DiCS-Index: Predicting student performance in computer science by analyzing learning behaviors

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Abstract—Many students with little pre-college exposure to computer science (CS) share widespread incorrect ideas and a negative attitude towards the subject, leading to wrong decisions when choosing their major. In order to support these students, we developed a questionnaire built on Kolb’s and Pask’s learning style theories. Our aim was to create an instrument that allows to predict student performance in CS based solely on non-subject specific information.

Using 62 items from two questionnaires to operationalize the three personality traits as described by Kolb and Pask, we selected a subset of 15 items by comparing the results of students with high and low achievements in CS. Subsequently, we determined the so-called DiCS-Index by adding up the values of all these 15 items, where a high DiCS-Index suggests a good performance in CS. Finally, the instrument was tested at our local CS department.

The analysis of the personality traits suggests that CS, as a course of studies, is open to a highly heterogeneous student body with varying preferences and strengths. The only significant difference found is a clearly better performance of students who prefer learning through abstract conceptualization as opposed to gathering concrete experience. Concerning the questionnaire, we found a clear distinction between students with high and low achievements indicated by a highly significant difference in their corresponding DiCS-Indices.

I. INTRODUCTION

Even though entering into a computer science (CS) profession promises high earnings and good job opportunities [1], the number of students enrolling in CS does not increase in several countries [2], [3]. The reasons for this include widespread incorrect ideas and negative attitudes towards CS among students [3], [4]. This misattribution leads to a high rate of dropouts among CS students [4] and convinces other students, who would be capable of performing well in CS, to choose another subject [2].

Of course, this is particularly true for students with little or no pre-college exposure to CS [4]. As the number of such students at our CS-department is considerable, we were looking for tools to support these students in choosing the best field of study.

Our work is based on the idea that different academic subjects vary in their demanded profile in regard to their mental information processing requirements [5]. Such profiles can be characterized by the use of learning style theories that have been discussed in the last 40 years. Meanwhile, the classification in learning styles has become less important. One major reason are persistent difficulties in proving the validity [6]. A second reason is the simple finding that the classification in learning styles or, more generally, the evidence of the existence of different learning styles does not lead to any substantial educational implications apart from the fact that teaching should address different ways of assimilation and processing of information (e.g. [7]). However, learning style theories offer large assortments of items concerning the mental information processing related to personality traits that may be relevant to CS and, in consequence, relevant to our purpose.

As these assortments of items are measuring personality traits, we could assume a high degree of independence of the pre-college exposure to CS when using them. In contrast, by using CS-specific tasks (as done in other approaches), it is likely that we would only measure the students’ prior knowledge or their prior programming experience. Especially this, however, should be avoided, since our focus lay on the general capability to achieve good grades in the CS course.

In a first step, we asked CS students to rate 62 Likert-scale items based on two well-known learning style theories. We analyzed the underlying personality traits in order to identify a specific profile of information processing related to CS students. The second purpose was to create a questionnaire to predict good performance in the CS course of study. Therefore, we selected the 15 items that showed the biggest significant difference between the ratings of CS students with high and low academic achievement. By means of a second survey, we tried to show a close connection between the results of this questionnaire and good CS grades.

II. RELATED WORK

A considerable amount of research has been dedicated to factors affecting the programming performance (see e.g. [8], [9] for comprehensive summaries). For example, pre-college math background, the degree of self-regulated learning, the perceived comfort level in class [8], students’ strategies for fixing errors [10], prior programming experience [11] and the submission behavior regarding the first assignments [12] could be identified as predictors for a good performance in the introductory programming courses.

Most of the investigated factors refer to the programming performance in particular. Hence, these approaches are often too narrow for our purpose. A second problem arises from
the fact that such approaches mostly use data gathered during the ongoing courses; thus, they can certainly not be used to provide advice for students before enrolling.

Finally, relatively objective measures like the grades in math or in a most general sense the school achievement in math, that strongly correlate with the programming performance [8], seem to be a good predictor. However, a strong math background is believed to be an advantage in every STEM\(^1\) subject and, of course, a talented computer scientist does not inevitably need to be a gifted mathematician.

### III. LEARNING STYLE THEORIES

A learning style is a “description of the attitudes and behavior which determine an individual’s preferred way of learning” [13]. In the last 40 years, several systems of learning styles - more than 70 - have been described [6]. The reasons for choosing the following two learning style systems were twofold: firstly, approaches should build on a plausible theoretical foundation and, secondly, approaches should operationalize personality traits considered relevant to CS.

#### A. Experiential Learning Theory

The first approach we used is the Kolb Learning Style Inventory (KLSI) developed by David A. Kolb [14]. The KLSI is based on Kolb’s own comprehensive learning theory. The inventory had undergone a continuous development over 30 years and was used in the meantime in more than 1,000 studies [15]. Kolb’s Experiential Learning Theory derives from the work of Kurt Lewin, John Dewey and Jean Piaget and conceives learning as a continuous four-stage process whereby knowledge is created through the transformation of experience. These four stages are concrete experience, observation and reflections, formation of abstract concepts and generalization and finally testing implications of concepts in new situations [5].

The KLSI operationalizes two primary personality traits, which Kolb named “dimensions of personality”: “The first dimension represents the concrete experiencing of events, at one end, and abstract conceptualization at the other. The other dimension has active experimentation at one extreme and reflective observation at the other.” [5]

The ability to abstract is essential to CS [16]. Therefore, Kolb’s first personality trait “abstract conceptualization ◊ concrete experience” (AC ◊ CE) can be considered relevant to CS.

The connection between Kolb’s second personality trait “active experimentation ◊ reflective observation” (AE ◊ RO) and CS can be established considering the typical students’ ways approaching CS: A typical way of approaching CS is characterized by a development from an impulsive, trial-and-error oriented strategy to a reflected, observing strategy in learning (e.g. [17], [18], [19]). Start and end of this process are relatable to the extremes of Kolb’s second personality trait.

#### B. Conversational Theory

The cyberneticist, Gordon Pask, defined learning as a dialectical process between two or more individuals (cognitive systems), who are trying to agree over a given concept through language-oriented interaction [20]. Learning is the gradual convergence of opposed meanings and understandings through conversation. This process will be much more effective, if the interactions suit the individuals’ preferred way of learning.

These ways of learning can be represented by a personality trait ranging from serialistic to holistic learning (SL ◊ HL) preference [21]. Serialists learn a body of information in terms of string-like cognitive structures and are intolerant of irrelevant or temporarily irrelevant information. Holists, again, learn as a whole and try to assimilate and associate all offered information right from the beginning [21].

Pask’s theory stands out through its dichotomous distinction between the two ways of learning. Learners decide, depending on their individual task, on the strategy to use. The ideal learner uses a versatile style that is located between the serialistic and holistic poles. In contrast to extreme serialistic or holistic learners, versatile learners are free to choose the adequate strategy on a case-by-case basis.

We chose Pask’s personality trait “serialistic learning ◊ holistic learning” because this cognitivist idea to arrange data in order to enhance the processing appears crucial to CS. As an example, Pask’s approach plays a major role in the design and development of web-based instruction [22]. In such systems, the teacher-student interaction is severely limited and therefore the individualized presentation and editing of information, for example, serialistic or holistic, is even more important.

### IV. METHODS

An actual KLSI item asks respondents to rank four sentence endings according to their preference by assigning the numbers 1 to 4. These four sentence endings correspond to the four endpoints of the two personality traits: concrete experience, reflective observation, abstract conceptualization, and active experimentation [15]. The test is evaluated by summing-up the assigned values for each of the four endpoints. This is followed by calculating the two differences of the respective personality traits (AC-CE and AE-RO). The learning style finally depends on these two differences. Such combined items were of no use to our purpose, as we were particularly interested in single items that could be integrated independently in a new questionnaire. Therefore, we used a KLSI operationalization consisting of 40 independent 4-point-Likert-scale items [23]. The 40 items must be rated on a scale of 0 = “does not apply” to 3 = “fully applies”. In this test, 10 items are assigned to each of the four poles as well as in the original KLSI. Therefore, the trait values and thus the learning styles could be determined in the same way by summing up the pole-associated ratings and building the two differences.

Pask developed a whole range of testing procedures to determine the learning style [24]. One example is the “Spy Ring History Test” which allows the attribution of a learning style by analyzing the task specific behavior. In this test, students are required to learn the growth of a spy ring and predict its activities [25]. These kind of tests are time-consuming and
too sophisticated for many people [24]. Hence, we used a corresponding operationalization with 22 independent 6-point-Likert-scale items [26]. The learning style depends on the sum of these 22 ratings. The 22 items must be rated on a scale of 1 = “never true” to 6 = “always true” or vice versa 6 = “never true” to 1 = “always true” depending on the item. A low score indicates that the learner prefers a serialistic strategy, while a high score indicates a holistic preference.

The first (anonymous) survey was taken in 2013 among all students at the CS department. Among others, we asked for the following information: major (either CS, Games engineering, Business informatics, or others), their current grade point average and the ratings of the 62 learning style items mentioned above. We asked respondents to specify their average grade in order to distinguish students with good, mediocre and bad performances. They could choose between the ranges: very good (1.0 to 1.4), good (1.5 to 1.9), satisfactory (2.0 to 2.4) and sufficient (2.5 to 4.0). Students were invited via e-mail to participate in the survey carried out in German by means of the online-survey tool LimeSurvey.

Concerning the three personality traits, we calculated the four sums of Kolb’s poles by adding up the ratings of the corresponding 10 items for each respondent. We considered only records with a completeness rate of at least 80% for each pole. Missing values were supplemented by the average of the existing values of the same pole. Subsequently, we built the two differences AC-CE and AE-RO. Pask’s trait was much easier to handle because it was sufficient to add up the individual rates of each respondent after excluding all records with less than or equal to 80% of completeness and supplementing the missing values of the remaining records by the corresponding means of existing values. Hence, we could carry out our investigation based on the three trait values assigned to each respondent.

As a first step, we interpreted the means of the three trait values in order to identify specific personality traits of our target group. Following, we compared the means of the students grouped by their majors and grade point average.

The second purpose was to create the mentioned questionnaire. In order to select the relevant items, we calculated the four average ratings relating to the four grade ranges for each item. Based on these four means we set two conditions that would broadly be met for acceptance of an item. Firstly, a high score indicates a holistic preference.

As the 15 items originated from two different rating scales, they had to be unified. All 15 selected items should be rated with the same 5-point Likert scale ranging from “applies” to “does not apply”. In order to obtain an individual aggregated value (DiCS-Index) of all the 15 items we had to consider that some items had to be counted the other way around.

As a result of the first survey we assigned 1 to 5 points to the items 1, 2, 3, 8, 10, 11 and 14, and 5 to 1 points to the remaining items (see table II). For example, good students (1.38) rated item 1 lower than bad students (2.00); in other words: students who believe that generalizing and theorizing right from the start is of little help will perform worse than those believing the opposite. In consequence, we assigned 1 point for a high (applies) up to 5 points for low (does not apply) approval. For example, item 4 got an average rating of 2.08 from good, and 1.35 from bad students. This means that good students are more likely to agree to the item than bad students. In such cases “applies” should be linked to a high score. Therefore, we added up the reversed rating (5 to 1 instead of 1 to 5) to the aggregated value. The DiCS-Index is determined by adding up all these points and can therefore, attain values between 15 and 75.

The second (anonymous) survey was carried out in 2015 among the CS students at our CS department. They were invited via e-mail to take part. Among others, we asked for the following information: their current grade point average (choosing between three different ranges of their grades), major and the ratings of our 15 items. The survey was carried out in German by means of the online-survey tool LimeSurvey.

This time we used only three grade ranges and shifted the limits to improve the comparability of data. The respondents could choose between the ranges: very good (1.0 to 1.7), good/satisfactory (1.8 to 2.7) and sufficient (2.8 to 4.0). Finally, we calculated the total values, compared students grouped by grades (“very good” and “sufficient”) and major with a t-test.

V. RESULTS AND DISCUSSION

A. Personality traits

In total, we had 274 relevant and appropriate results in the first survey. Table I shows the mean values for the three personality traits in groups formed on major.

<table>
<thead>
<tr>
<th>Course of study</th>
<th>AE-RO</th>
<th>AC-CE</th>
<th>SL-HL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Computer science</td>
<td>1.8 (139)</td>
<td>5.9 (124)</td>
<td>77.5 (149)</td>
</tr>
<tr>
<td>Business informatics</td>
<td>1.8 (38)</td>
<td>2.8 (35)</td>
<td>77.0 (37)</td>
</tr>
<tr>
<td>Games engineering</td>
<td>1.4 (34)</td>
<td>4.5 (31)</td>
<td>76.6 (35)</td>
</tr>
<tr>
<td>Total</td>
<td>1.8 (211)</td>
<td>4.9 (190)</td>
<td>77.3 (221)</td>
</tr>
</tbody>
</table>

Mean values for the three personality traits grouped by major: active experimentation ○ reflective observation (AE ○ RO), abstract conceptualization ○ concrete experience (AC ○ CE) and serialistic learning ○ holistic learning (SL ○ HL). The numbers in brackets indicate the respective sample size.

The values of the first two personality traits, active experimentation ○ reflective observation (AE ○ RO) and abstract conceptualization ○ concrete experience (AC ○ CE), can theoretically range from -30 up to 30. The value of -30, for example, would have been reached, if the respondent had rated all RO items with “fully applies” (3 points) and all AE items with “does not apply” (0 points). To calculate the means we could use 211 values deriving from records with a completeness rate of at least 80% for both AE item group and the RO item group (at least 8 of 10 items rated each).

A mean of approximately 2 suggests a very weak preference for active experimentation. We were investigating whether or not there are inherent differences in the groups that can be
significant differences could be found. The three individual means between whom expectably no
reached a value of around 77 located in the middle of trait range. We calculated the means based on the 218 records with
given requirements between serialistic and holistic learning, the versatile learner, who is able to switch in accordance to the
since all 22 items could be rated from 1 to 6. Thus, an ideal

p < .009 10s
p < .003 50s
p < .001 50s
p < .009 50s
p < .005 50s
p < .001 50s
p < .005 50s
p < .001 50s
p < .005 50s
p < .007 50s

TABLE II: DiCS-Index Test

<table>
<thead>
<tr>
<th>n.</th>
<th>Item</th>
<th>M+</th>
<th>M-</th>
<th>R</th>
<th>p</th>
<th>points</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>I believe it is of little help generalizing and theorizing right from the start.</td>
<td>1.38</td>
<td>2.00</td>
<td>0.3</td>
<td>&lt;.009</td>
<td>10s</td>
</tr>
<tr>
<td>2</td>
<td>I rather look for the peculiarities of things, incidents and persons than for their commonalities sharing with others.</td>
<td>0.90</td>
<td>1.47</td>
<td>0.3</td>
<td>&lt;.03</td>
<td>10s</td>
</tr>
<tr>
<td>3</td>
<td>Learning situations in which I should discover things by myself that had already been found out and could simply be recounted by experts are of little use to me.</td>
<td>0.89</td>
<td>2.00</td>
<td>0.3</td>
<td>&lt;.001</td>
<td>10s</td>
</tr>
<tr>
<td>4</td>
<td>I like learning situations that are characterized by the systematic analyses of facts and theories.</td>
<td>2.08</td>
<td>1.35</td>
<td>0.3</td>
<td>&lt;.003</td>
<td>50s</td>
</tr>
<tr>
<td>5</td>
<td>I am only satisfied after conceptually grasping a matter.</td>
<td>2.39</td>
<td>1.70</td>
<td>0.3</td>
<td>&lt;.02</td>
<td>50s</td>
</tr>
<tr>
<td>6</td>
<td>I learn most easily if I can base my reasoning on logical considerations.</td>
<td>2.86</td>
<td>2.47</td>
<td>0.3</td>
<td>&lt;.009</td>
<td>50s</td>
</tr>
<tr>
<td>7</td>
<td>When learning I proceed rationally.</td>
<td>2.56</td>
<td>2.12</td>
<td>0.3</td>
<td>&lt;.05</td>
<td>50s</td>
</tr>
<tr>
<td>8</td>
<td>I often get my teeth into details and cannot see the wood for the trees.</td>
<td>4.42</td>
<td>3.48</td>
<td>1.6</td>
<td>&lt;.03</td>
<td>10s</td>
</tr>
<tr>
<td>9</td>
<td>Recognizing resemblances and differences between various topics comes naturally to me.</td>
<td>2.18</td>
<td>3.34</td>
<td>1.6</td>
<td>&lt;.001</td>
<td>50s</td>
</tr>
<tr>
<td>10</td>
<td>Definitions, data, facts and other details in examinations trouble me.</td>
<td>3.89</td>
<td>2.67</td>
<td>1.6</td>
<td>&lt;.006</td>
<td>10s</td>
</tr>
<tr>
<td>11</td>
<td>It happens that I copy definitions to memory without knowing their actual meaning.</td>
<td>5.07</td>
<td>4.10</td>
<td>1.6</td>
<td>&lt;.002</td>
<td>10s</td>
</tr>
<tr>
<td>12</td>
<td>It will only become exciting to me if topics turn out to be complex and multifarious.</td>
<td>2.81</td>
<td>4.10</td>
<td>1.6</td>
<td>&lt;.001</td>
<td>50s</td>
</tr>
<tr>
<td>13</td>
<td>I can rely on my memory.</td>
<td>2.42</td>
<td>3.31</td>
<td>1.6</td>
<td>&lt;.02</td>
<td>50s</td>
</tr>
<tr>
<td>14</td>
<td>It is not always true... 0 = “does not apply” ... 3 = “fully applies”; 1 = “always true”...</td>
<td>2.26</td>
<td>1.52</td>
<td>1.6</td>
<td>&lt;.02</td>
<td>10s</td>
</tr>
<tr>
<td>15</td>
<td>I like well-defined and manageable learning targets compliable gradually.</td>
<td>2.04</td>
<td>2.75</td>
<td>1.6</td>
<td>&lt;.007</td>
<td>50s</td>
</tr>
</tbody>
</table>

M+ / M-: average rating of students with very good / sufficient grades; R. 0..3: 0 = “does not apply” ... 3 = “fully applies”; 1 = “always true”...; 6 = “never true”; p: p-value of the t-test; points: points to assign for ratings ranging from “1 = applies” to “5 = does not apply” or “5 = applies” to “1 = does not apply”.

TABLE III: DiCS-Index Test

Concerning the second trait, abstract conceptualization ◊ concrete experience, we found a notable preference for abstract conceptualization with a mean of 4.91. This was especially true for CS (5.9) and games engineering (4.48) students while the mean of business informatics students (2.8) was considerably lower. A t-test yielded a significant difference between CS and business informatics students (p < .006).

The value of the third personality trait, serialistic learning ◊ holistic learning (SL ◊ HL) can range from 22 up to 132, since all 22 items could be rated from 1 to 6. Thus, an ideal versatile learner, who is able to switch in accordance to the given requirements between serialistic and holistic learning, reaches a value of around 77 located in the middle of trait range. We calculated the means based on the 218 records with a completeness rate of at least 80% (at least 18 of 22 items rated).

As shown in Table I the total mean (77.29) is surprisingly close to the key value of 77. This remains true, even for the three individual means between whom expectably no significant differences could be found.

B. The questionnaire

The items for the new questionnaire (see III) should meet the two conditions described above: A significant difference (p < .05) between the two extreme categories (very good and sufficient) and an ascending or descending order of the four means. It is not obvious that the information processing which is needed in our three investigated majors (CS, business informatics and games engineering) is the same. Since subject-specific differences could lead to adverse side effects, we made the selection considering only the CS students’ ratings.

These conditions were broadly fulfilled by 19 items, where “broadly” means that minor deviations in the ascending or descending order had been accepted. We excluded four more items to reach the target number of 15. All of these four items had relatively weak p-values and were considered being less relevant. 7 out of these 15 items were taken form the AC ◊ CE personality trait, 8 from HL ◊ SL and none from AE ◊ RO.

Table II shows the 15 chosen items together with the means of the two extreme categories (very good and sufficient), the scale and the corresponding p-values.

In the second survey, we had a total of 136 usable responses. We considered only records of students enrolled in
CS with a completeness rate of at least 80% (12 of 15 items rated). Missing values were handled in the same manner as described above: Up to 3 missing values were supplemented by the average of the existing ones.

The average DiCS-Index of the 136 CS-students reached 49.7. The 25 students with “very good” grades achieved an average of 55.4 while the 29 with “sufficient” grades merely achieved 45.4. The comparison between these two groups showed a very strong significance difference ($p < .001$).

Against this background it can be assumed, that a DiCS-Index higher than 50 suggests good performances in the CS course of study.

VI. SUMMARY AND CONCLUSION

The results concerning the three personality traits yielded that CS students show relatively balanced preferences for active experimentation, reflective observation, serialistic and holistic learning. In contrast, CS students seem to prefer abstract conceptualization over concrete experience. Nevertheless, these results may be taken as evidence that CS is a course of study open to a highly heterogeneous student body with different preferences and strengths.

The surprisingly downward deviation of business informatics students (see tab. I) is difficult to explain. One possible reason may be, that a considerable part of these students is making a conscious decision for business informatics in order to work around certain CS topics requiring a distinct abstraction ability.

The aim of the second part of this study was to create an instrument suited to support the course guidance. Even though a clear correlation between a high DiCS-Index ($> 50$) and good grades in CS could be measured, these results should be viewed with caution. The questionnaire should primarily help as a basis of discussion in a counseling session. It gives a first impression of the learning behavior characteristic for CS students, regardless of the subjective pre-college exposure to CS.

REFERENCES