Developing New Software to Analyze the Emo-Sensory Load of Language

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Abstract Technology plays a crucial role in fully understanding all aspects of language and uncovering the hidden patterns, such as sense and emotion density in texts. Yet, it seems that remarkable attention has not been paid to the sensory and emotional loads of learning texts as the primary source of learning. This study attempts to present an objective way of analyzing English learning texts from both emotional and sensory perspectives to provide material developers to measure the emotional and sensory loads of the texts. For this purpose, a new kind of software was developed using two datasets; Sensicon and EmoLex. Then as an example, an English course book series, Interchange (5th ed.), was analyzed by this software to determine any probable pattern(s) concerning sensory and emotional loads. The results showed that the dominant sense in these books is hearing at all levels of language proficiency. In the emotion analysis part, the eight basic emotions were categorized as positive and negative emotions, and the results showed a higher frequency of positive emotions. It was also found that the frequency of negative emotions increases at higher levels, resulting in more authenticity.

Keywords: Sense analysis, Emotion analysis, Emotioncy pyramid, Sensory load, Emotional load

1. Introduction

Language as the primary means of communication has some unknown features and aspects that would not be fully understood if we did not use technology. Advances in technology in recent decades have led to the emergence of new sciences such as data mining and its subsets like text mining, emotion mining, and corpus linguistics. Simultaneously, researchers in different fields, especially in language learning and processing, worked on various aspects of language, including sense and emotion. For example, Rodriguez-Esteban and Rzhetsky (2008) showed the dominance of a sense-deprived style in biomedical texts by analyzing more than 250000 articles. Moreover, individuals’ perspectives of reality and outlook on the future can be influenced by their emotions and sensory inputs from their surroundings (Pishghadam & Shayesteh, 2016). Existing senses are primarily responsible for their connections to themselves, other persons, and other organisms (Pishghadam & Shakebaee, 2020). Therefore, Pishghadam and Shayesteh (2017) presented the idea of emo-sensory intelligence (ESQ) to underscore the role of sense and emotion in life. In addition, Gross (1992, p. 139) believed that "we can accelerate and enrich our learning, by engaging the
senses, emotions, imagination". In another study, Pishghadam, Adamson, et al. (2013) accentuated the emotional abilities of second/foreign language learners, proposing the idea that emotional involvement enhances language learning.

These studies demonstrated the special place of sense and emotion in effective communication, requiring more studies to be done. It seems that to evaluate and use sense and emotion systematically in language use, the existence of an objective system to detect and measure them for better analysis is indispensable. Due to advances in data analysis and text mining, it is possible to measure and quantify the sensory load of words and detect their emotion(s). With that in mind, this study introduces a new way to measure the emo-sensory load of texts by developing software and then analyzing the emo-sensory load of an English learning textbook series to find out any probable pattern in their emotion and sense.

2. Theoretical Framework

2.1. Sense, Emotion, and Cognition

Understanding the world through sensory information coming from our sensory organs has been a significant issue for a long time (Tekiroğlu et al., 2014). Senses are classified into five categories dating back to Aristotle, namely sight, hearing, smell, taste, and touch, and they can be considered human beings' information channels that connect us to the outside environment. These channels are not separated, and the flow of various stimuli that sensory organs receive are integrated, aiding us in constructing representations of the external environment in our mind (Pishghadam & Shayesteh, 2017). Multisensory integration in adults is the result of an emergent, experience-driven process (Werchan et al., 2018).

According to the recent findings in neuroscience, the senses have a vital role in constructing adaptation of self by interacting with the emotional and cognitive processes (Bernard, 2016). Because various multisensory inputs must be consistently integrated and adequately segregated to produce coherent perceptual representations, this offers a basic difficulty for cognitive, perceptual, and motor systems. In other words, multisensory processes are crucial for perception, cognition, learning, and behavior; they are pervasive and necessary for forming and maintaining correct perceptual and cognitive representations. (Murray et al., 2016). Our existing knowledge and experience are used unconsciously while interpreting sensory data to build a private experience (Bernstein et al., 2010). Life quality and emotional well-being are generally affected by sensory functions combined with emotional and cognitive reactions (Thomson et al., 2010). These help us better understand the surrounding environment (Dunn, 2000). It should be mentioned that in the absence of sensory experiences, it may be difficult to improve long-term memory (Tabata Bacae Farani et al., 2019), since the assessment of sensory loads will be challenging (Akbari, 2020), and the presentation of ideas may rely mostly on verbal connections (Shayesteh, 2019).

Concerning emotions, there are eight basic and prototypical emotions, including joy, sadness, anger, fear, trust, disgust, surprise, and anticipation (Kellerman & Plutchik, 1980). These basic emotions can be naturally paired with opposites, and complex emotions can be considered as a combination of these emotions (Mohammad & Turney, 2010). Emotions and senses are interweaved and affect each other mutually (Pishghadam & Shayesteh, 2017). Daily experiences show that recalling events or items with emotional information is better and more detailed than those without emotional information (Conway, 1990; Ochsner, 2000). Senses and emotions are connected forever (Heller, 2002), but the way of their connection is yet a matter of debate.

Pishghadam and Shayesteh (2017) introduced emo-sensory intelligence (ESQ → emotional sensory quotient) as a new type of intelligence that outweigh a simple combination of emotional intelligence (EQ) and sensory intelligence (SQ). In ESQ, a combinatory approach is used, and the focus is on the value of sense-induced emotions as the by-product of direct sensory interactions with the outside world, while in EQ, the pure emotions are highlighted without considering the sensory origins, and in SQ, just sensory experiences are emphasized aside from the resultant emotions. ESQ explored the close
relationship between sense and emotion, which is in line with the findings of Vuilleumier (2005) and Sacco and Sacchetti (2010) that emotions cultivate sensory cortices.

2.2. Emotioncy

Although there is no single universally accepted definition of emotion, there is a significant agreement that emotion is an “affective reaction that changes the way of thinking, behaving and expressing” (Pishghadam et al., 2016, p. 2). Pishghadam, Adamson, et al. (2013) accentuated the emotional abilities of second/foreign language learners, especially those related to their experiences in the first language (L1), and proposed the idea that emotional involvement enhances language learning. Their theory originated from Greenspan’s model of L1 acquisition, Developmental, Individual difference, and Relationship-based (DIR) model. They claimed that there are various levels of sense-induced emotions, technically called emotioncy (emotion + frequency), toward different items of a language for learners depending on whether they have heard, seen, smelled, touched, experienced, or done research on that particular item. Emotioncy asserts that individuals can construct an idiosyncratic understanding of the world through their senses (Pishghadam, 2015). The concept is developed by presenting a six-level emotioncy model (Pishghadam, 2015) with different kinds and various measures of emotioncy: “Null emotioncy (0) (i.e., Avolvement); Auditory (1), Visual (2), and Kinesthetic emotioncy (3) (i.e., Exvolvement); and Inner (4) and Arch emotioncy (5) (i.e., Involvement)” (Jajarmi & Pishghadam, 2019, p. 211). Table 1 clarifies emotioncy types and kinds.

Table 1

<table>
<thead>
<tr>
<th>Type</th>
<th>Kind</th>
<th>Experience</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avolvement</td>
<td>Null emotioncy</td>
<td>When an individual has not heard about, seen, or experienced an object</td>
</tr>
<tr>
<td></td>
<td></td>
<td>or a concept.</td>
</tr>
<tr>
<td>Exvolvement</td>
<td>Auditory emotioncy</td>
<td>When an individual has merely heard about a word/concept.</td>
</tr>
<tr>
<td></td>
<td>Visual emotioncy</td>
<td>When an individual has both heard about and seen the item.</td>
</tr>
<tr>
<td></td>
<td>Kinesthetic emotioncy</td>
<td>When an individual has touched, worked, or played with the real object.</td>
</tr>
<tr>
<td>Involvement</td>
<td>Inner emotioncy</td>
<td>When an individual has directly experienced the word/concept.</td>
</tr>
<tr>
<td></td>
<td>Arch emotioncy</td>
<td>When an individual has done research to get additional information.</td>
</tr>
</tbody>
</table>

To lighten the heavy load of vocabulary learning, Pishghadam, Tabatabaeian, et al. (2013) presented an emotion-based L2 teaching approach, based on Greenspan’s DIR, considering the L1 emotions that learners carry. They believed that “words bearing higher emotional responses would be acquired faster and also more easily than words bearing lower emotional responses” (Jajarmi & Pishghadam, 2019, p. 6).
The semantic aspect of language, "word", and the pragmatic aspect of language, "world", are simultaneously acquired during L1 acquisition. At the same time, in L2 learning, an individual only lacks the appropriate "word" because s/he possesses the "world" information from their L1. Due to this, the equivalent of L1 vocabulary items, having the emotional background knowledge, are learned better than new L2 vocabularies without L1 equivalent (Pishghadam, Adamson, et al., 2013).

Figure 2

*Educational Emotioncy Pyramid* [Adopted from Pishghadam, 2016, p. 9]

Figure three illustrates the educational emotioncy pyramid in which the senses that are engaged in each stage, Avolvement, Exvolvement, and Involvement are illustrated (Pishghadam, 2016). According to that, going from Exvolvement to Involvement, learners are engaged in more senses besides hearing until all senses are engaged in involvement. In fact, teachers are seen as envolvers, who may assist students in increasing their levels of emotioncy (Pishghadam et al., 2019).

2.3. Automatic Association of Senses with Words

To have a dataset in which the association degree of words can be determined, Tekiroğlu et al. (2014) adopted a computational approach including two phases; in the first phase, they generated a sufficient number of sensory seed words. They employed the bootstrapping strategy and generated these numbers of sensory seed words from a small set of the manually selected seed of sensory words. In the next stage, they performed a corpus-based probabilistic method to estimate the association degree of words to build a larger lexicon.

The first stage, as Tekiroğlu et al. (2014) declared, in the process of the lexicon construction relates to collecting sensorial seed words; the words relate directly to five senses, for example, tasty and sound. To have such a collection, they used the FrameNet (Baker et al., 1998), a lexical dataset that is constructed upon semantic frames based on the idea that the meaning of words can be understood according to a semantic frame. Semantic roles named frame elements that constitute semantic frames are manually annotated in approximately 170,000 sentences.

Since FrameNet includes syntactic features of sensational and perceptional concepts as well as semantic roles, they used this dataset to collect the sensational seed words. They determined manually 31 frames that were highly connected to senses like Hear, Temperature, and color and then asked three annotators...
to specify the senses that are associated with the lemma-POS pairs evoking the collected frames. At the end of this task, all pairs (i.e., 277) were collected with 100% agreement to construct their initial seed set containing 277 lemma-POS pairs associated with their special sense, such as verb click with its specific sense hearing, the nouns glitter and aromatic with sight and smell respectively.

The next step in their study would be expanding the seed list that emerged in the previous step from FrameNet by bootstrapping approach. For this purpose, they utilized an approach similar to the approach of Dies et al. (2014), in which a repetitive semantic expansion model was used. Figure 2.5 provides an overview of the bootstrapping process. Then they used some NLP techniques to validate their dataset by using FrameNet.

![Diagram](https://example.com/diagram.png)

**Figure 3:**
*Bootstrapping Procedure to Expand the Seed List [Adopted from Tekiroğlu et al., 2014, p. 1514]*

After extending the word lists and classifying them into five categories, representing the five senses, Tekiroğlu et al. (2014) used Pointwise Mutual Information (PMI) concept in text mining to determine the association degree of words with the five categories. PMI can be described simply as an associate degree of two events; if two events are assumed to be independent, the ratio of the probability of the co-occurrence of the two events to their individual probabilities (Church & Hanks, 1990). PMI can be used as a semantic similarity measure and can be calculated as:

$$\text{PMI} (x, y) = \log \left( \frac{p(x, y)}{p(x)p(y)} \right)$$

Since the serious problem of PMI is its sensitivity to low-frequency data (Bouma, 2009), they introduced Normalized Pointwise Mutual Information (NPMI) as a possible solution to mitigate the problem of PMI. NPMI normalizes the PMI values to the range (-1, +1) with this formula:

$$\text{NPMI} (x, y) = \frac{\text{PMI} (x, y)}{-\log p(x, y)}$$

Finally, they used this formula and calculated the scores for each candidate word and five senses events in their corpus and constructed Sensicon, which includes 22,684 lemma-POS pairs and a figure for each sense class that shows the association degrees.
2.4. Emotion Evaluation

As already mentioned, emotions are often expressed through different facial expressions. Different emotions can be expressed through different words as well. Mohammad and Turney (2010) have some examples: “For example, delightful and yummy indicate the emotion of joy, gloomy and cry are indicative of sadness, shout and boiling are indicative of anger, and so on” (p. 2). They conducted a study to find out how emotions manifest themselves through words in language. They described an annotation project in order to create a large lexicon of term-emotion association, term can be either a word or a phrase. In this lexicon, each entry has a term, an emotion and a scale indicating how strongly the term is associated with the emotion. The emotion evoked by a phrase or sentence is not simply the sum of emotions conveyed by the constituent words. However, the emotion lexicon can be a useful element for complicated emotion detection algorithms required for a lot of applications described in the following. This lexicon can be useful as a suitable scale for evaluating automatic ways that introduce the emotions associated with a word. These automatic methods may then be used to fill the gap in languages by generating emotion lexicons where no such lexicon exists. There are a few limited-coverage lexicons for a handful of languages, for example, the WordNet Affect Lexicon (WAL) (Strapparava & Valitutti, 2004), the General Inquirer (GI) (Stone et al., 1966), and the Affective Norms for English Words (ANEW) (Bradley & Lang, 1999).

3. Methodology

3.1. Materials

To use the software, Interchange books (Richards, et al., 2017a, 2017b, & 2017c) were analyzed and categorized into three groups, levels one, two, and three. Since the number of words in the Intro book of Interchange is limited, the first and second books of Interchange were considered as level one, book two as level two, and book three as level three in this study.

3.2. Procedure

To develop a reliable tool to measure the emo-sensory load of English texts, we needed a tagger and two datasets, one for determining the sense number of words, sense dataset (Sensicon), and the other one for detecting their emotion(s), emotion dataset (EmoLex).

In this study, the UCREL CLAWS5 tagger (C5) from Lancaster University was used to annotate the texts, and the sense dataset was the one developed by Tekiroğlu et al. (2014) and represents the degree of sense association of words with the five senses for approximately 22000 English words. In other words, this dataset presents five figures for each word illustrating the association degree of that word.
with sight, hearing, taste, smell, and touch senses, respectively. It is worth mentioning that these figures for each term are between -1 and +1 in the logarithmic scale with a base of 2. To interpret the figures, we consider that Zero, in the logarithmic scale, means that there is no association between the word and that sense. In contrast, minus figures represent a positive association degree between zero and one on the arithmetic scale, and positive figures show an association degree of more than one. To have a more concrete image of this association in the results of the present study, we converted the figures of this dataset to the arithmetic scale before processing. The parts of speech of each word are signed in front of that word, and it would be a great help in programming the software. Each word has a dominant sense that its sensory load is more than the other senses, and, in this study, the dominant sense of each word is taken.

The other dataset used in this inquiry is the emotion dataset developed by Mohammad and Turney (2010), in which they detect the emotion(s) of words. It includes approximately 14000 words, and each word might have more than one emotion. This dataset was developed based on the eight basic emotions, including trust, disgust, anger, fear, anticipation, surprise, joy, and sadness.

Both datasets annotate their words and determine the parts of speech of them so to use the information of sense and obtain the related figures to each word; first, the texts should be annotated. As mentioned before, the Lancaster tagger, UCREL CLAWS5, is used in this study.

The EmoLex figures consider if a word has the association with one of the eight basic emotions, it gets figure ’1’ below that emotion; otherwise, it gets ’0’. Unlike the Sensicon, in EmoLex, figures do not show the intensity or degree of association with special emotion, but they just represent the existence or lack of association of that word with that emotion through the ’0’ or ’1’ dichotomy.

To analyze the texts using these two datasets, we designed and developed special software. This software was designed by C# programming language to show the sensory load of each text and detect the emotions used in a text as well and is named Word Sense Analyzer, WSA. In the software, two separate windows are used to analyze two different texts simultaneously. There are result windows at the top of each window in which the sensory and emotional loads of texts are shown. They are defined as the ratio of the sum of figures of words in a special sense to the word numbers in the texts presented in percentage (Appendix 1).

Before tagging, the texts passed the pre-processing stage, where any extra space or sign should be omitted to be readable for the machine. The tagger of Lancaster University was used to make the texts readable for the software. The output of the tagger can be used as the input of the software, and then the results would be ready to be used by the user. To choose an online English Tagger, there are some choices, but the tagger of Lancaster is selected because of its accessibility and user-friendliness. There is also the possibility of annotating texts with a length of less than one hundred thousand words for free.

4. Results

The annotated texts were analyzed by WSA software, and the following results are the output of the software:

4.1. Sensory Analysis

Table 2 shows the sum of sensory loads of words for each sense in the four Interchange books.

<table>
<thead>
<tr>
<th>Level/Sense</th>
<th>Sight</th>
<th>Hearing</th>
<th>Taste</th>
<th>Smell</th>
<th>Touch</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intro</td>
<td>271</td>
<td>433</td>
<td>292</td>
<td>69</td>
<td>264</td>
</tr>
<tr>
<td>1</td>
<td>453</td>
<td>698</td>
<td>352</td>
<td>110</td>
<td>457</td>
</tr>
<tr>
<td>2</td>
<td>604</td>
<td>851</td>
<td>384</td>
<td>110</td>
<td>488</td>
</tr>
<tr>
<td>3</td>
<td>545</td>
<td>906</td>
<td>306</td>
<td>80</td>
<td>408</td>
</tr>
</tbody>
</table>
Then, these figures were divided by the number of words in each book, and the results are shown in percentage in Table 3.

Table 3
Sensory Loads of Interchange Books in Percentage

<table>
<thead>
<tr>
<th>Level</th>
<th>Sight</th>
<th>Hearing</th>
<th>Taste</th>
<th>Smell</th>
<th>Touch</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intro</td>
<td>9.38%</td>
<td>14.98%</td>
<td>9.08%</td>
<td>2.41%</td>
<td>9.13%</td>
<td>44.98%</td>
</tr>
<tr>
<td>1</td>
<td>9.64%</td>
<td>14.83%</td>
<td>7.49%</td>
<td>2.35%</td>
<td>9.72%</td>
<td>44.03%</td>
</tr>
<tr>
<td>2</td>
<td>10.76%</td>
<td>15.16%</td>
<td>6.84%</td>
<td>1.96%</td>
<td>8.69%</td>
<td>43.41%</td>
</tr>
<tr>
<td>3</td>
<td>10.28%</td>
<td>17.07%</td>
<td>5.76%</td>
<td>1.52%</td>
<td>7.7%</td>
<td>42.33%</td>
</tr>
</tbody>
</table>

The strongest sense in all levels is hearing, which is increasing from just under 15% (the ratio of the sum of the association degree of the dominant senses of words to the word number in each text) in level 1 (elementary), to just over 15% in level 2 (intermediate), to 17% in level 3 (advanced). The weakest sense in all levels is the smell, decreasing from approximately 2.5% to 2% to 1.5%, going from elementary to advanced one. The second strongest sense in all levels is sight that it does not have any specific trend across different levels. Touch and Taste senses are in third and fourth places among the other senses in all levels, decreasing from level 1 to level 3.

All in all, by going from elementary levels to advanced levels, while a load of hearing sense is increasing, loads of touch, taste, and smell senses are decreasing. The sensory load of sight is almost the same.

4.2. Emotion Analysis

The emotion analysis of materials in this study is not quantized and does not show the grade of special emotion in a word. Still, it just shows the dominant emotion of a word without determining the grade of that, according to EmoLex. In other words, it tells the existence of a type of emotion in a word as its dominant emotion and does not show its degree.

The annotated texts of each Interchange book were entered into WSA software, developed in this study to analyze their emotional loads of them. Tables 4 and 5 show the results for each book. To have comparable data with other series analyzed in this study, Intro book and book 1 were categorized as level one, book 2 as level 2, and book 3 as level 3. The results of the emotional loads of these levels are presented in Tables 6 and 7.

Table 4
Positive Emotions in Interchange Books

<table>
<thead>
<tr>
<th>Level/Emotion</th>
<th>Trust</th>
<th>Joy</th>
<th>Anticipation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intro</td>
<td>96(3.32%)</td>
<td>130(4.49%)</td>
<td>83(2.87%)</td>
</tr>
<tr>
<td>1</td>
<td>135(2.87%)</td>
<td>130(2.76%)</td>
<td>137(2.91%)</td>
</tr>
<tr>
<td>2</td>
<td>199(3.54%)</td>
<td>175(3.11%)</td>
<td>172(3.06%)</td>
</tr>
<tr>
<td>3</td>
<td>206(3.88%)</td>
<td>152(2.86%)</td>
<td>162(3.05%)</td>
</tr>
</tbody>
</table>

Table 5
Negative Emotions in Interchange Books

<table>
<thead>
<tr>
<th>Level/Emotion</th>
<th>Anger</th>
<th>Disgust</th>
<th>Fear</th>
<th>Sadness</th>
<th>Surprise</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intro</td>
<td>12(0.41%)</td>
<td>14(0.48%)</td>
<td>29(1%)</td>
<td>25(0.86%)</td>
<td>59(2.04%)</td>
</tr>
<tr>
<td>1</td>
<td>33(0.7%)</td>
<td>27(0.57%)</td>
<td>60(1.27%)</td>
<td>46(0.98%)</td>
<td>48(1.02%)</td>
</tr>
<tr>
<td>2</td>
<td>65(1.16%)</td>
<td>49(0.87%)</td>
<td>100(1.78%)</td>
<td>107(1.9%)</td>
<td>85(1.51%)</td>
</tr>
<tr>
<td>3</td>
<td>68(1.28%)</td>
<td>47(0.88%)</td>
<td>99(1.86%)</td>
<td>86(1.62%)</td>
<td>73(1.37%)</td>
</tr>
</tbody>
</table>
In the emotion analysis of Interchange books, positive emotions, including trust, joy, and anticipation, are more frequent than negative ones, including anger, disgust, fear, sadness, and surprise. The most frequent emotion in all levels is trust, and the least frequent one is disgust.

Total frequencies of positive emotions are almost the same, approximately 9%, 10%, and 10% in levels one, two, and three, respectively, and the total frequencies of negative emotions are 4.6%, 7%, and 7%, respectively. In all levels, positive emotions are more frequent, but by increasing the level of books, the frequency of negative emotions increases while the positive ones decrease; in other words, the texts are becoming more authentic.

Table 6
Positive Emotions in Interchange Books

<table>
<thead>
<tr>
<th>Level/Emotion</th>
<th>Trust</th>
<th>Joy</th>
<th>Anticipation</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1</td>
<td>3.04%</td>
<td>3.42%</td>
<td>2.89%</td>
<td>9.35%</td>
</tr>
<tr>
<td>Level 2</td>
<td>3.54%</td>
<td>3.11%</td>
<td>3.06%</td>
<td>9.71%</td>
</tr>
<tr>
<td>Level 3</td>
<td>3.88%</td>
<td>2.86%</td>
<td>3.05%</td>
<td>9.79%</td>
</tr>
</tbody>
</table>

Table 7
Negative Emotions in Interchange Books

<table>
<thead>
<tr>
<th>Level/Emotion</th>
<th>Anger</th>
<th>Disgust</th>
<th>Fear</th>
<th>Sadness</th>
<th>Surprise</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1</td>
<td>0.59%</td>
<td>0.54%</td>
<td>1.17%</td>
<td>0.93%</td>
<td>1.41%</td>
<td>4.64%</td>
</tr>
<tr>
<td>Level 2</td>
<td>1.16%</td>
<td>0.87%</td>
<td>1.78%</td>
<td>1.9%</td>
<td>1.51%</td>
<td>7.22%</td>
</tr>
<tr>
<td>Level 3</td>
<td>1.28%</td>
<td>0.88%</td>
<td>1.86%</td>
<td>1.62%</td>
<td>1.37%</td>
<td>7.01%</td>
</tr>
</tbody>
</table>

5. Discussion

The main objective of this study was to introduce an innovative way of measuring the emo-sensory load of English learning texts by developing software using two datasets, Sensicon and Emolex. For this, the software was developed using C# language programming to detect emotions, measure the sensory load of texts, determine each sense's load separately, and show the total score of all senses. The software makes the possibility of measuring the emo-sensory load of English texts which is a basic need for controlling and adjusting it in the material development phase.

Concerning the research question on finding a pattern in sense density in Interchange books, the results showed that the load of hearing increased in higher levels of the books, and the load of other senses decreased. In other words, the chance of involvement in higher levels would be less than in lower levels, which results in difficulty in the comprehensibility of texts. It is stated that humanizing can be done in both the teaching phase and the material development phase. The first one resulted in multisensory teaching techniques (Katai & Toth, 2010) that not only make learning more interesting and exciting but it does facilitate learning by reducing cognitive loads (Baines, 2008). Therefore, to improve understanding and lessen the cognitive load during the learning process, the multi-sensory characteristics of the instructional information should be considered by involving more of the learners' senses (Shayesteh et al., 2020). In the second one, material development, Rodriguez-Esteban and Rzhetsky (2008) showed the dominance of a sense-deprived style in biomedical texts by analyzing more than 250000 articles in this field. It illustrated that using sensory words in a text would benefit a more concrete image of an abstract concept.

According to the educational pyramid, Pishghadam (2016), moving from Exvolvement to Involvement, more senses, except hearing, are needed to be engaged. To facilitate English learning through texts, the ratio of other senses to hearing can be increased to maximize involvement and engage more parts of the brain. To do so, the load of hearing should be controlled, and the load of other senses can be increased to engage all parts of the brain and help learners to have more concrete imagination from abstract
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concepts. As Rodriguez-Esteban and Rzhetsky (2008) suggested, this can happen by using more analogies and metaphors.

Concerning the answer to the research question on emotion dispersion in these books, as mentioned before, the eight basic emotions are categorized as positive and negative ones. In all books, positive emotions are more frequent, and trust is the most frequent one among them. Going to higher levels, the frequency of positive emotions, trust, joy, and anticipation, is almost the same, but the frequency of negative emotions is increasing, which results in more authenticity in texts. All in all, using more emotions in texts can help learners to have more concrete imaginations that facilitate learning.

Various pedagogical implications arise from the findings of the present study. By using this objective system, the material developers can measure the sensory loads of their texts. They can alter loads of different senses to mitigate the difficulty of texts and facilitate learning through them. Besides, texts can be specialized in their sensory loads for special learners; for example, for congenitally blind-learner developers can decrease the sense of sight and increase the others to mitigate the difficulty of understanding. Since more sensory loads and emotions help learners to have better cognition by increasing them, the understandability of texts would increase. Another use of this system would be in writing articles in interdisciplinary studies. Instead of writing a dry and technical article, writers can use more sensory words to increase the understandability of their prose for readers from other fields. By making the possibility of measuring the emotional load of texts by this kind of software, material developers would be able to alter the emotional loads of texts according to special conditions such as gender or age.

The data sets used in the present study were limited and did not cover all learning words; future studies can develop the sense and emotion datasets to cover more English words to have more precise results. Besides, emotion detection in this study is at the word level, and future studies can examine that at the phrase or sentence level. Besides, further research on the evaluation and analysis of learning texts according to sensory load and emotion dispersion and the educational emotioncy pyramid is needed to help English learning materials developers with some creative solutions to mitigate the difficulty of texts and facilitate learning by increasing the chance of involvement. These findings can be used in other languages to improve the quality of learning texts and engage more senses.

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**References**


Appendix 1

The Output of the Software, WSA