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Perseverance Measures and Attainment in First Year Computing Science Students

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ABSTRACT

We investigate the link between concepts of perseverance such as conscientiousness and grit, and the academic attainment of first year computing students. We review the role that perseverance plays in learning models, as well as describing the trait of conscientiousness in the Five Factor Model of personality. We outline research that links this trait with academic success, before focussing on more recent, narrower conceptualisations of perseverance such as academic tenacity and grit. We describe one of the questionnaire tools that have been used to assess the construct of grit. We give details of an investigation that looked for correlations between student responses to Duckworth's Grit Survey, the Big Five Inventory (BFI) Personality Survey and summative attainment scores in a first year programming course. The results suggest a weak but significant correlation between conscientiousness, grit and programming achievement. We discuss these results as well as the limitations of the method used. Finally, we make some observations about the importance of these concepts in Computer Science education and outline further work in this area.

Categories and Subject Descriptors

K.3.2 [Computers and Education]: Computer and Information Science Education – *computer science education, information systems information.*

General Terms

Human Factors

Keywords

Perseverance; grit; conscientiousness; personality traits; programming.

1. INTRODUCTION

From any analysis of computer science education it is clear that different people learn things at different rates and that there are

marked differences in academic achievement among learners. This remains true even when situational variables such as age, sex, previous educational experience and social environment are taken into account. That otherwise similar students on similar courses can perform differently suggests that while the teaching and learning environment is undoubtedly important, the characteristics of the individual student and their response to that environment are also significant factors in academic success [1]. It is natural, therefore, to look for predictors of academic achievement and to try to understand their contribution in the educational process. Cognitive factors such as general intelligence, defined as “*the ability to understand complex ideas, to adapt effectively to the environment, to learn from experience, to engage in various form of reasoning, to overcome obstacles by engaging in thought*” [2] have long been seen as one such predictor [3], and measures of intelligence have been found to correlate with both academic and non-academic achievement [2, 4]. Similar results have been found with non-cognitive factors such as motivation, time-management and self-regulation [5 6, 7].

Within the field of computer science education, considerable effort has been expended looking for predictors of academic success in key areas such as programming. Some of these have focussed on aspects of the teaching and learning environment such as curriculum [8] while others have investigated cognitive abilities such as general intelligence [9], logical reasoning ability, previous academic background [10], a deep approach to learning [11] and the ability to articulate strategy [12]. Alongside this, there has also been research into non-cognitive factors which impact on student achievement. Investigations of such influences on motivation have often considered the contribution that a learner's affective reactions have on remaining in education. These studies have frequently used personality traits as significant variables and research suggests that some students may be predisposed to develop and exercise the kind of self-regulatory skills that promote successful academic performance [13]. Among the personality factors that have been studied in this way, those that link to conscientiousness and determination have been reported to provide strong correlation with academic success [19].

We begin this paper by presenting some reasons why we consider the subject of perseverance to be important, both in a general pedagogical sense and specifically for the discipline of computer science. We then give an overview of two distinct lines of educational research that suggest that concept of perseverance is of fundamental importance for successful learning, and consequently, for genuine academic achievement. The first of

these concern pedagogical models that draw on the work of John Carroll [14]. We then discuss research on non-cognitive contributions to academic performance often described in terms of personality traits. We describe work done using the conscientiousness factor in the Five Factor model of personality structure as a predictor for academic success. Following this, we focus on a more specific conception of perseverance subsumed in the conscientiousness trait, namely that of academic tenacity [15] or grit [16]. We give some relevant background research in this field and describe the factors that underlie the main tool used in our investigation. We describe an experiment using a group of first year programming students in which data from Duckworth's "Grit Survey" [16] is correlated with data from a "Big Five Inventory" personality questionnaire. We then reflect upon the results of this investigation. Finally, we discuss further research directions that would be relevant to Computer Science Education.

The main contribution of this paper is to initiate a study of the concept of grit in the context of computer science. While computing research linking personality traits, such as conscientiousness, with achievement has been carried out previously, e.g. [17], we believe that this is the first time any investigation has been performed comparing narrower perseverance measures with programming attainment scores in the context of an initial course unit. The results appear to indicate that it would be profitable to carry out further work of this kind.

2. BACKGROUND

As mentioned above, there are a number of different research strands that suggest that the concept of perseverance is particularly significant when considering contributory factors for academic success. Some of these arise from work on the cognitive (and metacognitive) aspects of learning while others emerge from investigation of affective and other non-cognitive elements. In this section, we look at two important constructs that use perseverance as a principal component in their conceptual structure. The first of these is Carroll's Model of School Learning, while the second is the Five Factor Model of Personality that uses conscientiousness as one high-level trait to characterise an individual's patterns of thoughts and behaviours. Since Carroll's model expresses perseverance as a function of time, and the perseverance facet of conscientiousness involves self-regulation of effort over extended periods of time, the concept of "learning time" appears as an important underlying factor in both these models.

2.1 Carroll's Model of Learning

Academic appreciation of the significance, and complex nature, of time, and its importance as a factor in learning, goes back at least as far as John Carroll's 1963 paper "A Model of School Learning" [14]. When considering time in the learning process, it is necessary to mediate between two extreme positions. On the one hand, it is fairly clear that learning takes time and that lack of access to this resource will mean that learning simply does not take place. However, merely increasing the amount of time available to a student to accomplish some activity does not entail that the student will complete the task or indeed will abstract the relevant lessons from the learning activity itself.

Carroll observed that there are two different time variables involved in any learning task: the time spent on the learning activity and the time actually needed to learn the task. He defined the degree of learning or academic achievement to be an increasing function of the ratio of these two times, i.e.

$$\text{degree of learning} = f\left(\frac{\text{time spent learning a task}}{\text{time needed to learn it}}\right)$$

Learning gains therefore emerge through one of two means: increasing the numerator or decreasing the denominator.

Carroll proposed that three factors influence the denominator, i.e. the time needed for learning: student aptitude, the student's ability to understand instruction, and the quality of the instruction. He defined student aptitude as "*the amount of time a student needs to learn a given task, unit of instruction, or curriculum to an acceptable criterion of mastery under optimal conditions of student motivation*" [18], while the ability to understand instruction was defined as the student's ability to figure out independently what the learning task is, and how to go about learning it [14, 18]. The final factor affecting the denominator is the quality of instruction, which Carroll took to depend on both the content of a learning activity and the way it is communicated. The alternative strategy for increasing learning would be to increase the numerator, i.e. the time spent in learning. Carroll suggested that for this to happen, one of two factors would need to be increased: the time allocated for the learning activity, which he termed "opportunity to learn", or the level of student perseverance, which he quantified as the amount of time that the learner is actually engaged in the learning task [18].

Subsequent work has generally tended to focus on characterising the amount of time that the student is actively engaged on the learning activities, i.e. "time on task" or "engaged time". However, as pointed out by Carroll, while it may be possible to measure the various elapsed time intervals, it is impossible to "*meaningfully measure what goes on in the head of the student during that time, or insure in any way that what goes on in the student's head is addressed to learning. All that we can say with some certainty is that any learning that happens to occur does require time*" [18]. One consequence of this is that while time on task may be an important variable in learning, it is difficult to measure, especially when trying to differentiate between the time spent engaged in learning and other types of time. One way to mitigate this is to try to increase the perseverance factor since doing this would enhance the quality of the time that is spent on a learning activity by increasing the proportion in which a student is actively engaged with the problem. This then increases the effective time spent on learning.

While Carroll's work has proved very influential as a pedagogical model, for the purposes of this paper, its importance lies in the identification of perseverance as a significant factor in learning. While the focus of later work was on the further refinement of concepts of educational time (e.g. defining *academic learning time*), Carroll's model nevertheless provides a basis from which the concept of perseverance could be further analysed.

2.2 Academic Achievement and Personality Traits

While it is clear that some measure of cognitive ability plays an important role in determining levels of academic achievement, it does not appear to account for the degree of variation that occurs [19] nor does it appear to be a particularly good predictor of success at higher levels of education [20]. Work on other predictors, such as motivational or non-cognitive factors affecting academic performance, have generally focused on attempting to understand which are the personality traits that have a significant contribution to academic success.

One of the most influential current models of personality structure is the Five-Factor model [21]. This model characterises individual behaviours in terms of a “Big Five” set of personality traits that subsume lower level personality attributes. The highest-level personality traits in the five-factor hierarchy are Extraversion, Neuroticism (or, conversely, Emotional Stability), Openness to Experience, Agreeableness and Conscientiousness. These are considered to be more-or-less independent dimensions of personality and individuals can be characterised by their scores in each category. For example, extraversion is characterised by a tendency to engage with the external world and, as such, subsumes lower level personality facets such as friendliness, gregariousness and assertiveness. Individuals high on the neuroticism scale (or conversely, low on an emotional stability scale) tend to strongly experience emotions such as anxiety and vulnerability. Openness to experience is characterised by intellectual curiosity and imagination. Agreeableness reflects tendencies towards sympathy, altruism and helpfulness. High scores on conscientiousness are associated with self-efficacy, organisation, cautiousness, self-discipline and persistence.

There are also developmental generalisations of these models in which personality traits change over time. For example, in the neo-socioanalytic model [22], personality matures with age, reflected in a rise in the levels of agreeableness, conscientiousness, and emotional stability. This maturity arises as individuals reflect upon their identity and engage in a broader range of social roles. These are very interesting extensions of the theory but we do not engage with them in this paper.

While extensive research has been carried out on attempts to link one or more of the five factor traits with academic achievement, only conscientiousness has consistently been associated with academic success [23]. A meta-analysis investigating the five-factor model and academic performance in university education [24] found that performance correlated significantly with the factors of agreeableness, conscientiousness, and openness. In particular, it reported that correlations between conscientiousness and academic performance were largely independent of measures of intelligence. Indeed, after controlling for academic performance at secondary level, conscientiousness added as much to the prediction of academic performance as did intelligence.

Within the academic computing discipline, investigation of the effect of personality traits on performance can be traced back to the work of Kaiser et al [25], who characterised the personality types of software engineers. More recent reviews, such as [26], detail attempts to use personality measures to better predict performance, while other authors found that Openness, Agreeableness, Conscientiousness, and Extraversion were factors affecting leadership abilities [27]. Another recurring context in which personality measures have been used is the effectiveness of pair programming techniques. Salleh [28], for example, lists twelve studies investigating the effect of different personality factors on the success of pair programming.

Despite this, a recent wide-ranging review of thirteen years worth of research into factors affecting university students' GPA [29] found that the importance of conscientiousness was diminished once the concept of “effort regulation” (that is the persistence and effort needed to engage productively with challenging academic situations) was added to the model, although there was a large correlation observed between these two variables. This may suggest that it is not conscientiousness per se that is important but

rather those aspects that promote self-efficacy and self-regulation. This aligns with work done by Paunonen and Ashton [30] which suggests that academic performance can be better predicted by narrower, more specific facets of personality than by the broader personality traits. It seems sensible then to investigate contributions to academic performance from individual components that the Five Factor Model subsumes into the conscientiousness trait. One such component that has recently received prominent attention is what Dweck [15] calls “Academic Tenacity”, or what Duckworth [16] terms “Grit”.

2.3 Grit, Academic Tenacity and Perseverance

A wide-ranging study by the U.S. Dept of Education, “*Promoting Grit, Tenacity, and Perseverance: Critical Factors for Success in the 21st Century*” [31], details a number of different terms used by various researchers – resilience, conscientiousness, agency – which cover general conceptions of tenacity, perseverance and the ability to keep going in the face of adversity and setbacks. For example, the US National Research Council report, “*Education for Life and Work: Developing Transferable Knowledge and Skills in the 21-st Century*” [32], places the trait of “Conscientiousness” at the heart of their description of intra-personal competency, as a cluster of skills which includes initiative, self-direction, responsibility, perseverance, productivity, grit, forethought, performance, and self-reflection.

Looking at more focussed constructs related to perseverance, Duckworth defines “Grit” as “*the disposition to pursue long-term goals with sustained interest and effort over time*” [16] and considers it to be distinct from other traditionally measured facets of conscientiousness by its emphasis on stamina. In particular, grit entails the capacity to sustain both effort and interest in projects that take months or years to complete. Writing from a perspective of Self-theory [36], Dweck et al [15] use the related term “Academic Tenacity” to denote “*a mindset that looks beyond short-term concerns to longer-term or higher-order goals, and so withstands challenges and setbacks to persevere toward these goals*”. Dweck’s emphasis on learner mindsets not only brings together aspects of personal epistemology with identity theory, but also considers the skills that are needed to overcome challenges and setbacks. An associated concept is “Academic Perseverance” [37] which refers to a student’s tendency to complete learning tasks in a timely and thorough manner despite distractions and, as such, includes elements of delayed gratification and self-control.

Recent research suggests that the concept of grit can be used as a basis for the explanation of educational phenomena such as variation in lifetime educational attainment [19]. More importantly, while it is one facet or component of the Five Factor personality trait of conscientiousness, Duckworth reports that grit better predicts achievement outcomes than the conscientiousness itself [19]. It is reasonable, therefore, to ask if grit predicts academic success in aspects of computing education.

3. METHOD

Our study used data obtained from a group of sixty first year undergraduate students (48 male, 12 female), in the School of Computing Science and Digital Media at Robert Gordon University, UK. The students in the investigation were aged between 17 and 27 with the majority having entered university directly from secondary school. They were registered on three

computing degrees: the largest group was studying Computer Science, with the remainder studying Computing (Graphics and Animation) and Business Information Technology. However, as these students took identical course units in their first year, no differentiation was made between them for the purposes of this study. The students had completed the first of two major sections of their year long programming course unit when the questionnaires were distributed, about three quarters of the way through their first semester of university. The programming class itself contained seventy-six students but data from sixteen of these were disregarded either because they were absent for one or more of the assessed labs (which would skew the attainment mark) or because they did not fill in the questionnaires due to absence.

3.1 The Questionnaires

The students were asked to complete two questionnaires. The first was the 12-item Grit Survey developed by Duckworth et al [19] and the second was the 44-item Big Five Inventory (BFI) [35]. All respondents completed the questionnaires in class time. Data analysis was done using the Minitab 16 statistical package.

The 12-item Grit Survey consists of twelve questions and tracks two factors, consistency of interests and perseverance of effort, both of which are hypothesised to contribute to the psychological construct "grit". Responses are given on a five-point Likert scale ranging from 1 (disagree strongly) to 5 (agree strongly). The "Consistency of Interests" factor was addressed through responses to statements such as "My interests change from year to year" and "I often set a goal but later choose to pursue a different one" whereas the "Perseverance of Effort" factor was tracked by statements such as "I finish whatever I begin", "Setbacks don't discourage me" and "I am diligent". When validating her Grit survey, Duckworth reported high internal consistency scores for both factors ($\alpha = 0.84$ and 0.78 resp.) with neither appearing individually to have a greater correlation with academic success. This was consistent with grit being a compound trait comprising perseverance in areas of interest and effort.

The BFI was selected for use in the survey as it was reported to show high convergent validity with similar questionnaires and with peer ratings of the Big Five personality traits. The BFI items were rated on a 5-point Likert scale ranging from 1 (disagree strongly) to 5 (agree strongly) and took the form of responses to the statements starting with "I am someone who...". For example, items related to the Conscientiousness factor were: "does a thorough job", "can be somewhat careless" (reverse coded), "is a reliable worker", "tends to be disorganized" (reverse coded), "tends to be lazy" (reverse coded), "perseveres until the task is finished", "does things efficiently", "is easily distracted" (reverse coded). These reveal the features of "Big Five" conscientiousness as reflecting perseverance, reliability, persistence and orderliness. Factor scores for each of the Big Five traits were calculated for each student. Responses to specific statements were then averaged to calculate scores for each category.

3.2 The Programming Assessment

The students were studying a first semester introductory procedural programming course unit using Javascript as the coding language. The course unit consisted of a nine-week block with six hours class time each week, made up of two one-hour lectures immediately followed by two two-hour labs. The students were not assumed to have any prior knowledge of either the specific language or of programming in general, although there

was a range of previous experience within the group and a minority of students had studied some procedural languages at secondary school. Three lab-based programming assessments, each lasting two hours, were administered. These were held in weeks 3, 6 and 9 and completed under exam conditions. The overall assessment mark was calculated as the average of the individual assessment scores. Each exercise was constructed so that the student had to complete a number of individual steps in order to satisfy the assessment marking criteria. For example, one assessment task involved the generation of a password from personal information such as name and date of birth. To complete this task, the student was required to implement a number of transformations using string or array methods.

4. RESULTS

The internal consistency of responses from the group of students (as measured by the Cronbach α statistic) showed a somewhat lower measure for the two grit factors ($\alpha = 0.70$ for Consistency of Interests and 0.73 for Perseverance and Effort) than that reported in the literature. The grit scores themselves ranged from 2.17 to 4.25 with a mean of 3.33 and standard deviation of 0.45. As expected, the grit scores showed a moderate to high correlation with the Conscientiousness factor from the Big Five Inventory with a correlation coefficient $r = 0.59$ and $p < 0.001$.

Factor analysis of the responses to the BFI showed five large eigenvalues for the correlation matrix indicating five factors, with the largest clearly corresponding to the conscientiousness variable. The next two biggest factors were distinguishable as extraversion and agreeableness. Internal consistency for the five factors was good, with α ranging from 0.88 down to 0.75.

The programming scores ranged from 22% to 88% with a mean of 66% and a standard deviation of 15.4. Analysis of the grit score with the programming mark showed a weak correlation with $r = 0.24$ and $p = 0.02$. The strength of this correlation is, for example, comparable to that found in Duckworth's study of undergraduate psychology majors at University of Pennsylvania [16, Study 3] in which the grit score was correlated with GPAs with $r = 0.25$ and $p < 0.01$. Correlations were also calculated for each of the Big Five personality traits and the programming score. These were not statistically significant ($p > 0.7$) for both agreeableness and openness, while low negative correlations without statistical significance ($r = -0.16$, $p = 0.2$) existed for extraversion and neuroticism. Interestingly, the score for the conscientiousness trait ($r = 0.30$, $p = 0.01$) actually had a higher correlation with the programming scores than the grit scores.

5. DISCUSSION

These results seem to suggest that there is a weak but statistically significant correlation between the concept of grit, as measured by the 12-item Duckworth Grit survey, and academic attainment in the initial programming class. This generally aligns with the experience that programming is hard and that progress can be slow, requiring perseverance and, in Dweck's terminology [36], a "growth mindset" in which failure is seen as providing an opportunity for further learning rather than an indication of lack of ability [37].

While it was expected, given the close relationship between conscientiousness and grit, that there would be a statistically significant correlation between both the conscientiousness trait and academic success, and the grit scores and academic success, it

was not expected that the conscientiousness correlation would be higher than that of grit. While our result may be an artefact of the current experimental set up, it might also suggest that those aspects of conscientiousness which were abstracted out of the big five personality trait to form the grit construct actually play a more important role in specific context of programming than were hitherto thought.

The validity of the results reported here can be challenged on a number of grounds. Although the sample size ($N = 60$) is relatively small and the correlations themselves are low, the results are nevertheless comparable with those found in more extensive studies on the subject. However, in order to calculate an attainment mark, students needed to be present for all sub-components of the assessment, since a non-submission in one of these would skew the overall mark considerably. In addition, the respondents had to be present on the day that the questionnaires were handed out. Only that subset of the entire cohort of students that satisfied these criteria was admitted for data analysis. This meant that sixteen students in the cohort, who, for whatever reason, missed one of the assessments were not included in the study. The use of a summative attainment score to measure programming achievement also meant that students who took part in the investigation had to have persisted at least to the end of the course unit which introduces a systematic bias into the data that was not quantified in this study.

A greater concern is the question of whether the surveys do in fact succeed in measuring the concepts on which they are based. In the case of the 12-item Grit survey, the overall score relies on responses to statements such as “I am a hard worker”. There are certainly questions of reliability here. Students are not immune from cultural norms that tend to stress hard work as a virtue, and as a result, their responses (though perhaps not their actual behaviour) may be conditioned by societal expectations. Duckworth [38] also acknowledges that respondents may answer positively to some items in anticipation of future success and suggested that longitudinal studies of both a quantitative and qualitative nature would be required to mitigate this phenomenon. Conversely, an additional confounding factor may be the predominance of males (80%) in the assessed group. There is anecdotal evidence that, in some programming classes, there exists a subculture of the (generally male) “hero programmer” in which programming ability is believed to be innate and in which it is deemed inappropriate to acknowledge more than minimal effort in such tasks. While no measures of the personal epistemology of individuals in the group were taken alongside the Grit survey, it is interesting to note that there were four examples where the grit score was in the lower quartile and the attainment mark was in the upper quartile. All of these students were male.

A further objection to the Grit survey may be the lack of specificity of some of the statements used. One example (which is also found in the BFI) is the item “My interests change from year to year”. It could certainly be argued that this statement is indeterminate as it is almost certain that some interests will indeed change over time while others remain the same. There would clearly then be some subjective judgement needed about the relative importance of the interests that remained unchanged which may not relate in a meaningful way to the “perseverance in interests” component of the grit score.

6. CONCLUSION

As, we hope, is evident from our discussion of the validity of this study, we do not consider that the results of this present work conclusively establish a correlation (still less a causal link) between concepts of conscientiousness, grit and perseverance, and that of achievement, in an initial programming course. We do, however, believe that the results suggest that further study should be carried out in this area. Such investigation would complement the significant amount of research that continues to be done seeking predictors of academic success in computing courses, especially programming course units [11, 12]. These often focus on either cognitive elements of learning or features of the learning environment rather than the non-cognitive aspects discussed here.

We would also argue that the concept of time is an important factor in learning that deserves greater consideration, although we have not made any attempt to capture this aspect in this initial study. Further work would also benefit from trying to understand how these students actually spend their time. This might shed light on some of the low-grit, high attainment behaviour found in our study. There are, however, issues with trying to measure learning time and to do this, it would be necessary to construct questionnaires that are tailored more to the specific computing context, e.g. programming in this case. Much of our previous work has been on upper level students working in open-ended educational settings ([39] and refs therein) some of which have applied similar data analysis to issues such as personal epistemology [40]. Consideration of the current topic, together with previous work strongly suggests that students may have different levels of perseverance for open-ended problems than for problems in more structured contexts. In our experience, we would say that perseverance is even more necessary in an open-ended problem setting than when dealing with more convergent problems, and as such, would give a stronger prediction of how well a student performs. Further investigation of this context would be useful.

In this current study, no differentiation was made between students registered on different degree courses. It would be interesting to investigate if significant differences characterise the responses from the three different degrees. Other issues, such as identity and gender could also be addressed, although this would require data collection that was more targeted towards computing. Finally, we point out that this work, and similar research, has a clear bearing on the issue of study techniques.

7. REFERENCES

- [1] Hook, J. and Eckerdal, A. 2015. An Analysis of Student Performance Factors. To Appear in the Proc. 2015 Learning and Teaching in Comp. & Eng. Conference, Taipei, Taiwan
- [2] Neisser, U., Boodoo, G., Bouchard Jr, T. J., Boykin, A. W., Brody, N., Ceci, S. J., & Urbina, S. 1996. Intelligence: knowns and unknowns. *American Psychologist*, 51 (2), 77.
- [3] Harris, D. 1940. Factors affecting college grades: a review of the literature, 1930-1937. *Psychological Bulletin*, 37(3), 125.
- [4] Ackerman, P. L., & Heggstad, E. D. 1997. Intelligence, personality, and interests: evidence for overlapping traits. *Psychological Bulletin*, 121 (2), 219.
- [5] Pintrich, P. R., & Schunk, D. H. 1996. *Motivation in education: Theory, research, and applications*. Englewood.
- [6] Busato, V. V., Prins, F. J., Elshout, J. J., & Hamaker, C. 2000. Intellectual ability, learning style, personality, achievement motivation and academic success of psychology students in higher education. *Personality and Individual Differences*, 29 (6), 1057-1068.

- [7] Heckman, J., and Rubinstein Y. 2001. The importance of noncognitive skills: Lessons from the GED testing program. *American Economic Review* 2001: 145-149.
- [8] Gluga, R., Kay, J., Lister, R., & Kleitman, S. 2013. Mastering cognitive development theory in computer science education. *Computer Science Education*, 23 (1), 24-57.
- [9] Mayer, R.E., Dyck, J.L., & Vilberg, W. 1989. Learning to program and learning to think: what's the connection? In Soloway, E., & Sphorer, J.C. (Eds.), *Studying the Novice Programmer*. Hillsdale, New Jersey: Lawrence Erlbaum.
- [10] Boyle, R., Carter, J., & Clark, M. 2002. What Makes Them Succeed? Entry, progression and graduation in Computer Science. *Journal of Further and Higher Education*, 26(1):
- [11] Simon, Fincher, S., Robins, A., Baker, B., Box, I., Cutts, Q., De Raadt, M., & Tutty, J. 2006. Predictors of success in a first programming course. In *Proceedings of the 8th Australasian Conference on Computing Education-Volume 52* (pp. 189-196). Australian Computer Society, Inc.
- [12] Simon, Cutts, Q., Fincher, S., Haden, P., Robins, A., Sutton, K., Baker, B., & Tutty, J. 2006. The ability to articulate strategy as a predictor of programming skill. In *Proceedings of the 8th Australasian Conference on Computing Education-Volume 52* (pp. 181-188). Australian Computer Society, Inc.
- [13] Chamorro-Premuzic, T., & Furnham, A. 2003. Personality predicts academic performance: Evidence from two longitudinal university samples. *Journal of Research in Personality*, 37 (4), 319-338.
- [14] Carroll, J. 1963. A model of school learning. *The Teachers College Record*, 64 (8), 723-723.
- [15] Dweck, C., Walton, G. M., & Cohen, G. L. 2011. *Academic tenacity: Mindsets and skills that promote long-term learning*. Paper presented at the Gates Foundation, Seattle, WA.
- [16] Duckworth, A. L., Peterson, C., Matthews, M. D., & Kelly, D. R. 2007. Grit: perseverance and passion for long-term goals. *Journal of personality and social psychology*, 92(6).
- [17] Salleh, N., Mendes, E., and Grundy, J. 2012. Investigating the effects of personality traits on pair programming in a higher education setting through a family of experiments, *Empirical Software Engineering*. □
- [18] Carroll, J. B. 1989. The Carroll model a 25-year retrospective and prospective view. *Educational Researcher*, 18 (1), 26-31.
- [19] Chamorro-Premuzic, T., & Furnham, A. 2008. Personality, intelligence and approaches to learning as predictors of academic performance. *Personality and individual differences*, 44 (7), 1596-1603.
- [20] Furnham, A., Chamorro-Premuzic, T., & McDougall, F. 2002. Personality, cognitive ability, and beliefs about intelligence as predictors of academic performance. *Learning and Individual Differences*, 14 (1), 47-64.
- [21] McCrae, R. R., & Costa Jr, P. T. 1997. Personality trait structure as a human universal. *American Psychologist*, 52 (5), 509.
- [22] Roberts, B. W. & Wood, D. 2006. Personality development in context of the neo-socioanalytic model of personality.
- [23] Nofle, E. E., & Robins, R. W. 2007. Personality predictors of academic outcomes: big five correlates of GPA and SAT scores. *Journal of personality and social psychology*, 93(1)
- [24] Poropat, A.E. 2009. A meta-analysis of the five-factor model of personality and academic performance. *Psychological bulletin*, 135 (2), 322.
- [25] Kaiser, K. M., and Bostrom, R. P. 1982. Personality Characteristics of MIS Project Teams: An Empirical Study and Action-Research Design," *MIS Quarterly* (6:4) 1982, 43
- [26] Cruz, S. S. J. O., Silva, F. Q. B., Monteiro, C. V. F., Santos, P., and Rossilei, I. 2011. Personality in Software Engineering: preliminary findings from a systematic literature review, *Conference on Evaluation & Assessment in Software Engineering*, Durham, 2011. 1-10. □
- [27] Aronson, Z. H., Reilly, R. R., and Lynn, G. S. 2006. The impact of leader personality on new product development teamwork and performance: The moderating role of uncertainty, *J. of Eng. and Tech. Man.* (23:3), 221-247. □
- [28] Salleh, N., Mendes, E., Grundy, J., and Burch, G. S. J. 2010. An empirical study of the effects of conscientiousness in pair programming using the five-factor personality model," *International Conference on Software Engineering*, ACM Press, Cape Town, 2010, 577-577. □
- [29] Richardson, M., Abraham, C., & Bond, R. 2012. Psychological correlates of university students' academic performance: a systematic review and meta-analysis. *Psychological bulletin*, 138 (2), 353.
- [30] Paunonen, S. V., & Ashton, M. C. 2001. Big five factors and facets and the prediction of behavior. *Journal of personality and social psychology*, 81 (3), 524.
- [31] Shechtman, N., DeBarger, A., Dornisfe, C., Rosier, S., & Yarnall, L. 2013. Promoting grit, tenacity, and perseverance: Critical factors for success in the 21st century. *Washington, DC: US Dept of Education, Dept of Educational Technology*.
- [32] Pellegrino, J. W., & Hilton, M. L. (Eds.). 2013. *Education for life and work: Developing transferable knowledge and skills in the 21st century*. National Academies Press.
- [33] Dweck, C. S. 2000. *Self-theories: Their role in motivation, personality, and development*. Psychology Press.
- [34] Farrington, C. A., Roderick, M., Allensworth, E., Nagaoka, J., Keyes, T. S., Johnson, D. W., and Beechum, N. O. 2012. *Teaching adolescents to become learners. The role of noncognitive factors in shaping school performance: A critical literature review*. Chicago, IL.
- [35] John, O. P., & Srivastava, S. 1999. The Big Five trait taxonomy: History, measurement, and theoretical perspectives. *Handbook of personality: Theory and research*, 2 (1999), 102-138.
- [36] Dweck, C. 2012. *Mindset: how you can fulfil your potential*. Robinson; 10th Edition. New York.
- [37] Cutts, Q., Cutts, E., Draper, S., O'Donnell, P., & Saffrey, P. 2010. Manipulating mindset to positively influence introductory programming performance. In *Proc. 41st ACM symposium on Computer science education*. 431-435. ACM.
- [38] Duckworth, A. L., & Quinn, P. D. 2009. Development and validation of the Short Grit Scale (GRIT-S). *Journal of personality assessment*, 91 (2), 166-174.
- [39] M. Daniels, Å. Cajander, A. Pears, and T. Clear, *Engineering Education Research in Practice: Evolving Use of Open Ended Group Projects as a Pedagogical Strategy for Developing Skills in Global Collaboration*, *Int. Journal of Engineering Education*, 26, 2010, pp. 795-806.
- [40] McDermott, R., Pirie, I., Cajander, Å., Daniels, M., and Laxer, C. 2013. Investigation into the personal epistemology of computer science students. In *Proc. of the 18th ACM conf. on Innovation and technology in computer science education* (pp231-236). ACM