International Journal of Communication Networks and Information Security
2024, 16(1), 6354
ISSN: 2073-607X,2076-0930
https://ijcnis.org/ **Research Article**

Adapting Users’ Intentions in Pervasive Environments

Abdelhadi Bouain [1*], Mohamed Nezar Abourraja [2], Mohamed Yassine Samiri [3], Mehdi Najib [4]

[1] Assistant Professor, Laboratory of Engineering Sciences (LabSI), Polydisciplinary Faculty, Ibnou Zohr University, Ouarzazate 45000, Morocco
[2] Doctor, Gamesa Renewable Energy, Siemens, A/S Vejle 7100, Denmark
[3] Assistant Professor, El Kelâa des Sraghna, Cadi Ayyad University, Marrakech 40000, Morroco
[4] Assistant Professor, TICLab, International University of Rabat, Sala Al Jadida 11100, Morocco
***Corresponding Author:** a.bouain@uiz.ac.ma

Citation: A. Bouain, M. N. Abourraja, M. Y. Samiri, and M. Najib, “Adapting Users’ Intentions in Pervasive Environments,” *International Journal of Communication Networks and Information Security (IJCNIS)*, vol. 16, no. 1, pp. 160-173, Apr. 20 24.

ARTICLE INFO

Received: 15 November 2023
Accepted: 6 April 2024

ABSTRACT

Pervasive computing, also called ubiquitous computing, is a revolutionary paradigm that aims to create intelligent environments composed of discrete and interconnected devices. These devices can collect, process, and disseminate various information in an invisible way, in order to provide the user with services tailored to their context and activities. Communicating with these services must be intuitive, not requiring any technical details and far from traditional user interfaces. To fulfill these requirements, we present, in this article, an approach to reformulating user intentions expressed in natural language in order to connect them with the execution context and facilitate the identification of services that best meet user needs. The proposed approach is based on concepts related to lexical semantics, ontologies, and contextual information.

Keywords: Pervasive Computing, Context-aware Services, Context Awareness, Intentions Reformulation, Human Computer Interaction.

INTRODUCTION

Marc Weiser envisioned a smart world surrounded by invisible devices that could offer information to users anytime, anywhere. This new paradigm, known as pervasive computing, has been enabled by recent advances in technology, particularly wireless sensor networks, Internet connections, and smartphones equipped with various sensors. This evolution of technology has led to a change in the trends of pervasive computing, allowing users to have spaces offering services tailored to their needs and context [1].

Users in pervasive environments are not expected to be computer experts. They should be able to express their needs as objectives to be achieved using natural, easily understandable language, and without worrying about the description or implementation of services; for example, converting a sum of money into foreign currency, consulting unpaid invoices, making reservations in hotels, etc. These objectives, expressed in natural language, are conventionally referred to as "intentions". To enable users to discover and communicate with existing services in a pervasive environment based on their intentions, it is necessary to reformulate these intentions while taking into account the user's context (any information originating from the execution environment, whether tangible or digital, the acquisition of which is beneficial for enhancing the performance and behavior of an application or service) in order to locate suitable services [2], [3], [4].

The reformulation of users' intentions aims to find semantic matches between services offered in the pervasive environment and intentions expressed by users, providing increased transparency by hiding the technical details and heterogeneity of different protocols and services available in the environment [2], [3], [4]. In this work, we present an approach based on lexical semantics, ontologies, and context information to reformulate users' intentions in a pervasive environment. This approach seeks to combine the information collected from various sensors and the techniques of lexical semantics used by search engines to accurately identify services that match the user's needs while taking into account his context.

The rest of this paper is structured as follows. Section 2 addresses concepts related to our work. Section 3 provides an overview of various existing approaches and strategies for query reformulation. Section 4 describes in detail our approach to reformulating users' intentions in pervasive environments, along with an illustrative example. Section 5 presents a comparison between our approach and those proposed in relevant literature. Finally, Section 6 concludes this work and outlines our future work.

RELATED WORKS

Pervasive Computing

The main concept behind pervasive computing, also called ubiquitous computing, calm technology, etc., is to provide users with information anytime and anywhere, making use of familiar objects. This paradigm has evolved with technological advances experienced by mobile devices and communication networks [1], [5].

Pervasive Service

The service in pervasive environments must take into consideration the information extracted from its surroundings in order to provide more relevant results. Additionally, the pervasive service must be intentional, allowing users to identify existing services in their environment and communicate with them using only natural language to express their specific needs, known as intentions. To meet all these requirements, a pervasive service can be defined as an entity that provides a set of functionalities to address users' intentions, while considering its context [3], [4], [6].

Intention in Pervasive Environment

In a pervasive environment, Human-Machine interaction must be different from the traditional approach based on graphical interfaces. Indeed, the principle of invisibility supposes that the discovery of pervasive services must be made with the minimum of Human-Machine interactions and maximum transparency by hiding the heterogeneity of services, protocols and all other technical details from users who are not necessarily IT experts and possibly unaware of all the services available in their environments [3], [4], [6].

The concept of intention in a pervasive environment can be seen as a high-level description of a user's needs, specifying what is expected of a service without indicating how to achieve it, or simply as an objective (goal) to be achieved [2], [3], [6]. In this work, we define user intentions as objectives (goals) to be achieved, expressed in understandable and non-technical language, ideally natural language.

Approaches of Reformulation of Users' Intentions

In a pervasive environment, users might not choose the right terms that best express their needs. One of the most intuitive solutions is to use a common language as close as possible to the users' natural language. This solution may be possible in small and closed environments experiencing a limited number of known users (e.g., a small company, administration, etc.) that must learn all the words and rules to follow in order to specify their intentions [4].

This solution will rapidly lose its effectiveness in front of environments experiencing a large number of occasional users (e.g., airports, supermarkets, etc.). In such environments, forcing users to learn words and rules to reformulate their intentions is contradictory to the principles of pervasive computing and can be considered as a burden and a waste of time. The solution then is to allow users to express intentions, using non-technical terms, ideally natural language. Then reformulate these intentions to facilitate the identification of services that better meet the needs expressed by users (Figure 1). The reformulation of intentions consists of adding significant terms, deleting or modifying unsuitable terms in order to obtain precise queries appropriate to the domain of execution.

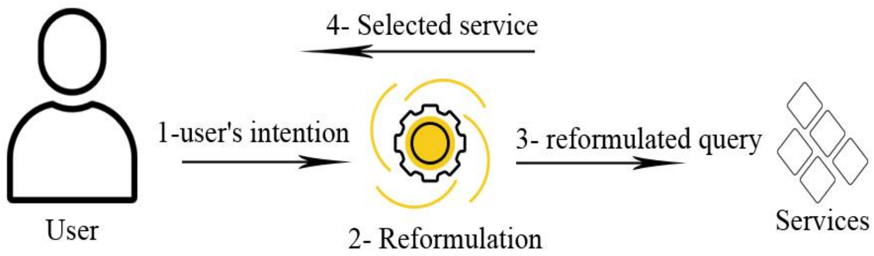

Figure 1. Intention Reformulation Process

Reformulation approaches can be classified into two categories: reformulation based on lexical semantics and reformulation based on context.

1. Approaches based on lexical semantics: Several approaches for the reformulation of users' intentions can be inspired by techniques used in information retrieval (e.g., search engines) based on lexical semantics, which is defined as the meaning of words in a language [7], [8]. The use of lexical semantics will identify the meaning and relationships between words forming the users' intentions in order to propose new queries with appropriate words.

Lexical semantics has led to several reformulation strategies such as word substitution, word addition and/or deletion, spelling correction, acronym expansion, word reorganization, punctuation and space modification, synonym use, etc. [7], [8]. The disadvantage of approaches based solely on lexical semantics is that intentions are regarded as a bag of words to which several expressions or words may be added, deleted, modified, etc. without making the connection between words and users' contexts, as a word is meaningful in a given context.

2. Approaches based on context: The approaches which we call "based on context" for the reformulation of users' intentions are the approaches that seek to link multiple information from various sources, such as user profile, location, etc. to users' intentions in order to obtain accurate and relevant services. Among these approaches, we mention the approach of [6], [9], [10], [11]. These approaches aim to make the match between functional and non-functional properties expressed in users' queries and those offered by services, using several techniques such as calculating the semantic similarity, user preferences and contextual requirements of each service, etc.

The advantage of approaches based on context for reformulating users' intentions is that they can be seen as lexical-semantic approaches reinforced by contextual information. These approaches play a significant role in enhancing the quality of the offered services and user satisfaction.

METHODOLOGY

In our work, intention is seen as goals to be reached and can be expressed by a verb, a target, and parameters; the target may be either a product or result; parameters can represent the place, manner, quantity, time, beneficiary, etc. [3], [4]. For instance, the intention "*book a room in Marrakech next weekend*" may be seen as follows:

$$(\text{Book})_{\text{verb}}\ (\text{a room})_{\text{product}}\ (\text{in Marrakech})_{\text{place}}\ (\text{next weekend})_{\text{time}}$$

This intention will be sent to the reformulation engine that will identify, for each intention *I (verb, target, location parameters, manner parameters, time parameters, beneficiary parameters)*, an intention *I' (verb', target', location parameters', manner parameters', time parameters', beneficiary parameters')* based mainly on domain-specific corpus, context information, and the following lexical-semantic relations: Hyponymy\ hypernymy, Meronymy and Synonymy [12], [13].

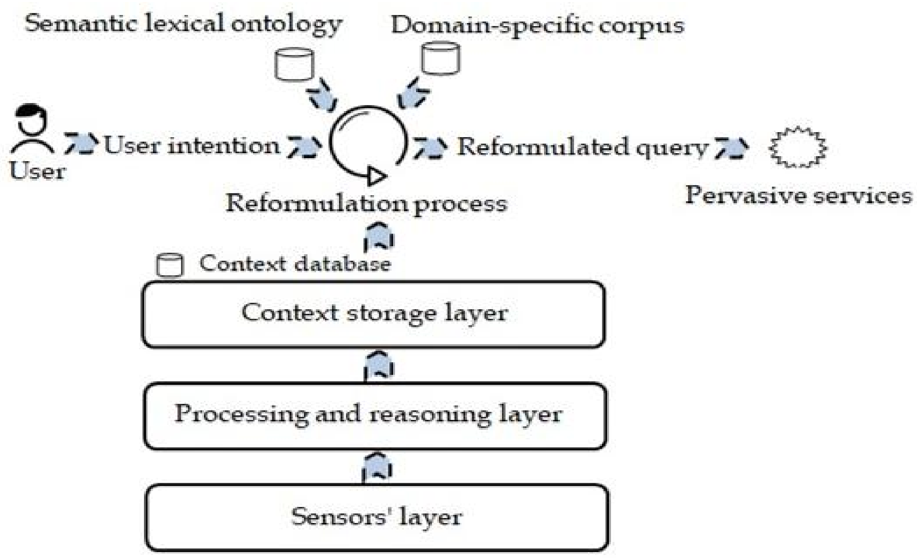

Figure 2. Overview of Proposed Approach

To implement these relations, we propose using the semantic ontology "WordNet" [13], [14] and a domain-specific corpus that refers to the data handled in the pervasive environment (medicine, education, tourism, etc.) in order to be more accurate. As for the context information extracted from various sensors, it must first be processed and structured in order to generate high-level context information. For example, transforming GPS coordinates into a physical address (city, street, etc.) and also removing some inconsistent information, etc. To this end, we use three layers; each layer has a specific role and transmits the result of its treatment to the upper layer (Figure 2).

The approach we propose revolves around three axes: context management; intention reformulation process; and the service selection strategy.

Context Management

Context management is covered in detail in another work by [15], and we only present in this article an overview of the three layers used to collect, process and store context information (Figure 2).

The Sensor Layer

The existence of multiple context information (spatial, environmental, temporal, physical and /or mental state of users, user identity and location, etc.) requires the use of various sensors to collect this information. Other context information such as the profile and user preferences can be derived from social networks, visited websites, web search engines, etc.

Processing and Reasoning Layer

The processing and reasoning layer aims to provide an informed interpretation of the extracted data before directing them to the context storage layer. A tangible example of this functionality could involve converting GPS coordinates into a physical address, encompassing details like street and city. This layer effectively divides into two distinct components: reasoning and processing.

Processing Component: The first pre-processing phase consists of carefully selecting data from different sensors, with the aim of eliminating data that does not conform to a set of predefined criteria. This step is followed by the aggregation and classification of the selected data. These steps are important for structuring contextual information according to a determined metamodel, as illustrated in Figure 3 [15].

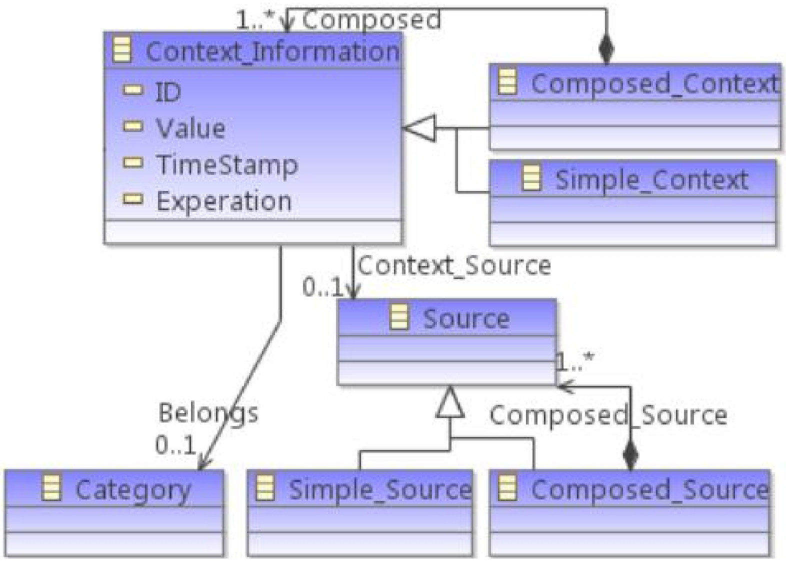

Figure 3. Context Information MetaModel

Reasoning Component: The objective of the reasoning element is twofold. Firstly, it strives to deduce higher-level of information from contextual data, stemming from sensors. Various reasoning mechanisms can be employed, including rule-based reasoning, description logic, probabilistic reasoning, Situation Calculus, Bayesian Networks, Hidden Markov Models, Linear Dynamical Systems, and more [16], [17]. These mechanisms contribute to an intricate process of deriving meaningful conclusions from extracted data, ensuring that contextual information is not only captured, but also comprehended, thereby leading to informed decision-making and enhanced understanding of the system [16], [17]. For the reasoning on the context, we propose to use the rule-based reasoning [15].

Context Storage Layer

In order to store the context information, we propose to use a relational database. This stored information must be in accordance with the MetaModel that we propose (Figure 3). In fact, each context information can be simple, such as age, or composed, such as a complete address (name, city, boulevard, etc.), and can be extracted from a single source or multiple sources. To facilitate the organization of context information, they are grouped into categories.

Intention Reformulation Process

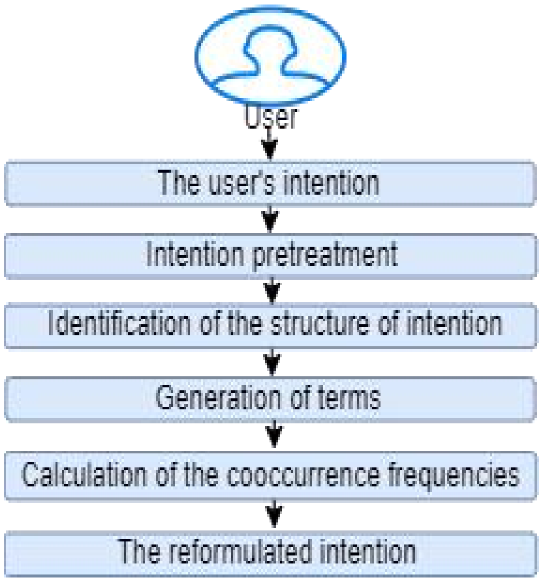

Figure 4. An Overview of the Intention Reformulation Process

The reformulation process goes through a set of steps, which we detail in the following subsections (Figure 4).

Intention Pretreatment

Intention pretreatment is a foundational step within the reformulation process. Indeed, this initial phase aims to eliminate all purely grammatical linguistic elements such as prepositions, articles, conjunctions, demonstrative and numeral adjectives, among others. This approach streamlines the intention by focusing on its essential elements.

Following this elimination, lemmatization comes into play. This process of transformation involves reducing each term within the intention to a canonical form, known as a lemma. For instance, terms like "friend", "friends", "friendship", and "friendships" are harmonized into "friend". Similarly, conjugated verbs are simplified to their infinitive form, thereby streamlining the content while retaining its core essence. This pre-processing step ensures that the reformulated intent discards non-essential elements while preserving its fundamental meaning. It lays the foundation for subsequent reformulation stages, enhancing the ease of manipulation and analysis of the intention while maintaining its clarity and relevance.

In the remainder of this section, we will use the following intention as an illustrative example:

I: "Search a hotel room in Marrakech at the end of the year for two adults and one child"

After removing all grammatical words and lemmatization, the intention becomes as follows:

I: "Search hotel room Marrakech end year adult child"

Identification of the Structure of Intention

The objective of this step is to break down the user's intention into verb, target and parameters (place, time, manner, beneficiary and reason) according to the linguistic model of Prat [18]. The example obtained from the previous pretreatment can be broken down as follows:

$(search)_{verb}\ (room)_{target}\ (hotel)_{place}\ (Marrakech)_{place}\ (end)_{time}\ (year)_{time}\ (adult)_{beneficiary}\ (child)_{beneficiary}$

Generation of Terms

This step aims to generate, for each element of the intention, a set of terms that are directly linked to it by the following lexical-semantic relationships: synonymy, hypernymy/hyponymy, and holonymy/meronymy. It is important to note that a large number of terms generated can negatively influence the processing time; therefore, a reasonable limit must be set and generation of synonyms should be promoted first, followed by hyponyms and finally holonyms/meronyms. Table 1 shows an example of terms generated for each item of our intention.

Table 1. Terms Generated for Each Item of Intention

Item of intention	Generated terms
Search	Seek, look for, look, research, explore, examine, see, investigate, look into, analyze, etc.
Room	Chamber, hall, foyer, lobby, vestibule, bedroom, sleeping room, bedchamber, lounge, cell, classroom, etc.
Hotel	Hostel, hostelry, inn, lodge, resort hotel, spa, Ritz, resort hotel, holiday resort, building, edifice, structure, tourist court, court, hotel room, etc.
Marrakech	Marrakesh, city, metropolis, urban center, municipality, district, territory, Morocco, Kingdom of Morocco, Maroc, Marruecos, Al-Magrib, etc.
End	Extremity, ending, last, final stage, goal, death, boundary, extreme, limit, deadline, conclusion, period, year-end, finale, moment, minute, second, instant, etc.
Year	Twelvemonth, time period, period of time, period, christian year, New Year, school year, academic year, month, season, decade, decennary, etc.
Adult	Grownup, person, individual, someone, somebody, mortal, soul, elder, senior, host, woman, etc.
Child	Kid, youngster, minor, baby, infant, juvenile, person, youth, younker, etc.

* The result presented in this table is obtained using WordNet [14]

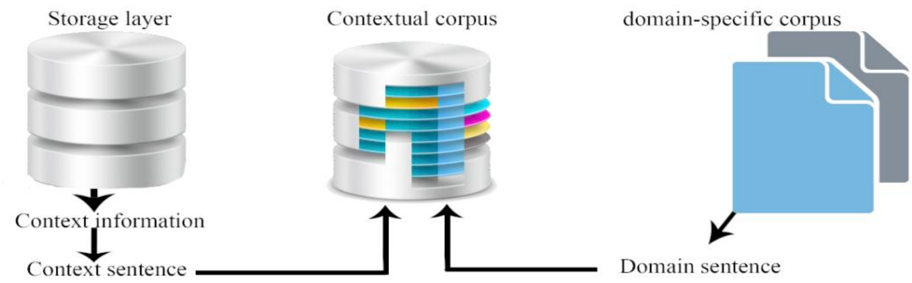

Figure 5. Creation of the Contextual Corpus

Calculation of the Co-occurrence Frequencies and Weights between the Generated Terms and the Context Corpus

In addition to direct lexical semantic relationships, another type of relevant relationship may exist between terms; it is co-occurrence which refers to terms often used in the same context without there being a direct semantic relationship between them (synonymy, antonymy, hyperonymy, meronymy, etc.). For example, doctors and nurses, airplanes and airports, students and teachers, etc.

Co-occurrence is defined as the simultaneous presence of two linguistic units within the same linguistic context (paragraph, sentence, text, etc.); it aims to identify potential connections that could exist between several terms in a specific context [19]. We use this type of relationship to choose from the generated terms that are strongly related to the user's context. In this regard, it is first necessary to create a contextual corpus composed of a set of sentences. Each sentence is obtained from one of two sources: the context information recorded in the database and the domain-specific corpus (Figure 5). Indeed, each context information has a name, a value, and a description; these constituents can form a sentence. Note that the sentences are formed as bags of words without paying attention to the meaning obtained, because the objective of our corpus is to group together the maximum number of terms related to the context of the user.

Several domain-specific corpora are offered and ready to be used, for example, Wikipedia Corpus, Coronavirus Corpus, Google Books corpus, etc. or can be created from different publications such as trade journals, forums, social networks, texts written by experts, etc. [20]. The contextual corpus will allow us to calculate the frequency of each term generated for the intention (Table 2). We will then keep only the terms with a high frequency, which depends on the size of the corpus (the number of terms it contains). Finally, we will calculate the weight of the co-occurrence for the selected terms (Table 3) using the formula of Dice [19].

$$\text{The formula of Dice } P(x,y) = \frac{2f\,(x,y)}{f\,(x) + f\,(y)} \quad (1)$$

P(x,y) represents the co-occurrence weight between x and y.

f(x,y) represents the number of times the words x and y are found together in the same sentence.

f(x), and f(y) represent respectively the number of times that x, y is repeated in the corpus.

Table 2. Calculation of the Frequency of the Terms Generated

Item of intention	Generated terms
Search 451	Seek 99, look for 04, look 6993, research 245, explore 339, examine 1, see 2323, investigate 22, look into 00, analyze 00, etc.
Room 55494	chamber 40, hall 1126, foyer 107, lobby 3481, vestibule 1, bedroom 1026, sleeping room 14, bedchamber 00, lounge 1671, cell 7452, classroom 02, etc.
Hotel 54199	Hostel 134, hostelry 00, inn 4301, lodge 88, spa 6539, Ritz 601, resort 9209, resort hotel 33, holiday resort 06, building 2215, edifice 00, structure 52, tourist court 00, court 1559, hotel room 941, etc.
Marrakech 02	Marrakesh 0, city 4430, metropolis 8, urban center 00, municipality 01, district 546, territory 12, Morocco 3, Kingdom of Morocco 00, Maroc 01, Marruecos 00, Al-Magrib 00, etc.
End 26973	Extremity 00, ending 996, last 681, final stage 01, goal 25, death 36, boundary 02, extreme 2128, limit 724, deadline 02, conclusion 106, period 192, year-end 00, finale 03, moment 485, minute 5848, second 1695, instant 85, etc.
Year 3259	Twelvemonth 00, time period 11, period of time 00, period 192, christian year 00, New Year 271, school year 03, academic year 00, month 737, season 676, decade 30, decennary 00, etc.
Adult 615	Grownup 00, person 2623, individual 179, someone 14, somebody 69, mortal 00, soul 71, elder 57, senior 49, host 501, woman 311, etc.
Child 1018	Kid 2405, youngster 06, minor 432, baby 250, infant 37, juvenile 01, person 2623, youth 26, younker 00, etc.

*The numbers shown as examples in this table were obtained using the "Tripadvisor Hotel Review Dataset which encompasses 20,491 customer reviews and ratings for numerous hotels worldwide [21].

*Contextual information (time, location, personal information, etc.) has been added to this dataset.

Table 3. The Co-occurrence Weight of the Generated Terms

Item of intention	Generated terms
Search	Seek:0.03, look for:0.01,look:0.04, *research:0.70*, explore:0.02, examine:0.004,see:0.053, investigate:0.0, look into:0.0, analyze:0.0, etc.
Room	Chamber:0.001, hall:0.038, foyer:0.0036, lobby:0.109, vestibule:0.0, bedroom:0.036, sleeping room:0.0005, bedchamber:0.0, lounge:0.053, cell:0.189, classroom:00, etc.
Hotel	Hostel:0.003, hostelry:0.0, inn:0.10, lodge:0.002, spa:0.160, ritz:0.017, resort:0.077, resort hotel:0.0012, holiday resort:0.0001, building:0.059, edifice:0.0, structure:0.0016, tourist court:0.0, court:0.046, hotel room:0.034, etc.
Marrakech	Marrakesh:0.0, city:0.0004, metropolis:0.0, urban center:0.0,municipality:0.0, district:0.0, territory:0.0, *morocco:0.333*, kingdom of morocco:0.0, maroc:0.0, marruecos:0.0, al-magrib:0.0, etc.
End	extremity:0.0,ending:0.071, last:0.037,final stage:0.00, goal:0.002, death:0.002, boundary:0.0001, extreme:0.106, limit:0.038, deadline:0.0001, conclusion:0.006, period:0.011, year-end:0.0, finale:0.0001, moment:0.025, *minute:0.239*, second:0.085, instant:0.004, etc.
Year	Twelvemonth:0.0, time period:0.0018,period of time:0.0, period:0.030, christian year:0.0, new year:0.153, school year:0.002, academic year:0.0, month:0.084, season:0.063, decade:0.006,decennary:0.0
Adult	Grownup:0.0, person:0.073, individual:0.033, someone:0.0, somebody:0.009, mortal:0.0, soul:0.012, elder:0.015, senior:0.006, host:0.031, woman:0.039
Child	*Kid:0.225*, youngster:0.0, minor:0.039, baby:0.061, infant:0.022, juvenile:0.0, person:0.107, youth:0.004, younker:0.0,etc.

*Only terms with a co-occurrence weight greater than or equal to 0.20 will be selected, this criterion can be modified according to the size of the corpus.

After this step, the new user intention will become using the expansion strategy as follows:

$$I = (Search)_{verb}\ (room)_{target}\ (Hotel;\ Marrakech)_{place}\ (end;\ year)_{time}\ (adults;\ child)_{beneficiary} \quad (2)$$

$$I = (Search;\ research)_{verb}\ (room)_{target}\ (hotel;\ Marrakech;\ Morocco)_{place}\ (end;\ minute;\ year)_{time}\ (adults;\ child;\ kid)_{beneficiary} \quad (3)$$

In addition to the expansion, another reformulation strategy that is used in the reformulation process is to change the elements of intention to other words. That is, if the frequency of an element of intention (the frequency in the contextual corpus) is much lower than the frequency of another term, the latter will be exchanged with the original element.

According to the example presented in Table 4, the word "Marrakech" will be exchanged with "city" and the calculation of the co-occurrence weight (Table 5) will be between the term "city" and the other terms, which implies on the one hand, the loss of the word "Marrakech" if its weight of co-occurrence with “city” is lower than the selection threshold (e.g. 0.20) and on the other hand, the appearance of other terms more related to "city" than “Marrakech”. This strategy, although it can improve our process, should be used with care, as it presents a risk of deviating from the original intention to an intention that is not desired by the user, even if it is related to the context. That is why we are currently limiting to the expansion strategy.

Table 4. Example of Selecting the Most Recurrent Term

Marrakech 02	Marrakesh 0, city 4430, metropolis 8, urban center 00, municipality 01, district 546, territory 12, Morocco 3, Kingdom of Morocco 00, Maroc 01, Marruecos 00, Al-Magrib 00, etc.

Table 5. Co-occurrence Weight of the Old and the Most Recurrent Term

Marrakech	Marrakesh:0.0, city:0.0004, metropolis:0.0, urban center:0.0,municipality:0.0, district:0.0, territory:0.0, morocco:0.333, kingdom of morocco:0.0, maroc:0.0, marruecos:0.0, al-magrib:0.0, etc.
City	Marrakech 0.0004, marrakesh:0.0, metropolis:0.0, urban center:0.0,municipality:0.0, district:0.057, territory:0.001, morocco:0.004, kingdom of morocco:0.0, maroc:0.0, marruecos:0.0, al-magrib:0.0, etc.

The Service Selection Strategy

After reformulating the user's intention, the final phase is the selection of the service that can meet this intention. In this regard, it is necessary to seek the correspondence between the elements of the reformulated intention and the service descriptions in the service directory. Figure 6 illustrates the service selection process, which commences with the search for correspondence between the verbs and then between the parameters, subsequently calculating the overall matching score, and ultimately returning the service with the highest score.

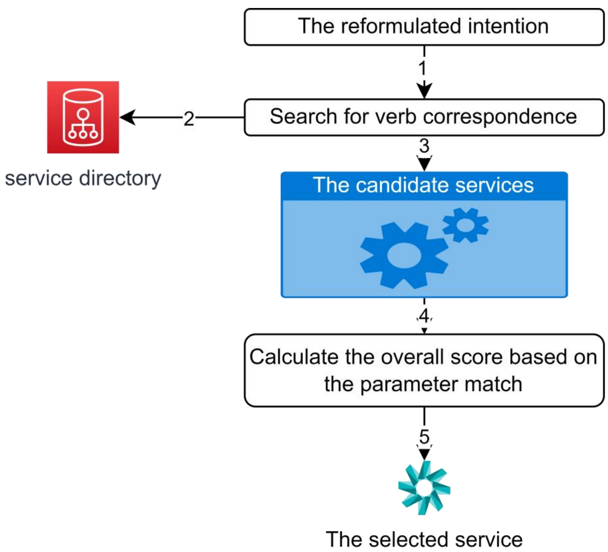

Figure 6. Service Selection Process

The search for correspondence is an exact search (seeking an exact match between the elements of the intention and the description of the services published in the directory). This precision is maintained throughout the reformulation process, wherein the intention undergoes expansion based on lexical semantic relationships, and only the most relevant terms, appropriate to the domain and context, are added.

For example, to identify the service that meets the reformulated intention in the previous section:

$$I = (Search;\ research)_{verb}\ (room)_{target}\ (hotel;\ Marrakech;\ Morocco)_{place}\ (end;\ minute;\ year)_{time}\ (adults;\ child;\ kid)_{beneficiary} \quad (4)$$

Initially, select the services with intention descriptions that include either the verb "Search" or "Research," and subsequently, calculate the total matching scores for the chosen services as presented in Table 6.

Table 6. Matching Scores

Intention Parameters	Score
Target	3
Place	1.25
Time	0.5
Beneficiary	0.25
Manner	0.25
Reason	0.25

Let's assume that in the service directory, five services use the verbs "Search” or “research" to describe the intentions they aim to fulfill. The calculation of the total matching score is as follows.

$$S1 : Search;\ house;\ \{end, year\}Time{:}0.5{+}0.5;\ rental. \Rightarrow S1_T = 1 \quad (5)$$

$$S2 : Search;\ \{room\}Target{:}3;\ Spain;\ April;\{adult;\ child\}Beneficiary{:}0.25{+}0.25. \Rightarrow S2_T = 3.50 \quad (6)$$

$$S3 : Research;\ \{room\}Target{:}3;\{hotel;\ Marrakech\}Place{:}1.25{+}1.25. \Rightarrow S3_T = 5.50 \quad (7)$$

$$S4 : Search;\ \{room\}Target{:}3;\ \{hotel\}Place{:}1.25;\{New\ Year\}Time{:}0.5;\ \{adult;\ child\}Beneficiary{:}0.25{+}0.25. \Rightarrow S4_T = 5.25 \quad (8)$$

$$S5 : Search;\ \{room\}Target{:}3;\ hostel;\{adult;\ child\}Beneficiary{:}0.25{+}0.25. \Rightarrow S5_T = 3.50 \quad (9)$$

The service that achieved the highest score is service (S3), even though service (S5) has more parameters that match the user's intention. However, the lack of information regarding the location parameter makes the service (S3) more appealing to present to the user as a top choice.

RESULTS AND DISCUSSION

The approach we propose for the reformulation of users' intentions in pervasive environments is based on lexical semantics and context in order to allow the user to express his intention in a non-technical language to locate the services that best suit his context and needs. The reformulation of users' intentions under our proposal passes through several stages. It starts with the decomposition of the user's intention into verbs, targets, and parameters. Subsequently, a set of terms is generated and filtered based on the domain-specific corpus. The new terms create a reformulated intention that will be sent to the services directory that selects the most appropriate service by calculating the correspondence weights between the reformulated intention and the description of the services. Only results that align with the context information will be presented to the user.

The main advantage of this approach is the use of non-technical words and the use of domain-specific corpus that can be easily exchanged according to the execution environment (health, tourism, education, etc.). Other approaches exist in the literature for users' intentions in pervasive environments; Among the oldest is the [22] approach, which is a strategy based on the theory of graphs to take into account users’ intentions in the composition of services. This approach describes the users’ intentions using a formal language called PsaQL (Pervasive Service Action Query Language) a language similar to SQL. On the contrary, our approach aims to use mainly natural language in order to respect the principle of transparency in pervasive environments. The information of context at the approach of Pascal Bilher et al.[22] is used to construct the graph of all possible compositions of services, without providing details on the process of collection, processing and reasoning on the context.

The approach of [23] considers the user's intention to be an answer to the question "What does the user want to do?" in order to make the system proactive. The authors of this approach do not present a description or model of users' intentions and only present a general description of the approach without technical details. In contrast, the approach we propose considers the user's intention to be a need expressed in a non-technical language, which has nothing to do with the prediction of the user's future needs. In our approach, the modeling of users' intentions was guided by the work which decomposes intention into a verb, target and parameters [3], [18].

Jaafar et al. [6] propose a multi-criteria method for selecting services to be returned to users based on context and intentions. Intentions, according to this approach, are considered a high-level description of users' goals with their requirements, without specifying how these criteria could be satisfied. Intentions and context are used to construct user preferences, which are then employed to filter the results to be returned to the user. This approach does not delve into the detailed process of collecting, processing, reasoning, and storing context, just as it does not extensively expose the process of processing and reformulating intentions. However, its main objective lies in the service selection phase. It suggests a dynamic K-Skyline algorithm and a TOPSIS method to optimize and rank the final selection of services according to user preferences. While the approach we propose aims to manage various aspects related to both context and intentions, it is accompanied by a detailed description of the intention reformulation processes, along with a proposal for a service selection algorithm based on reformulated intentions.

Qu et al. [24] in their approach, sought to predict and reformulate user intentions during the use of conversational assistants. This approach is based on machine learning, neural networks enriched with information about emotions, content, etc. This approach emphasizes the importance of using contextual information to achieve better results. Several other works related to user intentions in pervasive environments have aimed to predict the future behavior of the user based on their intentions, preferences, history, etc. Among them, we mention the work of [25] which considers intention as a future action to be executed rather than a goal to be achieved, as in our approach. This approach seeks to predict user activity using mixed reality (head orientation and hand gesture data) in addition to collecting data and past events to infer user intent and improve activity recognition.

In general, the approach we propose for the reformulation of users' intentions in pervasive environments (Figure 7) is an approach that considers user intentions as objectives expressed in natural language, rather than activities or tasks performed in the environment, and it takes into account both the context and the semantic-lexical aspect of the intention.

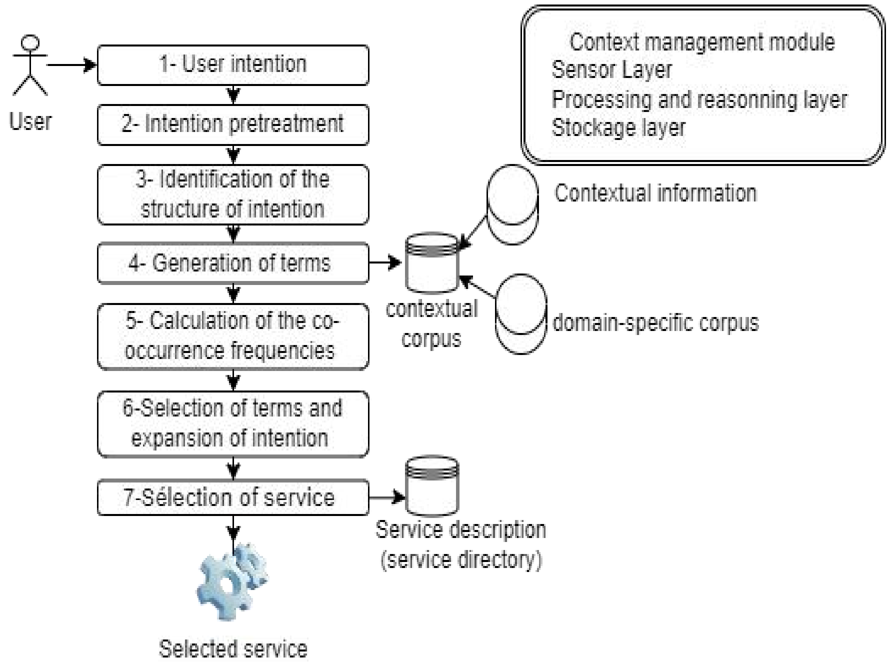

Figure 7. Process of the Proposed Approach

The Limitations of the Presented Approach

Our approach aims to be strongly linked to the context of the user and his environment, which is why the contextual corpus formed from information extracted from the environment and domain-specific corpus (tourism, education, health, etc.) forms the backbone of this approach. A poor choice of domain-specific corpus can lead to inconsistent results.

Table 7 and Table 8 present the result obtained using another domain-specific corpus which was scraped from Booking.com. Within this dataset, there are 515,000 customer reviews and ratings associated with 1,493 luxury hotels located across Europe [26].

Table 7. Frequency Calculation of Terms Generated ("515k hotel reviews data in Europe" dataset)

Item of intention	Generated terms
Search 190	Seek 52, look for 273, look 5015, research 94, explore 917, examine 4, see 7555, investigate 66, look into 155, analyze 00, etc.
Room 318745	chamber 81, hall 5924, foyer 850, lobby 8521, vestibule 4, bedroom 8402, sleeping room 31, bedchamber 00, lounge 6564, cell 287, classroom 01, etc.
Hotel 435021	Hostel 308, hostelry 04, inn 19480, lodge 2481, spa 13971, Ritz 1394, resort 70, resort hotel 03, holiday resort 03, building 9174, edifice 03, structure 2014, tourist court 00, court 7821, hotel room 2562, etc.
Marrakech 0	Marrakesh 0, city 38759, metropolis 1101, urban center 00, municipality 04, district 1669, territory 72, Morocco 279, Kingdom of 0.011 Morocco 00, Maroc 00, Marruecos 00, Al-Magrib 00, etc.
End 6964	Extremity 01, ending 104, last 4789, final stage 01, goal 13, death 36, boundary 17, extreme 214, limit 146, deadline 16, conclusion 43, period 626, year-end 04, finale 03, moment 1257, minute 6445, second 5685, instant 307, etc.
Year 2800	Twelvemonth 00, time period 08, period of time 45, period 626, christian year 00, New Year 318, school year 00, academic year 00, month 563, season 392, decade 18, decennary 00, etc.
Adult 374	Grownup 00, person 5477, individual 395, someone 3484, somebody 354, mortal 01, soul 106, elder 17, senior 138, host 179, woman 697, etc.
Child 1018	Kid 236, youngster 06, minor 2221, baby 1138, infant 53, juvenile 05, person 5477, youth 50, younker 00, etc.

Despite the fact that this corpus also belongs to the field of tourism, just like the one used in the example presented in our approach (Tripadvisor Hotel Review Dataset), and it contains more relevant information for example: hotel names and addresses, nationalities of reviewers, dates of reviews, as well as positive and negative reviews, etc. with a larger number of reviews (Figure 8), we are unable to obtain relevant information that can be used to enrich our intention. This can be explained by the fact that the used corpus is more focused on Europe, whereas the one we used in our approach holds a considerable amount of information related to Morocco. Another drawback is the execution time of the approach, which increases with the growth of information injected into the contextual corpus. Based on the example provided, it is crucial to carefully select the domain-specific corpus, which must reflect the reality of the user and be regularly updated to take into account the dynamics of ubiquitous environments.

Table 8. Co-occurrence Weight of the Generated Terms (“515K Hotel Reviews Data In Europe” Dataset)

Item of intention	Generated terms
Search	Look for 0.0086, look 0.0046, explore 0, see 0, look into 0, etc.
Room	Hall 0.018, foyer 0.0031, lobby 0.03, bedroom 0.021, lounge 0.020, cell 0.0013, etc.
Hotel	Hostel 0.0011, inn 0.0236, lodge 0.0084, spa 0.047, Ritz 0.0017, building 0.028, structure 0.0007, court 0.0240, hotel room 0.0110, etc.
Marrakech	City 0, metropolis 0, district 0, Morocco 0, etc.
End	Ending 0.0005, last 0.028, extreme 0.0022, limit 0.0014, period 0.006, moment 0.010, minute 0.024, second 0.027, instant 0.0022, etc.
Year	Period 0.0128, New Year 318, month 0.0125, season 0.0100, etc.
Adult	Person 0.0010, individual 0.0026, someone 0.0026, somebody 0, soul 0, senior 0.004, host 0.0036, woman 0, etc.
Child	Kid 0.018, minor 0.0043, baby 0.036, person 0.014, etc.

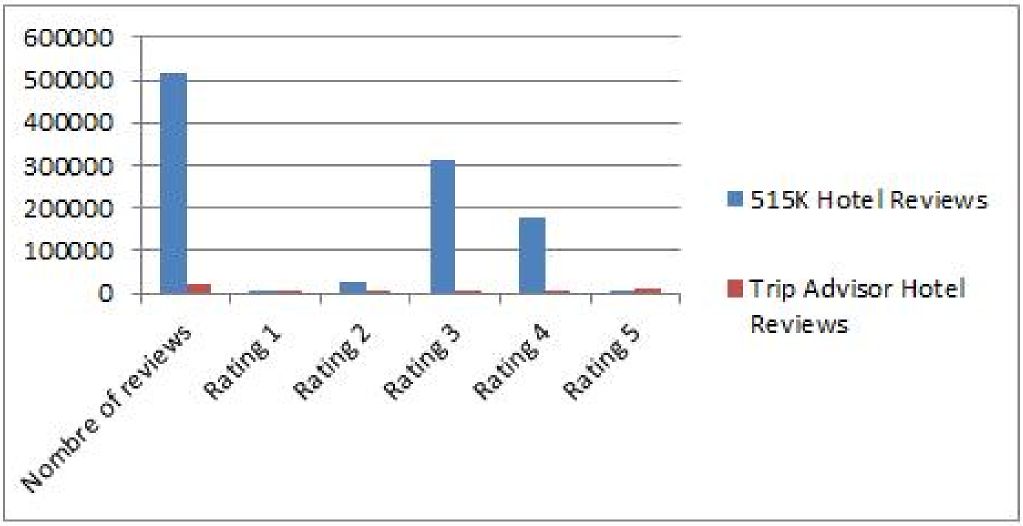

Figure 8. Comparison between the Two Datasets (515K hotel reviews and TripAdvisor hotel reviews)

CONCLUSION

In this article, we first presented an overview of the concept of ubiquitous computing, where services and computing devices seamlessly integrate into everyday life. Next, we elaborated on a set of notions related to this paradigm, notably context and invisibility. Furthermore, in the literature section, we explore other concepts such as user intentions, pervasive services, and reformulation techniques. These interconnected concepts form the foundation of the approach we propose for reformulating user intentions in pervasive environments. The main objective of this approach is to enable the user to discover services appropriate to their context and aligned with their intentions (objectives) expressed in natural language.

The proposed approach is based on concepts from lexical semantics and context information that are collected from various sensors, followed by a sequence of processing and reasoning to extract high-level context information. The reformulation of users' intentions under our proposal goes through several stages; starting with the decomposition of the user's intention into verb, target, and parameters, and then generating a set of terms to be filtered according to the domain-specific corpus, ontology, and context information. The new terms aim to link the users' intentions to their context. The selection of appropriate services from the directory is achieved by calculating a matching score between the service descriptions and the reformulated intention. The scores assigned to each element of the intention prioritize presenting the user with the most suitable services for their specific environment.

The comparison of our approach with other approaches in the literature allows us to classify it as a lexical-semantic approach reinforced by contextual information. The advantages of this approach, in addition to contextualizing intentions and selecting services appropriate to the user's intentions and context, lie in avoiding the use of technical language, and aligning with the principles of pervasive computing. The proposed approach remains closely related to the context information and the domain-specific corpus, highlighting the paramount importance of choosing the latter. Otherwise, the approach risks producing inconsistent results, as detailed in the section dedicated to the limitations of our approach.

Our future work will aim to investigate aspects not covered in depth in this article, such as the analysis of response time, security, and the utilization of large language models to enhance performance, particularly in pervasive environments known for their complexity and heterogeneity.

ETHICAL DECLARATION

Conflict of interest: No declaration required. **Financing:** No reporting required. **Peer review:** Double anonymous peer review.

REFERENCES

[1] M. Kirsch Pinheiro, P. Roose, L. A. Steffenel, and C. Souveye, "What is a Pervasive Information System (PIS)?," in *The Evolution of Pervasive Information Systems*, M. Kirsch Pinheiro, C. Souveyet, P. Roose, L. A. Steffenel, Eds, Cham, Switzerland: Springer, 2023, ch. 1, pp. 1-17.

[2] V. Ponce and B. Abdulrazak, "Intention as a context: An activity intention model for adaptable development of applications in the internet of things," *IEEE Access*, vol. 9, pp. 151167-151185, 2021.

[3] I. Choukri, H. Guermah, and M. Nassar, "Toward a better understanding of intentionality in service engineering: A systematic review," *International Journal of Web Engineering and Technology*, vol. 16, no. 1, pp. 53-82, 2021.

[4] A. Bouain, A. El Fazziki, and M. Sadgal, "Pervasive services vs. Web services: Survey and comparison," in *2014 International Conference on Multimedia Computing and Systems (ICMCS)*, Apr. 2014, pp. 552-557.

[5] S. G. Gollagi, M. M. Math, and A. A. Daptardar, "A survey on pervasive computing over context-aware system," *CCF Transactions on Pervasive Computing and Interaction*, vol. 2, no. 2, pp. 79-85, 2020.

[6] A. A. Jaafar, D. N. Jawawi, M. A. Isa, and N. A. Saadon, "Service selection model based on user intention and context," *Journal of King Saud University-Computer and Information Sciences*, vol. 35, no. 4, pp. 209-223, 2023.

[7] V. Gupta and A. Dixit, "Recent query reformulation approaches for information retrieval system-a survey," *Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science)*, vol. 16, no. 1, pp. 94-107, 2023.

[8] S. Akuma and P. Anendah, "A new query expansion approach for improving web search ranking," *International Journal of Information Technology and Computer Science*, vol. 15, no. 1, pp. 42-55, 2023.

[9] T. Tong, R. Setchi, and Y. Hicks, "Context change and triggers for human intention recognition," *Procedia Computer Science*, vol. 207, pp. 3826-3835, 2022.

[10] S. Aghaei, K. Angele, E. Huaman, G. Bushati, M. Schiestl, and A. Fensel, "Interactive search on the web: The story so far," *Information*, vol. 13, no. 7, p. 324, 2022.

[11] H. Bouazza, B. Said, and F. Z. Laallam, "A hybrid IoT services recommender system using social IoT," *Journal of King Saud University-Computer and Information Sciences*, vol. 34, no. 8, pp. 5633-5645, 2022.

[12] Y. Cai, S. Pan, X. Wang, H. Chen, X. Cai, and M. Zuo, "Measuring distance-based semantic similarity using meronymy and hyponymy relations," *Neural Computing and Applications*, vol. 32, pp. 3521-3534, 2020.

[13] A. M. Hasan, T. H. Rassem, N. M. Noor, and A. M. Hasan, "A review of recent trends: text mining of taxonomy using WordNet 3.1 for the solution and problems of ambiguity in social media," in *Intelligent Computing and Innovation on Data Science: Proceedings of ICTIDS 2019*, Nov. 2021, pp. 137-152.

[14] J. P. McCrae, E. Rudnicka, and F. Bond, "English WordNet: A new open-source wordnet for English," *K Lexical News*, vol. 28, pp. 37-44, 2020.

[15] A. Bouain, A. E. Fazziki, M. Sadgal, and M. N. Abourraja, "Towards a pervasive information system for patient triage and referral in emergency departments," *International Journal of Ad Hoc and Ubiquitous Computing*, vol. 25, no. 4, pp. 273-283, 2017.

[16] X. Chen, S. Jia, and Y. Xiang, "A review: Knowledge reasoning over knowledge graph," *Expert Systems with Applications*, vol. 141, p. 112948, 2020.

[17] S. Shishehchi and S. Y. Banihashem, "A rule based expert system based on ontology for diagnosis of ITP disease," *Smart Health*, vol. 21, p. 100192, 2021.

[18] N. Prat, "Goal formalization and classification for requirements engineering, fifteen years later," in *IEEE 7th International Conference on Research Challenges in Information Science (RCIS)*, May 2013, pp. 1-12.

[19] K. P. Mainali, E. Slud, M. C. Singer, and W. F. Fagan, "A better index for analysis of co-occurrence and similarity," *Science Advances*, vol. 8, no. 4, p. eabj9204, 2022.

[20] H. Wang, J. Li, H. Wu, E. Hovy, and Y. Sun, "Pre-trained language models and their applications," *Engineering*, vol. 25, pp. 51-65, 2022.

[21] M. H. Alam, W. J. Ryu, and S. Lee, "Joint multi-grain topic sentiment: Modeling semantic aspects for online reviews," *Information Sciences*, vol. 339, pp. 206-223, 2016.

[22] P. Bihler, L. Brunie, and V. M. Scuturici, "Modeling user intention in pervasive service environments," in *Embedded and Ubiquitous Computing–EUC 2005: International Conference EUC 2005*, 2005, pp. 977-986.

[23] K. Abhirami and K. Vasan, "Understanding user intentions in pervasive computing environment," in *2012 International Conference on Computing, Electronics and Electrical Technologies (ICCEET)*, Mar. 2012, pp. 873-876.

[24] C. Qu, L. Yang, W. B. Croft, Y. Zhang, J. R. Trippas, and M. Qiu, "User intent prediction in information-seeking conversations," in *Proceedings of the 2019 Conference on Human Information Interaction and Retrieval*, Mar. 2019, pp. 25-33.

[25] K. Rook, B. Witt, R. Bailey, J. Geigel, P. Hu, and A. Kothari, "A study of user intent in immersive smart spaces," in *2019 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom*

Workshops), Mar. 2019, pp. 227-232.
[26] J. Liu. “515K Hotel Reviews Data in Europe,” Booking.com. https://www.kaggle.com/datasets/jiashenliu/515k-hotel-reviews-data-in-europe (accessed May 15, 2024).