Survey on Ontologies for Affective States and Their Influences

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Abstract. Human behavior is impacted by emotion, mood, personality, needs and subjective well-being. Emotion and mood are human affective states while personality, needs and subjective well-being are influences on those affective states. Ontologies are means of representing real-world knowledge, such as human affective states and their influences, in a format that a computer can process. They allow researchers to build systems that harness affective states. By unifying terms and meanings, ontologies enable these systems to communicate and share knowledge with each other. In this paper, we survey existing ontologies on affective states and their influences. We also provide the psychological background of affective states, their influences and representational models. The paper discusses a total of 18 ontologies on emotion, one ontology on mood, one ontology on needs, and ten general purpose ontologies and lexicons. Based on the analysis of existing ontologies, we summarize and discuss the current state of the art in the field.

Keywords: Ontology, Affective State, Survey, Affective Computing, Emotion

1. Introduction

Ontologies have become more and more popular in fields such as web technologies or data integration and extraction [64]. An ontology can be seen as a catalog that shows entities in a specific field and the relationships between them. It represents structural knowledge for any domain and defines a common vocabularies to be shared. In addition, it defines data and data structures to be used in applications in the same field [52]. An ontology is defined as "an explicit specification of a conceptualization, and it contains the classes, properties and individuals that characterize a given domain" [49]. Classes are the focal point of ontologies and they describe the concept in a domain. A class represents a group of different Individuals that share similar characteristics. An instance of a class is called an individual. Object properties describe the semantic relationship between individuals [52]. People and systems communicate with each other from different backgrounds and contexts, using varying words and concepts [79]. A well-designed ontology provides standard definitions and vocabularies in a particular domain, allowing a flow of communication [84]. Figure 1 shows a representation of an ontology and its components. For example, person is a class, Jon is an individual, and "studies In" is a property.

Ontologies are created using a machine-processable language such as the Web Ontology Language (OWL), an international standard for the design and exchange of ontologies. The Web Ontology Language uses a set of classes, sub-classes and properties which are organized into a hierarchical structure by property axioms [33]. New ontologies may be developed from the foundation of pre-existing ones and potentially be de-

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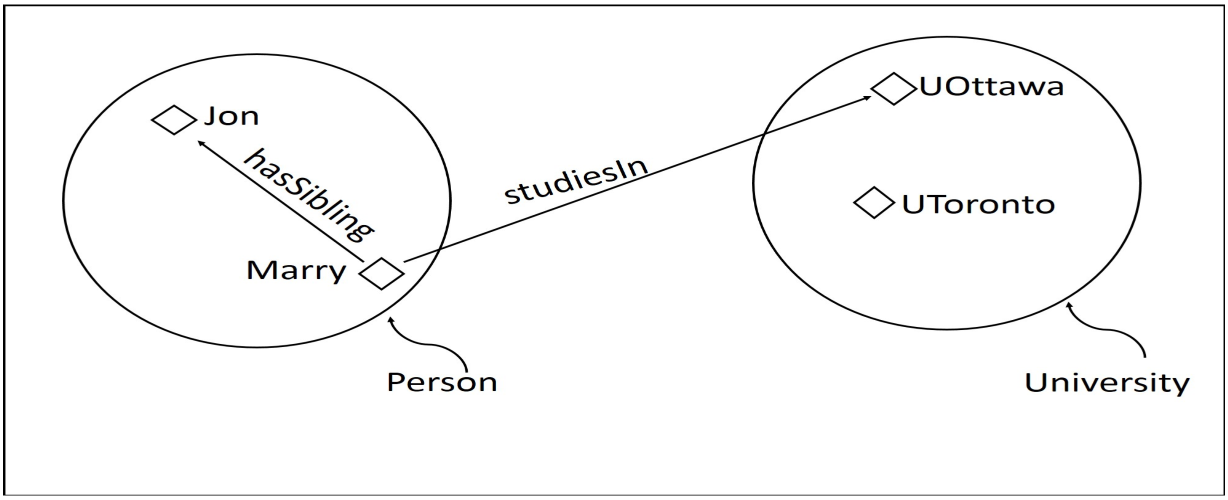

Fig. 1. Representation of Ontology components. The circle represents a class, the diamond represents an individual, and the arrow represents object properties.

signed with future reuse in mind. Ontologies can be designed at the top level (a general ontology) and then customized according to the domain or application. Moreover, ontologies can be designed for a particular application or system, which called application ontology. They can be reused as a whole or some classes depending on project needs [31], [9]. By not having to create an entire ontology from scratch, time is saved and the quality and maintainability of the new ontology is improved. Moreover, by reusing existing work, knowledge can be mapped from one domain to the domain of another ontology [22].

Not only does using an ontology allow for human affective states and their influences to be represented in an understandable computer format, but it also improves understanding and communication between people. Its structure reveals the definition of human affective states, influences and the relationships between them. It enables the sharing of human knowledge in a digital format.

Human behaviour is formed by affective states and their influences. While human interpretation of the relationship between states and influences is far from perfect, it is superior to computer interpretation. Therefore, representing human affective states and their influences in a semantic way enables the communication between humans and systems. Moreover, it inspires the development of applications that automatically detect and predict behaviors and meanings. Ontologies provide a unified vocabulary for each concept in a domain, so interpretation of messages shared between computer applications will be universal.

For example, an ontology that defines emotion, causes, and events to predict student emotions in e-learning session, can predetermine student emotions with regard to answering test questions [20].

Another example is an avatar that shows the corresponding expressions and gestures. These expression and gestures were represented based on an ontology that represents emotions associated with facial expressions and gestures [27].

In [63] a survey was carried about ontologies for human behavior recognition. The emphasis was on context ontologies to track human activities. In the survey upper ontologies and domain ontologies were presented. However,This paper aims to give an overview about existing ontologies in human affective states and their influences.

The remainder of this paper is organized as follows. In Section 2, we introduce the psychological theories used to build the existing ontologies for human affective states and their influences. Section 3 describes the lexicons used in the existing ontologies of emotion. Section 4 surveys current ontologies for human affective states and their influences as well as other related ontologies. Our conclusions are provided in Section 5.

2. Background in Affective states and their Influences

We argue that psychological theories represent the primary point of ontology design in the domain of human affective states and their influences. These theories form the basis for the existing ontologies that are discussed in Section 4. In Section 2.1, affective states (emotion and mood) are presented. In Section 2.2 the influences personality, subjective well-being and needs are introduced. Finally in Section 2.3, relationships between affective states and their influences are described.

2.1. Affective states

Emotion is the result of a person's exposure to an internal or external stimulus and is expressed by changes in facial expression, gesture, voice or physiological parameters [71]. Emotion plays an important role in a person's decision-making process. As such, emotion detection is an important step toward understanding human beings. Computationally, an emotion can be represented either in a discrete (categorical), dimensional or componential (appraisal) way [35]. Figure 2 represents the emotion representation models.

In the **discrete model**, emotions are classified by words and grouped into families that share similar characteristics. The most common ones are called basic emotions (archetypal) and they can be found in many cultures. These emotions include happiness, surprise, fear, sadness, anger and disgust [3]. Additionally, neutrality [3], contempt [57], anticipation, trust, and love [57] can be considered.

Izard added more emotions along with the basic emotions to his model. He added: contempt, distress, guilt, interest, and shame [37].

A discrete emotion classification was proposed by Douglas-Cowie, who listed 48 emotion categories arranged into 10 groups. They include negative forceful, negative/positive thoughts, caring, positive lively, reactive, agitation, negative not in control, negative passive and positive quiet [15].

Plutchik grouped eight basic emotions in a wheel, placing similar emotions together and opposing ones 180 degrees apart. The model is called Plutchik's wheel of emotions. The contrasting pairs consist of joy versus sadness; anger versus fear; acceptance versus disgust; and surprise versus expectancy. The model also includes advanced emotions made up of combined basic ones. In addition, each emotion in the model represents a basic level of intensity [57].

In the **dimensional model**, an emotion is represented by a number applied to each dimension. For instance, the Circumplex Model by Russell has two dimensions: valence and arousal. Valence is correlated with the degree of pleasantness or unpleasantness of an emotion while arousal refers to the amount of physiological change in the person's body [65]. Figure 3 represents the Circumplex model of affect with the horizontal axis representing the valence (pleasantness) dimension and the vertical axis representing the arousal (activation) dimension. As an example, happy is represented by positive valence along with high arousal, whereas relaxed is represented by positive valence along with low arousal (deactivation).

Likewise, Whissel reflects emotions as 2D space whose dimensions are evaluation and activation [81].

Mehrabian created the Pleasure-Arousal-Dominance (PAD) model of emotional states where dominance was added as a third dimension. It is the feeling of being in control of a situation versus the feeling of being controlled [48]. Osgood et al. use the names evaluation, activity and potency [55]. Cowie et al. use evaluation, activation and power [12]. A fourth dimension, unpredictability, was added by Fontaine. It denotes a person's reaction to a stimulus based on their familiarity with the situation [23].

Other researchers came up with different dimensions. For example, the model proposed by Watson and Tellegen includes the dimensions of negative affect (NA) and positive affect (PA) [80]. Feidakis et al. adopted dimensions of the intensity, frequency and duration of the emotion [21].

Componential appraisal model , has statement that emotions are chosen by human based on the event evaluation. This type of model highlights the cognitive background of emotions. Appraisal theory ties human emotions with the way they interpret events. This theory states that a person uses fixed criteria to evaluate a situation and to produce a suitable emotion(s). People appraise the situation based on their familiarity with the event (novelty), whether or not it is relevant to their goal, their ability to cope with the consequences of the

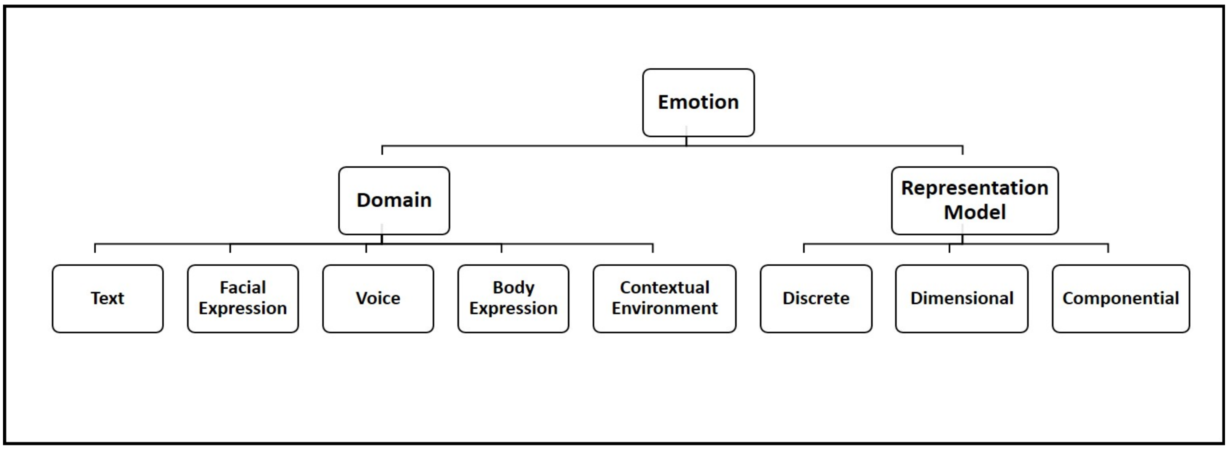

Fig. 2. The ways human express their emotions (Domain) are presented. The context impacts the expressed emotions. In addition, emotion representation models in Psychology (Representation Model).

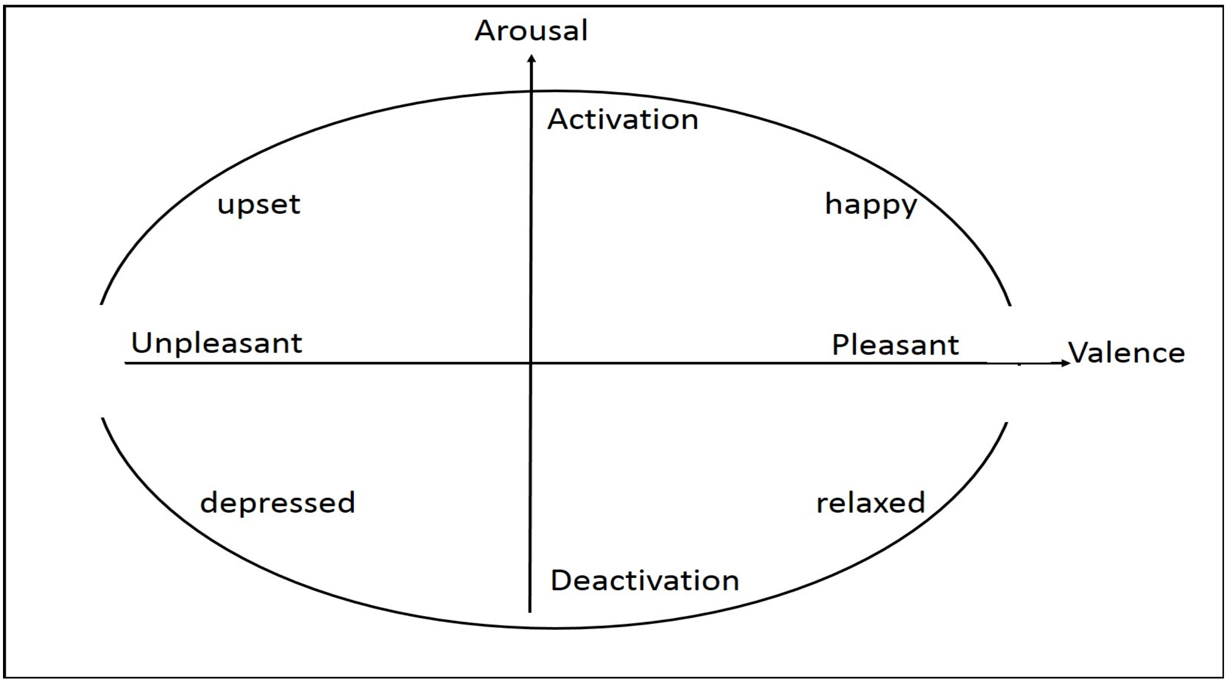

Fig. 3. A graphical representation of the Circumplex model.The horizontal axis representing the valence dimension, and the vertical axis representing the arousal dimension.

event (agency), and if it is well-matched to standards and social values (norms) [70].

OCC (Ortony, Clore, and Collins) is an appraisal model that reasons about agents, beliefs, objects and events. This model is popular in computer science systems that draw conclusions from emotions [54]. OCC model defines a finite set that allows for the characterization of emotions. Moreover, it delivers a semi-formal descriptive language of emotion types. The model classifies 22 emotions in three main categories: consequences of events (e.g., joy and pity), actions of agents (e.g., pride and reproach), and aspects of objects (e.g., love and hate). So the emotions activated by event can be joy, pity, hope. Based on the person's evaluation of an event, the originating emotion can be positive as pride, or negative as reproach

Moreover, the three main categories are classified further into subgroups. For instance, if the consequence of the event is focusing on the person or on others, the outcome emotion(s) will be different.

Mood is an emotional state that affects the experience and behavior of a person. It has a lower intensity but a longer duration than emotion [71]. Mood affects a person's judgment; people in a happy mood tend to draw optimistic conclusions. However, people in a bad mood are likely to make pessimistic judgments [42]. Although emotion and mood are feelings that people experience, they have differences between them. Emotions are caused by a specific situation, they last for a short duration and have a high intensity. However, mood has no clear causes, it lasts longer and has low intensity [36]. Mood can be represented by using discrete and dimensional models [41].

Sentiment is another human affective state defined by a person's opinion or feeling towards something. Sentiment is expressed with words such as like, dislike, good or bad. For example, people use social media to express their sentiments about products, movies, etc. [34].

2.2. *The Influences of Affect*

Personality is defined as an individual pattern of affect, behavior, cognition and goals over time and space [62]. Personality reflects a person's attitude and characteristics. The two most popular personality theories are the Myers-Briggs Type Indicator (Big Four) (MBTI), and the Big Five. MBTI is used in the training world Such as helping to decide the appropriate carer. However, Big Five is utilized for academic research [7].

The Big Five theory represents personality in five dimensions. An outgoing, energetic person is described by high Extroversion. A friendly and cooperative person is represented by the Agreeableness trait. Conscientiousness means that someone is responsible, dependable and organized. A sensitive and nervous person has Neurotic traits, and a social, intellectual person can be described by the Openness dimension [47].

In MBTI each personality fits into only one of 16 types. These types are based on four features of personality, each one combined with its opposite: Extroversion (E) vs Introversion (I), Sensing (S) vs Intuition (N), Thinking (T) vs Feeling (F) and Judgment (J) vs Perception (P) [69]. Because there are two features within each dimension, there are 16 potential personality types. Although MBTI is a very widespread test of personality, many psychologists do not support it and claim that no significant conclusions can be drawn from it. There is no evidence that every individual can be defined within 16 categories.

Subjective well-being refers to how people judge and evaluate their life. The term is a container for diverse types of evaluations. Life satisfaction, for example, is considered a cognitive component because it is based on evaluative beliefs. Positive and negative effects are another component of subjective well-being, reflecting the level of pleasant and unpleasant feelings that people experience in their lives [72].

Human Needs are necessities for the development of physical and mental growth of individuals. Human needs are the underlying layers that trigger emotions and feelings, which later empower and direct human behaviours [78]. Needs categories are classified and represented by the internal aspect within individuals and the external aspect of a particular community, including social, cultural, economic and political aspects. In the Self-Determination Theory (SDT) [66], a macro theory focusing on the individual's inner feelings, human needs are categorized into three basic psychological needs: Autonomy, Competence and Relatedness.

In Human Motivation Theory, Abraham Maslow presents a pyramid of five needs categories arranged in hierarchical levels based on their importance to human beings.

The five categories by decreasing importance are survival, security and safety, social, self-esteem and self-actualization. This model has been updated to adapt two new dimensions under the self-actualization category: cognition and aesthetic needs. Also, the theory explored the self-transcendent needs as the need to help others as a further category on the top of the pyramid [43].

In the Human Scale Development Model proposed by Max-Neef, the fundamental need categories for individuals and communities are formulated in a universal and interactional structure [45]. The model distinguishes between universal needs and the satisfiers, or strategies to meet these needs. The needs are finite and constant across all human cultures, while the satisfiers, which are the ways to satisfy these needs, are changeable over time and between cultures. The model defines the needs and satisfiers in a matrix with two dimensions; the need dimension in axiological categories consist of: subsistence, protection, affection, understanding, participation, idleness, identity, creation and freedom. Second, the satisfiers in existential categories are represented in the form of being, having, doing and interacting.

2.3. The Relationships between the Affective States and Their Influences

This section illustrates the relationships between human affective states and the influences. Emotion and mood can impact and influence each other. Moreover, there is a relationship between the affective states and the influences. Moods influence which emotions will be experienced. On the other hand, emotions often contribute to moods. For example, a negative mood can be triggered when a person interacts with an object or situation that is attached to frustration [10]. An individual's personality can impact their life evaluation. Indeed, the Big Five personality traits have a major impact on human emotions. People can show different emotional responses to the same situation. In some cases, personality is responsible for the difference. For example, when a person with an extroverted personality is offered help by a stranger, the person will probably be happy about the help. On the other hand, if the person has an introverted personality, they might react with fear [18]. Subjective well-being can also be influenced by personality. Extroversion is the most significant interpreter of positive affect Neuroticism is the most significant interpreter of negative affect and life satisfaction [28].

An interesting point is that subjective well-being influences a person's mood and emotion. When a person makes a positive judgement about his/her life, they will experience a good emotion and mood. When a person experiences a bad emotion or mood this is because he/she feels unhappy about their life expectations [13]. Feelings and emotions indicate the state of satisfaction of a person's needs [61].

```
<sentence id="sent1">
Do I have to go to the dentist?
</sentence>
category-set="http://www.w3.org/
TR/emotion-voc/xml#everyday
-categories">
<category name="afraid"
value="0.4"/>
<reference role="expressedBy"
uri="#sent1"/>
</emotion>
```

Fig. 4. EmotionML syntax in emotion text annotation encoded in XML.

3. Emotion related Lexicons and Language

This section describes the emotion lexicons that are used later in section 4.2. Emotion lexicons classify words into emotional dimensions, emotional categories, or both. In addition, they group emotion words into sets of synonyms.

Emotion Markup language (EmotionML) [73] is a general-purpose emotion annotation and representation language that provides a standard emotion representation format. It consists of the emotion vocabularies and their features. Figure 4 illustrates EmotionML syntax in emotion text annotation encoded in XML: the emotion category is "afraid" (emotion vocabulary) with intensity "0.4" (emotion feature).

Since the data is annotated in a standard way, the interpretation of the message between systems will be the same. EmotionML uses Ekman's discrete basic emotions and the PAD dimensional model to represent emotions and their features. The language is a "plug-in" that can be applied in different contexts, such as data annotation and emotion recognition. The an-

```
<emotion
category-set="http://www.w3.org/TR/
emotion-voc/xml#everyday
-categories"
expressed-through="face voice">
<category name="satisfaction"/>
</emotion>
```

Fig. 5. EmotionML syntax in emotion from face and voice annotation encoded in XML.

notation can be applied to text, static images, speech recordings and video. Figure 5 demonstrates a case where an emotion is recognised from face and voice.

WordNet [50] is an online lexicon for the English language. WordNet distributes the lexicon into five categories: nouns, verbs, adjectives, adverbs and function words. It clusters words together based on their meanings and defines semantic relations between words, as well as grouping them into sets of synonyms called synsets. WordNet currently contains 155,287 words organized in 117,659 synsets [1].

SentiWordNet [4] is an enhanced lexical resource for supporting sentiment classification and opinion-mining applications. It assigns three scores to each synset in WordNet: positive, negative and neutral. This annotation indicates how positive, negative and neutral the terms in each synset are. For example, a sentence with a positive word such as “happy” will have the following scores: 1 (positive), 0 (negative), 0 (neutral).

To incorporate affective concepts, **WordNet-Affect** [76] was developed as an extension of WordNet that labels synsets to represent affective concepts. For example, labels can be emotion, mood and behaviour. WordNet-Affect creates an additional hierarchy in WordNet with emotion labeling. The hierarchy of WordNet-Affect categorizes emotion words in classes such as: positive emotion, negative emotion and neutral emotion [2].

MultiWordNet [56] is an extension of WordNet with a multilingual lexical database. It is available in Italian, Spanish, Portuguese, Hebrew, Romanian and Latin. The important relationship between words is Synonym. A group of synonyms identifies a concept.

HowNet [14] is an online bilingual English, and Chinese ontology. It describes the semantic relations between concepts and their attributes. The semantic relation can be expressed as synonym, antonym, etc. Top level classification in HowNet includes entity, event, attribute and attribute value. HowNet uses 80,000 words and phrases to build the ontology [3].

The semantic relations between concepts is language-dependent. The nature of the Chinese language is unlike English. Therefore, the semantic relation between Chinese concepts is different from English concepts.

In Semantic Web, there are many lexicons available that represent data with different formats. For example, the number of values of speech parts can differ between lexicons. Moreover, it is difficult to link them with existing ontologies. **LEMON (Lexicon Model for Ontologies)** [46] supports the sharing of terminological and lexicon resources on the Semantic Web and connects them with existing ontologies. LEMON was built based on semantics by reference. This principle has two layers, lexical and semantic. The lexical layer describes the morphology and syntax of a word, while morphology deals with studying the minimal unit of a word. It also looks at the suffix and the prefix. Semantic layers describe the meaning of a word, and the core classes in the ontology allows for the definition of a lexicon with a specific language and topic. It also defines multiple formats and representations for the lexicon. Comparing LEMON with WordNet, we can tell that LEMON is richer in word format and representation.

4. Existing Ontologies in Affective states and their Influences

This section presents the existing affective state ontologies and their influences. In Section 4.1, we discuss general purpose ontologies that were reused by more specific emotion ontologies. Reuse can be a starting point for the creation of a new ontology and it can increase domain knowledge [52]. In Section 4.2, existing emotion ontologies are presented. There are more ontologies regarding emotion comparisons with mood and influences. In section 4.3 a mood ontology is presented and finally in Section 4.4, we exhibit a need ontology.

[1] https://wordnet.princeton.edu/
[2] https://www.gsi.dit.upm.es/ontologies/wnaffect/
[3] http://www.keenage.com/html/e_index.html

4.1. Reused ontologies

This section introduces general ontologies that are being re-used for the creation of the emotion ontologies that are discussed in Section 4.2.

CONtext ONtology (CONON) [30] is used for modeling context in pervasive computing environments. The purpose of CONON is reasoning and representation in context-aware applications. CONON defines an upper ontology (general) that represents the context. Moreover, CONON is capable of being extended by adding a domain-specific ontology. The upper level ontology represents classes that express the context and situation. For example, it contains classes about the person, his location (indoor space and outdoor space) and his activity. These classes describe the contextual environment that surround the person. In addition, the ontology includes a class for computing devices such as applications and networks.

Fiend of a Friend (FOAF)[4] is an ontology used to describe a person, their activities and their relations with other people. It has classes that represent person (first name, family name), gender, age, education, organization, homepage, information about organizational project(s) they are involved in, culture, etc. As well, it includes personality trait classes that represent the Myers Briggs taxonomy as mentioned in section 2.2. In a machine-readable format people with European culture can be found, or people who know a certain person can be found. Figure 6 shows a part of the FOAF ontology that represents person name, email, home-page and a person he knows.

The **Provenance Ontology** [51] is built to initiate trust in published scientific content. Three classes provide the starting point: *Agent*, *Activities* and *Entities*. The agent could be people, an organization, or software- that produce activity of the data (entity). The activity can be data processing, like transforming data into a different format. By using Provenance Ontology, the history and the life cycle of a document can be obtained. Moreover, Provenance allows systems to exchange data considered to be compatible between them.

[4]http://www.foaf-project.org/

```
a foaf:Person ;
foaf:name "Jimmy Wales" ;
foaf:mbox
<mailto:jwales@bomis.com> ;
foaf:homepage
<http://www.jimmywales.com> ;
foaf:nick "Jimbo" ;
foaf:depiction
<http://www.jimmywales.com
/aus_img_small.jpg> ;
foaf:interest
<http://www.wikimedia.org> ;
foaf:knows [
a foaf:Person ;
foaf:name "Angela Beesley"
] .
```

Fig. 6. Example from FOAF Ontology.

4.2. Emotion Ontologies

Daily human communication carries many emotions [3] which can be expressed through text, facial expression, voice and body language. Emotion can also be influenced by contextual environment. A person expresses the same emotion in different situation (context), but with different intensity. In addition, emotion ontologies can describe general concepts. Such ontologies are called general ontologies. We categorized existing emotion ontologies into five domains as is shown in Figure 2.

4.2.1. Text Domain

A lot of work has been put into building ontologies that analyze and detect emotion from text. People express their emotions with words in formal and informal ways. Text in social media has different characteristics: users write in slang languages and often use abbreviations. Additionally, users express their emotions via emoticons. Emoticons show facial expressions which can be represented by a digital icon or a sequence of characters. Therefore, many ontologies were built to analyse text in social media. Other ontologies in the text domain were created for a particular purpose, focusing on international languages like English, Chinese, Japanese, French and Italian. Table 1 summarizes emotion ontologies in the text domain. The table contains columns displaying the ontology name, the goal, the classes reading emotion, the reused ontology and the lexicons/ language. It should be noted that some ontologies were not based on reused systems or lexicons/ language. As a result, some rows are empty in Table 1.

In analyzing informal text, an ontology was built to analyze the unstructured data inside posts about electronic products to understand online consumer behavior in the market [67]. An ontology based on emotion and languages in social media was created for text-mining purposes. One of the main classes in the ontology is *Sentiment*, with two subclasses: *Happiness* and *sadness*. Under each of the subclasses, related keywords are listed. For example, under happiness: enjoy, fun, eager and smiling. Under sadness: dislike, disappointed, bad and worst. Additionally, the ontology contains classes about products. The system is comprised of four modules: the ontology module, user query processing module, information foundation module and query analysis engine module. So, the ontology models the product with the associated emotion based on the social media posts. Then a user can utilize the system to make a query about the product with a specific emotion.

Another example is an ontology that gives a student the correct feedback in an e-learning session [1]. The ontology is divided into two main classes: *Emotion Awareness* and *Affective Feedback*. In emotion awareness the emotion is analyzed; however, in affective feedback, the appropriate feedback that a teacher would give to a student is determined. The emotion awareness class includes the different types of emotions (categorical model), moods (bored, concentrate, motivated, unsafe) and behaviors that students experience in e-learning environments. The emotion is detected throughout collaborative virtual learning processes, including textual conversations, debates and wikis. Moreover, the ontology includes the following classes: reading community (student, teacher) and object (e-learning activities).

Ontologies were introduced using languages other than English such as French, Japanese and Chinese.

In [44] an ontology was built to automatically annotate emotions in texts and determine their intensity. The French ontology classifies 950 words (600 are verbs and 350 are nouns) into 38 semantic classes according to their meanings. Words in the lexicon are emotionally labelled as positive, negative and neutral. NaviTexte was used to apply the ontology, which is a software designed for text navigation. It understands and applies knowledge to a specific text [11]. The goal of the ontology is to automatic annotate emotions in texts and to automatically navigate through the text.

Humans express emotions when something happens. Therefore, an ontology of emotion objects was introducing [59]. Emotion objects were collected from a large, Japanese blog corpus. An emotive expression lexicon for Japanese language was used to distinguish emotion words. The ontology was created using the Emotion Markup Language (EmotionML) annotation scheme, however, it was modified to meet the needs of Japanese language. The ontology classes represent emotion according to Nakamura's classification which is "a collection of over two thousand expressions describing emotional states collected manually from a wide range of literature" [58]. Also, emotion is represented by using a dimensional model. The ontology has other classes, such as number of character, part of speech and semantic categories. In the latter class, emotion objects were categorized into groups such as human activities and abstract objects.

To define emotion words and their intensity in Japanese, an ontology was proposed [38]. Emotion words were taken from websites such as Twitter and the intensity calculation was based on how many time an emotion word appeared in a document. The words were categorized into ten emotions: joy, anger, sadness, fear, shame, like, disgust, exciting, comforted and surprise. Moreover, the authors adapted their ontology into other emotion classifications which are positive, negative and neutral. The Pleasure-Arousal-Dominance theory was adapted as well. To represent the ontology, the authors used OWL and EmotionML. One of the applications that applied the ontology used a character generator. The system can receive voice inputs where the audio is translated to text and then analyzed by the emotion ontology. The output is a character with facial animations.

To analyze Chinese text, an emotion ontology for Chinese language was created [82]. It was semi-automatically created using HowNet. The ontology contains 113 emotion categories and was created by first extracting affective events from the dictionary. Then, emotions were manually assigned to the semantic role of the events, producing the Emotion Prediction Hierarchy. Finally, the Emotion Prediction Hierarchy was transformed to emotion ontology. This step involved assigning verbs extracted from the dictionary to the Emotion Prediction Hierarchy.

Table 1
Summary of emotion ontologies in the text domain

Ontology	Goal	Emotion Model	Ontology Reuse	Llexicons/Llanguage
[67]	Analyze the unstructured data	Discrete		
[1]	Give the student the right feedback in e-learning	Discrete Model		
[44]	Automatically annotate emotion in text	Discrete		
[59]	Analyze emotion in text	Discrete and Dimensional		Emotion Markup Language
[38]	Define emotion words and their intensity	Discrete and Dimensional		Japanese Emotion, Expression Dictionary, EmotionML
[82]	Analyze emotion in text	Discrete		HowNet
[68]	Annotate emotion in user generated content	Discrete and Dimensional	Lemon, Provenance Ontology	EmotionML, WorNet-Affect
[60]	Represent the structure and the semantics of emoticons	Discrete		

For advanced emotion analysis, Onyx ontology was presented [68]. It offers a comprehensive set of tools for any kind of emotion analysis. Onyx reuses Provenance Ontology and is incorporated with LEMON model. In Provenance Ontology, the activity is an emotion analysis, which means turning plain data into semantic emotion information. Onyx ontology has a class called *Emotion Analysis* that is responsible for representing information about the information source, such as the website, the algorithm used as well as the emotion model. The *Emotion Set* class contains information about a group of emotions found in text, the person expressing the emotion, the domain, information about the original text and the sentence(s) that contains the emotion. Furthermore, the *Emotion* class contains information about the emotion model, appraisal, action tendency and emotion intensity. To support the annotation process, WorNet-Affect and EmotionML were used. A test on the ontology was carried out in order to evaluate. Two different testing scenarios were created: making queries against the ontology, and translating EmotionML resources to Onyx and vice versa.

Users of social media express their emotions using emoticons. An ontology to represent the structure and the semantic meaning of emoticons was presented [60], which allows an application to understand and utilize emoticons. Moreover, it allows applications to exchange emoticons with the right interpretation. The ontology design is based on Smiley Layer Cake [5]. This model consists of three layers: the bottom layer that deals with the message between the sender and the receiver called *Underlying Emotion*; the second layer is the *Structure* of the emoticon, representing which emoticon(s) the message contains, such as text, face or object. The top layer, *Visual Appearance*, describes the appearance of the emoticon, such as its color and whether it is animated or not. The core class of the Smiley Ontology is the *Emoticon* class, which represents the concept of an emoticon. Emoticons can be visually represented as a sequence of characters, a picture, or both. Each different system has its own set of pictures that represent emoticons. The ontology has a class named *Emoticon System* that contains all possible pictures for the emoticons generated from a social software tool. Emoticons represent emotions, therefore Smiley ontology has a class about *Emotion*.

[5]http://www.slideshare.net/milstan/beyond-social-semantic-web

4.2.2. Facial Expression Domain

A study indicated that emotional facial expression makes up 55% of our communications [3]. Emotion is expressed in humans by facial movement. For example, when a person is surprised, he opens his mouth and raises his eyebrows. Table 2 summarizes emotion ontologies in the facial expressions domain.

An emotion ontology was created to support the modeling of emotional facial animation expression within MPEG-4 in virtual humans [27]. Human actions translate into a virtual world through avatars by using an ontology. A virtual world (environment) is a computer-graphic-based environment generating the impression that users are in a different place than their actual location [19]. The ontology allows storing, indexing and retrieving the right information about facial animation that allows the representation of a given emotion. The ontology defines the relationships between facial animation concepts standardized in the MPEG and emotions. The ontology conations classes regarding: *Face*, *Face Animation*, *Face Expression*, *Emotion* and *Emotion Model* (Ekman, and Plutchik model). In addition, a facial animation parameters class was used. To use the ontology and extract the right information for a specific emotion, Racer Query Language interface for OWL was used [5]. This query language is close to natural language. For example, we can query the following question: What is the facial animation for expressing the depressed emotion?

Another ontology was proposed within a framework (Nonverbal Toolkit) for the cooperation of heterogeneous modules that gather, analyze and present nonverbal communication cues [32]. The aim of this framework is to gather nonverbal behaviour in the real world and represent it in a virtual environment, such as avatar and second life. To ease the communication and the exchange between the modules, an ontology was develped. The ontology can define shared vocabularies that can be understood and used by all modules. It represents emotion by using a categorical approach (Ekman Model) as well as complex emotions, which are a mix of more than one simple emotion. For good representation of the nonverbal communication cues level in the virtual environment, emotion intensity must be determined. Therefore, the ontology represents the emotional intensity. Moreover, the affective states are derived partially from personality traits. Human personality affects the expressed emotion and its intensity.

In the e-learning domain, an ontology for predicting students learners' affect (OLA) [20] was introduced. The ontology is based on the OCC model of emotions. An interactive application was designed to estimate student emotions when interacting with a quiz about Java programming. The application monitors and records student action when answering questions and saves them in the student's log file. For example, when the student does not answer a question correctly, the event status becomes confirmed and appreciation is set as disliking. On the other hand, when the student answers a question correctly, appraisal become desirable. So, the log file data is input for the ontology to compute the OCC model variables that predict student emotion by using ontology inference. Students may express different emotions while answering a single question. Therefore, student's emotions were studied: when the students see the question for the first time, when the students choose the answer, and when the correct answer is displayed.

4.2.3. Voice Domain

Emotion can be detected from voice by analyzing the change in voice tone, volume, rate, pitch, and the pause time between words [24]. In voice emotion extraction, the EmoSpeech system was built to convert unmarked input text to emotional voice. The developed emotion ontology (OntoEmotion) is organized in a taxonomy that covers-up the basic emotions to the most specific emotional categories [24]. OntoEmotion is presented in English and Spanish.

The emotion class in the ontology represents the categorical model. Moreover, it represents the specific words each language offers for denoting emotions in the class named *Word*. To classify the word in English and Spanish, the class Word has two subclasses: *English Word* and *Spanish Word*. Moreover, the ontology defines a class for emotion synonyms. The emotion concepts were linked to three emotional dimensions: Evaluation, Activation and Power. This model were created by Osgood et al. as mentioned in section 2.

All of these properties are numeric data. The system uses Emotag, which is a tool for automated mark-up of texts with emotional labels. When the system detects text as input, Emotag marks up the text with the three emotional dimensions. These values are the input for the ontology. Then, the ontology classifies the input under an emotional concept. Then, the text is read

Table 2
Summary of emotion ontologies in the facial expression domain

Ontology	Goal	Emotion Model
[27]	Model emotional facial expressions in virtual environments	Discrete and Dimensional
[32]	Represent nonverbal behaviour in virtual environments	Discrete
[20]	Predict students' emotions during e-learning	OCC

aloud with the emotion assigned by EmoTag to the sentences. For instance, Emotag was applied on fairy tale stories in English and Spanish to annotate emotions [25].

Another application was designed to extract rich emotional semantics of tagged Italian artistic resources over an ontology method [6]. To select the tags that contain emotional content, several Semantic Web and natural language processing tools were incorporated such as multilingual lexicons (MultiWordNet) and affective lexicons (WordNet-Affect, and SentiWordNet). The software uses OntoEmotion because it has a taxonomic structure that reflects psychological models of emotions and is implemented by using Semantic Web technologies. However, the ontology was enhanced by adding a new subclass named *Italian Word* to the root concept Word.

Table 5 summarizes individual ontologies from the following domain: Emotion Voice Domain (OntoEmotion), Emotion Body Expression Domain, mood (COMUS) , and need (FHN).

4.2.4. Body Expressions Domain

Human body expressions can convey emotions. In [26] an ontology to represent body gestures in Virtual Humans within MPEG-4 is presented. Animations were annotated with emotional information. Whissel's wheel model of emotion was used in the ontology. Because of the complexity of body expression, gestures were associated with emotions. For example, hand clapping was associated with joy and excitement. In the ontology, seven gestures were tested and mapped to Whissel's wheel model of emotion. To use the ontology, a query with natural language was used. For example, a query can be made about the animations that express joy.

4.2.5. Contextual Environment Domain

Analyzing emotions within context gives an insight to the relationship between an emotion and its cause. Table 3 summarizes emotion ontologies in the contextual environment domain.

An ontology to represent the affective states in context aware applications was generated [8]. It expresses the relationship between affective states and other contextual elements such as time and location. The ontology is built based on the existing ontology CONON. An *Emotion* class (state) uses Ekman's basic emotions. In addition, the *Secondary* class contains emotion that is related to the intentional scenario. The ontology was applied in a visit to an art museum. Therefore, the secondary emotions are: relaxed and stressed. Furthermore the ontology represents the most powerful emotion (dominant). Object properties were used to express the relation between emotions and context elements. The ontology was applied in a museum context, where a person moves from one room to another. By using the ontology, emotions were monitored and the relation between the affective states was expressed as well as the relation between the affective states and other contextual elements.

The ontology in [40] was built based on the previous ontology [8]. However, emotion was defined by three possible data type properties: positive, negative and neutral.

Another ontology (BIO_EMOTION) recognizes emotion based on the user's electroencephalographic (EEG) and bio-signal features, as well as the situation and environmental factors [83]. Additionally, it supports reasoning about the user's emotional states. The focus of the ontology is the mapping between low-level biometric features and high-level human emotions. It defines inference rules by using corresponding relationships between EEG and emotions. The BIO_EMOTION ontology consists of 84 classes and 38 properties. The *Emotion* class defines user affective states. Emotions were represented by: Ekman's discrete model and the dimensional Circumplex model. User context was represented by The *Situation* class such as location, time and event. Demographic information was integrated in the ontology such as: name, age, and gender. Additionally, a class to represent bio signals is provided. The machine learning software WEKA was used to gener-

Table 3
Summary of emotion ontologies in the contextual environment domain

Ontology	Goal	Emotion Model	Ontology Reuse
[8]	Represent the affective states for context aware applications	Discrete	CONON
[83]	Recognize emotion based on the user's biomedical factors and environment	Discrete and Dimensional	

ate IF-THEN statements in the reasoning process [6]. To evaluate the ontology, the DEAP dataset is used, which is a database for emotion analysis using physiological signals [39].

4.2.6. General Domain

General ontologies were proposed to recognize emotion. General ontologies are called upper level ontologies. They define the general concept that are the common in a domain. These kinds of ontologies can be extended according to the developer's purpose by defining domain-specific classes, or they can be linked to existing domain-specific ontology. Table 4 summarizes emotion ontologies in the general domain.

A high-level ontology named Human Emotions Ontology (HEO) was developed to annotate emotion in multimedia data [29]. The main class in the ontology is *Emotion* which is expressed in dimensional and categorical models. An emotion has an intensity, appraisals and action tendencies, and it can be expressed through face, text, voice and gesture. All the previous features were represented in the ontology. Additionally, the ontology represents classes regarding the multimedia content and the annotator of the media. The *Annotator* class has two subclasses: *human* or *machine*(automatic annotated). Since the emotion is expressed by a person, HEO reuses the Friend Of A Friend (FOAF) ontology. A subclass *observed person* of class person was created in FOAF and connected to class *Emotion* in HEO. Moreover, some object properties were added in FOAF that are relevant to emotion such as age, culture, language and education.

The Semantic Human Emotion Ontology (SHEO) [2] was built based on HEO to identify complex emotions that composed of two or more simple emotions. For instance, Contempt (Complex emotion) is the combination of two basic emotions: Anger and Disgust. Software was designed to use the ontology for analyzing simple and complex emotions in text. Moreover, it detects emotions in images.

In the general context, an ontology to describe emotional cues at different levels of abstraction was proposed [53]. The concepts are gathered into three modules to detect emotion. Emotion is represented by a categorical and dimensional model. Emotional cue can be simple or complex which are represent in the emotional cue module. The simple cue can be expressed through: facial expressions, gesture and speech. However, complex emotional cues mix two or more simple cues. Finally, the media module describes the properties of the emotional cues.

4.3. Mood Ontologies

Mood can affect a person's daily life choices. Building ontologies that can match person's mood with their desires allows for greater satisfaction. Often, people choose music to listen to based on their mood.

A recommendation-based music system was built with the Context-based Music Recommendation (COMUS) ontology to retrieve music in a semantic way [74]. The ontology reasons about the user's mood, situation and preferences. The COMUS Ontology is supported by many ontologies such as FOAF. Some classes in COMUS are similar to the FOAF ontology such as the person class that includes personal information. It consists of classes concerning the *Person*, their *Mood* and the *Music*. The *Person* class defines general personal properties such as: name, age, gender and hobby. In addition, the ontology represents the user context such as:

[6] http://www.cs.waikato.ac.nz/ml/weka/

Table 4
Summary of emotion ontologies in the general domain

Ontology	Goal	Emotion Model	Ontology Reuse
[29]	Annotate emotion in multimedia data	Discrete and Dimensional	FOAF
[53]	Describe emotional cues	Discrete and Dimensional	
[2]	Identify complex emotions in text	Discrete and Dimensional	HEO

event, time and location. The *Mood* class use a discrete model. Each mood class has a sub-class of mood similarity. For example, aggressive is similar to hostile, angry, etc. The other classes are domain-specific and related to music. Users can ask the music recommender system to find songs based on their mood. The system uses the ontology to deliver the appropriate music to them.

4.4. Needs Ontologies

Understanding and conceptualizing human needs leads to meet human satisfaction. Building ontologies that define human needs through vocabulary and relationships allows to build systems that can automatically interpret and serve human needs.

The Fundamental Human Needs ontology (FHN) was introduced to express the relationship between various needs and their satisfiers [17]. The ontology is based on the needs model by Max-Neef. The ontology represents the *Agent* and his or her *Role*, Need and Satisfier. A person can play different roles, and each role requires different satisfiers. For example, when a person is at home they need different satisfiers than when they are at work.

5. Conclusions

This paper surveys existing ontologies in human affective states (emotion and mood) and their influences (personality, needs and subjective well-being). Many emotion ontologies currently exist, though there are few that accommodate mood and human influence. There is great devotion in building ontologies to detect and annotate emotions. Emotions can be expressed in many ways such as in text, voice, facial expressions, and gestures. However, there should be considerations to mood and human influences.

Subjective well-being reflects human life satisfaction. Human life satisfaction can lead to positive emotion and good moods. After exploring existing ontologies, and to the best of our knowledge, we did not find ontologies regarding subjective well-being.

With regard to personality, the Friend OF A Friend ontology includes the Myers Briggs (MBTI) personality theory in its ontology. Although MBTI is a popular personality theory, it is only used in the training world such as business. The Big Five personality model is used in the academic research area. Consequently, the Big Five personality theory should be presented in a digital format more often.

Existing emotion ontologies display many similarities regarding the language, their classes and the Psychological theory that have been adapted. OWL language is common in many ontologies such as in [38], and [27].

The Ekman theory was adapted in many ontologies such as [77], [27], and [32]. This theory consists of the basic emotions. It can be helpful to analyze facial emotion expressions. The OCC model is a popular model in the computer science area. It take into consideration the event and the causes. Hence, it is a valuable model to track the shift of human emotion when an event take place, such as in an E-learning scenario. The dimensional emotion model plots emotions with multiple dimensions. As a result, it can show the variances of these dimensions for different persons within the same emotions. For example, two persons with the same emotion "happy", can have different numbers for each dimensions.

Existing ontologies were built to serve different languages such as English, Chinese, Japanese, French and Italian. An interesting observation is the existence of multilingual ontologies such as OntoEmotion. A multilingual ontology supports the collaboration and exchange of knowledge between experts in the same domain who speak different languages. Multilingual on-

Table 5
Summary of individual ontologies that do not fit into the domains of the other tables

Ontology	Goal	Model	Domain
OntoEmotion [24]	Convert unmarked input text to emotional voice	Discrete and Dimensional	Emotion Voice Domain
[26]	Represents body gestures in Virtual Environment	Dimensional	Emotion Body Expression Domain
[74]	Retrieve music in a sematic way	Discrete	Mood
[17]	Express the relationship between various needs and their satisfiers	Manfred Max-Neef	Need

tologies can be built by mapping (alignment) different ontologies that were created with different languages.

Ontology mapping can be seen as a reusing process, which is one of the benefits of building ontologies. Mapping can be managed by using a multilingual dictionary such as WordNet. Several projects have modified WordNet for the use with different languages. In the mapping process, the main step is finding semantic relations between concepts in different ontologies. Building a multilingual ontology allows for the building of multilingual applications that omit the language barrier. As a result, more users will be attracted to this kind of application [16], [75]. Many domains will be benefit from multilingual ontologies such as the medical domains. Physicians can make sure that they are talking and referring to the same concept in multiple languages. Social media application can benefit from a multilingual ontology since the users have different languages.

Creating a general emotion ontology that covers all the general emotions vocabularies can ensure unified terminologies and language [7].

As a result, greater and clearer communication can occur between humans, systems and applications. This general ontology can be extended based on the application and purpose of use.

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