information

Article

Using ChatGPT and Persuasive Technology for Personalized Recommendation Messages in Hotel Upselling

Manolis Remountakis [1], Konstantinos Kotis [2], Babis Kourtzis [1] and George E. Tsekouras [2,*]

[1] Upsell S.A., Kountouriotou 49, 81100 Mytilene, Greece; mr@upsell.ai (M.R.); bk@exclusivi.com (B.K.)
[2] Laboratory of Intelligent Systems, Department of Cultural Technology and Communications, University of the Aegean, 81100 Mytilene, Greece; kotis@aegean.gr
* Correspondence: gtsek@ct.aegean.gr; Tel.: +30-22-51036631

Abstract: Recommender systems have become indispensable tools in the hotel hospitality industry, enabling personalized and tailored experiences for guests. Recent advancements in large language models (LLMs), such as ChatGPT, and persuasive technologies have opened new avenues for enhancing the effectiveness of those systems. This paper explores the potential of integrating ChatGPT and persuasive technologies for automating and improving hotel hospitality recommender systems. First, we delve into the capabilities of ChatGPT, which can understand and generate human-like text, enabling more accurate and context-aware recommendations. We discuss the integration of ChatGPT into recommender systems, highlighting the ability to analyze user preferences, extract valuable insights from online reviews, and generate personalized recommendations based on guest profiles. Second, we investigate the role of persuasive technology in influencing user behavior and enhancing the persuasive impact of hotel recommendations. By incorporating persuasive techniques, such as social proof, scarcity, and personalization, recommender systems can effectively influence user decision making and encourage desired actions, such as booking a specific hotel or upgrading their room. To investigate the efficacy of ChatGPT and persuasive technologies, we present pilot experiments with a case study involving a hotel recommender system. Our inhouse commercial hotel marketing platform, eXclusivi, was extended with a new software module working with ChatGPT prompts and persuasive ads created for its recommendations. In particular, we developed an intelligent advertisement (ad) copy generation tool for the hotel marketing platform. The proposed approach allows for the hotel team to target all guests in their language, leveraging the integration with the hotel's reservation system. Overall, this paper contributes to the field of hotel hospitality by exploring the synergistic relationship between ChatGPT and persuasive technology in recommender systems, ultimately influencing guest satisfaction and hotel revenue.

Keywords: ChatGPT; persuasive technologies; recommender system; hotel hospitality

check for updates

Citation: Remountakis, M.; Kotis, K.; Kourtzis, B.; Tsekouras, G.E. Using ChatGPT and Persuasive Technology for Personalized Recommendation Messages in Hotel Upselling. *Information* **2023**, *14*, 504. https://doi.org/10.3390/info14090504

Academic Editors: Vladimír Bureš and David Martins de Matos

Received: 2 July 2023
Revised: 27 August 2023
Accepted: 11 September 2023
Published: 13 September 2023

1. Introduction

Hotel hospitality is one of the main directions of development in the tourism industry. During recent years, intelligent platforms such as smart mobile applications (MobApps), chatbots, internet of things (IoT) applications, etc., have been proven to be quite trustworthy from the points of view of both the hoteliers and the customers (i.e., guests) [1–4].

As intelligent and interactive MobApps can easily create effective personalization, their use has been recognized as an effective way to enhance guests' satisfaction, since they are in the position to affect the relative marketing factors rendering the guests as co-creators of the hotel's product value [5]. In addition, they provide the means to quantify that satisfaction assisting, in this way, is the hotel's management strategy [3,6].

Furthermore, intelligent MobApps support both human-to-machine and face-to-face interaction [6]. As a result, their usage supports the guests in establishing communication with the hotel before check-in, during their stay at the hotel, and after the check-out process [3,6]. Also, communication enables the hotel's staff to provide appropriate personalized responses and services to the customers [7].

In this paper, certain cutting-edge information technologies are combined in a uniform fashion to create an intelligent software platform that is able to generate personalized recommendations for guests of a hotel unit. The platform encompasses typical recommendation technologies encircled by ChatGPT and persuasive technologies.

So far, recommendation software has been integrated with various industries, providing personalized recommendations that enhance user experiences and drive customer satisfaction [8]. The hospitality sector, specifically the hotel industry, has recognized the importance of computational intelligence, and recommender systems in particular, in delivering tailored recommendations to guests, thereby improving their overall stay [9].

Persuasive technology, a concept introduced by Fogg [10], concerns the creation of interactive systems that aim to affect users' attitudes, behaviors, and decision-making processes. By incorporating persuasive technology into recommender systems, hotel hospitality providers can effectively guide and persuade guests towards specific choices and recommendations that align with their preferences, while also improving their own business outcomes.

As artificial intelligence (AI) grows, the emergence of large language models (LLMs) and, more specifically, ChatGPT, has revolutionized the way we interact with technology, opening new avenues for creating persuasive recommendation systems (PRSs). A recent extended review by Zhao et al. [11] reports on the topic, summarizes the available resources for developing LLMs, and discusses the remaining issues for future directions. ChatGPT has gained significant attention because it is in the position to create human-like text and understand the semantic meaning of natural language, demonstrating remarkable performance in language translation, text completion, and sentiment analysis [12,13].

The objective of this paper is to study the intersection between ChatGPT and persuasive technologies under the umbrella of recommender systems in the domain of hotel hospitality. We aim to investigate how ChatGPT elaborates on the persuasive structure of recommender systems, ultimately leading to improved user satisfaction, increased conversion rates, and enhanced business performance for hotels. Leveraging the power of ChatGPT in recommender systems creates promising opportunities for developing persuasive technologies that can engage users in meaningful interactions and provide highly personalized recommendations.

To accomplish this, we follow the research methodology that is outlined in the following lines of this paragraph: We first review the existing literature on recommender systems and persuasive technologies, highlighting their individual contributions to the field of hotel hospitality. We then delve into the advancements in LLMs, discussing their capabilities and potential applications. Furthermore, we evaluate our hypothesis by developing a new ad generation tool and conducting experiments on a real hotel hospitality environment managed by our commercial hotel marketing platform, eXclusivi, which is run on several sites, while integrating GPT 3.5 and GPT-4 in our existing recommender system. eXclusivi was extended with a new software module that works with ChatGPT prompts and persuasive ads created for its recommendations. In particular, we developed an intelligent advertisement (ad) copy generation tool for the hotel marketing platform. The proposed approach allows for the hotel team to target all guests in their language, leveraging the integration with the hotel's reservation system. By conducting such an investigation, this paper aims to provide significant results concerning the integration of ChatGPT and persuasive technologies for recommender systems in the domain of hotel hospitality with the goal of increasing sales. The outcomes of the current research can guide hotel industry professionals, technology developers, and researchers in leveraging these advancements to deliver highly persuasive and personalized recommendations, thereby enhancing the overall guest experience and driving business growth.

It must be pointed out that currently, we do not examine the ethical considerations associated with utilizing ChatGPT and persuasive technologies in hotel hospitality recommender systems. However, we discuss them in a separate section, selecting the most significant ones to be considered in our future work.

This paper is structured as follows: Section 2 briefly describes the preliminaries on the topics of ChatGPT, persuasive technology, and recommender systems. Section 3 presents related work focusing on the domain of hotel hospitality. Section 4 delineates the proposed approach, and Section 5 reports the experimental outcomes and the relative discussion. Section 6 discusses the challenges and ethical considerations. Finally, the paper concludes in Section 7.

2. Preliminaries

2.1. ChatGPT

2.1.1. Capabilities and Functionality of ChatGPT

ChatGPT belongs to the family of artificial intelligence (AI)-based large language models (LLMs) that are primarily used as natural language processing (NLP) tools [12–14]. LLMs are built in terms of deep learning techniques and learn how to perceive and reproduce human-based language. Compared to more traditional considerations, LLMs estimate their design parameters as well as the corresponding functional mechanisms in terms of end-to-end self-learning schemes, which are in the position to deal with more complex and inclusive knowledge content [13,15].

ChatGPT has been recognized as one of the most sophisticated LLMs [16–18]. Its learning procedures enable the recognition of patterns and relationships between words and sentences not by training on certain tasks, but rather in a more diffusive way [12]. The training process of ChatGPT is carried out by exposing the model to large data sets containing diverse text sources, books, articles, and websites [18,19], exhibiting remarkable performance in language-related tasks such as multilingual text creation, assistance in language translation, creative content generation, question answering, code creation and debugging, story writing, semantic analysis, and more [19–21].

One of the main advantages of ChatGPT, when compared to other LLM approaches, is its ability to recall in its memory the previous conversation with the user, rendering the dialogue highly interactive [15]. In that direction, the key points involved within its algorithmic structure to enhance the human–machine interaction can be enumerated as follows [12,18–22]: (a) the synthesis of grammatically correct logical arguments and responses, (b) appropriate scaling to certain requirements such as computational capabilities, workflow, and computational time needed by the user, (c) inherent inference mechanisms resulting from the implementation of specialized learning strategies, e.g., zero- and few-shot learning, which provide the ability to execute tasks without needing additional training, and (d) effective adaptation, making the design of custom applications an easy procedure.

Once trained, ChatGPT can perform content generation by creating coherent and contextually relevant responses to given statements (i.e., prompts) in terms of the subsequent two-step procedure [13–15,23]: (a) given the information and data provided by the user, ChatGPT deduces understandable data forms, and (b) based on the above forms, it generates content by predicting the most probable continuation based on the input context. Thus, as the model captures syntactic, semantic, and contextual information, when a user inputs a query or prompt, ChatGPT applies the above two-step process to come up with an optimal response.

The general steps performed by ChatGPT are described as follows [24,25]: (a) the system enables the user to create a prompt message, which may contain specific commands, types of questions, etc., (b) the system tokenizes the above message by separating it into words or sequences of words that are going to be analyzed, (c) the tokenized output from the previous step is fed into the transformer-based neural network, and (d) the transformer elaborates on the resulting input and, using specialized inference mechanisms, provides a text-based answer to the user.

2.1.2. GPT Versions and Technologies Involved

The technologies involved in the structure of ChatGPT encompass various types of learning procedures such as deep learning, reinforcement learning, unsupervised learning, in-context learning, and multi-task learning [12–14]. The very core of its design relies on generative pre-trained transformer models, which are deep neural networks that utilize the self-attention principle to assign different weights of significance to different inputs [26,27]. The transformer contains blocks, each of which is synthesized by multiple layers, including self-attention mechanisms and feedforward networks [26,27]. The self-attention mechanism encodes the input sequence and reveals sequences of hidden patterns in the form of representations. Based on this strategy, it then elaborates on the above-mentioned representations with the ultimate target of decoding them into an appropriate output [11–13,25,26]. A useful functionality of self-attention is related to the fact that it enables the model to capture relationships and correlations between different sequence parts [25–27].

The transformer network is encircled by various NLP techniques, such as chain-of-thought (CoT) prompting [28–30], that elaborates on the chat's inference mechanism through a step-by-step thought process under the framework of few- and zero-shot learning [31–33] and the reinforcement learning from human feedback (RLHF) technique, which acts to fine-tune the overall structure by applying reinforcement learning to train a reward model that involves human feedback [34,35]. In the latest version, GPT-4, multimodal learning is used to build the model, which is pre-trained over a very large amount of multimodal data [14,36]. This technology offers the advantage of representing highly diversified multimodal content such as images, text, multilingual content, and other modalities, rendering the user–machine interaction very sophisticated [14].

ChatGPT continuously improves both its structure and learning capabilities. All versions of GPT were trained on the basis of language modeling using vast text data such as collective works in the literature, books, internet sources, various types of written material, etc. In addition, the latest version, GPT-4, was trained on massive public data (e.g., internet data) and licensed data that, apart from text information, include images, information related to mathematical problems, weak and strong reasoning, etc.

So far, several GPT models were released, each of which is an improved version of the previous one. Within the subsequent paragraphs, we briefly describe the distinct properties and characteristics of the GPT-1, GPT-2, GPT-3, and GPT-4 models.

GPT-1 was released in June 2018. When given text in the form of a sequence of words, the objective of the pre-training procedure is the efficient prediction of the next upcoming word. The resulting model carries out translation in various languages, sentiment analysis, text classification, etc. The neural network used is a transformer decoder with 12 transformer blocks, 768 dimensions, and 117 million parameters [11,12]. The context window can handle 512 tokens, while the data set size used to conduct the unsupervised training process is approximately equal to 5 GB [13].

The full version of GPT-2 was released in November 2019. It constitutes an effective improvement of GPT-1 with increased capabilities in creating larger text sequences and generalizing new tasks. The training process is based on multi-task learning, while the training data set size is approximately equal to 40 GB of text data [11,13]. As a result, it appears to possess a more effective performance in various downstream endeavors related to classifying texts, answering questions, sentiment analysis, etc. The model also uses a transformer-based neural network with 48 transformer blocks, 1600 dimensions, and 1.5 billion parameters, while the context window uses 1024 tokens [13,24,25].

GPT-3 was released in May 2020, and it is significantly larger than GPT-2. It is in the position to carry out very complex language-processing operations without requiring task-specific training data. The neural network model is a transformer with 96 transformer blocks, 175 billion parameters, and 12,888 dimensions, where 2045 tokens are handled by the context window [13,25]. It employs CoT prompting [28–30], which enables the pre-trained model to explain issues related to its inference strategy in terms of step-by-step reasoning based on few-shot and zero-shot learning [31,32]. In addition, reinforcement learning from human feedback (RLHF) [34,35] helps to fine-tune the model, rendering it capable of understanding human preferences. The model's training procedure is based on multi-task and in-context learning. The data set size used for the training is equal to 45 TB [13,25]. The way it elaborates on the input sequence of tokens is described in the subsequent steps [12,37]. First, it utilizes an embedding layer to map (i.e., transform) the tokens in vector space. Second, the transformed tokens are inserted into the first transformer block and are processed in terms of the self-attention mechanism, yielding a sequence of hidden representations. In the third step, the derived representations propagate towards the rest of the transformer blocks, which also apply the self-attention mechanism. Finally, in the fourth step, the output of the last transformer block enters a linear projection layer that encompasses soft-max activation functions, and the model obtains the final output response.

The latest version, GPT-4, was released in March 2023, and it is a powerful LLM that is much larger than its predecessors. It is capable of processing both image and text data and derives text outputs. The transformer neural network encompasses a much larger number of layers and a larger training data set size when compared to the GPT-3, while the number of parameters is much greater than 1 trillion. The context window can handle 8195 tokens. The training process is carried out in terms of multimodal learning. Multimodal learning technology is in the position to use training data that consists of a fusion of image, text, and multilingual data sets, obtaining a significant diversity of the produced content. The architecture of GPT-4 is synthesized by three levels [13,25]. The first level encapsulates the database module, the hardware, and the software frameworks. The databases include the multimodal data, all the relative data annotations, and the data processing mechanisms such as data filtering, data pre-processing, etc. The hardware framework consists of cloud–edge computing platforms such as cloud servers along with powerful GPUs, TPUs, and AI chips that are able to perform fast and effective training of the neural network model and have massive storage devices. The software framework contains the transformer and cutting-edge diffusion models along with the corresponding training algorithms (i.e., unsupervised, multi-task, in-context, and multimodal learning algorithms) encoded in specially designed programming environments such as Python, Keras, TensorFlow, Pytorch, etc. The second level encompasses the pre-trained transformer model along with several technologies that are used to fine-tune the model's interaction performance with the user including CoT mechanisms, few- and zero-shot learning schemes, RLHF procedures, and additional multimodal technologies. It is worth noting that the pre-trained model is in the position to evolve following interactions with users on a daily basis. Finally, the third level provides a downstream information flow from ChatGPT to the user, which generates text responses, images, three-dimensional data, etc.

2.2. Persuasive Technology

Persuasive technology focuses on affecting and/or changing the behaviors of users of a system or service through persuasion [10]. They are often used in sales, diplomacy, politics, religion, public health, and generally in any field of human-to-human or human–computer interaction (HCI). The research on persuasive technologies relies on creating and enhancing the interaction between humans and machines under the framework of several platforms such as personal computers, cloud computing, web-based services, mobile devices, video games, etc. The resulting research methodologies are based on combining various potentially different fields such as psychology and computer science. They are categorized, based on their functional roles, into the following three main categories, i.e., tools, media, and social agents. In addition, they can also be classified into certain categories according to whether they influence and/or change attitudes and behaviors via straightforward interaction or via an intermediary role, i.e., whether they attempt to enhance persuasion in terms of HCI mechanisms or through computer-mediated communication [38]. Usually, the persuasion methodology is based on designing appropriate messages by monitoring and assessing their content in terms of theories coming from ongoing research in psychology.

In [39], Andrew Chak states that websites appearing to have the most effective persuasion act to make the users feel comfortable in making decisions as they help the users to make those decisions. Previous research has also used social motivations for persuasion, such as competition. A persuasive app supports the user's behavioral change by applying social motivations, rendering the user amenable to connecting with various groups of other users such as friends, families, or other users. Social media platforms like Facebook and Twitter support the implementation of such systems. It has been shown that social impact can lead to greater behavioral changes than when the user is isolated [40].

According to Halko and Kientz [41], there exists eight classes of persuasion mechanisms, which can be further classified into four general categories, where each category has two complementary attributes that are presented in the corresponding parentheses: (a) instruction (authoritative and non-authoritative), (b) social feedback (competitive and cooperative), (c) motivation type (intrinsic and extrinsic), and (d) reinforcement type (positive reinforcement and negative reinforcement). More recently, Lieto and Vernero [42] supported that logical fallacies are a class of persuasion methods that are widely used in MobApps and web-based applications. These methods have been recognized as being effective in large-scale research investigations of persuasive news recommendations [43] as well as in the thematic area of HCI [44].

Cialdini's [45] six principles, also known as the six weapons of influence [46], have become widely acknowledged as general principles of persuasion. The main idea behind those principles is that there is no magic strategy that can influence all people, and therefore, people can be persuaded in different ways. Cialdini's principles are enumerated as follows: (a) authority, (b) commitment, (c) social proof/consensus, (d) liking, (e) reciprocity, and (f) scarcity.

2.3. Recommender Systems

Recommendation technologies (RTs) refer to artificial intelligence (AI) software or application tools that are able to predict the preferences of a user and recommend relative services and/or products by applying machine learning-based techniques. RTs manage the problem of information overload that users commonly face, and influence how users make decisions by recommending appropriate actions or objects of interest. The main tasks involved in the design procedure of a recommendation system are as follows: (a) data collection and preprocessing, (b) the application of data-driven techniques to generate the corresponding models, (c) the implementation of the resulting models to existing and unseen data as well, and (d) model re-evaluation based on the information coming from the model's implementation as applied in the previous task [47]. The key features that affect the effectiveness of a recommender are the accuracy, coverage, relevance, novelty, and diversity of recommendations [48].

The typical recommendation strategies are defined in terms of three types of relationships:

1. User-to-item relationship: This relationship is influenced by the user profiling scheme and the user's explicitly documented preferences for a specific type of item (e.g., a product or service).
2. Item-to-item relationship: This relationship is based on the similarity or complementarity of the characteristics or items' descriptions.
3. User-to-user relationship: This relationship describes users who may have similar preferences as far as specific elements are concerned, such as location, age group, mutual friends, etc.

User preferences are determined by explicit/implicit ratings or comments derived from interactions between the users and the recommendation system. The main algorithmic strategy behind the recommendations is the partition of users into groups, where users belonging to the same group appear to have similar preferences. In general, there are two types of learning methods to perform the above task, namely, supervised learning and unsupervised learning. Both utilize the concept of similarity or distance between the objects to be partitioned. The typical supervised-learning-based procedure is the classification approach. Classification uses predefined tags and classes to categorize a group of users based on their preferences. It includes several algorithmic schemes such as k-Nearest Neighbors (kNN), Decision Trees, Naïve Bayes, etc. The typical unsupervised-learning-based procedure is clustering, where the labels or categories are unknown in advance and the task is to efficiently categorize specific input data using similarity-based criteria for pairs of objects. Examples of clustering algorithms are K-Means Clustering, DBSCAN (Density-based Spatial Clustering), etc.

A common problem related to the implementation of recommender systems is the so-called rating sparsity (i.e., cold-start problem), where the user preference matrix is a sparse matrix. The rating sparsity corresponds to a situation where the number of items is much larger than the number of users. As such, it is a typical problem when the recommender was recently set up to collect ratings or when it is not used by an appropriate number of users. In general, when the recommender operates normally, the presence of rating sparsity obtains inefficient and inaccurate recommendations. Popularity-based recommenders are often used to address the rating sparsity issue by selecting the most preferred items over others. Demographic techniques use information such as age and profile to classify users for future recommendations. In many cases, such techniques are embedded into the recommendation algorithm to substantially improve its robustness, yielding a hybrid mechanism [49].

One of the most used techniques in recommendation systems is collaborative filtering, which focuses on user–user or item–item relationships to make inferences about product/service evaluations. Collaborative filtering methods are similar to classifiers that create training models from labeled data. The basic idea of collaborative filtering is to use the observed ratings that are highly correlated across different users and items in order to categorize unspecified ratings. The main challenge related to the implementation of collaborative filtering is that, usually, the users only rate a restricted portion of items, resulting in a highly sparse user-to-item preference matrix. Thus, when user preferences are discovered, the recommendation model attempts to quantify the similarities between users. If the resulting similarity is successful, then the ratings of similar users are capable of decreasing the sparseness of the rating matrix by predicting values to populate that matrix [48].

Content-based recommenders employ the idea that items similar to those with high ratings will be preferred by the users. These systems create representations of the items in terms of their individual features and descriptions and extract the recommendations by matching them with items showing similar features. Therefore, they design the users' profiles and determine the respective interests/preferences in order to come up with a relevance score that quantifies the interest of a user regarding a specific item. The item's attributes are usually extracted from metadata or text descriptions. In that direction, regarding content-based recommendation approaches, there is a growing interest concerning the advantages offered by Semantic Web technologies. As there is a wealth of open knowledge semantic information sources, recent research endeavors are shifting from keyword-based representations to product and user representations based on conceptual formulations [50].

Beyond the rating of the elements (e.g., products), the context can refer to anything that can influence the attractiveness of specific recommendations during their creation. Context-aware-based RTs are a new trend. They consider that the profiles of users are dynamic in a sense, thus evaluating user preferences/interests in relation to other possible factors that may exist, such as the user's location, the user's company, the weather, etc. These RTs aim to provide personalized recommendations based on the user's profile and current environment/context conditions [51].

Knowledge-based RTs use domain knowledge generated by experts with the form of rules and/or ontologies for specific domains of knowledge, or they use the knowledge available on the internet as structured linked open data. Knowledge graphs appear to be very effective in exploiting explicit and fully determined connections between users and product entities or in extracting connections to define recommendations. As stated in [52], several studies on recommendation systems based on ontology structures, knowledge graphs, and linked open data show that they appear to have superior performance when compared to more traditional methodologies, especially in cases where there is a small number of sample ratings and incomplete rating tables.

Hybrid RTs take advantage of different approaches (mentioned above) depending on the use case. For example, for sparse data, they exploit the efficiency of approaches based on knowledge graphs, while for scores available from many users, they exploit collaborative filtering methods. Hybrid RTs take advantage of the strengths of several approaches by allowing for recommendation mechanisms to generate distinct ranked recommendations presented as sub-lists and merging the results into an overall recommendation list.

3. Related Work

Hotel Recommendation Systems (HRSs) fall into two main categories: those that recommend the appropriate hotel for accommodation, and those that recommend products, activities, and services to the current residents of a hotel [53,54]. Our work deals with the second category of HRS, focusing on better customer service and increasing a hotel's profits by selling the recommended goods/services that best suit its customers. Therefore, in a sense, the proposed work deals with eCommerce recommendation systems in hospitality environments.

Neuhofer et al. [55] performed a qualitative method to investigate the influence of intelligent MobApps in supporting efficient guests' personalized experiences. The main outcomes delineated the requirements for achieving guest satisfaction and the way intelligent MobApps could be integrated to obtain distinct stages of personalization.

Leal et al. [56] used crowdsourcing data taken from tourism platforms to study the effect of inter-guest trust and similarity post-filtering in generating more efficient recommendations in terms of collaborative filtering. The results seemed to be promising since they managed to decrease the prediction errors related to the online implementation of collaborative filtering.

Veloso et al. [53,54] developed a recommendation mechanism that relied on crowdsourcing data and matrix factorization based on a gradient descent learning procedure. Using that mechanism, they effectively performed post-recommendation filtering in terms of various factors (such as the hotel's location) and performed guest profiling in terms of multi-criteria ratings. The results of the investigation show that the classification accuracy and the theme- and hotel-based multi-criteria profile generation processes were substantially improved.

Tai et al. [57] utilized partial least squares to compare the effects of intelligent MobApp-based and human-related services. The main argument was that the latter is more vital than the former when it comes to influencing guests' satisfaction.

NOR1 (acquired by Oracle) developed a platform (namely, PRiME Decision Intelligence) based on big data to increase sales (revenue) and hotel guests' satisfaction [58]. It leverages ML and AI in general to create real-time, customized, and targeted offers for hotel guests. The system does not offer the same room type and selling price to all guests. PRiME considers customer interaction throughout the booking process and uses predictive models based on historical transactions before offering a product and price. This means that the right room and the right service are offered to the right customer at the right price, making NOR1's approach to upselling unique and highly effective. PRiME's decision intelligence can also predict guests' willingness to pay for upgrades beyond what they have already paid for their confirmed reservations. NOR1/Oracle's integrated solution seems to be the only competition today in the international field of specialized research and development in hotel hospitality upselling [59]. The basic functional architecture of the PRiME system consists of three basic operations [58,59]: (a) the eStandby Upgraden that refers to a targeted offer for a room upgrade that is sent to the customer before arrival, (b) the eStandby Add-ons that refer to additional available services that are sent to the customer in the form of ad messages, and (c) the eXpress Upgrade that refers to specially designed ad messages to sell last-minute inventory. Finally, all of the above are integrated under the CheckIn Merchandising platform in terms of a machine learning-based recommendation system that utilizes a large number of variables such as the length of stay, the number of guests, the arrival day of the week, the guest's history, any historical upsell data, the originally booked prices, etc. However, current research into the competition does not indicate the use of persuasive technology to increase the acceptance of recommendations generated by the platform's RT.

A related study on the use of persuasive technologies for hotels [60] shows the practical implications for hotel marketers in adapting green advertising strategies to substantially improve communication among and with guests. Considering green advertising as the main corporate social responsibility (CSR) in the marketing practices of hotels, this study examines the effects of green marketing on consumer perceptions and the procedural mechanism (perceptions, attitudes, and persuasive and behavioral intentions) in terms of the responses/reactions of consumers in advertising. By employing an experimental set-up that considers fictitious advertisements, it examines the effects on consumer perceptions and provides control for a certain level of environmental consciousness. The respective results were extracted from a sample of 711 American consumers and indicate that advertisements utilizing a public display purpose created more positive affective perceptions, while a "hard" sell appeal/practice created more positive cognitive perceptions. Furthermore, the experiment demonstrated that cognitive and affective perceptions appear to have positive influences on rendering the respective attitudes more significant towards advertising, while these attitudes led to persuasive and behavioral intentions. Finally, the experiment emphasized that cognitive advertising attitude, as a partial mediator between affective advertising attitude and persuasion, had a stronger influence on persuasion than affective advertising attitude.

An important issue related to the application of intelligent/interactive MobApps in hotel hospitality is the customer's unplanned spending. While many intelligent software tools were proposed, their influence on unplanned consumer spending in hotels remains unknown. The work presented in [5] uses data from a national sample of 841 hotel guests and validates a conceptual software system, which explains the unplanned consumer spending process [5]. Spending was found to be influenced by the degree of the value of co-creation in which the consumers are involved, as well as by marketing agents targeting consumer spending through interactive technologies. Furthermore, the above investigation determines the customer's need for interaction as an important factor in the model. Hence, this study scrutinizes theoretical insights in depth and provides practical suggestions that (1) recognize the importance of the value of co-creation by consumers using interactive technologies, and in particular, (2) offer insights into how interactive technologies should be marketed by hotels. The main limitations of this study are twofold. The first limitation concerns the generalizability/scalability of spending, as the approach does not provide information on the types of products that the consumer spent money on. As clearly stated, future research will focus on overcoming that limitation by splitting the expenditure variable into multiple variables that measure the extent of expenditure on specific products. The second limitation refers to the use of data only from the United States (US), as these data only reflect the infrastructure, development, and utilization methods in the US market. Future research could consider replicating this study in other national settings.

In [61], the literature on the evaluation of the persuasive characteristics of hotel chain websites is reviewed and analyzed. The paper uses latent class segmentation to divide the hotel chains based on the respective categories (i.e., luxury hotels and mid-scale and/or economy hotels) and then proposes to segment hotel chains into certain types given the persuasive power of their websites. To carry out the research, six directions of persuasion (i.e., usability, informative, inspiration, credibility, reciprocity, and involvement) were considered. The methodology used is based on the analysis of a sample of 229 hotel chain websites. The study provides evidence of current website persuasion and tips for improving it in a specific hospitality industry.

4. The Proposed Methodology

Upsell is a Greek company, which operates in the hotel hospitality tourism sector of providing information technology (IT) services in hotels. Upsell's eXclusivi platform [62] is an all-in-one platform that helps hotels and resorts to provide safe and profitable hospitality. It includes specialized smart MobApps for assisting both guests and hotel staff. The platform is integrated with leading Property Management Systems (PMSs) such as Oracle Opera [63], Fidelio [64], Protel [65], Pylon [66], Orange [67], etc. The MobApps mainly concentrate on suggesting personalized recommendations to the hotel's guests for hotel products, services, and activities of the following types: (1) reservations, (2) in-room breakfast and dining, (3) restaurants, (4) spa activities, (5) online (i.e., real time) chatting, (6) the monitoring of guests' requests and needs, (7) apps that use appropriate cleaning protocols for housekeeping and maintenance, (8) apps for performing smart room control, and (9) apps for info-channel activities and digital signage.

In the context of this research, a development project, namely, PROMOTE (Persuasive Technologies and Artificial Intelligence for Tourism) was initiated by Upsell. The target of PROMOTE is to integrate persuasive technologies and ChatGPT with eXclusivi's existing AI framework, which consists of specialized recommendation software related to a real upselling environment of hotel hospitality. The developed system is presented in the following subsections, demonstrating various scenarios for recommending a personalized choice of services and products to hotel customers. The key idea of the proposed approach is to combine, in a unified way, ChatGPT and a persuasive model that combines Persado's emotion model [68] and Cialdini's work on persuasive technology [45].

4.1. Description of the Recommendation System

Figure 1 illustrates the overall structure of eXclusivi's cloud platform. The cloud infrastructure employs real-time processes to read and store data coming from the above-mentioned PMSs and tour operators.

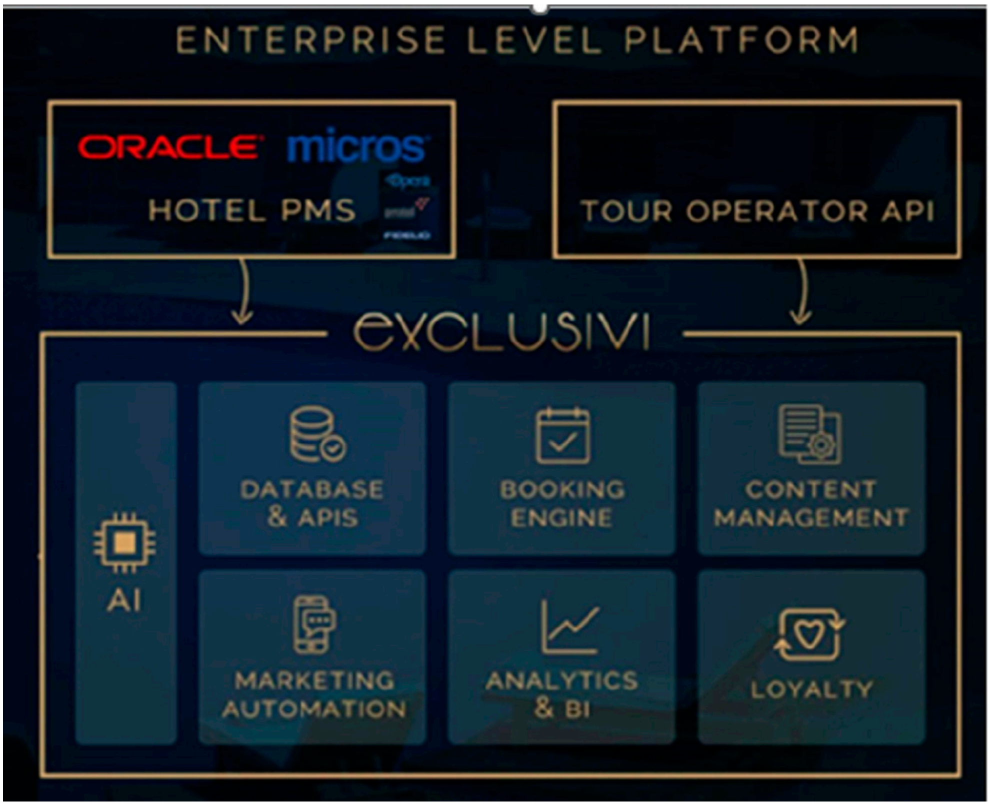

Figure 1. The overall architecture of eXclusivi's enterprise-level platform.

In a nutshell, the platform is synthesized by several modules such as (a) the database, (b) the booking engine, (c) the content management system, (d) the marketing automation procedures, (e) the data analytics and business intelligence module, (f) the loyalty part, and (g) the artificial intelligence framework.

In this paper, we focus on the artificial intelligence module, the basic structure of which is shown in Figure 2, while the input–output information flow in the recommender technology used is depicted in Figure 3.

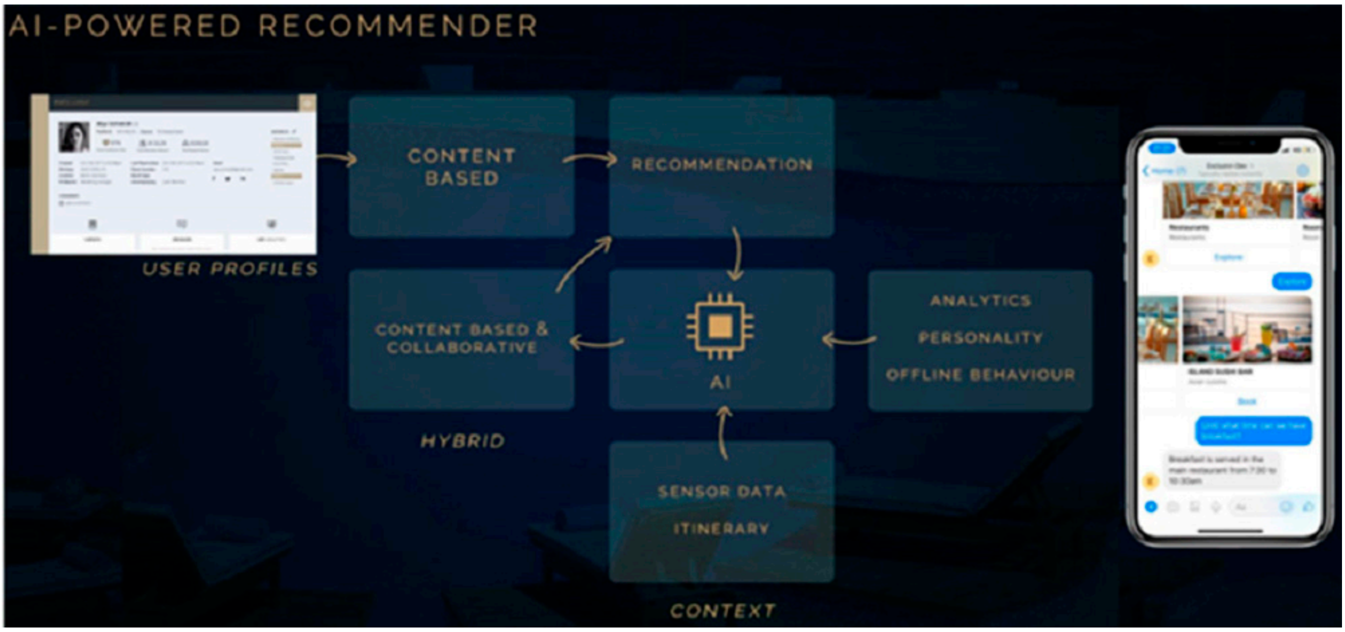

Figure 2. The structure of eXclusivi's recommendation system.

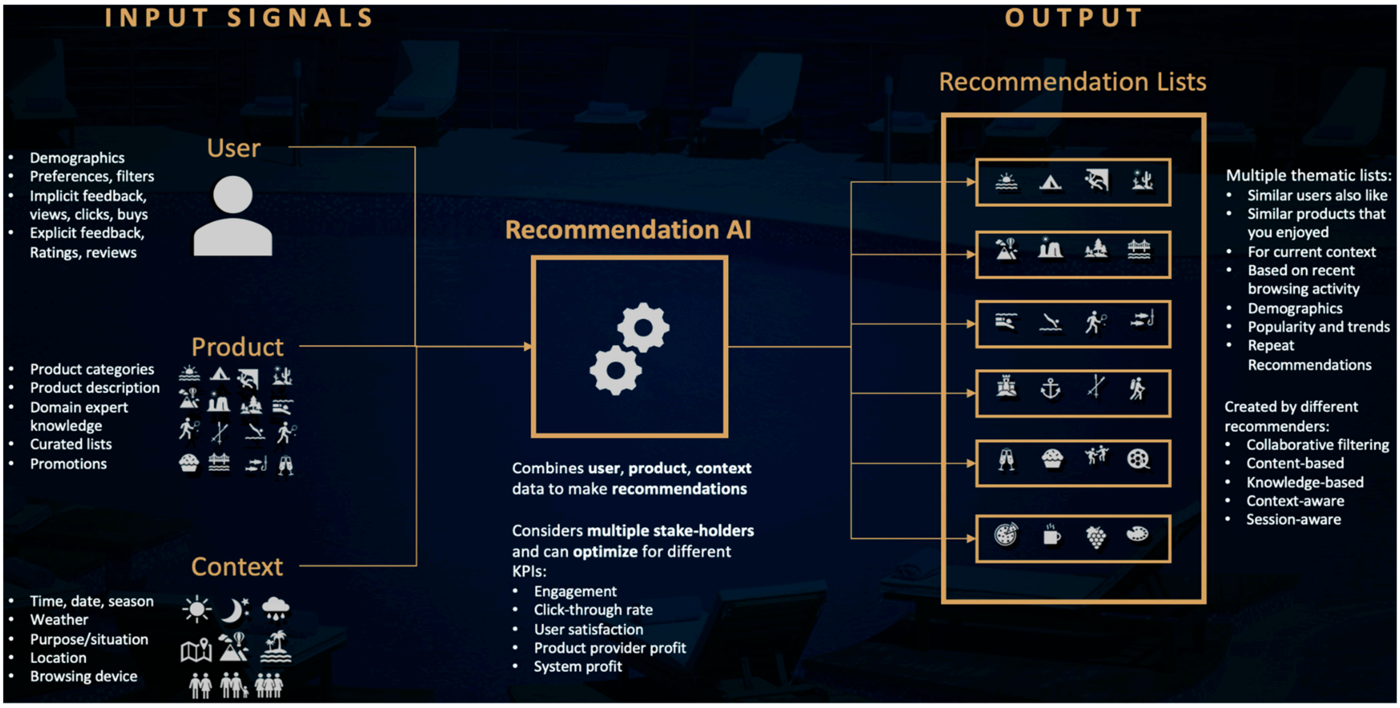

Figure 3. Input–output information flow in eXclusivi's recommendation technology.

eXclusivi's AI system encompasses a recommendation system, which uses the information taken from guests' profiles, the database, and the data analytics module. The system applies four recommendation strategies, namely, (a) a knowledge-based strategy, (b) a content-based strategy, (c) user-to-user collaborative filtering strategy, and (d) item-to-item collaborative filtering strategy.

4.1.1. Knowledge-Based Recommendation Strategy

The knowledge-based recommendation platform consists of five modules, namely, the domain knowledge, the items' features, the user profile, the recommendation mechanism, and the matching score list (see Figure 4).

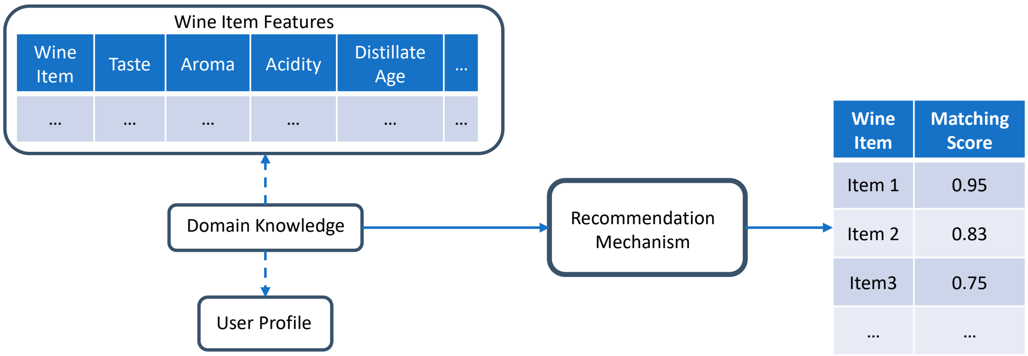

Figure 4. The structure of the knowledge-based recommender system for the wine case scenario.

The domain knowledge attempts to match the user's profile with the content of items via a knowledge model that is domain specific. For example, for wines, the model can specify how important the various features are in the content of an item when making recommendations, e.g., the aroma is particularly important for white wines. This entails an understanding of which features are important for people when deciding on items. In this direction, domain experts help Upsell's recommender design team in selecting the appropriate user and item features to be included in the process. For example, in the domain of wines, domain experts are typically wine producers and sommeliers. At the end of this step, the design team determines the type of information that needs to be collected for items and users. For example, for wines and food, we select several key item features; some of them are (a) Wine{"Taste", "Aroma", "Acidity", "Age", etc.} and (b) Food{"Appearance", "Smell", "Taste", "Texture", etc.}. The next step is populating the knowledge base with information about all of the items in the inventory. This is a tedious task that again requires the cooperation of domain experts that provide a classification of the various items. In the case of wines, for example, wine producers can provide their evaluation of the wine in terms of their characteristics. It is often the case that there is a slight disagreement between the experts on the appropriate values for the attributes of the items. In Upsell's recommendation framework, a voting mechanism is employed to reconcile any differences and agree on a unique description of items.

User profiling is carried out using indirect and direct data procedures. The former case is used to fill certain attribute fields in the user's profile and concerns demographical data, data related to the user's feedback in terms of questionnaires, etc. The latter case concentrates on collecting data related to the user's reactions to messages in terms of five-star Likert scale responses, the number of clicks, various user assessments, and quiz-based (i.e., quizzes) implicit preference elicitation mechanisms. In particular, quizzes can deliver a fun experience, but at the same time, can be quite as powerful in describing user preferences. They even have the power to extract information from users that the users do not even know they possess. This is possible by associating information from the target item domain with another more familiar domain. As an example, for the domain of wines, we developed a quiz that implicitly collects users' preferences for the wine features. The direct data constitute the most important source of data as they provide the ability to create a straightforward and real-time classification of the users.

The recommendation mechanism assigns a matching score to each combination of user and item, and derives a recommendation for a particular user by identifying the items with the highest matching scores. By mapping the user and item features in a multidimensional feature space, and by denoting the user and item vectors as $\boldsymbol{u}$ and $\boldsymbol{v}$, respectively, the above-mentioned matching procedure is calculated via the cosine similarity,

$$\cos(\boldsymbol{u},\ \boldsymbol{v}) = \frac{\langle \boldsymbol{u},\ \boldsymbol{v} \rangle}{\|\boldsymbol{u}\| \|\boldsymbol{v}\|} \tag{1}$$

To this end, based on the above calculations, we create the matching score list. Then, for each user, the matching scores are ranked in decreasing order, and the first few items, e.g., the top five, are returned as a recommendation list to the user.

4.1.2. Content-Based Recommendation Strategy

The basic structure of Upsell's content-based recommender system is depicted in Figure 5, with the case of wine recommendations as a reference. It requires three elements: (a) the user's profile, (b) the domain-knowledge-based item's feature extraction, and (c) user feedback. The first two are derived from exactly the same way as in knowledge-based recommenders. The third element is generated by observing interactions between the user and the items. The user's feedback information is typically stored in the user's profile. The recommender works by matching the content of items against the profile of the user and the content of items that the user has provided feedback on. In this way, the content-based recommender considers the domain knowledge, encoded by the content of the items and the profile of the user, as well as the user's behavior, as captured by the feedback. For example, for wines, the recommender might learn that the user likes wines with a strong aroma but does not particularly enjoy a specific type of wine, such as Pinot Noir.

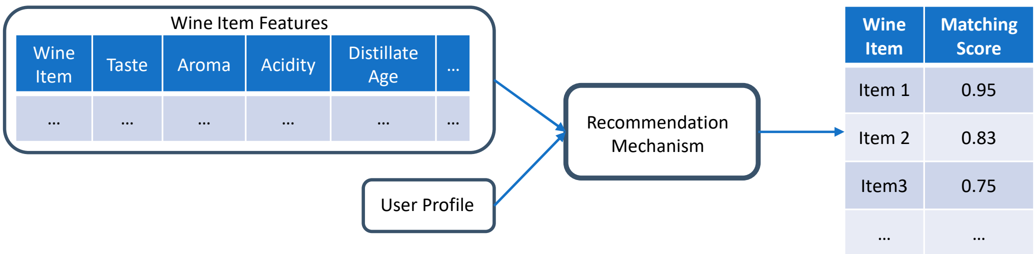

Figure 5. The structure of the content-based recommender system for the wine case scenario.

Two types of feedback are employed: explicit feedback, which is a rating that the user gives to an item in terms of a choice of five stars, and implicit feedback, which refers to information that we can collect about a user–item interaction. Examples include a purchase of an item, a click on an item, etc.

The recommendation mechanism calculates, for each item, a matching score that captures the degree of match between a user and an item. To accomplish that task, user vectors are created, which are then matched against item vectors using cosine similarity, as reported in Equation (2). The item vector ($\boldsymbol{v}$) is determined in the same way as in the previous recommender system. On the other hand, the user vector ($\boldsymbol{u}$) consists of three parts: (a) the user profile vector ($\boldsymbol{a}$), which is exactly the same as the user vector reported in the knowledge-based recommender, (b) the positive feedback vector ($\boldsymbol{b}$), which encodes all feedback that is considered positive (i.e., the user enjoyed a particular product), and (c) the negative feedback vector ($\boldsymbol{c}$), which encodes all feedback that is considered negative (i.e., the user did not enjoy a particular product). When dealing with explicit feedback, i.e., ratings, a simple way to distinguish negative/positive feedback is to compute the average rating that a user gives and take anything above it as positive feedback and take the rest as negative feedback. For implicit feedback, the distinction is harder. Typically, all feedback is considered positive, but with a varying weight or confidence level. That is, if a user keeps interacting with a particular item, we assume that there is stronger evidence in favor of this interaction actually being a positive one. The positive feedback vector is then computed as the (weighted) average of the vectors of the items for which the user has provided positive feedback; similarly, this is performed in the case of a negative feedback vector. As a result, the user vector reads as

$$\boldsymbol{u} = q\,\boldsymbol{a} + r\,\boldsymbol{b} + t\,\boldsymbol{c} \tag{2}$$

with the weight values being equal to $q = 0.5, r = 0.4,$ and $t = 0.1$.

To this end, the item and user vectors are used to calculate the matching scores and generate the respective list. For each user, the matching scores are ranked in decreasing order, and the first few items, e.g., the top five, are returned as a recommendation.

4.1.3. Collaborative-Filtering-Based Recommendation Strategy

Upsell's collaborative filtering (CF) recommender system relies on historical user–item interactions, with the basic premises that user preferences are relatively stable over time and similar users prefer similar items. Figure 6 illustrates the CF approach. The recommendation mechanism only uses information about the historical behavior of the target user, as well as the other users of the system. The output is a ranked list of items compiled by the collaborative filtering algorithm.

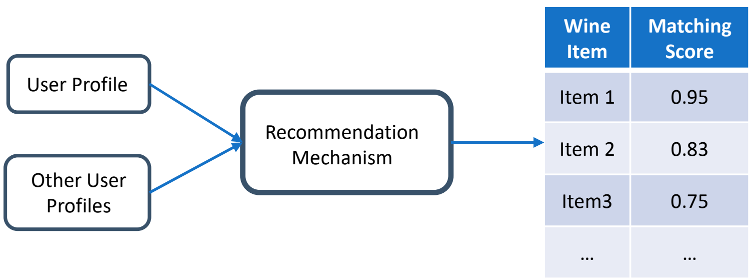

Figure 6. The structure of the collaborative filtering recommender system for the wine case scenario.

The relation between the users and items is captured by the user–item feedback matrix, which is depicted in Figure 7. The current recommendation system has only observed some of the interactions, e.g., the purchases, between users and items, which are shown as the dark cells in Figure 7. The goal of the recommender is to predict what the interactions would be for the other cells, e.g., whether a user would purchase a particular item.

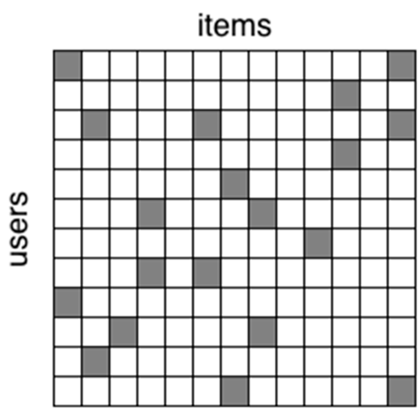

Figure 7. The user–item feedback matrix, where the dark cells indicate purchases between users and items.

The user's profile is only implicitly compiled based on the user's historical behavior, i.e., the feedback. So, if a user has purchased, rated, or viewed some items, their profile is built based on this information. Upsell's platform assumes the case of explicit feedback, meaning that a user has provided ratings for some items.

In our analysis, two CF approaches are applied, namely, user–user and item–item. In both cases, we use vector space representations, where the vector spaces of users and those of items are distinct and of different dimensionalities. Let us assume that the user–item feedback matrix is an $N \times M$ matrix, i.e., it contains N users and M items.

The user–user CF is carried out in the $\Re^M$ vector space by defining the rows of the user–item feedback matrix as user vectors, $\boldsymbol{U} = \{\boldsymbol{u}_1, \boldsymbol{u}_2, \ldots, \boldsymbol{u}_N\}$, with $\boldsymbol{u}_i \in \Re^M$ for $i = 1, 2, \ldots, N$. Thus, the i-th user vector can be represented as $\boldsymbol{u}_i = [u_{i1}, u_{i2}, \ldots, u_{iM}]^T$, where u_{ik} is the rating of user i to item k (with k = 1, 2, . . ., M). Each user vector is a sparse vector, meaning that only a few coordinates, corresponding to items the user has rated, are known. For most dimensions, we do not know the ratings, and thus, the respective coordinates. In fact, it is the goal of the user–user CF-based recommender to estimate what the missing coordinate values are. The key point behind the process is that two users $\boldsymbol{u}_i$ and $\boldsymbol{u}_j$ are similar if they have rated a large number of common items similarly, which is quantified by the following user–user similarity measure:

$$s(\boldsymbol{u}_i, \boldsymbol{u}_j) = \frac{\sum_{k \in I_i \cap I_j} (u_{ik} - \overline{u}_i)\left(u_{jk} - \overline{u}_j\right)}{\sqrt{\sum_{k \in I_i} (u_{ik} - \overline{u}_i)^2} \sqrt{\sum_{k \in I_j} \left(u_{jk} - \overline{u}_j\right)^2}} \tag{3}$$

where $\overline{u}_i$ is the average rating of user $\boldsymbol{u}_i$ and I_i is the set of items that the user $\boldsymbol{u}_i$ has rated. The above similarity is the mean-centered cosine, which is equivalent to computing Pearson's correlation coefficient.

User–user CF recommends items to a target user that were highly rated by similar like-minded users; this is called the neighborhood of a target user. Herein, the neighborhood of a target user is formed by taking a fixed number of other users (typically, 20–100) that are the most similar to the target user. The neighborhood of user $\boldsymbol{u}_i$ is denoted as T_i. Then, the predicted rating of a target user to the k-th item is computed as follows:

$$Q(\boldsymbol{u}_i, k) = \overline{u}_i + \frac{\sum_{\boldsymbol{u}_j \in T_i,\, j \neq i} s(\boldsymbol{u}_i, \boldsymbol{u}_j)(u_{jk} - \overline{u}_j)}{\sum_{\boldsymbol{u}_j \in T_i,\, j \neq i} \left|s(\boldsymbol{u}_i, \boldsymbol{u}_j)\right|} \tag{4}$$

To this end, the steps performed by the user–user CF are described next. First, by using Equation (3), the similarities between the pairs of users are computed. Second, for each user, the corresponding neighborhood is created. Third, by using Equation (4), for each item that the current user has not rated, the predicted rating is calculated. Fourth, for each user, all ratings are normalized in the interval of [0, 1], and the items are ranked based on the decreasing order of their normalized ratings (see Figure 6). Finally, for each user, the first few items (e.g., the top five) are returned as a recommendation list.

The item–item CF is carried out in the $\Re^N$ vector space by defining the columns of the user–item feedback matrix as item vectors, $\boldsymbol{V} = \{\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_M\}$, with $\boldsymbol{v}_k \in \Re^N$ for $k = 1, 2, \ldots, M$. Thus, the k-th item vector can be represented as $\boldsymbol{v}_k = [v_{k1}, v_{k2}, \ldots, v_{kN}]^T$, where v_{ki} is the rating of user i to item k (with i = 1, 2, . . ., N). Each item vector is a sparse vector, meaning that only a few coordinates, corresponding to users that have rated the item, are known. The similarity between items is computed in a similar way as with users:

$$s(\boldsymbol{v}_k,\ \boldsymbol{v}_\ell) = \frac{\sum\limits_{i \in Z_k \cap Z_\ell} (v_{ki} - \overline{v}_k)(v_{\ell i} - \overline{v}_\ell)}{\sqrt{\sum\limits_{i \in Z_k} (v_{ki} - \overline{v}_k)^2}\sqrt{\sum\limits_{i \in Z_\ell} (v_{\ell i} - \overline{v}_\ell)^2}} \tag{5}$$

where $\overline{v}_k$ is the average rating of item k, and Z_k is the set of users that have rated item k. Item–item CF recommends items to a target user that are similar to what the target user has highly rated. The neighborhood of a target item is computed by taking the most similar items with respect to the item similarity measure, and for the k-th item, it is denoted as F_k. Then, the predicted rating of user i to a target item $\boldsymbol{v}_k$ is computed as the sum over all item neighbors of their ratings weighted by their similarity to the target item as follows:

$$Q(\boldsymbol{v}_k,\ i) = \overline{v}_k + \frac{\sum\limits_{\boldsymbol{v}_\ell \in F_k,\ \ell \neq k} s(\boldsymbol{v}_k,\ \boldsymbol{v}_\ell)(v_{\ell i} - \overline{v}_\ell)}{\sum\limits_{\boldsymbol{v}_\ell \in F_k,\ \ell \neq k} |s(\boldsymbol{v}_k,\ \boldsymbol{v}_\ell)|} \tag{6}$$

To summarize, the steps performed by the item–item CF recommender are as follows: First, for each item that the target user has not rated, Equation (5) is used to compute its similarity to every rated item. Second, the neighborhood of each item that was not rated is created. Third, for each non-rated item, Equation (6) is used to compute its predicted ratings, and all ratings are normalized in the interval of [0, 1]. Finally, for each user, the items are ranked in the decreasing order of their normalized ratings, and the first few items (e.g., top five) are returned as a recommendation list to the user.

4.1.4. Examples Illustrating Upsell's Recommender System

In the following paragraphs, two examples of recommendations are described. The first example concerns wine recommendations, and the second one concerns food recommendations.

For wine recommendations, the four above-mentioned types of recommenders (i.e., knowledge-based recommender, content-based recommender, user-to-user collaborative filtering, and item-to-item collaborative filtering) are implemented. For the first two, a content description by wine experts is required (the process concerns the domain knowledge model), and the user profiles are created through special quizzes (the process concerns preference extraction and elicitation). For the last two types of recommenders, explicit feedback is required, which is collected via the number of the respective purchases performed by the user. The recommendations are generated through four services, as shown below.

(1) /wine/kbr?acm={acm} is used with the knowledge-based recommender algorithm for a specific reservationNumber. This is executed every time a user chooses to answer a quiz (preference extraction). The service returns recommendations for that user.
(2) /wine/cbr?acm={acm} is used with the content-based recommender algorithm for a specific reservation number. It is executed every time a user provides feedback on a purchased wine. The service returns recommendations for that user.
(3) /wine/uucf?acm={acm} is used with the user–user CF recommender for all reservations (reservationNumber). It is executed every time a user provides feedback on a purchased wine. The service returns recommendations to all users rather than to just the ones who provided feedback. This is because in collaborative filtering, one user's recommendations depend on the feedback of users with similar preferences.
(4) /wine/iicf?acm={acm} is used with user–user collaborative filtering for all reservations (reservationNumber). This is executed whenever a user provides feedback to a purchased wine. The service returns recommendations for all users rather than only for the one who gave feedback. The {acm} variable refers to the accommodation identity (id), i.e., a specific hotel of a network of hotel units, while the reser-

vationNumber refers to the visitor's id. Tables 1 and 2 depict the invocation of the services /wine/kbr?acm={acm} and /wine/cbr?acm={acm}, respectively. Table 3 gives the response of the invocation of the services /wine/uucf?acm={acm} and /wine/iicf?acm={acm}, which is a GET method.

Table 1. Example of the knowledge-based recommender for wine with the invocation of the /wine/kbr?acm={acm} service.

Post	Response

{
"_id": "5b0e5ee02ab79c0001557144",
"accommodationId": "smp",
"reservationNumber": "151792",
"profileName": "Bernd",
"preferences": {
"color": "2",
"tannins": "2",
"fruitness": "1",
"acidity": "1",
"body": "1",
"earthy": "2",
"spices": "2",
"herbal": "2",
"floral": "2",
"oaky": "1",
"price": "less_60"
},
"dateTime": "2018-05-30T11:20:48.000+03:00",
"_class": "com.infamous.persistence.documents.wineProfiles.
models.WineProfile"
}
	{
	"accommodationId": "smp",
	"recommendedWines": [
	"DI_MIN_PAL_WIN_46",
	"DI_MIN_PAL_WIN_33"
	],
	"reservationNumber": "151792",
	"timestamp": "2018-07-10T11:44:12.856229",
	"type": "kbr"
	}

Table 2. Example of the content-based recommender for wine with the invocation of the /wine/cbr?acm={acm} service.

Post	Response

{
"id": "5b4329beb9d8210001c446a2",
"accommodationId": "blv",
"reservationNumber": "30000184099",
"dateTime": {
"dayOfYear": 190,
"dayOfWeek": "MONDAY",
"month": "JULY",
"dayOfMonth": 9,
"year": 2018,
"monthValue": 7,
"hour": 12,
"minute": 24,
"nano": 366000000,
"second": 14,
"chronology": {
"calendarType": "iso8601",
"id": "ISO"
}
},
"ratings": [
{
"id": "wine",
"rating": "7"
}
],
"profileName": "EECKHOUT,",
"wineId": "DI_BLV_WIN_LIS_17",
"restaurantId": "DI_BLV_THE_PI1",
"dateTimeLong": 1531128254
}
	{
	"accommodationId": "blv",
	"recommendedWines": [
	"DI_MIN_PAL_WIN_46",
	"DI_MIN_PAL_WIN_33"
	],
	"reservationNumber": "151792",
	"timestamp": "2018-07-10T11:44:12.856229",
	"type": "cbr"
	}

Table 3. Example of the collaborative-filtering-based recommender response for wine with the invocation of the /wine/uucf?acm={acm} and /wine/iicf?acm={acm} services.

Response

{
"accommodationId": "blv",
"recommendedWines": [
{
"list": [
"DI_BLV_WIN_LIS_37",
"DI_BLV_WIN_LIS_20"
],
"reservationId": "30000184099"
},
{
"list": [
"DI_BLV_WIN_LIS_37",
"DI_BLV_WIN_LIS_20"
],
"reservationId": "30000194074"
},
{
"list": [
"DI_BLV_WIN_LIS_37",
"DI_BLV_WIN_LIS_20"
],
"reservationId": "blv"
}
],
"timestamp": "2018-07-10T11:44:12.856229",
"type": "uucf"
}

For recommendations of specific food dishes, two types of systems are implemented: (a) item–item collaborative filtering and (b) content-based recommendation strategy. For the first, implicit feedback is required, which, in this case, is the customer's purchase history. The recommendations are generated through two services as shown below:

(1) /pos/iicf is used with the item–item CF recommender for a specific order.
(2) /pos/pop is used with the content-based recommender for a specific order. This is also performed whenever a recommendation is requested for a specific order.

Internally, these algorithms use a third-party service to update the state of the algorithms based on current customer purchases:

(3) /pos/update_state?acm={acm} is used to update the state of a specific recommendation. It is run periodically to update the information that the recommendation algorithms rely on to derive their recommendations.

Table 4 depicts an example showing the invocation of the /pos/iicf and /pos/pop services, while Table 5 illustrates an example of the invocation of the /pos/update_state?acm={acm} service, which is a GET method.

The context of the first recommendation service is that the user is located in the restaurant and has already purchased some dish items, e.g., appetizers and a main course, and the system recommends the appropriate dessert as the third dish item. For this reason, the algorithm enters the current order as data and "searches" to find the appropriate items to complete it.

Table 4. Example of the item–item CF and content-based recommender for food with the invocation of the /pos/iicf and /pos/pop services.

Post	Response

{
"id": "5b4329beb9d8210001c446a2",
"accommodationId": "blv",
"reservationNumber": "30000184099",
"dateTime": {
"dayOfYear": 190,
"dayOfWeek": "MONDAY",
"month": "JULY",
"dayOfMonth": 9,
"year": 2018,
"monthValue": 7,
"hour": 12,
"minute": 24,
"nano": 366000000,
"second": 14,
"chronology": {
"calendarType": "iso8601",
"id": "ISO"
}
},
"ratings": [
{
"id": "wine",
"rating": "7"
}
],
"profileName": "EECKHOUT,",
"wineId": "DI_BLV_WIN_LIS_17",
"restaurantId": "DI_BLV_THE_PI1",
"dateTimeLong": 1531128254
}
	{
	"accommodationId": "blv",
	"recommendedWines": [
	"DI_MIN_PAL_WIN_46",
	"DI_MIN_PAL_WIN_33"
	],
	"reservationNumber": "151792",
	"timestamp": "2018-07-10T11:44:12.856229",
	"type": "cbr"
	}

Table 5. Example of updating the information that the recommenders rely on with the invocation of the /pos/update_state?acm={acm} service.

Response

{
"itemDict": [
{
"id": "DI_ROY_MIN_COF_72",
"value": 30
},
{
"id": "DI_ROY_MIN_COF_39",
"value": 32
}
],
"posixTime": 1532375562,
"r": [[ ]]
}

4.2. Recommendations Using ChatGPT and Persuasive Technology

In the PROMOTE project, we extended the recommender system (RS) of Upsell's eXclusivi platform by implementing a method based on ChatGPT and a combination of

Cialdini's [45] persuasion model and Persado's emotion model [68]. The basic structure of the proposed framework is illustrated in Figure 8.

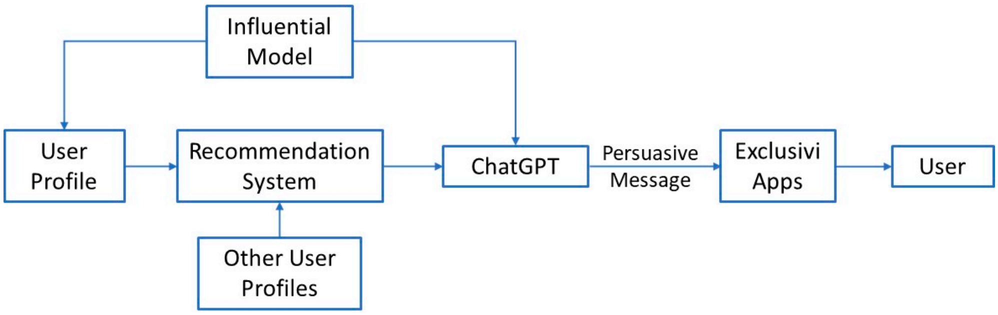

Figure 8. The basic structure of the PROMOTE system.

The main characteristic of the above system is that it has an automated approach in generating persuasive messages, allowing for advertisers to deliver many more messages than those that would have been created by humans (manually). This technology, because it does not have a predetermined message generation logic, creates variations that a human could not think of. The very core of the approach consists of the influential model and ChatGPT. Note that ChatGPT is used to generate the appropriate persuasive messages (ads), and is given (a) the output of the recommendation component and (b) the influential model as inputs. As such, ChatGPT is not enough to generate appropriate recommendations but is used as an effective assistive technology to accomplish the above task in an automatic way. Therefore, although the mechanism for generating messages can be replaced by a non-automated third-party one, in our case, it is necessary to integrate all the proposed technologies depicted in Figure 8 to create and deliver automatic persuasive messages.

The functionality of those modules is described within the subsequent subsections.

The influential model combines, in uniform fashion, Persado's Wheel of Emotions (see Figure 9) [68] and Cialdini's persuasion model [45].

Figure 9. Persado's Wheel of Emotions.

Persado maps human emotions to what is called a Wheel of Emotions [68]. The undertaking task is to generate and test different promotional messages/e-mails with business customer recipients. Persado describes this approach as "persuasion automation" in part because it can be extended beyond ads and content promotion to anywhere someone sends structured short messages that are designed to persuade. In 2015, in an Emotional Rankings report, Persado showed that the use of this technology (emotional language) in advertising messages produces more engaging content and leads to significant results, increasing the effectiveness of the content by up to 70%.

Based on Figure 9, Persado defined five emotion categories, each of which includes three emotions as follows:

1. Joy = {Gratification, Fascination, and Excitement}
2. Trust = {Intimacy, Gratitude, and Safety}
3. Pride = {Luck, Exclusivity, and Achievement}
4. Anticipation = {Encouragement, Curiosity, and Challenge}
5. Fear = {Guilt, Urgency, and Anxiety}

The set of the emotion categories is denoted as,

$$EC = \{Joy,\ Trust,\ Pride,\ Anticipation, Fear\} = \{ec_1,\ ec_2,\ ec_3,\ ec_4, ec_5\} \tag{7}$$

Cialdini's persuasion model [45] includes six principles, namely, authority, commitment, social proof/consensus, liking, reciprocity, and scarcity. Authority refers to individuals who are authoritative, commitment concerns people who are consistent with their identity, social proof/consensus refers to individuals who are influenced by others before making a choice, liking refers to people who are persuaded by the people they like, reciprocity refers to individuals who do not like to owe other people and repay favors, and scarcity refers to people who tend to buy products with a low availability. The set of Cialdini's principles is denoted as

$$\begin{aligned} CP &= \{Autority,\ Commitment,\ SocialProof/Consensus,\ \ Liking,\ Reciprocity,\ Scarcity\} \\ &= \{cp_1,\ cp_2,\ cp_3,\ cp_4,\ cp_5,\ cp_6\} \end{aligned} \tag{8}$$

To this end, the influential model combines Persado's emotion categories and Cialdini's principles, as shown in Figure 10, creating the respective user categories. Thus, the same message will appear differently to users of different categories, matching the requirements of each category.

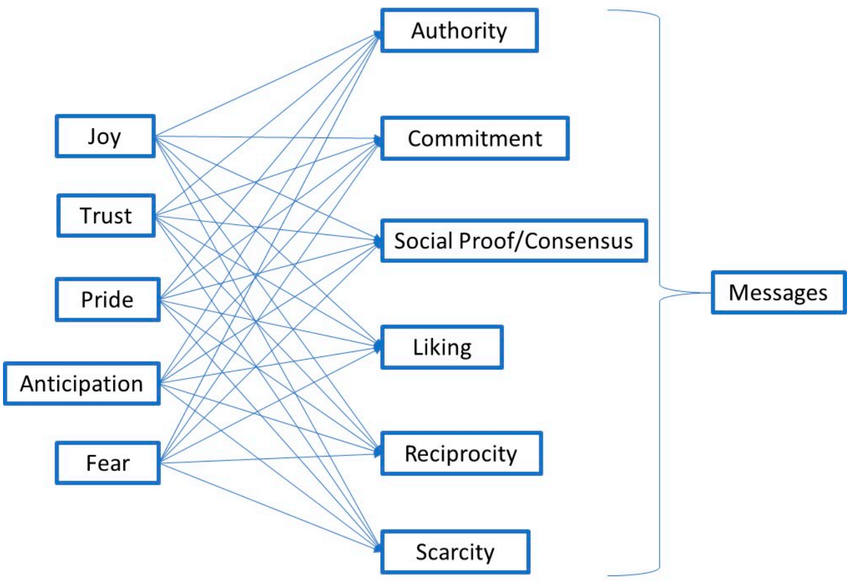

Figure 10. Combination between Persado's emotion categories and Cialdini's principles in the influential model.

However, the uniform combination between the elements of the *EC* and *CP* sets would not be convenient because too many distinct categories would arise, while not all of them are important. To resolve that problem, we developed an algorithmic tool (see Algorithm 1) that obtains a ranking of the elements of the CP set with respect to each element of the EC set. Then, each element of the EC set is linked to the corresponding highest (e.g., the top two) ranked elements of the CP set. The detailed analysis is described within the subsequent paragraphs. Equations (7) and (8) can be rephrased as follows: $EC = \{ec_i\}|_{i=1}^{5}$ and $CP = \{cp_j\}|_{j=1}^{6}$. Given that each of Persado's emotion categories include three emotions, i.e., $ec_i = \{em_{i1},\ em_{i2},\ em_{i3}\}$, for the emotion $em_{ik} \in ec_i$ (with $k = 1, 2, 3$), there are automatically generated n_{ik} messages $\left\{m^j_{ik1},\ m^j_{ik2},\ \ldots,\ m^j_{ikn_{ik}}\right\}$ that combine the emotion em_{ik} with the principle cp_j. In our analysis, for the message $m^j_{ik\ell}$ (with $\ell = 1,\ 2,\ \ldots,\ n_{ik}$), we use three variables. The first is denoted as $\varphi^j_{ik\ell}$ and defines the number of "impressions" related to that message, which is the number of times the message was viewed/opened by the guests. The second variable is denoted as $\vartheta^j_{ik\ell}$ and defines the number of clicks related to the message, which corresponds to the number of times the guests tap/click the message's "Call to Action" button (e.g., "Learn More", "Reserve Now", etc.). The third variable is denoted as $\delta^j_{ik\ell}$ and defines the number of reservations, which corresponds to the number of times the guests proceed with the reservation of the service/product that is advertised in the message.

The total number of impressions, clicks, and reservations that relate the emotion em_{ik} with the principle cp_j are, respectively, given as $\phi^j_{ik} = \sum\limits_{\ell=1}^{n_{ik}} \varphi^j_{ik\ell}$, $\theta^j_{ik} = \sum\limits_{\ell=1}^{n_{ik}} \vartheta^j_{ik\ell}$, and $\lambda^j_{ik} = \sum\limits_{\ell=1}^{n_{ik}} \delta^j_{ik\ell}$.

To quantify the strength of combining the emotion em_{ik} with the principle cp_j, we introduce two measures, the click-through rate ctr^j_{ik} and the reservation rate rrt^j_{ik}, which are calculated as follows:

$$ctr^j_{ik} = \frac{\theta^j_{ik}}{\phi^j_{ik}} \times 100 \tag{9}$$

$$rrt^j_{ik} = \frac{\lambda^j_{ik}}{\theta^j_{ik}} \times 100 \tag{10}$$

In that direction, to extend the above analysis and quantify the strength of combining the emotion category ec_i with the principle cp_j, we sum up the number of impressions, clicks, and reservations as $\Phi^j_i = \sum\limits_{k=1}^{3} \phi^j_{ik}$, $\Theta^j_i = \sum\limits_{k=1}^{3} \theta^j_{ik}$, and $\Lambda^j_i = \sum\limits_{k=1}^{3} \lambda^j_{ik}$. Thus, the extended click-through rates and reservation rates are determined as

$$CTR^j_i = \frac{\Theta^j_i}{\Phi^j_i} \times 100 \tag{11}$$

$$RRT^j_i = \frac{\Lambda^j_i}{\Theta^j_i} \times 100 \tag{12}$$

To this end, the algorithm that obtains the ranking of the elements of the CP set with respect to each element of the EC set is based on using the extended click-through rates CTR^j_i $(\ i = 1,\ 2,\ \ldots,\ 5;\ j = 1,\ 2,\ \ldots,\ 6)$ and it is described below.

Algorithm 1 Principles' Ranking Process

(*Step 1*). According to the functionality of the tool, when a guest logs in to the hotel's Wi-Fi or mobile app, she automatically receives a pop-up with ads for the hotel's services, like spas or restaurants. Each ad corresponds to one of the five emotion categories of Persado's wheel. Based on the resulting impressions and clicks, the guest is assigned to one of the elements of the *EC* set (i.e., one of Persado's emotion categories).
(*Step 2*). For the message $m^j_{ik\ell}$ (with $i = 1,\ 2,\ \ldots,\ 5;\ j = 1,\ 2,\ \ldots,\ 6;\ \ k = 1,\ 2,\ 3;\ \ell = 1,\ 2,\ \ldots,\ n_{ik}$), determine the values of $\varphi^j_{ik\ell},\ \vartheta^j_{ik\ell}$, and $\delta^j_{ik\ell}$.
(*Step 3*). For the emotion category ec_i, use Equation (11) to calculate the extended click $-$ through rates $\left\{CTR^j_i\right\}\Big|_{j=1}^{6}$.
(*Step 4*). For the emotion category ec_i, rank in descending order the extended conversion rates $\left\{CTR^j_i\right\}|_{j=1}^{6}$, and select highest (e.g., the 2 - top) ranked principles to be combined with ec_i.

In the experimental analysis (i.e., Section 5), a pilot experiment is presented that involves the above process.

At this point, it is emphasized that the above process is continuously applied by sending messages on a daily basis. Thus, its effectiveness in correctly categorizing guests continuously improves.

Having categorized a user in terms of Algorithm 1, the influential model suggests the basic emotional characteristics that should appear in the persuasive message. These characteristics, along with the product and/or service preferences coming from the RS, are fed into ChatGPT in terms of an appropriate prompting form. As a result, ChatGPT creates a structured persuasive message, which is then sent to the guest through eXclusivi's cloud applications.

5. Experimental Analysis

In this section, four experiments are conducted and analyzed to demonstrate the effectiveness of the proposed framework.

The first experiment concerns the prompts and the resulting messages derived from ChatGPT. Based on the proposed framework, the PROMOTE team can use ChatGPT prompts to easily create ads using emotions (Persado's emotion model) and tones (Cialdini's principles) in different languages. For instance, an example of prompts for the tool is the following:

> *"Create 3 ad copies about a special offer of −20% (Task) for Couples Massage (Topic), with excitement (Emotion), and funny (Tone), Use an emoticon, in 15 words (Length), in German (Language)"*

Figure 11 depicts three examples of prompts with different topics, languages, and emotions. The use of emoticons is also possible. Figure 12 includes the prompt "List 5 compelling Google Ads responsive meta descriptions about spa with a 20% special offer" (task) for a couples massage (topic), showing luck (emotion) and humor (tone) in 10 words (length). Note that the emotions are computed by ChatGPT based on the provided prompts.

In Figure 13, an example of an ad message creation (in German) for a couples massage, based on Persado's excitement emotion and Cialdini's liking principle, is depicted. The example is generated by the intelligent ad copy generation tool and served to customers via Wi-Fi. It requests three copies of a message that shows "excitement" about a 20% discount offer for a couples massage. Similarly, Figure 14 illustrates examples of ad messages for offers in couples spa services based on the encouragement emotion and the commitment tone.

Prompt		Prompt		Prompt	
Task:	write ad copy about spa with a 20% special offer	Task:	write ad copy about spa with a 20% special offer	Task:	write ad copy about spa with a 20% special offer
Topic:	Couples Massage	Topic:	Face Massage	Topic:	Couples Massage
Example:		**Example:**		**Emotion**	LUCK
Emotion	LUCK	**Emotion**	Excitement	Tone:	Funny
Tone:	Funny	Tone:	Funny	Language	German
Include an emoticon		Include an emoticon		Length:	10 words
Length:	10 words	Length:	10 words		

Figure 11. Examples of ChatGPT prompts engineered in Google Sheets (ChatGPT extension) to create ads with emotions.

Prompt		Ads
Task:	List 5 compelling Google Ads responsive meta descriptions about spa with a 20% special offer	👫 Relax and reconnect with 20% off couples massage!
		Indulge in a couples massage and save 20%. Bliss guaranteed!
		Love is in the air with 20% off a couples massage.
Topic:	Couples Massage	Take a break - Couples massage for 2, now 20% off!
Example:		Aromatherapy, hot stones, and 20% off couples massage. Yes, please! 😍
Emotion	LUCK	
Tone:	Funny	
Include an emoticon		
Length:	10 words	

Figure 12. Examples of ad messages created (in English) for couples massage based on luck.

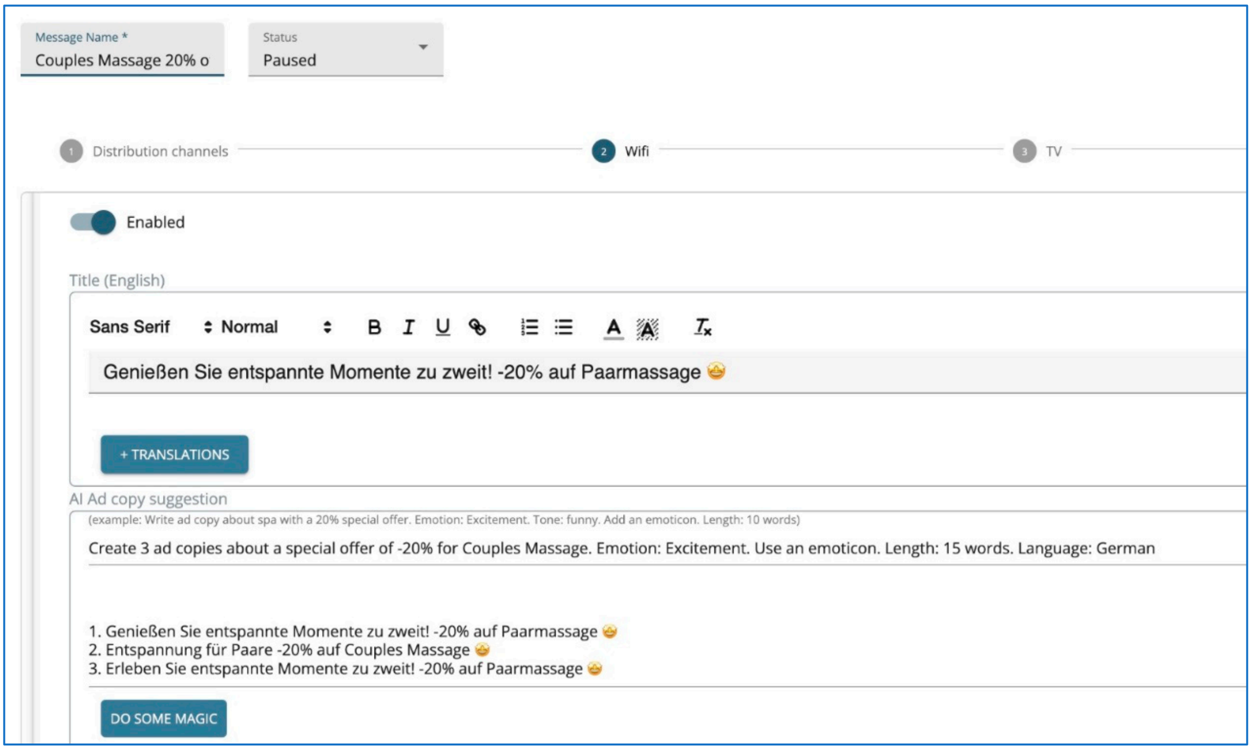

Figure 13. Upsell's eXclusivi-platform-integrated examples of ad messages created (in German) for couples massage based on excitement emotion (Persado) and liking principle (Cialdini).

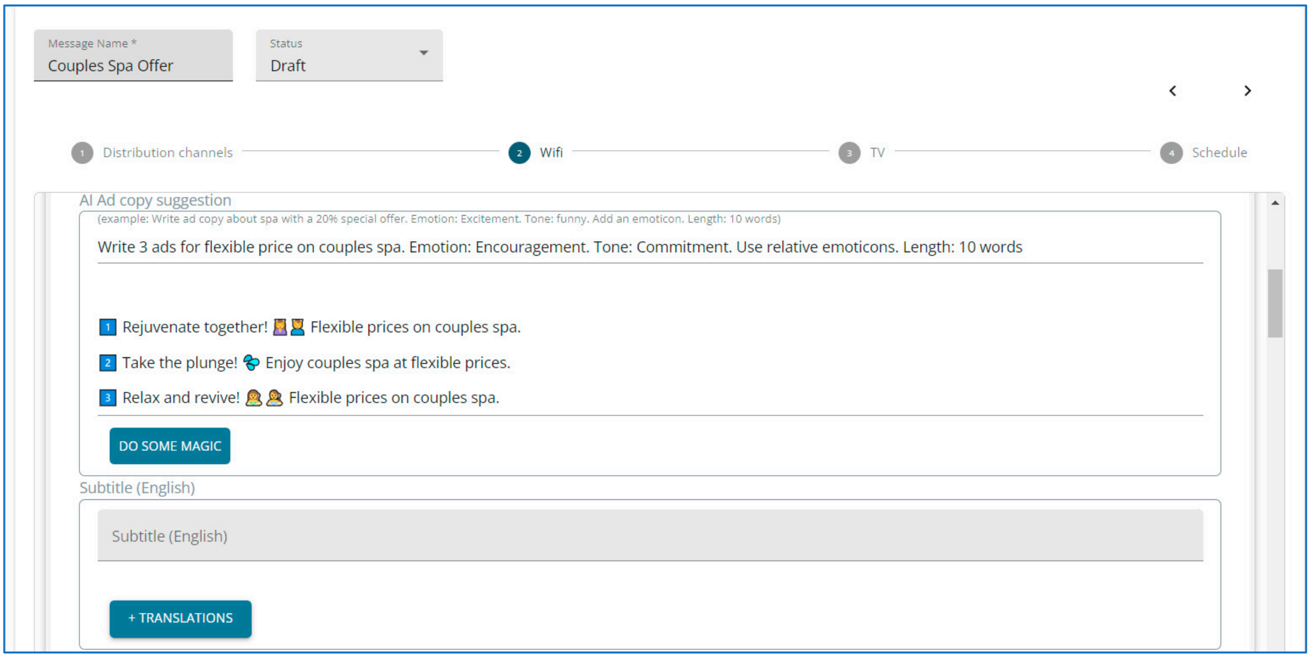

Figure 14. Upsell's eXclusivi-platform-integrated examples of ad messages created for couples spa based on encouragement emotion (Persado) and commitment principle (Cialdini).

The second experiment concerns the qualitative comparison between ad messages created manually and ad messages generated by ChatGPT. Figures 15 and 16 illustrate messages for spa services for all of Persado's emotions and for various Cialdini's principles. The messages in Figure 15 were generated manually by the PROMOTE team, while the messages in Figure 16 were generated by ChatGPT. Both cases took into account the influential model.

	Hotel Message for Spa
PRIDE	
ACHIEVEMENT	◯ Nicely done! We're treating you to this exclusive offer — Couples Massage
EXCLUSIVITY	☺ SNEAK PREVIEW! Reward yourself with something awesome at our huge Spa offers event
LUCK	Lucky you! We're releasing 10% OFF in Couples Massage
TRUST	
SAFETY	★ It's true! A discount of up to 35% off, but for a limited time only.
GRATITUDE	★ Early access! Because we appreciate you, here is our best Spa Offer ★
INTIMACY	⚡ Attn: Today's Deal of the Day – you're welcome
JOY	
EXCITEMENT	☞ WOW! Something awesome... Just for you
FASCINATION	Drop everything! We're announcing a discount of up to 35% off, starting right now.
GRATIFICATION	★ Drop everything! You're getting price cuts on Couples Massage during the 72 hour sale.
FEAR	
ATTENTION	Special Announcement 📢 We just announced a special Couples Massage offer!
URGENCY	>> 3. 2. 1. Go. SPECIAL Spa discount worth up to €50. Limited time. Move fast!
REGRET	Can't miss! Our summer Spa sale starts NOW!
ANTICIPATION	
CHALLENGE	🎯 Nicely done! Get prepared for over €40 off
CURIOSITY	☞ (1) invitation: Open now for up to 35% off (+ Couples Massage sale)
ENCOURAGEMENT	☞ For real! Reward yourself with Couples Spa treatment at a bargain price

Figure 15. Manually generated example messages for spa services for all of Persado's emotions and various Cialdini's principles.

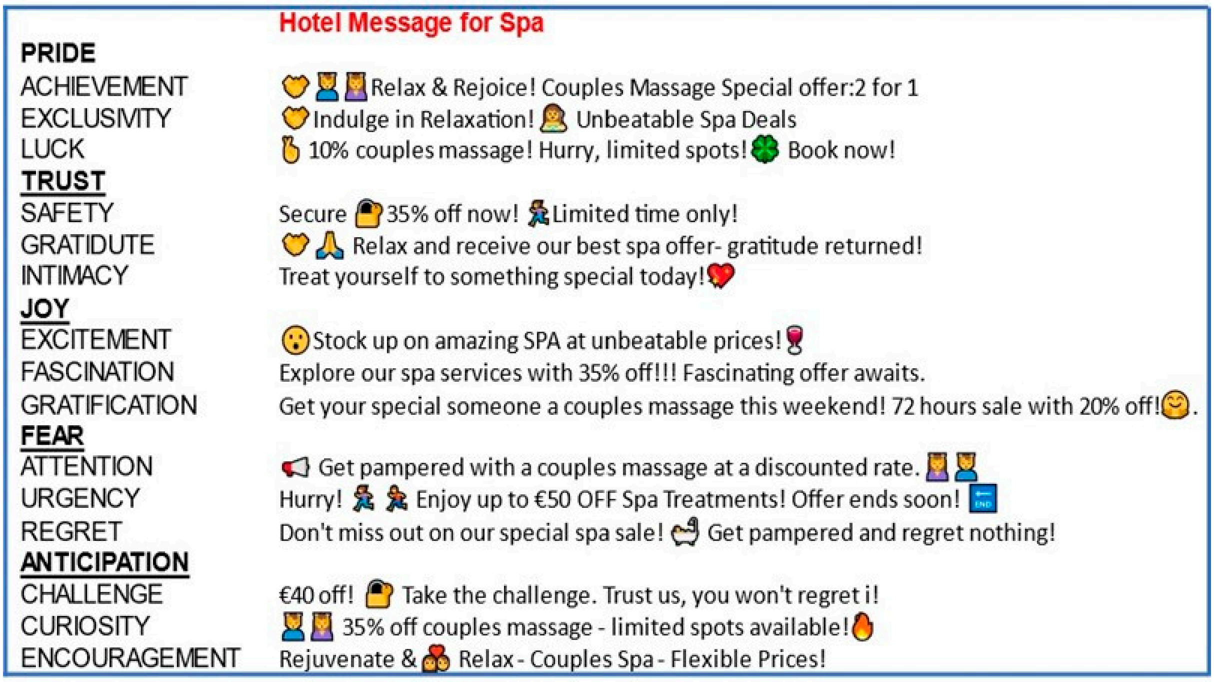

Figure 16. ChatGPT-generated example messages for spa services for all of Persado's emotions and various Cialdini's principles.

By comparing Figures 15 and 16, we come up with the following remarks. First, as an overall assessment, ChatGPT managed to generate consistent and inclusive messages. Second, in many cases, it used a smaller number of words. Third, in both cases, different emoticons were also used. However, in Figure 14, the prompt instructed ChatGPT to use relative/relevant emoticons, without stating which emoticons should be used, but the bot made decisions to use appropriate emoticon types based on the prompt's text. Also, the emoticons can be canceled and/or its number can be controlled.

The third experiment is a pilot study that concerns the ranking procedure presented in Algorithm 1 (see Section 4.2). As mentioned above, that procedure attempts to combine each emotion category with the highest ranked Cialdini's principles. The experiment was conducted over the course of 20 days and over 75 hotels (Upsell's customers). Since the experiment refers to emotion categories and not to single emotions, the measure used to conduct this experiment is the extended click-through rate (CTR) given in Equation (11). Tables 6–8 present the results of the experiment, where the variables Impressions and Clicks were defined in Section 4.2, and CTR is calculated in Equation (11). Based on these tables, Table 9 depicts the ranking of Cialdini's principles with respect to each emotion category. Finally, it is strongly emphasized that the categorization of guests according to the above strategy is a continuously updating process since a very large number of guests must participate to come up with an effective guest classification.

Table 6. Number of Impressions, Clicks, and *CTR* for Persado's emotion categories of Joy and Trust in relation to Cialdini's principles as obtained via the third experiment.

	Joy			Trust		
	Impressions	**Clicks**	***CTR***	**Impressions**	**Clicks**	***CTR***
Authority	1611	35	2.173	1723	71	4.121
Commitment	1843	68	3.690	2122	102	4.807
Social Proof/Consensus	1899	71	3.739	2109	89	4.220
Liking	1657	72	4.345	1978	92	4.651
Reciprocity	1533	33	2.153	1699	43	2.531
Scarcity	1522	64	4.205	1922	48	2.497

Table 7. Number of Impressions, Clicks, and *CTR* for Persado's emotion categories of Pride and Anticipation in relation to Cialdini's principles as obtained via the third experiment.

	Pride			Anticipation		
	Impressions	**Clicks**	***CTR***	**Impressions**	**Clicks**	***CTR***
Authority	1623	68	4.190	1892	77	4.070
Commitment	1957	79	4.037	2091	78	3.730
Social Proof/Consensus	2091	84	4.017	1863	93	4.992
Liking	1799	73	4.058	2326	118	5.073
Reciprocity	2079	97	4.666	2223	103	4.633
Scarcity	1967	89	4.525	2395	102	4.259

Table 8. Number of Impressions, Clicks, and *CTR* for Persado's emotion category of Fear in relation to Cialdini's principles as obtained via the third experiment.

	Fear		
	Impressions	**Clicks**	***CTR***
Authority	2012	84	4.175
Commitment	1718	88	5.122
Social Proof/Consensus	1802	82	4.550
Liking	1988	101	5.080
Reciprocity	1845	57	3.089
Scarcity	1703	52	3.053

Table 9. The ranking of Cialdini's principles with respect to each of Persado's emotion categories as obtained via the third experiment.

Joy	Trust	Pride	Anticipation	Fear
1. Liking	1. Commitment	1. Reciprocity	1. Liking	1. Commitment
2. Scarcity	2. Liking	2. Scarcity	2. Social Proof/Consensus	2. Liking
3. Social Proof/Consensus	3. Social Proof/Consensus	3. Authority	3. Reciprocity	3. Social Proof/Consensus
4. Commitment	4. Authority	4. Liking	4. Scarcity	4. Authority
5. Authority	5. Reciprocity	5. Commitment	5. Authority	5. Reciprocity
6. Reciprocity	6. Scarcity	6. Social Proof/Consensus	6. Commitment	6. Scarcity

In the fourth experiment, the proposed methodology is used to create one message for each emotion. Emotions belonging to the same emotion category are combined with the Cialdini's principle that appears to have the highest (top one) rank with respect to that emotion category, as reported in Table 9. For example, the emotions belonging to the Joy category are combined with the Liking principle, and so on.

The task is to advertise a EUR 50 discount on a couples massage. To monitor and quantify the net effect of the proposed methodology, we use one more message, namely, a Control Message, which is generated manually and is not influenced by the proposed methodology. Figure 17 depicts the messages used in the experiment. The experiment was conducted over the course of 2 months and over 175 hotels (Upsell's customers).

	Hotel Message for €50 Discount on Couples Message
PRIDE	
ACHIEVEMENT	Come to enjoy our Couples Massage Special offer - €50 off!!!
EXCLUSIVITY	Relax & Recharge with our best €50 off on Couples Massage
LUCK	Get Lucky and relax! €50 Couples Massage special offer: Limited spots
TRUST	
SAFETY	Save €50 on Couples Massage !! Limited time only!
GRATIDUTE	Gratitude returned! Receive our €50 off Couples Massage offer
INTIMACY	Treat yourself to something special today! €50 off in Couples' Massage
JOY	
EXCITEMENT	Enjoy an amazing Couples Massage at an unbeatable price! €50 off!!
FASCINATION	Explore our Couples Massage services with a Fascinating offer of up to €50
GRATIFICATION	Call it a day and get a couples massage with €50 off!! .
FEAR	
ATTENTION	Attention couples ! Enjoy a luxurious couples massage for a special offer: €50 off
URGENCY	Hurry up ! Enjoy a €50 offer on Couples Massage! Offer ends soon!
REGRET	Don't miss out on our €50 Coules Massage offer! Get pampered and regret nothing
ANTICIPATION	
CHALLENGE	€50 off on Couples Massage! Trust us and take the challenge!
CURIOSITY	€50 off couples massage - limited spots available!
ENCOURAGEMENT	Rejuvenate & Reward Yourself - Couples Spa - €50 discount
CONTROL MESSAGE	Special Offer: Get €50 off in Couples Massage

Figure 17. Messages generated by ChatGPT and used for the fourth experiment, where emotions belonging to the same emotion category are combined with the principle that appears to have the highest rank with respect to that emotion category.

Since the experiment refers to emotions and not to emotion categories, the measures used to conduct this experiment is the click-through rate and the reservation rate given in Equations (9) and (10), respectively.

Tables 10 and 11 depict the results of the current experiment. Table 10 shows the impressions and clicks for each emotion and the derived click-through rates as calculated using Equation (9). In the *ctr* column, it is observed that nine emotions (i.e., Achievement, Exclusivity, Luck, Safety, Gratitude, Intimacy, Attention, Urgency, and Curiosity) obtain a greater *ctr* value when compared to the Control Message. The last column of that table presents the % increase (positive value) or % decrease (negative value) of the *ctr* in relation to the Control Message. From the results reported in that column, we can extract the following remarks. First, only six out of fifteen emotions (i.e., Excitement, Fascination, Gratification, Regret, Challenge, and Encouragement) obtain a decrease in *ctr* when compared to the Control Message. Second, the cases for the emotions of Achievement and Intimacy show a 31% and a 41% increase, respectively. This implies that the positive impact of the proposed methodology in those cases is significant.

Table 10. Number of Impressions/Clicks, the resulting conversion rates (*ctr*), and the increase (positive value)/decrease (negative value) in each emotion's *ctr* in relation to the Control Message's *ctr*.

	Emotion	Impressions	Clicks	*ctr*	% Increase in Emotion's *ctr* vs. Control's *ctr*
Pride	Achievement	**27,988**	**1484**	**5.302%**	**31%**
	Exclusivity	31,378	1485	4.733%	17%
	Luck	29,932	1386	4.630%	14%
Trust	Safety	31,276	1413	4.518%	12%
	Gratitude	28,244	1308	4.631%	14%
	Intimacy	**29,788**	**1697**	**5.697%**	**41%**
Joy	Excitement	31,504	1069	3.393%	−16%
	Fascination	31,804	1278	4.018%	−1%
	Gratification	29,524	1122	3.800%	−6%
Fear	Attention	29,571	1407	4.758%	17%
	Urgency	28,184	1257	4.460%	10%
	Regret	28,206	1022	3.623%	−11%
Anticipation	Challenge	28,992	1132	3.905%	−4%
	Curiosity	29,068	1314	4.520%	12%
	Encouragement	31,708	1255	3.958%	−2%
Control Message		27,674	1121	4.051%	0%

More interesting results are reported in Table 11, where in addition to the Clicks and Impressions, the number of reservations and the reservation rates (*rrt*) are provided. The columns that include the Impressions and Clicks are the same as the respective columns in Table 10. The *rrt* values are calculated using Equation (10). From the *rrt* column, we observe that eleven emotions (i.e., Achievement, Exclusivity, Gratitude, Intimacy, Excitement, Gratification, Attention, Urgency, Regret, Curiosity, and Encouragement) obtain larger values for the *rrt* variable when compared to the Control Message. A more interesting result is illustrated in the last column, where the % increase (positive values) or % decrease (negative values) in the emotions' *rrt* values in relation to the respective value of the Control Message are shown. From this column, we can easily conclude that the emotions of Attention, Intimacy, Achievement, Urgency, and Gratification have a significant increase when compared to the Control Message. On the other hand, the emotions of Luck, Safety, Fascination, and Challenge have negative values, meaning that they are outperformed by the Control Message.

To summarize, the eXclusivi platform was extended with a new software module that works with ChatGPT prompts and persuasive ads created for its recommendations. In particular, we developed an intelligent advertisement (ad) copy generation tool for the hotel marketing platform. The proposed approach allows for the hotel team to target all guests in their language, leveraging the integration with the hotel's reservation system.

Table 11. Number of Impressions/Clicks, the resulting reservation rates (*rrt*), and the increase (positive value)/decrease (negative value) in each emotion's *rrt* in relation to the Control Message's *rrt*.

	Emotion	**Impressions**	**Clicks**	**Reservations**	***rrt***	**% Increase in Emotion's *rrt* vs. Control's *rrt***
Pride	Achievement	27,988	1484	54	3.639%	36%
	Exclusivity	31,378	1485	51	3.434%	28%
	Luck	29,932	1386	36	2.597%	−3%
Trust	Safety	31,276	1413	33	2.335%	−13%
	Gratitude	28,244	1308	39	2.982%	11%
	Intimacy	29,788	1697	66	3.889%	45%
Joy	Excitement	31,504	1069	36	3.368%	26%
	Fascination	31,804	1278	33	2.582%	−4%
	Gratification	29,524	1122	39	3.476%	30%
Fear	Attention	29,571	1407	60	4.264%	59%
	Urgency	28,184	1257	45	3.580%	34%
	Regret	28,206	1022	33	3.229%	21%
Anticipation	Challenge	28,992	1132	30	2.650%	−1%
	Curiosity	29,068	1314	45	3.425%	28%
	Encouragement	31,708	1255	39	3.108%	16%
Control Message		27,674	1121	30	2.676%	0%

At this point, it must be emphasized that the use of ChatGPT-enabled ad copy generation led to over +40% of Wi-Fi ad conversion rates and reservation rates, while its ease of use drove a more than doubled adoption of the tools from the hotel's marketing team.

On the limitation side of the approach, we report the availability and accuracy of the ChatGPT service, although the latest version of this LLM service (ChatGPT-4) and its paid subscription significantly minimize these limitations.

By considering Cialdini's (2001) persuasion models and combining them with Persado's (Wheel of Emotions) model of emotions, PROMOTE follows an emotion-centric approach to persuasion, creating appropriate personalized messages for hotel customers. Specifically, PROMOTE develops a new approach based on recommendation and persuasion technology, expanding the existing technology of Upsell's infrastructure.

6. Challenges and Ethical Considerations and the Role of the Mediator in User Experience

6.1. Challenges and Ethical Considerations

Integrating ChatGPT into persuasive technology for recommender systems presents a range of challenges and ethical considerations, mainly concerning privacy, fairness, and user autonomy. As these language models become more prevalent in various applications, it is essential to address these concerns to ensure the responsible and ethical use of such technologies. Below are some of the key challenges and ethical considerations that we selectively summarize but leave for future works since this is not the focus of this paper and the current research effort.

1. Privacy: ChatGPT, being data-driven, requires vast amounts of user data for training, which may include sensitive information about these users. Recommender systems that leverage LLMs need to handle user data with the utmost care to safeguard user privacy. Collecting and storing user data must comply with relevant data protection regulations, e.g., GDPR, and data anonymization techniques should be employed to minimize the risk of data breaches.
2. Fairness and Bias: ChatGPT learns from large data sets, which can inadvertently perpetuate human biases that are present in the data. If these biases are not carefully identified and mitigated, the recommendations generated by ChatGPT may be biased towards certain groups or demographics, e.g., black people. This can lead to unfair treatment, discrimination, or the exclusion of particular individuals or communities. Ethical recommender systems should be designed to mitigate biases and promote fairness in their recommendations.
3. User Autonomy: Persuasive technology, including recommender systems, should respect the autonomy of users. While personalized recommendations can enhance user experiences, they must not be manipulative in their intent. Users should have the option to control and customize the level of personalization they desire, with clear and transparent mechanisms for opting in or out of persuasive features.
4. Transparency and Explainability: ChatGPT is often considered a "black box" model, meaning its decision-making processes can be challenging to interpret and understand. For ethical recommender systems, it is crucial to provide explanations for the recommendations that are offered to users. Users have the right to know why specific recommendations are being made and how their data are being utilized to generate those suggestions.
5. Trust and User Perception: Integrating ChatGPT into persuasive recommender systems may lead to concerns about trust and user perception. If users feel that the system is exploiting their data or manipulating their choices, they may lose trust in the technology and the service provider. Ethical communication and transparency about the technology's capabilities and limitations are essential to build and maintain user trust.
6. Security and Adversarial Attacks: ChatGPT, like any AI model, may be vulnerable to adversarial attacks, where malicious actors attempt to manipulate the system's output by inputting specific crafted data. Ensuring robust security measures to protect against such attacks is crucial for maintaining the system's integrity and user trust.

Addressing these challenges and ethical considerations requires a multidisciplinary approach involving AI researchers, ethicists, policymakers, and industry stakeholders. By adhering to ethical principles and incorporating user feedback, we can responsibly harness the power of ChatGPT in persuasive technology for recommender systems, ensuring a positive impact on users and society at large.

6.2. The Role of the Mediator in User Experience

A mediator, such as empathy, plays a crucial role in shaping the user experience when interacting with LLMs like ChatGPT in the context of hotel bookings. Empathy, in this context, refers to the ability of the AI system (ChatGPT) to understand and respond to the user's emotional state and needs in a sensitive and supportive manner.

1. Establishing Trust: Related to what we have already stated in the ethical considerations, when users feel that the AI system understands and cares about their concerns, they are more likely to trust the system's recommendations. Empathy can help to build this trust, making users more receptive to the persuasive techniques employed by the AI.
2. Enhancing Communication: An empathetic ChatGPT can better interpret user inquiries, providing more accurate and relevant responses. This can lead to a more engaging and satisfying user experience.

3. Emotional Connection: Empathy in ChatGPT can create an emotional connection between the user and the AI system. This connection can lead to increased user satisfaction and a higher likelihood of booking a hotel or buying a hotel product/service through the AI platform (e.g., eXclusivi).

ChatGPT, being an AI language model, incorporates persuasive technology principles in its design to influence user behavior and decision making. The goal is to push/encourage users towards performing specific actions, such as booking a discount spa service or buying the wine that is offered with their meal, through various persuasive techniques. Some ways in which persuasive technology is applied in ChatGPT for hotel hospitality/bookings towards upselling have already been discussed in previous sections, and include personalization, social proof, scarcity and urgency, and reciprocity.

The combination of an empathetic AI (ChatGPT) and persuasive technology principles can have a significant impact on hotel bookings/sales:

I. Increased Conversion Rate: Empathy in ChatGPT can make users feel understood and valued, which, when combined with persuasive techniques, can increase the likelihood of users following through with hotel bookings.
II. Improved User Satisfaction: An empathetic AI that provides personalized and relevant recommendations can lead to higher user satisfaction, resulting in repeat bookings and positive word of mouth.
III. Higher Engagement: Persuasive techniques like social proof and scarcity can increase user engagement with the AI system, leading to more extensive interactions and potentially more bookings.
IV. Potential Ethical Concerns: While persuasive technology can be effective, there are ethical considerations regarding how far it should go in influencing user behavior. Striking a balance between persuasion and user autonomy is crucial to avoid manipulative practices.

In conclusion, an empathetic AI like ChatGPT, when combined with persuasive technology in a responsible manner, can enhance the user experience and positively impact hotel bookings/sales by fostering trust, personalization, and higher user engagement. However, ethical considerations must guide the implementation of persuasive techniques to ensure a fair and transparent user experience.

7. Conclusions

In conclusion, this research paper explored the potential of using ChatGPT and persuasive technology in enhancing hotel hospitality recommender systems. Through our investigation, we highlighted the capabilities of ChatGPT in understanding and generating human-like text, thereby enabling more accurate and context-aware recommendations. Furthermore, we examined the role of persuasive technology in influencing user behavior and enhancing the persuasive impact of hotel recommendations. By incorporating techniques such as social proof, scarcity, and personalization, recommender systems can effectively influence user decision making and encourage desired actions, such as booking a specific hotel or upgrading one's room. To validate the efficacy of ChatGPT and persuasive technology, we presented a case study involving a hotel recommender system and ChatGPT, and conducted an experiment to evaluate the impact of integrating these technologies on user engagement, satisfaction, and conversion rates. The preliminary results demonstrate the significant potential of ChatGPT and persuasive technology in enhancing the overall guest experience and improving business performance.

By way of the next steps, future efforts will be concentrated on addressing issues related to data privacy, transparency, and the potential for algorithmic bias, emphasizing the importance of responsible design and implementation.

Author Contributions: Conceptualization, K.K. and G.E.T.; methodology, M.R., B.K. and G.E.T.; software, M.R. and K.K.; validation, K.K. and B.K.; formal analysis, B.K. and G.E.T.; investigation, M.R. and K.K.; supervision, G.E.T. All authors contributed to writing the final version of the paper. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially funded by the PROMOTE (Persuasive Technologies and Artificial Intelligence for Tourism) project (MIS 5093219) of the Operational Program "Competitiveness, Entrepreneurship and Innovation". The action was co-funded by the European Regional Development Fund (ERDF) and the Greek Government (Partnership and Cooperation Agreement 2014–2020).

Data Availability Statement: The data are available upon request.

Acknowledgments: The authors would like to thank the anonymous reviewers for their efforts in providing valuable comments that improved the paper.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Hui, T.L.T.; Au, N.; Law, R. Customer experiences with hotel smartphone: A case study of Hong Kong hotels. In *Information and Communication Technologies in Tourism 2016*; Inversini, A., Schegg, R., Eds.; Springer International Publishing: Cham, Switzerland, 2016; pp. 455–466.
2. Ivanov, S.; Seyitoglu, F.; Markova, M. Hotel managers' perceptions towards the use of robots: A mixed-methods approach. *Inf. Technol. Tour.* **2020**, *22*, 505–535. [CrossRef]
3. Padma, P.; Ahn, J. Guest satisfaction & dissatisfaction in luxury hotels: An application of big data. *Int. J. Hosp. Manag.* **2020**, *84*, 102318.
4. Buhalis, D.; Cheng, E.S.Y. Exploring the use of chatbots in hotels: Technology providers' perspective. In *Information and Communication Technologies in Tourism 2020*; Neidhardt, J., Wörndl, W., Eds.; Springer Nature: Cham, Switzerland, 2020; pp. 231–242.
5. Morosan, C.; DeFranco, A. Using interactive technologies to influence guests' unplanned dollar spending in hotels. *Int. J. Hosp. Manag.* **2019**, *82*, 242–251. [CrossRef]
6. Han, S.H.; Lee, L.; Edvardsson, B.; Verma, R. Mobile technology adoption among hotels: Managerial issues and opportunities. *Tour. Manag. Perspect.* **2021**, *38*, 100811. [CrossRef]
7. Yang, H.; Song, H.; Cheung, C.; Guan, J. How to enhance hotel guests' acceptance and experience of smart hotel technology: An examination of visiting intentions. *Int. J. Hosp. Manag.* **2021**, *97*, 103000. [CrossRef]
8. Peng, Y. A survey on modern recommendation system based on big data. *arXiv* **2022**, arXiv:2206.02631.
9. Guerra-Montenegro, J.; Sanchez-Medina, J.; Lana, I.; Sanchez-Rodriguez, D.; Alonso-Gonzalez, I.; Del Ser, J. Computational intelligence in the hospitality industry: A systematic literature review and a prospect of challenges. *Appl. Soft Comput.* **2021**, *102*, 107082. [CrossRef]
10. Fogg, B.J. *Persuasive Technology: Using Computers to Change What We Think and Do*; Morgan Kaufmann: San Francisco, CA, USA, 2002.
11. Zhao, W.X.; Zhou, K.; Li, J.; Tang, T.; Wang, X.; Hou, Y.; Min, Y.; Zhang, B.; Zhang, J.; Dong, Z.; et al. A survey of large language models. *arXiv* **2023**, arXiv:2303.18223v10.
12. Ray, P.P. ChatGPT: A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope. *Internet Things Cyber-Phys. Syst.* **2023**, *3*, 121–154. [CrossRef]
13. Wu, T.; He, S.; Liu, J.; Sun, S.; Liu, K.; Han, Q.-L.; Tang, Y. A brief overview of ChatGPT: The history, status quo and potential future development. *IEEE/CAA J. Autom. Sin.* **2023**, *10*, 1122–1136. [CrossRef]
14. Wang, Y.; Pan, Y.; Yan, M.; Su, Z.; Luan, T.H. A survey on ChatGPT: AI–generated contents, challenges, and solutions. *arXiv* **2023**, arXiv:2305.18339v1. [CrossRef]
15. Jiao, W.X.; Wang, W.X.; Huang, J.-T.; Wang, X.; Tu, Z.P. Is ChatGPT a good translator? Yes with GPT-4 as the engine. *arXiv* **2023**, arXiv:2301.08745.
16. Lund, B.D.; Wang, T. Chatting about ChatGPT: How may AI and GPT impact academia and libraries? *Libr. Hi Tech News* **2023**, *3*, 26–29. [CrossRef]
17. Qin, C.; Zhang, A.; Zhang, Z.; Chen, J.; Yasunaga, M.; Yang, D. Is Chat GPT a general-purpose natural language processing task solver? *arXiv* **2023**, arXiv:2302.06476.
18. Du, H.; Teng, S.; Chen, H.; Ma, J.; Wang, X.; Gou, C.; Li, B.; Ma, S.; Miao, Q.; Na, X.; et al. Chat with ChatGPT on intelligent vehicles: An IEEE TIV perspective. *IEEE Trans. Intell. Veh.* **2023**, *8*, 2020–2026. [CrossRef]
19. Sallam, M. ChatGPT utility in healthcare education, research, and practice: Systematic review on the promising perspectives and valid concerns. *Healthcare* **2023**, *11*, 887. [CrossRef] [PubMed]
20. Ali, S.R.; Dobbs, T.D.; Hutchings, H.A.; Whitaker, I.S. Using ChatGPT to write patient clinic letters. *Lancet Digit Health* **2023**, *5*, e179–e181. [CrossRef] [PubMed]

21. Haleem, A.; Javaid, M.; Singh, R.P. An era of ChatGPT as a significant futuristic support tool: A study on features, abilities, and challenges. *BenchCouncil Trans. Benchmarks Stand. Eval.* **2022**, *2*, 100089. [CrossRef]
22. Pu, D.; Demberg, V. ChatGPT vs human-authored text: Insights into controllable text summarization and sentence style transfer. *arXiv* **2023**, arXiv:2306.07799v1.
23. Hassani, H.; Silva, E.S. The role of ChatGPT in data science: How AI-assisted conversational interfaces are revolutionizing the field. *Big Data Cogn. Comput.* **2023**, *7*, 62. [CrossRef]
24. Kolides, A.; Nawaz, A.; Rathor, A.; Beeman, D.; Hashmi, M.; Fatima, S.; Berdik, D.; Al-Ayyoub, M.; Jararweh, Y. Artificial intelligence foundation and pre-trained models: Fundamentals, applications, opportunities, and social impacts. *Simul. Model. Pract. Theory* **2023**, *126*, 102754. [CrossRef]
25. Zhang, C.; Zhang, C.; Li, C.; Qiao, Y.; Zheng, S.; Dam, S.K.; Zhang, M.; Kim, J.U.; Kim, S.T.; Choi, J.; et al. One small step for generative AI, one giant leap for AGI: A complete survey on ChatGPT in AIGC era. *arXiv* **2023**, arXiv:2304.06488v1.
26. Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A.N.; Kaiser, L.; Polosukhin, I. Attention is all you need. *arXiv* **2017**, arXiv:1706.03762.
27. Devlin, J.; Chang, M.-W.; Lee, K.; Toutanova, K. BERT: Pre-training of deep bidirectional transformers for language understanding. *arXiv* **2018**, arXiv:1810.04805v2.
28. Wei, J.; Wang, X.; Schuurmans, D.; Bosma, M.; Ichter, B.; Xia, F.; Chi, E.; Le, Q.; Zhou, D. Chain-of-thought prompting elicits reasoning in large language models. *arXiv* **2022**, arXiv:2201.11903.
29. Wang, B.; Min, S.; Deng, X.; Shen, J.; Wu, Y.; Zettlemoyer, L.; Sun, H. Towards understanding chain-of-thought prompting: An empirical study of what matters. *arXiv* **2023**, arXiv:2212.10001v2.
30. Xu, B.; Yang, A.; Lin, J.; Wang, Q.; Zhou, C.; Zhang, Y.; Mao, Z. ExpertPrompting: Instructing large language models to be distinguished experts. *arXiv* **2023**, arXiv:2305.14688v1.
31. Xian, Y.; Schiele, B.; Akata, Z. Zero-shot learning—The good, the bad and the ugly. In Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 21–26 July 2017; pp. 3077–3086.
32. Liu, Z.; Chen, C.; Wang, J.; Chen, M.; Wu, B.; Che, X.; Wang, D.; Wang, Q. Chatting with GPT-3 for zero-shot human-like mobile automated GUI testing. *arXiv* **2023**, arXiv:2305.09434v1.
33. Bragg, J.; Cohan, A.; Lo, K.; Beltagy, I. FLEX: Unifying evaluation for few-shot NLP. *arXiv* **2021**, arXiv:2107.07170v2.
34. Ziegler, D.M.; Stiennon, N.; Wu, J.; Brown, T.B.; Radford, A.; Amodei, D.; Christiano, P.; Irving, G. Fine-tuning language models from human preferences. *arXiv* **2019**, arXiv:1909.08593v2.
35. MacGlashan, J.; Ho, M.K.; Loftin, R.; Peng, B.; Wang, G.; Roberts, D.L.; Taylor, M.E.; Littman, M.L. Interactive learning from policy-dependent human feedback. *arXiv* **2023**, arXiv:1701.06049v2.
36. Rombach, R.; Blattmann, A.; Lorenz, D.; Esser, P.; Ommer, B. Highresolution image synthesis with latent diffusion models. *arXiv* **2022**, arXiv:2112.10752v2.
37. Hagendorff, T.; Fabi, S.; Kosinski, M. Machine intuition: Uncovering human-like intuitive decision-making in GPT-3.5. *arXiv* **2022**, arXiv:2212.05206.
38. Oinas-Kukkonen, H.; Harjumaa, M.A. Systematic framework for designing and evaluating persuasive systems. *Lect. Notes Comput. Sci.* **2008**, *5033*, 164–176.
39. Perfetti, C. Guiding Users with Persuasive Design: An Interview with Andrew Chak. UX Articles by UIE, 2003. Available online: https://articles.uie.com/chak_interview/ (accessed on 15 January 2023).
40. Chiu, M.-C.; Chang, S.-P.; Chang, Y.-C.; Chu, H.-H.; Chen, C.C.-H.; Hsiao, F.-H.; Ko, J.-C. Playful bottle: A mobile social persuasion system to motivate healthy water intake. In Proceedings of the 11th International Conference on Ubiquitous Computing (UbiComp'09), Orlando, FL, USA, 30 September–3 October 2009; pp. 185–194.
41. Halko, S.; Kientz, J.A. Personality and Persuasive Technology: An Exploratory Study on Health-Promoting Mobile Applications. *Lect. Notes Comput. Sci.* **2010**, *6137*, 150–161.
42. Lieto, A.; Vernero, F. Influencing the others' minds: An experimental evaluation of the use and efficacy of fallacious-reducible arguments in web and mobile technologies. *PsychNology J.* **2014**, *12*, 87–105.
43. Gena, C.; Grillo, P.; Lieto, A.; Mattutino, C.; Vernero, F. When personalization is not an option: An in-the-wild study on persuasive news recommendation. *Information* **2019**, *10*, 300. [CrossRef]
44. Augello, A.; Citta, G.; Gentile, M.; Lieto, A. A Storytelling Robot managing Persuasive and Ethical Stances via ACT-R: An Exploratory Study. *Int. J. Soc. Robot.* **2021**. [CrossRef]
45. Cialdini, R.B. Harnessing the science of persuasion. *Harv. Bus. Rev.* **2001**, *79*, 72–81.
46. Alslaity, A.; Tran, T. On the impact of the application domain on users' susceptibility to the six weapons of influence. *Lect. Notes Comput. Sci.* **2020**, *12064*, 3–15.
47. Mintz, J.; Aagaard, M. The application of persuasive technology to educational settings. *Educ. Technol. Res. Dev.* **2012**, *60*, 483–499. [CrossRef]
48. Kembellec, G.; Chartron, G.; Saleh, I. *Recommender Systems*; John Wiley & Sons Inc.: Hoboken, NJ, USA, 2014.
49. Bobadilla, J.; Ortega, F.; Hernando, A.; Gutierrez, A. Recommender systems survey. *Knowl. Based Syst.* **2013**, *46*, 109–132. [CrossRef]
50. Ricci, F.; Rokach, L.; Shapira, B. Introduction to recommender systems handbook. In *Recommender Systems Handbook*; Ricci, F., Rokach, L., Shapira, B., Kantor, P.B., Eds.; Springer: New York, NY, USA, 2011; pp. 1–35.

51. Barranco, M.J.; Noguera, J.M.; Castro, J.; Martinez, L. A context-aware mobile recommender system based on location and trajectory. In *Management Intelligent Systems*; Casillas, J., Martinez-Lopez, F.J., Rodriguez, J.M.C., Eds.; Springer: Berlin/Heidelberg, Germany, 2012; pp. 153–162.
52. Chicaiza, J.; Valdiviezo-Diaz, P. A comprehensive survey of knowledge graph-based recommender systems: Technologies, development, and contributions. *Information* **2021**, *12*, 232. [CrossRef]
53. Veloso, B.M.; Leal, F.; Malheiro, B.; Burguillo, J.C. On-line guest profiling and hotel recommendation. *Electron. Commer. Res. Appl.* **2019**, *34*, 100832. [CrossRef]
54. Veloso, B.M.; Leal, F.; Malheiro, B.; Burguillo, J.C. A 2020 perspective on "Online guest profiling and hotel recommendation": Reliability, scalability, traceability and transparency. *Electron. Commer. Res. Appl.* **2020**, *40*, 100957. [CrossRef]
55. Neuhofer, B.; Buhalis, D.; Ladkin, A. Smart technologies for personalized experiences: A case study in the hospitality domain. *Electron Mark.* **2015**, *25*, 243–254. [CrossRef]
56. Leal, L.; Malheiro, B.; Burguillo, J.C. Incremental hotel recommendation with inter-guest trust and similarity post-filtering. In *New Knowledge in Information Systems and Technologies: WorldCIST'19 2019*; Rocha, A., Adeli, H., Reis, L., Costanzo, S., Eds.; Springer Nature: Cham, Switzerland, 2019; Volume 930, pp. 262–272.
57. Tai, Y.-F.; Wang, Y.-C.; Luo, C.-C. Technology- or human-related service innovation? Enhancing customer satisfaction, delight, and loyalty in the hospitality industry. *Serv. Bus.* **2021**, *15*, 667–694. [CrossRef]
58. Nor1. Available online: https://www.oracle.com/corporate/acquisitions/nor1/ (accessed on 17 February 2023).
59. Young, A. Nor1′s PRiME Decision Platform with Real-Time Merchandising Banners Driving Double-Digit Conversion Rate for Hotels. Available online: https://www.hospitalitynet.org/news/4094347.html (accessed on 23 January 2023).
60. Yoon, D.; Kim, Y.-K.; Fu, R.J.C. How can hotels' green advertising be persuasive to consumers? An information processing perspective. *J. Hosp. Tour. Manag.* **2020**, *45*, 511–519. [CrossRef]
61. Díaz, E; Koutra, C. Evaluation of the persuasive features of hotel chains websites: A latent class segmentation analysis. *Int. J. Hosp. Manag.* **2013**, *34*, 338–347. [CrossRef]
62. eXclusivi. Available online: https://exclusivi.com/contactless/ (accessed on 12 December 2022).
63. Oracle Opera Hotel Property Management. Available online: https://www.oracle.com/uk/hospitality/hotel-property-management/ (accessed on 20 May 2023).
64. Fidelio Suit 8. Available online: http://www.micros.rs/en/fidelio-suite-8.html (accessed on 25 May 2023).
65. Protel Net. Available online: https://www.protel.net/ (accessed on 11 April 2023).
66. Pylon Hospitality. Available online: https://www.pylon.gr/product.aspx?id=2047&mID=1048,1056 (accessed on 22 April 2023).
67. Orange PMS. Available online: https://www.orangepms.com/ (accessed on 10 June 2023).
68. Persado. Available online: https://www.businesswire.com/news/home/20151210005927/en/Persado-Releases-Annual-Emotional-Rankings-Report (accessed on 20 November 2022).