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ARTICLE

Computing of Learner's Personality Traits Based on Digital Annotations

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Abstract Researchers in education are interested in modeling of learner's profile and adapt their learning experiences accordingly. When learners read and interact with their reading materials, they do unconscious practices like annotations which may be, a key feature of their personalities. Annotation activity requires readers to be active, to think critically and to analyze what has been drawn up, and to make explicit annotations in the margins of the text. Readers make annotation traces through underlining, highlighting, scribbling comments, summarizing, asking questions, expressing confusion or ambiguity, and evaluating the reading content. In this paper, we present a semi-automatic approach to building learners' personality profiles based on their annotation traces yielded during an active reading session. The experimental results show the system's efficiency to measure, with reasonable accuracy, the scores of a learner's conscientiousness and neurotics traits.

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Introduction

Different factors can be considered to personalize the learning activity such as the ability levels, patterns of diverse abilities, learning styles, personality characteristics, and cultural backgrounds. Actually, the rapid changes and increased complexity of today's education systems present new challenges and puts extra demands relative to the learning process. Thus, there is a strong need to adapt teaching activities to the diverse learners' characteristics by using more differentiated teaching strategies.

In the literature of psychology, it has been widely accepted that human personality traits have decisive effects on different concepts. For decades, psychologists have searched to understand the human personality hoping to find a systematic way to measure it. After research works, they show a relation of dependence between human personality traits and different behaviors. Ryckman (2008) reported the Allport[1] definition of personality: "personality is the dynamic organization within the individual of those psycho-physical systems that determine his characteristic behavior and thought". According to Allport's view, human behaviors are really controlled by internal forces known as personality traits.

Several works have shown that learners' personality traits are correlated significantly to diverse learning parameters (academic performance, learning achievement, learning motivation, online course impressions, learning styles, learning approaches, etc.) (Poropat 2009; Duff et al. 2004; Burton and Nelson 2006; Sahinidis et al. 2013; Ghazi et al. 2013; Beaujean et al. 2011; Shahri et al. 2012; Chamorro-Premuzic and Furnham 2009; Komarraju et al. 2011; Pornsakulvanich et al. 2012; Ibrahimoglu et al. 2013; Nikoopour and Amini Farsani 2011; Ariani 2013; Keller and Karau 2013). For instance, Al-Dujaily et al. (2013) shown the impact of personality traits (introversion vs extroversion) on learners' motivation and ability to learn with adaptive e-learning system. Such empirical works constitute the theoretical basis for applications tending to develop classrooms that are student-centered (El Bachari et al. 2010; Fatahi et al. 2009). Researchers in education emphasize the importance to consider learners' personality differences in teaching which can lead consequently to student's positive academic outcomes (Ambrose and Lovett 2014; Seifert and Sutton 2009).

In face-to-face learning model, there are more differences among students. This has made teaching more challenging. Actually, experts in educational psychology train teachers to use flexible, open-ended teaching plans and to adjust their instructional strategies and relationships with students so as to consider and respect their unique individual characteristics. By experience, teachers acquired proficiency as well as knowledge, attitudes, and skills required for their teaching career.

[1]Gordon Willard Allport (November 11, 1897 October 9, 1967) was an American psychologist. He was one of the first psychologists to focus on the study of the personality, and is often referred to as one of the founding figures of personality psychology.

In the digital era, organizations and institutions are increasingly moving toward adopting online learning. This method of learning uses the web as the medium for delivering instruction to a remote audience. In the online learning context, instructors and learners are isolated physically, so it is challengeable to diversify instructions according to students' characteristics. To do so, we need to implement an effective online instructional system based on proven and sound theories from the science of learning, to have a clear view of any learner as a way for personalizing, monitoring and evaluating online teaching process.

We discuss, in this article, learners' personality recognition through their digital annotation traces captured during their online reading activity.

The rest of this paper is as follows. In the next section, we present an overview of relationships between learner's personality and learning process. Then, we show reader's personality markers in handwritten annotations. Thereafter, we propose a semi-automated system used to recognize learners' personality traits through their digital annotations. Next, we evaluate the system's performance to measure accurately the Big Five scores of learners' traits. Finally, we discuss our results. We draw some conclusions and we suggest certain possible directions for future works.

Personality and Learning

Learning is an essential part of human capital which helps people to increase their effectiveness and improve their competitiveness through acquiring, modifying or reinforcing new knowledge, skills or behaviors. Educational researchers show the necessity to learn about students' characteristics to support them efficiently during their learning activities (Ambrose and Lovett 2014; Pornsakulvanich et al. 2012; Komarraju et al. 2011). These scholars, as well as, others show how important to change the traditional "one-size-fits-all" educational system to respond to learner's individual characteristics and needs. Actually, students cannot be educated with the same pacing, resources, and instructional pedagogy due to their diversity.

Personality traits are one of the student's individual characteristics which extensively interest educational experts. Several research works study the impact of learner's personality on academic achievement and the learning process in general (Ntalianis 2010; Caprara et al. 2011; Swanberg and Martinsen 2010). Further studies shed light on the relationship between the learners' personality and certain factors relative to the learning construct like approaches to learning, learner's autonomy, motivation towards achievements and academic achievement (Chue 2015; Poropat 2009). Such works conduct empirical studies that demonstrate the need to establish guidelines for incorporating learners' personality traits in designing computer-based learning systems. For instance, Kim et al. (2013) demonstrated that the extraversion level could influence the ease with which a learning activity in e-learning system can be performed. The authors contend that an introvert learner needs more assistance to enhance his learning experience in computer-based learning system than an extrovert learner. Furthermore, they claim that learners' personalities dictate their preferences for a specific instructional style. Indeed, an introvert learner prefers a bottom-up approach which means starting with low-level details to proceed to more abstract concepts. An extrovert learner prefers the opposite strategy that focuses on establishing an overview of learning content before proceeding to the details.

By reference to the richer literature on the relation between personality and learning process, experts in e-learning domain suggest that the attractiveness of virtual learning environments would be increased by inserting the human personality characteristics in these environments. For instance, Fatahi et al. (2009) propose a new model presented according to the learning model based on emotion, personality and the model of the virtual classmate. First of all, the proposed system identifies the learner's personality using the Myers-Briggs Type Indicator (MBTI) questionnaire. Thereafter, the virtual teacher and classmate express suitable instructional behaviors to improve the process of learning according to the identified learner's personality model and emotional status. The experimental results show the significance of the proposed instructional approach to increase the learning quality and to satisfy the learners. Abrahamian et al. (2004) show the significant effect of a personality-aware human-computer interface in the learning process. Indeed, the authors design a set of user interfaces which fit personality types identified using the MBTI test. Then, they provide a given user interface to participants with the matching personality type. They find that users prefer user interfaces designed for their own personality type which indicates the positive effect of personality-aware user interfaces on learning. El Bachari et al. (2010) suggest an Adaptive e-learning model based on learner's personality. The proposed system uses the MBTI psychometric test to recognize the learner's personality and suggests a learning style that matches learner's preference.

Although the results shown in previous works are fruitful, we believe these researches have left certain open issues concerning the followed approach to obtain the required data in learner's personality modeling process. In the context of online learning using psychometric standards[2] to determine learners' personality has many challenging aspects related to the validity of self-reported data. Knowing the crucial constraint in the profiling process is to model a credible student's profile which reflects truly the learner in the learning environment (Gong et al. 2011; Lintean et al. 2012; Chieu et al. 2010). The contact with test-takers using the psychometric tests via the web are indirect, and because of the diminished control over the testing situation, there is no way to confirm that they have understood instructions and/or items correctly or to provide them with ongoing guidance (Barak 1999). This situation may influence the reliability of the test results. Furthermore, the users tend usually, to preserve their privacy over the web, and they do not wish to reveal their personalities information through filling the psychometric forms. Consequently, the test-takers, either, do not fill the forms or cheat the answer when the motivation to do is obvious (Barak et al. 2004).

Generally, according to psychology experts, the personality tests are designed to be administered under controlled, and standardized conditions which are not the case

[2]Psychometric tests are a standard and scientific method used to measure individuals' mental capabilities, behavioral style and personality traits. This technique tends to focus on questionnaires: asking candidates about their personal information. An example of psychometric tests: Minnesota Multiphasic Personality Inventory, the Myers-Briggs Type Indicator, International Personality Item Pool - Neuroticism, Extraversion, and Openness, etc.

of Web-based assessment tests (Barak et al. 2004). As a way to collect credible data from people, certain psychologists seek to alternative measurement instruments that reduce participants' ability to control their responses and do not require introspection for the assessment of psychological attributes (Gawronski and De Houwer 2014). Several works shed light on the possibility of personality computing through users' observed actions or their captured digital behavioral-residues in different on-line working environments. In this scope, there is an increasing interest in understanding human perception based on reading and writing behaviors. Many researchers are interested in studying the ability to profile users' personality from human text production and peculiarities of reading behaviors.

For instance, Wright and Chin (2014), Celli (2012), and Mairesse et al. (2007) show the opportunity to derive users' personality from text and linguistic cues. Further works suggest extracting personality traits from users' handwriting (Rahiman et al. 2013; Fisher et al. 2012; Parmeet and Deepak 2012; Prasad et al. 2010; Rahiman et al. 2013). Other researchers are interested in extracting users' trait from posts written in online social spaces (Iacobelli et al. 2011; Sumner et al. 2012). Mezghani et al. (2012) propose deriving personality from social annotations and Omheni et al. (2014) and Jackson (2001) show the relation between readers' personality and their annotations made during the reading activity.

We aim of the current work to present new tendency of personality modelling in computer-based learning systems. Our goal is to increase the credibility of learner's personality profile by computing the required data, implicitly, based on learner's observed annotation traces.

Personality Markers in Annotations

Annotation is a handwritten practice which bridges between reading and writing and constitutes the most prominent habit of reading activity (Lamb 2007; Marshall 2009).

Annotation activity is "a basic and often unselfconscious way in which readers interact with texts" (Marshall 2009, p. 38). Furthermore, the annotation is described as a natural human activity that is used in daily life as an integral part of reading activity (Marshall 2009; Boot 2009).

Kirwan (2010, p. 5) considers the reader's marginalia (annotations) as the "most direct, reactionary response to the text that can feasibly be considered" to study the relation between the reader identity and the text. According to Kirwan (2010) the annotations provide the link between reader, text, and meaning and reflect the subjective individuality of the annotator's responses to the text. Based on this subjective relationship, the author suggests expanding the psychology-based reader theory to include reader's annotation practices.

Every annotator has unique individual patterns in making annotations (Naghsh 2007). According to Jackson (2001, p. 5) "if you ask annotators today what systems they use for marking their books and where they learned them, they generally tell you that their methods are private and idiosyncratic". Hence, the individuality of annotation patterns shows us very plainly that there can be some sort of connection between annotation practices and annotator's personality. Jackson (2001) assumes that “marginalia [annotations] express a reader’s impulsive and unguarded reactions to a book” and she “consider[s] them to be an exceptionally reliable guide to personality” (Jackson 2001, p. 87).

In the educational context, many scholars recommend using annotation as strategy of critical reading and learning skill that helps students to read expertly and to learn content area topics more deeply (Zywica and Gomez 2008; Porter-O’Donnell 2004; Brown 2007). Recently, several works present online learning environments integrating annotation functionalities to help learners enhancing their personal learning experiences (Glover et al. 2007; Chen et al. 2012, 2012, 2014; Yueh et al. 2010; Su et al. 2012; Kalboussi et al. 2014, 2013; Gao 2013; Mostefai et al. 2012; Lai et al. 2011).

In this essay, we suggest utilizing digital annotations to compute learner’s personality in an online learning environment. In what follows, we explain which type of personality trait we are going to take into account in our study. Then we present our prior work conducted to show the relation of connection between learners’ personality and their handwritten annotations made during the reading activity.

The Big Five Personality Model

The big five model is the best accepted and the most commonly used scientific measure of personality and have been extensively researched (Peabody and De Raad 2002). That personality is well described as five traits, was discovered through the study of the adjectives from natural language that people used to describe themselves and then analyzing the data with a statistical procedure known as factor analysis that is used to reduce lots of information down to its most important parts. In the following, we cite a brief explanation of the five personality traits.

Openness to Experience

Openness includes traits like imagination, appreciation for art, depth of emotions, adventure, unusual ideas, intellectual curiosity, and willingness to experiment. People who score high in openness like usually to learn new things and enjoy new experiences.

Conscientiousness

Conscientiousness includes traits like orderliness, self-discipline, deliberateness, and striving the achievement. People that have a high degree of conscientiousness are planned, have the tendency to act dutifully, have the sense of responsibility and competence.

Extraversion

Extraversion includes traits like energy, positive emotions, surgency, assertiveness, sociability, and talkativeness. Extraverts people get their energy from interacting with others, while introverts get their energy from within themselves.

Agreeableness

Agreeableness includes traits like trust in others, sincerity, altruism, compliance, modesty and sympathy. People that have a high degree of agreeableness are friendly, cooperative, and compassionate, while people with low agreeableness may be more distant.

Neuroticism

Neuroticism is related to one's emotional stability and degree of negative emotions. This dimension measures the person's degree of anxiety, angry, moodiness, and the sensitivity to stress. People that score high on neuroticism often experience emotional instability and negative emotions.

Prior Work

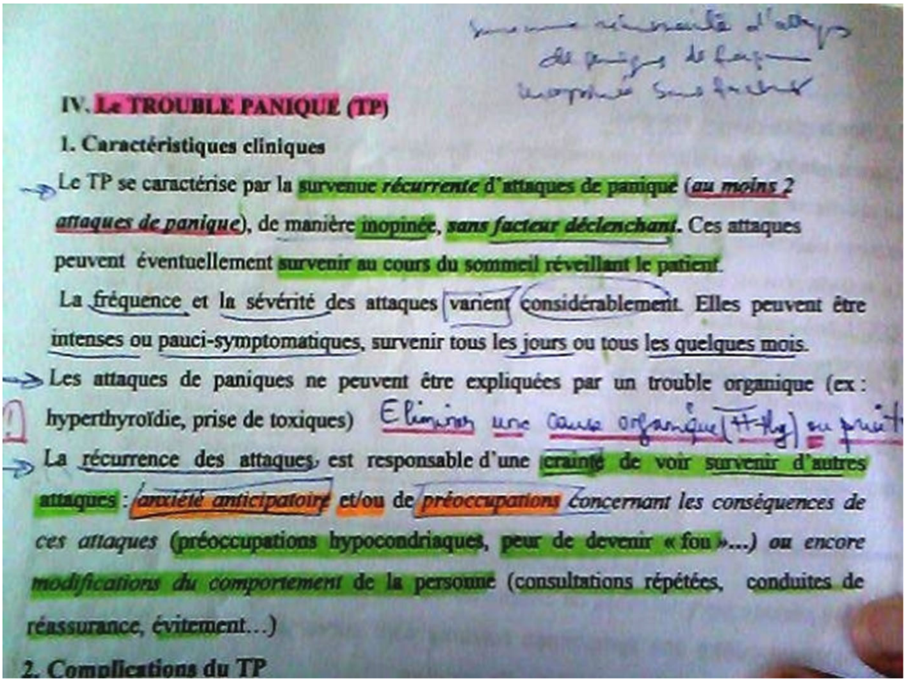
In prior work, we conducted an empirical study to show the implicit relation between the annotator activity and his personality traits (Omheni et al. 2014). Indeed, we consider a group of 120 volunteers. The subjects selected were recruited with respect to certain criteria. In fact, the age of the volunteers is equal or superior to 18 and they have different occupations and interests. In our sample, we have the two sexes (44 women and 76 men). Furthermore, all the selected volunteers have frequently the habit of reading and annotation.

On the other hand, each subject was instructed to answer a standard Five Factor Model questionnaire (the NEO-IPIP Inventory).[3] He obtained a feedback regarding his personality based on his responses. This step gives us the personality scores based on the Big Five Model for each volunteer. To associate personality scores to subjects' annotative activities, we gathered annotation practices for each person (Fig. 1) and we collected a simple set of statistics about their annotative activity. These included the following:

1. Total Number of Annotation Act (TNAA)
2. Average Number of Annotation Act (number of annotation acts per a single annotated page)(ANAA)
3. Number of Graphical Annotation Act (NGAA)
4. Number of Textual Annotation Act (NTAA)
5. Number of Reference Annotation Act (NRAA)
6. Number of Compounding Annotation Act (textual sign, graphic sign and reference sign of annotation act can be compounded together in order to express complex meanings of annotation). (NCAA)

This set of statistics tends to characterize quantitatively the reader's annotation practices. We studied the Pearson correlation between subjects' personality scores

[3] http://www.psychometrictest.org.uk/ipip-neo/



IV. Le TROUBLE PANIQUE (TP)

1. Caractéristiques cliniques

Le TP se caractérise par la survenue récurrente d'attaques de panique (au moins 2 attaques de panique), de manière inopinée, sans facteur déclenchant. Ces attaques peuvent éventuellement survenir au cours du sommeil réveillant le patient.

La fréquence et la sévérité des attaques varient considérablement. Elles peuvent être intenses ou pauci-symptomatiques, survenir tous les jours ou tous les quelques mois.

Les attaques de paniques ne peuvent être expliquées par un trouble organique (ex : hyperthyroïdie, prise de toxiques)

La récurrence des attaques est responsable d'une crainte de voir survenir d'autres attaques : anxiété anticipatoire et/ou de préoccupations concernant les conséquences de ces attaques (préoccupations hypocondriaques, peur de devenir « fou »…) ou encore modifications du comportement de la personne (consultations répétées, conduites de réassurance, évitement…)

2. Complications du TP

Fig. 1 Reader's Annotations on Paper Support

and each of the features obtained from analyzing their annotative activities. We reported the correlation values in Table 1. Those that were statistically significant for ($p < 0.05$) are bolded. The study shows significant correlations for Neuroticism, Conscientiousness, and Extraversion traits. We may explain these results as follows:

1. Conscientiousness trait : Conscientiousness is positively related to the number of textual annotation act (Fig. 2). The rest of the correlation values are not considered because of p-value > 0.05. But this is not a reason to reject definitively the rest of annotation features as a larger sample size may produce other significant correlations.

Table 1 Pearson correlation values between scores of annotation features and personality traits

	Open.	Consc.	Extra.	Agree.	Neuro.
TNAA	−0, 059	0,128	−0, 138	0,089	**−0, 287**
ANAA	0,003	0,080	**−0, 210**	0,163	**−0, 183**
NGAA	−0, 067	0,040	−0, 130	0,105	**−0, 207**
NTAA	0,001	**0,182**	0,040	0,085	**−0, 211**
NRAA	−0, 075	0,045	−0, 122	0,077	**−0, 207**
NCAA	−0, 059	−0, 012	−0, 147	0,014	**−0, 219**

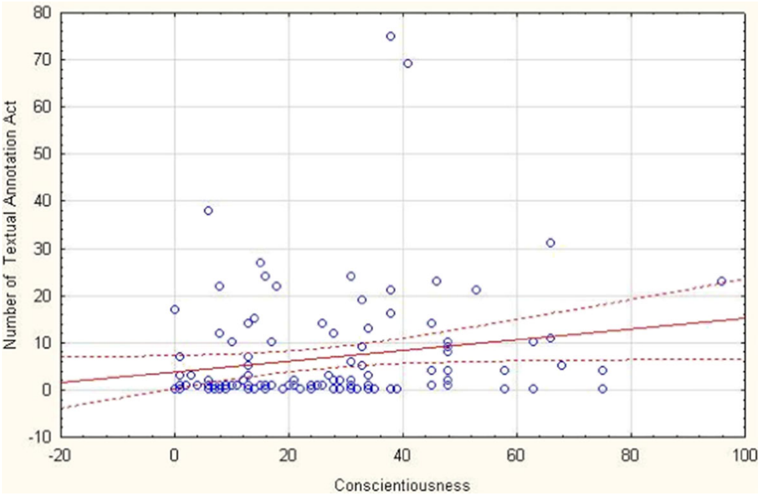


Fig. 2 Scatter Plot showing Number of Textual Annotation Act against Conscientiousness scores

The considered correlation may indicate that conscientious people are interested to use textual annotation acts. In fact, conscientious individuals are prudent which means both wise and cautious, better organized and they avoid acting spontaneously and impulsively. Thus, it may be the case that people who have a high degree of conscientiousness are interested in using textual annotation more than other annotation acts as it demands more reflexion, reasoning and cognitive effort.

2. Extraversion trait : Extraversion is negatively correlated with the average number of annotation act (Fig. 3). The rest of the correlation values can be probably significant with a larger sample size. We can interpret the regression fit shown in Fig. 3 as follows: The fit is correlated negatively, which is not surprising as extraversion is marked by pronounced engagement with the external world where extroverts tend to be energetic and talkative while introverts are more likely to be solitary and reserved. Thus, it may be the case that reading and annotation are intimate activities, we do it in private, so people who are socially active are less willing to practice annotation.
3. Neuroticism trait : Neuroticism is negatively correlated with all the features of annotation activity (e.g. Fig. 4). Here, the sample size is sufficient to have significant correlations for all the annotation features. The different correlation values are very significant which can show the sensitivity of annotation practices to the neuroticism trait.

   One possible explanation for these correlations is that more Neurotic people are emotionally reactive and they experience negative emotions for unusually long periods of time which can diminish the neurotic's ability to think clearly and make decisions. Thus, those who score high on Neuroticism are less eager to use annotation act as they cannot actively and critically engaging with the content for long periods of time.

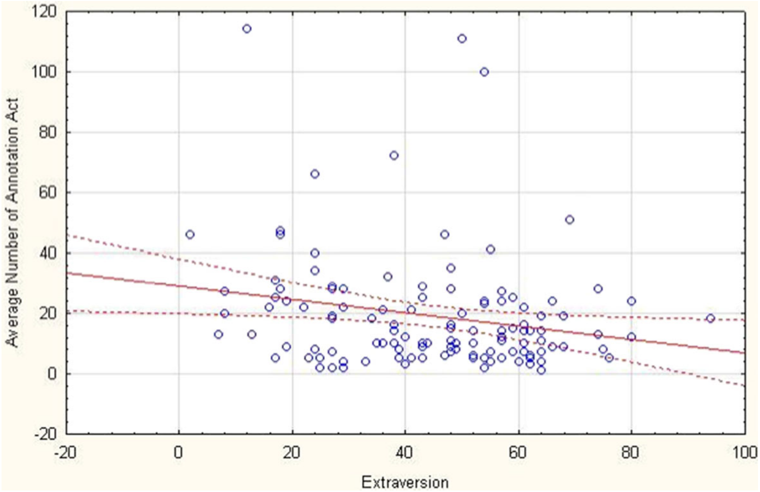


Fig. 3 Scatter Plot showing Average Number of Annotation Act against Extraversion scores

Furthermore, we make predictions about a subject's personality based on multiple annotation features. Our findings show that Neuroticism and Conscientiousness can be predicted with reasonable accuracy, using features of annotation activity, whereas other traits are more difficult to be predicted (Table 2). Based on the values of the coefficient of multiple determination R^2 which measures the strength of the correlation fit and the F-test which measures the statistical significance of the collective influence that have the annotation features on the personality traits presented in Table 2, we show that prediction regarding Conscientiousness is reasonably accurate, with R^2 value of 0.12, $F_{observed}$ value of 2.52 which exceeds the $F_{critical}$ value and

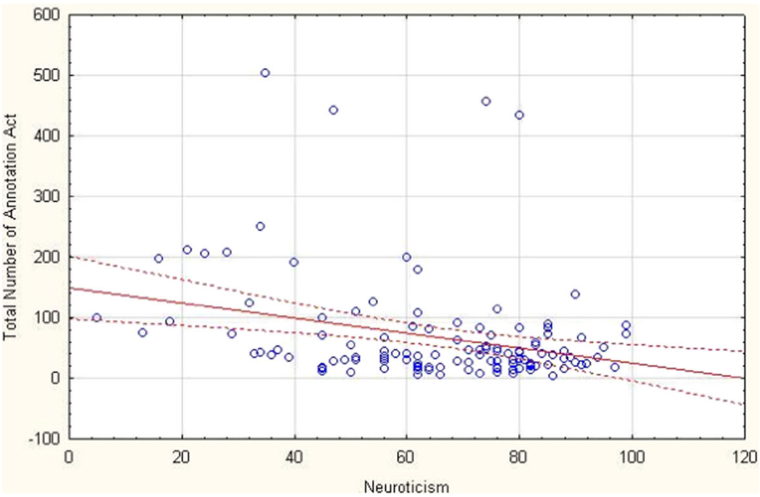


Fig. 4 Scatter Plot showing Total Number of Annotation Act against Neuroticism scores

Table 2 Predicting personality traits using annotation activity features through multivariate linear regression

Personality trait	R^2	F-test	P-value
Openness	0.03	0.57	0.76
Conscientiousness	0.12	2.52	0.03
Extraversion	0.07	1.32	0.25
Agreeableness	0.05	1.03	0.41
Neuroticism	0.14	3.11	0.01

P-value of 0.03 which is lower than the α[4] value where P-value is the probability of the F-test statistic is larger than the observed F-value. For Neuroticism we obtained the model with the best fit, with an R^2 value of 0.14, $F_{observed}$ value of 3.11 and P-value of 0.01, indicating quite accurate a prediction. The model for Extraversion has a lower fit and the model for Agreeableness is even less accurate. It seems that Openness is the hardest trait to predict using annotation activity features.

Extraction of Personality from Digital Annotations

Based on what previously cited, it is plain, that reader's annotations are really an expression of his personality traits. Indeed, we saw very plainly that the considered annotation features in our study may appear insignificant in themselves, but, they are nevertheless all very significant as indications of the annotator's personality traits.

Recent researches endeavor to replace the "pen-and-paper" paradigm for the annotation needs by employing the technology of free-form digital ink annotations which add the flexibility and natural expressiveness of the traditional handwriting method to the digital annotation process. Such tools enable readers to annotate their digital documents similarly to "pen-and-paper" case. For instance, iAnnotate (Plimmer et al. 2010) is an annotation tool for the android system which enables users to add annotations with the pencil, highlighter, and note tools to their digital texts. Hence, the digital context of free-form annotation process is very close to the context of pen-and-paper. The high degree of proximal similarity among these two contexts constitutes a strong evidence to consider our study's results (Omheni et al. 2014) in the digital annotation environment. Therefore, we are driven to take advantage of digital annotations which can be considered as a source of knowledge to automatically predict annotator's personality traits.

The proposed system called "i-Read" is an online reading environment where learners can upload their reading materials, annotate and share their annotated document with others.

The following figure (Fig. 5) illustrates the interaction between the various modules of the "i-Read" system along with the flow of information/data. The system's

[4]The alpha level is defined as the probability of what is called a Type I error in statistics. That is the probability of rejecting H_0 when in fact it was false.

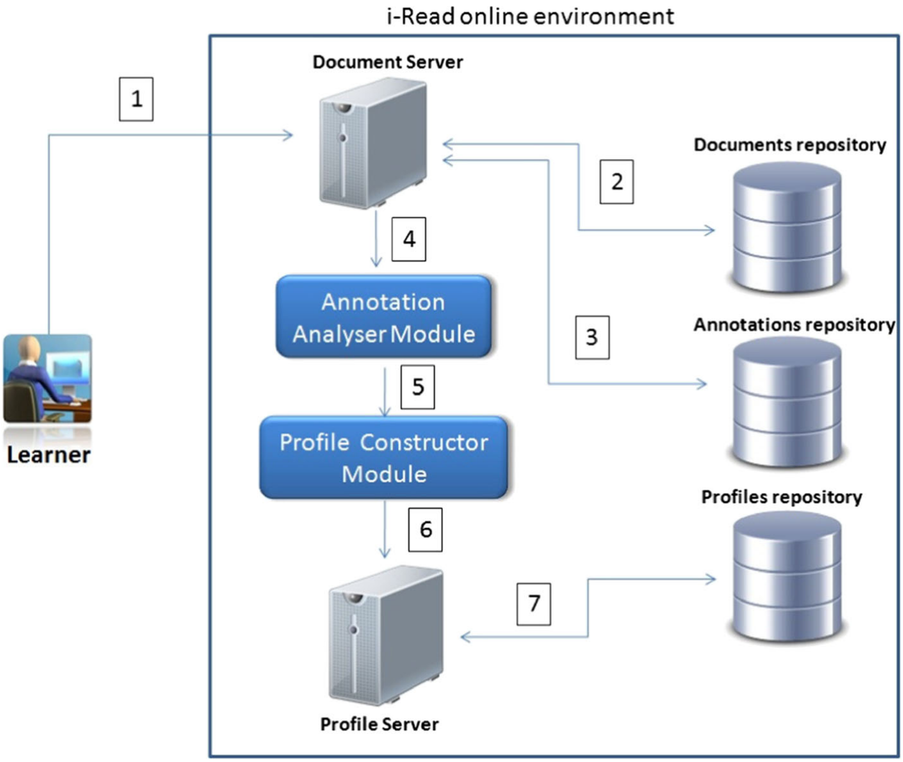


Fig. 5 The "i-Read" Architecture System

architecture consists of a user annotation interface, the annotation analyzer module, the profile constructor module and three databases with two servers.

To avoid destroying the original version of reading materials, our system uses an independent annotation database, which differs from the document database, to store annotations' parameters and contexts from learners. Moreover, the annotation interface provides several powerful annotation functionalities, such as scribbling, highlighting, underlining, commenting, as a way to engage users actively with their reading materials.

The Annotation Analyser Module

In the literature and according to Azouaou et al. (2003) there is no consensus definition for the annotation, but rather there are more general or specific definitions varying according to the research areas. In our concept, a user annotation is an act that affects an element of the document reading. Typically, an annotation has a single **Body**, which is a comment or other descriptive resource, and a single **Target** that the **Body** is somehow "about". The annotation likely also has additional descriptive properties.

In our case, we consider a reader's annotation to be a set of connected resources, typically including a body and target, and convey that the body is linked to the target. The body of annotation is materializing through a visual sign. This perspective leads to a basic model with three parts, depicted below (Fig. 6):

1. target : contains the values of coordinate points that define the annotated element in the logical structure of document reading,
2. body : the content of the annotation trace
3. sign : we classify annotations into three general categories. This categorization is based on how annotations can appear and be represented. Agosti and Ferro (2003) define three ways to represent the meaning of annotation:

   (a) Textual annotation expressed by a piece of text added to the annotated document,
   (b) Graphic annotation expressed by a graphic mark added to a document,
   (c) Reference annotation expressed by a link between two texts or two textual pieces in the same document.

   The authors called these basic ways "signs of annotation" and they define the term sign as a formation of a meaning. Furthermore, according to Agosti and Ferro (2003), these signs can be combined together to express more complex signs of annotation.

In our work, we consider the annotation sign parameter as the main characteristic which constitutes the cornerstone to study quantitatively the digital annotations. In fact, we compute certain features with reference to the visual sign of annotation traces (graphic, text, reference, composed). Technically, to implement the system annotation tool, we refer to Annotator.js library.[5] The annotation model adopted in our work follows a simple JSON format with three fields:

```
{
"anchor": "some text to anchor to" ,
"text": "the annotation text" ,
"type": "flag"
}
```

Where "anchor" (target) is the specifications used to position the annotation on the reading material. Technically, we have used the anchoring strategy inherited from the Annotator project,[6] which anchors annotations to their targets by saving exact locations in the form of XPath range descriptions of the involved DOM elements and the string offsets inside them. When the anchor needs to be located again, the DOM elements are found by using the same XPath expressions. Regarding the other annotation's parameters, "text" is the body of the annotation to show, and "type" (sign) is the kind of annotation.

[5] https://github.com/openannotation/annotator
[6] http://annotatorjs.org/

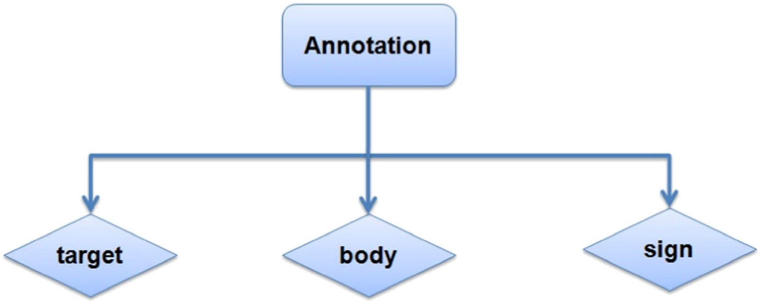


Fig. 6 The "i-Read" Annotation Model

This module is used to observe reader's annotations yielded during a reading session[7] and to compute certain parameters related to the total number of annotations, average number of annotations (number of annotations per one page of document reading), number of graphical annotations, number of referential annotations, number of textual annotations and number of composing annotations.

According to the annotation sign parameter (graphical, reference, textual, composed), the system classifies learners' annotations and computes the required parameters employed to construct a personality profile of the connected learner. The annotation features are modeled into a vector space, where each term of the vector is an annotation feature. The first term of the vector represents "the number of graphical annotations". The second represents "the number of reference annotations" and so on. We use the annotation-frequency to compute each feature in our vector space; the annotation-frequency is nothing more than a measure of how many times the annotation of a special category of a sign (textual, graphical, referential and composed) is present in the document as read.

The annotation module provides several powerful annotation functionalities, such as scribbling, highlighting, underlining, commenting, as a way to engage users actively with their reading materials (Fig. 7).

The Profile Constructor Module

The profile constructor module is used to predict readers' personality scores through their observed annotations. To compute user's traits, we utilize the multivariate linear regression algorithm. The following equation represents the mathematical format of the collective influence of the considered annotations' features on one single personality trait.

$$Y = b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 + b_4 X_4 + b_5 X_5 + b_6 X_6 \tag{1}$$

[7] In our case, we consider a reading session between user login and logout.

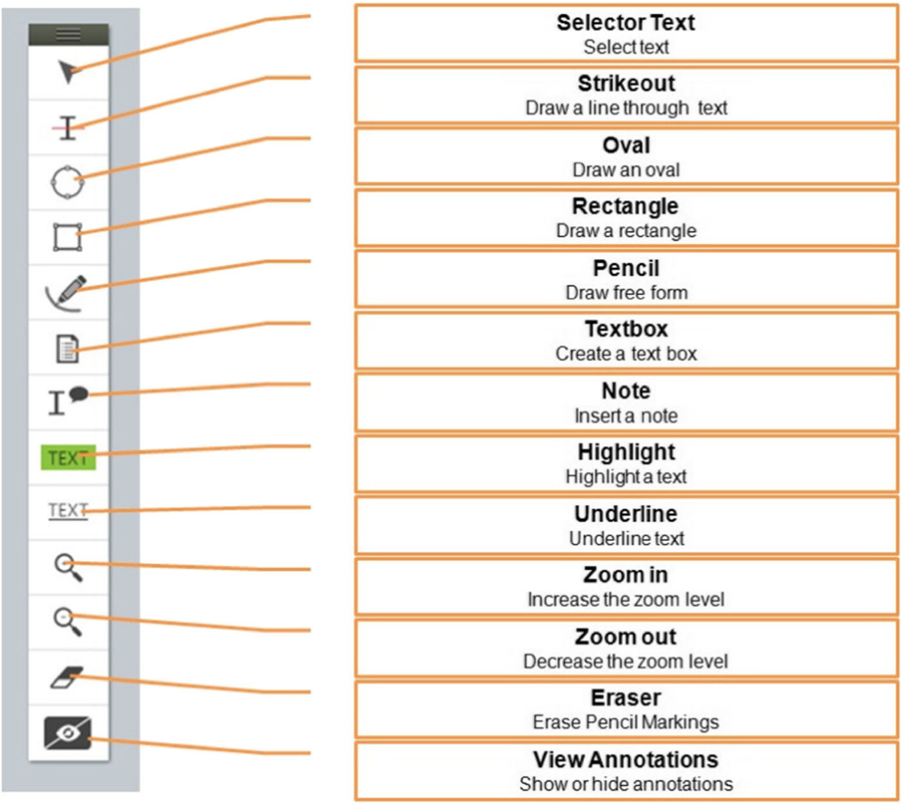


Fig. 7 The "i-Read" Annotation functionalities

Where Y is the predicted or expected value of the dependent variable representing the score of the focused user's personality trait, X_1 through X_6 are the distinct, independent or predictor variables representing the different annotation features considered in our study, b_0 is the value of Y when all of the independent variables (X_1 through X_6) are equal to zero, and b_1 through b_6 are the estimated regression coefficients. Based on this main function, we can determine the expected annotator's personality trait as long as we know certain peculiarities characterizing quantitatively his annotation practices.

We cite in Table 3 the different estimated regression coefficients used to predict the score of reader's traits given the values of the different considered features (x variables). The coefficient values are derived based on data obtained through the "pen-and-paper" experiment.

System Operation Procedure

Based on the system architecture (Fig. 5), the functional scenario of "i-Read" system is described and summarized as follows.

Table 3 The different estimated regression coefficients used to predict the score of reader's traits

Independent Variables	Conscientiousness	Neuroticism
Intercept (b_0)	21.82	70.06
Number of Graphical Annotations (b_1)	0,66	0,18
Number of Reference Annotations (b_2)	$-0,02$	$-0,13$
Avrage Number of Annotations (b_3)	0,14	0
Total Number of Annotations (b_4)	$-0,81$	$-0,38$
Number of Textual Annotations (b_5)	0,32	$-0,06$
Number of Compounding Annotations (b_6)	0	0

1. The connected learner uploads his/her reading document on the "*i-Read*" online environment;
2. The system saves the document in the documents repository;
3. The learner annotates his/her reading material;
4. The system saves learner's annotations in the Annotations repository;
5. The annotation analyzer module captures learner's annotations and extracts certain features;
6. The annotation analyzer module sends the computed information to the profile constructor module to build learner's personality profile;
7. The profile constructor module considers the received information as an input data to the multivariate linear regression algorithm used to estimate the scores of learner's traits;
8. The system saves the modelled user's profile in the Profiles repository.

System's Performance Evaluation

In this section, we are interested in checking our system's performance for personality recognition compared to the Neo-IPIP inventory which is the most scientifically based test of personality traits, and is generally accepted worldwide as one of the most highly regarded, and accurate, personality questionnaires.

Participants

We recruited 100 volunteers (35 women and 65 men) aged between 22 and 50 years. Most of the participants have the Bachelor's degree in scientific or literary disciplines. All the invited people have participated in our previous experimentation (Omheni et al. 2014). We have the decision to re-invite the same people because they have the required criteria to participate in our experimentation. Indeed, they are academic people who annotate frequently during their learning activities.

Fig. 8 Uploaded Document on "i-Read" online Enviroment

Procedure

We instructed the participators to upload their textual materials (three pages of maximum) on the "i-Read" environment and to use the system to carry out their reading and annotation activities (Figs. 8 and 9). Volunteers are free to select their reading

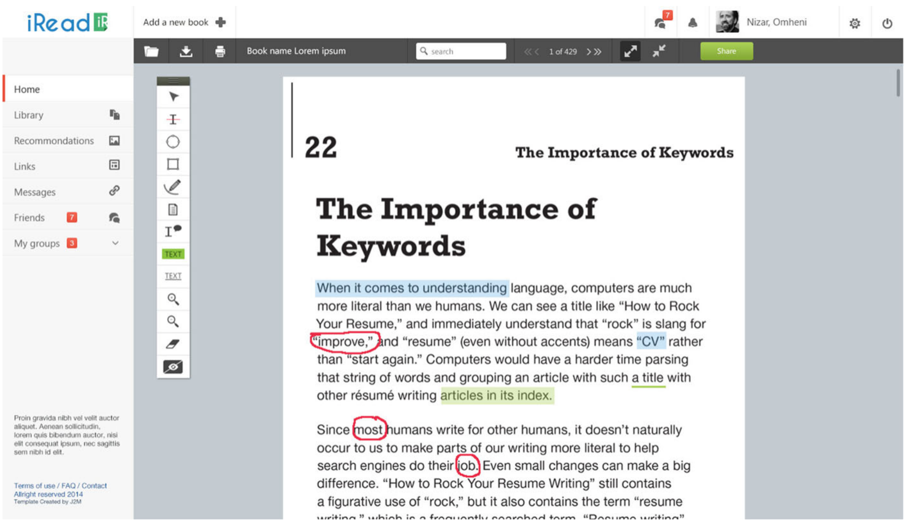


Fig. 9 Annotated Document on "i-Read" online Enviroment

content that interested them and the text's language (English, Arabic or French), all depends on their linguistic skill. The sample members did not differ on their reading comprehension ability. A large majority of the participants indicated that they had prior knowledge of the topic of their reading materials which are not hard so that its doesn't need much cognitive effort from the reader's side.

We consider all the previous conditions because we are very careful to the comfortability of the volunteers during the experience to guarantee their spontaneous and natural reactions.

In the second step, we instructed the participators to answer the standard Five Factor Model questionnaire (NEO-IPIP Inventory) to compute the scores of their personality traits based on their responses.

In the third step, we are interested in evaluating the system's performance to compute accurately the learner's scores of conscientiousness and neuroticism traits compared to the values determined using the NEO-IPIP Inventory (Figs. 10 and 11). To do, we measured some statistical coefficients like, the R-squared, the mean absolute error (MAE) and the root-mean-square error (RMSE), which is the root mean squared differences between predicted values (scores measured with the i-Read system) and observed values (scores measured with Neo-ipip inventory).

We report the statistical coefficient values in Tables 4 and 5 for the conscientiousness and neuroticism traits respectively. Regarding the conscientiousness trait, we have a low value of R-squared and RMSE>MAE. These values show a variation in the deviation margin. But, RMSE-MAE value isn't large enough to indicate the presence of a very large difference between the scores of conscientiousness trait measured by the i-Read system and the Neo-ipip inventory. We have the same results for the neuroticism traits.

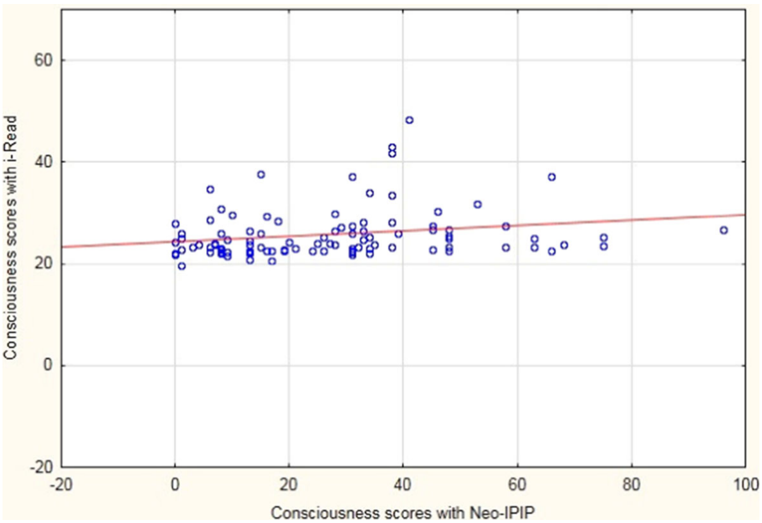


Fig. 10 Scatterplot of Conscientiousness scores with Neo-IPIP inventory against Conscientiousness scores with i-Read system

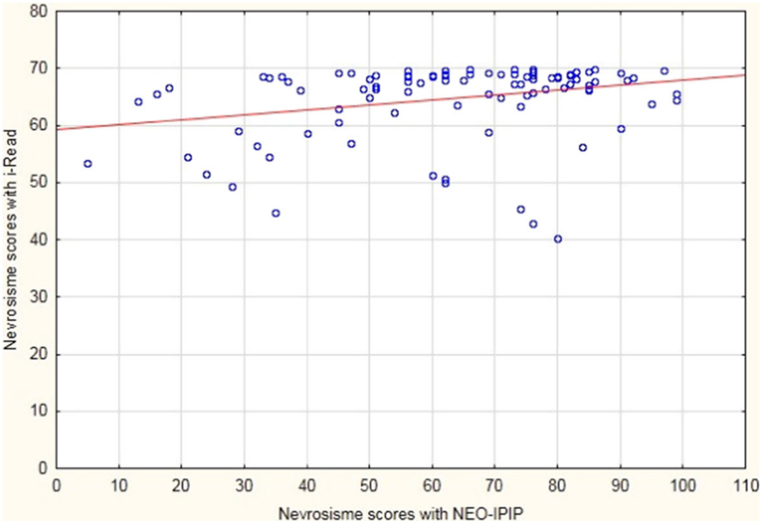


Fig. 11 Scatterplot of Neuroticism scores with Neo-IPIP inventory against Neuroticism scores with i-Read system

To assess more precisely the degree of agreement between the two above systems, we utilize another statistical method. The Bland-and-Altman method is used for analysing the difference and to quantify the agreement between two quantitative measurements by constructing limits of agreement (Giavarina 2015). The Bland and Altman method calculates the bias and confidence limits for the bias (called the limits of agreement) and displays these as solid and dotted horizontal lines, respectively, on the graph as showed in Figs. 12 and 13. The overall mean difference in values obtained by the two methods is called the bias. When plotted differences represent the new method minus the established method, the bias quantifies how much higher (i.e., positive bias) or lower (i.e., negative bias) values are the new method compared with the established one.

Figure 12 shows the bias value is -0.72 units. This means that, on average, the i-Read system measures 0.72 units more than the Neo-IPIP inventory. The bias value is so low, which is an acceptable difference. Thus, our computational model used to compute the conscientiousness score would be an acceptable alternative to the Neo-IPIP inventory.

Figure 13 shows the bias value is 1.29 units. This means that, on average, the Neo-IPIP inventory system measures 1.29 units more than the i-Read. The bias value is

Table 4 Coefficients of linear correlation between the scores of Conscientiousness trait measured with two different systems

Scores measured with	R^2	RMSE	MAE
“i-Read” system	.	.	.
Neo-IPIP inventory	0.04	19.9	15.56

Table 5 Coefficients of linear correlation between the scores of Neuroticism trait measured with two different systems

Scores measured with	R^2	RMSE	MAE
"i-Read" system	.	.	.
Neo-IPIP inventory	0.07	20.47	16.84

low and not significant. Thus, our computational model used to compute the Neuroticism score would be a suitable alternative to the Neo-IPIP inventory in the context of online personality measuring for learning purposes.

Discussions

The experimental results show the efficiency of the "i-Read" system to measure some personality traits (Conscientiousness and Neuroticism) with reasonable accuracy using digital annotation activity. These results are coherent to our theoretical findings in "pen-and-paper" context, and constitute a great supporting evidence to accept our pretension of the possibility of modeling users' personality profiles based on their annotation traces.

Actually, the annotation of digital documents is a practice that many people prefer doing during their reading activities. Consequently, many annotation tools have been developed for various applications. The different developed tools have the same purpose: help reader annotating their reading materials in a faster and

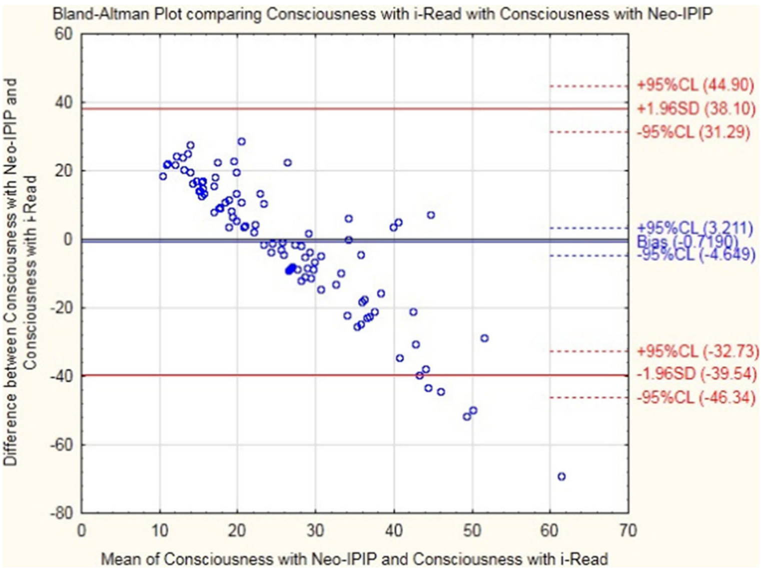


Fig. 12 Plot of differences between I-Read system and Neo-IPIP inventory vs. the mean of the two measurements (Conscientiousness trait). The bias of −0.72 units is represented by the gap between the X axis, corresponding to a zero differences, and the parallel line to the X axis at −0.72 units

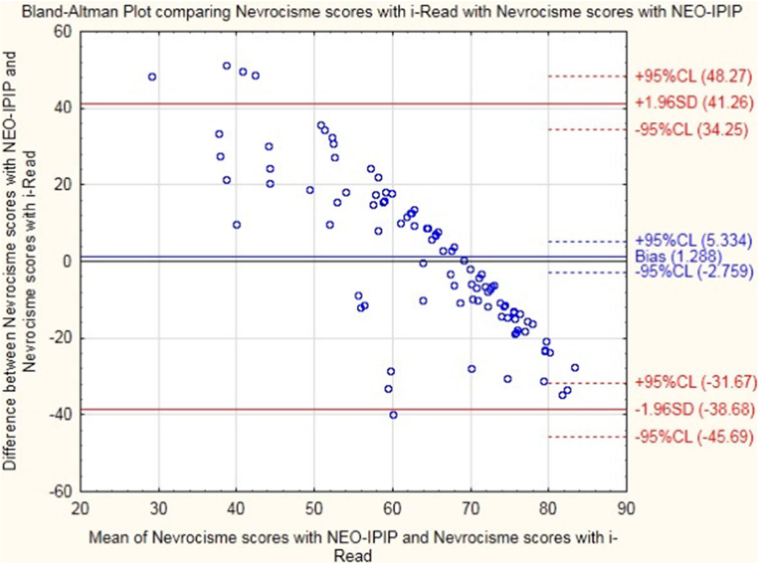


Fig. 13 Plot of differences between I-Read system and Neo-IPIP inventory vs. the mean of the two measurements (Neuroticism trait). The bias of 1.29 units is represented by the gap between the X axis, corresponding to a zero differences, and the parallel line to the X axis at 1.29 units

easier manner. Thus, annotations can be created, archived, shared, searched, and easily manipulated. So, annotation tools help users to be engaged more actively and deeply with their reading content. Although most of early annotation tools, such as iAnnotate (Plimmer et al. 2010), u-Annotate (Chatti et al. 2006), A.nnotate,[8] Group-Docs.Annotation,[9] Diigo,[10] etc., incorporates different options used to invite readers to physically interact with their reading materials through marking passages by highlighting, underlining, crossing out words, adding comments and so many other annotations acts, we think that we still miss a tool which can treat certain aspects of annotation activity that can serve as scheme to predict personality traits. Another word, even though these tools are efficient, but they focus on the annotation process without interest to benefit from the implicit meanings of annotations which differ to our proposed system. In fact, the present system offers, besides the traditional annotation functionalities of creation, archiving and sharing, the functionality of readers' personality modeling based on their digital annotation traces. Thus, this essay tries to present a new dimension of personality computing based on annotation practices. That dimension is missing in the abundant annotation systems.

Further works, are interested in designing computer-based learning systems based on user personality, utilize classical methods to recognize learners' personalities which tend to focus on questionnaires. Such works enter their participants into a cash

[8]http://www.a.nnotate.com/
[9]http://www.groupdocs.com/apps/annotation/
[10]https://www.diigo.com/

prize draw to externally motivate them to the experimental task (Al-Dujaily et al. 2013; Kim et al. 2013). Without such external motivational acts, learners are not ready to answer a range of 40 or more questions about their personality information. Usually, learners prefer to preserve their privacy and refuse communicating their personal information with a third party. Personality recognition based on learners' annotations is not presented here as a replacement for psychometric tests, but rather as additional information that may help combat some of the difficulties encountered with questionnaires. Possibly the biggest advantage is that personality trait measurement through annotation traces can be taken in parallel with the interaction rather than wearying the learner to answer a long form or too many questions.

On the other hand, based on our findings, we show that the neuroticism trait is negatively correlated to the different annotation features considered in our study. This result clearly indicates that learners with a high level of emotional stability are more productive of annotation traces which reflect their deep reading of the textual material. Thus, those who have a low score of neuroticism are more stable and they have the ability to pay greater attention on their current activities and they can deal with reading materials with a high level of complexity.

Looking to the consciousness trait, we show that this trait is correlated positively with annotation features. This evidence reflects that conscientious learners produce more annotation traces during their reading. We may interpret the case that learners who have a high degree of conscientiousness choose to read their reading materials deeply.

Based on the previous interpretations, we believe that learners with high degree of consciousness and high level of emotional stability are more able to deal with hard textual materials through using annotation skill, knowing that the process of annotation is viewed as learning strategy used to improve reading comprehension and favors deeper processing and understanding of the text (Brahier 2006; Porter-O'Donnell 2004; Brown 2007; Huang 2014). For those who have a low level of consciousness and high level of anxiety should be treated carefully to enhance their reading comprehension performance.

These findings may be viewed as a guide to design personality-based e-learning system of virtual reading classes. Actually, many learning systems offer annotation functionalities to their users to increase their reading performance (Yueh et al. 2012; Chen et al. 2012, 2014; Su et al. 2010). Such works show the efficiency of annotation tools to enhance users' learning experience. Further studies in the literature indicate the agreement of the researchers in the learning domain about the relationship between personality and reading comprehension achievement (Sadeghi et al. 2012; Agosti and Ferro 2003; Ali and Bano 2012). These works conduct empirical studies that support the theory of personality as a predictor of reading comprehension skills. Therefore, we think that our work steps forward for these works to use annotation traces as an indicator of learners' personality traits that reflects their reading performance level. This information may be useful to assist learners having difficulties in reading comprehension.

Finally, although our results are promising and constitute a new tendency in computing learners' personality traits based on their behavioral residues of reading and writing activities in an online learning environment, some limitations of the current study need further consideration. The most important issue is the sample size as we expect more significant results around the relation between annotations and readers' traits (agreeability, extraversion, and openness) with a larger sample. Further limitations concern the considered sample study, relevance to only courses with online reading, the lack of experimentally controlled texts beyond length restriction, and the use of absolute totals that are not normalized for the size of the annotated reading. Indeed, we have decided to restrain our analysis to graduate students, as they are generally more reflexive about their practices, often due to the shift to a higher level of scholarly activity. This reflexivity leads to an adaptation of methods and techniques deployed in their daily activities as the graduate students are confronted with different intellectual situations. Another point concerns the selection of participants for this study. We sought individuals who would provide rich accounts of their personalities and annotation practices. In fact, we have used purposive sampling since the topic and scope of the study called for certain participants' qualifications. We should indicate that this type of sampling prevents us from generalizing our findings outside of our population. However, while this limitation may have serious consequences, we believe that this sampling procedure yielded more in-depth findings and insights that may not have been detected if we used a more standardized, probabilistic sampling. On the other hand, our study is appropriate for any subject as annotation is a reading skill, and reading happens in every course.

Our research can be extended to study the influence of readers' demographic characteristics (gender, age, ...) and factors which are likely to influence annotation behaviour such as familiarity with annotation tools and interest in the content topic.

Right now, we are attempting to apply our findings to design adaptive personality-based learning strategies to help students, enhancing their reading performance and to assist them during their learning experience. To overcome the shortcomings of reading online, the proposed system assists collaborative learning because it enables the students to upload, annotate and share their personal reading experiences which have the potential to facilitate understanding of the reading texts and helps develop a reader into a writer and promote collaborative learning. The "i-Read" system builds the learners' personality profiles based on their traces of annotation, after which readers will be classified according to their scores of neuroticism and consciousness traits, to a good reader, ordinary reader, and a poor reader. Those suffering of reading comprehension difficulties will receive the annotations of skilled readers. In the "i-Read" reading environment, there are no instructors, just the students teach each other through sharing their learning experiences and knowledge. In a forthcoming paper, we'll give more details about this work and the conducted experiments to show the efficiency of the proposed approach to supporting learners with low reading abilities.

Conclusions

This study investigates the possibility of personality recognition based on digital annotations. This work may be viewed as a new tendency in the personality-computing research area and a step forward for indirectly assessing learners' personality in an online learning environment. Another way, the relation between learners personality traits and the annotation activity may reflect their reading performance level. That is helpful to assist students who have difficulties in reading comprehension.

As future work, we expect to apply the peer learning as an instructional strategy, to construct virtual reading groups, where good readers assist poor readers through sharing their reading experiences. In the next work, we'll show the effectiveness of the proposed strategy to help students to enhance their learning experience in reading comprehension activity.

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