Learners' non-cognitive skills and behavioral patterns of programming: A sequential analysis

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Learners' non-cognitive skills and behavioral patterns of programming: A sequential analysis

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***Abstract*—The interest in artificial intelligence (AI) education is growing exponentially; nevertheless, how to learn about AI, particularly Natural Language Processing (NLP), has been a challenging problem for educators and researchers worldwide. This study used a graphical programming platform *Snap!* to facilitate learning by allowing learners to explore AI and its NLP techniques in class. Data from 18,452 logged events were collected and Lag Sequential Analysis (LSA) was used to examine how learners behaved and learned sequentially. Non-cognitive factors were used to group learners as detailed and subtle behavior sequences that did not occur by chance could be uncovered. The results showed that five groups of learners, that is Passive Learners, Performers, Adaptive Learners, Interested Learners, and Dedicated Learners. They presented varied learning behavior patterns, which should be considered further in designing personalized and intelligent learning platforms to support AI education.**

Keywords—Graphical programming; non-cognitive factors; behavioral sequences; K-means Cluster; Lag Sequential Analysis

I. Introduction

In recent years, there has been a growing interest in designing AI and NLP instruction. This has attracted numerous educational researchers and practitioners [1, 2]. The explorative nature of AI and NLP, however, imposes new challenges for teaching such subjects in class using chalk and blackboard. Unlike learning mathematical equations, when learners can use pen and paper for practice, they need hands-on experiences to understand how these technologies work [3]. Such learning processes are iterative and can be challenging for learners, as they do not know where to start or what follows next [4]. Their participation in course activities can be highly heterogeneous and relatively individualized [5]. For example, some learners are able to get started quickly while others were confused; some explore and persist stubbornly, while others seek help actively. When there are no significant differences between learners who are studying the same program, in terms of intelligence level and educational background, it seems to be their non-cognitive skills that affect the way they learn.

Recent evidence has shown that disparities in non-cognitive skills, rather than general intelligence, affect learning experiences and performance [6]. In cognitive science, a fruitful group of studies has appeared, measuring non-cognitive skills. Recently, the term "non-cognitive skills" has been used as an umbrella term to encompass broader categories of traits and competences, such as conscientiousness, self-control, grit [7], social awareness [8], empathy, and self-regulation. In short, "non-cognitive skills" is used to refer to traits or competences that are not assessed in the same ways as cognition and knowledge [9].

Therefore, this study attempted to explore how learners behave and learn using a new programming environment to learn about AI and NLP. Non-cognitive factors were used to group learners as detailed and subtle behavior sequences that did not occur by chance could be uncovered.

II. Literature Review

The fields of learning analytics (LA) and educational data mining (EDM) focus on using data analytics approaches to fully understand the learning-related behaviors and accordingly to inform better learning design [10].

A. Non-cognitive skills

Many studies have attempted to identify different groups of learners who exhibit varied learning behavior patterns. One approach is to identify common behavior patterns to cluster learners [11], while another approach is to use learners' profiles

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and characteristics to group learners before examining their diverse learning behaviors. The later approach assumes that learners with different personal traits behave differently in learning actives. In recent years, the discussion of non-cognitive skills, as an important capability of learners, has been a heated topic. Non-cognitive factors have been explored from different perspectives, for example, interest is an important factor that influences students' motivation to take part in activities. Effort, persistence, etc. are regarded as psychological characteristics [12], which influence the degree of commitment and persistence in students' learning behaviors. Self-efficacy plays a key role in how learners manage their learning. Learners with high collaborative self-efficacy are more inclined to cooperate with others in their learning. Academic self-efficacy has also been examined carefully and found to have positive impacts on students' academic achievement, learning engagement and persistence in MOOCs [13], especially on their knowledge-sharing behaviors [14]. As well, many studies have found that students varying in achievement goal orientation differ in learning strategies, interaction patterns and tool-use patterns in the online learning environment [15-17]. Although non-cognitive skills have been discussed widely, there has not yet been any exploration of how different learners associated with diverse non-cognitive factors behave or learn in graphic programming environments to understand the conceptual and procedural knowledge of AI and NLP.

B. *Lag sequential Analysis*

In LA, one particular approach, lag sequential analysis (LSA), is used widely to explore significant behavior sequences from temporality perspectives; this is often overlooked comparing with other popular data analytics [18]. The LSA method, proposed by [19], allows researchers to examine behavior patterns that occur at frequencies greater than chance [20]. Since 2013, the LSA method has been adopted for different learning environments, for example, online interactive patterns in the Augmented Reality (AR) based environment [21], online discussion patterns in continuing education [22], interaction patterns during knowledge construction [23], the learning behaviors of high-achievement or low-achievement students [24], visual programming learning patterns in Blockly [25, 26], and pairs' discourse patterns and characteristics in a pair programming course using Python connected with Minecraft [27]. Most of the studies using the LSA method in the programming environments have focused on the behavioral sequences of students with different learning performance. Clearly, LSA has a well-demonstrated potential to examine significant behavior patterns in varied contexts, hence it is worth investigating its use to identify learners' behavior patterns associated with different non-cognitive factors in the rather new programming contexts for AI and NLP training.

III. Research Methods

A. *Participants and dataset*

An open-source blocks-based programming library in Snap![28]could facilitate novice learners to construct machine learning applications, such as "Learning NLP toolset on *Snap!*" (see Fig.1). The study was conducted in a compulsory course in an educational technology program at a Beijing university, and thus instructions were given by the lecturer and students were provided with the same task. 30 participants, who were taking the course were recruited and they were given the opportunity to opt out for taking part in research. AI and NLP lectures began with an introduction by the teacher for about 30 minutes, followed by a 50-minute practice session. In total, 30 questionnaires relating to non-cognitive factors and 18,452 logged events from 30 participants were collected. "Non-cognitive skills are those attitudes, behaviors, and strategies which facilitate success in school and workplace, such as motivation, perseverance, and self-control. These factors are termed 'non-cognitive' as they are considered to be distinct from the cognitive and academic skills usually measured by tests or teacher assessments"[29]. The questionnaires examined non-cognitive factors including grit, adapted from Duckworth[30], self-efficacy of group learning, adapted from Gwo-Jen Hwang [31], patterns of adaptive learning scales (PALS), adapted from Midgley[32].

Fig. 1. A screenshot of *Snap!*

B. *Analysis Method*

To classify the different types of learners, we extracted clustering variables by revising the structure of the questionnaire based on validity analysis and by selecting the main non-cognitive factors represented by each dimension (or a combination of several dimensions) based on the dimensional classification of the revised questionnaire. We relied upon modifications to Snap! by the iSnap: Intelligent Programming Support project at North Carolina State University in order to capture logs of all the user actions performed while running Snap!. Using the logs of *Snap!*, key behaviors relevant to this study were selected and merged for coding. LSA was conducted for different clusters associated with disparities in non-cognitive factors. GSEQ5.1 was used for frequency statistics and standard score conversion, based on the clustering of the learners.

IV. Results

A. *Using non-cognitive factors to cluster learners*

TABLE I. Dimensional division of the premeasurement scale

Subscale	Dimension	Questions
Grit	consistency of interests	Q1-Q3
	perseverance of effort	Q4-Q6
Self-efficacy of Group Learning	self-efficacy of group learning	Q7-Q10
Patterns of Adaptive Learning	mastery goal orientation	Q11-Q13
	academic efficacy	Q14-Q16
	performance-approach goal orientation	Q17-Q19
	performance-avoid goal orientation	Q20-Q22

Prior to working on the *Snap!* Graphical Programming, the researcher administered a questionnaire relating to the non-cognitive factors of "Grit", "Self-efficacy of Group Learning", "Patterns of Adaptive Learning", and "Self-efficacy of Group Learning" (see Table 1).

K-means clustering algorithm was performed to group learners according to their predominant non-cognitive factors. Normalization (Z-scores) of the five-point Likert scales were used as inputs, and the most optimal value of 5 clusters was identified by using the Elbow method [33].

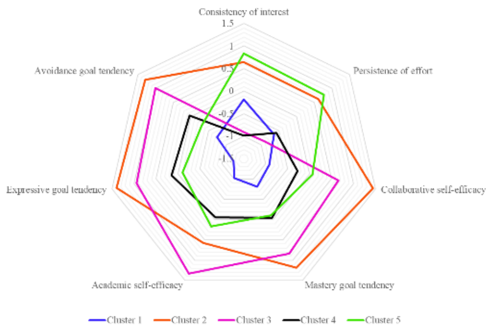

Fig. 2. Radar chat of learners associated with non-cognitive factors

As shown in Fig. 2, a radar chart was used for visualizing five clusters of learners.

Cluster 1 (6 learners): Passive learners. These learners had relatively low scores on all seven dimensions, with low self-efficacy in graphical programming learning activities. They were neither interested in the activities nor goal-oriented learners and were not willing to make much effort in exploration.

Cluster 2 (4 learners): Performers. This second smallest group of learners tended to have "expressive goal tendencies," "avoidance goal tendencies," "mastery goal tendencies," and "collaborative self-efficacy. In particular, they presented the highest "collaborative self-efficacy".

Cluster 3 (2 learners): Adaptive learners. This was a very small group of learners, who presented high "academic self-efficacy," "control-oriented goal tendencies," and "avoidance-oriented goal tendencies," but without "consistency of interest" or "persistence of effort". Although they tended to have low grit, they showed a tendency to excel in adaptive learning.

Cluster 4 (8 learners): Achievers. The second largest group of learners presented average non-cognitive skills, except for "Consistency of Interest". This implies that they tended to have low interest in participating in learning activities.

Cluster 5 (10 learners): Dedicated learners. This was the largest group of learners. They presented the highest "Consistency of Interest" and "Persistence of Effort" dimensions but reported average capacity for adaptive learning.

B. Lag Sequential Analysis to understand learning behaviors

Lag Sequential Analysis was used to examine the learning behaviors of different groups of learners. The behavior logs were cleaned, and 23 behaviors occurred more than once. For example, "Block.clickRun" appeared most frequently, 5008 times; "Block.showHelp", and "Scripts.exportPicture", "Sprite. setName" had the least number of occurrences. Two researchers worked "back-to-back" to code, and the researchers discussed conflicting views about codes until they reached agreement. In total, 14 behaviors were classified (See table II).

Taking the "Passive learners" as an example, the behavior "BC" was followed by another "BC" behavior 530 times. It was followed by "BG" 227 times, and by "BD" 47 times. We also calculated the residuals of the frequency of learning behaviors. Significant behavior sequences (z-score>1.96) among the five clusters of learners have been illustrated from Fig. 3 to Fig.-7.

TABLE II. CODING OF BEHAVIORS

Behaviour	**Module**	**Coding**
Run block	Block	BC
Crawl code	Block	BG
Duplicate code	Block	BD
Create a new block	Block	BR
Discard block	Block	BU
Specific operations (entering text, variable names, changing colors, etc.)	InputSlot & MultiArg & ColorArg	IE
Change category	IDE	IC
Select sprite	IDE	IS
Select sprite tab	IDE	IT
Toggle sprite display (zoom in/out)	IDE	IA
Open project	IDE	IO
Stop project running	IDE	IP
Undo scripts	Scripts	SU
An error occurs	Error	ER

a) Passive: One of the distinctive features of the passive learners' behavioral sequences was the "significant repetition of multiple behaviors", as in the "IC", "IO". In other words, this was evident in the repetition of non-significant behaviors such as "switch directory" and "open item". Second, the behavioral sequences of these learners were extensive and illogical. For example, there were 31 behavioral sequences in this category and some were difficult to explain logically, such as "IO→IT" and "IP→IT". These learners also had a certain number of "ER →ER" repeated error sequences (See Fig. 3).

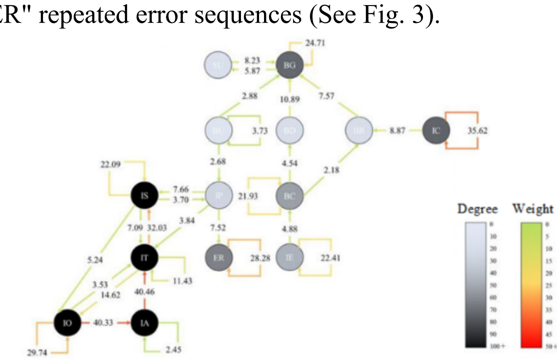

Fig. 3. Cluster 1: Behavior sequence conversion diagram of the Passive

b) Performers: Compared to the Passive group, the Performers had significantly fewer repetitive behavioral sequences and disordered sequences. As shown in Fig. 4, they also made attempts to move from "IDEs" (i.e., projects) to "blocks" (i.e., blocks of code) (behavioral fragmentation still existed). In addition, these learners tended to make more connections between the behaviors related to the code block and the task objective, which implies that they more focused on finding the correct answers to the encountered problems rather than simply exploring them using the visualization tools embedded in *Snap!*.

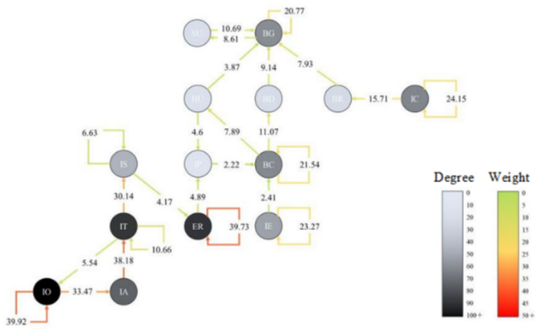

Fig. 4. Cluster 2: Behavior sequence conversion diagram of the Performers

c) Adaptive: The Adaptive group only exhibited 21 significant behavioral sequences, in contrast to other learners showed more behavioral sequences. Their fewer behavioral attempts reflect their "low level of consistent interest and persistent effort". In addition, we found that the behavioral sequences of this group showed a high degree of consistency. Their behaviors could be grouped into two behavioral sequences as "explore project →execute task" and "create code →debug code" respectively (See Fig. 5). This reflects these learners are adaptive to complex learning tasks, putting forward problem-solving ideas and thoughts.

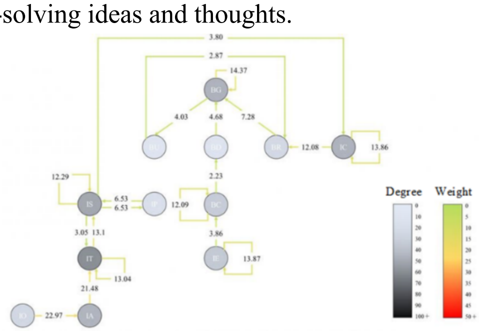

Fig. 5. Cluster 3: Behavior sequence conversion diagram of the Adaptive

d) Achievers: Although the Achievers tended to have "significant repetition of multiple behaviors" as the Passive, the Passive tended to repeat multiple times on nonrepetitive behaviors, whereas the Achievers are more likely to repeat meaningful behaviors such as "BC" to "BG" (See Fig. 6). This reflects the fact that these learners tend to complete tasks and perform debugging. In addition, these learners did not frequently follow the "ER→ER" sequence, that is repeated error behaviors. This indicates that they tend to follow the task instructions for reasoning a while, rather than mindlessly exploring it through trial and error.

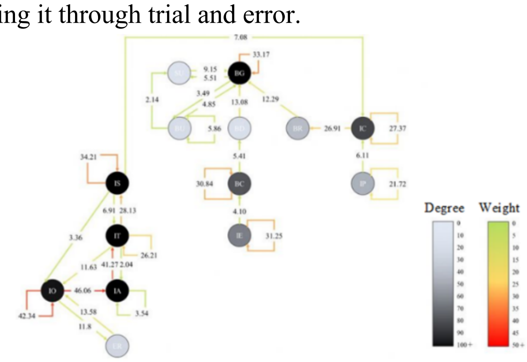

Fig. 6. Cluster 4: Behavior sequence conversion diagram of the Achievers

e) Dedicated: The Dedicated learners showed the highest "ER→ER" behavior sequence, presenting an image of "always repeating a behavior multiple times" in the repetitive behaviors, with high weighting of the ring-like behavioral paths (See Fig. 7). In addition to this significant behavior pattern, it is interesting to note that, when such loop behavior sequences were removed, the behavior sequences for completing the tasks become unidirectional, linear structures. This implies that the Dedicated learners exhibited a tendency to persist in their attempts and efforts, but lacked flexibility.

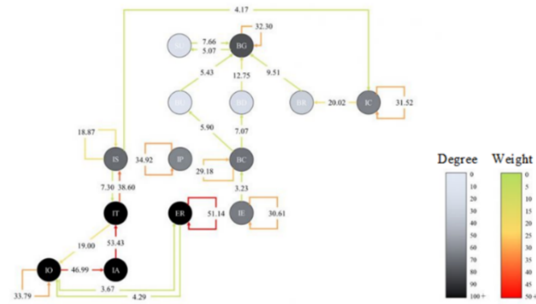

Fig. 7. Cluster 5: Behavior sequence conversion diagram of the Dedicated

V. Discussion and Conclusion

The results of this study have shown that using non-cognitive factors to group learners is an attainable approach for examining behavior patterns in the *Snap!* Programming environment. Their different patterns of behavior sequences imply, to some degree, that their non-cognitive skills affect their behavior sequences.

Using the K-means clustering algorithm, we identified five groups of learners associated with different non-cognitive skills. These five groups showed more typical variations in non-cognitive skills. For example, the Passive learners had low non-cognitive skills, while the "Expressive learners" excelled in all non-cognitive skills, and particularly tended to be goal oriented. Adaptive learners, who are capable to adapt to new and challenging tasks, are very different from hardworking learners, who do not address the nature of the tasks or problems, but thoughtlessly put more interest and effort into using the approaches they are used to. Unlike hardworking learners, "task-engaged learners" often lack interest and motivation. Such results echo findings of a number of studies, such as [11, 15-17]. Built upon earlier studies, such as that of Arora et al. [11], our study explored different behaviors using LSA, and the findings were consistent with those of a number of analytics studies [12-14]. As we only had 30 participants in this study, it was difficult to measure the correlational effects between non-cognitive factors and behavior patterns. Nevertheless, unlike previous studies [21, 22] using observation to code behaviors, our study used detailed behavior logs to explore the subtle changes in behavior which did not occur by chance. By doing this, more clear and real pictures of how these different types of learners behave can be uncovered. Interestingly, although different groups behave very differently, we found that three patterns of behavior sequences appeared significantly in all five groups of learners. These patterns were "open project →switch sprite display →select sprite's tab →select sprite", "specific operation →run code block →copy code block →grab code block" and "switch directory →new code block →grab code block". These three patterns were related to sprite operations, debugging operations and new code block operations respectively, which showed that different learners shared similar working patterns of dealing with programming tasks to learn AI and NLP.

Some limitations are also noted. The sample of only 30 participants in this study might be an under-representation of wider populations who have also taken the initiative to use programming to learn AI and NLP. Nevertheless, a detailed explorative study like this was needed before we could conduct a further, large-scale study to test theories or identity relationship between non-cognitive factors and learning behavior patterns and learner types, as well as the factors affecting the results. For future research, we plan to use Petri Nets to visualize the significant behavioral sequences derived from the results of LSA more clearly and precisely to offer better learner support strategies for students using programming to learn AI and NLP.

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