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Perspective

Fog Computing-Based Smart Consumer Recommender Systems

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Abstract: The latest effort in delivering computing resources as a service to managers and consumers represents a shift away from computing as a product that is purchased, to computing as a service that is delivered to users over the internet from large-scale data centers. However, with the advent of the cloud-based IoT and artificial intelligence (AI), which are advancing customer experience automations in many application areas, such as recommender systems (RS), a need has arisen for various modifications to support the IoT devices that are at the center of the automation world, including recent language models like ChatGPT and Bard and technologies like nanotechnology. This paper introduces the marketing community to a recent computing development: IoT-driven fog computing (FC). Although numerous research studies have been published on FC "smart" applications, none hitherto have been conducted on fog-based smart marketing domains such as recommender systems. FC is considered a novel computational system, which can mitigate latency and improve bandwidth utilization for autonomous consumer behavior applications requiring real-time data-driven decision making. This paper provides a conceptual framework for studying the effects of fog computing on consumer behavior, with the goal of stimulating future research by using, as an example, the intersection of FC and RS. Indeed, our conceptualization of the "fog-based recommender systems" opens many novel and challenging avenues for academic research, some of which are highlighted in the later part of this paper.

Keywords: fog computing; recommender system; internet of things (IoT); edge computing; artificial intelligence (AI); software defined networks (SDNs)

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1. Fog Computing-Based Smart Consumer Recommender Systems

"*Fog computing is considered a formidable next-generation complement to cloud computing*" [1].

The ongoing transformation of information and communication through the integration of digital technologies, automation, data exchange, and advanced analytics, represents a significant shift in how organizations and individuals operate and interact with technology. This development follows Industry 4.0, with its focus on intelligent or smart devices. Smart devices involve data analytics capabilities empowered with technological advancements such as the internet of things (IoT), deep learning (DL), machine learning (ML), artificial intelligence (AI) (including language models; [2]virtual reality (VR), big data analytics (BDA), and ultimately, intelligent device-free sensing (IDFS) nanotechnology [3,4] and genetic data (DNA) [5]—all of which will become an eminent part of Industry 4.0. These technologies, where human input is not required, promise to revolutionize marketing and consumer behavior and research as we know it.

Computing is regarded as a critical driving force in the development of human systems. Technological advances in measurement devices over the past few years have provided firms, researchers, policy makers, and consumers access to individual-level data of an unprecedented amount. Digital footprints of electronic behavior provide enormous measurements of attitudes toward social influences, information search, language use, and content. Due to the large volume of consumer data and information, humans are unable to fully uncover and compute useful information for personal decisions. Recent developments in intelligent computing are expected to precipitate a major breakthrough not only in intelligence-oriented computing but also in intelligence-empowered computing [6,7]. Intelligent computing provides autonomous, scalable, efficient, reliable, universal, secure, and transparent computing services to support large-scale and complex computational tasks in today's "smart world" [8,9]. It has significantly broadened the scope of computing by extending it from traditional data computing to increasingly multiple computing paradigms, such as perceptual intelligence, cognitive intelligence, autonomous intelligence, affective computing, and human–computer fusion intelligence [10]. With the expansion of the IoT and wide proliferation of wireless networks, the number of edge devices (e.g., sensors, monitors, scanners, and wearables) and the massive data generated from them has been growing fast. Also, many services, such as online gaming and image processing, rely on AI to achieve the required smartness and autonomy. Above all, the digital world is advancing rapidly [11–13], and developments in networking technologies, including low-power wide area networks (LPWAN), 4G long-term evolution (LTE), wireless broadband (WiBro), 5G, and nano datacenters (NaDa or nDCs), are leading to the emergence of sophisticated data services. Billions of devices, ranging from user gadgets to more complex devices, are generating massive amounts of data for research and applications. The pervasive usage of smart, interconnected devices is estimated to reach 58.2 billion units by 2025 [14]. This exponential growth is nourished by the proliferation of mobile devices (e.g., mobile phones and tablets) with smart sensors serving different vertical markets, such as smart cities, smart healthcare, and smart marketing. The latest trend of the computing paradigm is to push elastic resources such as computation, storage, and applications to the edge of networks, and thus to provide a new breed of services and applications to end users with high bandwidth, low latency, and location awareness. For this reason, the IoT-driven fog computing (FC) platform supported by software-defined networking (SDN) [15–17] was introduced to bridge the distance and address some of the aforementioned challenges.

The term "fog computing"—derived from the phrase "fog is a cloud that is closer to the ground"—was coined by Cisco Systems to describe the need for computing capabilities at the network edge to address the challenges posed by the increasing volume and velocity of data generated by IoT devices. Thus, FC aims to reduce latency, conserve network bandwidth, improve efficiency, and enable real-time processing and analysis of data—all with the potential to support consumer decision processes. In November 2015, an alliance of industries and academia, including Intel, ARM, Microsoft, Dell, Cisco, and Princeton University, launched the OpenFog Consortium to introduce and promote the use of FC. By 2018, FC had become a leading platform for developing IoT frameworks [18] among governments and academic institutions. The OpenFog Consortium Architecture Working Group defined FC as "[a] system-level horizontal architecture that distributes resources and services of computing, storage, control and networking anywhere along the continuum from Cloud to Things." [19].

Study Objectives

> "*The latest technologies like Fog computing can be utilized to make a recommendation system faster and independent of internetwork connection*" [20] (p. 13).

Despite the scholarly consensus that FC is significant to organizations and individuals, its applications to marketing and consumer behavior is nascent. Inspired by recent successful applications of FC to various smart ecosystems, in the present study we present a new conceptual framework for conducting research into FC's effects on marketing and consumer behavior, following the general conceptual frameworks, qualitative review, and propositional inventories that delineate a conceptual entity [21,22]. By way of illustration, we highlight part of the conceptual framework by using a consumer recommender system (RS) as a significant future application of FC serving smart consumers. To advance these objectives, precisely during an era in which marketing scholars are calling for more conceptual work (e.g., [22–24]), first, we provide an overview of FC and related concepts relevant to marketing and consumer behavior.

Second, we present some illustrations of FC marketing applications. Third, given the importance of RSs to marketing and consumer research and researchers' attempts to find ways to overcome the various RS limitations, we propose a conceptual framework based on what we term "fog-based recommender systems." Fourth and finally, we identify a number of fundamental research challenges for consumer research to fully exploit FC for recommender systems.

Employing a multi-perspective approach, this paper also aims to deliver valuable insights into FC, offering a perspective on impacted consumer areas. FC has been applied to various industries and organizations. Recent innovations in FC, like mobile FC [25], have placed applications in the hands of individual users. Thus, a major novelty of this paper is the application of FC to individual consumers. Positioned as an important contribution within the emerging FC-focused literature, we discuss future research issues emanating from our framework and outline interdisciplinary research avenues. This paper, we hope, will serve as a valuable reference for marketing scholars and practitioners and foster future conceptual and practical research innovations in FC-driven consumer research.

Within the developing "smart world" [8], our discussion addresses what has been recently termed "smart consumers" (closely related to "digital consumers"), i.e., consumers who use smart technologies—e.g., [26,27], which provide them with data used to make "intelligent decisions" [28]. The combination of these smart technologies determines the extent of consumers' "smartness" [29].

2. Fog Computing

> "*Nowadays, the pointer of the trending paradigm is pointing at fog computing. As efficiency and quality of service stand as important objectives in the world of computing, it is viewed as a promising application*" [30].

Fog computing, also known as fogging, is expanding frontiers of computing data, applications, and services away from a centralized cloud to the logical stream of the network edge. While cloud computing has been widely used in practice, it cannot cope with the issues arising in many IoT scenarios, such as resource-constrained devices, stringent latency requirements, network bandwidth constraints, and uninterrupted services with intermittent connectivity to the cloud [30,31]. FC has proven to be an effective solution to these issues [32,33]; for a comprehensive review, see [34].

The large amount of data produced by the IoT is growing exponentially through ongoing electronic devices. Indeed, IoT devices are producing an avalanche of information, which is disruptive for analytics processing, usually managed properly by the cloud. FC solves this tendency with a strong complementary cloud system based on the deployment of micro clouds (fog nodes) at the edge of data sources. However, big IoT data analytics by FC structures is in its inception and requires much research to provide added proficiency and smart decisions [35]. For individual consumers, it is important to emphasize that FC is able to serve mobile consumers and IoT devices by actively searching and processing the vital data. Thus, in contrast to traditional internet consumers, mobile consumers and IoT devices have different requirements; for example, they are more interested in predictable location-based information [36]. By leveraging FC, users can harness the benefits of both local edge processing and centralized cloud computing, producing a more efficient and responsive computing infrastructure (see Figure 1, with more elaboration in Web Supplementary S1). In an FC system, multiple servers can cooperate with each other securely (e.g., by utilizing a blockchain platform) to serve terminal devices and thereby improve fog server utilization [37]. Notably, what is undoubtedly happening with FC is that the single-cloud, static model is turning into an ultimately novel framework, which is much more diverse, dynamic, and located on different, heterogeneous, and commonly mobile fog premises, providing varied services that can be linked jointly as well as capacities that can be offered together (for a comparative analysis of cloud computing and FC, see Web Supplementary S2).

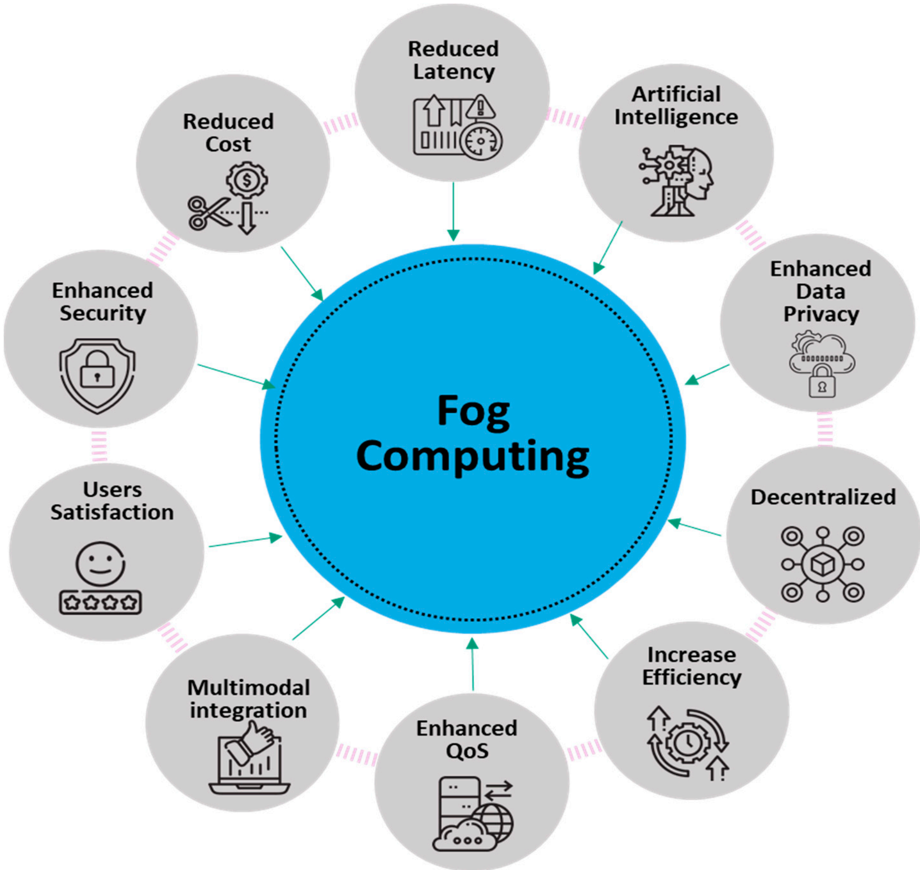

Figure 1. FC major benefits.

FC-enabled AI offers the opportunity to combine resources and modalities into a hybrid digital data system, which supplies comprehensive information for various "smart" applications. Nowadays, the system expedites the use of distributed, latency-aware services and applications and consists of fog nodes (physical or virtual), which are located between smart end-devices and unified (cloud) services. This architecture is able to process data in a matter of milliseconds with connectivity options varying by use case. An IoT sensor in a store, for example, can likely use a wired connection, whereas mobile resources, such as autonomous vehicles or consumer-grade GPS devices, will require alternate forms of connectivity.

To facilitate new network innovations while drastically simplifying FC network operations, software-defined networks (SDNs) have been developed [16,38]. SDNs, as a software architecture, help to solve the IoT-FC heterogeneity problem, enabling the formation of independent protocols and addressing issues related to restricted hardware and proprietary software [15]. Unlike traditional IP systems, in which control and data planes are strongly coupled and embedded in the same system elements, SDN-based FC separates the control plane from the data plane and system elements [30], thus allowing service providers to be optimized and service needs supported from a centralized user interface (UI). All of which affords greater agility and programmability as well as the capacity to add network automation [17,28,38]. Due to advanced technologies, FC is using a rapidly growing number of devices, while computerized models like SDNs are helping to provide higher service quality [15]. For example, a smartwatch may collect data related to an individual consumer's physical activities, including heartbeat and pulse, and transmit it to their smartphone, whereupon an SDN-based FC system can process the data and make suggestions to the consumer regarding how to adjust their activities, diet, and lifestyle according to their physical condition. Consumer data are collected by FC deploying data-producing systems like scanners, monitors, mobile devices, smart cards, eye gaze trackers (EGTs), odor measurements—e.g., [39], semantic analyses, computerized haptic measures, voice analog scales (VAS), computerized visual analog scales (VAS), vocal monitors [40,41], emerging biomedical innovations such as magnetic resonance imaging (MRI), genotyping, and hormonal assays, which quantify the building blocks of the biological processes that shape preferences, cognition, and decision making, and in the near future, mobile robots and nano-devices as well. Importantly, research into the use of physiologic sensors, equipped with skin conductance, heart rate, respiration, blood pressure, ECG, EEG, EMG, and other tools capable of measuring emotions as well, is expanding FC applications, see [42] and Web Supplementary S3. An array of new and unobtrusive devices, which promise to considerably enhance precision, are presently being tested [3]. The advanced technologies embedded in these devices are able to provide computerized scalable digitalized data; some employing remote physiological measurements [43,44], while others are able to track behaviors over time, measuring "streak" behaviors performed consecutively [45]. Most smartphones and some smartwatches can accommodate ambient light sensors, internal motion sensors (accelerometers), gesture sensors, gyroscopic sensors, temperature and humidity sensors, magnetometers, and barometers. Communication interfaces commonly found on smartphones include WiFi, GPS, Bluetooth, near field communications (NFC), and infrared (IR) LEDs [46]).

The widespread diffusion of numerous wireless technologies, especially high-speed 5G networks, can further optimize real-time sensing and collecting of massive repositories of spatiotemporal data, which represent proxies for consumer sentiments, interactions, communications, activities, and situational factors like time and location [11]. With the assistance of decision software, data can be converted into information for consumer consideration and decision making. For example, comprehensive solutions exist for automatically evaluating sleep. One of these is the FC-enabled Beddit Sleep Monitor [42], which measures breathing patterns, sleep time, heart rate, movement, and several other factors. These functions in turn can be integrated into other physiological, behavioral, and mental monitors. Indeed, it seems that virtually any human behavior and sensation can and will be monitored and scaled by FC along four basic dimensions—intensity, quality, extension, and duration [31]. Emotional data are distinct from cognitive data because they are individual-specific, commonly multimodal (speech, gestures, and language), and contextual [47]. Such data relate to the consumer in context, meaning that the RS will need, for instance, to include contextual and individual-unique data and information into framing the emotional state of consumers. FC is capable of successfully integrating a vast spectrum and amount of mental and physiological techniques and measurements, which are expected to deliver more precise information for identifying emotion and behavior—thus, creating value for market stakeholders. This immense amount of digitalized data ('big data') obtained from smart devices can be offloaded subsequently to the fog for storage, processing, aggregation, and computation. Consumers then will be able to shift this data to the optimum place for processing, and decisions can be based on how fast results are needed. For instance, time-sensitive consumer decisions will be made closer to the things producing and acting on the data. In contrast, big data analytics dealing with historical information might require the computing and storage resources of the cloud. The ability to triage consumer data and make critical judgments within the device's own context will aid in extracting essential insights from the massive volume of available consumer data.

All these advances and futuristic technologies are typically powered by FC, which can be transformed into a consumer experience. For example, if millions of consumers around the world wish to play a particular song simultaneously on a music streaming service and that song is on a server in the United States, then processing that request would create a long queue, slowing service to consumers. By contrast, fog servers, which are located closer to the devices requesting the song, are able to stream it immediately to the edge device with minimal latency. The fog node maintains a copy of the song, enabling other consumers in the same geographic area to stream the song instantaneously.

Additionally, FC-enabled virtual reality will allow consumers to visualize, for instance, how different garments might look on them in various lighting conditions, contexts (e.g., office or street), and situations (e.g., party or business meeting). Meanwhile, advances in molecular genetics have led to the exponential growth of private databases [48]. Sorting DNA data is valuable since it exhibits stability over time, retains integrity (as it is extremely difficult to break down a DNA molecule), and is less prone to technical failures. Thus, it proves to be a good solution for data security. By using, for example, DNA data available through the direct-to-consumer genetic testing (DTC-GT) market, FC-enabled generic data will be able to provide consumers with unique information on their likelihood of balding, becoming addicted to nicotine, developing different health problems, etc. Because genetic variation correlates with many personal characteristics, it provides a source for studying the relationships between traits and the question of whether they arise from genetic or environmental causes. Noteworthy, in this context, is the music streaming service Spotify's recent partnership with Ancestry DNA to allow their approximately 217 million users to upload their genetic data and create playlists that "match their genetic ancestry" [48]. Adding genetic information to predictive consumer models that use other FC-enabled databases may improve their predictive accuracy at the individual consumer level.

FC Applications

With the FC-enabled IoT "which seeks to support the dream of smart world, it is no longer enough to have only quality of service as it does not satisfy the user experience. As such, quality of experience has now become a key to get user's satisfaction regarding reliability, availability, scalability, speed, accuracy, and efficiency" [49] (p. 2). FC can be used to support applications and deployments in the IoT, Cloud of Things (CoT), and a number of other applications that demand real-time or predictable latency [50]. Indeed, the adoption of FC has increased rapidly due to recent developments in IoT smart devices and technologies (major marketing/consumer-related smart applications have been compiled in Supplementary S1). However, FC is constantly undergoing modification, and the number of applications administered in fog platforms is expected to grow [34,51]. The new FC structure and use cases are strongly influenced by an array of innovative applications, which demand additional platform attributes, and can only be delivered if the applications are deployed closer to end users, such as in "smart vehicles," "smart supply chain systems" (Gupta and Singh 2023), "smart healthcare systems" [52] (accessed on 1 October 2023), "smart banking," and more.

In August 2018, Dell partnering with Intel introduced a new secure, implementable, and scalable solutions for IoT and edge computing use cases. Intel has contributed its unique perspective and computer analysis technologies to the package [53]. The proposal included sensors and licensed software customized for specific consumers use cases, along with the diverse Dell architecture (PC hardware, edge gateways, integrated servers, etc.). Software that expedites large-scale operation and monitoring was also included. Likewise, in 2018, Huawei Technologies introduced the Hilink platform, which combines mobile solutions and products designed to address the technological requirements of the various stakeholders, connecting intelligent products, including storage solutions, air quality monitors, remotely controlled infrared lights, intelligent electrical sockets, and fans, etc. [53]. Likewise, in January 2023, Intel acquired FogHorn Systems, a leading provider of FC software, in a deal that will help Intel to expand its FC offerings and provide businesses with a more comprehensive suite of "smart" solutions. Meanwhile, shortly thereafter, in March 2023, Dell acquired Nimbix, a provider of FC solutions for the telecommunications industry (smart telecommunications), thus enabling the former company to meaningfully expand its FC offerings in telecommunications and meet the growing demand for FC in this market [54] (accessed on 3 January 2024). Likewise, FC has recently been used to assist the current trend in Fintech including online credit, risk analysis, and use of large amounts of data to improve consumer services [33]. Finally, "The Pentagon is exploring new collaborations with technology companies that can provide potentially game-changing edge and fog computing capabilities to support military missions" [55].

FC is generally considered to be more secure than cloud computing for several reasons. First, the collected data is transiently maintained and analyzed on local fog nodes closest to data sources, which decreases dependency on internet connections. Second, local data storage, exchange, and analysis potentially make it more difficult for hackers to gain access to user data since there can be separate and different security barriers at different fog nodes. This limits the amount of accessible data in any given breach compared to a more centralized cloud computing environment. However, the same level of security risks could apply to the data exchange between user devices and the FC node or the data exchange between different fog nodes [49]. In sum, using the IoT, social media, mobile apps, and other digital technologies has become an integral part of consumers' daily lives. In this environment, a major source of consumer information is recommender systems.

3. Recommender Systems (RSs)

The widespread adoption of the internet has led to an explosion in the number of choices available to consumers. The core idea of RSs is to find online "neighbors" based on similarities and then, according to prediction scores, offer recommendations (for a recent marketing review, see [56]). Thus, RSs first use algorithms to collect the original data, second, they calculate the similarity, third, they score the prediction, and lastly, they make recommendations. Consumers expect personalized content in modern e-commerce, entertainment, and social media platforms. RSs comprise a subclass of information filtering systems, which identify and recommend items based on consumer tastes and preferences and seek to predict "rating" or "preferences" for an item not yet considered through a model built from item characteristics or the consumer's social environment [20,57] RSs have been established as a crucial solution to keep consumers engaged and satisfied with personalized content in addition to helping users navigate a vast array of choices. Felfernig and Burke (2020) define RSs as encompassing "[a]ny system that guides a user in a personalized way to interesting or useful objects in a very large space of possible options or that produces such objects as output" [58] (p. 1).

RSs stem from the simple observation that consumers take recommendations from others or use systems that provide signals to consumers about the preferences of other like-minded customers. For example, consumers will search online for product reviews before deciding to purchase a product. Consumers are often faced with information overload as the amount of content and information available in a given platform expands at an ever-increasing rate, making it difficult to make an appropriate choice among the large number of items. Recommendation is primarily concerned with a decision-making process, whether it concerns the next movie to watch, or story to read. RSs address this issue by filtering out a few highly relevant items the consumer may find interesting from the vast number of irrelevant items in the list. Successful systems span a wide variety of platforms such as Amazon's book recommendations, Netflix's movie recommendations, and Pandora's music recommendations [59].

There are three widely used RS approaches: collaborative filtering (CF), content-based, and hybrid approaches. CF is the process of filtering or evaluating a preference through the opinions of others ("neighbors"). It unifies the views of many interconnected communities on the internet and supports the filtering of large amounts of data [60].The content-based approach recommends items similar to those in which the user has previously shown interest. It combines CF methods and content-based methods, thus exploiting the advantages of both while avoiding their specific limitations [61]. Hybrid RSs can be considered a combination of any two or more RSs. RSs have significantly developed in recent years along with advancements in both IoT and AI technologies. Accordingly, multiple forms of data are expected to be developed and incorporated into these systems, e.g., social, local, and personal information, which improve RSs' performance and expand their applicability to traverse different disciplines. More recently, an emotion-aware recommender system (EARS) [59] has been proposed based on hybrid information fusing user rating data, social networking data, and sentiments culled from user reviews. The data is both explicit and implicit. The model directly converts recommended tasks into user selection behavior probabilities. Indeed, it has proven to be an effective approach to fusing user ratings and emotional information employing hybrid features from explicit and implicit data [62]. Alongside these upsides, however, there are some notable limitations.

RS Limitations

The major RS issues are as follows:

Cold start problem. The cold start problem occurs when the RS cannot properly recommend existing items to new users (new user problem) or recommend new items to the existing users (new item problem). In such events, because consumers have not yet rated a sufficient number of items, the RS is unable to monitor interest in new items. Some RSs try to overcome this issue by forcing the consumer to first rate a given set of items. However, these initial ratings are liable to introduce biases into the RS [59].

Sparsity. Sparsity occurs when transactional or consumers' response data are scant and insufficient for identifying "neighbors". In most RSs, it refers to the situation where the user–item interaction matrix is largely empty, meaning that most users have not interacted with most items. This occurs frequently in real-world scenarios because users tend to interact with only a small fraction of the available items, leading to a sparse matrix [63]. In such cases, finding similarities among different consumers or items is challenging.

Scalability. Refers to the challenge of treating large and changing datasets, which demands efficient and robust architectures and algorithms [63]. It signifies the limited capability of RSs to secure valid recommendations, with a growing amount of information about consumers and items, because it relies on complicated computations.

Latency. Latency occurs when new items are supplemented more frequently to the RS database and the RSs solely recommend the already rated items, while the more newly introduced items have not been rated yet.

Synonymy. The synonymy problem in RSs refers to the challenge of dealing with items that are similar or semantically related but may not share the exact same keywords or tags. This can lead to difficulties in accurately recommending items to users based solely on explicit user–item interactions or metadata.

Shilling attacks. Also known as a data poisoning attack or profile injection attack, this is a type of malicious activity aimed at manipulating the recommendations provided by an RS. In a shilling attack, an attacker introduces fake or manipulated data into the system in order to bias the recommendations towards certain items or to degrade the quality of recommendations for other users. Several methods affecting both model-based and neighbor-based [60] algorithms have been introduced in the past. These have reduced, although only partially, the shilling problem.

Privacy. While supplying RSs with personal information presumably leads to the best recommendations, security issues frequently arise in the process. There is an undeniable trade-off between providing highly personalized recommendations and respecting user privacy.

Grey-sheep problem. "Grey-sheep users" are defied as users with unique preferences and tastes, which make it difficult to develop accurate profiles. When it comes to such users, the similarity search approach usually followed during the recommendation process fails to yield valuable results. As most research neglects these users, it is unable to cater to more exotic tastes and emerging trends, leading to a subsequent loss of valuable information. One possible solution is to use one-class classification to provide a prediction list for these users, while decision boundaries are learned that distinguish between normal and grey-sheep users [62].

Information overload. The massive amounts of RS data being generated have rendered "information overload" a serious problem. Unwieldy quantities of sometimes unrelated, redundant RS information can seriously interfere with the consumer decision process.

Implicit emotions. Despite the enhanced quality of emotional data from, for example, EARSs, which, as aforementioned, are based on hybrid information fusion using user rating data, social networking, and explicit sentiments data from user's responses, can be generated by RSs. However, these do not apply to implicit emotions [60]. Implicit emotions refer to feelings or emotional responses that are not consciously recognized or expressed by an individual. These emotions may be hidden, subtle, or not readily apparent, even to the person experiencing them. They can influence behaviors, thoughts, and decision making without the individual being fully aware of their presence [64].

Filter bubbles. Although existing RSs achieve high accuracy through backtracking tests, considering accuracy alone may lead to the phenomenon of "filter bubbles" [60], which isolates consumers from a diversity of content. Moreover, the accuracy inferred from historical records may not reflect the real correlations among products very well when "concentration bias" is heavy [65].

Additional challenges are related to recent advancements in RSs such as merging RSs with other successful systems and EEG-based neuro-RSs [20]. While the RS furnishes purchase information based on similar others and past behavior, neuromarketing-based systems add real-time brain state information during purchase behaviors. Also, EARSs are undoubtedly improving RSs. However, some researchers have proposed that only FC-based RSs can assist in solving these challenges by way of conceptualizing RSs as part of an integrated smart system that provides consumers with decision-supporting social information as well as personal and situational data [66].

4. Conceptualizing Fog-Based Recommender Systems

> "*Despite the many advantages of fog computing, which comprise low latency, privacy, uninterrupted service and location awareness, there is still no research that combines fog computing with recommendations systems*" [60]. (p. 121).

To advance RSs, to propose solutions to the above listed limitations, and to apply RSs in the field of marketing and consumer behavior, we conceptualized a novel fog-based RS, depicted in Figure 2. Fog-enabled solutions leverage the capabilities of edge devices, such as IoT devices, and other local computing resources to enhance the RS process. The proposed system can run independently on a single fog server or collaboratively on a group of fog servers. All these will be able to provide the following:

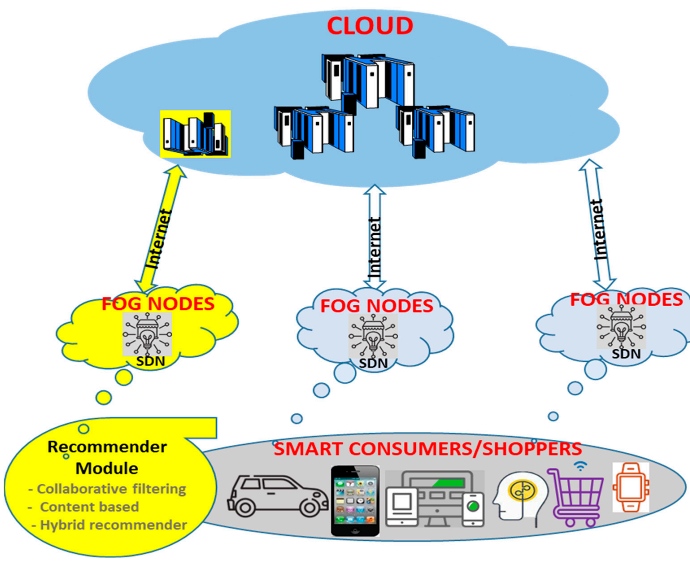

Figure 2. Conceptual framework.

Data proximity. Fog-based RSs can benefit from data generated and collected at the edge of the network. These edge devices are able to gather valuable consumer cognitive, emotional, and behavioral data, which is then processed locally to provide recommendations. By processing recommendation algorithms at the edge (i.e., closer to the end user), it is possible to significantly reduce the latency associated with using recommendations from a distant cloud server. This will lead to faster response times, which can be crucial in real-time or interactive applications.

Low latency. FC can help to reduce RS latency by bringing computation and data storage closer to end devices. This is important for applications where real-time recommendations are needed, such as e-commerce and online advertising.

Privacy and security. Since data is processed locally at the edge, the potential exists to address privacy concerns [67]. User data can remain within the local network, thus reducing the need to transmit sensitive RS information to distant cloud servers. This makes it more difficult for attackers to access the data.

Offline capability. Fog-based RSs continue to make recommendations even when connectivity to the cloud is lost, since fog nodes are able to store consumers data and historical interactions locally. This allows for generation of recommendations even when the device in question is not connected to the internet or when network connectivity is limited, a benefit that is crucial in scenarios where network interruptions can occur. In other words, fog nodes can continue to learn and adapt even when not connected to the cloud. This will allow RSs to refine models based on local interactions and feedback, providing a more personalized experience.

Bandwidth efficiency. By performing computations at the edge, fog-based RSs can reduce the need to transmit large amounts of data to the cloud for processing, thus saving bandwidth and potentially lowering data transmission costs [68].

Scalability. FC allows for distributed processing across multiple edge devices, enabling better scalability for RSs as the number of users and devices increases. FC can help to improve the scalability of RSs by distributing the workload across multiple fog nodes. This is important for applications with a large number of users and items, such as social media and healthcare. A more recent and advanced technology designed to deal not only with data scalability but also with sparsity is neural networks, which are powerful models that can learn complex and nonlinear features and interactions from data [34]. FC-enabled neural networks can be applied to various aspects of RSs, such as embedding, ranking, prediction, and generation. For instance, they can learn low-dimensional embedding of consumers and items from sparse and high-dimensional data and use them to predict ratings or interactions. Neural networks can also learn to rank items according to their relevance or preference for each consumer or generate new and diverse items based on user feedback or context.

Contextual recommendations. Fog-based RSs hold the potential to leverage local contextual information from edge devices (such as location, device type, and local events) to enhance the quality of recommendations. FC can use a large-scale sensor network to monitor the environment. This additional context in turn may be leveraged by RSs to offer more accurate and relevant recommendations based on the user's current situation.

Personalization. By processing data locally, fog-based RSs can provide more personalized recommendations in real-time, adapting to user preferences faster. FC enables the provision of personalized services directly at the edge. RSs can tailor content and products based on individual user preferences, behavior, and context, without the need to send data back and forth to the cloud.

Reducing overload. To address overload, various strategies can be employed, including load balancing, resource allocation, and dynamic task offloading [68]. Load balancing distributes tasks across multiple fog nodes to ensure even utilization of resources. Resource allocation involves allocating additional resources or scaling fog nodes when needed to handle increased workloads. Dynamic task offloading allows tasks to be transferred from overloaded fog nodes to less busy ones to maintain efficient processing [32]. Thus, a fog-based RS can be considered an overload reduction system and information optimization tool, which provides more specific recommendations to users.

Overcoming sparsity. The sparsity problem is a challenge in IoT systems where devices are often geographically dispersed and have limited resources. This can make it difficult to collect and process RS data from all of the devices in real time. FC can help to solve the sparsity problem by providing a distributed computing platform deployable closer to the edge of the network. This allows fog nodes to process data locally, reducing the need to send it all the way to the cloud. An analytical method was proposed to address data sparsity that uses FC matrix factorization, which decomposes the user–item rating matrix into two low-rank matrices, one representing the latent features of users and the other representing the latent features of items [69]. By learning these latent features, FC-enabled matrix factorization can capture the underlying patterns and RS preferences of users and items and predict the missing ratings or interactions. Matrix factorization can also incorporate additional information, such as user or item attributes, temporal dynamics, and social relations, to enhance the accuracy and diversity of recommendations.

Resilience to network failures. FC can operate in disconnected or partially connected environments. This means that even in situations where network connectivity is unreliable, RSs can continue to function at the edge.

Edge-centric consumer models. FC can enable new consumer models where edge devices or fog nodes play a more active role in generating value through recommendations.

The effectiveness of FC-based RSs depends on factors such as the nature of the recommendation task, the available edge resources, and the specific requirements of the application. As technology continues to advance, new systems will offer innovative FC consumer applications and solutions for overcoming RS limitations, especially in regard to the efficiency, scalability, latency, and privacy aspects of RSs. Also, due to the velocity of information flow over social networks, the RS is growing into big data research. Thus, the evolution of FC-based RSs is a promising direction for future marketing and consumer behavior work.

One of the major concerns in FC-based RSs is how to construct a system evaluation process. Evaluation metrics are the indicators or criteria that can be used to assess the effectiveness and usefulness of RS-generated recommendations [32].FC provides different kinds of evaluation metrics. Offline FC evaluation metrics are obtained based on historical or simulated data, such as accuracy, recall, precision, and diversity, while online evaluation metrics rely on real-time or live data, such as conversion rate, click-through rate, and user satisfaction. They can assist users in identifying the strengths and weaknesses of the RS and guide improvements. For example, energy RSs have become an essential solution for energy efficiency in buildings, physical stores, and neighborhoods, while a large number of current frameworks are focused on using cloud-to-edge architectures in which recommended energy-saving implementations are transmitted to edge devices (e.g., smartphones) after completing the computing task in the cloud server [50]. Although these architectures assist in achieving good efficiencies, they are prone to serious probable delays in system feedback and user response because of the network bandwidth and latency between the cloud and edge [69]. By contrast, implementing recommender algorithms directly on the edge can allow real-time computing and identify consumer interests and preferences more accurately, thereby enhancing consumer satisfaction and trust in the generated recommendations. Therefore, research should be devoted to developing and implementing RSs on the fog nodes, which should significantly reduce computational time, minimize cloud hosting costs, ensure privacy, and overcome many of the aforementioned RS challenges.

5. Future Trends and Challenges

"*Fog computing is the next generation computing paradigm*" [17]. (p. 129).

FC's full potential has yet to be realized because several challenges are still being addressed by the research community. According to SkyQuest Technology's Global Fog

Computing Market Report for 2023, the following are some future trends for FC growth with marketing and consumer implications: embracing of 5G technology and its alliance with FC; emergence of fog-to-cloud composition and hybrid cloud architectures; assimilation of AI and ML capabilities; edge analytics for real-time data processing and decision making; development of edge devices and sensors in IoT systems; language models; merging of FC with blockchain technology; edge-native implementation and services; and more advancements in edge privacy and security [70].Intelligent device-free sensing (IDFS) will probably signify one of the most important IoT breakthroughs in the near future. Current transpiring methods for IDFS include wireless device-free centralized gesture recognition, action recognition, and computer vision-based sensing. FC not only acts in favor of latency-sensitive applications but also lays the foundations for smarter mobility support, which is important for individual consumers. As usage of smart and wearable devices rises every day, intelligent location-based mobility support to maintain the benefits of consumer proximity assumes paramount importance [3]. Research gathering accurate information about consumer activities and environments is particularly critical. However, handling such issues is challenging due to complex interference from dynamic environments, moving targets, ambient noise, etc. [3].

As the market for smart devices develops, so does the number of internet users. FC was designed to connect billions of intelligent entities, which can help to create a better future. Thus, the need for efficient algorithms to manage the large data, fog devices, and cloud servers is also expected to grow [30]. In this regard, there are several fundamental challenges that marketing science and informatics will have to investigate. The first is related to AI. As AI decision support systems and other applications are currently under much criticism, it is important to investigate which market stakeholders are more inclined to adopt FC-enabled AI and which are more vulnerable in the face of this emerging technology [71]. Also, technological advances have resulted in a hyperconnected world [72], requiring a reassessment of FC-enabled smart consumers from the perspective of organizations, consumers, and society. In other words, what are the managerial focuses in adopting FC?

Although algorithmic improvement is noteworthy in the case of RSs along with novelty in applications, RSs using the FC paradigm are a completely novel development, which exposes a prominent research gap. However, accuracy measures (mean absolute error, root-mean-square error) should be deployed to check the robustness of the proposed framework [73]. In addition, there are many relevant research questions linked to the conceptual framework that might be posed in future research, such as the following:

RQ$_1$: How should RSs and FC collaboration resonate with consumers?

RQ$_2$: How can marketing research scale relative consumer trust in the different data-generating devices?

RQ$_3$: Although FC has strong data-collection and integration capabilities, very often data contexts are lost, creating problems in modeling, especially as it concerns emotional data. The automated process of data collection also makes customer intimacy less achievable because it is machines talking to machines [47]. Thus, *how can data loss be prevented/reduced in an FC-based RS?*

RQ$_4$: Both FC and RSs rely on digital data to make recommendations. The proficiency to collect and analyze big data for decision making is crucial, provided that the functionality of digital technologies all rely on digital data [74]. *What levels of digital knowledge will be needed for consumers to understand FC recommendations?*

RQ$_5$: As consumer choices of items might change with time, temporal-based data are important for enhancing RS accuracy validity [75]. Therefore, *how can FC-based RSs include temporal-based data?*

RQ$_6$: The quantities of data and information produced by RS consumers are very large, thus raising the issue of information overload. The RS only partially treats this problem by attempting to automatically recommend items that activate consumer interest [26]. While the major aim of any RS is to reduce complexity by processing the huge amount of data and selecting the information most pertinent to consumer's specification, information overload remains [75]. Therefore, *how can the new FC-based RS assist in reducing the overload?*

RQ$_7$: One of the problems in recommending an algorithm for RSs is deciding the attributes composing the recommendation [76]. As different considerations might affect RSs differently, *how can FC assign appropriate weights to the different attributes?*

RQ$_8$: RSs are mainly based on the fact that consumer interests and behavior are influenced by their social "neighbors." However, consumers might have different trust attitudes for different social domains, which depends upon the RS situations. Thus, situational information might play a critical role in decision making. Situational information is based on consumers' mental, physical, emotional, and social situations [75]. *How can FC incorporate situational information for generating effective recommendations?*

RQ$_9$: There are significant cultural differences in consumer responses to the new technologies. It was demonstrated that individuals with stronger interdependent and collectivistic tendencies are more receptive to non-personalized recommendations than others [62]. In the context of our framework, the question is as follows: *can cultural differences also explain differences in responses to FC?*

RQ$_{10}$: There is a long tradition in marketing and consumer behavior showing different responses to different products (e.g., high/low involvement; hedonic/utilitarian). *Do the same differences apply to FC-based RS product recommendations?*

RQ$_{11}$: FC is claimed to be an effective computational paradigm for any data-related ecosystem [1], and while this paper has used FC-based RSs to elaborate on possible FC implications for marketing and consumer behavior, the following intuitive question is as follows: *can all big data marketing benefit from FC?*

RQ$_{12}$: FC has proven to be an interdisciplinary paradigm. When conducting FC research, how can marketing and consumer behavior benefit from related disciplines (e.g., economics, psychology, and sociology)?

RQ$_{13}$: Virtualization is an important paradigm for providing isolated environments in FC and the main factor of fog node performance [74]. Therefore, *what FC-enabled virtualization techniques should be used for RSs and other consumer domains?*

RQ$_{14}$: As already noted, offloading is a unique component that has an impact on all design goals. Offloading in FC to RSs and other consumer issues must resolve several questions: *(1) what kinds of consumer data are needed in offloading decisions, (2) how can marketing partition applications for offloading, and (3) how can optimal offloading systems be designed?*

6. Limitations

This study has some noteworthy limitations. It has been our objective to present future FC applications in consumer behavior RSs in a concise way and to derive important research questions. Consequently, we did not elaborate on the many subtleties and intricacies of FC technologies, which are undoubtedly important subjects for future research. We also recommend that future research explore the effects of the value of FC information, trust in smart technology [77–79], technology-mediated life, and enjoyment of technology-enriched experiences [80,81], among many other questions that ought to be investigated in the general context of FC. Although the present article has focused on consumers, many of these issues are also relevant in business-to-business contexts, and we expect further research to apply the proposed framework in B2B e-commerce marketplaces. Users should also consider some of the inherent limitations of FC like the fact that fog nodes require additional processing power and storage compared to simple edge devices, which might increase initial costs. In fact, managing and maintaining a distributed network of fog nodes is more complex and expensive than centralized cloud setups. Also, the lack of standardized protocols and technologies can create compatibility issues and hinder scalability. Despite the discussed challenges and future research issues, FC has the potential to revolutionize the way marketing and consumer research sectors compute and store data. By addressing these future FC challenges, scholars can make FC more reliable, efficient, and secure and pave the way for its widespread adoption.

7. Technical Contributions of FC

FC can make several key technical contributions to the field of distributed computing to enhance RSs. In particular, FC can be helpful in bridging the gap between edge devices and the cloud, like with reduced latency and improved responsiveness, optimized network bandwidth, increased reliability and resilience, and most importantly for RSs, by facilitating emerging technologies and enhancing scalability and flexibility. These technical contributions highlight the transformative potential of fog computing to RSs and its ability to improve various aspects of RS distributed computing. As technology evolves and new applications emerge, fog computing is poised to play a vital role in shaping the future of RS research.

8. Conclusions

It is clear that "[t]he era of the cloud's total dominance is drawing to a close" [18]. Emerging technologies such as neural networks, blockchains, the metaverse (e.g., virtual reality and augmented reality), cyber–physical systems, artificial intelligence, genetic data, and nanotechnologies, some of which are used independently in marketing ecosystems, are revolutionizing the smart consumer domain as we know it. One of the most remarkable changes brought about by FC is the unprecedented interactive system that cuts across physical, sensory, virtual, and digital data, not only for consumers, but also regarding products, stores, locations, and store shelves.

Theoretical and Practical Implications

The ubiquity of FC usage compels marketing scholars to study its effects on the vast array of marketing and consumer domains. Marketing managers as well as consumers need FC to augment data analytics, limit communication latency and costs, increase human situational awareness, enable adaptive decisions, and provide energy-efficient computing and architectures for data collection and processing. FC's major benefit for smart consumers lies in its ability to collect and compute big data sets in milliseconds from an array of different sources, including location-based applications (e.g., mobile devices), user-centric services, and behavioral and emotional modalities. Also, implementing practices like device refurbishment and recycling will promote responsible resource management in fog networks. The FC-based RS framework presented here suggests that FC is developing into a fully functional and potentially disruptive opportunity for consumer behavior. FC presents a platform for combining all kinds of data in a scalable manner to enrich consumers' knowledge. In this context, FC can play a crucial role in big data analytics in terms of anticipating and providing consumers with guided valuable information to meet expectations. The combination of IoT–SDN devices and decision-support software will provide smart consumers with improved systems to monitor not only their attitudes and preferences but also various recommendations and decision options. Also, IoT devices can unobtrusively insert themselves into the consumers' lives, automate regular activities, and escalate functionality by reducing the need for human intervention. In short, FC is expected to become a unifying concept, rich enough to provide a new breed of emerging services and enable the development of new consumer applications. Research on FC remains in its initial phases. Throughout this paper, we have provided a holistic view of FC as a smart world facilitator. FC is a relatively new paradigm, which has swiftly garnered wide recognition, and found broad applications, due to its significant contribution to advanced computing technology (for an updated list of references, see Web Supplementary S4).

In this paper, we have argued that FC is well suited for smart consumers, where there is a constant need to quickly analyze and react to new technologies and real-time data. Indeed, FC's ability to accelerate awareness of and response to events with minimal latency makes it perfect for smart consumers. It seems clear, as well, that IoT-enabled FC may have the potential to revolutionize the future of emotion and behavior measurement in using hybridizing approaches. With the evolution of the IoT and AI services and technologies, which establishes a new "smart world" where everything is monitored automatically, merely providing quality of service is no longer acceptable, as it fails to offer a satisfactory user experience [82]. Indeed, quality of experience (QoE), which gratifies consumer experience and enhances consumer performance, has become far more vital, and FC is considered a major technological breakthrough in terms of the advancement of QoE [33,49]. Smart consumers can exist and grow only when they continuously and rapidly adapt to changing technologies.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/jtaer19010032/s1, Supplementary S1: Fog Computing Benefits; Supplementary S2: Summary Comparison Between Cloud and Fog Computing; Supplementary S3: Affective FC for Marketing; Supplementary S4: FC Selected Publications.

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