the generator and discriminator are enhanced by leveraging the refined knowledge via adversarial learning. Gao et al. [23] discussed the use of generative adversarial networks (GANs) to enhance recommender systems by addressing data noise and data sparsity issues.

Cho and Oh [57] presented a novel framework of Variational Autoencoder (VAE) for the collaborative filtering by using multiple experts and stochastic expert selection. Stochastic expert technique can enhance VAEs beyond collaborative filtering. Rajput et al. [58] discussed the potential of generative retrieval model to improve recommender system results using sequence-to-sequence model with semantic IDs to improve cold-start item retrieval. Conditional image quilting algorithm splices patterns based on minimum cost path. Yang et al. according to [59] in their review paper proposed a novel cross-domain recommendation framework called MPVAE. MPVAE utilizes memory pool and variational autoencoder to improve recommendation performance. Liu et al. [60] in their review proposed DGLGM that can be efficiently inferred by minimizing the aid of local variational optimization technique. Zhang et al. [40] provides a systematic survey of autoencoder-based recommender systems, the paper reviews recent research on autoencoder-based recommender systems. Park et al. [61] proposes an autoencoder-based recommender system, the system detects and removes natural noise in rating data, the system improves the performance of collaborative filtering-based recommender systems. Li et al. [62] in their study proposed a deep sparse autoencoder prediction model based on adversarial learning for cross-domain recommendations (DSAP-AL) to improve the accuracy of rating predictions in similar cross-domain recommender systems. According to [40] which provides a systematic survey of autoencoder-based recommender systems, in their paper they review recent research on autoencoder-based recommender systems. The authors present the differences between autoencoder-based recommender systems and traditional recommender systems. It discusses potential research directions for autoencoder-based recommender systems.

The purpose of conducting literature review on recommender systems utilizing generative AI is to deliver a thorough analysis and synthesis of existing research, aiming to provide a comprehensive overview of the current state of the field. Our literature review aims to summarize and compare different generative AI techniques/models employed in recommender systems, pinpointing the primary challenges and limitations of current systems, and proposing potential avenues for future research. While other similar reviews exist, they either concentrate on a specific generative AI; generative adversarial networks models or variation autoencoder or the combination of the models not comprehensive enough. This review offers a comprehensive summary of the current state-of-the-art in the field from various perspectives, along with a structured presentation of the topic categorized into four main theoretical frameworks. The review makes the following contributions:

- It identifies and categorizes key generative AI models and techniques utilized in recommendation systems.
- The application domains and datasets of these generative AI -based recommender systems will be summarized.
- Additionally, the analysis will be conducted on the current state-of-the-art implementations to identify existing obstacles and limitations.
- Moreover, to identify the potential future research directions in the field of generative AI -based recommendation systems will be identified.

To the best of our knowledge, there are numerous reviews and survey papers in recommender systems based on GANs, VAEs, and other models, but no comprehensive systematic literature review has been conducted in recommender system using generative AI.

Our review gives priority to peer-reviewed journal articles and conference papers due to their quality research and reliability; they undergo thorough evaluation by experts and offer detailed analyses. The one major advantage of our method is the use of broad search keywords, allowing us to capture a wide array of research studies that might have been missed in previous reviews. Through this strategy, we aim to provide a comprehensive and current analysis of the most recent research on generative AI-based recommender systems. Our review serves as a resource for researchers and practitioners keen on comprehending the latest advancements in the rapidly evolving field of generative AI-based recommender systems, so our study is different from previous studies by comprehensively reviewing the current models and techniques been utilized.

III. BACKGROUND

A. RECOMMENDER SYSTEMS

A recommender system (RSs) is an algorithm that uses data analysis to suggest relevant information (movies, news, items, contents) to the users. Recommender systems (RSs) are designed as information filtering systems tasked with suggesting products and services, commonly referred to as items that are most likely to be of interest to a user [63]. Recommender systems analyze large amounts of data about the users' past behavior, preferences, and interests using machine learning algorithms like clustering, collaborative filtering method, and deep neural networks to generate personalized recommendations. Recommender systems are ubiquitous and have been applied in diverse fields, such as e-commerce [64], [65], education [66], and more.

Recommender systems learn about the users' preferences, past selections, and product attributes by gathering information on how users interact with products, these include impressions, clicks, purchases, share and likes [67], [68]. Recommender systems can anticipate customers' interests and preferences with a high degree of personalization, they are widely used by content and product providers. Recommender systems can point clients toward almost any product or service that catches their attention, such as clothing, films, novels, songs, and fitness programs. Some of the challenges in recommendation systems include ***cold start***, ***data sparsity***, and ***diversity*** despite the benefits of employing generative AI techniques for their development. Cold start is a problem in the context of recommender systems that refers to a situation where the system encounters difficulties or limitations in making accurate recommendations for new users or items that have limited or no historical interaction data available [58]. For new users, the system lacks information about their preferences and behaviors, making it challenging to provide personalized recommender tailored to their interests, [59]. Similarly, for new items that have not yet been rated or interacted with by users, the system lacks sufficient data to understand their characteristics and relevance to users' preferences. Data sparsity is a situation where the available data in a dataset is insufficient or sparse, meaning that there are many missing values or gaps in the data. In the context of recommender systems, data sparsity often refers to the limited amount of information available about user-item interactions [44], [69]. Diversity in recommender systems refers to the variety or range of recommendations provided to users. It involves ensuring that the recommended items are not only relevant to the user's preferences, but also encompass a broad spectrum of different types, categories, or characteristics. In other words, a diverse set of recommendations includes items that cater to various tastes, interests, and needs of the user, rather than just offering similar or redundant suggestions [70], [71].

TABLE 1. Content-based movie genres filtering techniques.

Movies	User 1	User 2	User 3	User 4	Comedy	Action
Item A	1	-	3	4	Yes	No
Item B	5	5	1	2	No	Yes
Item C	2	5	-	4	Yes	Yes
Item D	4	3	3	3	No	Yes

B. MAJOR APPROACHES IN RECOMMENDATION SYSTEMS USING TRADITIONAL TECHNIQUES

1) CONTENT-BASED FILTERING TECHNIQUES

Content-based filtering techniques use the information about user's preferences and items they have interacted with to recommend similar items [72]. Content-based filtering technique recommends items that are like the ones a customer/user has liked or had interactions with previously. Content-based filtering technique attempts to predict the behaviors or features of a user by given the item's features the user reacts to positively. Unlike collaborative filtering technique, which recommends new contents based on the similarities between users with similar contents, content-based filtering's central idea is to recommend new content based on the similarities between the features of new items and user tastes in the past. Reference [72] in their review explained how content-aware neural architecture search approach for recommender systems, which aims to automatically discover neural network architectures tailored for content-based recommendations.

From table 1, the final pair of columns Comedy and Action tells us about the movie genres. Now that we know which users prefer which genres based on these categories, we can create features tailored to that specific user based on how he or she responds to films in that genre.

Once the RSs is aware of the preferences of the users, it can use the feature vector that was generated to embed the user in an embedding space and make recommendations based on the user's preferences. In the process of making a recommendation, the item's feature vectors and the user's favorite feature vectors from prior records are used to calculate the similarity metrics (more on this later). The best few are then suggested,

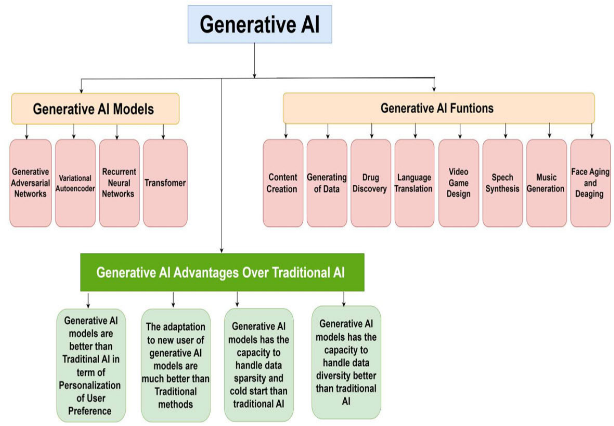

FIGURE 1. **Generative AI Models, Functions, and Advantages of over Traditional AI.**

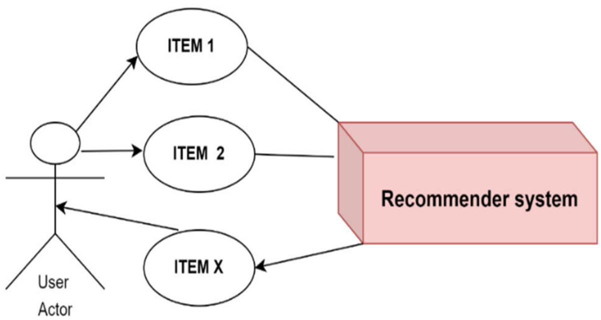

FIGURE 2. **Content-based filtering method.**

in making recommendations to a single user, content-based filtering does not need the data of other users.

This method's drawback is that it requires comprehensive familiarity with the features of the items to provide a recommendation that is accurate. For certain items, this knowledge or information might not always be accessible. Furthermore, this method is not very effective at extending the users' current preferences or interests. Given that user preferences are subjected to change over time, this approach can quickly adjust to these shifting preferences. The algorithm does not need the profiles information of other users, because each user's profile is unique and has no bearing on the recommendation process.

Supervised machine learning is closely related to content-based filtering recommendations. Learning a set of user-specific classifiers with classes that are "valuable to the user" and "not valuable to the user" can be seen as the problem. The quality of features is one of the main problems with content-based recommendation. To learn the user's preferences in a significant way, the objects to be recommended must be defined. Figure 2 illustrates how items are recommended on content-based filtering method.

a: LIMITATIONS AND CHALLENGES OF CONTENT-BASED FILTERING TECHNIQUES

Some of the problems of content-based filtering technique are the limited content coverage and difficulty in capturing user preferences. Content-based systems rely heavily on the content features of items and may struggle to capture complex user preferences that go beyond simple content-based characteristics, content-based filtering techniques also encounter cold start, data sparsity and scalability problems [73].

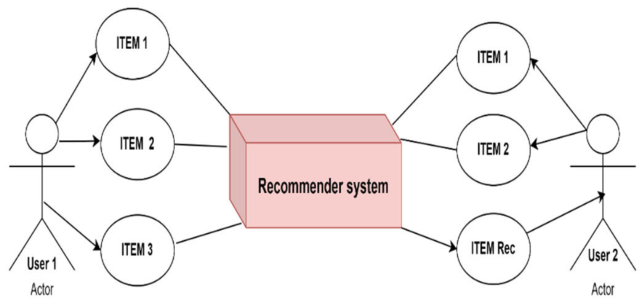

FIGURE 3. **Collaborative filtering technique.**

2) COLLABORATIVE FILTERING (CF) TECHNIQUES

In collaborative filtering techniques, items or contents are recommended to the targeted user(s) by the collaborative technique which is based on the prior preferences of other users with related tastes [74]. This type of recommendation technique is also called user-user and item-item collaborative based collaborative filtering; it recommends the preference items of the neighbor. Information can be filtered through collaborative filtering by utilizing the exchanges and information gathered from other users by the system. This is predicated on the notion that individuals who expressed agreement when evaluating items are probably going to do so in the future. To predict what a user might like; the collaborative filtering algorithms create a model based on the user's historical behavior and compare it to data from other users [75].

a: LIMITATIONS AND CHALLENGES OF COLLABORATIVE FILTERING TECHNIQUE

Collaborative filtering technique faces some drawbacks, for instance, the cold-start issue [76], data scarcity, and scalability [77]. Numerous reviews have been conducted in recent years to analyze and assess this traditional recommendation system method. Reference [74] presented a comprehensive study on collaborative filtering (CF) methods for recommendation systems, which was among the pioneering works in this field. The researchers examined various recommendation methods and compared them based on their advantages and limitations. Various research have been carried out to improve the effectiveness of collaborative filtering in addressing the cold-start problem. This includes efforts such as integrating multiple CF techniques [75] and focusing CF on smaller datasets rather than large ones [78], [79]. Figure 3 is an illustration of how item(s) are recommended to the user.

3) HYBRID RECOMMENDATION APPROACH

A hybrid-based recommendation system (RS) integrates two or more recommendation techniques to enhance the performance while mitigating the limitations of individual systems [80]. This approach effectively tackles common issues in RSs, including cold start, and data sparsity problems. There are three primary methods for creating a hybrid RS: combining multiple RSs, integrating various recommendation algorithms, and merging features from diverse data sources as input [80]. Hybrid-based recommendation approach can combine two or more models or techniques together to generate an enhanced recommendations [81].

4) A KNOWLEDGE-BASED RECOMMENDATION SYSTEM

A knowledge-based recommendation system (RS) generates recommendations by considering the needs and preferences of users [82]. Unlike content-based and collaborative filtering methods, which assumes that user interests remain stable over time, knowledge-based RSs recommends items to users based on their current needs and to also consider potential changes in their preferences [66]. Acquiring and representing knowledge is a critical aspect of knowledge-based recommendation systems [83].

5) DEMOGRAPHIC FILTERING RECOMMENDER SYSTEMS

Demographic filtering recommender systems leverage demographic information to generate personalized recommendations tailored to individual users or user segments. Demographic filtering relies on the assumption that users with similar demographic characteristics share similar preferences and interests. Demographic filtering recommends items based on the demographic information of users, such as age, gender, and location [39].

C. MAJOR TECHNIQUES AND APPROACHES IN RECOMMENDATION SYSTEMS USING GENERATIVE AI MODELS

Generative artificial intelligence has become a hot topic of research and is revolutionizing several fields, including natural language processing, marketing, spots, sales, and the creative arts, they propose a temporal generative model for predicting future user behavior in e-commerce scenarios. RSs is now playing a significant role in the lives of the users online, RSs serves as personalized filtering methods for the users to find relevant items from the display of varieties, owing to their efficiency, RSs have been largely active in consumer-oriented e-commerce platforms [23]. Generative AI has become a significant field of study, transforming various domains, such as natural language processing, computer vision, and others. Our study aims to examine the essential and essential aspects of generative AI on cross-domain, including the models, generative types, requirements, and evaluation metrics, to gain a wide-ranging understanding of the discipline [68]. Generative AI majorly focuses on the development of algorithms and models that can generate synthetic data that closely resembles real-world data.

Generative AI has the capability to mitigate the problems been faced by the traditional methods as earlier mentioned, and improve the functions of the RSs, leveraging on cross-domain methods, and generative AI models can predict new items to the users [23]. Generative AI is one of the artificial intelligence (AI) technologies that have started to be used in programming education [84]. Generative AI has some models which includes generative adversarial networks (GANs) and variational autoencoders (VAEs), they have the ability to create new contents that are more reliable in generating novel, a very high quality data, which will enhance the problems been faced by the traditional methods in recommender systems on cross domain. According to some academics scholars, generative AI has the ability to improve and bring benefits to education [30], [31].

Generative AI has the capacity to produce original content on its own, in contrast to traditional AI models that depend on large-labelled datasets for a particular task. One of the features of Generative AI is its ability to identify patterns and structures in the data that already exists, then use those patterns to create new contents.

The current RSs mostly use collaborative filtering, content-based technique, and hybrid approaches, while these methods have demonstrated effectiveness in specific situations, but they still encounter problems like the cold-start issue and data sparsity, diversity etc. Conversely, generative AI methods like GANs and VAEs have proven to be effective at creating artificial data and identifying hidden patterns in complicated distributions. Figure 3 shows the models, functions, and advantages of generative AI. Generative AI can create or generate new content that resembles the original dataset it was trained on [30], [31], and [32].

1) GENERATIVE ADVERSARIAL NETWORKS (GANS)

The concept of GANs was originally introduced by Goodfellow and his co-authors in 2014 [85]. Since its inception, GANs have gained significant attention and have become a pivotal aspect of generative model research. Generative Adversarial Networks (GANs) are the class of generative AI models which consist of two neural networks, the neural networks are: a generator and a discriminator. In their review paper [85] introduced the groundbreaking concept of Generative Adversarial Networks (GANs). GANs operate through a two-player adversarial game between a generator and a discriminator network, enabling the generation of data that closely mimics real-world examples.

According to [23] in their study observed that GAN has capabilities to enhance RSs by tackling the challenges been faced by the systems. According to [23] GAN-based recommendation models can reduce data noise and alleviate data sparsity. Reference [37] in their review also proposes the use of GANs to overcome the limitations of data noise and alleviate data sparsity.

In their review paper [86] discussed the development and important of generative AI methods for the computation of Bayesian, they used a large training dataset and deep neural network for the inference and decision making, Gen-AI methods were developed for Bayesian Computation, and another study by [45] also proposes a generative AI model for recommender systems.

In recommender systems, generative adversarial networks (GANs) are highly effective at producing the interactions of user-item [81]. The GANs loss function is tailored to train a generator network (G) to generate recommendations that closely mimic real user-item interactions. At the same time, a discriminator network (D) is utilized to differentiate between authentic and generated interactions. The main aim of this adversarial setup in GANs for recommendation is to minimize the discrepancy between the generated and real interactions [87]. The objective function for the generator (G) and the discriminator (D), as previously stated, is defined as a loss function (L):

$$min\ max[E_{(u,i)\sim pdata(u,i)} (logD(u, i)) + E_{z\sim pz(z)}(1-logD(G(z, i)))][88] \quad (1)$$

From the equation above, $(u,\ i)$ represents the interaction of user-item that is sampled from the actual data distribution, and $G(z,\ i)$ denotes the generation of user-item interactions based on latent variables $z$and i(the item). The main aim is to make the generated interactions indistinguishable from the genuine ones. Generative adversarial networks (GANs) is one of the promising models that synthesizes data samples that are like real data samples [88]. The aim of generative models is to generate new data points that conform to the distribution of the training dataset. To accomplish this aim, GANs consists of two networks, which are the generator that gets a random noise vector as input and discriminator [89].

D. RECENT ADVANCE IN GAN

1) CONDITIONAL GANS (cGANS)

In [85], the model lacks control over the type of generated samples. These samples could belong to any category within the training data distribution. Consequently, during sampling, the generated samples may not encompass all the potential variations present in the training data. Conversely, (cGAN) [90] introduces a condition to both the generator and the discriminator. In cGANs, the generator and discriminator are conditioned on additional information, such as class labels or attributes, allowing for controlled generation of samples.

The loss function for CGAN is a modified version of the GANs loss function [85] in equation (1):

$$minG\ maxDL(D, G) = Ex \sim pr(x)[logD(x|c)]Ez \sim pz(z)[log(1D(G(zc))[94] \quad (2)$$

where c is the condition added to the model. In [52] and [90] the authors present cGANs which are used to produce more samples from the joint distribution of sparse custom training data.

2) CONVOLUTIONAL GANs

The proposed GANs [85], which are considered the simplest type of GANs, employs Multi-Layer Perceptron (MLP) in both generator and the discriminator. However, a key drawback of [85] GANs is their unstable training process [91]. One potential solution to this issue is to utilize convolutional neural networks (CNNs) instead. In convolutional GANs [90] the generator employs a deconvolution structure, while the discriminator utilizes convolutional layers to differentiate between generated and real image. Although the network types differ between vanilla GANs and convolutional GANs, their overall architectures remain identical. Many recent GAN frameworks have adopted CNNs in their generators, discriminators, or both, owing to the superior performance, sample quality (typically images), and training stability offered by CNNs compared to MLPs in vanilla GANs [89].

3) WASSERSTEIN GAN

Another modified GANs utilized in recommendation is known as Wasserstein GAN (WGAN). In [85] the discriminator's task is to differentiate between real and fake data points. However, in WGAN [92] the discriminator, often referred to as a ''critic,'' evaluates the distance between the distributions of real and fake samples by assigning scores. WGAN employs this approach leads to significant improvements in both the quality of generated images and the stability of the training process [89].

4) FairGAN

Reference [91] proposes a learning algorithm called FairGAN, based on generative adversarial networks (GANs), which addresses the exposure fairness problem by reframing it as a challenge of negative preferences in implicit feedback data. FairGAN does not directly consider unobserved interactions as negative, instead, it employs a unique fairness-aware learning approach to dynamically generate fairness signals. This allows FairGAN to optimize its search direction, enabling it to explore the space of optimal rankings that can allocate exposure to individual items fairly while maximizing users' utilities [93].

5) STRGAN (SOCIAL TRUST RELATIONSHIPS GENERATIVE ADVERSARIAL NETWORK)

In recommendation method, social trust relationships Generative Adversarial Network (STRGAN) leverages the advantages of (GANs) to tackle the data sparsity problems, by the integration of the user ratings and social relationships [44]. Incorporating both types of information, STRGAN aims to improve the accuracy and quality of recommendations provided to users. STRGAN model employs negative sampling techniques to ensure that the generated recommendations align with the real data.

6) MRNGAN MODEL BASED

MRNGAN model based is a twin-tower generator designed by [47], the paper successfully embedded user neighborhood information as feature embedding into the generator of GAN. In addition, they also propose a heuristic negative sampling mechanism in the recall phase in Recommendations.

E. VARIATIONAL AUTOENCODERS (VAES)

The variational autoencoders (VAEs), introduced by [94] is a type of autoencoder that learns to encode data into a lower-dimensional latent space and generate new data samples resembling the input. Unlike traditional autoencoders, VAEs are generative models capable of capturing the underlying distribution of input data. The VAE loss function is defined as:

$$LVAE = -E(q(Z|X))[log[p(X|Z)]] + KL(q(Z|X)||p(Z)) \tag{3}$$

The first term evaluates the dissimilarity between the original input data (p(X|Z)) and the data reconstructed by the decoder. The second term, acting as a regularization component, assesses the Kullback-Leibler (KL) divergence between q(Z|X) and p(Z), often a standard Gaussian distribution. This loss function guides VAE training to strike a balance between precise data reconstruction and shaping a structured latent space for generative purposes. Variational Autoencoders (VAEs) are being applied in recommender systems, especially in collaborative filtering technique and personalized recommendations [40]. VAE translate user and item interactions into a latent space, enabling a deeper understanding the preferences of user [95]. Using generative models in recommender systems has expanded the scope of user recommendations, improved their experience and boosted engagement [88]. In their review [57] asserts that Variational Autoencoders (VAE) have shown to outperform other models in collaborative filtering. However, VAEs may have simple and restrictive prior distributions. Autoencoders (AEs) serve as a foundational component that can be hierarchically employed to construct deep models [40]. They arrange, condense, and uncover high-level features, enabling unsupervised learning and the extraction of nonlinear features [96]. Autoencoders (AEs) play a crucial role in reducing data storage needs, improving interpretability by uncovering essential data features, and showcasing robustness by generalizing effectively to new data and adeptly handling noisy or incomplete datasets [97]. There are different authors that have worked on different improvements on Variational Autoencoders [98], Auto-Encoding Variational Bayes [98] Supervised Prototypical Variational Auto-Encoder (SP-VAE), Conditional variational autoencoders (CVAEs) [57], SE-VAE for collaborative filtering [59], Memory Pool Variational Autoencoder (MPVAE). Autoencoder system detects the natural noise in the rating data based on the reconstruction errors after training [61]. Autoencoder can be used to improve the performance of collaborative filtering-based recommender systems [61].

F. COMBINATION OF VAEs AND GANs

According to our research, GANs have the capability to produce more accurate representation of input than VAEs, but VAEs trains faster than GANs. Some Authors also combined the VAEs and GANs to enhance RSs, [45] used GANs and VAEs to extract features and constrain inter-domain relations, it is effective in solving cold start problems and supporting cross-selling. Some other Authors that combine VAEs with GANs includes [99], [100], they combine VAEs and GANs to enable their model to learn features representation during adversarial training and improve the learning ability of the model.

IV. RESEARCH METHOD

In this segment, we offer a summary of our thorough and organized analytical method for evaluating recommender systems built on generative AI. We classify our discoveries using precise search criteria, sorting them according to different factors like methodologies, application areas, and types of recommendation systems. Our main objective is to methodically assess the present status of generative AI-based recommender systems and emphasize significant discoveries within each classification.

We incorporate research questions, a search strategy, screening process, literature search, quality assessment, data extraction, and data synthesis, all of which are comprehensively described. Our systematic review employs specific search terms, and we evaluate the quality of the studies included using suitable quality assessment tools. This review process aids in pinpointing research gaps and enhances comprehension of the fundamental concepts and variables linked to generative AI-based recommender systems, thereby fostering future research.

A. RESEARCH QUESTIONS (RQ)

1. What are the state-of-the-art and the approaches used in generative AI-based recommender system domains?
2. What are the performances of recommender systems using traditional AI and generative AI?
3. What are the current trends and future directions to researchers who are looking for new research opportunities in recommender systems using generative AI?
4. Which type of models, techniques, application domains, datasets, and evaluation metrics are currently used in generative AI-based RSs?

B. SEARCH STRATEGY

This research utilized automated methods to scour six prominent digital libraries to identify the most relevant publications related to the research topic. The libraries included were Web of Science, Springer, IEEE, ACM, Elsevier, and Sci-

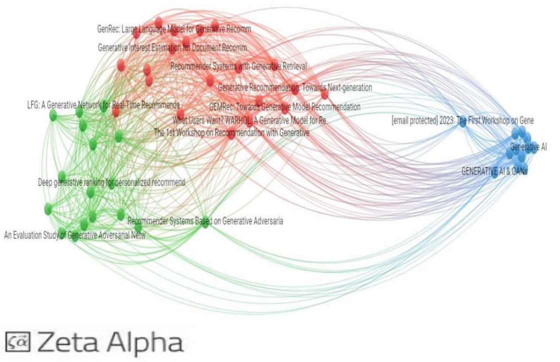

FIGURE 4. Frequency of keywords in the publications.

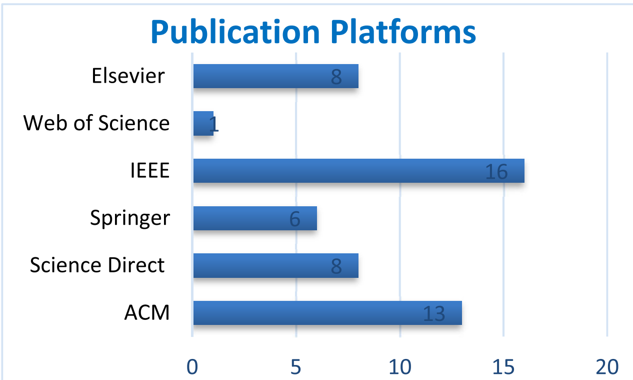

FIGURE 5. Publication platform.

enceDirect; they were selected due to their widespread use and extensive collection of research articles. To refine the search parameters, various combinations of keywords were employed. The search terms used are as follows:

"("recommendation system" OR "recommender system" OR "recommendation" OR "recommender") AND ("generative AI" OR "GAN" OR "VAE") AND ("generative adversarial")" In the process of selecting our articles, we included the most used generative AI models as search terms and other articles that discussed the terms "GANs" or "VAEs" in the title for their technique keywords. On the side of the recommender system, we intentionally included more general terms rather than to limit ourselves to only "*recommendation system*" or "*recommender system*." This tactic allows us to capture a wider range of research that made use of generative AI models for the recommendations and encompasses various frameworks or systems designed for recommendation purposes. This strategy helps us to explore potential opportunities for applying generative AI techniques in different domain applications, making our systematic literature review more relevant and comprehensive.

Overall, our search strategy is designed to recognize the articles that are efficient and effective for our systematic literature review, to ensure we cover a wide range of research in recommender systems that utilize generative AI models or techniques. In our review, for a paper to be selected for evaluation, a set of criteria must be completed to narrow down the search area. Our review included articles that satisfied the set down criteria.

TABLE 2. Quality assessment.

No.	Quality Assessment Questions
1.	What is the level of rigor in research methodology?
2.	Is the study's goal obvious?
3.	Is the paper's topic relevant to research questions of the review or study?
4.	Is there a clear description of the validity context?
5.	Is the Generative AI models explained correctly?
6.	Is there concise summary of the findings in the review or study

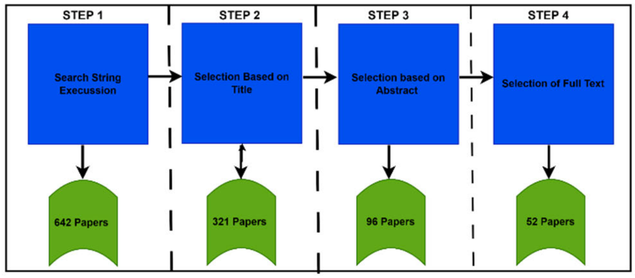

FIGURE 6. Paper selection process.

C. SCREENING PROCESS

Paper selection criteria define the criteria for paper selection to identify the most relevant studies after the search plan. *This review also included the articles that satisfied the below criteria*:

- Papers published from 2019 to February 2024 only.
- Only journal articles and conference papers were accepted for publication.
- Papers that are published in English language.
- A research paper or article that answers at least one research topic.

Articles that did not meet the criteria were excluded from the review:

- The paper that does not relate to generative AI-based recommender systems.
- The paper that does not relate to the topic of recommender systems.
- The paper that does not discuss models directly related to Generative AI-based Recommender Systems.
- Full paper not accessible.

Figure 7 shows the search plan flowchart of our study. The articles' keywords were evaluated and shown in Figure 4, we extracted the relationship between the co-occurrence of terms linked to the study issue using **Zeta Alpha.**

Numerous publications were sourced from online platforms to conduct a thorough review of research within the field. These papers were written in English and focused on at least one selected research topic. The study exclusively considered articles published between 2019 and February 2024, encompassing both conference and journal publications. Figure 5 and figure 6 illustrates the paper selection process, which followed the [79] guidelines. Articles were

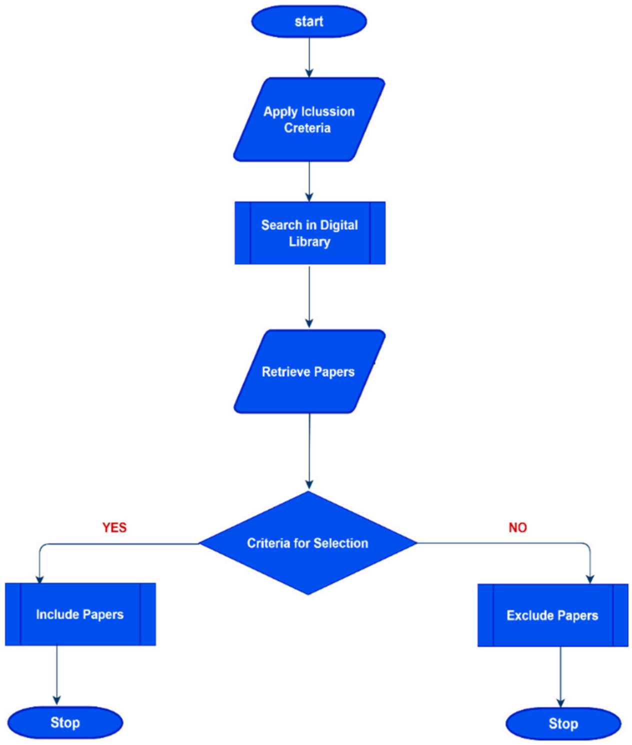

FIGURE 7. Search plan flowchart.

TABLE 3. The inclusion and exclusion criteria for selecting the papers.

Inclusion Criteria for Selecting Papers	Exclusion Criteria for Selecting Papers
• Papers published between 2019 and February 2024 only	• Papers published before 2019
• Papers related to the research questions (RQ1 to RQ4)	• Papers not related to the research questions (RQ1 to RQ4)
• Published conference and journal papers	• Papers not published
• Peer reviewed papers/articles only	• Non-peer-reviewed article papers
• Papers written in English language only.	• Papers not written English language
	• Duplicate article papers
	• PhD and Master's dissertations

TABLE 4. Summary of the search results.

S/N	Digital Library	Search results	Relevant papers	Selection of text	% of relevant papers
1.	ACM	241	153	13	25
2.	IEEE	184	112	16	31
3.	Science Direct	101	32	8	15
4.	Elsevier	37	17	8	15
5.	Springer	67	14	6	12
6.	Web of Science	12	4	1	2
	Total			52	100%

sourced from six international publications and addressed four research questions. Following an initial automated

TABLE 5. URL of the Selected digital libraries.

S/N	Digital Library	URL to Access
1.	ACM	http://www.acm.org
2.	IEEE	http://www.ieeexplore.ieee.org
3.	Science Direct,	http://www.sciencedirect.com
4.	Elsevier	https://www.scopus.com
5.	Springer	http://www.springerlink.com
6.	Web of Science	http://www.webofknowledge.com

search, 642 papers were identified, subsequent screening reduced this number to 96 articles after eliminating duplicates and inaccessible content. Finally, employing all four steps outlined in Figure 5, 52 papers were finally selected for inclusion.

The method adopted involved utilizing a set of questions outlined in Table 2, as described in [79] to evaluate the quality of the work. To refine the search results, each criterion was assigned a score of 2 (fully met), 1 (partially met), or 0 (not met). Subsequently, a total score was calculated for each study based on these criteria. Only studies scoring 9 or higher were considered for inclusion.

The final subset of papers, totaling 52 studies, underwent thorough examination by the researchers, addressing all research issues comprehensively.

The below Flowchart describes the search plan and search criteria for selecting the papers:

D. DATA EXTRACTION

Various factors were considered during the selection of relevant research publications for this study. Different aspects and characteristics of the research articles were categorized into columns, and the columns were merged into a spreadsheet, which was utilized to complete the study. Examples of these information clusters include authors and publication year, article title, application domain, metrics, dataset, generative AI model, recommender system (RS) method, and utilized measures. As depicted in Figure 5 and table 4, the final set of publications, totaling 52 papers, was identified, and the most prevalent platform was ***IEEE***, comprising sixteen (16) papers, thirteen (13) papers were published in ***ACM***, Eight (8) in ***ScienceDirect***, Eight (8) from ***Elsevier***, Six (6) from ***Springer***, and One (1) in ***Web of Science***. We meticulously examined these publications and addressed research inquiries. The data extraction method encompasses RS techniques and models, analysis of classical methods, domains and applications, metrics, datasets utilized, and performance evaluation measures.

E. DATA SYNTHESIS

We employed qualitative and quantitative methods to synthesize the data extracted from the selected studies to answer our research questions (1-4).

For ***Research Question 1***, we used a quantitative meta-summary method to identify the approaches used in generative AI-based recommender system domains. To address ***Research Question 2***, we used quantitative and

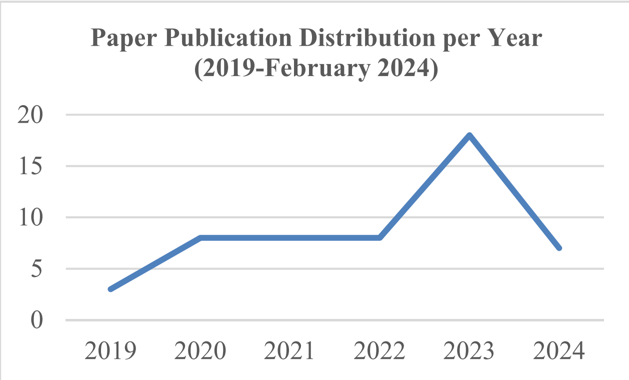

FIGURE 8. Distribution of publication per year.

qualitative methods to summarize the characteristics of each study's results. For ***Research Question 3***,we extracted information related to the dataset and metrics from each study. We mapped the information back by domain and techniques to understand the trends in the fields for different types of dataset usage. Finally, we used descriptive analysis techniques to describe the current status of classification strategies, strengths and limitations of recommender systems for ***Research Question 4***, we employed a qualitative narrative synthesis method to summarize the defining characteristics of each study's results in a narrative to identify consistency across studies.

F. VALIDATION

One way to ensure the credibility of the results of a systematic literature review (SLR) is to thoroughly evaluate its validity. For external validity, publications from 2019 to February 2024 were sought to extend the generalizability of the review findings. Finally, the validity of conclusions was confirmed by employing methodologies consistent with those used by various authors.

V. RESULTS, INTERPRETATION AND DISCUSSION

In this section, we addressed the research questions formulated earlier to facilitate the analysis of recent research on recommendation systems leveraging generative AI. Our focus was on identifying state-of-the-art generative AI techniques highlighted in the term summary, along with their associated performance metrics and the datasets utilized in these studies. We also delved into the diverse domains where generative AI techniques have been applied within recommender systems, categorizing them accordingly. Furthermore, we explored the datasets used by researchers to assess these techniques across various recommendation domains. Lastly, we investigated the most effective approach for categorizing generative AI techniques and analyzed the strengths of each technique within the realm of generative AI.

A. PRIMARY STUDIES (PS)

Table 6 shows a list of selected primary studies (PS) with the reference number of each study.

TABLE 6. Selected papers used for the study.

Paper No.	References	Author and Publication Year	Paper No.	References	Author and Publication Year
PN01	[47]	Tiansheng Zheng et al, 2024	PN27	[57]	Yoon-Sik Cho and Min-hwan Oh, 2022
PN02	[50]	Zhen Chen et al, 2024	PN28	[113]	Iwao Tanuma et al, 2022
PN03	[64]	Kamal Berahmand et al, 2021	PN29	[117]	Wafa Shafqat et al, 2022
PN04	[119]	Ilham Saifudin, et al, 2024	PN30	[89]	Nuha Aldausari et al. 2022
PN05	[54]	Syed Zain Ul Hassan et al, 2024	PN31	[93]	Jie Li et al, 2022
PN06	[72]	Jon Nicolas Bondevik et al, 2024	PN32	[107]	Chongxuan Li et al, 2022
PN07	[59]	Jie Yang et al, 2024	PN33	[56]	Yu Zhao et al, 2022
PN08	[111]	Ricardo Ribeiro Pereira et al, 2023	PN34	[130]	Betul Ay et al, 2019
PN09	[101]	Eoin Brophy et al, 2023	PN35	[102]	Divya Saxena & Jiannong Cao, 2022
PN10	[44]	Xiangxia Li et al, 2023	PN36	[67]	Zhengwei Wang, et al 2021
PN11	[38]	Wenjie Wang et al. 2023	PN37	[104]	Abdul Jabbar, et al, 2021
PN12	[112]	Maryam Etemadi et al, 2023	PN38	[37]	Yashar Deldjoo et al, 2022
PN13	[48]	Xiaoyuan Song and et al, 2023	PN39	[123]	Qian Zhang et al, 2021
PN14	[84]	Ramazan Yilmaz, et al, 2023	PN40	[109]	Le Wu et al, 2021
PN15	[58]	Shashank Rajput, et al, 2023	PN41	[62]	Yakun L, et al 2021
PN16	[49]	Bahareh Jahanyar et al, 2023	PN42	[60]	Huafeng Liu et al, 2020
PN17	[105]	Jun-Ho Cho, et al, 2023	PN43	[114]	Minh-Duc Nguyen et al, 2020
PN18	[32]	Stefan Feuerriegel, et al, 2023	PN44	[115]	Ahlem Drif et al, 2020
PN19	[106]	Athanasios Karapantelakis, etb al, 2023	PN45	[116]	Parichat Chonwiharnphan, et al, 2020
PN20	[80]	Atharva Patil, et al, 2023	PN46	[45]	Yao Zhou et al, 2020
PN21	[52]	Arpana Dipak Mahajan, 2023	PN47	[40]	Guijuan Zhang et al, 2020
PN22	[61]	Hyeseong Park et al, 2023	PN48	[55]	Joel R. Bock et al., 2020
PN23	[108]	Muhammad Hamza et al, 2023	PN49	[23]	Min Gao et al, 2020

TABLE 6. ***(Continued.)*** **Selected papers used for the study.**

PN24	[120]	Mohamad Ballout et al, 2023	PN50	[86]	Ting Zhong, 2020
PN25	[56]	Jichuan Zhao, et al, 2023	PN51	[51]	Linh Nguyen & Tsukasa Ishigaki, 2019
PN26	[118]	Deepjyoti Roy, et al, 2022	PN52	[53]	Dong-Kyu Chae et al, 2019

B. GENERATIVE AI-BASED RSs

This section presents the result for *Research Question 1 (RQ1)*, which assists in categorizing the research included in this review and is centered on systematic literature reviews (SRS) utilizing generative AI. Figure 7 illustrates the distribution of journal articles by publication year from 2019 to February 2024. Numerous studies have identified the generative AI techniques employed for recommender systems (RSs) through graphical representations. Table 8 presents the selected studies based on generative AI methods.

There are lots of research that employed various generative AI algorithms for RSs. Reference [57] proposed a novel framework of VAE for collaborative filtering using multiple experts and stochastic expert selection. Stochastic expert technique can enhance VAEs beyond collaborative filtering. Proposed a novel framework of VAEs for collaborative filtering using multiple experts and stochastic expert selection (SE-VAEs). Reference [59] used a novel cross-domain recommendation framework called MPVAE. The MPVAE utilizes memory pool and variational autoencoder to improve recommendation performance [86], introduced a generative Session-Based Recommendation (SBR) framework named Variational Session-based Recommendation (VASER). VASER is a non-linear probabilistic methodology that enables Bayesian inference for flexible parameter estimation in sequential recommendations.

The study [23], [41], [67], [84], [101], [102], [103], [104], [103], [106], [107], [108] discusses the significance of generative adversarial networks (GANs) to enhance recommender systems by addressing data noise and data sparsity issues. GAN-based recommendation models can reduce data noise and alleviate data sparsity. Reference [65] in their study integrate knowledge distillation (KD), in the form of a teacher–student architecture) into GANs to reduce the model complexity while improving the accuracy of GANs on recommender systems. They used a student discriminator to refine the teacher's knowledge, and then both the generator and discriminator are enhanced by leveraging the refined knowledge via adversarial learning, which constrains the generator to produce fake data approximating both the ground truth and teacher's predicted preferences, and enables the discriminator to distinguish between the preferences of the generator and more confusing preferences of the teacher from the ground truth. Another study by [55] proposes a conditional, coupled generative adversarial network (*RecommenderGAN*) that learns to produce samples from a joint distribution between *(view, buy)*behaviors found in extremely sparse implicit feedback training data. User interaction is represented by two matrices having binary-valued elements. Also [52] presents conditional generative adversarial networks (cGANs) which are used to produce more samples from the joint distribution of sparse custom training data. Reference [44] also proposes a recommendation method, named STRGAN (Social trust relationships Generative Adversarial Network), it leverages the advantages of Generative Adversarial Networks (GANs) to tackle the data sparsity problem, by integrating user ratings and social relationships. The authors [47] did not only explores heuristic algorithms for neighbor selection, but also extends the application of neighbor selection to the GANs framework and negative sampling. To capture user neighbors that contain more potential feature information, the authors propose a neighbor strategy that integrates explicit and implicit user information. Some authors also work on the survey on accuracy-oriented neural recommender models in recommendation systems [109].

Reference [110] in their survey discussed how Autoencoders find valuable applications in recommender systems, which aim to suggest items to users based on their historical behavior or preferences. Also [61] proposes an autoencoder-based recommender system. The system detects and removes natural noise from rating data. The system improves the performance of collaborative filtering-based recommender systems [109]. The methodology used in [111] the GANfather involved the development of a method to generate samples with properties of getting malicious activity without the need for labeled data. The traditional Recommender Systems encounter some problems [112] which can be solved by generative AI. VAE can be combined(hybrid) with other models to generate items and to mitigate recommender system's problems [113], [114], [115] GAN can also be combined with other models to generate items and to solve the problems of recommender system [116], [117].

C. DATASETS

In some studies, evaluations may involve multiple datasets. Table 8 presents the datasets identified in the selected papers, along with their respective domains and the research that utilized them. Each research paper included in the analysis utilized at least one dataset. MovieLens is an online platform designed to recommend movies to users, using their ratings to generate personalized user profiles for future recommendations. MovieLens datasets are available in various sizes, including 100K, 1M, 10M, and 20M. Dataset is a significant aspect in Recommender systems [118], [119], [120], [72], [79], [79]. Movielens dataset is notably prominent, appearing in 17 articles. These datasets contain user-item

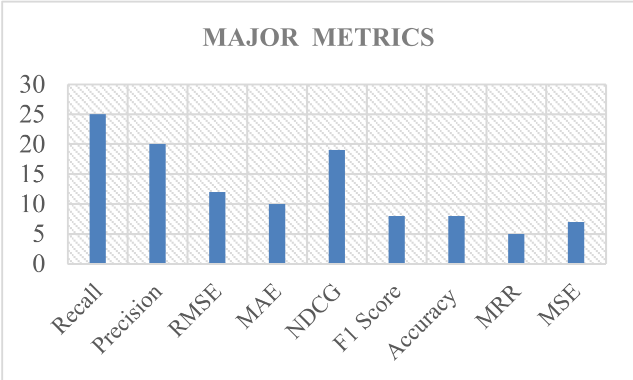

FIGURE 9. Distribution of major metrics per study.

TABLE 7. Performance analysis of state-of-art RSs using generative AI.

Evaluation Metric	Paper reference Number
Recall	[44], [47], [49], [50], [51], [53], [54], [56], [57], [58], [60], [61], [62], [64], [86], [93], [106], [123], [101], [111], [112], [114], [117], [118], [119]
Precision	[44], [45], [47], [48], [49], [50], [53], [54], [55], [56], [61], [62], [64], [89], [106], [123], [111], [112], [115], [119]
NDCG	[23], [44], [45], [47], [48], [52], [53], [54], [64], [57], [58], [60], [61], [89], [114], [115], [117], [113],
RMSE	[50], [60], [61], [62], [101], [123], [112], [116], [117], [118], [119]
MAE	[53], [60], [62], [101], [123], [112], [117], [118], [119]
F1 Score	[49], [50], [61], [62], [64], [117], [118], [119]
Accuracy	[49], [50], [64], [106], [123], [112], [118], [120]
MSE	[50], [59], [64], [89], [101], [113]
MRR	[44], [45], [54], [86], [117]
IS	[89], [104], [107]
COSINE	[38], [112]
DCG	[114], [117]
PCC	[56], [101]
RMS	[105], [115]
Others	[38], [84], [89], [107], [114], [116], [117].

rating pairs, timestamps, movie attributes, tags, and user demographic features [87]. The Amazon dataset features an extensive collection of 142.8 million reviews on Amazon products, spanning nearly two decades. This dataset includes user profiles, item metadata, and user-generated reviews [87]. Amazon Datasets appears in 10 articles. The Yelp datasets are significant in 9 articles, like Amazon's dataset, Yelp is also offering includes reviews, user ratings, and other contextual information as shown in figure 10. Researchers have utilized this dataset to investigate user-item collaborative filtering and Point of Interest (POI) recommendation tasks. Netflix and Ciao are other datasets commonly used in generative AI-based recommender systems, the two datasets are significantly used in 7 articles each. There are some other datasets been commonly use according to our review, like Filmtrust, Epinions, Bookcrossing, CIFAR and some other datasets as highlighted in Table 8, this has answered the *Research Question RQ 4 on type of dataset* been used in Generative AI-based Recommender systems.

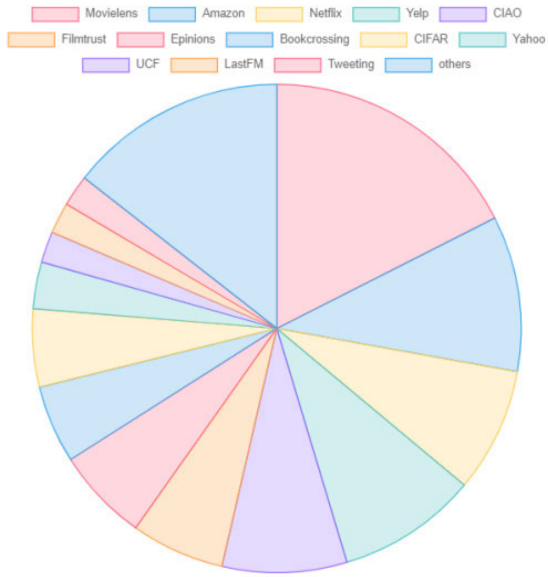

FIGURE 10. Major datasets used by the study.

TABLE 8. Dataset of state-of-art RSs using generative AI.

Dataset	Paper reference Number
Movielens	[23], [37], [45] [47], [53] [54], [57], [60] [61], [62], [64], [123], [111], [112], [115], [118], [119].
Amazon	[37], [51], [54], [59], [61], [57], [112], [115], [118], [119].
Netflix	[23], [57], [60], [61], [123], [112], [118], [119].
Yelp	[37], [45], [54], [60], [61], [130], [101], [118], [119].
Ciao	[23], [37], [47], [53], [56], [61], [118], [119].
Filmtrust	[44], [47], [61], [123], [118], [119].
Epinions	[60], [61], [62], [123], [118], [119].
Bookcrossing	[54], [123], [118], [119].
CIFAR	[67], [101], [104], [107], [120].
Yahoo	[37], [118], [119].
UCF	[89], [108].
LastFM	[56], [114].
Tweeting	[108], [119].
Others	[37], [48], [49], [50], [55], [72], [86], [101], [105], [101], [111], [116], [117], [113],

In summary, the selection of a dataset is crucial in recommendation system research. The preference for particular datasets like MovieLens dataset, Amazon dataset, Yelp dataset, and Netflix dataset, Ciao dataset reflects their suitability for different recommendation tasks. Researchers utilize these datasets to evaluate collaborative filtering, sequential recommendation, and other recommendation system paradigms, thereby enhancing the understanding and capabilities of the field [119].

D. EVALUATION METRICS

The effectiveness of recommender systems is determined by evaluating their outcomes. Since the beginning of recommender systems, assessing predictions and recommendations has been crucial to ensure users receive the best experience. Research on recommender systems requires various metrics or measures to assess the quality of different methods, techniques, and algorithms used to generate recommendations [121]. The *Research QuestionRQ4* emphasizes the evaluation perspective of recommender systems, focusing on the following inquiry: "*Which evaluation metric are utilized to gauge the quality of generative AI-based recommender systems*?"

The evaluation criteria might not always align with the recommendation algorithms utilized in recommender systems (RSs). Furthermore, the objectives of assessment could vary across different scenarios.

1) PROBABILISTIC METRICS

Probabilistic metrics are highly efficient for assessing the accuracy of predictions made by recommenders, regardless of whether they involve recommendations for items with low or high probabilities of relevance. Examples of these metrics include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Square Error (MSE) etc.

2) QUALITATIVE METRICS

Qualitative metrics are prevalent in the field of recommender systems (RSs) and prove highly beneficial when the goal is to minimize errors in models. These measures find extensive use across various RS applications. Key examples include Accuracy, F-measure, Kappa statistic, and Coverage. Some are particularly suitable for balanced or imbalanced datasets, signal or fault detection, or information retrieval tasks. In quality assessment, items are categorized as relevant or irrelevant to a user, after which a metric is selected to evaluate the quality of items recommended by the RSs.

3) RANKING METRICS

Ranking metrics are widely used in recommender systems (RSs), focus on how effectively the recommender ranks recommended items. Key examples of these metrics include Precision, Recall, Normalized Discounted Cumulative Gain (NDCG), Mean Average Precision (MAP), Hit Rate (HR), Fallout, and Area under the ROC Curve (AUC), among others. Unlike previous categories, these metrics assess the quality of a ranked list of items rather than the average quality of raw scores generated by the recommender system. In this -category, the recommendation task is perceived as a ranking problem.

The performance evaluation metrics used for analyzing different Generative AI-based recommender systems are presented in Table 7 and figure 9 which answered the *Research Question RQ4 on evaluation metric use in generative AI-based recommender systems*. Among the studies, 25 studies utilized the recall measure, 20 employ Precision, 19 used NDCG, 12 applied Root Mean Square Error (RMSE), 10 utilize Mean Absolute Error (MAE), 8 analyze F1-measure, 8 consider Accuracy, 7 apply Mean Square Error (MSE), and 5 employ MRR to validate the performance of the recommender systems. Additionally, some additional measures are also considered for validating the performance in a few applications as shown in table 7.

However, Recall, Precision, NDCG, RMSE, and MAE were the most evaluation metrics used in the domain of Generative AI-based Recommender systems.

E. DOMAIN CATEGORIZATION AND ANALYSIS

Generative AI-powered recommender systems have gained widespread adoption across diverse sectors. Researchers have segmented these systems into specific domains to offer personalized recommendations tailored to particular context. However, concerns have been raised about the adequacy and precision of existing classifications due to the rapid evolution of this field. The quest for categorization has yielded valuable insights, enabling researchers to delve into specific applications, enhance domain-specific recommendations, and uncover the intricate relationships among different data types, industries, and application formats.

This review article delves into the various domains that have emerged from such categorization efforts, encompassing areas like application, entertainment and media, e-commerce and retail, education and learning, scholarly research, user information, social media, and tourism. Each domain represents a distinct facet of the recommendation system landscape, aiming to unravel its inherent complexities and potential future directions.

Accurate and relevant terms play a crucial role in refining and optimizing the effectiveness of domain-specific recommendation systems. These terms are typically extracted from the content of articles, and researchers can continuously strive for improved classifications, harnessing the power of precise terminology to enhance the future of deep learning-based recommendation systems.

The subsequent paragraphs delve into the primary domains identified in the classification of these recommendation systems, emphasizing their implications and potential trajectories for further advancement. The domains applications in the study are listed in table 9. This exploration aims to address the *Research Question RQ4 on the types of domains used in Generative AI-based Recommender systems*.

1) CROSS-DOMAIN RECOMMENDER SYSTEMS

Cross-domain recommender system is an effective tool to address the data sparsity and cold start problem [122], [59], [123]. Most recommender systems only offer recommendations for single domain; YouTube, for instance, suggests videos to its customers or users. While the single domain recommender system is tailored to specific markets, occasionally it is discovered that they have less user and item data than their rivals. The foundation of cross-domain recommender systems can be laid by helping the recommender systems to transfer knowledge from related domains [124].

TABLE 9. Selected studies of RSs using generative AI.

References	Author and Publication Year	Domains Application	Dataset	Generative AI Model	Additional Recommender Technique	Metric
[47]	Tiansheng Zheng et al, 2024	Information Retrieval	Movielens, Filmtrust, and CiaoDVD.	MRNGAN model	Twin-Tower Generator	Precision, Recall, NDCG, and MAP
[50]	Zhen Chen et al, 2024	Cloud API Recommender	WS-DREAM	GAN	API-QoS	Precision, Recall, F1, Score, MAE, RMSE.
[64]	Kamal Berahmand et al, 2024	Personalized Recommendations	Real word Dataset	Autoencoders	Historical Behavior	Accuracy, Precision, Recall, F1 Score, MSE
[119]	Ilham Saifudin, et al, 2024		Movilens, Netflix, Yahoo Music, Film Trust, Epinions, BookCrossing, Movie Tweetings, Yelp, Ciao, Amazon,	Collaborative Content-Based	Hybrid	Precision, Recall, F1, MAE, NDCG, RSME
[54]	Syed Zain Ul Hassan et al, 2024	Extracts Users' Interest and Satisfaction	Movielens, Amazon, Yelp, Book Crossing	GS2-RS	Rating Matrix	Precision, Recall, (NDCG), and Mean Reciprocal Rank (MRR)
[72]	Jon Nicolas Bondevik et al, 2024	Food Recommender	Offline Evaluation with accuracy-based metrics is the most common	Content-Based	GNN	Yummly, Recipe 1M, Kaggle
[59]	Jie Yang et al, 2024	Cross-Domain Recommendation	Amazon	MPVAE	VAE	RMSE, *MAE*
[111]	Ricardo Ribeiro Pereira et al, 2023	Detection of Illicit Activity	Financial transactions and MovieLens	GANfather	GAN	Alert Rate, Recall, Precision

TABLE 9. *(Continued.)* Selected studies of RSs using generative AI.

[101]	Eoin Brophy et al, 2023	Time-Aware	CIFAR, MNIST, ImageNet	Discrete-Variant GANs	Continuous-Variant GANs	RMSE, MAE, PCC, PRD, MSE, MRE
[44]	Xiangxia Li et al, 2023	Social Relationship for Recommender Systems	FilmTrust	STRGAN	GAN	Precision, Recall, NDCG, and MRR
[38]	Wenjie Wang et al. 2023	Personalized Content Generation	They utilize a high-quality micro-video dataset	GeneRec	AI Generator	Cosine and Prediction Score (PS)
[112]	Maryam Etemadi et al, 2023	Healthcare Recommender	Real World Dataset	Taxonomically Classify		Accuracy, Precision, MAE, RSME, Cosine, Recall
[48]	Xiaoyuan Song and et al, 2023	Improvement of GAN	Real Public Dataset	CFGANs	Collaborative Filtering, VAE	Precision, NDCG
[84]	Ramazan Yilmaz, et al, 2023	Education	Computational Thinking Scale	ChatGPT	**Transformer**	ANCOVA test
[58]	Shashank Rajput et al, 2023	Retrieval model Recommendation	Beauty, Sport and Outdoors, Toy and Games	RQ-VAE	ANN, Generative Retrieval Model	Recall, NDCG
[49]	Bahareh Jahanyar et al, 2023	Healthcare Recommender	NCBI Repository	MS-ACGAN	DAE	Accuracy, Precision, Recall, And F1-Score
[105]	Jun-Ho Cho, et al, 2023	Comparative Study	Vivo Datasets	GAN	Conventional Dental Software	RMS
[32]	Stefan Feuerriegel et al, 2023	Information Systems	Review			
[106]	Athanasios Karapantelakis et al, 2023	Mobile Networks		Generative AI		Accuracy, Precision, MSE, and Recall

TABLE 9. *(Continued.)* Selected studies of RSs using generative AI.

[80]	Atharva Patil, et al, 2023	Job Recommender				
[52]	Arpana Dipak Mahajan, 2023	Cluster Recommendation	300 epochs	cGANs		
[61]	Hyeseong Park et al, 2023	Natural Noise Removal	Movielens	Autoencoder-Based	Collaborative Filtering	RMSE, MAE, Recall, Precision and F1
[108]	Muhammad Hamza et al, 2023	Video Framework	UCF 101. FaceForensic, Kinetics-600	GANs	Conditional GANs	
[120]	Mohamad Ballout et al, 2023	Cross-Domain	Long Listops, CIFAR-10 from LRA	BART, BERT, and GPT-2	T5	Accuracy
[56]	Jichuan Zhao, et al, 2023	Image Quilting	A real training image	VAE-GAN		MSE, PCC
[118]	Deepjyoti Roy, et al, 2022	Review	Movilens, Netflix, Yahoo Music, Film Trust, Epinions, BookCrossing, Movie Tweetings, Yelp, Ciao, Amazon,			Recall, F1, MAE, RMSE, Accuracy
[57]	Yoon-Sik Cho and Min-hwan Oh, 2022	Item Prediction/e-commerce	MovieLens and Netflix	SE-VAEs	Collaborative Filtering	Recall, NDCG
[113]	Iwao Tanuma et al, 2022	Interactions Prediction	MSD-A dataset, Echo Nest Taste Profile Subset	Variational Autoencoder-Based Hybrid	Collaborative Filtering	NDCG and MSE
[117]	Wafa Shafqat et al, 2022	Solve Imbalanced Data	Online Shopping Mall in Jeju known as the eJeju Mall	PacGAN	Conditional Wasserstein	RMSE, MAE, MCC, recall, F-score, MRR, DCG, and NDCG.
[89]	Nuha Aldausari et al. 2022	Video Generation	UCF-101 and Kinetics dataset	GANs		MSE, PSNR, IS

TABLE 9. *(Continued.)* Selected studies of RSs using generative AI.

[93]	Jie Li et al, 2022	Learning Recommendations	Toys and Games, Beauty, Office Products, Digital Music	FairGAN	Collaborative Filtering	Precision, Recall, NDCG
[107]	Chongxuan Li, et al, 2022	Game Recommender	SVHN, Tiny ImageNet and STL10 CIFAR10	Triple-GAN		IS, FID
[56]	Yu Zhao et al, 2022	Knowledge Distillation Recommender	Ciao and LastFM	StuGAN.	GAN	Precision, Recall, NDCG
[130]	Divya Saxena & Jiannong Cao, 2021	Review Recommendation		GANs		Parzen window estimate
[102]	Zhengwei Wang, et al 2021	Survey Recommendation	CIFA 10, IMAGE NET, LSUN, CALEBA	GAN		
[67]	Abdul Jabbar, et al, 2021	Survey Recommendation	CIFAR-10 Dataset	GAN	VAEs	IS and FID
[104]	Yashar Deldjoo et al, 2021	Recommendation attack	Movielens, FilmTrust, EachMovie, CiaoDVD, Yelp, Pinterest, Amazon, 30Music, Yahoo, AotM: Art of the Mix, Foursquare, Tradesy.com	GANs	AML	
[37]	Qian Zhang et al, 2021	Methodologies in RSs	Movilens, Netflix, Yelp, Film Trust, Epinions, BookCross.			Accuracy, Precision, MAE, RSME, Recall
[123]	Le Wu et al, 2021	Accuracy-oriented Neural Recommendation	Microsoft News Dataset, Yelp	Collaborative filtering	GNN	

TABLE 9. *(Continued.)* Selected studies of RSs using generative AI.

[109]	Yakun L, et al 2021	Prediction model Recommender	Amazon Books, Epinions, MovieLens	Autoencoder Models, DSAP-AL	Matrix factorization	Precision, recall, and F-measure, RMSE, MAE
[62]	Huafeng Liu et al, 2020	e-commerce Recommendation	Yelp Dataset, Movielens, Netflix and Epinions	DGLGM	AUTO-ENCODER	Recall and NDCG
[60]	Minh-Duc Nguyen et al, 2020	Online Behavior Recommendation	goSFloc, goNYloc, Gowalla, lastfm	VAE	EM algorithm	Recall, AverageRank, DCG, NDCG
[114]	Ahlem Drif et al, 2020	Accurate predictions. Prediction	MovieLens, Amazon Review	EnsVAE	GloVe-CBF	Precision, MAP, NDCG
[115]	Parichat Chonwiharnphan, et al, 2020	New Products Recommender	Facebook, Google	CGAN	Gumbel estimator	RMSE, RSM, CORR, EMD
[116]	Yao Zhou et al, 2020	Recommendation With Positive-Unlabeled Sampling	Movielens, and Yelp	GAN	PURE based	Precision, NDCG, MAP, and Mean Reciprocal Rank (MRR)
[45]	Guijuan Zhang et al, 2020	Review Recommendation	Movilens, Netflix, Yelp, Film Trust, Epinions, BookCross.	AUTOENCODER-BASED	Traditional recommender systems.	NDCG, Recall, RMSE, Link Rank and AUC
[40]	Joel R. Bock et al., 2020.	Product Recommendation	Retailrocket	*Recommender GAN*	Matrix factorization	Novelty, precision
[55]	Min Gao et al, 2020	User Preferences Recommender	Monielense, Ciao, Yahoo	GAN-based		NDCG,
[23]	Ting Zhong, 2020	Session-Based Recommendation	Yoochoose, Diginetica	VASER	Deep Generative Networks and Bayesian Inference	Recall, MRR
[86]	Linh Nguyen & Tsukasa Ishigaki, 2019	Features Extraction	Amazon, Video TV	VAE-GAN	Collaborative Filtering	Recall, NDCG,

TABLE 9. *(Continued.)* Selected studies of RSs using generative AI.

[51]	Dong-Kyu Chae et al, 2019	Accurate Recommendation	It is a privately released dataset, Ciao, Movielens	Collaborative Adversarial Autoencoders (CAAE)	Matrix Factorization, Bayesian Personalized Ranking	Precision, Recall, MAE, NDCG, Discounted Cumulative Gain (DCG)
[53]	Betul AY et al, 2019	Image retrieval system for e-commerce Recommendations	Zap50K dataset	InfoGAN	Collaborative Filtering	Precision

2) E-COMMERCE

E-commerce recommender recommends items to the users based on their browsing history, purchase history, and demographic information [55], [60], [116]. Online retailers like Amazon uses recommender systems to suggest products to customers based on their browsing history, purchase history, and preferences. These systems help improve customer experience and drive sales. Reference [54] used the serendipity item to improve the diversity of recommended items, which relieves the filter-bubble problem for the users. The adoption of recommender systems in retail and e-commerce has surged alongside the rapid expansion of online shopping. Nevertheless, this domain lags behind others in terms of development, highlighting a necessity for the implementation of more sophisticated recommendation techniques. With the ongoing growth of online retail, and e-commerce, there arises an increasing demand for enhanced and personalized recommendation to enhance user satisfaction and boost sales [87].

3) E-LEARNING

E-learning in the context of recommender system, is the use of technology to provide personalized recommendations to learners. These recommendations could include suggesting courses, modules, or learning materials based on the learner's preferences, past activities, performance, and goals. Reference [50] proposed a student discriminator that will be able to refine the knowledge of the teacher, and then both the generator and discriminator are enhanced by leveraging the refined knowledge via adversarial learning, which constrains the generator to produce fake data approximating both the ground truth and teacher's predicted preferences, and enables the discriminator to distinguish between the preferences of the generator and more confusing preferences of the teacher

TABLE 10. Significance of generative AI over traditional AI techniques on recommender systems.

S/N	Significance of Generative AI over traditional AI Techniques on Recommender Systems	Reference
1	Personalized Content: Generative AI models can generate personalized contents according to the behaviors, and preferences of individual, but traditional recommender systems rely on the explicit user-item interactions, generative AI models can gather implicit preferences.	[12], [60]
2	Diversity in Recommendation: Generative AI can generate diverse and novel recommendations by generating new content or items based on users' historical interactions and preferences.	[38]
3.	Cold Start Problem: Generative AI models can solve the cold start problem, where traditional recommender systems struggle to make accurate recommendations for new users.	[12], [21], [60]
4.	Feedback on Adaptability: Generative AI models can integrate user feedback in real-time and modify their recommendations accordingly, but traditional recommender systems are weak on this.	[7], [117]
5.	Data Sparsity Problem: Generative AI models can mitigate data sparsity problems which are commonly encountered in traditional collaborative filtering approaches.	[21]
6.	Diversity Improvement: Generative AI models can get a better balance between recommendation diversity and accuracy compared to traditional techniques	[38]
7.	Generation of Contents: Generative AI can create items such as item representations, reviews, and product descriptions compared to traditional systems that depend on metadata or user-item interactions	[29], [37], [50], [58], [95], [123], [108], [111]

from the ground truth. Reference [93] also proposes a generative adversarial networks (GANs) based learning algorithm called FairGAN. FairGAN dynamically generates fairness signals to address the exposure fairness issue. FairGAN optimizes the search direction to find the optimal ranking that fairly allocates exposure to individual items while maximizing users' utilities. FairGAN proposes a fairness-aware learning strategy using GANs.

4) SOCIAL MEDIA RECOMMENDATIONS

Social media recommends people to follow or connect on social media platforms based on mutual interests, connections, and activity. Facebook and Twitter utilize recommendation systems to suggest friends, pages, groups, and posts to users based on their interests, connections, and interactions. These recommendations help users to discover relevant content and engage with the platform. Reference [38] in their paper proposes a recommendation method, named Social Trust Relationships Generative Adversarial Network (STRGAN), it leverages on the advantages of Generative Adversarial Networks (GANs) to tackle the data sparsity problem, by integrating user ratings and social relationships.

TABLE 11. Future work and problems in recommendation.

Problem/challenge	Recommendation Technique	Direction for Future Work	References
Enhancing VAEs	VAE with Collaborative Filtering	Explore effectiveness on general VAEs	[57]
Attack/Defense on Recommender Systems	AML with GANs	Diverse user information	[37]
Create New Items	GeneRec which adopts an AI Generator	Utilize user feedback to complement instructions	[38]
Implicit Feedback	FairGAN	improving items and users' fairness	[93]
Information mining	MRNGAN Model	Mine deeper into the information	[47]
Improves Recommender System Results	RQ-VAE	Increase new single stage	[58]
Multi-domain	VAE-GAN with Collaborative Filtering	Cross-Domain	[57]
Noise Removal	Autoencoder-Based Recommender	Detection performance	[61]
Online Behavior Recommendation	VAE with MM	Incorporating additional side information	[114]
Accurate Predictions.	EnsVAE	Exploring different aggregation functions and context-awareness integration	[115]
Generate Realistic User Data	CGAN with Gumbel Estimator	Add a demand forecasting component	[116]
Imbalanced Data Problem	Hybrid GAN	Using open-access datasets	[117]
User Interaction	GAN	Focus on numerical optimization	[55]
Prediction Model	Deep sparse Autoencoder (Cross-Domain)	Explore the influences of temporal and contextual information	[62]
Generates Embedding Representations	MPVAE	Analysis of merging the memory pool into the dual- target	[56]
User preferences	GAN	Choosing a suitable adversarial training position	[23]

5) MUSIC/VIDEO RECOMMENDATION

Some platforms like Netflix and YouTube employ recommendation systems to suggest movies, TV shows, and videos to users based on their viewing history, ratings, and preferences. These systems aim to increase user engagement and retention. Services like Spotify and Apple Music use recommendation systems to suggest songs, albums, and playlists based on users' listening history, music preferences, and behavior patterns. These recommendations help the users discover new videos, movies, TV shows, and music the user might enjoy. Reference [40] propose a novel Generative Recommender paradigm named GeneRec, which adopts an AI generator to personalize content generation and leverages user instructions to acquire users' information needs.

6) FOOD RECOMMENDATIONS

Platforms like Grab, Uber Eats and Grubhub use recommendation systems to suggest restaurants and food items to users based on their previous orders, cuisine preferences, and location. These recommendations aim to enhance the user's ordering experience. In their review [72] reveals that the domain of food recommendation is very diverse, and most FRS are built using content-based filtering and Machine Learning approaches to provide non-personalized recommendations.

7) APPLICATION DOMAINS

The initial category in the classification of terms of the domain for recommender system is labeled as "Application." The category encompasses domains such as mobile, web, page, app, and session, which are frequently utilized in recommendation systems [87].

8) USER INFORMATION RECOMMENDATION

Within the "User Information" category, diverse recommendation techniques are employed to create personalized suggestions derived from user feedback, interest, career information, and Point of Interest (POI) data. One method involves feedback-based recommendations, utilizing a dual closed-loop structure to concurrently train both the encoder and decoder. This innovative framework facilitates the exchange of feedback signals between these elements, resulting in more precise and impactful recommendations [125].

9) HEALTH RECOMMENDATION

Health recommendation refers to the practice of utilizing recommendation systems to provide personalized advice, guidance, or suggestions related to health and wellness. These recommendations can cover a wide range of areas including diet, exercise, lifestyle modifications, medication adherence, preventive screenings, and healthcare services utilization. Health recommendation systems typically analyze various factors such as individual health data, medical history, preferences, goals, and sometimes external data sources like research findings or expert guidelines to generate tailored recommendations for users. In their article [49] developed a modified GAN architecture for schizophrenia sample augmentation. Enriched GAN evaluation measures using confidence interval and calibration. Generated artificial samples close to the original samples.

F. APPLICATIONS AND TECHNIQUES OF GENERATIVE AI IN RECOMMENDER SYSTEMS

1) PERFORMANCE OF GENERATIVE AI OVER TRADITIONAL AI IN RECOMMENDER SYSTEMS

Generative AI offers several advantages over traditional AI in recommender systems, this aspect answers the *Research Question RQ2 on the performance of recommender systems between Traditional AI and Generative AI*. It can address data sparsity issues by modeling implicit feedback [35], and generate personalized content to meet diverse user needs. Deep generative ranking models, such as the Wasserstein autoencoder framework, can enhance accuracy and generalization, particularly for near-cold-start users [126]. Additionally, generative models that combine collaborative filtering and text processing can outperform traditional systems, while also being faster These findings collectively suggest that generative AI has the potential to significantly improve the performance and user experience of recommender systems [127]. Recent advancements in recommender systems have seen the integration of generative artificial intelligence to address limitations in traditional retrieval-based systems [38]. This shift has led to the development of new paradigms, such as generative retrieval models that use semantic IDs for item identification. A range of studies have explored the use of Generative Adversarial Networks (GANs) in recommender systems. In their article [45] introduced a GAN-based framework using positive-unlabeled sampling, which was shown to be effective and efficient in comparison to other baselines. [117] incorporated user trust information into a GAN-based recommender system, resulting in improved recommendation accuracy, and [43] focused on the security aspect, using a modified GAN architecture to detect data pollution attacks on recommender systems. These studies collectively demonstrate the potential of GANs in enhancing the performance and security of recommender systems.

G. GENERATIVE AI TECHNIQUES ON RECOMMENDER SYSTEMS

1) GENERATING SYNTHETIC USER PROFILES

Generative AI techniques can be used to generate synthetic user profiles, enabling recommender systems to address data sparsity and cold start problems. Synthetic user profiles can be generated by learning from existing user profiles and capturing their underlying characteristics and preferences.

2) GENERATING ITEM EMBEDDING

Generative AI techniques can generate item embedding that captures the underlying characteristics of items. These embeddings can be used to improve recommendation accuracy by capturing subtle item relationships and enabling better similarity calculations.

3) ADDRESSING DATA SPARSITY AND COLD START PROBLEMS

Generative AI techniques can generate synthetic user-item interactions to address data sparsity, and cold start problems. By generating synthetic interactions, recommender systems can augment the training data, making it more diverse and representative of user preferences.

4) ENHANCING DIVERSITY IN RECOMMENDATIONS
Generative AI techniques can be employed to generate diverse recommendations by exploring the latent space of user preferences. By manipulating the generative model, recommender systems can generate recommendations that cater to different user tastes and preferences, thus enhancing diversity in the recommendations.

5) IMPROVING RECOMMENDATION QUALITY AND ACCURACY
Generative AI techniques can improve recommendation quality and accuracy by generating synthetic user-item interactions that reflect user preferences more accurately. This can help overcome biases and noise in the data and enable recommender systems to make more accurate predictions.

6) PERSONALIZED RECOMMENDATION GENERATION
Generative AI techniques can enable personalized recommendation generation by capturing individual user preferences and generating recommendations tailored to each user. This can lead to a more personalized and engaging user experience.

7) CROSS-DOMAIN AND CROSS-PLATFORM RECOMMENDATIONS
Exploring generative recommender systems in cross-domain and cross-platform settings is a promising avenue for future research.

Some of the authors are now enhancing the collaborative recommender systems with Generative AI, Generative AI can enhance collaborative filtering algorithms by generating synthetic data that fills in gaps or biases in existing user-item interactions. This can lead to more accurate and diverse recommendations for users [53], [57], [128], [129], [113]. GAN is very significant in the aspect of e-commerce platforms for recommender systems [130]

VI. LIMITATIONS AND FUTURE WORK
A. LIMITATIONS
This segment addresses the constraints of our study and suggests potential directions for future research. While we have gained valuable insights, it is important to recognize the limitations inherent in our approach. The current study has several limitations, including:

(a) There is no standardized method for conducting searches across all digital libraries, leading to potential inconsistencies.

(b) The papers presented in this review are solely based on English-language publications, as non-English publications were excluded.

(c) The selection of papers relied on criteria such as the title, abstract, keywords, and in some cases, the full text. This method may have overlooked relevant articles.

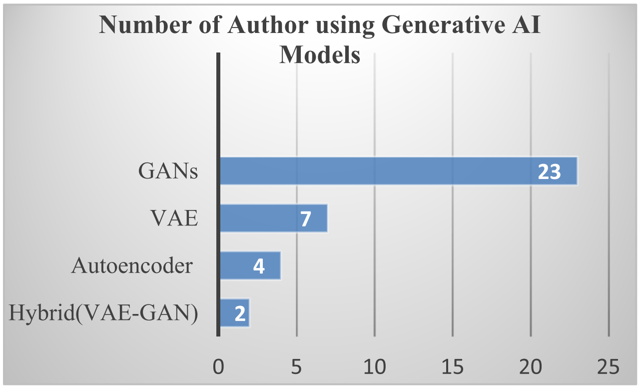

FIGURE 11. Most utilized models/techniques.

(d) We focused on only conference papers and peer-reviewed articles; we might have left out some articles in other forms.

(e) We did not access the paper to be purchased that may be relevant to our study.

Despite these limitations, our findings remain valuable in comprehending the techniques utilized and dataset preferences, providing a broad view of the recommender systems field. This knowledge can serve as a basis for future research endeavors and offer guidance to both researchers and practitioners. Hence, despite the constraints, this study still offers valuable insights for individuals engaged in recommender systems research and application.

Table 9, table 11 and figure 11 answers the Research Question RQ3 about the current trends and future directions in recommender systems using generative AI.

B. FUTURE WORK
Figure 11 illustrates that generative adversarial Networks (GAN) are the most used models or technique in the selected studies, though some of the authors combine with collaborative filtering method and with other models to enhance its performance.

VII. CONCLUSION
Our study concentrated on examining recommender systems using Generative AI models. We discovered that generative adversarial networks (GANs) emerged as the predominant technique/model across diverse domains, preference for specific techniques varied, depending on the application domains. This shows the significance of taking a specific domain characteristic into account when choosing an appropriate technique.

We anticipate that this review will offer readers and researchers a comprehensive understanding of the significant facets within this field, along with clarifying key advancements, and enlightening future research directions. Additionally, Recommender Systems (RSs) have become widely utilized across various domains in this modern era, this includes movies, books, social media, news, articles, and tourist recommendations. Various methods and models have been employed to enhance recommendations by predicting user preferences and intentions. The integration of generative AI in RSs has demonstrated notable effectiveness and achieved competitive performance. A variety of methods and domains have been reviewed to determine the most suitable approaches. Furthermore, datasets and metrics used in RSs have been extensively discussed and categorized. Generative AI has exhibited robust performance by generating suggestions based on user interests.

In conclusion, our review has significantly contributed to the progression of generative AI recommender systems over traditional recommender systems Our efforts have enhanced our insights into current models, patterns, simplified domain-specific terminology, and it will furnish researchers with valuable resources to engage with.

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