big data and cognitive computing

Review

From Traditional Recommender Systems to GPT-Based Chatbots: A Survey of Recent Developments and Future Directions

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Abstract: Recommender systems are a key technology for many applications, such as e-commerce, streaming media, and social media. Traditional recommender systems rely on collaborative filtering or content-based filtering to make recommendations. However, these approaches have limitations, such as the cold start and the data sparsity problem. This survey paper presents an in-depth analysis of the paradigm shift from conventional recommender systems to generative pre-trained-transformers-(GPT)-based chatbots. We highlight recent developments that leverage the power of GPT to create interactive and personalized conversational agents. By exploring natural language processing (NLP) and deep learning techniques, we investigate how GPT models can better understand user preferences and provide context-aware recommendations. The paper further evaluates the advantages and limitations of GPT-based recommender systems, comparing their performance with traditional methods. Additionally, we discuss potential future directions, including the role of reinforcement learning in refining the personalization aspect of these systems.

Keywords: conversational recommender systems; context-aware recommenders; generative pre-trained transformer (GPT); hybrid recommenders; natural language processing (NLP)

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1. Introduction

Recommender systems have emerged as indispensable tools in numerous applications, such as e-commerce [1], streaming media platforms [2], social media [3], energy [4], behavioral change [5], and personalized content recommendations [6]. These systems play a pivotal role in alleviating information overload for users by suggesting items that match their preferences and interests [7]. They mainly act as information filtering tools, and thus traditional recommender systems have relied on collaborative filtering, content-based filtering, or hybrid approaches to provide recommendations [8] among huge lists of options. While these methods have demonstrated effectiveness, they also come with inherent limitations [9].

In recent years, groundbreaking technology has captured the attention of the research community and industry alike: generative pre-trained transformers (GPT). These state-of-the-art deep learning (DL) models have demonstrated remarkable natural language understanding and generation capabilities. One of the most compelling applications of GPT technology is the development of GPT-based chatbots, which can engage in human-like conversations and comprehend the nuances of user queries [10].

The blend of GPT-based chatbots with recommender systems marks an exciting and transformative shift in the field of personalized recommendations [11,12]. With their ability to process vast amounts of textual data and engage users in interactive conversations, GPT-based chatbots hold the promise of offering recommendations that are not only accurate but also more contextually relevant and engaging than ever before [13,14]. By leveraging natural language processing (NLP) and DL techniques, these chatbots can better understand user intentions and preferences and deliver personalized suggestions that align with individual tastes and evolving interests [15]. They can also provide new ways of delivering filtered information to the users, thus improving the quality of the experience for them.

This survey paper aims to provide an in-depth exploration of the paradigm shift from traditional recommender systems to GPT-based chatbots as recommenders. We aim to offer a comprehensive review of recent developments and emerging trends in this exciting domain, shedding light on the potential advantages and challenges associated with GPT-based solutions. Therefore, the main contributions and unique aspects of our work include:

- **Comprehensive Categorization of Recommender Methods:** We provide a comprehensive categorization of various methods utilized to integrate GPT-based chatbots as recommenders. The paper also offers a clear and simplified taxonomy of these different techniques, enabling readers to easily understand and compare the diverse approaches employed in the domain of personalized recommendations.
- **Simplified Presentation of Previous Study Data:** In addition to presenting an overview of various techniques, we present data obtained from previous studies in a simplified manner. This simplification facilitates quick comprehension and comparison of the results of prior research, allowing readers to gain valuable insights into the performance of different GPT-based chatbot recommenders.
- **Recommendations and Future Directions for Research:** The survey paper concludes by providing informed recommendations and future research directions to enhance the effectiveness of GPT-based chatbots as recommenders. These recommendations are based on the findings of previous studies, serving as a roadmap for future researchers seeking to advance the field of personalized recommendations.

By adopting an engineering perspective, we aim to bring a fresh and innovative approach to the study of recommender systems and GPT-based chatbots, shedding light on the potential advantages and challenges these emerging technologies pose. Our paper aims to be a valuable resource for researchers and practitioners seeking to understand the exciting and dynamic landscape of GPT-based chatbots as recommenders and explore opportunities for further advancements in personalized recommendations.

In this paper, we aim to address the following key research questions:

- What are the recent developments and emerging trends in leveraging GPT-based chatbots for personalized recommendations?
- How can GPT models be fine-tuned and adapted to enhance the performance of recommender systems?
- What are the advantages and limitations of using GPT-based chatbots as recommenders compared to traditional collaborative filtering and content-based approaches?
- How can GPT-based chatbots facilitate context-aware and interactive recommendations, improving user engagement and satisfaction?
- What are the potential real-world applications and case studies demonstrating the effectiveness of GPT-based chatbots in recommendation scenarios?

Throughout the paper, we will systematically explore these research questions, providing insights and analyses based on our comprehensive literature review and synthesis of state-of-the-art techniques.

While our paper primarily focuses on the application of GPT models in recommender systems, it is important to note that many of the discussed techniques and principles can be extended to other large language models (LLMs), including open-source alternatives [16–19]. The field of LLMs is rapidly evolving, and we aim to provide a comprehensive understanding of how these powerful models can revolutionize personalized recommendations, regardless of the specific model architecture or training approach.

The paper continues with a description of the review methodology in Section 2, where the approach used to gather and analyze the data for this comparative study is outlined. Next, Section 3 explores traditional recommender systems, while Section 4 delves into emerging trends focusing on GPT technology. GPT-based chatbots for recommendation tasks are discussed in Section 5, along with case studies and real-world applications in Section 6. Section 7 raises several open issues of the emerging recommender systems and provides future research directions. The paper concludes in Section 8, summarizing key findings and prospects for GPT-based chatbots in recommender systems.

2. Review Methodology and Taxonomy

A systematic and rigorous literature review was conducted to provide a comprehensive overview of the recent developments in GPT-based chatbots for recommender systems.

2.1. Search Strategy, Inclusion/Exclusion Criteria, and Quality Assessment

Search Strategy: A systematic search strategy was employed to conduct a comprehensive review of GPT-based chatbots as recommenders and identify relevant academic papers and articles. The search was performed across various reputable academic databases and more specifically on Google Scholar, Scopus, and IEEE Xplore. Scopus was used first to get an idea of the volume of publications per year and the domains from which they come. The initial search parameter employed in Scopus was *"TITLE-ABS-KEY ("chatbot" AND "recommender systems")"*, which returned 134 results. To further narrow down the results, we added the term *("natural language processing" OR "personalized recommendations" OR "GPT")*, which resulted in 37 papers. The focus was mainly on peer-reviewed academic journals such as IEEE Xplore, IEEE Transactions, ACM Computing Surveys, AI Magazine published by Wiley, MDPI AI journal, and open-access articles from Springer. Also, various pre-print archiving services, such as arXiv, SSRN, and medRxiv, are included in Scopus. Finally, the search was extended to Google Scholar (with the full query), where we focused on "Review Articles". The result set included 310 articles.

Search Criteria: By screening the abstracts, assessing their credibility, and prioritizing the peer-reviewed sources, we finally selected articles that distinguish the different approaches of conversational recommender systems and their components. Employing a snowballing technique, references from selected articles were explored, while iterative refinement helped us adjust our search strategies. Figure 1 illustrates the process for selecting papers for this survey.

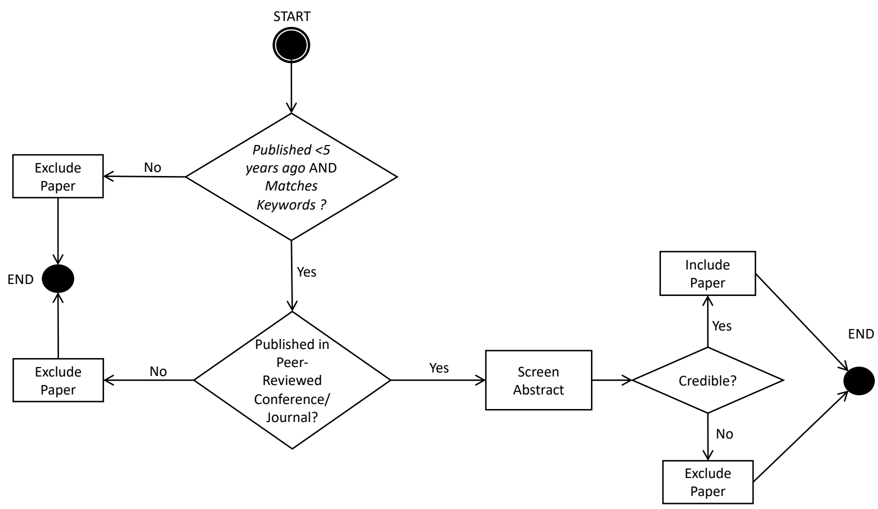

Figure 1. Flowchart illustrating how papers were systematically selected for the survey.

Inclusion and exclusion criteria: The criteria for the selected papers were as follows:

- **Inclusion criteria**
  - Focus on GPT-based chatbot applications in the context of recommender systems.
  - The publication date should be 2010 or later, focusing on the recently published articles in 5 years. However, all the resulting papers from Scopus were published after 2017.
  - Relevance to the research objectives, including discussions on technical aspects, implementation, performance evaluation, and future directions.
  - Investigations that provide insights into recent developments in GPT-based chatbots for recommender systems.
  - Publications available in English.
- **Exclusion Criteria**
  - Literature not related to, or does not focus on the application of GPT-based chatbots in recommender systems.
  - Studies that solely explore GPT-based applications in non-recommendation domains.
  - Studies that lack sufficient technical depth.
  - Articles not published in English.

After applying the inclusion and exclusion criteria, the remaining papers were selected for further analysis.

Given the dynamic nature of the field, the review prioritizes recently published articles, as clearly depicted in Figure 2, ensuring a focus on cutting-edge advancements. Moreover, the distribution of all papers utilized (i.e., papers that were both reviewed and used for supporting arguments) by year is as follows: 2004 (1), 2012 (1), 2013 (1), 2015 (3), 2016 (3), 2017 (1), 2018 (2), 2019 (7), 2020 (8), 2021 (6), 2022 (6), 2023 (37), and 2024 (23). While not delving too deep into each algorithm's technical intricacies, the review does explore relevant technical aspects, implementation considerations, and performance evaluations to provide a balanced understanding of the state-of-the-art GPT-based chatbots as recommenders.

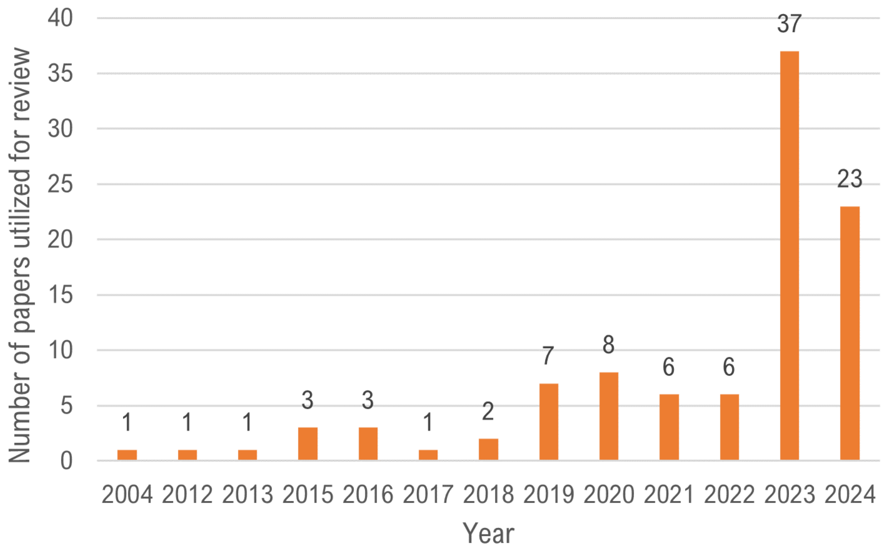

Figure 2. Year of publication of the reviewed papers.

Quality Assessment: The quality of the selected papers was evaluated based on their relevance, methodological rigor, the impact factor of the journals, and citation counts, ensuring the inclusion of credible and significant studies.

The results of our bibliography research are presented in the sections that follow. Moreover, the overall detailed selection process can be described in a PRISMA flow diagram, as shown in Figure 3.

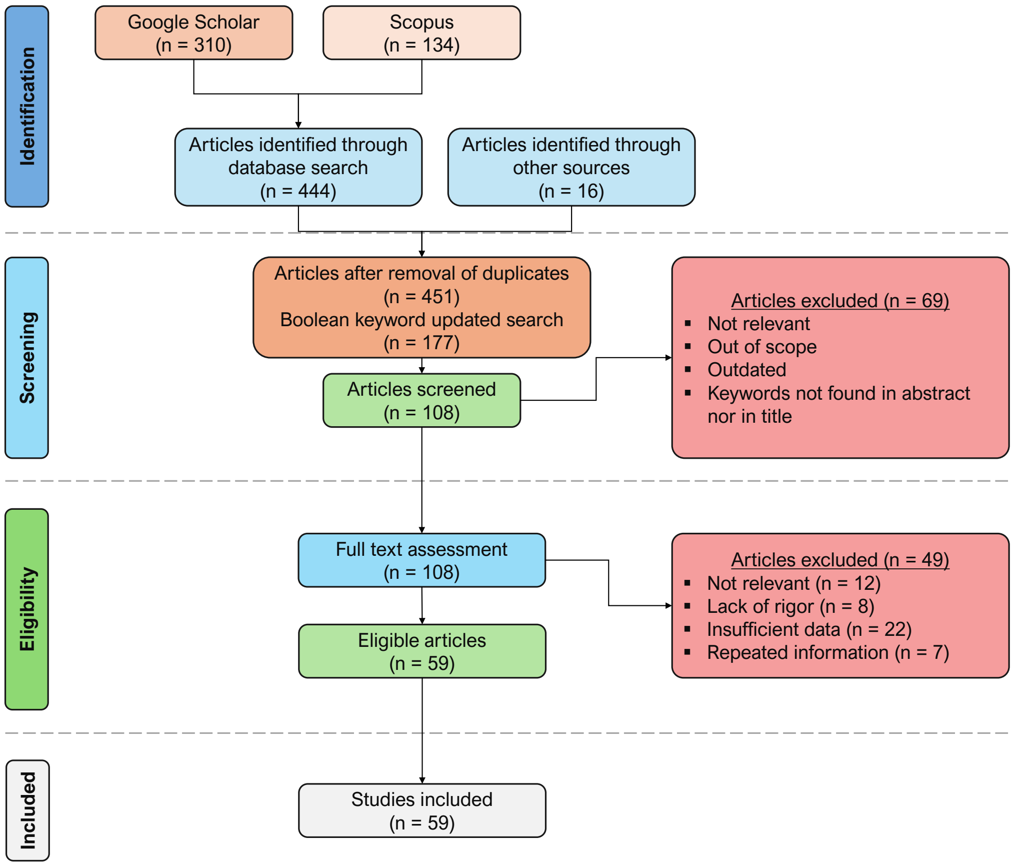

Figure 3. PRISMA flow diagram illustrating the systematic selection process.

2.2. Classification of GPT-Based Chatbots as Recommenders

In this paper, we present a comprehensive conceptual framework, as seen in Figure 4, that examines the landscape of recommender systems, focusing on the paradigm shift from traditional methods to GPT-based chatbots as recommenders. The framework is organized into key sections, each addressing distinct aspects of the research domain:

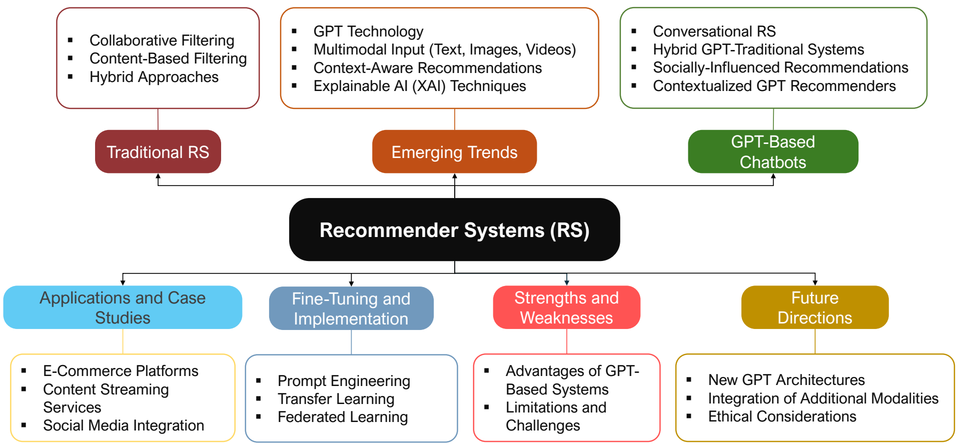

Figure 4. Dimensions of recommender systems.

- **Traditional Recommender Systems:** We start by providing an overview of traditional recommender systems, including collaborative filtering, content-based filtering, and hybrid approaches. Key techniques used in traditional recommender systems, such as matrix factorization and singular value decomposition, are explored in detail [20]. Additionally, we address the limitations and challenges faced by traditional recommender systems, including the cold start problem, data sparsity, and scalability issues [21].
- **Emerging Trends in Recommender Systems:** The respective section introduces GPT and highlights its transformative capabilities in the field of recommender systems. It discusses the advantages of GPT-based chatbots over traditional approaches, emphasizing their potential to revolutionize personalized recommendations. Moreover, it explores other emerging trends in recommender systems, such as incorporating additional data sources from social media and the Internet of Things (IoT), utilizing multimodal input (e.g., text, images, videos), and leveraging Explainable Artificial Intelligence (XAI) techniques for enhanced transparency and user trust [22].
- **GPT-based Chatbots for Recommendation:** Delving deeper into GPT-based chatbots, the respective section examines their application in recommendation tasks. It presents numerous examples of GPT-based chatbots in progress, demonstrating their efficacy in offering personalized suggestions to users. Furthermore, it explores the various ways GPT can be fine-tuned for enhancing recommendation tasks, including prompt engineering and transfer learning. A critical analysis of the strengths and weaknesses of GPT-based chatbots compared to traditional recommender systems sheds light on their potential impact on the field.
- **Case Studies and Real-World Applications:** To provide concrete insights, the section presents specific case studies and real-world applications where GPT-based chatbots have been employed in recommendation scenarios. These examples showcase the versatility and effectiveness of GPT-powered systems across diverse domains. Through these case studies, we derive valuable lessons and identify potential avenues for future research and comparative analysis.

This review paper's methods and taxonomy aim to thoroughly analyze the field of GPT-based chatbots as recommenders, considering various subcategories and recent advancements while maintaining a broader understanding of the technical foundations that underpin these novel systems.

3. Traditional Recommender Systems

In the realm of personalized recommendations, traditional recommender systems have played a foundational role, shaping the way users discover and engage with content across various domains. These systems, rooted in well-established methodologies, have been instrumental in alleviating the challenges posed by information overload and assisting users in navigating through the vast sea of choices [23]. Traditional recommender systems, commonly categorized, as shown in Figure 5, into collaborative filtering, content-based filtering, and hybrid approaches, have been the cornerstone of many recommendation platforms [24]. They operate based on historical user-item interactions, content attributes, or a combination of both to deliver tailored suggestions to users [25].

Collaborative filtering is a widely used technique in traditional recommender systems. It leverages the collective behavior of users to make recommendations [26,27]. It analyzes the similarities and patterns in user-item interactions to identify items that are likely to be of interest to a particular user [23,28,29]. Content-based filtering, on the other hand, focuses on the characteristics of the items themselves [30,31]. It recommends items to users based on the similarity between the content attributes of items and the users' preferences [25,32,33]. Hybrid approaches combine both collaborative and content-based filtering techniques to overcome the limitations of each approach and provide more accurate recommendations [34].

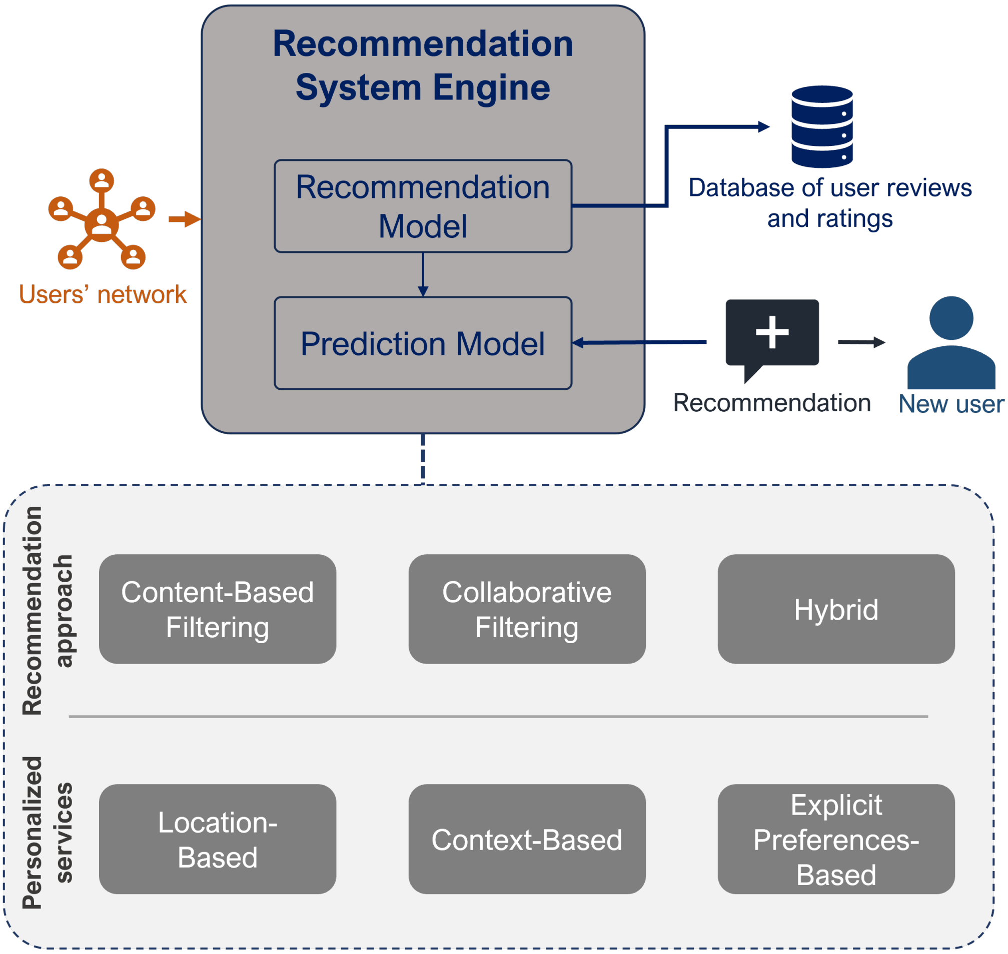

Figure 5. Basic diagram and classification of traditional recommender systems based on the user and content relation.

However, traditional recommender systems still have many open challenges. One of the key challenges is the cold start problem [25,35,36], scalability [34,37,38], and data sparsity [35,39,40]. To address these challenges, researchers have proposed various solutions. For example, some studies have focused on improving the accuracy of recommendations by incorporating additional information, such as user demographics or item features [41,42]. Others have explored the use of parallelization techniques, such as Apache Spark, to enhance the scalability of recommender systems [34,43]. Additionally, efforts have been made to evaluate the quality of traditional recommender systems through user studies and simulation frameworks [44,45].

In the subsequent sub-sections ahead, we will delve into the intricacies of these traditional methods, uncovering the techniques that underpin their functioning and critically examining their strengths and limitations. This comprehensive understanding will serve as a backdrop for our exploration of the transformative potential of GPT-based chatbots in ushering in a new era of personalized recommendations that transcend the constraints of traditional approaches.

3.1. Types of Traditional Recommender Systems

Traditional recommender systems encompass a spectrum of methodologies, each tailored to address specific recommendation challenges. By understanding these types, we gain insights into the diverse strategies employed in the quest for enhancing user experiences:

- **Collaborative Filtering:** Collaborative filtering hinges on the collective behaviors of users to generate recommendations. User-based collaborative filtering identifies users with similar preferences and suggests items enjoyed by others with similar preferences. On the other hand, item-based collaborative filtering identifies similarities among items and recommends those often favored by users who prefer a given item. The strengths of collaborative filtering include its ability to capture complex user preferences and adapt to evolving tastes, solely using the implicit or explicit preferences of users for items captured in a rating or interaction matrix. However, collaborative filtering can face challenges when dealing with sparse data and the cold start problem for new users or items [41,46–49].

- **Content-Based Filtering:** Content-based filtering centers on the intrinsic characteristics of items and users' historical preferences. By analyzing attributes like item descriptions, genres, and user profile information, this approach can make informed recommendations even when user-item interactions are limited. Content-based filtering excels at tackling the cold start problem, enabling accurate suggestions for new items. However, it may struggle to introduce users to novel or unexpected options due to its reliance on historical preferences [25,41,46,47,50,51].
- **Hybrid Approaches:** Hybrid recommender systems combine the strengths of collaborative and content-based filtering to deliver more accurate and diverse recommendations. Rule-based hybrids blend results from multiple recommendation techniques, optimizing their combined benefits. Model-based hybrids integrate different methods within a single model, learning to balance their contributions. Hybrid approaches seek to mitigate the limitations of individual methods, offering improved recommendation quality. However, designing effective hybrid solutions requires careful consideration of model complexity, data availability, and domain-specific challenges [41,46,47,51–53].

3.2. Key Techniques in Traditional Recommender Systems

Behind the scenes of traditional recommender systems are foundational techniques that drive recommendation generation and enhance user experience satisfaction. These techniques and algorithms are briefly presented in the following:

- **Matrix Factorization:** Matrix factorization involves decomposing the user-item interaction matrix into latent factor matrices. By capturing hidden patterns within the data, matrix factorization uncovers relationships between users and items. This technique enables accurate prediction of missing values, facilitating personalized recommendations. Matrix factorization methods include singular value decomposition (SVD), non-negative matrix factorization (NMF), and probabilistic matrix factorization (PMF) [23,54,55].
- **Singular Value Decomposition:** SVD is a widely used matrix factorization technique in recommender systems. It decomposes the user-item interaction matrix into three matrices: the user matrix, the item matrix, and a diagonal matrix of singular values. The resulting latent factors represent user preferences and item attributes. SVD-based methods offer interpretability and reveal underlying dimensions driving user-item interactions [54].
- **Other Techniques:** Traditional recommender systems extend beyond matrix factorization to encompass various techniques. Nearest-neighbor methods leverage user/item similarity metrics to make recommendations based on the preferences of similar users or items. Bayesian models combine user preferences with item attributes to predict preferences. Clustering algorithms group users or items with similar behaviors, facilitating recommendation generation [55–57].

3.3. Limitations and Challenges

While traditional recommender systems have proven valuable, they encounter inherent limitations that need further attention.

- **Cold-start Problem:** The cold start problem surfaces when new users or items lack sufficient interaction history for accurate recommendations. Traditional systems struggle to make relevant suggestions in such scenarios, hindering user satisfaction.

Solutions involve leveraging auxiliary data sources or employing hybrid methods to alleviate this challenge [25,41].

- **Scalability Issues:** As user bases and item catalogs expand, the scalability of traditional recommender systems becomes a concern. Processing large datasets and maintaining real-time responsiveness demand efficient algorithms and distributed computing frameworks [34].
- **Lack of Personalization:** Content-based filtering can lead to over-personalization, where users are confined within their existing preferences, missing out on serendipitous discoveries. Collaborative filtering might fail to capture fine-grained individual tastes, resulting in less precise recommendations. Striking a balance between diversity and relevance remains a persistent challenge [25].

To provide a comprehensive understanding of these systems, we present Table 1, which offers a detailed comparison of key aspects of collaborative filtering, content-based filtering, and hybrid approaches. This table highlights various dimensions, including the technique used, strengths, challenges, scalability, interpretability, diversity, adaptability, novelty, data requirements, and recommendation explanation.

Table 1. Comparison of traditional recommender systems.

Aspect	Collaborative Filtering	Content-Based Filtering	Hybrid Approaches
Technique	User/item similarity	Item characteristics	Combines both
Strengths	Captures complex user preferences, adapts to evolving tastes	Tackles cold start problem, provides accurate suggestions for new items	Balances collaborative and content-based filtering, offers improved recommendation quality
Challenges	Sparse data, cold start problem for new users/items	Limited novelty, reliance on historical preferences	Model complexity, data availability, domain-specific challenges
Scalability	Scales well with large user/item datasets, can be parallelized for efficiency	Scalable to large item catalogs, efficient for large datasets	Scalability depends on hybridization approach, complexity
Interpretability	User behavior-driven, harder to explain recommendations	Easy to explain based on item attributes	Interpretability varies based on hybrid approach
Diversity	Can struggle to provide diverse recommendations, may lead to filter bubbles	Offers diverse recommendations based on item attributes	Aims to balance diversity and relevance
Adaptability	Adapts to evolving user preferences over time	Less adaptable to changing user tastes	Adaptability depends on hybridization approach
Novelty	Might not recommend entirely new items to users	More likely to introduce users to novel options	Strives for a balance between familiarity and novelty
Data Requirements	Relies on historical user-item interactions	Requires item attribute data and user preferences	Data requirements vary based on hybrid approach
Explanation	May lack explainability in recommendations	Can provide clear explanations based on item attributes	Explanation varies based on hybrid approach
Handling Sparsity	Sensitive to data sparsity issues	Less sensitive to data sparsity, thanks to item attributes	Handling sparsity depends on hybridization approach

4. Emerging Trends in Recommender Systems

Recommender systems are constantly improving as user needs change and technology advances. New techniques are replacing old ones and transforming personalized recommendations. Recommender systems have made significant progress lately, driven by emerging trends that go beyond incremental improvements. These trends leverage cutting-edge technologies and novel approaches to deliver more accurate and engaging recommendations. From harnessing the prowess of GPT to embracing multimodal input, the following sections highlight the transformative potential of these emerging trends in recommender systems.

4.1. Introduction to GPT and Its Capabilities

The advent of GPT has marked a pivotal moment in NLP and artificial intelligence (AI). GPT models, particularly GPT-3 and GPT-4, are pre-trained on massive text corpora, enabling them to learn intricate language patterns, nuances, and semantics. This pre-training equips GPT models with the ability to generate coherent and contextually relevant text, making them valuable tools in conversational contexts. The generative capacity of GPT opens doors to crafting dynamic and engaging interactions with users. In the context of recommender systems, GPT's capabilities extend beyond static recommendations, transforming interactions into personalized, insightful conversations that mirror human communication [58–60].

4.2. Overview of GPT-Based Chatbots and Their Advantages

GPT-based chatbots represent a fusion of NLP and recommendation technology, revolutionizing how recommendations are delivered. These chatbots engage users in natural, human-like conversations, enhancing user interaction and personalization. Leveraging GPT's language generation ability, chatbots can offer real-time responses, comprehend user preferences expressed in natural language, and adapt recommendations within the flow of conversation. This dynamic interaction results in an immersive user experience where recommendations seamlessly integrate into dialogues, enhancing user engagement and satisfaction [59,60].

4.3. Beyond Item Descriptions and User Profiles: Incorporating Additional Data Sources

Modern recommendation platforms are venturing beyond traditional data sources to encompass a broader spectrum of user behaviors and preferences. By integrating data from social media interactions, IoT devices, location-based services, and more, these systems gain a holistic view of user context. This contextual understanding empowers recommender systems to deliver recommendations that resonate with users' real-world experiences. For instance, a user's social media activities (e.g., likes, comments, reviews) can unveil preferences not explicitly expressed, enriching the recommendation process [60].

4.4. Embracing Multimodal Input for Enhanced Recommendations

The digital landscape is increasingly multimodal, featuring a fusion of text, images, and videos. This trend has prompted recommender systems to expand their scope beyond text-only interactions. By analyzing and interpreting visual content, these systems gain insights into users' aesthetic preferences and visual interests. The incorporation of images and videos augments recommendation accuracy and relevance, offering users a more comprehensive and immersive experience [60].

One of the most prominent applications of multimodal recommendation lies in the synergy between visual and textual data. Consider an e-commerce platform where users seek fashion recommendations. By analyzing both textual descriptions and images of products, recommendation algorithms can gauge users' aesthetic preferences, color choices, and style inclinations. This fusion enables more accurate and appealing suggestions, leading to heightened user satisfaction and increased engagement [61].

Beyond fashion, the biomedical field exemplifies how multimodal recommendation can revolutionize industries. Imagine a medical diagnosis platform where healthcare professionals seek assistance in identifying diseases. By combining textual patient history with medical images, such as X-rays or MRI scans, the system can deliver precise diagnostic recommendations. This multimodal approach enhances diagnostic accuracy, reduces human error, and accelerates patient care, underscoring the transformative potential of multimodal recommendation in critical domains [62,63]. There are several other modalities that could benefit and create multiple opportunities to be carried out, as depicted in Figure 6.

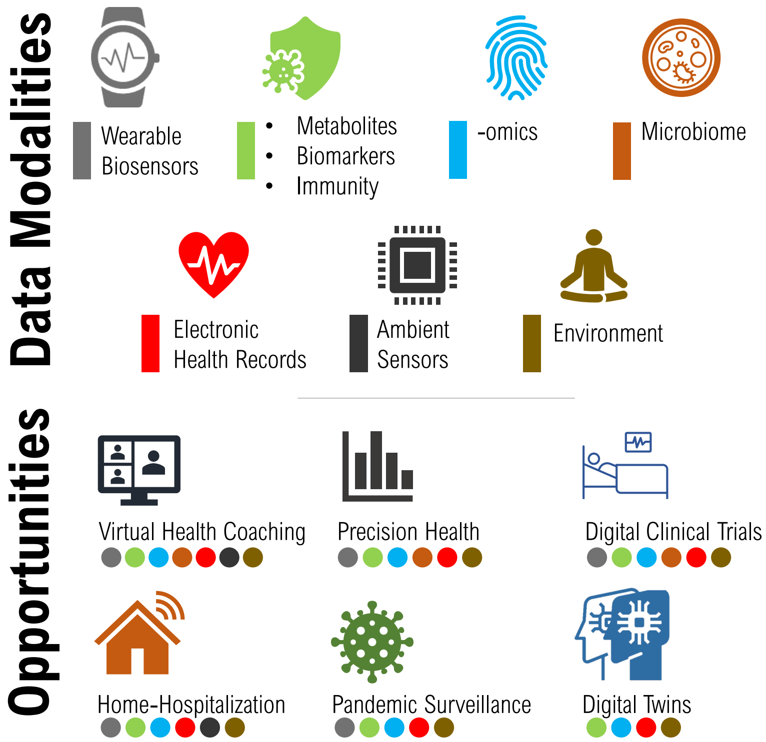

Figure 6. Potential multimodal biomedical AI data modalities and opportunities.

4.5. Leveraging XAI Techniques

As recommendation algorithms grow in complexity, understanding the rationale behind generated recommendations becomes crucial. Traditional recommendation models, while effective, often operate as black boxes, leaving users with little insight into the reasoning behind their recommendations. This opacity raises concerns about bias, fairness, and accountability. XAI techniques address the opacity often associated with complex models, enabling users to comprehend the rationale behind suggestions and fostering a sense of transparency and trust. They unveil the inner workings of the model, providing a clear line of sight into how recommendations are determined. By doing so, users are empowered to make informed decisions and have deeper engagement with the recommendation process [61].

4.5.1. Techniques for Transparent Recommendations

XAI encompasses a spectrum of techniques, each aimed at revealing different facets of recommendation generation. Feature attribution methods highlight the influence of specific user-item interactions or attributes on the final recommendations. Model visualization tools provide intuitive representations of complex models, offering users a graphical understanding of the decision landscape. Rule-based explanations generate human-readable rules that describe how recommendations are generated based on input features [61].

4.5.2. Enhancing User Trust and Interaction

Integrating XAI techniques goes beyond mere transparency; it fosters user trust and interaction. When users comprehend the logic behind recommendations, they are more likely to engage with and act upon them. Transparent explanations lend a sense of legitimacy to recommendations, making users feel valued and understood. This user-centric approach not only enhances the recommendation experience but also cultivates a long-term relationship between users and the recommendation platform [22,61].

4.5.3. Addressing Bias and Ethical Considerations

XAI techniques also play a pivotal role in addressing ethical concerns related to recommendation algorithms. They allow for detecting and mitigating biases that may emerge from historical data. Through transparent insights, XAI enables the identification of biased patterns and the implementation of fairness-aware models that strive to provide equitable recommendations for all users [61]. Fairness in recommendations ensures that users are not subjected to discriminatory or biased outcomes. Several approaches have been proposed to tackle this issue. Authors in [64] introduced the study of fairness in multi-armed bandit problems, where fairness demands that a worse applicant is never favored over a better one. The work presented in [65] emphasized the importance of providing personalized fair recommendations to satisfy users' personalized fairness demands. They highlighted the need to address potential unfairness problems in recommendations and provide personalized fairness based on users' preferences. Additionally, fairness issues on the user side have been less studied in recommender systems, and it is important to consider fairness from different perspectives, including user-side, item-side, or seller-side. Techniques such as adding fairness constraints to the learning objective and assessing fairness through different metrics have been explored. Advancing from associative fairness notions to causal fairness notions has also been proposed to assess fairness more properly in recommender systems [65]. These approaches aim to ensure that recommendations are fair, unbiased, and equitable for all users, addressing the ethical considerations associated with recommendation algorithms.

4.5.4. Balancing Complexity and Interpretability

While XAI techniques offer transparency, there is a delicate balance to strike between model complexity and interpretability. As models grow in sophistication, explanations can become intricate. Achieving a meaningful level of transparency without oversimplifying the model's intricacies is an ongoing challenge. Striking this balance ensures that recommendations remain insightful and actionable without sacrificing the benefits of advanced recommendation methodologies [61].

Overall, in Table 2, we summarize the emerging trends in recommender systems, highlighting their descriptions, applications, benefits, and corresponding references. These trends represent the forefront of recommender system research, leveraging advanced technologies and novel approaches to enhance user experiences. From GPT-based chatbots that enable dynamic and personalized interactions to the incorporation of multimodal recommendations that analyze both text and visual content, these trends offer exciting possibilities for the future of recommendation technology.

Table 2. Emerging trends in recommender systems.

Trend	Description	Applications and Benefits	Reference Works
GPT-Based Chatbots	Integration of GPT models into chatbots for dynamic and personalized interactions.	Enhanced user engagement, natural language conversations, and immersive recommendation experiences.	[59,60]
Multimodal Recommendations	Incorporation of visual content analysis into recommendations.	Improved recommendation accuracy, relevance, and user experience, especially in domains like e-commerce and healthcare.	[60,61]
Contextual Understanding	Utilization of contextual information from diverse sources, including social media and IoT data.	Recommendations aligned with users' real-world experiences, expanding the scope beyond historical preferences.	[60]

Table 2. *Cont.*

Trend	Description	Applications and Benefits	Reference Works
XAI Techniques	Implementation of XAI techniques for transparent and trustworthy recommendations.	User trust, fairness, bias mitigation, and ethical considerations addressed, fostering informed decision-making.	[22,61,64,65]

5. GPT-Based Chatbots for Recommendation

In the dynamic landscape of recommender systems, a transformative shift is unfolding with the integration of GPT into conversational agents or recommenders. This section delves into the intersection of advanced NLP and recommendation technology, elucidating how GPT-based chatbots are reshaping user engagement by seamlessly fusing language fluency with personalized suggestions.

This exploration begins with an examination of the GPT model's fine-tuning techniques tailored for recommendation tasks. We delve into prompt engineering, a process of linguistic calibration that leverages GPT's linguistic capacity to enhance personalized recommendations. Furthermore, we delve into the domain of transfer learning, exploring how GPT models integrate pre-existing knowledge with recommendation complexities to produce sophisticated recommendations.

5.1. Fine-Tuning GPT for Recommendation Tasks

Fine-tuning is a process that involves further training of a generic pre-trained language model, such as GPT, on a specific task or domain to improve its performance. It allows the model to learn from specific recommendation datasets, enabling it to understand the nuances of user preferences and generate more accurate suggestions [58,66].

Prompt engineering is a crucial aspect of fine-tuning GPT models for recommendation tasks. It involves designing effective prompts or input formats that elicit the desired recommendation outputs [58]. By carefully crafting prompts, we can guide the model to generate recommendations that align with user preferences and context, enhancing the relevance and personalization of GPT-based recommendations.

Transfer learning is another important technique for fine-tuning GPT models for recommendation tasks. It involves infusing pre-trained knowledge from large-scale language models into the recommendation context [58]. By leveraging the pre-trained knowledge, GPT models can benefit from understanding language patterns and semantics, enabling them to generate more coherent and contextually relevant recommendations. Transfer learning enhances the performance and adaptability of GPT-based recommendation models [59,67].

Federated learning is a collaborative training approach that can be applied to GPT-based models for enhanced recommendations [68], especially in a multi-user/multi-agent setup. In federated learning, multiple GPT models are trained on different local datasets from various sources, and the knowledge is shared and aggregated to improve the overall recommendation performance. This collaborative training allows GPT-based recommendation models to learn from diverse data sources while preserving privacy and security. Federated learning enables the creation of more robust and comprehensive recommendation models [68].

By exploring these fine-tuning techniques, GPT-based recommendation models can be optimized for recommendation tasks, providing personalized and context-aware suggestions to users. These techniques enhance the linguistic abilities of GPT models, infuse pre-trained knowledge, and enable collaborative training, ultimately improving the quality and effectiveness of recommendations.

5.2. Context-Aware Recommendations with GPT-Based Chatbots

GPT models have demonstrated the ability to comprehend conversational nuances and generate responses that align with ongoing interactions [69]. By utilizing this context understanding, GPT-based chatbots can provide recommendations tailored to the conversation, enhancing the user experience and engagement.

To achieve context-aware recommendations, GPT-based chatbots can adapt their suggestions based on the evolving user context [70]. By continuously analyzing the conversation and understanding the user's preferences and needs, the chatbot can offer personalized recommendations relevant to the specific context at hand. This dynamic adaptation ensures that the recommendations remain timely and enhance user satisfaction and engagement.

Several techniques have been proposed to enhance context-aware recommendations with GPT-based chatbots. For instance, diversity-promoting objective functions can be employed to generate more diverse and interesting responses, thereby expanding the range of recommendation options for users [69]. Additionally, personalization techniques, such as incorporating user-specific information and preferences, can further enhance the context-awareness of the recommendations [70].

Integrating context-aware recommendations with GPT-based chatbots opens up new possibilities for personalized and engaging interactions. By leveraging the inherent context understanding of GPT models and crafting recommendations that align with ongoing conversations, GPT-based chatbots can provide users with more relevant and tailored suggestions. This context awareness enhances the user experience, increases user satisfaction, and fosters a deeper level of engagement.

5.3. Comparative Analysis: GPT-Based Chatbots vs. Traditional Recommender Systems

GPT-based chatbots offer several advantages in personalized interactions. Firstly, they leverage the power of language models, such as GPT, to generate responses that are fluent, coherent, and contextually relevant [69]. This linguistic ability enhances the quality of recommendations and provides a more engaging user experience. Additionally, GPT-based chatbots have the potential to understand conversational nuances and adapt recommendations based on ongoing interactions, leading to more personalized and tailored suggestions.

However, GPT-based chatbots also have limitations and areas for potential improvement. One limitation is their tendency to generate generic or safe responses that lack specificity [69]. This can impact the diversity and novelty of recommendations, as the chatbot may tend to provide common or generic suggestions. Another challenge is the fine-tuning process, which requires a substantial amount of labeled data for training the model on specific recommendation tasks. Obtaining large-scale labeled datasets can be resource-intensive and time-consuming.

To assess the impact of GPT-based chatbots on recommendation accuracy and user satisfaction, various evaluation metrics can be employed. Traditional recommender systems have been evaluated using metrics such as precision, recall, and mean average precision [23]. These metrics can be adapted to evaluate the performance of GPT-based chatbots in generating accurate and relevant recommendations. Additionally, user satisfaction can be measured through user surveys, feedback, and user engagement metrics to gauge the effectiveness and user acceptance of GPT-based chatbot recommendations.

6. Case Studies and Real-World Applications

Using ChatGPT as a recommender system involves leveraging its NLP capabilities to provide personalized recommendations to users. Instead of just generating text-based responses, ChatGPT can analyze user preferences, interests, and contextual information from conversations to suggest products, services, content, or actions that align with the user's needs [10]. This approach goes beyond traditional recommendation algorithms by enabling more interactive and human-like interactions, resulting in more accurate and engaging recommendations tailored to individual users.

In recent years, there has been a growing interest in AI-driven conversational agents for personalized recommendations. These agents, often powered by advanced language models like GPT-3, can understand and respond to user queries more naturally and context-awarely. This enables them to gather richer information about user preferences, behaviors, and intents through conversations, leading to more accurate and personalized recommendations. Traditional recommendation systems often rely on user behavior and historical data, which can limit capturing the full spectrum of user interests. AI-driven conversational agents can engage users in dynamic conversations, asking clarifying questions and understanding nuances, allowing them to provide recommendations that align with users' real-time needs and preferences. This trend represents a shift towards more interactive and human-like recommendation experiences, ultimately enhancing user satisfaction and engagement.

Due to the increasing interest in AI-driven conversational agents for personalized recommendations, this section will review relevant works that showcase real case studies of utilizing ChatGPT as a recommender system. These case studies highlight how ChatGPT's capabilities have been harnessed to create more interactive, context-aware, and human-like recommendation experiences, contributing to the evolution of recommendation systems beyond conventional approaches. By examining these practical implementations, we can gain insights into the effectiveness and potential challenges of using ChatGPT for personalized recommendations in various domains.

6.1. Applications

In the upcoming sub-section, we will delve into the various applications that emerge from utilizing ChatGPT as a recommender system. This examination will illuminate the wide range of contexts and industries in which ChatGPT's abilities have been successfully utilized to offer individualized and captivating recommendations.

6.1.1. Book Recommendation

Chatbots have gained significant popularity as a growing method for delivering immediate assistance to library patrons [71]. Thus, authors in [72] discussed how the changing landscape of LLMs, such as GPT, has brought new life to various fields, leading to a fresh look at conventional scenarios and unveiling novel opportunities. Focusing on ChatGPT, the study pioneered the infusion of LLM technology into book resource comprehension and recommendation. A novel framework called BookGPT was developed, deploying ChatGPT for three distinctive book recommendation tasks: book rating recommendation, user rating recommendation, and book summary recommendation. The paper discussed BookGPT's strengths and limitations within book recommendation scenarios through meticulous evaluation and comparative analysis with established recommendation models. Notably, BookGPT demonstrated promising results in classic book recommendation tasks, excelling in situations with limited target information. Moreover, BookGPT outperformed manual editing methods in book summary recommendation and exhibits proficiency in generating personalized, interpretable content recommendations grounded in reader attributes. The study concluded by releasing datasets and code, inviting further exploration of LLMs' applications and theoretical research in book recommendations and beyond.

Likewise, the paper discussed in [73] centered on creating a specialized chatbot for the Zayed University Library in the UAE. This chatbot, named Aisha, was implemented using Python and the ChatGPT API. Its primary objective was to offer swift and effective reference and support services to students and faculty beyond the library's usual operational hours. The project served as an exploration of the potential of a ChatGPT-powered bot within academic libraries. It offered valuable insights into the future of AI-driven chatbot technology in this specific context.

6.1.2. Nutrition Recommendation

The correlation between low socioeconomic status (SES) and insufficient nutrition during pregnancy is associated with health disparities and adverse outcomes, including a heightened likelihood of preterm birth, low birth weight, and intrauterine growth restriction. AI-powered computational agents have significant potential to address this concern by providing nutritional guidance or suggestions to individuals with diverse levels of health literacy and varying demographic backgrounds. In light of this, Tsai et al. [74] conducted an initial investigation into developing a GPT-powered AI chatbot named NutritionBot, assessing its potential impact on pregnancy nutrition recommendations. The authors took a user-centered design approach to define the target user persona and collaborated with medical professionals to co-create the chatbot. They seamlessly integrated their proposed chatbot with ChatGPT to generate personalized pregnancy nutrition recommendations tailored to the patient's lifestyle.

6.1.3. Healthcare Recommendations

Due to ChatGPT's capability to offer human-like responses to intricate inquiries, it holds the potential to serve as an easily accessible resource for medical guidance sought by patients. Nonetheless, the extent to which it can aptly and equitably address medical inquiries remains a subject of exploration. In [75], the authors engaged ChatGPT with 96 vignettes involving requests for advice across diverse clinical contexts, medical histories, and social characteristics. They investigated the responses regarding their clinical appropriateness in alignment with established guidelines, the nature of recommendations provided, and the consideration of social factors. Remarkably, 93 out of 96 (i.e., 97%) responses were deemed appropriate and adhered to clinical guidelines without explicit violations. However, recommendations in response to advice-seeking queries were mainly absent. Notably, 53 responses (i.e., 55%) explicitly accounted for social factors such as race or insurance status, which sometimes led to modifications in clinical recommendations.

The paper in [76] presents XrayGPT, a novel conversational medical vision-language model. This model can answer open-ended questions about chest radiographs using a simple linear transformation to align medical visual encoders (MedClip) with a LLM named Vicuna. This alignment enables the model to excel in understanding radiographs and medical domain knowledge. To boost the performance of LLMs in the medical field, the authors generated 217,000 high-quality summaries from free-text radiology reports, which were used to fine-tune the model. This approach opens up new avenues for advancing the automated analysis of chest radiographs.

6.1.4. Hotel Recommendation

Recommender systems have evolved into crucial tools within the hotel hospitality industry, molding individualized guest experiences. There are now more opportunities to improve these systems by leveraging recent developments in LLMs like ChatGPT and persuasive technologies. The research presented in [77] examined the incorporation of ChatGPT and compelling technologies to elevate hotel hospitality recommender systems. The study initially delved into ChatGPT's adeptness in comprehending and generating human-like text, focusing on context-aware recommendations. The incorporation of ChatGPT into recommender systems was investigated, and this included user preference research, information obtained from online evaluations, and the development of tailored suggestions based on guest profiles.

Furthermore, the study also looked at how persuasive technology might influence user behavior and boost the impact of hotel recommendations. Strategies such as social proof, scarcity, and personalization were examined for their ability to influence user choices and desired behaviors. A pilot study examined how user engagement, satisfaction, and conversion rates were affected by ChatGPT and persuasive strategies. This study featured a hotel recommender system as a case study. The preliminary results highlighted these technologies' potential to improve guest experiences and business performance. Overall, this research contributed to the hotel hospitality field by delving into the complementary relationship between language models and persuasive technology, with positive implications for guest satisfaction and revenue outcomes.

6.1.5. Emotion Aware Recommendations

The field of research pertaining to emotion aware recommender systems (EARS) is characterized by its intricate and multifaceted nature, striving to offer personalized recommendations based on users' emotional preferences. The study presented in [78] emphasized the employment of a GPT NLP database, mainly focusing on ChatGPT, to identify affective attributes and generate affective indices. The affective index indication (AII) methodology evaluates human emotions by quantifying them into probability values. This technique has evolved through multiple iterations involving techniques like word lists, machine learning (ML) algorithms, and lexicon-based methods. Nonetheless, there remains a need for additional research endeavors to bolster the precision and reliability of models aimed at detecting, categorizing, and predicting emotions.

ChatGPT can offer a probabilistic assessment of the affective index, enabling the estimation of probabilistic values associated with Ekman's fundamental six human emotions, happiness, sadness, anger, fear, surprise, and disgust, within a given subjective passage. By measuring the resemblance between an affective index and a set of affective indices using a similarity metric, an AII list is generated, depicting the extent of similarity in affective indices between the reference object and its peers. This similarity score can be applied in various recommendation scenarios, encompassing collaborative-based, content-based, contextual-based, decision-based, and hybrid-based recommendation approaches [78].

Table 3 provides an overview of recent GPT-based chatbots employed as recommender systems across different domains and applications.

Table 3. Summary of recent GPT-based chatbots utilized as recommender systems in various applications.

Work	Approach	Dataset	Application	Performance	Advantage/Limitation
BookGPT [72] (2023)	Douban, Wenxin and ChatGPT 3.5	N/A	Online Shopping	Book recommendation	BookGPT shows promise in multiple types of recommendation tasks, displaying a wide range of utility within the book recommendation ecosystem.
Aisha [73]	ChatGPT API	Education	Library	Developing of the chatbot and discussing its perceived capabilities and limitations.	Pioneering application of ChatGPT-based chatbot technology in academic libraries, specifically for Zayed University Library in the United Arab Emirates.
[74] (2023)	NutritionBot: a GPT-powered chatbot	Data retrieved using the model of ChatGPT 3.5 Legacy	Healthcare	Produce nutrition advice for users	This study successfully integrated ChatGPT into NutritionBot, enabling the chatbot to generate pregnancy nutrition advice tailored to the patients' lifestyles, indicating the feasibility of using language models in healthcare applications.
[75] (2023)	ChatGPT	N/A	Healthcare	97% of the responses were considered suitable and did not explicitly breach clinical guidelines.	The study utilized three distinct clinical scenarios, and the responses generated by ChatGPT may not be broadly applicable to other clinical contexts.
XrayGPT [76] (2023)	GPT-4	Healthcare	Chest Radiographs Summarization	XrayGPT scored 82% in this evaluation compared to the baseline's 6%, further highlighting its superior performance in generating radiology-specific summaries.	Developing a conversational medical vision-language model named XrayGPT. This model is designed to analyze and answer open-ended questions about chest radiographs, bridging the gap between large vision-language models and specialized medical applications.
[77] (2023)	ChatGPT	N/A	Hospitality	Overall enhanced hotel guest experience.	This study investigated the integration of a hotel recommender system with ChatGPT, aiming to assess how this integration affected user engagement, satisfaction, and conversion rates.
[78] (2023)	GPT-3	N/A	EARS	Employing ChatGPT with conventional recommender system approach.	The paper proposed an approach that advocates for a separation of responsibilities. In this approach, users safeguard their emotional profile data, while EARS service providers abstain from retaining or storing this type of data.

6.2. Case Studies

This subsection delves into a collection of case studies exploring how ChatGPT has been employed to enhance recommendation strategies, foster engagement, and drive user satisfaction in various industries and contexts. These case studies give us insights into the transformative power of fusing state-of-the-art language models with recommendation systems, illuminating the path toward more intelligent and empathetic user interactions.

The study discussed in [79] established a benchmark to assess the effectiveness of ChatGPT in recommendation tasks while also comparing its performance against conventional recommendation models. The process of utilizing ChatGPT for recommendation tasks, depicted in Figure 7, comprises three sequential steps:

1. **Prompt Construction:** Tailored prompts are devised following the distinct attributes of the recommendation tasks at hand.
2. **Input for ChatGPT:** These constructed prompts are furnished as inputs to the ChatGPT model. In response, ChatGPT generates recommendation outcomes in alignment with the guidelines stipulated within the prompts.
3. **Refinement of the Output:** Within the refinement module, the recommendations generated by ChatGPT are examined and improved. The user is then given the final suggestion results, which are the refined results.

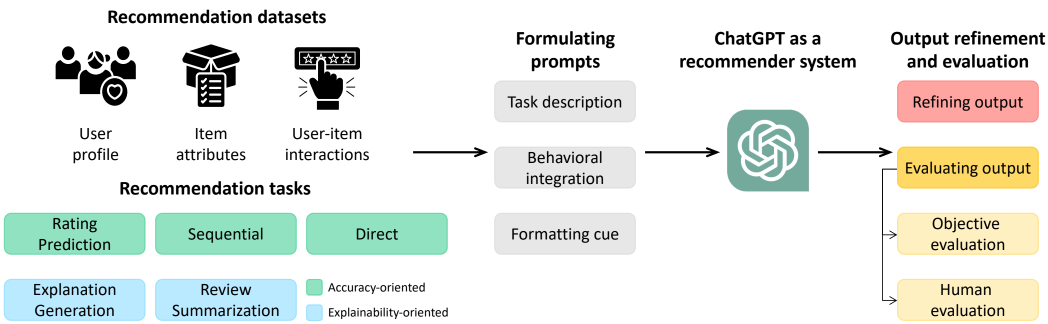

Figure 7. Overview of the sequence of steps for employing ChatGPT to execute five recommendation tasks and evaluate recommendations' quality.

To evaluate ChatGPT's capabilities as a recommender system, the researchers conducted comprehensive experiments using a real-world Amazon dataset. The results of these experiments revealed that ChatGPT excels in rating prediction tasks but demonstrates subpar performance in sequential and direct recommendation tasks [79]. This implies the need for additional research and skill development in these areas. Despite its shortcomings, ChatGPT outperformed cutting-edge human evaluation techniques for explainable recommendation tasks, highlighting its ability to produce summaries and explanations that support recommendations.

Furthermore, GPT4Rec, an innovative and adaptable generating framework inspired by search engines, was introduced by Li et al. [80]. The framework's process involves generating speculative search queries based on the titles of items in a user's history, which are then employed to retrieve recommended items through query-based searching. This approach overcame limitations by learning user and item preferences within the language space. A method for multi-query generation was proposed, incorporating beam search to effectively capture user interests across varying aspects and levels of detail, thus enhancing both relevance and diversity. The resulting queries can be used to suggest cold-start items that serve as naturally interpretable renderings of user interests. With a 75.70% and a 22.20% improvement in Recall@K on the 5-core Amazon review dataset, the framework outperformed state-of-the-art techniques. It was achieved by using and employing the GPT-2 language model and the BM25 search engine. Further experiments indicated that multi-query generation with beam search enhances item diversity and coverage of a user's interests. The framework's adaptability and the interpretability of generated queries were explored through qualitative case studies. In addition, Gao et al. [2] presented a new method known as Chat-Rec that makes use of LLMs to create conversational recommender systems. This method converts user profiles and past interactions into prompts. Through contextual learning, Chat-Rec demonstrated its efficiency in deciphering user preferences and creating links between customers and items, boosting the interactive and explanatory elements of the recommendation process. Notably, the Chat-Rec architecture enables the integration of prompt-based information into LLM-enabled management of cold-start scenarios with new items while transferring user preferences to a variety of products for cross-domain recommendations. In real-world tests, Chat-Rec significantly improved top-k recommendation results and excelled at zero-shot rating prediction challenges.

Similarly, in their case study, Dai et al. [81] performed an initial assessment of using off-the-shelf LLMs for recommendation tasks, examining them from point-wise, pair-wise, and list-wise perspectives. To comprehensively explore the personalized recommendation potential of ChatGPT and GPT-3.5, the authors conducted performance assessments using datasets from four domains: movies, books, music, and news. The outcomes across the four datasets demonstrated that ChatGPT displayed enhanced performance in few-shot/zero-shot recommendations compared to the three ranking approaches. It was noted that LLMs excelled in list-wise and pair-wise ranking. ChatGPT also exhibited the potential to address zero-shot cases and generated explainable recommendations.

Although the study delved into ChatGPT's ranking capabilities across diverse domains, certain limitations warrant additional investigation. Questions persist regarding how ChatGPT can be more effectively integrated with existing recommendation models and how it can be calibrated to incorporate user feedback data better. These areas present prosperous fields for further research and exploration. Table 4 summarizes recent GPT-based chatbots used as recommender systems in various case studies.

Table 4. Summary of recent ChatGPT-based studies.

Work	ChatGPT Version	Domain	Dataset	Performance
[79]	Not specified	Online shopping	Amazon beauty dataset	ChatGPT demonstrated superior performance compared to state-of-the-art methods in human evaluations for explainable recommendation tasks. This emphasizes its capability to produce explanations and summaries effectively.
[80]	GPT-2	Online shopping	5-core Amazon review data	The framework achieved significant performance improvements over state-of-the-art methods by utilizing the GPT-2 language model and the BM25 search engine. It outperformed them by 75.7% and 22.2% regarding Recall@K on two publicly available datasets.
[2]	GPT-3/3.5	Movies	MovieLens 100K	Chat-Rec notably enhanced the outcomes in terms of top-k recommendations and exhibited superior performance in zero-shot rating prediction tasks.
[81]	GPT-3	Movies, books, music, and news	MovieLens-1M, Books-Amazon, CDs & Vinyl-Amazonand MIND-small datasets	The results suggested that ChatGPT achieved an ideal equilibrium between cost and performance when it is equipped with list-wise ranking capabilities.

The capacity of ChatGPT to gather and analyze substantial volumes of personal data has brought up privacy apprehensions, and its potential to propagate biases necessitates careful design and testing of the resulting products. Moreover, ChatGPT's implementation can potentially result in job displacements by automating tasks that humans traditionally conducted. Despite these potential challenges, ChatGPT has garnered considerable interest and excitement within the academic and practitioner communities in marketing. AI, particularly ChatGPT and GPT4, holds immense potential to revolutionize marketing practices and define its future landscape [82].

7. Recommendations and Future Directions

In this section, detailed answers, derived from the information and analyses presented in the paper, are provided, demonstrating how the listed research questions have been comprehensively addressed throughout the manuscript.

1. What are the recent developments and emerging trends in leveraging GPT-based chatbots for personalized recommendations?
   The paper discusses several recent developments and emerging trends in leveraging GPT-based chatbots for personalized recommendations:
   - **Integration of GPT models into conversational agents or chatbots for dynamic and personalized interactions** (Section 4.2): "GPT-based chatbots represent a fusion of NLP and recommendation technology, revolutionizing how recommendations are delivered. These chatbots engage users in natural, human-like conversations, enhancing user interaction and personalization [83]".
   - **Incorporation of additional data sources from social media and the IoT to provide contextual recommendations** (Section 4.3): "By integrating data from social media interactions, IoT devices, location-based services, and more, these systems gain a holistic view of user context. This contextual understanding empowers recommender systems to deliver recommendations that resonate with users' real-world experiences [84]".
   - **Embracing multimodal input, such as text, images, and videos, for enhanced recommendations (Section** 4.4): "The digital landscape is increasingly multimodal, featuring a fusion of text, images, and videos. This trend has prompted recommender systems to expand their scope beyond text-only interactions. By analyzing and interpreting visual content, these systems gain insights into users' aesthetic preferences and visual interests [85,86]".
2. How can GPT models be fine-tuned and adapted to enhance the performance of recommender systems?
   The paper discusses various techniques for fine-tuning and adapting GPT models to enhance their performance in recommendation tasks:
   - **Fine-tuning GPT models on specific recommendation datasets** (Section 5.1): "Fine-tuning is a process that involves further training of a generic pre-trained language model, such as GPT, on a specific task or domain to improve its performance. It allows the model to learn from specific recommendation datasets, enabling it to understand the nuances of user preferences and generate more accurate suggestions [17]".
   - **Prompt engineering to guide GPT models to generate relevant recommendations** (Section 5.1): "Prompt engineering is a crucial aspect of fine-tuning GPT models for recommendation tasks [87]. It involves designing effective prompts or input formats that elicit the desired recommendation outputs. By carefully crafting prompts, we can guide the model to generate recommendations that align with user preferences and context, enhancing the relevance and personalization of GPT-based recommendations [88]".
   - **Transfer learning to infuse pre-trained knowledge from large-scale language models** (Section 5.1): "Transfer learning is another important technique in fine-tuning GPT models for recommendation tasks. It involves infusing pre-trained knowledge from large-scale language models into the recommendation context. By leveraging the pre-trained knowledge, GPT models can benefit from understanding language patterns and semantics, enabling them to generate more coherent and contextually relevant recommendations [89]".
3. What are the advantages and limitations of using GPT-based chatbots as recommenders compared to traditional collaborative filtering and content-based approaches?
   The paper discusses both the advantages and limitations of using GPT-based chatbots as recommenders compared to traditional approaches.

- **Advantages (Section 5.3)**:
  - Leverage the power of language models to generate fluent, coherent, and contextually relevant responses, enhancing recommendation quality and user experience.
  - Understand conversational nuances and adapt recommendations based on ongoing interactions, leading to more personalized and tailored suggestions.
  - Potential to address the cold-start problem and provide explainable recommendations.
- **Limitations (Section 5.3)**:
  - Tendency to generate generic or safe responses, impacting the diversity and novelty of recommendations.
  - Requirement for substantial amounts of labeled data for fine-tuning on specific recommendation tasks.
  - Challenges in effectively integrating GPT-based chatbots with existing recommendation models and incorporating user feedback data.

4. How can GPT-based chatbots facilitate context-aware and interactive recommendations, improving user engagement and satisfaction?
   The paper discusses how GPT-based chatbots can facilitate context-aware and interactive recommendations, improving user engagement and satisfaction:
   - **Context-aware recommendations** (Section 5.2): "GPT models have demonstrated the ability to comprehend conversational nuances and generate responses that align with ongoing interactions. By utilizing this context understanding, GPT-based chatbots can provide recommendations tailored to the conversation, enhancing the user experience and engagement [90]".
   - **Adapting recommendations based on evolving user context** (Section 5.2): "To achieve context-aware recommendations, GPT-based chatbots can adapt their suggestions based on the evolving user context. By continuously analyzing the conversation and understanding the user's preferences and needs, the chatbot can offer personalized recommendations relevant to the specific context at hand [91]".
   - **Engaging users in natural, human-like conversations** (Section 4.2): "GPT-based chatbots engage users in natural, human-like conversations, enhancing user interaction and personalization. Leveraging GPT's language generation ability, chatbots can offer real-time responses, comprehend user preferences expressed in natural language, and adapt recommendations within the flow of conversation [92,93]."
5. What are the potential real-world applications and case studies demonstrating the effectiveness of GPT-based chatbots in recommendation scenarios?
   The paper presents several real-world applications and case studies demonstrating the effectiveness of GPT-based chatbots in recommendation scenarios:
   - **Book recommendation** (Section 6.1.1): The paper discusses the BookGPT framework, which employs ChatGPT for book recommendation tasks such as book rating recommendation, user rating recommendation, and book summary recommendation.
   - **Nutrition recommendation** (Section 6.1.2): The paper explores the development of NutritionBot, a GPT-powered chatbot that generates personalized pregnancy nutrition recommendations tailored to patients' lifestyles.
   - **Healthcare recommendations** (Section 6.1.3): The paper presents case studies where ChatGPT is used to provide medical guidance and recommendations, considering diverse clinical contexts, medical histories, and social characteristics.
   - **Hotel recommendation** (Section 6.1.4): The paper discusses the integration of ChatGPT and persuasive technologies into hotel hospitality recommender systems, aiming to enhance user engagement, satisfaction, and conversion rates.

- **Emotion-aware recommendations** (Section 6.1.5): The paper explores the use of ChatGPT in EARS, employing the AII methodology to quantify and incorporate emotional preferences into recommendations.

Moreover, we will address key open research questions in the field of recommender systems. These questions are intended to provide direction for future research efforts and contribute to the progress of recommendation technology.

- **Explainability and Transparency:** One central concern revolves around enhancing the explainability and transparency of recommender systems. As recommendation algorithms become more intricate, providing users with comprehensible explanations for their recommendations becomes paramount. Investigating techniques to generate interpretable explanations and develop transparent recommendation models is essential to fostering user trust and satisfaction [94,95].
- **Ethical Considerations:** Ethical considerations in recommender systems present another significant challenge. These systems can significantly influence user behavior and preferences, necessitating a focus on issues such as fairness, diversity, and privacy in recommendation algorithms. Research should concentrate on developing fair and unbiased recommendation models, ensuring diversity in recommendations, and safeguarding user privacy [96].
- **Contextual Recommendations:** Improving contextual recommendations is a pivotal research direction. Context profoundly influences user preferences and decision-making. Incorporating contextual information, such as time, location, and social context, into recommendation algorithms can enhance the relevance and effectiveness of recommendations. Investigating techniques to capture and utilize contextual information in recommender systems is an important research direction [97].
- **Long-Term User Modeling:** The construction of long-term user models is another key area of interest in recommender systems. User preferences evolve over time, requiring recommender systems to adapt accordingly. Developing user modeling techniques capable of capturing long-term user behavior and preferences can lead to more accurate and personalized recommendations. Research in this area should explore methods for modeling user preferences over extended periods and incorporating temporal dynamics into recommendation algorithms [98].
- **Cross-Domain Recommendations:** Enhancing cross-domain recommendations presents an intriguing challenge. Recommender systems often focus on specific domains, yet users have diverse interests spanning multiple areas. Investigating techniques for effectively recommending items across different domains and addressing the challenges of data sparsity and domain adaptation are critical research directions [99].

These open research questions provide a foundation for future investigations in the field of recommender systems. By addressing these challenges, we can advance the state-of-the-art in recommendation technologies and improve user experiences in various domains. Recommender systems have become integral in our daily lives, guiding us to relevant information, products, and services. However, several open questions and challenges remain, requiring further research to enhance the effectiveness and usability of these systems.

8. Conclusions

In conclusion, this survey paper has comprehensively explored the paradigm shift from traditional recommender systems to GPT-based chatbots as recommenders. Through a systematic review methodology and taxonomy, we have examined the diverse landscape of GPT-powered solutions in the context of personalized recommendations.

The discussion on GPT-based chatbots for recommendation tasks offered insights into their applications, fine-tuning methods, and a critical analysis of their strengths and weaknesses compared to traditional systems. By examining specific case studies and real-world applications, we demonstrated the versatility and potential impact of GPT-powered solutions in diverse recommendation domains.

We have also provided detailed answers to the research questions posed in this study. By addressing these research questions and providing valuable insights into the applications and implications of GPT-based chatbots in personalized recommendations, this survey paper contributes to the evolving landscape of recommendation systems and sets the stage for future advancements in this dynamic field.

As a result of our survey, we identified open research questions and presented potential future directions. These recommendations provide researchers with valuable insights to further explore new GPT architectures, training methods, the integration of several additional modalities, and ethical considerations in recommender systems.

Overall, this survey paper underscores the significance of GPT-based chatbots as game-changers in personalized recommendations. As the field continues to evolve rapidly, we believe that GPT-powered solutions hold the promise of redefining user experiences in various domains, from e-commerce to content streaming platforms. The seamless integration of GPT technology with traditional recommender systems showcases the potential for creating more contextually relevant and engaging user experiences.

This survey paper provides a thorough knowledge of GPT-based chatbots as recommenders and serves as a significant resource for scholars and practitioners in the rapidly evolving field of AI and recommender systems. It also encourages additional study and innovation in this fascinating field. As we look towards the future, we call upon the research community to collaborate and push the boundaries of GPT-based solutions, ultimately advancing the state-of-the-art in personalized recommendations for users worldwide.

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References

1. Regàs, B.I. Recommendatory System for Supermarket Online Shopping. Master's Thesis, Universitat Politècnica de Catalunya, Barcelona, Spain, 2022.
2. Gao, Y.; Sheng, T.; Xiang, Y.; Xiong, Y.; Wang, H.; Zhang, J. Chat-rec: Towards interactive and explainable llms-augmented recommender system. *arXiv* **2023**, arXiv:2303.14524.
3. Li, Y.; Tan, Z.; Liu, Y. Privacy-Preserving Prompt Tuning for Large Language Model Services. *arXiv* **2023**, arXiv:2305.06212.
4. Sayed, A.; Himeur, Y.; Alsalemi, A.; Bensaali, F.; Amira, A. Intelligent edge-based recommender system for internet of energy applications. *IEEE Syst. J.* **2021**, *16*, 5001–5010. [CrossRef]
5. Varlamis, I.; Sardianos, C.; Dimitrakopoulos, G.; Alsalemi, A.; Bensaali, F.; Himeur, Y.; Amira, A. Rehab-c: Recommendations for energy habits change, future generation computer systems. *Future Gener. Comput. Syst.* **2020**, *112*, 394–407.
6. Geng, S.; Liu, S.; Fu, Z.; Ge, Y.; Zhang, Y. Recommendation as language processing (rlp): A unified pretrain, personalized prompt & predict paradigm (p5). In Proceedings of the 16th ACM Conference on Recommender Systems, Seattle, WA, USA, 18–23 September 2022; pp. 299–315.
7. Himeur, Y.; Alsalemi, A.; Al-Kababji, A.; Bensaali, F.; Amira, A.; Sardianos, C.; Dimitrakopoulos, G.; Varlamis, I. A survey of recommender systems for energy efficiency in buildings: Principles, challenges and prospects. *Inf. Fusion* **2021**, *72*, 1–21. [CrossRef]

8. Yannam, V.R.; Kumar, J.; Babu, K.S.; Sahoo, B. Improving group recommendation using deep collaborative filtering approach. *Int. J. Inf. Technol.* **2023**, *15*, 1489–1497. [CrossRef]
9. Kumari, T.S.; Sagar, K. A Semantic Approach to Solve Scalability, Data Sparsity and Cold-Start Problems in Movie Recommendation Systems. *Int. J. Intell. Syst. Appl. Eng.* **2023**, *11*, 825–837.
10. Sohail, S.S.; Farhat, F.; Himeur, Y.; Nadeem, M.; Madsen, D.Ø.; Singh, Y.; Atalla, S.; Mansoor, W. Decoding ChatGPT: A Taxonomy of Existing Research, Current Challenges, and Possible Future Directions. *J. King Saud-Univ. Inf. Sci.* **2023**, *35*, 101675.
11. Rima, S.; Meriem, H.; Najima, D.; Rachida, A. Toward a Generative Chatbot for an OER Recommender System Designed for the Teaching Community: General Architecture and Technical Components. In Proceedings of The International Conference on Artificial Intelligence and Computer Vision, Marrakesh, Morocco, 5–7 March 2023; pp. 348–357.
12. Omara, J.; Talavera, E.; Otim, D.; Turcza, D.; Ofumbi, E.; Owomugisha, G. A field-based recommender system for crop disease detection using machine learning. *Front. Artif. Intell.* **2023**, *6*, 1010804. [CrossRef]
13. Goktas, P.; Karakaya, G.; Kalyoncu, A.F.; Damadoglu, E. Artificial Intelligence Chatbots in Allergy and Immunology Practice: Where Have We Been and Where Are We Going? *J. Allergy Clin. Immunol. Pract.* **2023**, *11*, 2697–2700. [CrossRef]
14. Sohail, S.S.; Farhat, F.; Himeur, Y.; Nadeem, M.; Madsen, D.Ø.; Singh, Y.; Atalla, S.; Mansoor, W. The Future of GPT: A Taxonomy of Existing ChatGPT Research, Current Challenges, and Possible Future Directions. *SSRN* **2023**. [CrossRef]
15. Pathak, A. Exploring ChatGPT: An Extensive Examination of its Background, Applications, Key Challenges, Bias, Ethics, Limitations, and Future Prospects. *SSRN* **2023**. [CrossRef]
16. Deldjoo, Y. Understanding Biases in ChatGPT-based Recommender Systems: Provider Fairness, Temporal Stability, and Recency. *arXiv* **2024**, arXiv:2401.10545.
17. Spurlock, K.D.; Acun, C.; Saka, E.; Nasraoui, O. ChatGPT for Conversational Recommendation: Refining Recommendations by Reprompting with Feedback. *arXiv* **2024**, arXiv:2401.03605.
18. Wang, Z. Empowering Few-Shot Recommender Systems with Large Language Models-Enhanced Representations. *IEEE Access* **2024**, *12*, 29144–29153. [CrossRef]
19. Xu, L.; Zhang, J.; Li, B.; Wang, J.; Cai, M.; Zhao, W.X.; Wen, J.R. Prompting Large Language Models for Recommender Systems: A Comprehensive Framework and Empirical Analysis. *arXiv* **2024**, arXiv:2401.04997.
20. Varlamis, I.; Sardianos, C.; Chronis, C.; Dimitrakopoulos, G.; Himeur, Y.; Alsalemi, A.; Bensaali, F.; Amira, A. Using big data and federated learning for generating energy efficiency recommendations. *Int. J. Data Sci. Anal.* **2022**, *16*, 353–369. [CrossRef]
21. Alsalemi, A.; Himeur, Y.; Bensaali, F.; Amira, A.; Sardianos, C.; Varlamis, I.; Dimitrakopoulos, G. Achieving domestic energy efficiency using micro-moments and intelligent recommendations. *IEEE Access* **2020**, *8*, 15047–15055. [CrossRef]
22. Sardianos, C.; Varlamis, I.; Chronis, C.; Dimitrakopoulos, G.; Alsalemi, A.; Himeur, Y.; Bensaali, F.; Amira, A. The emergence of explainability of intelligent systems: Delivering explainable and personalized recommendations for energy efficiency. *Int. J. Intell. Syst.* **2021**, *36*, 656–680. [CrossRef]
23. Herlocker, J.L.; Konstan, J.A.; Terveen, L.G.; Riedl, J.T. Evaluating collaborative filtering recommender systems. *ACM Trans. Inf. Syst.* **2004**, *22*, 5–53. [CrossRef]
24. Tharwat, M.; Jacob, D.W.; Fudzee, M.F.M.; Kasim, S.; Ramli, A.A.; Lubis, M. The role of trust to enhance the recommendation system based on social network. *Int. J. Adv. Sci. Eng. Inf. Technol.* **2020**, *10*, 1387–1395. [CrossRef]
25. Lee, Y.; Jung, Y. A Mapping Approach to Identify Player Types for Game Recommendations. *Information* **2019**, *10*, 379. [CrossRef]
26. Natarajan, S.; Vairavasundaram, S.; Natarajan, S.; Gandomi, A.H. Resolving data sparsity and cold start problem in collaborative filtering recommender system using linked open data. *Expert Syst. Appl.* **2020**, *149*, 113248. [CrossRef]
27. Ye, H.; Li, X.; Yao, Y.; Tong, H. Towards robust neural graph collaborative filtering via structure denoising and embedding perturbation. *ACM Trans. Inf. Syst.* **2023**, *41*, 1–28. [CrossRef]
28. Xia, L.; Huang, C.; Shi, J.; Xu, Y. Graph-less collaborative filtering. In Proceedings of the ACM Web Conference 2023, Austin, TX, USA, 30 April–4 May 2023; pp. 17–27.
29. Xu, S.; Tan, J.; Heinecke, S.; Li, V.J.; Zhang, Y. Deconfounded causal collaborative filtering. *ACM Trans. Recomm. Syst.* **2023**, *1*, 1–25. [CrossRef]
30. Jozani, M.; Liu, C.Z.; Choo, K.K.R. An empirical study of content-based recommendation systems in mobile app markets. *Decis. Support Syst.* **2023**, *169*, 113954. [CrossRef]
31. Mishan, M.T.; Amir, A.L.; Supir, M.H.B.M.; Kushan, A.L.; Zulkifli, N.; Rahmat, M.H. Integrating Business Intelligence and Recommendation Marketplace System for Hawker Using Content Based Filtering. In Proceedings of the 2023 4th International Conference on Artificial Intelligence and Data Sciences (AiDAS), Ipoh, Malaysia, 6–7 September 2023; pp. 200–205.
32. Nosrati, V.; Rahmani, M.; Jolfaei, A.; Seifollahi, S. A Weak-Region Enhanced Bayesian Classification for Spam Content-Based Filtering. *ACM Trans. Asian-Low Lang. Inf. Process.* **2023**, *22*, 1–18. [CrossRef]
33. El-Shaikh, A.; Seeger, B. Content-based filter queries on DNA data storage systems. *Sci. Rep.* **2023**, *13*, 7053. [CrossRef]
34. Ikhsanudin, R.; Winarko, E. Parallelization of Hybrid Content Based and Collaborative Filtering Method in Recommendation System with Apache Spark. *IJCCS Indones. J. Comput. Cybern. Syst.* **2019**, *13*, 149–158. [CrossRef]
35. Patro, S.G.K.; Mishra, B.K.; Panda, S.K.; Kumar, R.; Long, H.V.; Taniar, D. Cold start aware hybrid recommender system approach for E-commerce users. *Soft Comput.* **2023**, *27*, 2071–2091. [CrossRef]
36. Chen, C.C.; Lai, P.L.; Chen, C.Y. ColdGAN: An effective cold-start recommendation system for new users based on generative adversarial networks. *Appl. Intell.* **2023**, *53*, 8302–8317. [CrossRef]

37. Nazari, A.; Kordabadi, M.; Mansoorizadeh, M. Scalable and Data-Independent Multi-Agent Recommender System Using Social Networks Analysis. *Int. J. Inf. Technol. Decis. Mak.* **2023**, 1–22. [CrossRef]
38. Hu, H.; Dobbie, G.; Salcic, Z.; Liu, M.; Zhang, J.; Lyu, L.; Zhang, X. Differentially private locality sensitive hashing based federated recommender system. *Concurr. Comput. Pract. Exp.* **2023**, *35*, e6233. [CrossRef]
39. Idrissi, N.; Zellou, A. A systematic literature review of sparsity issues in recommender systems. *Soc. Netw. Anal. Min.* **2020**, *10*, 15. [CrossRef]
40. Salas, J. Sanitizing and measuring privacy of large sparse datasets for recommender systems. *J. Ambient. Intell. Humaniz. Comput.* **2023**, *14*, 15073–15084. [CrossRef]
41. Choi, S.M.; Jang, K.; Lee, T.D.; Khreishah, A.; Noh, W. Alleviating item-side cold-start problems in recommender systems using weak supervision. *IEEE Access* **2020**, *8*, 167747–167756. [CrossRef]
42. Chaimalas, I.; Walker, D.M.; Gruppi, E.; Clark, B.R.; Toni, L. Bootstrapped personalized popularity for cold start recommender systems. In Proceedings of the 17th ACM Conference on Recommender Systems, Singapore, 18–22 September 2023; pp. 715–722.
43. Kalla, D.; Smith, N.; Samaah, F.; Polimetla, K. Hybrid Scalable Researcher Recommendation System Using Azure Data Lake Analytics. *J. Data Anal. Inf. Process.* **2024**, *12*, 76–88. [CrossRef]
44. Rajput, S.; Mehta, N.; Singh, A.; Hulikal Keshavan, R.; Vu, T.; Heldt, L.; Hong, L.; Tay, Y.; Tran, V.; Samost, J.; et al. Recommender systems with generative retrieval. *Adv. Neural Inf. Process. Syst.* **2024**, *36*, 10299–10315.
45. Alkan, O.; Daly, E.M.; Botea, A. An evaluation framework for interactive recommender systems. In Proceedings of the Adjunct Publication of the 27th Conference on User Modeling, Adaptation and Personalization, Larnaca, Cyprus, 9–12 June 2019; pp. 217–218.
46. Zahra, S.; Ghazanfar, M.A.; Khalid, A.; Azam, M.A.; Naeem, U.; Prugel-Bennett, A. Novel centroid selection approaches for KMeans-clustering based recommender systems. *Inf. Sci.* **2015**, *320*, 156–189. [CrossRef]
47. Safoury, L.; Salah, A. Exploiting User Demographic Attributes for Solving Cold-Start Problem in Recommender System. *Lect. Notes Softw. Eng.* **2013**, *1*, 303–307. [CrossRef]
48. Hansel, A.C.; Wibowo, A. Using Movie Genres in Neural Network Based Collaborative Filtering Movie Recommendation System to Reduce Cold Start Problem. *Int. J. Emerg. Technol. Adv. Eng.* **2022**, *12*, 63–73. [CrossRef]
49. Vairachilai, S.; Kavithadevi, M.K.; Raja, M. Alleviating the Cold Start Problem in Recommender Systems Based on Modularity Maximization Community Detection Algorithm. *Circuits Syst.* **2016**, *7*, 1268–1279. [CrossRef]
50. Fan, Z.; Burgun, E.; Schleyer, T.; Ning, X. Improving information retrieval from electronic health records using dynamic and multi-collaborative filtering. In Proceedings of the 2019 IEEE International Conference on Healthcare Informatics (ICHI), Xi'an, China, 10–13 June 2019. [CrossRef]
51. Anthony Jnr, B. A case-based reasoning recommender system for sustainable smart city development. *AI Society* **2021**, *36*, 159–183. [CrossRef]
52. Vaz, P.C.; de Matos, D.M.; Martins, B.; Calado, P. Improving a hybrid literary book recommendation system through author ranking. In Proceedings of the 12th ACM/IEEE-CS Joint Conference on Digital Libraries, ACM, Washington, DC, USA, 10–14 June 2012. [CrossRef]
53. Li, X.; Li, D. An Improved Collaborative Filtering Recommendation Algorithm and Recommendation Strategy. *Mob. Inf. Syst.* **2019**, *2019*, 1–11. [CrossRef]
54. Liu, Y.; Huang, F.; Xie, X.; Huang, H. Research on Singular Value Decomposition Recommendation Algorithm Based on Data Filling. *Int. J. Inf. Technol. Syst. Approach* **2023**, *16*, 1–15. [CrossRef]
55. Bin, S.; Sun, G. Matrix factorization recommendation algorithm based on multiple social relationships. *Math. Probl. Eng.* **2021**, *2021*, 6610645. [CrossRef]
56. Mann, S.K.; Chawla, S. Cluster-Based Cab Recommender System (CBCRS) for Solo Cab Drivers. *Int. J. Inf. Retr. Res.* **2022**, *12*, 1–15. [CrossRef]
57. Wan, P. Development of the Employment Recommendation System based on K-Means Improved Collaborative Filtering Algorithm. In Proceedings of the 2022 2nd International Conference on Management Science and Software Engineering (ICMSSE 2022), Chengdu, China, 24–26 June 2022; pp. 489–494.
58. Devlin, J.; Chang, M.W.; Lee, K.; Toutanova, K. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv* **2018**, arXiv:1810.04805.
59. Brown, T.; Mann, B.; Ryder, N.; Subbiah, M.; Kaplan, J.D.; Dhariwal, P.; Neelakantan, A.; Shyam, P.; Sastry, G.; Askell, A.; et al. Language models are few-shot learners. *Adv. Neural Inf. Process. Syst.* **2020**, *33*, 1877–1901.
60. Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A.N.; Kaiser, Ł.; Polosukhin, I. Attention is all you need. *Adv. Neural Inf. Process. Syst.* **2017**, *30*, 6000–6010.
61. Zhang, S.; Yao, L.; Sun, A.; Tay, Y. Deep learning based recommender system: A survey and new perspectives. *ACM Comput. Surv. (CSUR)* **2019**, *52*, 1–38. [CrossRef]
62. Zou, J.; Thoma, G.; Antani, S. Unified deep neural network for segmentation and labeling of multipanel biomedical figures. *J. Assoc. Inf. Sci. Technol.* **2020**, *71*, 1327–1340. [CrossRef]
63. Eggl, E.; Schleede, S.; Bech, M.; Achterhold, K.; Loewen, R.; Ruth, R.D.; Pfeiffer, F. X-ray phase-contrast tomography with a compact laser-driven synchrotron source. *Proc. Natl. Acad. Sci. USA* **2015**, *112*, 5567–5572. [CrossRef] [PubMed]

64. Joseph, M.; Kearns, M.; Morgenstern, J.H.; Roth, A. Fairness in learning: Classic and contextual bandits. *Adv. Neural Inf. Process. Syst.* **2016**, *29*, 1–9.
65. Li, Y.; Chen, H.; Xu, S.; Ge, Y.; Zhang, Y. Personalized Counterfactual Fairness in Recommendation. *arXiv* **2021**, arXiv:2105.09829.
66. Fan, W.; Zhao, Z.; Li, J.; Liu, Y.; Mei, X.; Wang, Y.; Tang, J.; Li, Q. Recommender systems in the era of large language models (LLMs). *arXiv* **2023**, arXiv:2307.02046.
67. Yang, Z.; Dai, Z.; Yang, Y.; Carbonell, J.; Salakhutdinov, R.R.; Le, Q.V. Xlnet: Generalized autoregressive pretraining for language understanding. *Adv. Neural Inf. Process. Syst.* **2019**, *32*, 11.
68. Konečnỳ, J.; McMahan, H.B.; Yu, F.X.; Richtárik, P.; Suresh, A.T.; Bacon, D. Federated learning: Strategies for improving communication efficiency. *arXiv* **2016**, arXiv:1610.05492.
69. Li, J.; Galley, M.; Brockett, C.; Gao, J.; Dolan, B. A diversity-promoting objective function for neural conversation models. *arXiv* **2015**, arXiv:1510.03055.
70. Zhang, S.; Dinan, E.; Urbanek, J.; Szlam, A.; Kiela, D.; Weston, J. Personalizing dialogue agents: I have a dog, do you have pets too? *arXiv* **2018**, arXiv:1801.07243.
71. Panda, S.; Kaur, N. Exploring the viability of ChatGPT as an alternative to traditional chatbot systems in library and information centers. *Libr. Hi Tech News* **2023**, *40*, 22–25. [CrossRef]
72. Zhiyuli, A.; Chen, Y.; Zhang, X.; Liang, X. BookGPT: A General Framework for Book Recommendation Empowered by Large Language Model. *arXiv* **2023**, arXiv:2305.15673.
73. Lappalainen, Y.; Narayanan, N. Aisha: A Custom AI Library Chatbot Using the ChatGPT API. *J. Web Librariansh.* **2023**, *27*, 223–231. [CrossRef]
74. Tsai, C.H.; Kadire, S.; Sreeramdas, T.; VanOrmer, M.; Thoene, M.; Hanson, C.; Berry, A.A.; Khazanchi, D. Generating Personalized Pregnancy Nutrition Recommendations with GPT-Powered AI Chatbot. In Proceedings of the 20th International Conference on Information Systems for Crisis Response and Management (ISCRAM), Omaha, NE, USA, 28 May–31 May 2023; Volume 2023, p. 263.
75. Nastasi, A.J.; Courtright, K.R.; Halpern, S.D.; Weissman, G.E. Does ChatGPT provide appropriate and equitable medical advice?: A vignette-based, clinical evaluation across care contexts. *medRxiv* **2023**, [CrossRef]
76. Thawkar, O.; Shaker, A.; Mullappilly, S.S.; Cholakkal, H.; Anwer, R.M.; Khan, S.; Laaksonen, J.; Khan, F.S. Xraygpt: Chest radiographs summarization using medical vision-language models. *arXiv* **2023**, arXiv:2306.07971.
77. Remountakis, M.; Kotis, K.; Kourtzis, B.; Tsekouras, G.E. ChatGPT and Persuasive Technologies for the Management and Delivery of Personalized Recommendations in Hotel Hospitality. *arXiv* **2023**, arXiv:2307.14298.
78. Leung, J.K.; Griva, I.; Kennedy, W.G.; Kinser, J.M.; Park, S.; Lee, S.Y. The Application of Affective Measures in Text-based Emotion Aware Recommender Systems. *arXiv* **2023**, arXiv:2305.04796.
79. Liu, J.; Liu, C.; Lv, R.; Zhou, K.; Zhang, Y. Is chatgpt a good recommender? a preliminary study. *arXiv* **2023**, arXiv:2304.10149.
80. Li, J.; Zhang, W.; Wang, T.; Xiong, G.; Lu, A.; Medioni, G. GPT4Rec: A generative framework for personalized recommendation and user interests interpretation. *arXiv* **2023**, arXiv:2304.03879.
81. Dai, S.; Shao, N.; Zhao, H.; Yu, W.; Si, Z.; Xu, C.; Sun, Z.; Zhang, X.; Xu, J. Uncovering ChatGPT's Capabilities in Recommender Systems. *arXiv* **2023**, arXiv:2305.02182.
82. Rivas, P.; Zhao, L. Marketing with chatgpt: Navigating the ethical terrain of gpt-based chatbot technology. *AI* **2023**, *4*, 375–384. [CrossRef]
83. Ha, J.; Jeon, H.; Han, D.; Seo, J.; Oh, C. CloChat: Understanding How People Customize, Interact, and Experience Personas in Large Language Models. *arXiv* **2024**, arXiv:2402.15265.
84. Bansal, G.; Chamola, V.; Hussain, A.; Guizani, M.; Niyato, D. Transforming Conversations with AI—A Comprehensive Study of ChatGPT. *Cogn. Comput.* **2024**, *1*, 1–24. [CrossRef]
85. Martins, A.; Nunes, I.; Lapão, L.; Londral, A. Unlocking Human-Like Conversations: Scoping Review of Automation Techniques for Personalized Healthcare Interventions using Conversational Agents. *Int. J. Med. Inform.* **2024**, *1*, 105385. [CrossRef]
86. Wang, P.; Wei, X.; Hu, F.; Han, W. TransGPT: Multi-modal Generative Pre-trained Transformer for Transportation. *arXiv* **2024**, arXiv:2402.07233.
87. Feng, S.; Chen, C. Prompting Is All You Need: Automated Android Bug Replay with Large Language Models. In Proceedings of the 46th IEEE/ACM International Conference on Software Engineering, Lisbon, Portugal, 14–20 April 2024; pp. 1–13.
88. Wu, Y.; Xie, R.; Zhu, Y.; Zhuang, F.; Zhang, X.; Lin, L.; He, Q. Personalized Prompt for Sequential Recommendation. *IEEE Trans. Knowl. Data Eng.* **2024**, *early access*.
89. Wang, C.; Chen, T.; Liu, Y.; Kang, M.; Su, S.; Li, B. TransMI: A transfer-learning method for generalized map information evaluation. *Cartogr. Geogr. Inf. Sci.* **2024**, *1*, 1–17. [CrossRef]
90. Zhang, H.; Cheah, Y.N.; Alyasiri, O.M.; An, J. Exploring aspect-based sentiment quadruple extraction with implicit aspects, opinions, and ChatGPT: A comprehensive survey. *Artif. Intell. Rev.* **2024**, *57*, 17. [CrossRef]
91. Kim, M.; Adlof, L. Adapting to the Future: ChatGPT as a Means for Supporting Constructivist Learning Environments. *TechTrends* **2024**, *68*, 37–46. [CrossRef]
92. Bansal, R. Unveiling the Potential of ChatGPT for Enhancing Customer Engagement. In *Leveraging ChatGPT and Artificial Intelligence for Effective Customer Engagement*; IGI Global: Hershey, PE, USA, 2024; pp. 111–128.

93. Khan, R.; Khan, S.P.; Ali, S.A. Conversational AI: Dialoguing Most Humanly with Non-Humans. In *Conversational Artificial Intelligence*; Rawat, R., Chakrawarti, R.K., Sarangi, S.K., Vyas, P., Alamanda, M.S., Srividya, K., Sankaran, K.S., Eds; Scrivener Publishing LLC: Beverly, MA, USA, 2024; pp. 249–268.
94. Krishna, S.; Ma, J.; Slack, D.; Ghandeharioun, A.; Singh, S.; Lakkaraju, H. Post hoc explanations of language models can improve language models. *Adv. Neural Inf. Process. Syst.* **2024**, *36*, 65468–65483.
95. Wang, X.; Li, Q.; Yu, D.; Li, Q.; Xu, G. Reinforced path reasoning for counterfactual explainable recommendation. *IEEE Trans. Knowl. Data Eng.* **2024**, *early access*.
96. Stahl, B.C.; Eke, D. The ethics of ChatGPT–Exploring the ethical issues of an emerging technology. *Int. J. Inf. Manag.* **2024**, *74*, 102700. [CrossRef]
97. Lim, D.Y.Z.; Tan, Y.B.; Koh, J.T.E.; Tung, J.Y.M.; Sng, G.G.R.; Tan, D.M.Y.; Tan, C.K. ChatGPT on guidelines: Providing contextual knowledge to GPT allows it to provide advice on appropriate colonoscopy intervals. *J. Gastroenterol. Hepatol.* **2024**, *39*, 81–106. [CrossRef]
98. Wen, X.; Nie, W.; Liu, J.; Su, Y.; Zhang, Y.; Liu, A.A. CDCM: ChatGPT-Aided Diversity-Aware Causal Model for Interactive Recommendation. *IEEE Trans. Multimed.* **2024**, *early access*.
99. Ma, H.; Xie, R.; Meng, L.; Chen, X.; Zhang, X.; Lin, L.; Zhou, J. Triple sequence learning for cross-domain recommendation. *ACM Trans. Inf. Syst.* **2024**, *42*, 91. [CrossRef]