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A Linear General Type-2 Fuzzy Logic Based Computing With Words Approach for Realising an Ambient Intelligent Platform for Cooking Recipes Recommendation

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***Abstract*—This paper addresses the need to enhance transparency in Ambient Intelligent Environments by developing more natural ways of interaction, which allow the users to communicate easily with the hidden networked devices rather than embedding obtrusive tablets and computing equipment throughout their surroundings. Ambient Intelligence vision aims to realize digital environments that adapt to users in a responsive, transparent and context aware manner in order to enhance users' comfort. It is therefore appropriate for employing the paradigm of '*Computing With Words*' (CWWs), which aims to mimic the ability of humans to communicate transparently and manipulate perceptions via words. One of the daily activities that would increase the comfort levels of the users (especially people with disabilities) is cooking and performing tasks in the kitchen. Existing approaches on food preparation, cooking, and recipe recommendation stress on healthy eating and balanced meal choices while providing limited personalization features through the use of intrusive user interfaces. Herein, we present an application, which transparently interacts with users based on a novel CWWs approach in order to predict the recipe's difficulty level and to recommend an appropriate recipe depending on the user's mood, appetite and spare time. The proposed CWWs framework is based on Linear General Type-2 (LGT2) Fuzzy Sets, which linearly quantify the linguistic modifiers in the third dimension in order to better represent the user perceptions while avoiding the drawbacks of type-1 and interval type-2 fuzzy sets. The LGT2 based CWWs framework can learn from user experiences and adapt to them in order to establish more natural human-machine interaction. We have carried numerous real-world experiments with various users in the University of Essex intelligent flat. The comparison analysis between Interval Type-2 Fuzzy Sets and LGT2 Fuzzy Sets demonstrates up to 55.43% improvement when general type-2 fuzzy sets are used than when interval type-2 fuzzy sets are used instead. The quantitative and qualitative analysis both show the success of the system in providing a natural interaction with the users for recommending food recipes where the quantitative analysis shows the high statistical correlation between the system output and the users' feedback; and the qualitative analysis presents social science evaluation confirming the strong user acceptance of the system.**

***Index Terms*— ambient intelligence, computing with words, general type-2 fuzzy sets**

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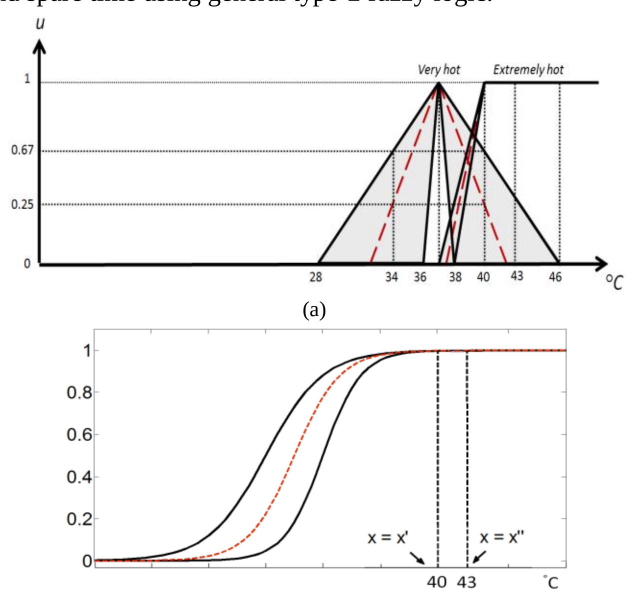
I. Introduction

The recent years have witnessed a rapid increase in the miniaturization of computers which enabled to embed computing throughout our spaces in familiar objects such as home appliances (e.g. washing machines, refrigerators, etc.), portable devices (e.g. mobile phones, tablets, etc.), cars, etc. In addition, the advances in communications allowed such devices to be networked and connected to the Internet. Among the highlights of the connected and miniaturized devices bring to real life is the opportunity of customization and therefore personalization. Lately, it is getting more important to deliver personalized content in areas such as food planning which is becoming an important personal issue that affects the individual's health and comfort. There are several factors to take into account and many researchers have different approaches in the literature where Freyne and Berkovsky [61] presented preliminary design of a recipe recommender, which focussed on food-recipe relationships based on user ratings. In [81], researchers have examined the ingredients and the relationships between them within tens of thousands of recipes from websites to find out which ingredients go well together as well as regional preferences of the users. As another perspective, using recipe recommendation experiments, Forbes and Zhu [82] investigated content-boosted matrix factorization for recommender systems. However, these studies have not considered user conditions that affect food selection. Correspondingly, Mino and Kobayashi [78] proposed a method to recommend recipes for a diet taking into account the user's personal activities categorized in event types such as party, lunch, sports, etc. Additionally, Ueda et al. [62] explored a method for extracting the user's favourite ingredients using recipe browsing and cooking history to tackle the problems of picky eating for nutritional health concerns. Moreover, Yajima and Kobayashi [63] developed a recommendation system that analyses the content of the recipes (in terms of number of ingredients, cooking processes, etc.) as well as the user's condition (with regards to the possessed seasonings, user's preference and schedule, date and season, etc.). Even though these studies considered user's conditions to provide personalization, they have not taken into account the uncertainties introduced by personal recommendations which can be handled using fuzzy logic systems. Accordingly, Lee et al. [83] used type-1 fuzzy logic to calculate the calorie allowance in an intelligent ontological agent for diabetic food recommendation. In their following studies, they have further developed their system to involve type-2 fuzzy ontology [84] as well as Fuzzy Markup Language [85]. However, these studies concentrated on the diabetics as a health condition and not on the user's mood, appetite and spare time which are quite crucial in deciding what to eat. In this paper, we present an ambient intelligent platform for cooking recipes recommendation which predicts the level of difficulty of a recipe and recommends a recipe that would be appropriate to the user depending on the user's mood, appetite and spare time using general type-2 fuzzy logic.



(a)

(b)

Fig. 1. Problems with using (a) IT2 fuzzy sets (shown in solid black lines) and type-1 fuzzy sets (shown in red dashed lines) in CWW scenarios (b) Type-1 fuzzy sets (shown in red dashed lines) and IT2 (shown in solid black lines) shoulder sigmoidal fuzzy sets.

On the other hand, the aforementioned widespread availability of networked computing resources sparked the emergence of the Ambient Intelligence (AmI) vision, which aims to realise digital environments that adapt to users in a responsive, transparent and context aware manner [57][69]. The previous years have witnessed an increase of applying AmI technologies to enhance users' comfort [60] and to help the elderly and people with disabilities especially those having vision impairment (according to World Health Organization statistics[1], the estimated number of visually impaired people worldwide is 285 million). Such AmI applications included alerting carers for emergency cases such as falling down [70], using robots to assist the elderly in daily tasks [71] or suggesting safe navigation techniques for the blind via GPS, RFID, etc. [72][73]. One of the major daily activities that would increase the comfort levels of the users and help people with disabilities is cooking and performing tasks in the kitchen. As mentioned previously, most approaches on food preparation, cooking, and recipe recommendation stress on healthy eating and balanced meal choices [74]-[78]. In addition, the existing applications such as the 'recipe recommenders' mentioned in [61]-[64], [81], [83]-[85] provide limited personalization features while neglecting the notion of adaptation and they also require the use of intrusive user interfaces. Hence, there is a need to enhance transparency in AIEs (especially when dealing with disabled and elderly people) by developing more natural ways of interaction which allow the users to communicate easily with the hidden networked devices rather than embedding obtrusive tablets and computing equipment throughout their surroundings.

The most widely used inter-human communication is via spoken language conversations which can inspire a transparent human-computer interaction. This necessitates having systems capable of modelling words and computing with them. For this purpose, the paradigm of '*Computing With Words*' (CWWs) was coined by Zadeh in mid 90s to mimic the ability of humans to communicate and manipulate perceptions via words [1]. CWWs have been studied within various approaches including human-interpretable decision making [7], judgment analysis [8], perceptual reasoning [9] leading to perceptual computing [10], fuzzy automata [11], text categorization [12], linguistic modelling of words essentially stressing the use of interval type-2 (IT2) fuzzy systems [13]-[18]. In this work, CWWs paradigm is used in order to create adequate word models which are capable of representing the human's perceptions. This requires improving the naturalness of communication between humans and machines. For example, making the AmI space sensitive enough to distinguish between 40°C and 43°C in order to capture the user perception and provide better response to the user needs.

As Mendel [65] states, using a type-1 fuzzy set to model a word is scientifically incorrect because a word is uncertain whereas a type-1 fuzzy set is certain. In addition, type-1 and IT2 fuzzy sets have problems when employed to model words from a linguistics perspective where Klein [22] argues that natural ordering on real numbers can be lost in fuzzy semantics. Fig. 1a shows a situation where x'=40°C and x''=43°C and both x' and x'' have a membership value of 1 to the linguistic term *Extremely hot* (when either type-1 or IT2 fuzzy sets are employed). The same applies to the temperature values of 34°C and 40°C which will have the same type-1 and IT2 membership values to the linguistic term *Very hot*. Hence, from the machine point of view, there is no way to distinguish between x' and x'' (although the difference can be perceived

[1]http://www.who.int/mediacentre/factsheets/fs282/en/

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by humans) as they belong to the same linguistic term with the same membership degrees. Hence, by using type-1 or IT2 fuzzy sets, we might lose essential information. Even, if a shoulder sigmoidal type-1 fuzzy set is used as shown in Fig. 1b, we might have different membership values for x' and x'', however, this poses a restricted representation when it comes to interpreting the difference in the membership degrees where the differences in the membership degrees of x' and x'' might not represent the natural ordering difference in real-world.

TABLE I
CONTRIBUTION AND NOVELTY OF THE PAPER WITH REGARDS TO THREE MAJOR DOMAINS

Domain	Contribution	Novelty
General Type-2 Fuzzy Logic	A special kind of GT2 FS named Linear General Type-2 FS	First nested Footprint of Uncertainty approach in the third dimension that indicate linguistic modifiers Better represent the perceptions while avoiding the drawbacks of type-1 and interval type-2 fuzzy sets Inter-disciplinary approach (inspired from linear adjectives, antonyms, and modifiers)
Computing With Words (CWWs)	Architecture for a CWWs Framework	First comprehensive framework for CWWs paradigm, which is capable of modelling words using human experience Merging inter-disciplinary approaches from neuroscience, psychology, linguistics (using LGT2 FSs), and artificial intelligence to mimic human reasoning
Ambient Intelligence (AmI)	Ambient Intelligent Platform for Cooking Recipes Recommendation	First application of CWWs in AmI Enhance transparency in AIEs and establish natural communication between humans and machines Learn from user experiences and adapt to them while increasing user comfort levels in terms of food planning

This paper presents the novel application of an ambient intelligent platform for cooking recipes recommendation which interact with users via natural language based on a CWWs approach. Such a platform can increase the user comfort in AIEs and it can be a very important tool for AIEs which care for the elderly and people with major disabilities including vision impairment. The presented CWWs approach is based on Linear General Type-2 (LGT2) Fuzzy Sets which quantify the third dimension in a linear fashion. Moreover, the proposed LGT2 based CWWs framework can learn from user experiences and adapt to them in order to link the computers and users in a humanlike manner for an improved interaction in AIEs. The contribution and novelty of this paper is also outlined in Table I.

We have carried numerous real world experiments with various users in the University of Essex intelligent apartment (iSpace). We will report results from the comparison analysis between IT2 Fuzzy Sets and LGT2 Fuzzy Sets as well as the quantitative and qualitative analysis which show the success of the system in providing a natural interaction with the users for recommending food recipes considering the user's mood, appetite and spare time. The comparison analysis demonstrates 49% improvement when general type-2 fuzzy sets are used than when interval type-2 fuzzy sets are used instead. The quantitative analysis shows the high statistical correlation between the system output and the users' feedback. In addition, the qualitative analysis presents social science evaluation that confirms the strong user acceptance of the system.

The rest of the paper is organized as follows. In Section II, we introduce LGT2 FSs. Section III provides an in-depth description of the proposed CWWs Framework. Section IV details the application of the proposed CWWs Framework to an ambient intelligent platform for cooking recipes recommendation. Section V presents the experiments and results. Finally, Section VI presents the conclusions and the future work.

II. LINEAR GENERAL TYPE-2 FUZZY SETS (LGT2 FSS)

Any CWWs paradigm necessitates having -as a basic building block- adequate models which are capable of representing 'words' to capture the human's perceptions. Formally, from linguistics perspective, Klein [22] considers the following condition in fuzzy semantics regarding *Extremely hot* temperature: For all $x, x' \in X, \mu_{Extremely\ hot}(x) = \mu_{Extremely\ hot}(x')$, if x is exactly as *Extremely hot* as x'. If we want to interpret the claim "43ºC is *hotter* than 40ºC" in fuzzy semantics using the information $\mu_{Extremely\ hot}(40)$ and $\mu_{Extremely\ hot}(43)$, we would obviously let $\mu_{Extremely\ hot}(43) > \mu_{Extremely\ hot}(40)$ where $>$ is the natural ordering on the real numbers. But this conflicts with the reasonable assumption that if the temperature x reaches a certain value, say 40ºC, then x is definitely *Extremely hot* and hence $\mu_{Extremely\ hot}(40) = 1$ (the case of shoulder membership functions (MFs)). Hence, $\mu_{Extremely\ hot}(40) = \mu_{Extremely\ hot}(43)$, and the claim "43ºC is *hotter* than 40ºC is" comes out false. Another perspective was cited by Greenfield and John [46] regarding the propositions under different types of logic. In crisp logic, the statement S ={*The perpetrator is tall.*} is equivalent to the below statement [46]:

S_{crisp} ={*'The perpetrator is tall.' is true.*}

On the other hand, in type-1 fuzzy logic, the statement S can take the form of:

S_{type-1} = {*'The perpetrator is tall.' has a truth value of 0.8.*}

whereas in IT2 fuzzy logic, the statement S can take the

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following forms [46]:

S_{IT2} = *{The statement {'The perpetrator is tall.' has a truth value of 0.8} has a truth value of 1.}*

$S_{IT2}{}'$ = *{The statement {'The perpetrator is tall.' has a truth value of 0.5} has a truth value of 1.}*

Hence, according to [46], the statements S_{IT2} and $S_{IT2}{}'$ are inconsistent and the examples above show how an IT2 fuzzy set can generate a number of incompatible statements. According to [46], in the case of modelling statements using general type-2 (GT2) fuzzy logic, the statements S_{GT2} and $S_{GT2}{}'$ would be consistent as follows:

S_{GT2} = *{The statement {'The perpetrator is tall.' has a truth value of 0.8} has a truth value of 1.}*

$S_{GT2}{}'$ = *{The statement {'The perpetrator is tall.' has a truth value of 0.5} has a truth value of 0.6.}*

Hence, from the above discussion, we can see that type-1 fuzzy sets cannot handle the linguistic uncertainties associated with words. In addition, as shown in Fig. 1a, IT2 as well as type-1 fuzzy sets have problems when employed to model words from a linguistics perspective as the natural ordering on real numbers can be lost in fuzzy semantics [22] and also IT2 FSs can lead to incompatible statements [46]. This has motivated us to investigate the use of general type-2 (GT2) FSs to overcome the abovementioned problems faced when modelling words for CWWs.

One of the most important characteristics of GT2 FSs is the additional degrees of freedom they provide which can enable handling higher uncertainty levels. As GT2 FSs have membership grades which are type-1 FSs; they are very useful in circumstances where it is difficult to determine an exact membership value for a given input and hence, they can be useful for handling the linguistic uncertainties [28]. Furthermore, it has been concluded by Hisdal [29] that increased fuzziness in a description means increased ability to handle inexact information in a logically correct manner. Recently, the introduction of zSlices [31] and alpha-planes [79] [87] has helped to bridge the gap caused by the complexity of the design and implementation of GT2 FSs.

In this paper, we will present a special kind of GT2 FSs termed Linear General Type-2 Fuzzy Sets (LGT2 FSs) [4] where the third dimension is quantified in a linear fashion. The theoretical formulation of LGT2 FSs is based on linear adjectives [22], antonyms [21] and modifiers [23]. From the linguistics perspective, we observed that the words (i.e. linguistic terms for linguistic variables) used in fuzzy logic are possibly adjectives (e.g. hot, cold, high, low, etc.), which have the distinctive characteristic of gradability [22] as they are modelled in a sortal range[2] within their mathematical domain. Formally, given that A is an adjective, Klein [22] puts forward two types of adjectives classified according to the following condition: "*Whenever c is a context of use, NP_1,NP_2 denote individuals within the sortal range of A, then the sentence NP_1 is $A - \boldsymbol{er}$ than NP_2 has a definite truth value in c.*" [22]. Accordingly, the linear adjectives are those that satisfy this condition and the ones that do not are called to be nonlinear [22]. For example, let c be a context of temperature, $NP_1 = 43$ and $NP_2 = 40$ within the sortal range of $= 'hot'$, then the sentence "$43\ is\ hot(t) - \boldsymbol{er}\ than\ 40$" has a definite truth value in temperature context; therefore, 'hot' is a linear adjective as it satisfies the above condition.

From another linguistics perspective, Kennedy [23] presents a decompositional approach where he argues that "… *the meaning of a gradable adjective contains a measure function"* [23]. To illustrate, let 'hot' be a gradable adjective and 'extremely' be a measure function which determines the degree to which a variable *x* is 'hot'; in this case 'extremely' alone is not the core meaning of the adjective according to [23]. In linguistics literature, modifiers as measure phrases have been studied in detail [24]-[26] where it is agreed that semantics of measure phrases require an adjustment in the meaning of an adjective [25]. However, the adjustments caused by measure phrases (i.e. modifiers) also introduce linguistic uncertainties.

In order to model a word for CWWs, there is a need to deal with the linguistic uncertainty that modifiers encapsulate as their level of intensifying or diminishing the meaning of an adjective changes from one person to another. For example, when the modifier 'extremely' is used to intensify the meaning of an adjective, it might mean different amount of intensifications to different people. Herein, we aim to handle the linguistic uncertainty conveyed by modifiers in a novel way and we propose to model modifiers as second-order word uncertainty. The point of departure for this is twofold: 1) there exists a hierarchical analogy (see Fig. 2c) between the linear adjectives and a linguistic variable in a fuzzy system 2) as mentioned by [23], the major meaning of the linguistic term is delivered by the adjective and this semantically justifies modelling the adjective as first-order uncertainty.

On the other side, antonyms are regarded to be an important phenomenon of language that is needed for building up linguistic variables in fuzzy logic [21]. In Fig. 2a, Zadeh [66] uses nested FSs where the linguistic terms (i.e. small and large) represent the two opposite sides of a phenomenon, and the modifiers (i.e. very, not very), which are used to intensify or weaken the meaning of a word, are nested in the type-1 primary membership functions of the antonyms. Furthermore, [32]-[34] suggest that antonyms can provide an insight to the operation of the human mind with regards to making perceptual judgments, which is a matter of deciding between two opposite sides (e.g. hot and cold, good and bad, etc.). Moreover, according to Trillas and Guadarrama [21], *"… many words are better managed once we have used pairs of words (P, opposite of P).*"

Consequently, the abovementioned studies from linguistics [23], fuzzy logic [21][66], and neuroscience [32]-[34] lead to the following proposal: for modelling the linguistic terms, we cluster the major meaning of the linguistic variable into two

[2] The definition of the word 'sortal' in English is "Denoting or relating to a term representing a semantic feature that applies to an entity as long as it exists, classifying it as being of a particular kind." (Source: http://www.oxforddictionaries.com/definition/english/sortal)

Hence, 'sortal range' in this paper can be defined to be the numerical domain (universe of discourse) of the variable in question whose values can be sorted. For example, for variable 'hot' assuming that the numerical domain is [20, 30], the values in this domain can be sorted as in 24<25.

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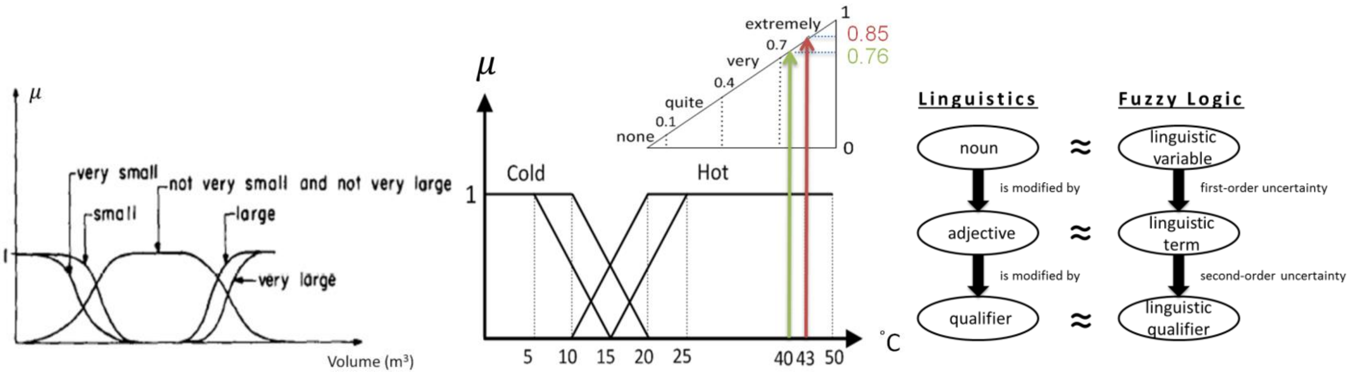

(a) (b) (c)

Fig. 2. (a) Use of antonyms in linguistic terms (adapted from [66]) (b) Example of LGT2 FS with the primary domain [below] and the secondary domain [top] for showing how the third dimension is quantified (c) Hierarchical analogy between linguistics and fuzzy logic.

opposite sides (i.e. antonyms) by using two shoulder (left and right) trapezoidal membership functions as shown in Fig. 2b; and for the modelling of linguistic modifiers, we propose a nested way similar to Zadeh's approach [66] but instead of designing primary memberships for all the linguistic modifiers, we propose to design secondary memberships using GT2 FSs as shown in Fig. 2b. To avoid misunderstanding, it should be noted that 'none' in Fig. 2b is not used as a linguistic modifier; instead, it is used to indicate the lack of linguistic modifier (i.e. empty space), and is omitted in the implementation. For example, if someone would like to say 'hot', the linguistic modifier from the system point of view is an empty space, hence 'none'.

A. Mathematical Definition of the LGT2 FSs

Formally, based on the notation of a general type-2 fuzzy set in [86], a Linear General Type-2 FS denoted $\tilde{L}$ can be expressed as follows [4]:

$$\tilde{L} = \int_{x\in X}\int_{u\in J_x}\mu_{\tilde{L}}(x,u)/(x,u) \quad J_x \subseteq [0,1] \tag{1}$$

More on the mathematical definition of the LGT2 FSs can be found in [4]. In order to represent GT2 FSs, we have opted to use zSlices approach introduced by Wagner and Hagras [31]. However, the equivalence between alpha-plane and zSlices representations has been proven in [80]. Accordingly, LGT2 FSs can also be represented using alpha-planes introduced by Liu [87] and Mendel et al. [79].

A zSlice $\tilde{Z}_i$ is formed by slicing a GT2 FS in the third dimension (z) at level z_i and is equivalent to an IT2 FS with the exception that its membership grade $\mu_{\tilde{Z}_i}(x,u)$ in the third dimension is not fixed to 1; instead is equal to z_i where $0 \leq z_i \leq 1$. Thus, the zSlice $\tilde{Z}_i$ can be written as follows [31]:

$$\tilde{Z}_i = \int_{x\in X}\int_{u_i\in J_{i_x}} z_i/(x,u_i) \tag{2}$$

where at each x value, zSlicing creates an interval set with height z_i and domain J_{i_x}, $1 \leq i \leq I$, and I is the number of zSlices (excluding $\tilde{Z}_0$) and $z_i = i/I$.

We have employed zSlices to represent the LGT2 FSs for real world applications where Fig. 3b shows zSlices representation of the LGT2 FSs namely 'dark' and 'bright' for the linguistic variable Ambient Light Level. The novelty of LGT2 FSs is to quantify the third dimension in a linear way where the modifiers (e.g. extremely, very, etc.) are nested for preserving the natural ordering. For simplicity, we have used equally spaced FOUs for the third dimension as a design decision and ease of implementation. It should be noted that the design process does not restrict the number of zSlices used to be equal to the number of linguistic modifiers to be modelled. In other words, a linguistic modifier can be represented using multiple zSlices (as seen in Fig. 3b and in Appendix B) based on the experience data. It is important to note that, by nesting the Footprint of Uncertainties (FOUs) at different levels in the third dimension (i.e. zLevels), we can achieve the same level of profoundness (yet different resolution) as an IT2 model (see Fig. 3a and Appendix A[3]) while simplifying the primary MF design of the linguistic variable.

B. Benefits of LGT2 FSs

One of the major advantages of LGT2 FSs is that they can overcome the drawbacks of type-1 and IT2 FSs as the LGT2 FSs (through their linear third dimension) allow preserving the natural ordering of numbers. For example, distinguishing between 40°C and 43°C as shown in Fig. 2b where $\mu_{\tilde{L}}(43,1) > \mu_{\tilde{L}}(40,1)$ for *Extremely hot* linguistic term. Furthermore, with the highlight of human experience, the design features of LGT2 FSs can eliminate the problem of resolution (due to natural ordering) as well as the need for expert interference during creation of adaptive systems using FSs.

Another major advantage of LGT2 FSs is their compact design which is based on the use of antonyms. Employing LGT2 FSs decreases the number of linguistic terms to be designed to two while keeping the same level of profoundness as in an IT2 design (see Fig. 3a). Hence, using LGT2 FSs not only simplifies the modelling process of a linguistic variable, but also decreases the number of fuzzy rules in the rulebase of a Fuzzy Logic System (FLS). In our previous studies [3][19][20], we have realized further practical benefits of LGT2 FSs which can be outlined as follows:

[3] Appendices can be downloaded from the web: http://www.aysenurbilgin.com/#!publications/mainPage

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- LGT2 FSs can facilitate the intelligent systems to respond faster [3]. That is, the processing time of a complete rulebase (having all the combinations of the input linguistic terms) of a LGT2 based FLS is significantly lower than the processing time of a complete rulebase of an IT2 based FLS.
- Use of LGT2 FSs can enrich the system's outputs as LGT2 FSs can model the small differences in the input [3][19]. In other words, LGT2 FSs offer a richer output range as they have a distinct secondary membership for every x value in the universe of discourse, which in turn has a crucial impact on generating unique outputs.
- Due to the concise design of LGT2 FSs, they are more advantageous than IT2 FSs regarding the convenience in learning and adaptation aspect of fuzzy membership functions. It has been shown in [20] that LGT2 FSs can easily accommodate the changes in the inputs and can dynamically represent human perceptions as they reflect on the experienced information rather than data collected through surveys ahead of time.

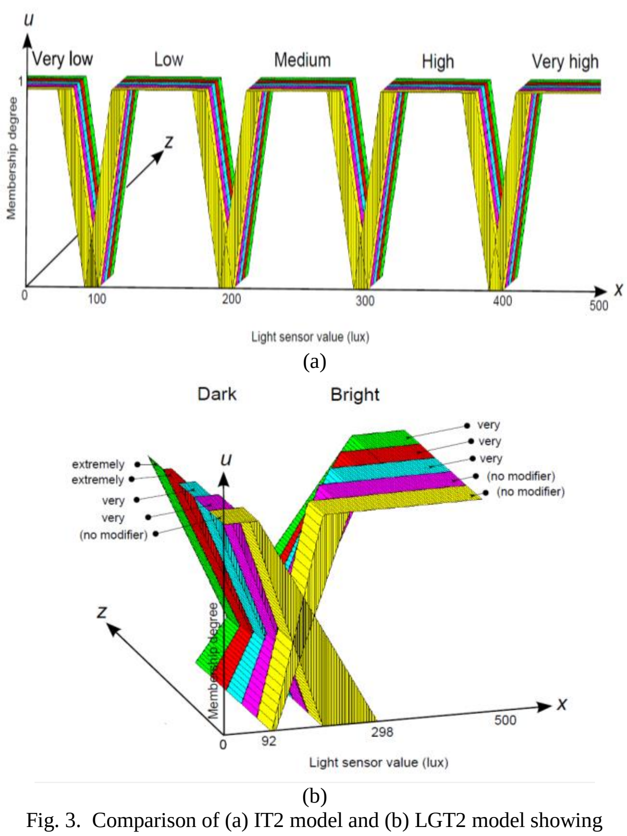

Fig. 3. Comparison of (a) IT2 model and (b) LGT2 model showing zSlices implementation and also showing the different characterization of the various zLevels.

III. The Proposed CWWs Framework

The far-reaching objective of the proposed CWWs Framework is to enable the humans to communicate with computers as if they are communicating with another human being in the course of rather complex reasoning and problem solving. This is why, the proposed CWWs Framework has been blended from eclectic literature review about human problem solving behaviours/approaches from neuroscience [32][33][41][44][51], psychology [2][27][37][52][53], linguistics [54], cognitive science [55] and artificial intelligence (AI) [6][38][40][42][45][48][50][59] perspectives.

In the following subsections, we will give brief background information on the literature review that has guided the construction of the proposed CWWs Framework. Then, we will introduce the operation principles of the proposed CWWs Framework with an example. In Subsections C and D, we will detail the theoretical grounds of the two important segments of the framework, which are named ***granulation*** and ***causation-organization***.

A. Background Literature

Zadeh [50] stresses that there is a connection between the machinery of fuzzy logic and human reasoning. Furthermore, he [50] groups the concepts underlying the human cognition into three: ***granulation***, ***organization*** and ***causation***. These concepts are informally defined in [50] as follows: ***granulation*** involves decomposition of whole into parts; ***organization*** involves integration of parts into whole; and ***causation*** involves association of causes with effects.

Following Zadeh's [50] suggestions, the proposed CWWs Framework is divided into two segments which are ***granulation*** and ***causation-organization*** as shown in Fig. 4a. Words, as the building blocks of natural language, can be referred to be natural language representations of human perceptions. Being a key component of inter-human communication, perceptions are defined to be a particular way of experiencing and organizing the stimulus [52] by calling on stores of ***memory*** data and by performing classification, comparisons and myriad decisions [51].

Our past sensory experiences, which are stored in ***memory*** and brought online in working memory, are combined with current sensory inputs to inform our perceptual decisions. In their work, Heekeren et al. [32] suggest a mechanism where 'the neural architecture for perceptual decision-making' can be viewed as a system that consists of four distinct but interacting processing modules. Accordingly, the first of these modules (denoted ***NA1*** in Fig. 4a) accumulates and compares ***sensory evidence***; the second (denoted ***NA2*** in Fig. 4a) detects perceptual ***uncertainty*** or difficulty and signals when more attentional resources are required to process a task accurately; the third (denoted ***NA3*** in Fig. 4a) represents ***decision variables*** and includes motor and premotor structures; and the fourth (denoted ***NA4*** in Fig. 4a) is involved in ***performance monitoring***, which detects when errors occur and when decision strategies need to be adjusted to maximize performance [32]. Hence, it can be deduced from [32] that accumulation of ***sensory evidence*** requires some sort of storage/***memory***.

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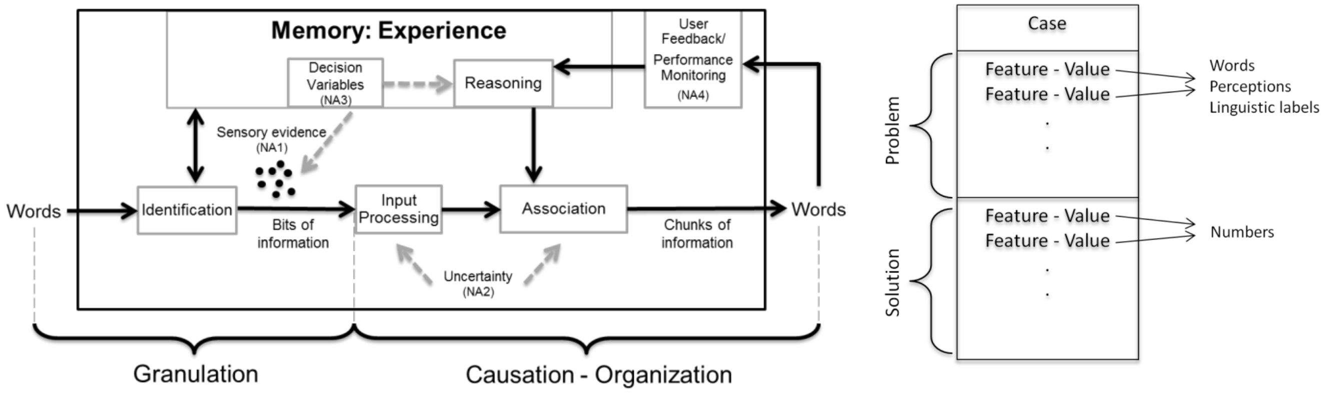

(a) (b)

Fig. 4. (a) Components of the proposed CWWs Framework that mimics human-like communication (the black arrows show the direction of information flow, and the grey dashed arrows show the possible impact factors that should be handled) (b) The role of case representation in granulation and how words are decomposed into numbers by the help of case representation in CBR

B. The Operation Principles

The operation of the proposed framework is as follows: input words represent a problem that needs to be answered/solved and to do this; in ***granulation*** segment, the input words are first granulated by being mapped into ***sensory evidence*** of remembered solution in the human ***experience***. The ***sensory evidence (bits of information)*** retrieved from the ***memory*** is regarded to be numerical descriptors of a solution that relates to the ***decision variables*** in human ***reasoning***. For example, on an ordinary weekday, you come home from work *tired* and *very hungry* and you need to prepare something *very easy* considering your status. Your interpretation of 'very easy' depends on some criteria which happen to be the preparation time and the cooking time of the recipe. The problem descriptors in this case are tiredness and hungriness (in words), whereas the solution descriptors are preparation time and cooking time of the recipe in minutes (hence numerical). In other words, the ***identification*** element in the ***granulation*** segment takes tiredness and hungriness in words and outputs ***bits of information*** for preparation time and cooking time in numbers.

Next is ***causation-organization*** segment in the proposed CWWs Framework. As human ***reasoning*** is done using natural language, the numerical ***sensory evidence*** is converted into words by ***input processing*** element so that the ***bits of information*** are classified to cope with the ***uncertainty*** (mentioned in [32]) associated to it in the human mind. The mapping of ***sensory evidence*** is done using fuzzy representations of the ***decision variables*** that characterize the human ***reasoning***, which is represented in IF-THEN fuzzy rule format. For example, the decision variables in the previously mentioned scenario are preparation time and cooking time (linguistic variables), which have fuzzy representations using the linguistic terms 'short' vs. 'long' for the preparation time, and 'quick' vs. 'slow' for the cooking time. Moreover, the solution is described by the difficulty level of the recipe and has a fuzzy representation using the linguistic terms 'challenging' vs. 'easy'. So, in this scenario, the human ***reasoning*** is represented using fuzzy rules such as '*If preparation time is short and the cooking time is very quick then the difficulty level of the recipe is very easy*'. Depending on the numerical inputs (***bits of information***), active rules are found by the ***association*** element and the output is drawn by first aggregating active rules into an interval format and then generalizing this interval into ***chunks of information*** (words) to be communicated back to the user. This concludes one way information flow of the ***causation-organization*** segment. After the solution is presented to the user, for ***performance monitoring*** purposes, the output word needs to be evaluated by the user so that the proposed CWWs Framework can learn and adapt. This can be done by asking the user via natural language to provide interpretations for the decision variables and concludes the two way information flow in the ***causation-organization*** segment. For example, the user is asked to provide words for preparation time and cooking time as well as the difficulty level of the recipe in his/her opinion. Upon receiving this ***feedback***, the human ***reasoning,*** which is in the form of IF-THEN fuzzy rules, can be modified to incorporate the incoming information. Hence, the proposed CWWs Framework follows a cyclic and integrated process of identifying in the ***granulation*** segment, and associating together with adapting in the ***causation-organization*** segment.

Granulation in the proposed CWWs Framework is a means to mimic human problem solving and achieve human reasoning in machine processes by correlating words with past experiences. From human psychology perspective, reasoning by re-using past situations or experiences is a powerful and frequently applied way to solve problems [38]. Consequently, several studies from cognitive psychology research have embarked on an approach, coined as 'Case Based Reasoning' (CBR), which is based on the recall and reuse of specific experiences [39]. In particular, CBR can mean adapting old solutions to meet new demands; using old cases to explain new situations; or reasoning from precedents to interpret a new situation or create an equitable solution to a new problem [40].

C. Granulation in the Proposed CWWs Framework

The foundation of CBR can be complementary to the foundation of CWWs paradigm from a human-centric perspective as CBR is laid on reflecting human use of remembered problems/solutions to new problem solving [59],

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whereas CWWs is laid on mimicking human use of natural language for computing and reasoning. It has been emphasized that the fundamental characteristic that distinguishes CBR from other problem solving techniques in artificial intelligence is being ***memory*** based [59]. In support to [59], studies from neuroscience [32], neurobiology [41], neuropsychology [53], psycholinguistics [54], and cognitive science [55] point out keeping past events in memory and using past ***experiences*** in coordination with the current situation in forming perceptual judgments as well as in human ***reasoning***. Similar to the steps taken in everyday problem solving behaviour of humans [42], principal tasks in CBR are to identify the current problem situation and find a past case similar to the new one (Retrieve), use that case to suggest a solution to the current problem (Reuse), evaluate the proposed solution (Revise), and update the system by learning from this experience (Retain). In fact, CBR is a cyclic and integrated process [38] of remembering, adapting and storing.

The first process in CBR, which is marked as ***Identification*** in Fig. 4a and analogous to Retrieve step, is the case retrieval task and it plays a pivotal role, which has been the focus of a considerable amount of research [59]. Equally important, case representation, which is influenced by the intended purpose of a CBR system [42], is a prior design decision that needs to be made. In our approach, we will refer to one of the most traditional representations of a case, which consists of '*problem*' and '*solution*' parts. Furthermore, both the *problem* and the *solution* parts will involve *feature-value* pairs (see Fig. 4b) where the values can take the form of fuzzy linguistic terms or numbers.

CBR literature assumes that similar experiences can guide future reasoning, problem solving, and learning [42]. Hence, the similarity concept is a very important issue in the case retrieval process. One of the most common forms used in computing relatedness among cases is the weighted feature-based similarity [42]. In the proposed CWWs Framework, we use a *global similarity measure* applied to the *feature-value* pairs of *problem* parts of cases under comparison. The values of the features in problem parts of cases are in the form of linguistic terms, which are represented in ***memory*** using zSlices based LGT2 FSs. In [42], a global similarity degree between two cases having multiple-feature descriptions is obtained by aggregating degrees of similarities pertaining to each feature, referred to as *local similarity*. We apply *local similarity measure* to each corresponding *feature-value* pair of the *problem* parts of the cases under comparison. In implementation, we use Jaccard similarity measure (as it is proven to be better than other similarity measures for IT2 FSs [67]) formulated as follows [67]:

$$s(\tilde{A},\tilde{B}) = \frac{\int_x min\left(\overline{\mu}_{\tilde{A}}(x),\ \overline{\mu}_{\tilde{B}}(x)\right)dx + \int_x min\left(\underline{\mu}_{\tilde{A}}(x),\ \underline{\mu}_{\tilde{B}}(x)\right)dx}{\int_x max\left(\overline{\mu}_{\tilde{A}}(x),\ \overline{\mu}_{\tilde{B}}(x)\right)dx + \int_x max\left(\underline{\mu}_{\tilde{A}}(x),\ \underline{\mu}_{\tilde{B}}(x)\right)dx} \quad (3)$$

In a zSlices based LGT2 system, let F_n be a feature, and V_n be the value of F_n where $n = 1 \dots N$, and N is the total number of features. Herein, we assume that the number of features are consistent for all the cases in Case Base CB, which is stored in ***memory***. As mentioned earlier, V_n is represented by zSlices based LGT2 FS $\tilde{L}$.In comparing zSlices based LGT2 FSs, we need to compare each zSlice $\tilde{z}_i^{\tilde{L}}$ of $\tilde{L}$ with zSlice $\tilde{z}_j^{\tilde{Q}}$ of $\tilde{Q}$, which is another LGT2 FS. Given that a zSlice $\tilde{z}_i$ is equivalent to an IT2 set with particular height in the third dimension $ht_i = i/I$ where $1 \leq i \leq I$, and I is the number of zSlices, we can infer $\tilde{z}_i^{\tilde{L}}$ and $\tilde{z}_j^{\tilde{Q}}$ are special cases of IT2 FSs having heights $ht_i^{\tilde{L}} = i/I$ and $ht_j^{\tilde{Q}} = j/I$, respectively, where $i, j = 1 \dots I$. The adapted definition of Jaccard similarity in Equation (3) to be applied on individual zSlices $\tilde{z}_i^{\tilde{L}}$ and $\tilde{z}_j^{\tilde{Q}}$ is shown in Equation (4) [20].

$$s_z\left(\tilde{z}_i^{\tilde{L}}, \tilde{z}_j^{\tilde{Q}}\right) = \frac{\int_x min\left(\overline{\mu}_{\tilde{z}_i^{\tilde{L}}}(x)*ht_i^{\tilde{L}},\ \overline{\mu}_{\tilde{z}_j^{\tilde{Q}}}(x)*ht_j^{\tilde{Q}}\right)dx + \int_x min\left(\underline{\mu}_{\tilde{z}_i^{\tilde{L}}}(x)*ht_i^{\tilde{L}},\ \underline{\mu}_{\tilde{z}_j^{\tilde{Q}}}(x)*ht_j^{\tilde{Q}}\right)dx}{\int_x max\left(\overline{\mu}_{\tilde{z}_i^{\tilde{L}}}(x)*ht_i^{\tilde{L}},\ \overline{\mu}_{\tilde{z}_j^{\tilde{Q}}}(x)*ht_j^{\tilde{Q}}\right)dx + \int_x max\left(\underline{\mu}_{\tilde{z}_i^{\tilde{L}}}(x)*ht_i^{\tilde{L}},\ \underline{\mu}_{\tilde{z}_j^{\tilde{Q}}}(x)*ht_j^{\tilde{Q}}\right)dx} \quad (4)$$

For calculating the overall Jaccard similarity measure between two LGT2 FSs $\tilde{L}$ and $\tilde{Q}$, we need a weighting factor which will increase if the two zSlices under comparison are closer (e.g. $i = 3, j = 3, I = 5$) in their level in the third dimension, and will decrease if the two zSlices under comparison are further (e.g. $i = 0, j = 5, I = 5$) in their level in the third dimension. Hence, we use weighting factor t, which denotes the effect of difference in the zLevels of two LGT2 FSs, as follows [20]:

$$t = 1 - \left(\frac{|i-j|}{I}\right) \quad (5)$$

According to Equation (5), the further the zSlices are from each other, the less weight for similarity the zSlices have. Likewise, the closer the zSlices are to each other, the more weight for similarity the zSlices have. The final *local similarity measure*, denoted $s_{local}(\tilde{L}, \tilde{Q})$, is based on weighted average calculation as shown in Equation (6) [20]:

$$s_{local}(\tilde{L}, \tilde{Q}) = \frac{\sum_i^Z \sum_j^Z s_z\left(\tilde{z}_i^{\tilde{L}}, \tilde{z}_j^{\tilde{Q}}\right)*t}{\sum_i^Z \sum_j^Z t} \quad (6)$$

Next, we need to calculate the global similarity between two cases C_l and C_k where there are multiple features defined and $l, k = 1 \dots M$, M is the number of cases in CB. As mentioned earlier, for each feature F_n, there exists a value V_n. For cases C_l and C_k, the values will be denoted as V_n^l and V_n^k, respectively. By applying weighted average on local similarities for each feature in the *problem* part of the case representation, the *global similarity* is calculated as shown in Equation (7) where w_n denotes the weights of the features that are predefined by the user [20].

$$s_{global}(C_l, C_k) = \frac{\sum_n^N s_{local}(V_n^l, V_n^k)*w_n}{\sum_n^N w_n} \quad (7)$$

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Retrieving the most similar cases from the ***memory*** can be analogous to the humans' remembering [38]. The *solution* parts of these retrieved cases consist of feature-value pairs and this is where ***granulation*** segment ends. The remembered information represented as the ***bits of information*** is used in the ***causation-organization*** segment, which will be detailed in the next section.

D. Causation-Organization in the Proposed CWWs Framework

The processes for ***causation*** and ***organization*** in the proposed CWWs Framework are quite integrated and follow the approach of 'Fuzzy Composite Concepts' (FCCs) proposed by Wagner and Hagras [45] to mimic the way humans organize the stimulus. In addition to [50][51][52], studies from psychology literature claim that humans intuitively combine, summarize and hence generalize information where particularly Miller [37] has distinguished between '***bits of information***' and '***chunks of information***' in the human mind. Herein, the ***sensory evidence*** (individual stimulus) can be regarded as ***bits of information*** and the composite concept (perceptions, words) can be regarded as ***chunks of information*** since it composes various stimuli. Fig. 4a shows where the analogy is mapped to the proposed CWWs Framework: '***bits of information***' refer to the granulated information in numerical format (***sensory evidence***) and '***chunks of information***' refer to the organized information (output words) following the rules of causation in the human mind.

1) Input Processing Element

Formally, the input processing element uses the representative LGT2 models for the decision variables, which are stored in memory. These models are created using the data accumulated in memory [32][44] according to Algorithm 1. The aim of the input processing element is to calculate the degrees of membership of the sensory evidence to the LGT2 FSs of the decision variables. This mapping of the numerical sensory evidence to the LGT2 models can handle the uncertainty mentioned in [32] and can help mimic human reasoning via the association element using IF-THEN fuzzy rules with linguistic terms.

2) Association Element

The ***association*** element helps in two areas: 1) forming the representative mathematical models for the output perceptions using the human ***experience*** encoded in cases and 2) combining the ***sensory evidence*** using human ***reasoning*** to relate to output perceptions. For the first functionality, the formal explanation of forming the mathematical models for the output perception is done according to Algorithm 2, which explores the human ***experience*** (the case base) in order to calculate the ratio of occurrences of the two antonyms (linguistic terms of the output) relative to each other. According to [35], sensory experience in general is characterized by self-adjustment to the prevailing level of stimulation. Hence, the calculation of this relative ratio mimics self-adjustment to the most frequently experienced perceptions. Fig. 5 shows how the ratio, which is normalized to be in the unit interval [0,1] for ease of calculations, is applied to construct the LGT2 FSs for the output perception. The ratio $pEndorsing$ in Fig. 5 represents the occurrences of the endorsing linguistic term whereas the opposing ratio $pOpposing$ represents the occurrences of the opposing linguistic term. The definition of endorsing and opposing linguistic terms are configured at the time of vocabulary creation. Also, the uncertainty (FOU width) is pre-defined (as a design decision) and is applied as shown in Algorithm 2. We use Equations (8) and (9) to mark the parameters of the LGT2 FSs in modelling the output perception.

Algorithm 1: *Forming the mathematical models for the input decision variables*	
1	Create vocabulary (database) for linguistic terms and modifiers (can be defined by either the user or the system in the beginning and only once)
2	For each decision variable d, analyse the experience (accumulated data in memory)
3	Organize the experience by counting the number of occurrences per unique value
4	Find weighted average of step 3
5	Group the experience into two linguistic terms (antonyms) according to weighted average of step 4 *If the value in the experience < weighted average of step 4* *Add the value to ResourcesRight (data to be modelled as right shoulder MF)* *Else* *Add the value to ResourcesLeft (data to be modelled as left shoulder MF)* *End*
6	Group the linguistic labels (ResourcesLeft, ResourcesRight) into modifiers ResourcesLeftModifiers and ResourcesRightModifiers
7	Find the weighted average values for the ResourcesLeftModifiers and ResourcesRightModifiers
8	Create type-1 upper MFLeft [als,bls,cls,dls] : *als = minimum value of ResurcesLeft* *bls = als* *cls = last value of ResourcesLeftModifiers* *dls = first value of ResourcesRightModifiers*
9	Create type-1 lower MFLeft = upper MFLeft (no uncertainty yet)
10	Create type-1 upper MFRight [ars,brs,crs,drs] : *ars = cls* *brs = dls* *crs = maximum value of ResourcesRight* *drs = crs*
11	Create type-1 lower MFRight = upper MFRight (no uncertainty yet)
12	Aggregate different data sources for the decision variable to create adaptive FOU [19]

$$a_{rs} = c_{ls} = pOpposing \tag{8}$$

$$b_{rs} = d_{ls} = 1 - pEndorsing \tag{9}$$

As ***experience*** accumulates (new cases are added to the case base), the ratios $pEndorsing$ and $pOpposing$ will be recalculated. Hence, the critical data points (c and d for the left shoulder MF, a and b for the right shoulder MF) will shift

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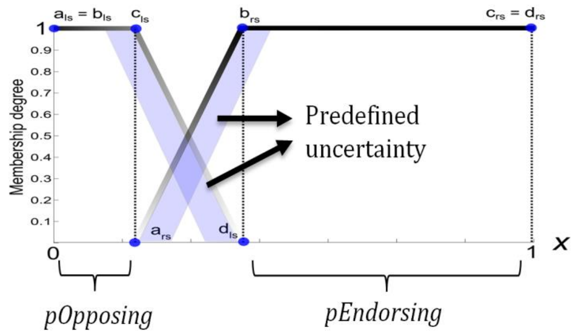

Fig. 5. The configuration of LGT2 FS modelling for the output perception

on the horizontal x-axis. According to Michalski [48], modifying or constructing representations of what is being experienced is identified to be '*learning*'. Hence, we can infer that the proposed CWWs Framework has the potential to learn and to adapt, which not only satisfies the requirements of a real-world application, but also paves the way for establishing a high-level interaction between the humans and the machines.

Algorithm 2: *Pseudocode for forming the mathematical models for the output perception*

For each case c in the case base
  For each solution s in the solution part of c
    Find the active rules in human reasoning using numerical feature values of s
    Count the occurrences of each output linguistic term (*oll*)
Calculate ratios of occurrences to the number of solutions:
If *oll* is right shoulder MF
  pEndorsingInitial = number of occurrences of oll / number of solutions
Else if *oll* is left shoulder MF
  pOpposingInitial = number of occurrences of oll / number of solutions
Apply predefined uncertainty u on *pEndorsingInitial* and *pOpposingInitial*:
pEndorsing = pEndorsingInitial – u
pOpposing = pOpposingInitial – u

Moreover, the second functionality of the ***association*** element is to combine the ***sensory evidence*** using human ***reasoning*** in order to produce an interval for the representation of the aggregated output. The procedure to aggregate ***sensory evidence*** to produce the aggregated output (FCC) in an interval form can be referred to as a simplified case of Linguistic Weighted Average (LWA), which has been introduced as a generalization of fuzzy weighted average [47] and employed within existing CWWs engines [49]. The well-known formula of the weighted average, which is the origin of the LWA, is given in Equation (10) [47]:

$$y = \frac{\sum_{i=1}^{n} x_i w_i}{\sum_{i=1}^{n} w_i} \tag{10}$$

where w_i are the weights that act upon the attributes x_i. In the proposed CWWs Framework, x_i are type-1 interval fuzzy numbers, i.e. $x_i = [a_i, b_i]$ where the interval end-points a_i and b_i denote respective lower and upper membership degrees of the corresponding linguistic term; and w_i is a crisp number calculated according to the human ***experience***.

Algorithm 3: *Pseudocode for retrieving the output perception from aggregated interval*

For each LGT2 FS *L*
  For each zSlice *z* of *L*
    Discretize interval *Y*
    For each discretized value *v* of *Y*
      Calculate the *average* of upper and lower membership degree of *v* with *z*
      If *average* is maximum
        Retrieve the linguistic term of *z*

Formally, let $\tilde{L}_s^j$ be a zSlices based LGT2 FS, c_s^j be the linguistic term for the ***sensory evidence*** and w_s^j be the corresponding association weight where $w_s^j \in \{0,1\}$, $s = 1 \dots S$, S is the total number of ***sensory evidence*** (equals number of decision variables) and $j = 1 \dots J$, J is the number of linguistic terms used to model the linguistic variable (e.g. in an LGT2 system, $J = 2$). The process of combining the ***sensory evidence*** with human ***reasoning*** starts with analysing IF-THEN fuzzy rules. The analysis involves grouping the linguistic terms of the ***decision variables*** in accordance to the two linguistic terms for the output perceptual judgment. We will refer to the two linguistic terms for the output perceptual judgment as the *fuzzy composite label* 'LB' and '*the opposite of* LB' as mentioned in [21]. Moreover, the analysis of the fuzzy rules involves counting the occurrences of c_s^j that give rise to either of the two fuzzy composite labels. The prevailing stimuli label c_s^j for each fuzzy composite label is interpreted to have an effect as follows: if the fuzzy composite label LB is indicated to be a right shoulder MF (at the time of vocabulary creation), then the prevailing stimuli label c_s^j for this LB are said to have an *endorsing* effect. Similarly, the prevailing stimuli label c_s^j for *the opposite of* LB, which is indicated to be a left shoulder MF, is said to have an *opposing* effect. Consequently, if the stimuli label c_s^j has an opposing effect, then $w_s^j = 1$ and we use the *complement* operation on the type-1 fuzzy interval number $x_i = [a_i, b_i]$ in Equation (10). As denoted in [50], the complement of IT2 fuzzy set $\tilde{A}$, $\overline{\tilde{A}}$ is formulated as follows:

$$\overline{\tilde{A}} = 1/\left[1 - \overline{\mu}_{\tilde{A}}(x), 1 - \underline{\mu}_{\tilde{A}}(x)\right] \; \forall x \in X \tag{11}$$

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where $\overline{\mu}_{\tilde{A}}(x)$ is the upper membership degree and $\underline{\mu}_{\tilde{A}}(x)$ is the lower membership degree. Hence, the type-1 fuzzy interval number x_i in this case is specified as $x_i = [1 - b_i, 1 - a_i]$. If the stimuli label c_s^j has an endorsing effect, then $w_s^j = 1$ and we use the type-1 fuzzy interval number $x_i = [a_i, b_i]$ in Equation (10) as it is. The zero weight ($w_i = 0$) marks the redundancy of the stimuli label c_s^j and it is used in circumstances where the numbers of occurrences of stimuli labels in the entire experience are equal for one sensory evidence, i.e. $k_{c_1^j} = k_{c_2^j} = \cdots = k_{c_s^j}$. Using the above information, the details of the algorithm that the ***association*** element follows to combine the ***sensory evidence*** using human ***reasoning*** in order to produce an interval are listed below:

1. For each zSlice $\tilde{z}_q^{\tilde{L}_s^j}$ having height ht_q, where $ht_q = \frac{q}{Q}, q = 1 \ldots Q$ and Q is the number of zSlices, and for each rule R^d where $d = 1 \ldots D$, D being the total number of rules in the human ***reasoning***, the crisp inputs per ***sensory evidence*** s are mapped to $\tilde{L}_s^j$ in order to find type-1 interval fuzzy numbers, i.e. $x_q^s = [a_q^s, b_q^s]$, where $a_q^s \equiv \underline{\mu}_{\tilde{z}_q^{\tilde{L}_s^j}}(x)$ and $b_q^s \equiv \overline{\mu}_{\tilde{z}_q^{\tilde{L}_s^j}}(x)$. The aggregated output of one rule $y_q^d = [y_{lq}^d, y_{rq}^d]$ is an interval and is found as follows [3]:

$$y_{lq}^d = \frac{\sum_{s=1}^{S} a_q^s w_s^j}{\sum_{s=1}^{S} w_s^j},\ y_{rq}^d = \frac{\sum_{s=1}^{S} b_q^s w_s^j}{\sum_{s=1}^{S} w_s^j} \qquad (12)$$

2. For aggregating the outcome of all the activated rules in the human ***reasoning***, assume that all the rules have the same association weight $g^d = 1$. Activated rules are differentiated as follows: if the aggregated output of one rule $y_q^d \neq [0, 0]$, then the rule is activated. In the proposed CWWs Framework, the aggregated output for the activated rules $y^q = [y_l^q, y_r^q]$, which is an interval belonging to zSlice $\tilde{z}_q^{\tilde{L}_s^j}$, is shown in Equation (13) [3]:

$$y_l^q = \frac{\sum_{d=1}^{D} y_{lq}^d g^d}{\sum_{d=1}^{D} g^d},\ y_r^q = \frac{\sum_{d=1}^{D} y_{rq}^d g^d}{\sum_{d=1}^{D} g^d} \qquad (13)$$

3. The final aggregation is performed on all the zSlices having height ht_q of the LGT2 FS $\tilde{L}_s^j$. Hence, the output of the ***association*** element, Y, is an interval $[Y_l, Y_r]$ found using Equation (14) [3]:

$$Y_l = \frac{\sum_{q=1}^{Q} y_l^q ht_q}{\sum_{q=1}^{Q} ht_q},\ Y_r = \frac{\sum_{q=1}^{Q} y_r^q ht_q}{\sum_{q=1}^{Q} ht_q}\ and\ ht_q = q/Q \qquad (14)$$

The last step in the proposed CWWs Framework before outputting words to the user is to take the aggregated output interval in Equation (14) and to map it to the representative mathematical models for the output perceptions. The ***association*** element of the proposed CWWs Framework finds the output linguistic term that best represents Y using Algorithm 3 that returns a word to be communicated back to the user and completes *one-way communication* between the human and the machine. However, in order for the machine to develop its understanding, the output perceptions need to be evaluated by the user. The ***user feedback/performance monitoring*** element in the proposed CWWs Framework gets feedback from the user in natural language in order to *learn* human ***reasoning*** and accumulate ***experience***.

3) Performance Monitoring Element

Essentially, the ***performance monitoring*** element can mimic *two-way communication* between the human and the machine as follows: As the user interacts with the system, the proposed CWWs Framework learns the rules of human ***reasoning*** and accumulates ***experience*** in the case base. In return, these changes in the rules of human ***reasoning*** and case base of human ***experience*** affect the forming of LGT2 models detailed in Algorithm 1 and Algorithm 2. In other words, the mathematical representations of the ***decision variables*** and the output perception in the ***memory*** can *adapt* to new ***experience*** and ***reasoning*** with each interaction. This can be seen analogous to interaction between two humans where one can learn from the other. From psychology and neuroscience perspectives applied to artificial intelligence, learning is a very important feature of CBR [38] and can be seen as a key to unravel human intelligence, which complies with the ultimate aim of the CWWs paradigm. As Roy [43] points out, an important part of the human learning process is remembering relevant facts and examples experienced before; and learning involves collecting and storing some information about the problem at hand, all of which are referenced in the proposed CWWs Framework.

The proposed CWWs Framework can also be employed in other domains. For example: In cancer research, in order to infer health status and to monitor response to treatment, researchers are using established biomarkers, which can be a component in body fluid (e.g. blood, tissue or urine) that indicates health condition [68]. The values of biomarkers can be represented using words 'low', and 'high', which reflect the clinical parameters such as tumour grade, tumour size, etc. that have numerical results. In the proposed CWWs Framework, the biomarker having value 'low' can be the input to the system. Using the test results, which can be retrieved from a database of many other patients and their clinical information, for the ***granulation*** segment of the framework, the ***identification*** element granulates the biomarker input value into ***sensory evidence*** of corresponding cases in terms of clinical parameters consisting of tumour grade and tumour size (***bits of information***). Once the clinical parameters are known, the specialists analyse the information to anticipate the prognosis, which is a forecast on how likely the cancer is going to progress, and which takes the values 'poor', and 'good'. In the ***causation-organization*** segment of the proposed CWWs Framework, the ***reasoning*** on the clinical parameters can take the form of IF-THEN fuzzy rules such as

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'If the tumour grade is low and the tumour size is small then the prognosis is good'. The ***input processing*** element maps the ***bits of information*** to the natural language representations of the ***decision variables*** so that the ***association*** element can aggregate the active rules into an interval format and then generalize this interval into ***chunks of information*** (words). Moreover, conducting more tests to confirm the evaluation is common in cancer research. In the proposed CWWs Framework, the ***feedback*** can be taken from the specialist's opinion and hence the system can learn and adapt.

The next section describes how the proposed CWWs Framework is applied to an ambient intelligent platform for cooking recipes recommendation.

IV. Application of the Proposed CWWs Framework to Ambient Intelligent Platform for Cooking Recipes Recommendation

The objective of the system is to suggest recipes according to the status of the user which is defined using three indicators (linguistic variables) for the user's mood, appetite and spare time. These indicators (named as tiredness, hungriness and free time) represent the *problem* description of a case (see Fig. 4b). The values of these linguistic variables are linguistic

TABLE II
THE RETRIEVED CASES FROM THE MEMORY SHOWING THEIR ZLEVELS AND SIMILARITY VALUES

Order in List	Query case Feature-Value Pairs	Retrieved Case Feature-Value Pairs	Similarity
Recipe 1	Very tired (zLevels: 3, 4) Extremely hungry (zLevels: 5) Busy (zLevels: 1,2)	Very tired (zLevels: 3, 4) Extremely hungry (zLevels: 5) Busy (zLevels: 1,2)	1.0
Recipe 2		Extremely tired (zLevels: 5) Very hungry (zLevels: 3, 4) Very busy (zLevels: 3, 4)	0.679
Recipe 3		Tired (zLevels: 1, 2) Hungry (zLevels: 1, 2) Free (zLevels: 1, 2)	0.347

TABLE III
THE SOLUTIONS BELONGING TO THE RETRIEVED CASES IN TABLE II AND THE GRANULATED INFORMATION

Recipe number	Recipe name	Granulated Information: Preparation Time	Cooking Time	Overall Time	Difficulty Interval	Difficulty Perception
Recipe 1	Chicken with mushrooms	10	20	30	[0.573, 0.871]	Easy
Recipe 2	Pasta Primavera Alfredo	5	15	20	[0.878, 0.939]	Extremely easy
Recipe 3	Spanish style brown rice	5	40	45	[0.489, 0.694]	Easy

TABLE IV
IF THEN FUZZY RULES LEARNT FROM THE USER AS A REPRESENTATION OF HUMAN REASONING

Antecedents (Decision variables)			Consequent	Rule Occurrence
Preparation Time	Cooking Time	Overall Time	Level of Difficulty	
Short	Quick	Little	Easy	4
Long	Slow	Big	Challenging	1
Short	Slow	Big	Easy	2

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terms, which are designed using LGT2 FSs based on expert opinion. The linguistic terms for tiredness are 'tired' and 'energetic', for hungriness are 'hungry' and 'full', and for free time are 'busy' and 'free' where the modifiers constitute of 'very', 'extremely' and 'no modifier'. The ***memory*** as shown in Fig. 4a acts as a case base where all the previous past solutions are kept. In this scenario, the *solutions* are the recipes that are characterized with a difficulty level derived from the ***decision variables*** preparation time, cooking time and overall time (preparation time + cooking time). The ***decision variables*** are represented by linguistic variables, which have the labels of 'short' and 'long' for the preparation time, 'quick' and 'slow' for the cooking time, and 'little' and 'big' for the overall time. The ***reasoning*** in the ***memory*** which is represented using IF-THEN fuzzy rules is empty in the beginning and is populated as the user interacts with the system as part of learning capability of the proposed CWWs Framework. For ease of explanations, let the system be adapted to the user over a couple of interactions (e.g. 7 interactions) where the LGT2 FSs of the ***decision variables*** and the ***reasoning*** are not in the default starting state. Accordingly, the steps taken by the proposed CWWs Framework are exemplified below:

Let the inputs to the proposed CWWs Framework be 'very tired', 'extremely hungry' and 'busy' describing the user's status (see Table II). The ***identification*** element of the proposed CWWs Framework goes through the case base and compares the zSlices 'very tired', 'extremely hungry' and 'busy' with the zSlices belonging to the corresponding features, which are tiredness, hungriness and free time, respectively, of the problem definition of the cases in the ***memory***. This operation involves converting the string inputs (words) to the zSlices representations of the linguistic variables and then applying Equations (4)-(7). In order to apply the equations, the domains of the zSlices under comparison are discretized. The comparison occurs between the zSlices of the input and the zSlices of the corresponding features in the problem part of the cases in the ***memory***. The global similarities (see Equation (7)) calculated between the input and the corresponding features in the cases are sorted in descending order and stored in a list, which links the global similarities to the cases and hence to the solutions. Consequently, ***identification*** element retrieves the most relevant solutions from the ***experience***. There exists various ways for deciding the number of retrieved cases: 1) introducing a threshold value for similarity and retrieving the cases that have a higher similarity value than the threshold or 2) retrieving the N most relevant cases. In this example, we have used the second approach where $N=3$. Hence, the number of recipes to be recommended to the user will be the three most likely recipes to be chosen by the user. Furthermore, the solution parts of the cases are composed of preparation time, cooking time and overall time criteria, which have numerical values in ***memory*** (see Table III). The zLevels (that can take the values of 1, 2, 3, 4, and 5 as the number of zSlices=5 for the application) of the linguistic terms, which are used in Equation (5), are also displayed in Table II. Table III complements the information in Table II where the feature-value pairs for the *solution* parts of the cases are presented for the retrieved recipes. The granulated ***bits of information***, which includes the ***decision variables*** preparation time, cooking time and overall time, is shown in Table III. This step concludes how input words are decomposed into numbers (***bits of information*** in Fig. 4a) in relation to the *solution*.

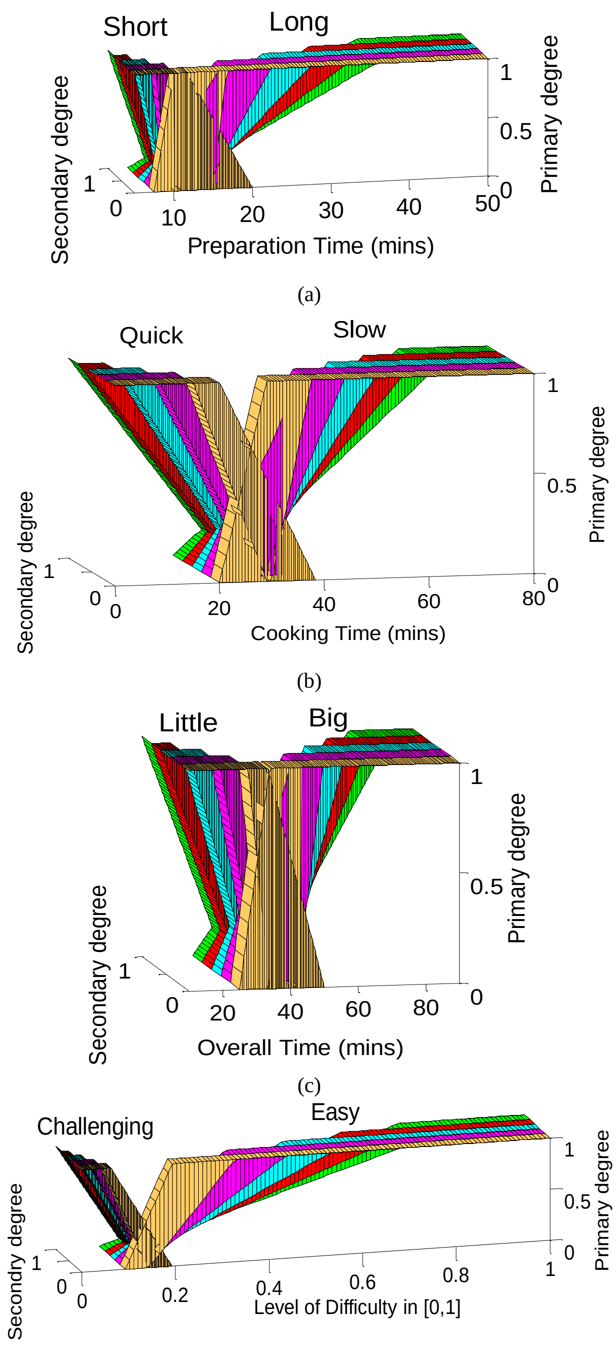

Fig. 6. LGT2 models for (a) preparation time (b) cooking time (c) overall time (d) level of difficulty.

The ***causation-organization*** segment deals with forming perceptual judgments using the granulated ***bits of information*** and the human ***reasoning***. As mentioned before, the human ***reasoning*** is learnt from the user interactions and represented using IF-THEN fuzzy rules (Table IV) where the antecedents

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are preparation time, cooking time, and overall time; and the consequent is the level of difficulty of the recipe. Table IV also shows how many times the rules have occurred. It can be observed that the user had 7 (4+1+2) interactions with the system. The ***input processing*** element in Fig. 4a takes the granulated information of the solution and maps the numerical information detailed in Table III (Granulated Information column) into the ***decision variables*** which are the antecedents shown in Table IV. In order to map this numerical information to the ***decision variables***, the ***input processing*** element first creates the LGT2 models for the ***decision variables***. In the creation of LGT2 models for the ***decision variables***, Algorithm 1 is applied to the ***experience*** and the accumulated information (preparation time, cooking time and overall time). For this scenario, we have also used default information at the beginning. Accordingly, the parameters of the created LGT2 models (with detailed zSlices information) for the ***decision variables*** are presented in Table V – Table VII. Also, Fig. 6a, Fig. 6b and Fig. 6c illustrate the LGT2 models that are created according to the parameters reported in Table V – Table VII.

Following the creation of the LGT2 models for the ***decision variables***, the ***input processing*** element maps the granulated ***bits of information*** to the LGT2 models to facilitate the process of the ***association*** module. ***Association*** module has the responsibility of 1) forming the representative mathematical models for the output perceptions using the human ***experience*** encoded in cases and 2) combining the ***sensory evidence*** using human ***reasoning*** to relate to output perceptions. In order to form the representative LGT2 model for the output perception, which is the level of difficulty in the case study, Algorithm 2 is employed and the rule base is evaluated for all the 7 cases having 7 different solutions (hence recipes). By counting how many times the ***experience*** infers 'challenging' or 'easy' recipes, the ratios are calculated according to Algorithm 2. Given that the predefined uncertainty is $u = 0.05$, the ratio $pOpposing = 1/7 - 0.05$ whereas the ratio $pEndorsing = 1 - 6/7 + 0.05$. Hence, the calculations lead to the creation of an LGT2 model for the level of difficulty in the unit interval [0, 1] where the variable ratio $pOpposing = 0.092$ and the variable ratio $pEndorsing = 0.907$. In order to combine the ***sensory evidence*** using human ***reasoning*** to relate to perceptions, we need to find the *opposing* and *endorsing* labels and their associated weights. The rule base analysis is performed as described in Section III-B. For example, the prevailing *opposing* stimuli labels for the output linguistic term 'challenging' are found to be 'long', 'slow' and 'big', whereas the prevailing *endorsing* stimuli labels for the output linguistic term 'easy' are found to be 'short', 'quick' and 'little' by analysing the rule base for human ***reasoning*** given in Table IV. Accordingly, the fuzzy interval numbers obtained from the *opposing* labels will be inverted using Equation (11) and the fuzzy interval numbers obtained from the *endorsing* labels will remain unchanged. The ***association*** element then evaluates the rule base using the ***bits of information*** via Equations (12)-(14). For example, let the system be processing Recipe 1 where the ***bits of information*** to be mapped to the ***decision variables*** are 10, 20, and 30 for preparation time, cooking time and overall time, respectively. Equations (12)-(14) are used to calculate the type-1 interval fuzzy numbers (indicating the primary memberships for the lower and upper MFs of the corresponding zSlice of the LGT2 FS) from input values 10, 20 and 30. Specifically, for zLevel = 1 and for the first rule shown in Table IV (short-quick-little), the interval fuzzy numbers are found as [1.0, 1.0], [0.642, 1.0], and [0.599, 1.0], respectively. Applying Equation (12) with the associated weights of the labels, which are all endorsing hence the weight is 1.0, the aggregated output interval is found as follows: [1.0 + 0.642 + 0.599,1.0 + 1.0 + 1.0] / 3.0 = [2.242, 3.0] / 3.0 = [0.747, 1.0]. For zLevel = 1 and for the other activated rules, which are (long-slow-big, and short-slow-big), we get the following aggregated output intervals per rule [0.476, 1.0] and [0.809, 1.0], respectively. Applying this to the all the activated rules in the human reasoning per zSlice, that is applying Equation (13), we obtain [0.747 + 0.476 + 0.809, 1.0 + 1.0 + 1.0] / 3.0 = [2.033, 3.0] / 3.0 = [0.677, 1.0]. When we continue the calculations for all the zSlices, we get the following aggregated output intervals: [0.551, 0.963] for zLevel = 2, [0.562, 0.896] for zLevel = 3, [0.565, 0.848] for zLevel = 4, [0.574, 0.812] for zLevel = 5. Applying Equation (14) gives the following aggregated final output interval where the heights of the zLevels are 0.2, 0.4, 0.6, 0.8 and 1.0, respectively: [0.677*0.2 + 0.551*0.4 + 0.562*0.6 + 0.565*0.8 + 0.574*1.0, 1.0*0.2 + 0.963*0.4 + 0.896*0.6 + 0.848*0.8 + 0.812*1.0]/ (0.2 + 0.4 + 0.6 + 0.8 + 1.0) = [0.573, 0.871] as shown in Table III.

The final step of the proposed CWWs Framework is to map the aggregated final output interval to the representative mathematical models for the output perceptions (chunks of information) by employing Algorithm 3. For example, when the aggregated final output interval [0.573, 0.871] is mapped to the LGT2 model for the level of difficulty in Fig. 6d, the average upper and lower membership degrees for the linguistic term 'challenging' gives 0.0 for all the zSlices, whereas the average upper and lower membership degrees (avg) for the linguistic term 'easy' gives the following: for 'easy' zSlice = 1, avg = 1.0; for 'easy' zSlice = 2, avg = 1.0; for 'very easy' zSlice = 3, avg = 0.999; 'very easy' zSlice = 4, avg = 0.968; and for 'extremely easy' zSlice = 5, avg = 0.879. Hence, according to Algorithm 3, the maximum avg is chosen with the highest zLevel, which is in this case 'easy' zSlice = 1, avg = 1.0, and the word output is therefore 'easy' as shown in Table III.

The detailed calculations above emphasize how we provide natural communication through a system that uses words as inputs and words as outputs. Regarding recipe recommendation, as can be seen from Table III, recipes to be recommended have similar difficulty levels (which are easy and extremely easy) depending on the user's mood, appetite and spare time. This also translates into the following behaviour pattern for the personalized recipe recommendation: The user has chosen to cook easy or extremely easy recipes when s/he was feeling tired, extremely hungry and busy in the past, and the recipe recommendations will follow similar logic

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to recommend easy recipes to the user when s/he is feeling tired, extremely hungry and busy.

TABLE V
PARAMETERS OF THE LGT2 MODELS OF THE DECISION VARIABLES FOR PREPARATION TIME

zSlice No	Preparation Time Decision Variable Parameters					
	Short (Left Shoulder LGT2 MF)			Long (Right Shoulder LGT2 MF)		
	Modifier	LMF [a,b,c,d]	UMF [a,b,c,d]	Modifier	LMF [a,b,c,d]	UMF [a,b,c,d]
5	Extremely	[5.0,5.0, 5.0,10.0]	[5.0,5.0, 5.0,20.0]	Very	[15.0,43.33, 50.0,50.0]	[7.5,36.66, 50.0,50.0]
4	Extremely	[5.0,5.0, 5.0,10.0]	[5.0,5.0, 6.66,20.0]	Very	[15.0,36.66, 50.0,50.0]	[7.5,30.0, 50.0,50.0]
3	Extremely	[5.0,5.0, 6.66,10.0]	[5.0,5.0, 8.33,20.0]	Very	[15.0,30.0, 50.0,50.0]	[7.5,23.33, 50.0,50.0]
2	Extremely	[5.0,5.0, 8.33,10.0]	[5.0,5.0, 10.0,20.0]	No modifier	[15.0,23.33, 50.0,50.0]	[7.5,16.66, 50.0,50.0]
1	Extremely	[5.0,5.0, 10.0,10.0]	[5.0,5.0, 11.66,20.0]	No modifier	[15.0,16.66, 50.0,50.0]	[7.5,10.0, 50.0,50.0]

TABLE VI
PARAMETERS OF THE LGT2 MODELS OF THE DECISION VARIABLES FOR COOKING TIME

zSlice No	Cooking Time Decision Variable Parameters					
	Quick (Left Shoulder LGT2 MF)			Slow (Right Shoulder LGT2 MF)		
	Modifier	LMF [a,b,c,d]	UMF [a,b,c,d]	Modifier	LMF [a,b,c,d]	UMF [a,b,c,d]
5	Extremely	[0.0,0.0, 0.0,29.0]	[0.0,0.0, 0.0,38.33]	Very	[30.0,71.5, 80.0,80.0]	[20.0,63.0, 80.0,80.0]
4	Very	[0.0,0.0, 0.0,29.0]	[0.0,0.0, 5.0,38.33]	Very	[30.0,63.0, 80.0,80.0]	[20.0,54.5, 80.0,80.0]
3	No modifier	[0.0,0.0, 5.0,29.0]	[0.0,0.0, 10.0,38.33]	Very	[30.0,54.5, 80.0,80.0]	[20.0,46.0, 80.0,80.0]
2	No modifier	[0.0,0.0, 10.0,29.0]	[0.0,0.0, 15.0,38.33]	No modifier	[30.0,46.0, 80.0,80.0]	[20.0,37.5, 80.0,80.0]
1	No modifier	[0.0,0.0, 15.0,29.0]	[0.0,0.0, 20.0,38.33]	No modifier	[30.0,37.5, 80.0,80.0]	[20.0,29.0, 80.0,80.0]

TABLE VII
PARAMETERS OF THE LGT2 MODELS OF THE DECISION VARIABLES FOR OVERALL TIME

zSlice No	Overall Time Decision Variable Parameters					
	Little (Left Shoulder LGT2 MF)			Big (Right Shoulder LGT2 MF)		
	Modifier	LMF [a,b,c,d]	UMF [a,b,c,d]	Modifier	LMF [a,b,c,d]	UMF [a,b,c,d]
5	Extremely	[10.0,10.0, 10.0,33.75]	[10.0,10.0, 10.0,50.0]	Very	[45.0,80.62, 90.0,90.0]	[25.0,71.25, 90.0,90.0]
4	Very	[10.0,10.0, 10.0,33.75]	[10.0,10.0, 15.83,50.0]	No modifier	[45.0,71.25, 90.0,90.0]	[25.0,61.87, 90.0,90.0]
3	No modifier	[10.0,10.0, 15.83,33.75]	[10.0,10.0, 21.66,50.0]	No modifier	[45.0,61.87, 90.0,90.0]	[25.0,52.5, 90.0,90.0]
2	No modifier	[10.0,10.0, 21.66,33.75]	[10.0,10.0, 27.49,50.0]	No modifier	[45.0,52.5, 90.0,90.0]	[25.0,43.12, 90.0,90.0]
1	No modifier	[10.0,10.0, 27.49,33.75]	[10.0,10.0, 33.33,50.0]	No modifier	[45.0,43.12, 90.0,90.0]	[25.0,33.75, 90.0,90.0]

V. REAL-WORLD EXPERIMENTS AND RESULTS

The aim of the evaluation of a prototype for the Ambient Intelligent Platform for Cooking Recipes Recommendation (AIPCRR) was to quantify the performance of the system in mimicking human reasoning as well as to assess the user experience; specifically whether the participants perceived that the system adapted with repeated usage, and if so, whether the perceived adaptation was valuable.

The application is implemented using Java programming language. The experiments were conducted with 17 lay users over a period of two weeks in the University of Essex intelligent apartment (iSpace). We will report results from the quantitative and qualitative analysis which show the success of the system in providing a natural interaction with the users. The quantitative analysis will show the high statistical

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correlation between the system output and the users' feedback which is aimed to be mimicked. Also, the comparison with Interval Type-2 (IT2) Fuzzy Sets will justify the employment of LGT2 Fuzzy Sets which outperform IT2 Fuzzy Sets by up to 55%. In addition, the qualitative analysis will present social science evaluation that confirms the strong user acceptance of the proposed system.

In this paper, due to the space limitations, we have focussed on the ***causation-organization*** segment of the proposed CWWs Framework.

A. Experimental Design

In order to gather data from the user as well as to display the information to the user, we have developed a user friendly Graphical User Interface (GUI). A new account was created for each participant upon first login. Fig. 7 shows photos from the experiments performed by various participants in the iSpace. During the experiments, we used Nuance's VoCon® 3200 engine[4] based Speech-Driven Dialogue System developed for the iSpace [56], which was integrated with the AIPCRR to replace the keyboard and mouse interaction with voice interaction.

The participants were asked to complete three types of questionnaire. The first gathers demographics such as age, gender, level of education and attitude towards cooking. The second, Core Data Collection Questionnaire (CDCQ), provides the main survey data regarding the adaptation and personalization aspects of the application. Based on Roto [30], the questions were designed to focus on eliciting participants' perceptions of improvements in the recipe suggestions offered by the system over time/usage, based on the participants own on-going difficulty ratings. This questionnaire was completed after each cycle of browsing and choosing a recipe to be cooked. Over a period of two weeks, the participants used the system at least 10 times and after each trial, the users were prompted to fill in the CDCQ. In the closing questionnaire, participants were asked to report on their overall experience of using the system, and their opinions regarding potential improvements and perceived benefits. The demographics and closing questionnaires were completed only once by each participant.

In order to display recipes to the user, we used a Web API called FatSecret Platform [36], which provides free access to a comprehensive database of accurate food and nutrition information. The information that can be retrieved through the FatSecret API includes but is not limited to the preparation time, the cooking time, calories, ingredients and directions of the recipes as seen in the screenshot in Fig. 8a. Initially, the GUI offers two options to the user: viewing the tried recipes and exploring new recipes. In the first option where the user chooses to navigate through the tried recipes, the system behaves as a personalized recipe book and displays the difficulty level as shown in the screenshot in Fig. 8b. On the other hand, in the second option where the user chooses to navigate through new recipes, the system behaves as a recommender. The system displays estimation to the interpretation of the difficulty level of the recipe as marked red in Fig. 8c. Hence, recipes are recommended with attention to their difficulty levels (shown as 'very easy' in Fig. 8) which are learnt from the user feedback and adapted accordingly. Upon completion of the cooking process, the user is asked to provide feedback on the preparation time, the cooking time and the level of difficulty in his/her words. After submitting this feedback, the participant is prompted to fill in the CDCQ as described previously. This entire cycle of operations performed is referred to be one trial. The participants were asked to perform at least 10 trials so that the adaptation would be perceived over time and over the various uses.

[4]VoCon® 3200 - http://www.nuance.com/industries/automotive/products/VoCon-3200.asp

Fig. 7. Photos showing participants performing the experiments in the iSpace, University of Essex, UK.

In the background, the two inputs to be processed by the ***causation-organization*** segment of the proposed CWWs Framework are the preparation time and the cooking time (provided by the FatSecret API Platform). Moreover, there is the third input to the system, which is the overall time calculated by adding the preparation time to the cooking time. Using these inputs, causation-organization segment of the proposed CWWs Framework derives the level of difficulty, which is the key to the adaptivity aspect of the system.

B. Quantitative Analysis and Results

We have performed quantitative analysis on the data collected through the various questionnaires. The following 6 statements assessed on a 5 point Likert-style scale were used as the key instrument for eliciting participants' perceptions of

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adaptation in the CDCQ:

- The system suggests the level of difficulty of the recipes appropriate to my skills
- I can see how the system is adapting to my feedback
- I noticed the system is improving its level of difficulty suggestion for recipes each time I use it
- The way the system adapts to my choices is valuable to me
- I would use this type of system if it was available to me outside this trial
- Using the system feels like a personal experience

The statements were designed to encourage reflection on the experience of using the system from 6 slightly contrasting angles so that in combination they would provide a nuanced indication of attitude for each participant in relation to each interaction. When combined over time/use for all participants, a shift along the continuum from Strongly Disagree (1) towards Strongly Agree (5) would indicate that adaptation was both perceived and valued. Indeed, Fig. 9 illustrates the positive tendency of the predicted viewpoints of the participants. All of the above statements were assessed using the same scale and the items have been represented with the corresponding numbers (Strongly Disagree: 1 – Strongly Agree: 5) as shown on the vertical axis in Fig. 9. Hence, the results suggest that the positive tendency based on the 6 statements above has an average outcome of ~4.35, which corresponds to the Likert item 'Agree', with a standard deviation of 0.59.

Over 270 trials performed by 17 participants show that the

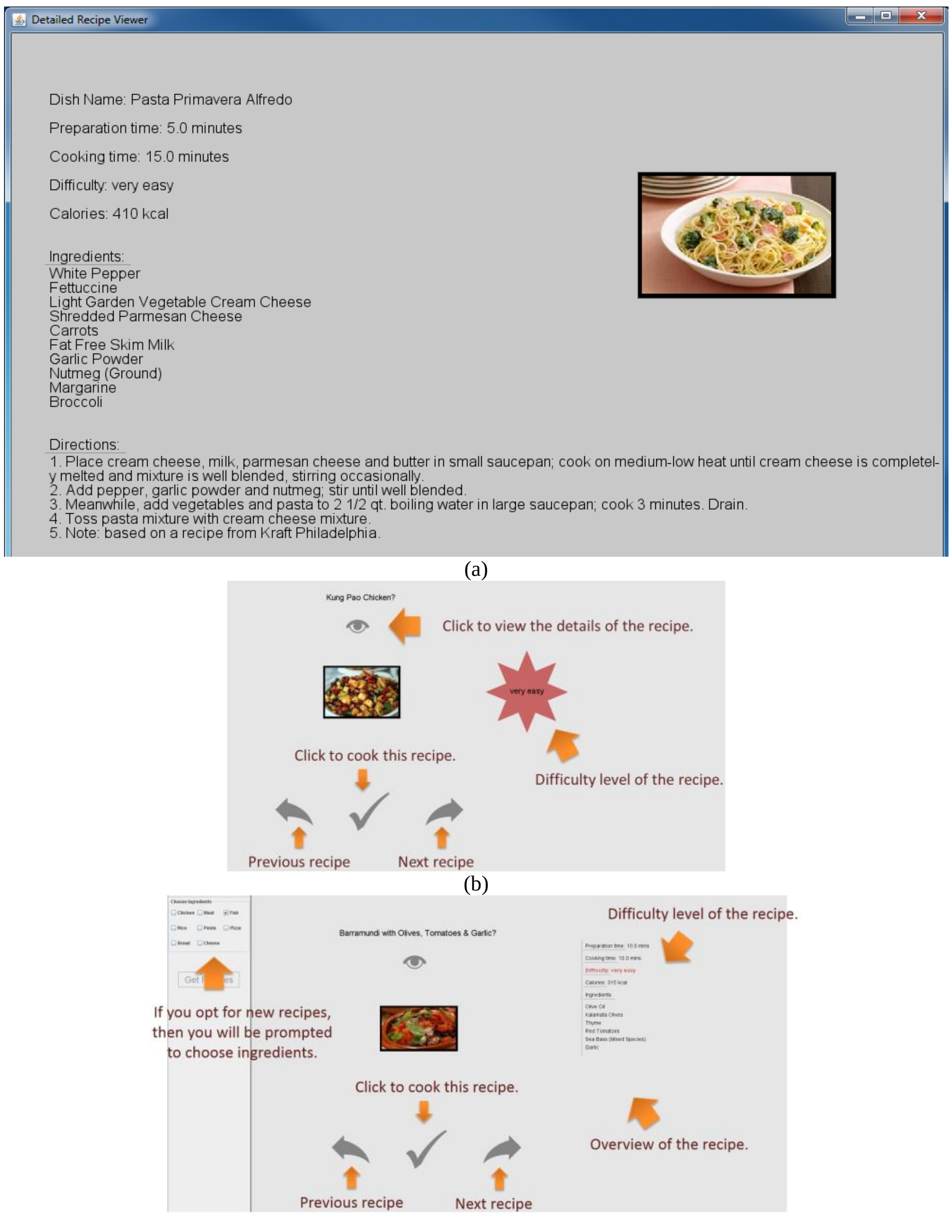

Fig. 8. (a) Screenshot of GUI used in the experiments showing the detailed information that is available through the FatSecret API Platform. Navigation screens with introductory information showing the functionality of interface elements for (b) Tried recipe (c) New recipe (images are taken from the User's Guide created for the application)

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average rating per trial is ~4.5 with a standard deviation of 0.69. Table VIII shows the results of the statistical t-Test for paired two sample for means. The two samples are the initial ratings and the final ratings regarding the participants' experiences of using the system. The initial ratings are recorded after the first use of the system, and the final ratings are recorded in the closing questionnaire. It can be observed from the p-value (P(T<=t) two tail) given in Table VIII that the means of the two samples are significantly different as p-value (0.016) < 0.05 where the confidence level has been specified to be 95%. Moreover, it can also be observed from the two means that the final rating has increased compared to the initial rating. This increase can be interpreted to be a positive tendency for the use and acceptance of the system.

TABLE VIII
RESULTS FOR T-TEST: PAIRED TWO SAMPLE FOR MEANS APPLIED TO PARTICIPANTS RATINGS ON EXPERIENCE OF USING THE SYSTEM

	Initial rating	**Final rating**
Mean	3.882352941	4.529411765
Variance	1.235294118	0.264705882
Observations	17	17
Pearson Correlation	0.443622131	
t Stat	-2.677754726	
P(T<=t) one-tail	0.008253276	
t Critical one-tail	1.745883676	
P(T<=t) two-tail	0.016506552	
t Critical two-tail	2.119905299	

The adaptation through learning from the user experience facilitates better representation of the word models from CWWs perspective. Fig. 10 depicts the initial and final LGT2 models for the level of difficulty, which is the output of the proposed CWWs Framework and represented in the domain [0, 1]. The semantic meaning of the level of difficulty conveys the perception of the user whether the recipe is challenging or it is easy according to the user's experience. For example, for an experienced cook, the recipes that take short time to prepare might be perceived as very easy – meaning straightforward for the user to perform; whereas for an inexperienced cook, recipes that require slow cooking might be perceived as challenging – meaning difficult for the user to achieve a successful resulting meal. So, it is important to have adaptive models that can represent the user's perceptions, which can also change by time. In other words, as the user gets more experienced, his/her perception regarding the difficulty level would possibly change. And the adaptive word models using LGT2 FSs take into account these uncertainties. Particularly, it can be observed from Fig. 10a that the initial default LGT2 model at the beginning of the experiment for one participant is very different from the LGT2 model shown in Fig. 10b, which is the final model for the level of difficulty for the same participant. Hence, the change in the LGT2 model for the level of difficulty shows the adaptation to the participant over time.

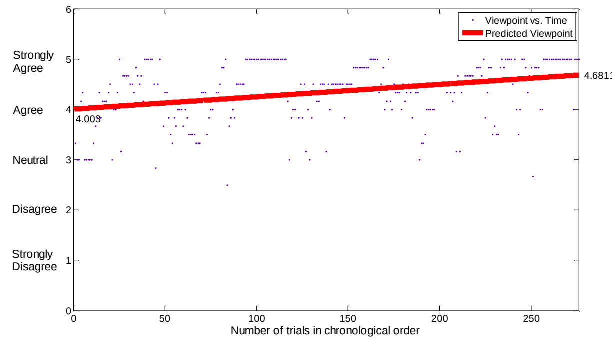

Fig. 9. Positive tendency on predicted viewpoint of the participants based on the average results obtained from 6 statements

Fig. 10c and Fig. 10d show the final LGT2 models for the level of difficulty for other participants. As can be observed from Fig. 10, the final adapted LGT2 models for different participants may vary. From the machine point of view, the domain for the linguistic term 'challenging' for Participant 3 in Fig. 10b is [0, 0.33]. However, the domain for the linguistic term 'challenging' for Participant 9 in Fig. 10c is [0, 0.47]. This is because different people have different experiences and different interpretations of concepts. Similarly, the LGT2 model in Fig. 10b is different from the one illustrated in Fig. 10d, and the LGT2 model in Fig. 10c is different from the one illustrated in Fig. 10d. Over time, the system learns and adapts to the user, and the LGT2 models for the level of difficulty are updated after each interaction of the user with the system. Hence, we can conclude that LGT2 FSs are adequate for representing the changes in the word models for CWWs for different user experiences accumulated over time.

TABLE IX
PEARSON AND SPEARMAN'S RANK CORRELATION TESTS APPLIED ON USER FEEDBACK AND SYSTEM RESPONSE

Participant #	**Pearson Correlation**	**Spearman's Rank Correlation**
1	0.755928946	0.8660
2	1	1
3	0.5	0.5
4	1	1
5	1	1
6	1	1
7	0.5	0.5
8	0.654653671	0.5
9	0.866025404	0.8660
10	0.5	0.5
11	0.866025404	0.8660
12	0.866025404	0.8660
13	1	1
14	0.866025404	0.8660
15	1	1
16	0.5	0.5774
17	1	1
Mean	**0.816157896**	**0.818082353**

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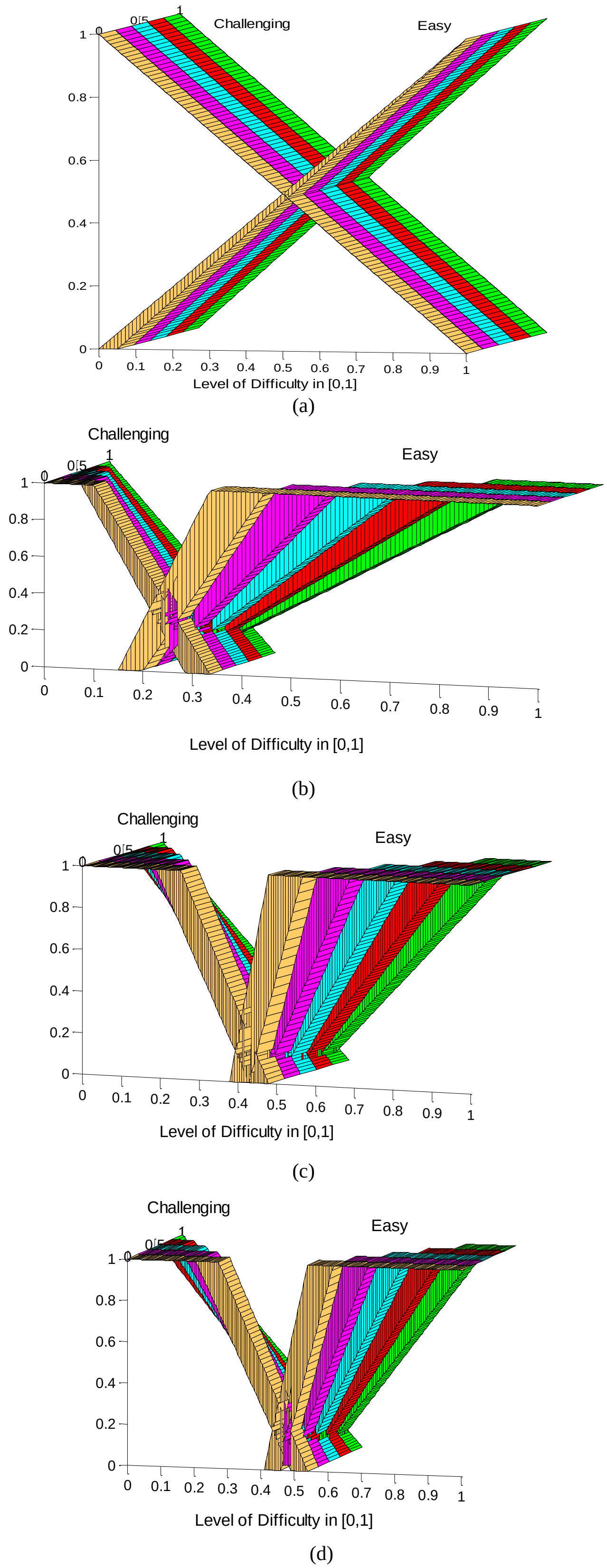

Fig. 10. (a) Initial LGT2 model. Final LGT2 models of the linguistic variable level of difficulty for (b) Participant 3 (c) Participant 9 (d) Participant 5

In order to evaluate whether the system responses are able to replicate the human responses, we have conducted statistical correlation tests on the user feedback (regarding the level of difficulty of the recipe) and the proposed CWWs Framework output (which is the level of difficulty of the recipe) for each participant. As we are dealing with word outputs, we have chosen a numerical representation for the linguistic terms as follows: extremely challenging:6, very challenging:5, challenging:4, easy:3, very easy:2 and extremely easy:1. The results are listed in Table IX and confirm that the system shows adaptation to the human experience over time as the Pearson correlation coefficient has increased up to ~0.816, whereas Spearman's rank correlation coefficient has increased up to ~0.82.

C. Comparison With Interval Type-2 Based CWWs Framework

For comparison purposes, we collected data from 17 subjects and applied EIA [88] in order to create Interval Type-2 Fuzzy Sets (IT2 FSs) for the inputs to the causation-organization segment of the proposed CWWs Framework. These inputs are preparation time, cooking time and overall time of the chosen recipe. The participants were asked to indicate what the given words meant to them using an interval of [0, 10]. In total, 18 words to be modelled using EIA [88] are as follows: for food preparation time linguistic variable: extremely short, very short, short, long, very long, extremely long; for cooking time linguistic variable: extremely quick, very quick, quick, slow, very slow, extremely slow, for overall time linguistic variable: (which is the summation of preparation time and cooking time) extremely little, very little, little, big, very big, extremely big.

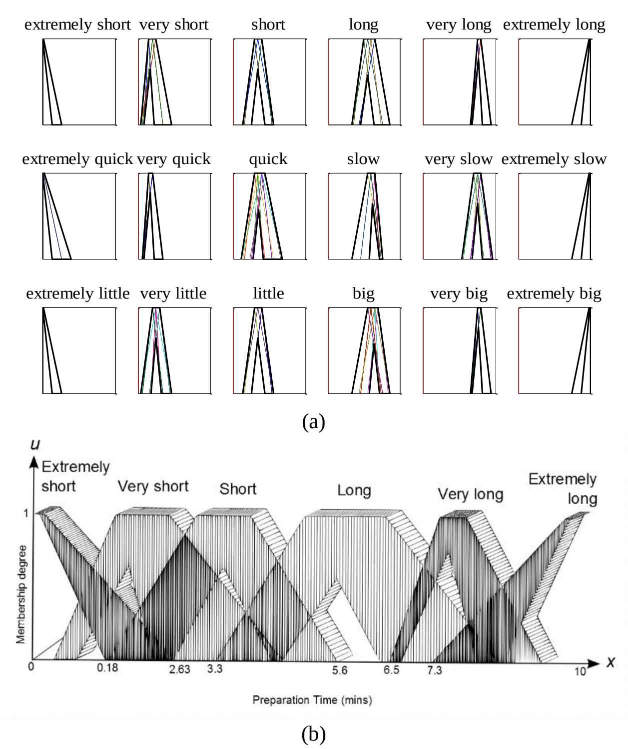

Fig. 11. (a) EIA [88] output for 18 linguistic terms based on survey data (b) Whole IT2 design for the linguistic variable preparation time using EIA [88]

The parameters of the IT2 FS models belonging to 18

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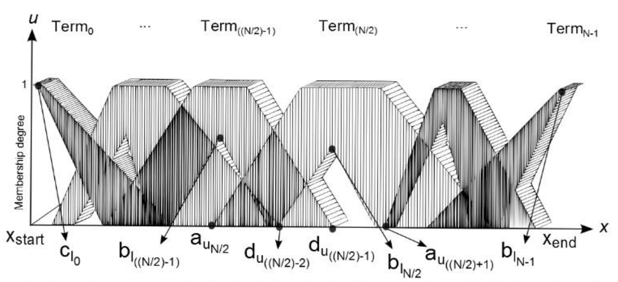
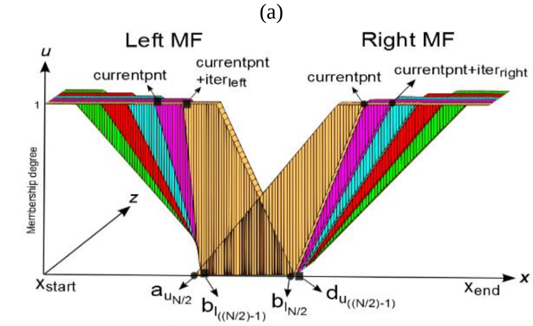
linguistic terms using the EIA are given in Appendix A whereas Fig. 11a illustrates the linguistic terms individually. With this information, the whole design for one of the linguistic variables, for example preparation time, using IT2 fuzzy sets is presented in Fig. 11b.

For comparison purposes, we have developed a conversion paradigm to redesign (using LGT2 FSs) the linguistic variables, which are modelled using EIA [88]. The conversion paradigm takes several key points within the parameters of IT2 fuzzy sets (as marked in Fig. 12a) to redesign the linguistic variable using LGT2 FSs (as reflected in Fig. 12b). Appendix B gives the resulting parameters of the LGT2 fuzzy sets including each zSlice derived using the paradigm detailed in Fig. 13a.



(a)



(b)

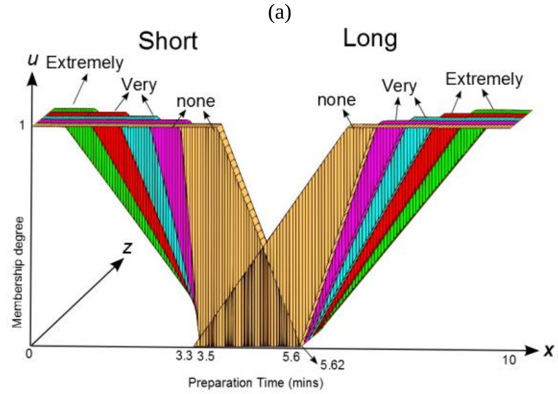
Fig. 12. (a) The theoretical view of IT2 FS model b) The theoretical view of LGT2 FS model showing the parameters and key points used in the Conversion Paradigm in Fig. 13a

The design of the LGT2 fuzzy set based models for one of the inputs (i.e. preparation time) to the causation-organization segment is given in Fig. 13b. The illustrated LGT2 fuzzy set has been created using the parameters in Appendix B and the paradigm described in Fig. 13a. The linguistic modifiers marked as 'extremely', 'very' and 'none' are pointed with arrows in Fig. 13b and are modelled in the third dimension using zSlices representation. As illustrated below, among visual advantages of LGT2 FSs is their compact design, which is based on the use of antonyms. Employing LGT2 FSs reduces the number of MFs to be designed to two while keeping the same level of profoundness as in an IT2 design. It is important to note that, for this paper, both IT2 and LGT2 fuzzy sets have been fixed ahead of time based on the survey data collected from 17 subjects.

Converting IT2 FSs into LGT2 FSs

Steps	
0	Define the support of the linguistic variable: $[x_{start}, x_{end}]$, and S to be the number of zSlices
Left_1	Calculate iteration value $iter_{left} = \left(du_{\frac{N}{2}-2} - cl_0\right)/(S+1)$
Left_2	Set $currentpnt = c_{l_0}$
	For each zSlice s
Left_3	Decide on the linguistic modifier by comparing *currentpnt* with linguistic modifier range (given by IT2 design)
	Create UMF_s and LMF_s for zSlice s using:
Left_4	$LMF_s = \left[x_{start}, x_{start}, currentpnt, b_{l_{\frac{N}{2}-1}}\right]$
	$UMF_s = \left[x_{start}, x_{start}, currentpnt + iter_{left}, d_{u_{\frac{N}{2}-1}}\right]$
Right_1	Calculate iteration value $iter_{right} = \left(b_{l_{N-1}} - a_{u_{\frac{N}{2}+1}}\right)/(S+1)$
Right_2	Set $currentpnt = a_{u_{\frac{N}{2}+1}}$
	For each zSlice s
Right_3	Decide on the linguistic modifier by comparing *currentpnt* with linguistic modifier range (given by IT2 design)
	Create UMF_s and LMF_s for zSlice s using:
Right_4	$UMF_s = \left[a_{u_{\frac{N}{2}}}, currentpnt, x_{end}, x_{end}\right]$
	$LMF_s = \left[b_{l_{\frac{N}{2}}}, currentpnt + iter_{right}, x_{end}, x_{end}\right]$

(a)



(b)

Fig. 13. (a) The conversion paradigm where steps are categorized according to left shoulder and right shoulder MFs (b) The whole LGT2 word model for preparation time linguistic variable created using conversion paradigm

In practice, the result of mimicking the human reasoning can be determined by comparing the classified outputs (words represented by numbers) using the distance (absolute value of the numerical difference between the system output and the user feedback). When the words are represented with numbers (extremely challenging:6, very challenging:5, challenging:4, easy:3, very easy:2 and extremely easy:1), the absolute difference between the LGT2 based system response and the user feedback is significantly less when compared to the absolute difference between the IT2 based system response and the user feedback for all of the participants. We have employed two statistical measures for error calculation, which are MAPE (Mean Absolute Percentage Error) and RMSE (Root Mean Square Error). The formulas used for the MAPE and RMSE calculation are given in Equation (15) where the variable $xSys$ represents the system response in numbers and the variable $xUser$ represents the user feedback in numbers stated above.

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$$MAPE(x) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{xSys - xUser}{xUser}\right|$$
$$RMSE(x) = \sqrt{\frac{1}{n} * \sum_{i=1}^{n}(xSys - xUser)^2} \quad (15)$$

According to EIA [88], the supports of the data-driven linguistic variable designs (i.e. $[x_{start}, x_{end}]$) are [0, 10]. Since the original domain of the linguistic variables might be different than [0, 10], the original domain of the input linguistic variables require to be scaled into the interval [0, 10][5]. Correspondingly, we have noticed in our experiments that changing the minimum and maximum values in the input data that are used in the scaling of the linguistic variables causes greater disturbance in the RMSE and MAPE results belonging to IT2 based CWWs Framework than those belonging to LGT2 based CWWs Framework. Table X gives the corresponding values of mean and standard deviation of the MAPE and RMSE results (derived from 17 subjects) for both IT2 based and LGT2 based CWWs Framework as well as the improvement percentage for LGT2 based system over IT2 based system (calculated using: 100*(Mean of IT2 - Mean of LGT2) / Mean of IT2).

TABLE X
RESULTS OF THE MAPE AND RMSE CALCULATIONS FOR LGT2 AND IT2 BASED CWWS FRAMEWORK WHERE PREPARATION TIME DOMAIN IS [2, 120], COOKING TIME DOMAIN IS [2, 120], AND OVERALL TIME DOMAIN IS [5, 150]

	MAPE		RMSE	
	LGT2	**IT2**	**LGT2**	**IT2**
Mean	48.984	109.904	1.596	2.525
Standard Deviation	16.835	32.080	0.340	0.371
Improvement of LGT2 over IT2	**55.43%**		**36.77%**	

It can be observed from the results that the improvement of LGT2 based system can increase up to 55.43% for MAPE and to 36.77% for RMSE. Most importantly, we have noticed over four different scales that the disturbance caused by the change of the input domain is much more in an IT2 based system compared to LGT2 based system. For example, for another scale where preparation time domain is [2, 120], cooking time domain is [2, 420], and overall time domain is [5, 435], the mean of MAPE for LGT2 based system is 55.57% whereas the mean of MAPE for IT2 based system is 61.3%. When compared to the mean values given in Table X, this can be interpreted as LGT2 based system can better handle the extreme value ranges in the input, and hence can be more robust when compared to IT2 based system for CWWs Framework.

In our experiments, we have also recorded the progressive MAPE and RMSE, which are recalculated after each interaction, in other words, after each input in a periodical manner. Herein, the results can be interpreted in terms of convergence regarding the decrease in the MAPE and RMSE. The faster the convergence, the better the learning and adaptation capabilities of the system. The progressive MAPE and RMSE results are illustrated in Fig. 14a and Fig. 14b for one participant due to space constraints. The graphs in Fig. 14 demonstrate the fast convergence for LGT2 based CWWs Framework as well as the lower overall MAPE and RMSE results compared to IT2 based CWWs Framework. Hence, it can be observed that LGT2 based CWWs Framework outperforms IT2 based CWWs Framework in the pace of learning and adaptation.

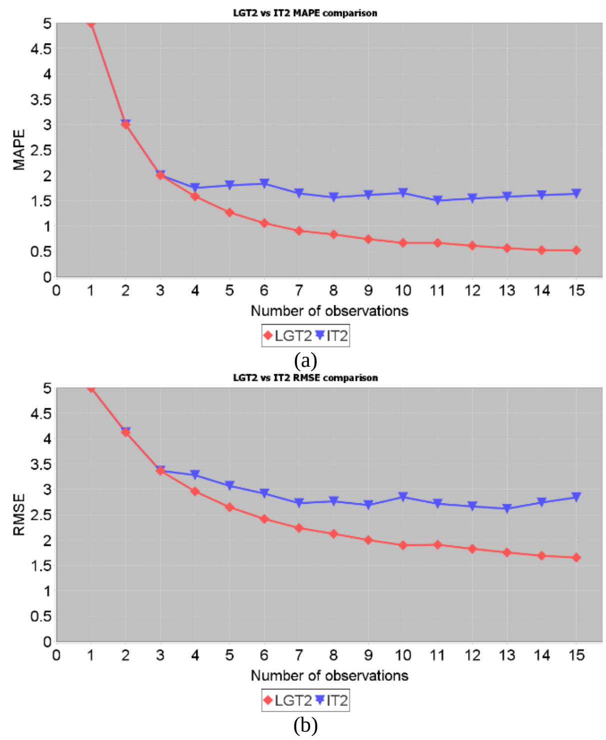

Fig. 14. (a) Comparison of progressive MAPE for LGT2 and IT2 based CWWs Framework for Participant 7 (b) Comparison of progressive RMSE for LGT2 and IT based CWWs Framework for Participant 7

The overall results suggest that LGT2 based CWWs Framework outperforms IT2 based CWWs Framework by up to 55.43% in MAPE and up to 36.77% in RMSE. Hence, we can deduce that LGT2 based system mimics the human reasoning better as it can replicate the user responses much more closely when compared to its counterpart IT2 based system. Also, we can conclude that LGT2 fuzzy sets provide better performance for the whole system. In other words, for the application of the proposed CWWs approach, we have achieved up to 55.43% improvement when we use general type-2 fuzzy sets than when we use interval type-2 fuzzy set instead.

D. *Social Science Qualitative Analysis and Results*

In this social science qualitative analysis, participants were asked to interact with the prototype through two cycles of

[5] We would like to clarify that the examples in [88] were for word data for which there was no context, and so the scale [0, 10] was appropriate. However, in our paper, the data are collected for linguistic terms that are associated with linguistic variables that have a physical scale, where the subjects need to provide their interval end-points on the physical scale [*l*, *r*] where l and r are the two end-points of the physical scale. However, to facilitate the representation in accordance with the representation in [88], we scaled the interval [*l*, *r*] to be the range [0, 10].

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recipe browsing and selecting (one cycle for the tried recipes, and another cycle for the new recipes). The aims of the trial were twofold; firstly to assess the perceived naturalness of the interaction including comparisons with the graphical interface; and secondly to complement the broader quantitative study with in-depth qualitative insight into the perceived value of the adaptive nature of the application and elicit ideas for its further development.

In this instance, the inquiry was concerned with understanding the participants' step-by-step experience, their inner thoughts, feelings and reactions to each engagement with the application in the flow of browsing and selecting. To achieve this insight without constantly interrupting the experience, participants were asked to be conscious of their own moments of hesitation, uncertainty, frustration, pleasure and satisfaction as they moved through the process of browsing and selecting, and to signal with a thumbs up (positive) or thumbs down (negative) when such a moment occurred. Their interactions with the application were video recorded and a semi-structured interview schedule was designed to focus on the signalled moments. The participant and the interviewer then played back the video together stopping at each signal and exploring the participants' reactions and perceptions. Participants were also asked for their overall responses to adaptation and naturalness of the AIPCRR. Five and a half hours of interview data were recorded and transcribed; this material was then subject to a systematic analysis which focussed on resonances and contrasts in participants' responses in relation to their identified moments. The analysis was conducted with the support of Nvivo Qualitative analysis software[6].

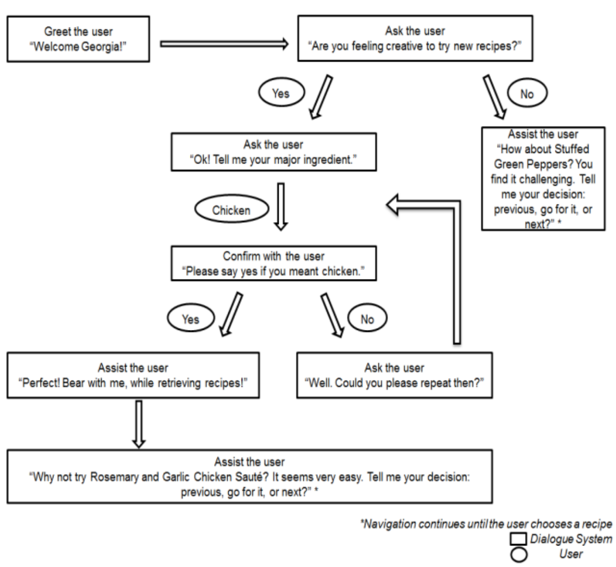

Fig. 15. Example dialogue between the user and the AIPCRR using speech-driven dialogue system

The entire dialogue is exemplified in Fig. 15. The qualitative study clearly supported the findings of the earlier quantitative outcomes by demonstrating that all four participants, in repeated references, perceived and valued the adaptation aspect of the prototype, for example P2 and P3 mentioned (in their own words) that the system was adaptive over time and it was interesting to see that the system was giving personalized options.

The users also valued the fact that their personalized recipe ratings could be accessed via the internet from anywhere, and when asked about how the application compared to using a conventional cook book, three of the four participants expressed a clear preference. When the interaction was passing back and forth from user to system seamlessly, participants reported a feeling of enjoyment, control and engagement, verging for some on anthropomorphised companionship, as P3 expresses: "it is like having some companion, some entity there helping you.". This feedback actually affirms that the system was able to establish a natural human-machine communication as intended.

An evaluation of this nature highlights what works well and where things can be improved, and it is often the case that incidents where things do not go to plan provide the most interesting insight. There was also, naturally, a greater emphasis on the voice-controlled interface in comparison to the quantitative evaluation. However, when asked to reflect on the overall acceptability and convenience of the adaptive ambient intelligent platform for food recipe recommendation concept as embodied in both the GUI and speech interface versions of the prototype, participants demonstrated a balanced understanding and were unanimously positive. For example, P1 mentioned its convenience in a busy life at home together with the advantage of updated content (from web), P4 referred to its usefulness and integrated architecture, and all the participants quoted that they 'like it'.

VI. Conclusions and Future Work

In this paper, we have presented a CWWs framework merging the advancements from neuroscience, psychology, linguistics, cognitive science and artificial intelligence. As an initial step in the accomplishment of getting the machines understand the human beings, we have pointed out the significance of past experience, and the aggregation of bits of information to form granulated chunks of information. Also, we have introduced the theory and a real-world application of Linear General Type-2 Fuzzy Sets, which have nested FOUs in the third dimension as a novelty. By this feature, in order to represent words for CWWs paradigm, LGT2 FSs have significant advantages over type-1 and interval type-2 fuzzy sets. First of all, LGT2 FSs assure mimicking human reasoning with regards to preserving natural ordering as human beings can do. Second, LGT2 FSs show adaptation capabilities over time which can be easily represented by the LGT2 model after each interaction. Third, LGT2 FSs facilitate the modelling of third dimension for the linguistic modifiers and hence offer a more compact and efficient design for the word model. Finally, the comparison analysis for LGT2 based and IT2 based CWWs Framework demonstrates up to 55.43% improvement when general type-2 fuzzy sets are used than when interval type-2 fuzzy sets are used instead.

Furthermore, to our knowledge, there is no real-world

[6]http://www.qsrinternational.com/products_nvivo.aspx

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application of CWWs in an AmI scenario, in particular, in a scenario using past experiences of the users. In an inter-disciplinary manner, we have also got support from social evaluation on the perception of adaptation and the overall concept of CWWs. Consequently, we presented interesting and promising qualitative and quantitative results for the first real-world prototype for the Ambient Intelligent Platform for Cooking Recipes Recommendation. We have carried numerous real world experiments with various users in the University of Essex intelligent apartment (iSpace). We reported results from the comparison analysis between Interval Type-2 Fuzzy Sets and LGT2 Fuzzy Sets as well as the quantitative and qualitative analysis which showed the success of the system in providing a natural interaction with the users for recommending food recipes. The comparison analysis demonstrated encouraging improvement on the use of general type-2 fuzzy sets instead of IT2 fuzzy sets. The quantitative analysis showed the high statistical correlation between the system output and the users' feedback. In addition, the qualitative analysis presented social science evaluation that confirms the strong user acceptance of the system. To recapitulate, the participants perceived, valued and acknowledged the adaptation of the system and also gave positive indications to take the study further.

With regards to future research, there is a myriad of options to improve the system to have different activities or various composite concepts in addition to the options for further investigating learning and adaptation aspects of particular components of the proposed CWWs Framework.

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