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# *The effect of personality traits on students' performance during Computer-Based Testing: a study of the Big Five Inventory with temporal learning analytics*

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*Abstract*— **Provision of adaptive and personalized Computer Based Assessment (CBA) services to learners is a multidimensional research field. In this paper we investigate the effect of extraversion and conscientiousness with temporal learning analytics on students' performance during computer based testing. For this purpose, we used the LAERS assessment environment to track the temporal activity – time-spent behavior – of 96 students and the Big Five Instrument (BFI) questionnaire to record their personality traits. Partial Least Squares (PLS) was used to find fundamental relationships between the collected data. Preliminary results indicate a positive effect of conscientiousness on (un-)certainty and a positive effect of extraversion on goal expectancy. Further implications of these results are also discussed.**

***Keywords-** computer based testing; prediction of performance; personality traits; temporal learning analytics*

## I. INTRODUCTION

Assessment measures students' progress and has always been a challenge in the educational setting. In order to offer improved Computer Based Assessment (CBA) services, we should consider the parameters that lead to improved performance, and consequently, construct more accurate predictive models of performance and assessment. An open challenge is how we could exploit data-driven decision making research results to automate the accurate prediction of performance and provision of adaptive and personalized assessment services.

### *A. Temporal learning analytics*

Temporal learning analytics are about gaining insight into students' learning procedures and understanding and explaining how students learn based on their time-spent behavior during assessment activities [1]. The temporal interpretation of students' performance in activity could be used for predicting their progress. In other words, interpreting students' participation and engagement in terms of "time-spent" could lead to a complementary dimension of a more concise predictive model [1].

Former studies [2, 3, 4, 5] examined the effect of student's response time on the prediction of their performance, modeled unobservable factors (such as engagement), explored the relationships between study-time and motivation, and proposed what should be adapted in the Computerized Adaptive Testing (CAT) context regarding orientation to time.

Preliminary results [1] highlighted a detected trend that temporal learning analytics have a statistically significant capability on predicting actual performance during computer based testing. In particular, total time to answer correct (TTAC) and total time to answer wrong (TTAW) have a direct positive and a direct negative effect on Actual Performance (AP) respectively. In addition, in the same study, goal-expectancy (GE) – i.e. the students' self-confidence regarding their study and the assessment and their perception of preparation – was found to be an indirect determinant of AP. Furthermore, (un-)certainty – i.e. the students' cautiousness during testing in terms of time-spent on answering the quiz – explains satisfactorily the students' AP [6]. In a sense, (un-)certainty seems to increase students' effort to answer the quiz, and consequently, the motivational effect of the (un-)certainty parameter should be further explored. In addition, the detected indirect effect of goal-expectancy (GE) on (un-)certainty indicates that students' perception of preparation affects their cautiousness [6].

In [1], the authors set under discussion the issue of considering and combining temporal learning analytics with learners' personality traits.

### *B. Personality traits*

In order to offer improved personalized CBA services to students, we should consider and include their personality traits [7].

According to [8, p. 10], "personality represents those characteristics of the person that account for consistent patterns of feeling, thinking, and behaving". In a sense, personality could be defined as the set of an individual's characteristics and behaviors that guide him/her to make decisions and act accordingly under specific conditions [9].

Researchers have concluded to five factors that describe personality traits [10, 11]. The Big Five factor model of personality is one conceptualization of personality that has been increasingly studied and validated in the scientific literature [7, 12, 13]. According to the Big Five model of personality, these factors are: a) extraversion, b) agreeableness, c) conscientiousness, d) neuroticism and e) openness.

In this paper we investigate the effect of extraversion and conscientiousness with temporal learning analytics – measuring and modeling students' time-spent behavior for prediction purposes – on students' performance during computer based testing. Our goal is to explore the relationships between temporal factors and personality factors. For this purpose, we used the LAERS assessment environment to track the temporal activity of 96 students and the Big Five Instrument (BFI) questionnaire to record their personality traits. We discovered a positive effect of conscientiousness on (un-)certainty and a positive effect of extraversion on goal expectancy. Further research is required in order to validate these preliminary results.

The rest of this paper is organized as follows: in section II, we present our experiment methodology. In section III, we analyze the results from the case study. In section IV, we discuss about our findings, share our initial conclusions and describe possible implications.

## II. Methodology

### A. Research participants and data collection

For our case study we configured the LAERS assessment environment [14]. We implemented a testing mechanism (Fig. 1) and a tracker that logs students' temporal activity data.

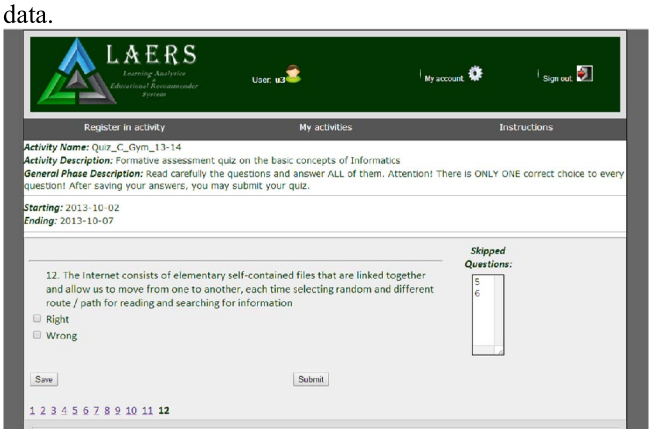


Figure 1. The LAERS assessment environment.

For the purpose of our case study, we also embedded into the system two questionnaires: a pre-test questionnaire, in order to measure each student's goal expectancy, and the BFI questionnaire to extract their personality traits.

In specific, items that measure GE are [15]:

- GE1: Courses' preparation was sufficient for the CBA
- GE2: My personal preparation for the CBA
- GE3: My performance expectations for the CBA

To measure these items, we used the seven point Likert-type scale with 1 = strongly disagree to 7 = strongly agree [15].

The BFI has 44 items to measure personality traits [11]. From those, 8 items measure Extraversion and 9 items measure conscientiousness. In specific, the BFI items that measure Extraversion (E1-E8) are 1, 6R, 11, 16, 21R, 26, 31R, 36. The BFI items that measure Conscientiousness (C1-C9) are 3, 8R, 13, 18R, 23R, 28, 33, 38, 43R. "R" denotes reverse-scored items. The five point Likert-type scale with 1 = strongly disagree to 5 = strongly agree was used to measure each item.

Data from the questionnaires were logged on two separated files (pretest.csv and bfi.csv).

Data were collected from a total of 96 participant students of a European High School, aged 16 years old. 9 groups of 10 to 12 students attended the midterm exams, for 30 minutes each group, from 2nd to 7th of October 2013. The 12 multiple choice questions of the test were related to the basic concepts of Informatics. All questions used in the current case study correspond to the lower three levels of the cognitive domain of Bloom's taxonomy (Remembering, Understanding and Applying) [16]. The final log file (results.csv) contained 4133 rows of raw data.

### B. Research model and hypotheses

A variable which measures self-confidence and goal orientation regarding the use of a CBA is Goal Expectancy (GE), which was proposed in Computer Based Assessment Acceptance Model (CBAAM) [15]. This measure could be considered as an indicator of students' perception of preparation. Further, "(un-)certainty" is a measure of cautiousness during the assessment [6]. GE along with (un-)certainty and total time to answer (in-)correctly have been proposed in [1, 6] as predictors of performance during computer based testing. This study goes a step further by correlating these factors to personality traits.

*1) Extraversion:* Extraversion implies an energetic personality and includes traits such as sociability, activity, assertiveness, and optimism. This trait is related to leadership [11] and was correlated with a deep style and higher general knowledge [17]. Extrovert students are associated with self-efficacy, motivation, positive perceptions and goal learning orientations [7]. These imply that an extrovert student is more likely to have higher expectations from his/her preparation. Thus, we hypothesized that:

> ***H1**: Extraversion will have a positive effect on goal-expectancy*

*2) Conscientiousness:* Conscientiousness describes impulse control that facilitates task- and goal-oriented behavior, such as thinking before acting, delaying gratification, planning, organizing, and prioritizing tasks. Conscientiousness is a personality trait used to describe persons being careful, responsible, with high level performance and with a strong sense of purpose and will [11, 18]. This characteristic is related to school and college grades [11, 19]. Studies have shown that conscientiousness was very strongly correlated with an achieving style and modestly correlated with a deep style [17]. Conscientious students are described as achievement oriented [11]. These imply that a conscientious student is more likely to be cautious during assessment. Thus we hypothesized that:

> ***H2**: Conscientiousness will have a positive effect on (un-)certainty*

Fig.2 presents the explored research model and hypotheses.

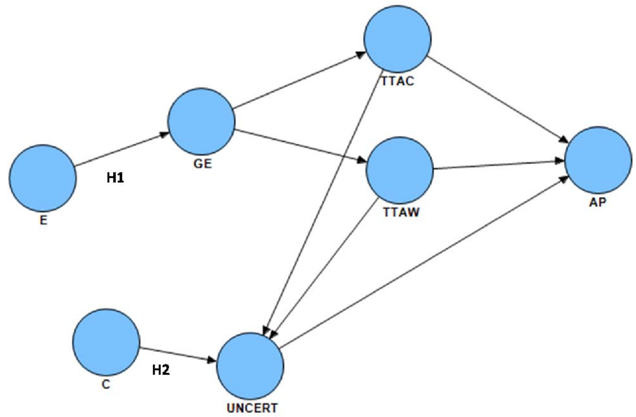


Figure 2. Research model and hypotheses.

## C. *Measures*

We used the technique of partial least-squares (PLS) analysis to structure the "causal" network of our model. PLS follows two guidelines regarding the sample size. The first is that the sample has to be 10 times larger than the number of items for the most complex construct. The second is that the sample has to be 10 times the largest number of independent variables impacting a dependent variable [20]. The most complex variable of the proposed model is Conscientiousness with nine items. Thus our minimum sample size should be 90, which is lower than the 96 participants.

Reliability and validity of the measurement model are proved by measuring the internal consistency, convergent validity and discriminant validity [21, 22]. In our proposed model the measurement model analysis is necessary for extraversion, conscientiousness, goal expectancy and (un-)certainty which are latent variables. More specifically, a value higher than 0.7 is acceptable regarding the items' factor loadings on the corresponded constructs. In order to analyze discriminant validity, Average Variance Extracted (AVE) should be higher than 0.5 [20, 21]. Finally, Composite reliability and Cronbach alpha are considered acceptable when they scored over 0.7 [23, 24].

The structural model and hypotheses are examined mainly by: a) evaluating the variance measured ($R^2$) by the antecedent constructs. Previous studies suggested 0.02, 0.13 and 0.26 as small, medium and large variance respectively [25]; b) the significance of the path coefficients and total effects by using bootstrapping procedure and calculating the t-values.

In order to examine the measurement and the structural model we use SmartPLS 2.0 [26].

# III. Results

Table I confirms the adequate values (Factor Loadings, Cronbach alpha, Composite reliability and Average Variance Extracted) for the measurement model.

TABLE I. RESULTS FOR THE MEASUREMENT MODEL

| **Construct Items** | **Factor Load.(>0.7)[a]** | **Cronb. a (>0.7) [a]** | **C. R (>0.7) [a]** | **AVE (>0.5) [a]** |
|---|---|---|---|---|
| **UNCERT** | | 0.84 | 0.93 | 0.86 |
| TIT [b] | 0.92 | | | |
| TACV [b] | 0.93 | | | |
| **GE [b]** | | 0.74 | 0.84 | 0.65 |
| GE1 | 0.78 | | | |
| GE2 | 0.77 | | | |
| GE3 | 0.85 | | | |
| **E [b]** | | 0.91 | 0.93 | 0.61 |
| E1 | 0.79 | | | |
| E2 | 0.73 | | | |
| E3 | 0.74 | | | |
| E4 | 0.84 | | | |
| E5 | 0.80 | | | |
| E6 | 0.75 | | | |
| E7 | 0.82 | | | |
| E8 | 0.78 | | | |
| **C[b]** | | 0.95 | 0.96 | 0.72 |
| C1 | 0,82 | | | |
| C2 | 0,94 | | | |
| C3 | 0,86 | | | |
| C4 | 0,78 | | | |
| C5 | 0,69 | | | |
| C6 | 0,89 | | | |
| C7 | 0,84 | | | |
| C8 | 0,88 | | | |
| C9 | 0,87 | | | |
| **TTAC[b]** | 1.00 | 1.00 | 1.00 | 1.00 |
| **TTAW [b]** | 1.00 | 1.00 | 1.00 | 1.00 |
| **AP [b]** | 1.00 | 1.00 | 1.00 | 1.00 |

[a] Indicates an acceptable level of reliability and validity

[b] TIT: Total_Idle_Time, TACV: Total_Answer_Check_Views, GE: Goal-Expectancy, E: Extraversion, C: Conscientiousness, TTAC: Total_Time_AnswerCorrect, TTAW: Total_Time_Answer_Wrong, AP: Actual_Performance

Table II presents the correlation matrix. The diagonal elements (Table II) are the square root of the AVE of a construct. According to the Fornell-Larcker criterion [27], the AVE of each latent construct should be higher than the construct's highest squared correlation with any other latent construct. Discriminant validity is established when an indicator's loading on a construct is higher than all of its cross loadings with other constructs. Consequently, discriminant validity is confirmed since the diagonal elements are higher than any correlation with another variable.

TABLE II. DISCRIMINANT VALIDITY FOR THE MEASUREMENT MODEL

| **Constr.** | **UNCERT** | **GE** | **E** | **C** | **TTAC** | **TTAW** | **AP** |
|---|---|---|---|---|---|---|---|
| UNCERT | **0.92** | | | | | | |
| GE | 0.12 | **0.8** | | | | | |
| E | 0.37 | 0.34 | **0.78** | | | | |
| C | 0.41 | 0.36 | 0.76 | **0.85** | | | |
| TTAC | 0.54 | 0.34 | 0.69 | 0.76 | **1** | | |
| TTAW | 0.10 | 0.23 | -0.56 | -0.62 | -0.47 | **1** | |
| AP | 0.41 | 0.37 | 0.68 | 0.78 | 0.74 | 0.58 | **1** |

A bootstrap procedure with 1000 resamples was used to test the statistical significance of the path coefficients in the model. The results for the hypotheses are summarized in Table III and illustrated in Fig. 3.

Extraversion and conscientiousness have significant direct positive effect on goal-expectancy and (un-)certainty respectively. Thus all the hypotheses were confirmed.

TABLE III. HYPOTHESIS TESTING RESULTS

| Hypothesis | Path | Path coeff. | t value | Results |
|---|---|---|---|---|
| H1 | E->GE | 0.34* | 4.54 | support |
| H2 | C->UNCERT | 0.26* | 2.10 | support |

*p<0.01

Moreover, in the PLS analysis the $R^2$ values are used as a goodness-of-fit measure [28]. The model explains almost the 63% of the variance in AP. The total effects of TTAC (0.59), of TTAW (-0.29) and GE (0.26) are strong, while the total effect of UNCERT (0.14) is medium. (Table IV).

TABLE IV. $R^2$ AND DIRECT, INDIRECT AND TOTAL EFFECTS

| Dependent Variable | $R^2$ | Independent Variables | Direct effect | Indirect effect | Total effect |
|---|---|---|---|---|---|
| AP | 0,631 | TTAC | 0,59 | 0.00 | 0.59* |
| | | TTAW | 0,29 | 0.00 | 0.29* |
| | | GE | 0.00 | 0,26 | 0.26* |
| | | UNCERT | 0,14 | 0.00 | 0.14* |
| | | E | 0.00 | 0,10 | 0.10* |
| | | C | 0.00 | 0,04 | 0.04 |

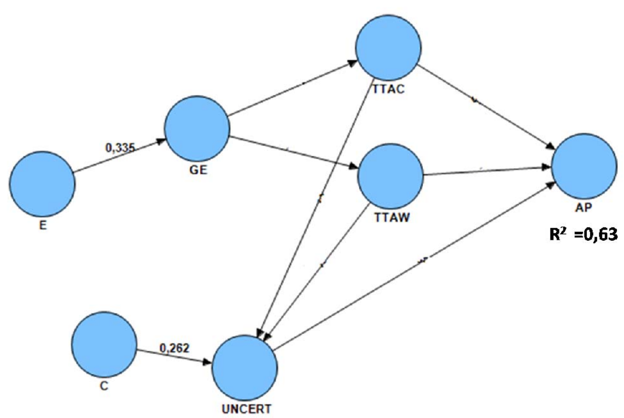


Figure 3. Path coefficients of the research model.

## IV. DISCUSSION AND CONCLUSIONS

The aim of this study was to examine the effect of personality traits on students' time-spent behavior during computer based testing. We conducted a case study with 96 participants from a European Secondary Education school and measured both their temporal attitudes during testing and personality factors as well. In particular, we used the LAERS assessment environment to track for each student the time to answer (in-)correctly, the idle time spent on viewing the answers (without saving an answer) and the times he/she views each question – expressing (un-)certainty, as defined in [6]. We also logged each student's goal expectancy [11] through a pre-test questionnaire and extracted each student's extraversion and conscientiousness traits through the BFI questionnaire.

Since extraversion is related to energetic and optimistic attitudes and behaviors, we assumed that it is expected to have a positive effect on goal expectancy. Although prior studies [7] did not reveal this relationship, in our case the initial hypothesis was supported. This finding indicates that extrovert students tend to set high goal expectations and believe that they are prepared enough to achieve their goals. Going a step beyond, this finding could suggest that students with a leader behavior designate their goal orientations more precisely. As a result, they seem to be more self-aware regarding their perceptions of preparation. A possible implication of this finding would be to appropriately scaffold the extrovert students during assessment through a real-time visualization (for example) that associates time-spent with goal-achievement.

Furthermore, conscientiousness is related to responsibility towards goal achievement and describes students that think before acting. Consequently, we assumed that this trait is expected to have a positive effect on (un-)certainty. This hypothesis was also supported form the analysis on the collected data. This finding suggests that the conscientious students will spent more time to view the questions again and again before saving an answer, trying to assure that they will submit the correct answer. Due to their strong sense of purpose, conscientious students demonstrate a deeper engagement with the assessment activity. This engagement could be formalized in terms of time-spent. It would be interesting to examine possible time-related factors that define, explain and promote engagement in activity, as indicators of students' performance.

In this study we examined only two out of five personality traits. The preliminary results are encouraging, explaining satisfactorily the effect of personality factors on students' time-spent behavior. However, these findings need to be validated by additional experimentation and bigger participant samples. Further analysis regarding the remaining traits (agreeableness, neuroticism and openness) is also required. In addition, other personal factors, such as gender or learning styles, should be examined.

To conclude, this study introduces personality traits with temporal learning analytics during computer based testing. We have strong indications that temporal learning analytics could be used for the construction of automated, adaptive and personalized CBA services, by exploiting the time dimension. From the results derives that personality factors are significant predictors in the temporal estimation of students' performance, but additional research should be conducted.

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