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# Learning Patterns in STEAM Education: A Comparison of Three Learner Profiles

**Xiaofang Liao [1], Heng Luo [1,*], Yang Xiao [2], Lin Ma [1], Jie Li [1] and Min Zhu [1]**

[1] Faculty of Artificial Intelligence in Education, Central China Normal University, Wuhan 430079, China
[2] Wuluolu Primary School, Wuhan 430079, China
* Correspondence: luoheng@mail.ccnu.edu.cn

**Abstract:** A learner profile is a method of classifying learners through their characteristics. Much of the current research on learner profiles has focused on online learning environments; there is a lack of in-depth category profiling and learning behavior analysis of student profiles in the STEAM context. To address this research demand, this study conducted a cluster analysis based on observed higher-order thinking behaviors, leadership behaviors, and verbal and non-verbal interaction behaviors of 81 primary school students in a STEAM project to explore the differences in learning outcomes, learning perception, and social recognition among different types of learners. The results revealed that STEAM students can be divided into three categories: Thinkers, Speakers, and Followers. There are significant differences between Thinkers and Followers in terms of positive emotions. Speakers and Followers have notable differences in their contributions and active participation. The research results can help teachers acquire a deeper understanding of student types in STEAM and thus provide more relevant and personalized instructional facilitation and class management.

**Keywords:** STEAM; learner profile; learning outcome; learning perception; social recognition; K-means clustering

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## 1. Introduction

STEAM is an acronym for Science, Technology, Engineering, Arts, and Mathematics, a slight adaption from a more commonly known term, STEM. The 1986 National Science Foundation (NSF) of the United States published the "Undergraduate Science, Mathematics and Engineering Education" report, which first used STEM as a generic label for any event, policy, program, or practice that involves one or several of key disciplines mentioned in the report [1]. Recognizing the importance of art-related disciplines for disciplinary integration and authentic problem-solving, Yakman (2008) put forward the concept of STEAM education by adding the letter A representing art into the acronym [2]. The NMC Horizon Report: 2015 Higher Education Edition pointed out that STEAM is the key to shaping future education changes over the next 2–3 years [3]. STEAM is an essential tool for covering the growing demand for human capital and economic development [4–6]. In light of the importance of the STEAM movement, various countries consider the provision of solid STEAM training as necessary in current times [7]. Several studies have revealed that STEAM training stimulates students' learning performance, learning perception, and leadership [8–11]. STEAM highlights the importance of individual differences among learners. Individual differences means that different learners have different learning styles, approaches, behaviors, characteristics, and preferences [12]. This heterogeneity in the learner population poses a considerable challenge to teaching practice. Paying attention to learner differences can improve learning outcomes in a complex educational environment such as STEAM [13–15]. It is important to classify learners based on their behavioral patterns.

Cluster analysis is a common data-mining method used to classify learners into different profiles [16,17]. Learner profiles can visually mark and classify learners by integrating their basic information and behavioral data. A large and growing body of literature uses learner profiles to optimize instructional design, provide targeted learning support services, and promote the realization of learners personalized learning [18]. Yet, previous research had a major limitation. Most of the studies focused on online teaching contexts such as MOOCs [19,20], and they seldom involved face-to-face teaching contexts such as STEAM. The data were mainly obtained automatically from education big data platforms, derived from either demographic information, course engagement, survey data, or academic performance [21–23], lacking attention to data on learners' cognitive and emotional engagement, which is very important in a STEAM context.

In view of this limitation, this research employed k-means clustering to discover attractive characteristics of participants' behavior and construct learner profiles in a STEAM context. Additionally, we sought to compare the differences among those profiles in three aspects: social recognition, learning perception, and learning outcomes. Two research questions guided our investigation:

(1) According to learners' learning behaviors in the STEAM context, what types of learner profiles can be extracted? What are the characteristics of these learner profiles?
(2) What are the differences between learner profiles of students in terms of learning outcomes, learning perception, and social recognition?

## 2. Literature Review

### *2.1. Key Constructs of STEAM Learning*

The unique characteristics of STEAM as a social-constructivist educational innovation highlights the importance of reexamining the key constructs of learning in this particular context, which include learning outcome, learning perception, and social recognition. Regarding learning outcomes, traditional education focuses on a single disciplinary knowledge and test scores, whereas STEAM education focuses on students' ability to integrate across disciplines, such as computational thinking and self-efficacy. Computational thinking involves solving problems, designing systems, and understanding human behavior by drawing on the concepts fundamental to computer science. Computational thinking skills, as a key ability required to solve problems, have gradually become an important indicator to measure whether the goals of STEAM education are achieved [24]. Self-efficacy is defined as judgment or assessment of one's capabilities to perform a particular given task successfully [25]. The interdisciplinary nature of STEAM poses a greater challenge to learners' learning ability than the learning of single-subject knowledge. Students may perceive STEAM subjects as difficult and hard to master [26]. This perception will reduce students' self-efficacy and thus affect their learning practice.

Further, motivation and emotion deserve our special attention in STEAM. Motivation is a prerequisite for students to participate in STEAM learning, as when individuals are intrinsically motivated, they will engage in activities out of interest in them [27]. Intrinsic motivation can increase learning value and reduce learning pressure. More importantly, motivation encourages a positive attitude toward STEAM disciplines, becoming a stimulus for students to pursue any of the STEAM subjects in their future career [28]. Emotional differences also affect students' learning achievement. Emotions are usually divided into two categories: positive (e.g., happiness) and negative emotions (e.g., sadness) [29]. Emotional differences promote students' participation, performance, and personality development in the STEAM context. Children who are willing to actively participate in learning and who can regulate their emotions tend to perform well in school and build positive social relationships [30,31].

Lastly, social recognition is another construct that indicates individual participation and contribution in STEAM, and shares close relations with the other constructs of learning outcome, motivation, and emotion. Social recognition is similar to social approval. It refers to the positive response to an individual's social behavior [32]. It is the perception of other members of the group and reflects the interaction with social learning. Low social recognition overtime is known to induce psychological stress for students, which can adversely affect their social interaction in learning, and thus leave a lasting detrimental impact on student performance, personal development, and satisfaction [33–35]. The literature has suggested three indicators of social recognition: participation, contribution, and popularity [36]. Participation is the degree to which students engage in classroom learning in different ways, such as answering, explaining, and presenting their own ideas and facilitating, questioning, and responding to others in class [37]. Contribution is an assessment of individual performance in facilitating group task completion [38]. A student's popularity is measured by the number of likes and dislikes of their classmates, indicating the student's social position and power status in the friendship network of a class [39]. Moreover, peer evaluation is often used to gauge students' social recognitions measured by perceived participation, contribution, and popularity within social learning contexts.

### *2.2. Learner Profiles*

Learner profiles, as an application of user profiles in the field of education, have been commonly used in educational research [40]. Through cluster analysis of learner attributes, such as their skills, interests, and motivations, learner profiles are often used to provide accurate personalized services for students. Clustering refers to methods of grouping data in such a way that the grouped elements exhibit the greatest similarity. There are various clustering technologies, such as K-means, hierarchical clustering, fuzzy C-means, etc. The clustering method adopted in this study is K-means clustering because it is simple, effective, and relatively efficient [41,42].

In the previous literature, behavioral data were collected based on online data platforms to make profiles of learners. For example, Talavera and Gaudiso applied clustering to student interaction data to construct profiles of student behaviors [43]. The research was conducted in the context of a course teaching Internet use, with data collected from forums, emails, and chats in the Learning Management system. The goal of their study was to support the evaluation of collaborative activities, and although only preliminary results were provided, their work confirmed the differences in behavioral patterns of different types of learners during collaboration.

However, the availability and richness of data are two challenges facing learner profile research, which undermines the credibility of research findings. In previous literature, learner behavior data were mostly derived from the log records of online learning systems, such as video-viewing behavior, forum discussion behavior, and homework submission behavior. These data are hard to collect in face-to-face learning context where STEAM learning typically takes place. Additionally, the data cannot reflect the complexity of social learning and knowledge construction. Common behavioral data include reply, watching videos, consulting documents, logging in, etc. [44]. There is a lack of records of interaction behaviors and leadership behaviors. Therefore, this study emphasized the interaction of cognitive and social factors in affecting behavior. In order to more comprehensively construct students' behavior patterns in STEAM face-to-face teaching context, learning behaviors are measured by higher-order thinking behaviors (HOT), leadership behaviors, verbal interactions, and nonverbal interactions.

## **3. Method**

### *3.1. Participants and Research Context*

A total of 91 sixth-grade students (52 boys and 39 girls) from a primary school in central China participated in this quasi-experimental study. Among them, 10 students did not participate in the whole project due to physical reasons and time conflicts, so the final data analysis was based on 81 students (44 boys and 37 girls). The students ranged in age from 11 to 12. The students in the elementary school all came from nearby communities and have similar family and economic backgrounds. They came from two parallel classes and were randomly divided into 15 groups. All participants were made aware of the research protocol and had submitted the informed consent forms approved by their parents before participating in the research study. The research protocol was evaluated and approved by the Ethics Committee of the Central China Normal University (protocol code-ccnu-IRB-202111047, approved on 2021/11/11).

The research context of this study was a student-led STEAM project. Before the class began, the research team placed cameras and microphones in the best position for each group, and read instructions to the participants informing them that their activities during the STEAM class would be recorded, but that their performance and learning outcomes would not affect their grades in the session. During the class, the learner's behaviors were recorded on camera, and the four researchers also carefully observed one or two groups each to get prepared for the video coding process in the latter stage.

The project theme "causes and current situation of myopia" was divided into three lessons. The three lessons were a closely linked whole, and the former was the basis for the latter. In the first lesson, students discussed the causes and current situation of myopia and created a group questionnaire. In the second lesson, students presented the survey results with mathematical statistics charts through group discussion. In the third lesson, students needed to draw posters in a team to show their project results. The whole project had certain requirements for students' collaborative abilities. In the process of collaboration, individual differences among learners may lead to different types of learners. Therefore, we hoped to draw the learner profiles through learners' behavioral data and explore the differences in learning outcomes, learning perceptions, and social recognition among different types of learners.

### *3.2. Data Collection*

This study collected two types of data. The first type of data is learning behavioral data used for formulating learning profiles. The second type of data measure the key constructs of STEAM learning, including learning outcomes, learning perceptions, and social recognition, which indicate the efficacy of individual learning in STEAM context.

#### 3.2.1. Behavioral Data

Behavioral data can be used to reflect learner patterns. Student behavior in class reflects student engagement in STEAM context. According to the social learning theory proposed by Bandura [45], learner behavior is influenced by the interaction between the environment and the individual, so we emphasized the cognitive and social factors of student behavior in this study. We selected higher-order thinking behavior, leadership behavior, verbal interaction behavior, and non-verbal interaction behavior as the variables of learner profiles. The detailed coding protocol is listed in Table 1.

**Table 1.** Behavioral variables used to construct learner profiles.

| Category | Variable | Description | Source |
|---|---|---|---|
| Learning behaviors | HOT behaviors | | Video recording |
| | Analysis | Identifying the problem, make logical reasoning, etc. | |
| | Application | Applying knowledge or technical skills to solve problems | |
| | Evaluation | Comments and gestures of approval/disapproval/feedback | |
| | Leading behaviors | Task assignment and decision-making behaviors | |
| | Verbal interaction | Communication through oral conversation | |
| | Non-verbal interaction | Communication through writing, gestures, or eye contact | |

Higher-order thinking and behavior are prevalent in STEAM education [5]. According to Bloom's taxonomy of cognitive learning objectives [46], higher-order thinking behaviors in this study included three observable behaviors: analysis, application, and evaluation, which referred to students' mental activities at a higher cognitive level. Leadership behaviors emerged as another important measurement of student participation and performance in STEAM [47], due to its great demand on learner autonomy and social interactions [48]. In this study, they were measured by the number of times students took the initiative to assign tasks and make decisions. Additionally, we also focused on the interaction between student behaviors, which emphasizes the social constructivist nature of STEAM [49]. We focused not only on student communication through oral conversation, but also on non-verbal communication through writing, gestures, or eye contact based on body language theory [50,51].

### 3.2.2. Performance Data

Learning outcomes, learning experiences, and social recognition are key constructs of STEAM learning performance. Due to the particularity of STEAM education context, we chose two variables, computational thinking and self-efficacy, to measure the learning outcome, both of which were assessed by questionnaires after the completion of the project. The self-efficacy questionnaire (Cronbach's $\alpha$ value = 0.773) and computational thinking questionnaire (Cronbach's $\alpha$ value = 0.762) were respectively composed of 8 and 20 five-point lower-scale items, indicating good internal reliability.

Learning perception includes learning motivation and positive and negative emotions. Learning motivation is measured by questionnaires (Cronbach's $\alpha$ value = 0.814) which was composed of 12 five-point lower-scale items. Emotion is a short intuitive experience, and self-reported emotional data measured by questionnaires cannot accurately reflect students' feelings in class [52]. Therefore, we used more accurate audio and video coding to restore students' emotional states in class. We coded students' emotions with the dimension of emotion sociology proposed by Stets (2010). Stets divided emotions into positive emotions and negative emotions [29]. Positive emotions refer to students' happiness, pride, and interest in group cooperation, whereas negative emotions refer to students' boredom, frustration, and anger in group cooperation. The observers classified the students' emotions on the bases of facial expressions, gross body movements, and conversational cues. Table 2 lists the common types of emotion expressions observed during STEAM learning and assigns them into the proper categories.

**Table 2.** Key Constructs of STEAM Learning Performance.

| Category | Variable | Operation | Source |
|---|---|---|---|
| Learning outcomes | Self-efficacy | Average rating of self-efficacy items | Questionnaire |
| | Computational thinking | Average rating of computational-thinking items | |
| Learning perception | Learning motivation | Average rating of motivation items | Questionnaire |
| | Positive emotions<br>Joy | Sum of expressions such as clapping hands or laughing with pleasure; statements such as "Yes!" or "I got it!" | Video recording |
| | Pride | Sum of expressions such as elation; statements such as "I'm really good!" | |
| | Interest | Sum of expressions such as leaning forward; statements such as "It's really interesting!" | |
| | Negative emotions<br>Boredom | Sum of expressions such as slouching, and resting the chin on his/her palm; statements such as "Can we do something else?" or "This is boring!" | |
| | Frustration | Sum of expressions such as banging on the desk or pulling at his/her hair; statements such as "This is annoying!" | |
| | Angry | Sum of expressions such as clenching teeth and increase voice and tone; statements such as "Shut up!" | |
| Social recognition | Participation | Sum of peer ranking of participation | Questionnaire |
| | Contribution | Sum of peer ranking of contribution | |
| | Popularity | Sum of peer voting of popularity | |

Social recognition is measured by peer evaluation in the questionnaire. Social recognition includes participation, contribution, and popularity. Participation was measured by ranking the group members' level of active participation in the collaborative process. The contribution was derived by having students rank the contributions of members in the team collaboration process. After that, we summed reversed item ranking of the questionnaire. Popularity was defined as the sum of votes each student received. We asked students to rank the five people in the class they would most like to work with next time. The variables, their operations, and data sources are listed in Table 2. The higher the average score and the sum of ranks, the better the social recognition performed on that variable.

#### 3.2.3. Data Collecting Process

Firstly, for data that requires video coding, we have obtained 15 groups of students' class videos in total. After cutting the videos unrelated to the class, we can get the video source file. The video screen can see the action behavior of each student in class, and the microphone recorded the speech of each student. The video coding process consists of two stages. In the first phase (January–February 2022), the first, third, and fourth authors split video recordings into 2-min segments as units of analysis, as most learning events can be captured in such segment lengths and the workload can be managed by manual coding. The total length of the video is 225 min and it is divided into 113 coding segments. In the first stage, the three authors freely coded about 30% of the video clips in order to further validate and modify the preliminary coding protocol. After determining the coding protocol, we launched the second phase (March–April 2022), recruiting 12 undergraduate students as volunteers to code the video clips. All the coding volunteers received 4 hours of strict coding training, and passed the 30-min coding test of the sample video. After all the volunteers passed the test, 15 people, including three authors, participated in the coding process, and each video segment was coded by 2 people to ensure the reliability among the rater. Any disputes and disagreements that arose during the coding process were resolved through weekly discussions by the research team. After satisfactory reliability is achieved, the average score of the two encoders is taken as the final coding statistics. The average Spearman's correlation coefficients for the video segments coded by two persons ranged between 0.72 and 0.94, indicating an overall good interrater reliability of the coding results.

Furthermore, for the questionnaire data, all the questionnaires were handed out immediately in class after students completed the whole project. We sent out 81 questionnaires and recovered 81 questionnaires with a response rate of 100%. We also eliminated all the questionnaires with the same choice and incomplete answers. There were 77 valid questionnaires, and the effective rate was 95%.

### *3.3. Data Analysis*

There are two major types of data analysis approaches. The first type is cluster analysis of behavioral data. The clustering analysis algorithm adopted in this study was K-means clustering. The K-means algorithm groups the data into 'k' partitions by minimizing the distance of individual data points from their cluster centroids. The number of clusters must be determined before the iterative process, which is the key problem of this algorithm. In this study, the number of k values was chosen by an elbow test, which plots the variance associated with each value of k. A key metric of the elbow test is the sum of the squared errors (SSE). The SSE is the clustering error of all samples, representing the quality of the clustering effect.

$$\mathrm{SSE} = \sum_{I = 1\; p\in C_i}^{K} |\, p - m_i \,|^2 \tag{1}$$

where $C_i$ is the ith cluster; p is the sample point in $C_i$; $m_i$ is the mean of all the samples in $C_i$

When K is less than the true cluster number, SSE decreases greatly. However, when K reaches the true cluster number, the decline of SSE tends to be gentle as the k value continues to increase. Therefore, the graph of SSE and K takes the shape of an elbow, and the k value corresponding to the elbow is the real cluster number. The elbow test of behavioral data is shown in Figure 1. The figure shows that the elbow test is bent between K = 2 and K = 4. Therefore, the best clustering can be obtained when K = 3.

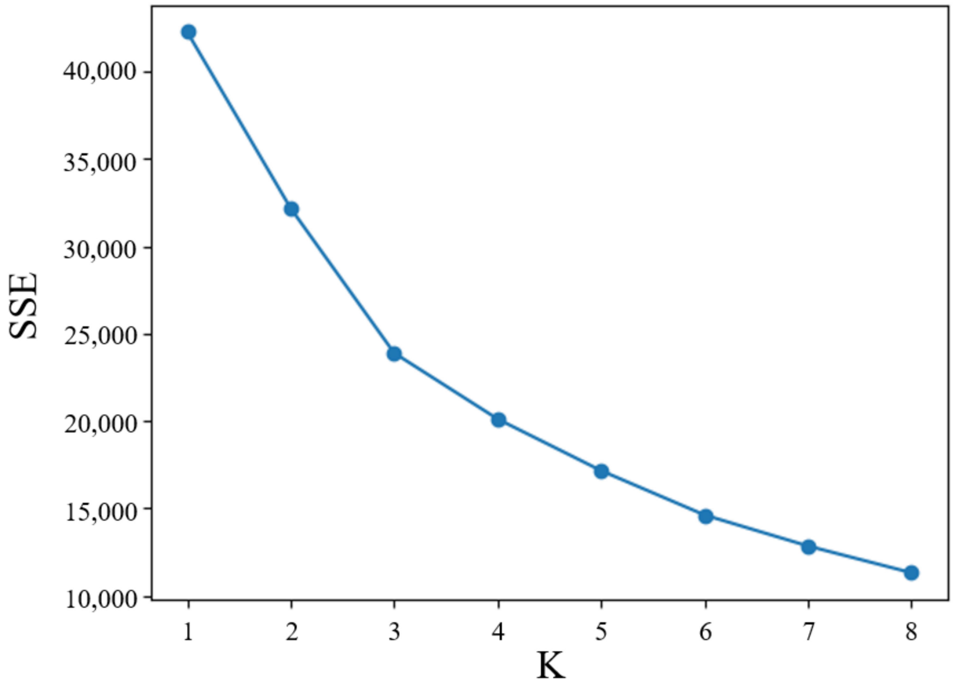


**Figure 1.** Optimal number of clusters of the behavior data.

The second type is a nonparametric test. Since the questionnaire data was mostly nominal, with ordinal data that were non-normally distributed, we used the non-parametric Kruskal–Wallis test to examine differences in learning outcomes, learning perceptions, and social recognition among students with different behavior patterns. Additionally, we used the Kruskal–Wallis test to detect pairwise differences. All statistical analyses were performed using IBM SPSS software (version 21).

## 4. Results

### *4.1. Learner Profiles*

According to the result of the elbow test, we clustered the HOT behaviors, leadership behaviors, verbal interactions, and nonverbal interactions behaviors with K = 3, obtaining the results as scatterplots. There are six scatterplots for the four behavioral variables, but only four plots are obvious in some dimensions, as shown in Figure 2. Table 3 describes the results of descriptive statistics between different learner profiles. In this study, the clusters are represented as Thinkers, Speakers, and Followers.

**Table 3.** Means and standard deviations for HOT behaviors, leading behaviors, verbal interaction behaviors, and non-verbal interaction behaviors among three learner profiles.

| Group | HOT Behaviors | Leading Behaviors | Verbal Interaction | Non-Verbal Interaction |
|---|---|---|---|---|
| Thinkers ($n$ = 35) | 19.471 ($SD$ = 9.191) | 5.500 ($SD$ = 5.618) | 54.729 ($SD$ = 5.894) | 24.157 ($SD$ = 11.033) |
| Speakers ($n$ = 16) | 14.281 ($SD$ = 6.575) | 6.000 ($SD$ = 4.608) | 78.563 ($SD$ = 9.752) | 15.3750 ($SD$ = 7.516) |
| Followers ($n$ = 30) | 11.783 ($SD$ = 6.812) | 1.85 ($SD$ = 2.077) | 38.350 ($SD$ = 7.414) | 18.433 ($SD$ = 7.088) |

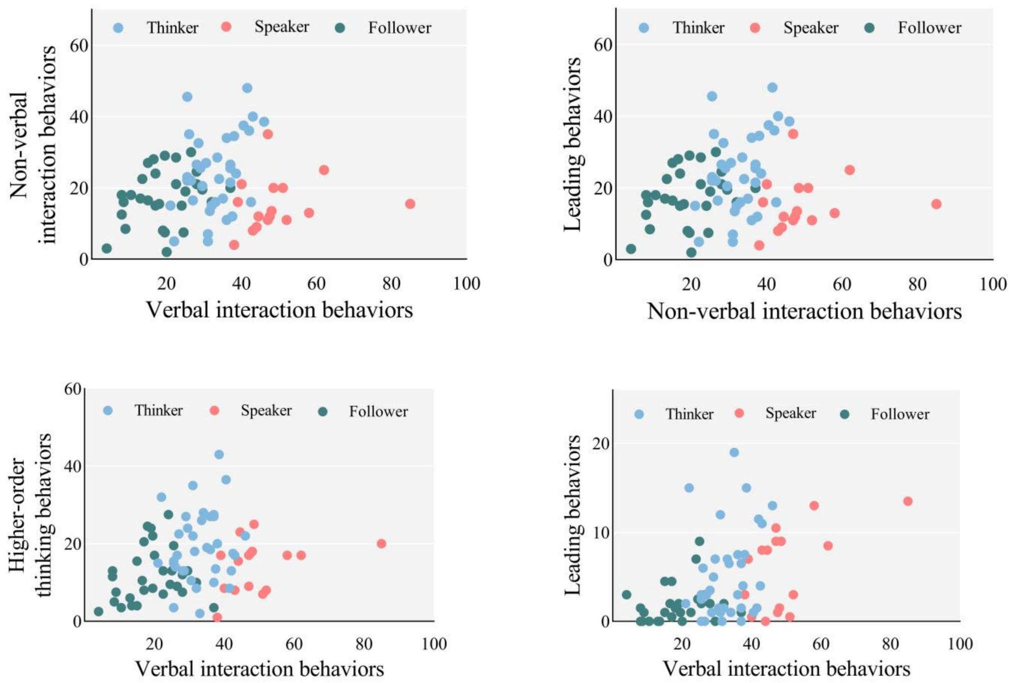


**Figure 2.** Scatterplot analysis.

Group 1 was named Thinkers. This type of student showed more higher-order thinking activities and preferred non-verbal interaction to cooperation in a team. The learners in group 2 had the highest degree of verbal interaction behaviors, and their leading behaviors were also high. Thus, this second group was labeled Speakers. We called the third group Followers because this group showed lower leadership behavior and HOT behavior. In this group, they were more inclined to agree with other students' opinions and were more often silent. When compared from different perspectives, the following points should be noted: (1) the three groups differed significantly in terms of their verbal interaction behaviors; (2) groups 1 and 2 showed a high level of leadership behavior.

We are interested to understand the gender distribution within each learner profile with the purpose of exploring the possible interaction effect between students' gender and learning patterns. As shown in Figure 3, over 50% of boys were classified as Thinkers, a proportion larger than Speakers and Followers combined. Contrarily, there were more Followers among girls, accounting for about 50% of the overall girl population. The proportions of boys and girls being Speakers were about equal, less than the other two learner profiles.

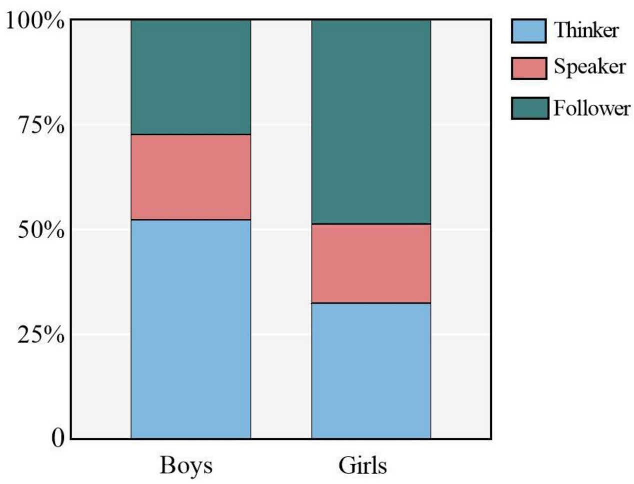


**Figure 3.** Gender differences among the three learner profiles.

### 4.2. Differences in Learning Outcomes

Table 4 demonstrates means and standard deviations for learning outcomes, learning perception, and social recognition in each learner profile. Figure 4 displays the average scores of Thinkers, Speakers, and Followers in self-efficacy and computational thinking. The results of non-parametric tests showed no significant difference in students' learning outcomes. To observe the overall distribution of the data, we plotted a box plot. The median self-efficacy of the Followers was slightly lower, and the median of the Thinkers' computational thinking was slightly higher. Both Thinkers and Followers had some anomalous data.

**Table 4.** Means and standard deviations for higher-order thinking behaviors, leading behaviors, verbal interaction behaviors, and non-verbal interaction behaviors in each learner profile.

| Categories | Variable | Thinkers (*n* = 35) | | Speakers (*n* = 16) | | Followers (*n* = 30) | |
|---|---|---|---|---|---|---|---|
| | | *MD* | *SD* | *MD* | *SD* | *MD* | *SD* |
| Learning outcomes | Self-efficacy | 4.091 | 0.656 | 4.094 | 0.592 | 3.855 | 0.731 |
| | Computational thinking | 4.106 | 0.345 | 4.033 | 0.419 | 3.858 | 0.800 |
| Learning perception | Learning motivation | 4.288 | 0.921 | 4.063 | 0.522 | 4.053 | 0.662 |
| | Positive emotions | 25.357 | 11.859 | 23.844 | 11.882 | 18.667 | 11.660 |
| | Negative emotions | 4.386 | 4.148 | 3.438 | 3.558 | 5.817 | 8.057 |
| Social recognition | Active participation | 4.486 | 3.239 | 5.813 | 4.246 | 3.667 | 2.454 |
| | Popularity | 22.936 | 9.729 | 27.375 | 7.247 | 18.786 | 8.319 |
| | Contribution | 24.871 | 8.838 | 26.313 | 5.594 | 20.536 | 8.307 |

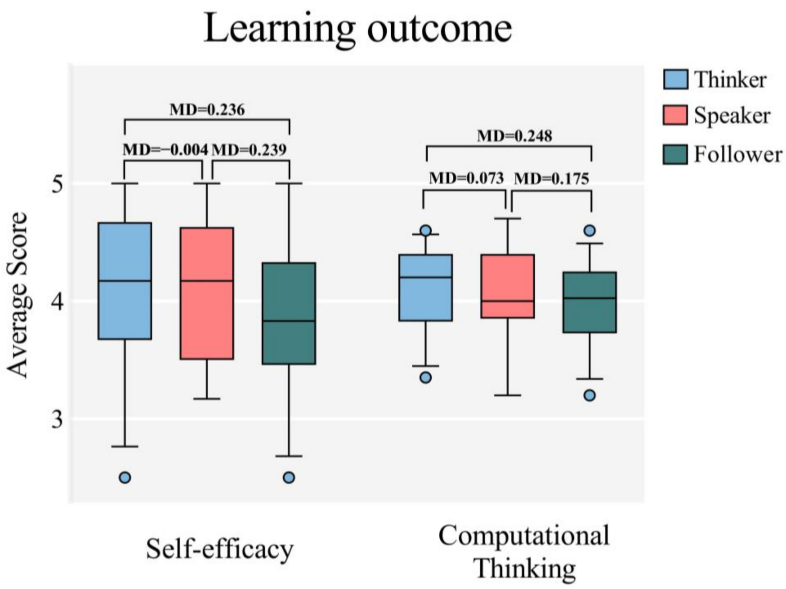


**Figure 4.** Differences in learning outcomes among three profiles (*MD*: mean difference).

### 4.3. Differences in Learning Perceptions

Figure 5 shows the differences in learning perception between the three learner profiles. Positive and negative emotions were encoded through a dynamic video, so we counted the frequency with which these emotions appeared in the three learner profiles. The results of the non-parametric test indicated significant differences in positive emotions ($MD = 7.017$, $p < 0.05$), while the results revealed no significant differences in negative emotions. The negative emotions of Speakers appear the least frequently, and the negative emotions of Followers appear the most frequently. Non-parametric test results showed that there was no significant difference in learning motivation among the three types of learners.

According to the results of the box plot, the median of Thinkers was slightly higher than those of Speakers and Followers for learning motivation.

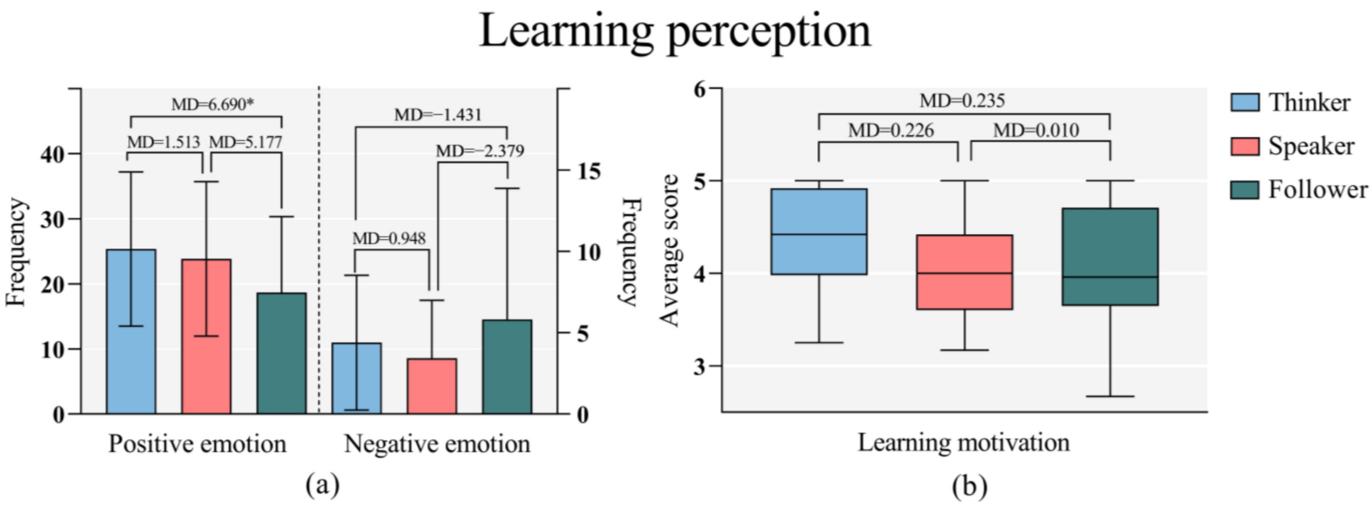


**Figure 5.** Learning perception counts for three types of students: (**a**) difference between positive and negative emotions among three types of students; (**b**) differences in learning motivation among three types of students (*MD:* mean difference; * $p < 0.05$).

### 4.4. Differences in Social Recognition

Figure 6 demonstrates the social recognition of the three types of learners in STEAM. Compared to Followers and Thinkers, Speakers were considered to make more of a contribution ($MD$ = 9.081, $p$ < 0.01) and actively participate ($MD$ = 6.198, $p$ < 0.01) in team collaboration. The non-parametric test results showed a statistically significant difference between Speakers and Followers. In other words, participants were more likely to approve of the Speaker's contribution and participation. The Thinkers had a higher Upper Whisker. Based on the frequency distribution curve of popularity, the three groups of learners differed even more in popularity. We found that, when the popularity value was low, the distribution frequency of Followers was higher, and most of the Thinkers were in the middle for popularity. When the popularity value was higher, the distribution frequency of Speakers was higher, and some Speakers were particularly popular. So, overall, the Speakers were the most popular, followed by the Thinkers, and finally, the Followers.

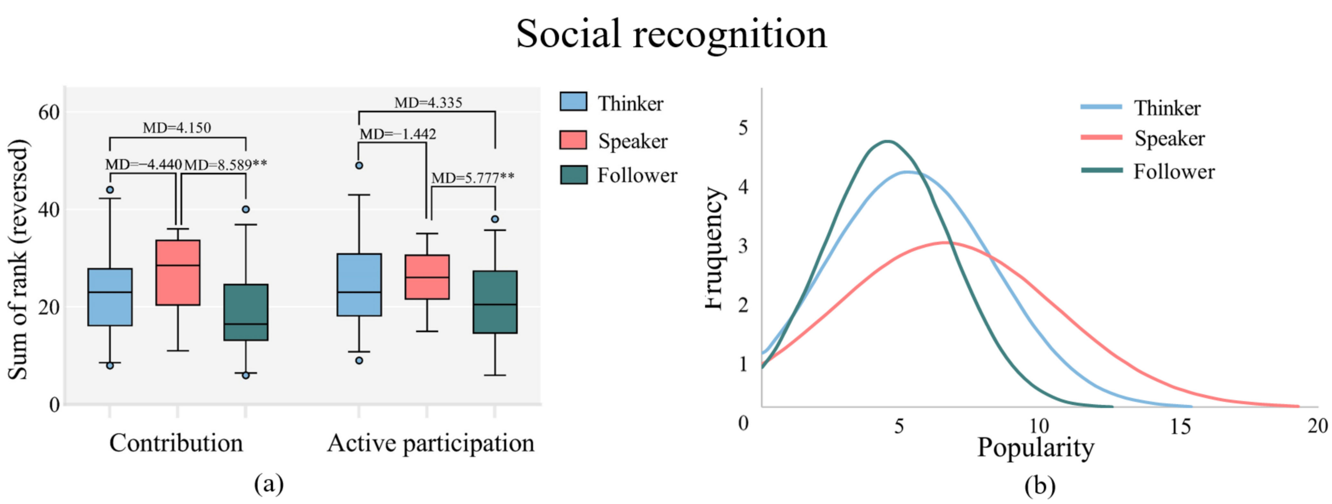


**Figure 6.** Social recognition counts for different types of students: (**a**) difference in contribution and active participation among the three types of students; (**b**) difference in popularity among the three types of students (*MD:* mean difference; ** $p < 0.01$).

## 5. Discussion and Conclusions

We sought to explore the differences between students' learning outcomes and learning perception and social recognition in the collaborative learning process in the STEAM context. This study explored the potential categories and characteristics of student behavior patterns through K-means cluster analysis, and the research results can initially answer the research questions: (1) The learner profiles in the STEAM context can be roughly divided into three types: Thinkers, Speakers, and Followers. Compared to Thinkers and Followers, the number of Speakers is lower. (2) There is no significant difference between the three types of learners in learning outcomes, but there are significant differences in learning perception and social recognition. (3) Thinkers showed more positive emotions, and Speakers were considered the most actively engaged and to have made a greater contribution to group learning. (4) Compared with the other two types of learners, Followers showed lower positive emotions and peer evaluation. A comparison of the three learner profiles revealed several interesting findings.

Firstly, compared to the other two types of learners, Thinkers demonstrated superior learning perception as indicated by their positive emotions during the STEAM learning process. This finding highlights the potential correlation between higher-order thinking behaviors and positive emotions, which corroborates the previous findings in the literature [53–55]. One possible reason is that STEAM courses are interdisciplinary and problem-oriented, thus placing a higher demand on students' problem-solving and decision-making capacities [56]. Therefore, students with good higher-order thinking skills tend to receive more positive feedback and a sense of achievement, leading to more positive emotions during the learning process.

Secondly, Speakers with frequent verbal interactions are more likely to become team leaders and gain more social recognition. This finding is consistent with Boutillier (1975) who revealed that the number of verbal interactions predicted group members' perceptions of leadership [57]. Speakers are more likely to express their views verbally, and the frequency of verbal interactions is often perceived as an essential indicator of group participation and learning engagement [58], leaving a strong impression of leadership on team members. For example, in the process of drawing posters, a student talked a lot and actively engaged in verbal interaction with team members. In fact, he mostly expressed content unrelated to the theme, lacking a substantial contribution in terms of task completion.

Lastly, the overall inferior performance of Followers revealed the important role of agency in STEAM learning. Compared to Thinkers and Speakers, Followers lacked a sense of ownership and leadership behaviors, which can lead to poor emotional engagement during collaborative learning. Additionally, we found that Followers were evaluated as the lowest scoring by other students. This observation supports the finding of [59]: students gave higher peer ratings to those involved in task assignment, coordination, and organization, and there is a significant correlation between leadership and social recognition.

Finally, in our comparison of gender differences, more girls than boys assumed Follower roles. According to status theory [60,61], individuals who are assigned a higher status in a group tend to assume more instructional roles, whereas individuals of a lower status assume more supportive roles. Hogue (2007) showed that in mixed-gender groups, boys exhibited high-status behaviors more frequently, such as directiveness and guidance; whereas girls exhibited low-status behaviors more frequently, such as support and assistance [62]. This is also related to China's cultural characteristics. In primary school, girls are often expected to have a submissive and well-behaved personality, and boys are encouraged to be brave and responsible. There are fewer girls classified as Thinkers as girls demonstrated fewer higher-order thinking behaviors. This outcome is contrary to the discovery of Mai (2015) who found that girls outperformed boys in higher-order thinking development in Malaysia [63]. The reason is likely due to the fact that, compared to boys, Chinese girls' cognitive activity is more implicit and inward, often lacking explicit behavioral expressions.

### 5.1. Implications

The findings of this study have several implications for teachers' practice in STEAM contexts. First, we need to pay attention to the differences between students and carry out targeted teaching for students with different characteristics. In teamwork, sometimes the group appears to be active because of the presence of one or two Speakers, yet the other group members are not fully engaged. Thinkers and Followers, despite their large proportion in groups, are easily overlooked by the teacher. Additionally, followers are susceptible to negative emotions; teachers should pay attention to their emotional state, and should help them better take on tasks by assigning responsibilities and using other means.

In addition, when organizing group collaborative learning, teachers should not only pay attention to the dialogue content in the student interaction process but also pay attention to non-verbal interaction behaviors such as student gestures, posture, and expression cues. Compared to verbal interaction, non-verbal interaction is obscure and easy to be ignored by teachers in class. Yet, some learners prefer to use non-verbal communication, and the effect of cooperation is better. For example, in the process of collaborative learning, some groups do not speak much more often, but everyone is actively involved in teamwork, only carrying out the necessary verbal communication, and the cooperation is very tacit. While we acknowledged the difficulty of perceiving non-verbal classroom interactions, several researchers argued that such a skill can be developed with teaching experience and provided observational instruments for teachers [64,65].

Lastly, considering the large proportion of Followers among girls, we recommend teachers assign more leadership roles to girls during STEAM education. Teachers should encourage girls to express different opinions and encourage them to think deeply and make decisions. Teachers should also actively create a harmonious collaborative learning environment to encourage girls to express their opinions bravely and reduce prejudice against girls in leadership.

### 5.2. Limitations and Future Research

There were two limitations to the present study. Firstly, in terms of learning outcomes, this study focused on computational thinking and self-efficacy in the STEAM context, but lacked empirical data such as knowledge test scores or performance evaluations. Further studies will be conducted on students' knowledge test scores or performance evaluation. Additionally, different STEAM problem contexts may produce different learner dynamics and structures. Our study was conducted within the STEAM context of a particular topic, and the results might lack transferability to other educational contexts. Consequently, we suggest that future studies employ more diverse methods of data collection and collect diverse learning outcome data to explore the validity of the three learner profiles identified in this study and their intricate relationship in STEAM.

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## References


1. Bybee, R.W. Advancing stem education: A 2020 vision. *Technol. Eng. Teach.* **2010**, *70*, 30–35.
2. STEAM Education: An Overview of Creating a Model of Integrative Education. 2008. Available online: https://www.researchgate.net/publication/327351326_STEAM_Education_an_overview_of_creating_a_model_of_integrative_education (accessed on 13 June 2022).
3. Johnson, L.; Becker, S.A.; Estrada, V.; Freeman, A. *NMC Horizon Report: 2015 Higher Education Edition*; The New Media Consortium: Austin, TX, USA, 2015.
4. National Research Council; Division of Behavioral and Social Sciences and Education. Transforming undergraduate education in science, mathematics, engineering, and technology. *J. Eng. Educ.* **1999**, *89*, 127.
5. Martín-Páez, T.; Aguilera, D.; Perales-Palacios, F.J.; Vílchez-González, J.M. What are we talking about when we talk about STEM education? A review of literature. *Sci. Educ.* **2019**, *103*, 799–822. [CrossRef]
6. The Case for STEM Education: Challenges and Opportunities. 2013. Available online: https://www.abe.pl/en/book/9781936959259/the-case-for-stem-education-challenges-and-opportunities (accessed on 2 July 2022).
7. Caprile, M.; Palmén, R.; Sanz, P.; Dente, G. *Encouraging STEM Studies: Labour Market Situation and Comparison of Practices Targeted at Young People in Different Member States*; European Union: Brussels, Belgium, 2015.
8. Petrov, P.D.; Atanasova, T.V. The effect of augmented reality on students' learning performance in STEM education. *Information* **2020**, *11*, 209. [CrossRef]
9. Mote, C.; Strelecki, K.; Johnson, K. Cultivating high-level organizational engagement to promote novel learning experiences in STEAM. *STEAM J.* **2014**, *1*, 18. [CrossRef]
10. Rice, K.G.; Lopez, F.G.; Richardson, C.M. Perfectionism and performance among STEM students. *J. Vocat. Behav.* **2013**, *82*, 124–134. [CrossRef]
11. Gorman, S.T.; Durmowicz, M.C.; Roskes, E.M.; Slattery, S.P. Females in the academy: Female leadership in STEM education and the evolution of a mentoring web. *Forum Public Policy Online* **2010**, *2*, 1–21.
12. Dörnyei, Z. *The Psychology of the Language Learner*; Lawrence Erlbaum: Mahwah, NJ, USA, 2005.
13. Wu, Y.; Tian, Y.; Guo, S.; Zhu, L.; Ma, X. Research on the model of learner behavior analysis based on online 3D education platform—taking geek cad online platform as an example. *China Educ. Technol.* **2019**, *12*, 61–67.
14. Park, W.; Cho, H. The interaction of history and STEM learning goals in teacher-developed curriculum materials: Opportunities and challenges for STEAM education. *Asia Pac. Educ. Rev.* **2022**, 1–18. [CrossRef]
15. Sakunova, A.; Moroz, I. Formation of informational and digital competence of learner of physics under the premium of Steam education. *Phys. Math. Educ.* **2018**, *15*, 285–289. [CrossRef]
16. Takahashi, S. The effects of learner profiles on pragmalinguistic awareness and learning. *System* **2015**, *48*, 48–61. [CrossRef]
17. Khalil, M.; Ebner, M. Clustering patterns of engagement in massive open online courses (MOOCs): The use of learning analytics to reveal student categories. *J. Comput. High. Educ.* **2017**, *29*, 114–132. [CrossRef]
18. Higginbotham, G. Individual learner profiles from word association tests: The effect of word frequency. *System* **2010**, *38*, 379–390. [CrossRef]
19. Ferguson, R.; Clow, D. Examining engagement: Analyzing learner subpopulations in massive open online courses (MOOCs). In Proceedings of the Fifth International Conference on Learning Analytics and Knowledge, Poughkeepsie, NY, USA, 16–20 March 2015.
20. Chen, Y.; Gao, Q.; Yuan, Q.; Tang, Y. Discovering MOOC learner motivation and its moderating role. *Behav. Inf. Technol.* **2020**, *39*, 1257–1275. [CrossRef]
21. Castejón, J.L.; Gilar, R.; Miñano, P.; González, M. Latent class cluster analysis in exploring different profiles of gifted and talented students. *Learn. Individ. Differ.* **2016**, *50*, 166–174. [CrossRef]
22. Corrin, L.; de Barba, P.G.; Bakharia, A. Using learning analytics to explore help-seeking learner profiles in MOOCs. In Proceedings of the Seventh International Learning Analytics & Knowledge Conference on-LAK, Vancouver, BC, Canada, 13–17 March 2017.
23. Watson, S.L.; Watson, W.R.; Yu, J.H.; Alamri, H.; Mueller, C. Learner profiles of attitudinal learning in a MOOC: An explanatory sequential mixed methods study. *Comput. Educ.* **2017**, *114*, 274–285. [CrossRef]
24. Swaid, S.I. Bringing computational thinking to stem education. *Procedia Manuf.* **2015**, *3*, 3657–3662. [CrossRef]
25. Bandura, A.; Freeman, W.H.; Lightsey, R. Self-efficacy: The exercise of control. *J. Cogn. Psychother.* **1999**, *13*, 158–166. [CrossRef]
26. Aschbacher, P.R.; Li, E.; Roth, E.J. Is science me? high school students' identities, participation and aspirations in science, engineering, and medicine. *J. Res. Sci. Teach.* **2009**, *47*, 564–582. [CrossRef]
27. Reeve, J.; O'Donnell, A.M.; Smith, J.K. Motivation in education. *Hippokrates* **2010**, *44*, 120–124.
28. Buxton, C.A. Modeling science teaching on science practice? painting a more accurate picture through an ethnographic lab study. *J. Res. Sci. Teach.* **2001**, *38*, 387–407. [CrossRef]
29. Jan, E. Stets. Future directions in the sociology of emotions. *Emot. Rev.* **2010**, *2*, 265–268.
30. Lepper, M.R.; Corpus, J.H.; Iyengar, S.S. Intrinsic and extrinsic motivational orientations in the classroom: Age differences and academic correlates. *Child. Educ.* **2006**, *82*, 184–196. [CrossRef]
31. Fine, G.A. Interaction ritual chains. *Soc. Forces* **2005**, *83*, 1287–1288. [CrossRef]

32. Larsen, K.S.; Martin, H.J.; Ettinger, R.H.; Nelson, J. Approval seeking, social cost, and aggression: A scale and some dynamics. *J. Psychol.* **1976**, *94*, 3–11. [CrossRef]
33. Magolda, M.; Astin, A.W. What matters in college? Four critical years revisited. *J. High. Educ.* **1993**, *22*, 482.
34. DeRosier, M.E.; Kupersmidt, J.B.; Patterson, C.J. Children's academic and behavioral adjustment as a function of the chronicity and proximity of peer rejection. *Child Dev.* **1994**, *65*, 1799–1813. [CrossRef]
35. Haynie, D.L.; Payne, D.C. Race, friendship networks, and violent delinquency. *Criminology* **2006**, *44*, 775–805. [CrossRef]
36. Breed, M.D. Social Recognition. In *Encyclopedia of Animal Behavior*; Academic Press: Cambridge, MA, USA, 2010; pp. 267–272.
37. Nainabasti, B.; Brookes, D. Connection between participation in interactive learning environment and learning through teamwork. In Proceedings of the 2015 Physics Education Research Conference, College Park, MD, USA, 29–30 July 2015.
38. Friess, W.A.; Goupee, A.J. Using continuous peer evaluation in team-based engineering capstone projects: A case study. *IEEE Trans. Educ.* **2020**, *63*, 82–87. [CrossRef]
39. Cillessen, A.H.N.; Borch, C. Developmental trajectories of adolescent popularity: A growth curve modelling analysis. *J. Adolesc.* **2006**, *29*, 935–959. [CrossRef] [PubMed]
40. Aoyama, M. Persona-and-Scenario based requirements engineering for software embedded in digital consumer products. *J. IEEE Comput. Soc.* **2005**, 85–94.
41. Witten, I.H.; Frank, E. *Data Mining: Practical Machine Learning Tools & Techniques with Java Implementations*; Morgan Kaufmann: Burlington, VT, USA, 2005; Volume 13, pp. 1–371.
42. Witten, I.H.; Frank, E. Data mining: Practical machine learning tools and techniques. *ACM SIGMOD Rec.* **2011**, *31*, 76–77. [CrossRef]
43. Talavera, L.; Gaudioso, E. Mining student data to characterize similar behavior groups in unstructured collaboration Spaces. In Proceedings of the Workshop on Artificial Intelligence in CSCL, 16th European Conference on Artificial Intelligence ECAI2004, Valencia, Spain, 22–27 August 2004.
44. Ying, Z.; Oussena, S.; Clark, T.; Kim, H. Use data mining to improve student retention in HE—A case study. In Proceedings of the 12th International Conference on Enterprise Information Systems, DISI, Funchal, Portugal, 8–12 June 2010.
45. Bandura, A. *Social Learning Theory*; ReCAPP: Scotts Valley, CA, USA, 1977.
46. Bloom, B.S.; Engelhart, M.D.; Furst, E.J.; Hill, W.H.; Krathwohl, D.R. *Taxonomy of Educational Objectives: The Classification of Educational Objectives. of Educational Goals' Handbook Cognitive Domain*; Longman: London, UK, 1956.
47. Koeslag-Kreunen, M.; Bossche, P.; Hoven, M.; Klink, M.; Gijselaers, W. When leadership powers team learning: A meta-analysis. *Small Group Res.* **2018**, *49*, 475–513. [CrossRef]
48. Luo, H.; Han, X.; Chen, Y.; Nie, Y. Should you become a leader in online collaborative learning? Impact of assigned leadership on learning behaviors, outcomes, and perceptions. *PLoS ONE* **2022**, *17*, e0266653. [CrossRef]
49. Li, J.; Luo, H.; Zhao, L.; Zhu, M.; Ma, L.; Liao, X. Promoting STEAM education in primary school through cooperative teaching: A design-based research study. *Sustainability* **2022**, *14*, 10333. [CrossRef]
50. Krauss, R.M. Nonverbal behavior and nonverbal communication: What do conversational hand gestures tell us? *Adv. Exp. Soc. Psychol.* **1996**, *28*, 389–450.
51. Williams, D.S. The Role of Verbal and Nonverbal Communication between Students with Special Needs and Their Teachers in Middle School. Ph.D. Thesis, Walden University, Minneapolis, MN, USA, 2009; p. 124.
52. Rodrigo, M.M.T.; Baker, R.S.; Lagud, M.C.; Lim, S.A.L.; Macapanpan, A.F.; Pascua, S.A.M.S.; Santillano, J.Q.; Sevilla, L.R.; Sugay, J.O.; Tep, S.; et al. Affect and Usage Choices in Simulation Problem-Solving Environments: Artificial Intelligence in Education, Building Technology Rich Learning Contexts That Work. In Proceedings of the 13th International Conference on Artificial Intelligence in Education, AIED 2007, Los Angeles, CA, USA, 9–13 July 2007.
53. Wesely, J.K. Skimming the surface or digging deeper: The role of emotion in students' reflective journals during an experiential criminal justice Course. *J. Exp. Educ.* **2021**, *44*, 167–183. [CrossRef]
54. Izard, C.E. Four systems for emotion activation: Cognitive and noncognitive processes. *Psychol. Rev.* **1993**, *100*, 68–90. [CrossRef]
55. Gray, J.R. Integration of emotion and cognitive control. *Curr. Dir. Psychol. Sci.* **2010**, *13*, 46–48. [CrossRef]
56. Boix Mansilla, V.; Miller, W.C.; Gardner, H. On Disciplinary Lenses and Interdisciplinary Work. *Interdiscip. Curric. Chall. Implement.* **2000**, 17–38.
57. Boutillier, S. The effect of quantity and quality of verbal interaction on ratings of leadership ability. *J. Exp. Soc. Psychol.* **1975**, *11*, 403–411.
58. Bass, B.M. An analysis of the leaderless group discussion. *J. Appl. Psychol.* **1949**, *33*, 527–533. [CrossRef]
59. Dingel, M.; Wei, W. Influences on peer evaluation in a group project: An exploration of leadership, demographics and course performance. *Assess. Eval. High. Educ.* **2014**, *39*, 729–742. [CrossRef]
60. Berger, J.; Rosenholtz, S.J.; Zelditch, M., Jr. Status organization processes. *Annu. Rev. Sociol.* **1980**, *6*, 479–508. [CrossRef]
61. Ridgeway, C.L. Gender, status, and leadership. *J. Soc. Issues* **2001**, *57*, 637–655. [CrossRef]
62. Hogue, M.; Lord, R.G. A multilevel, complexity theory approach to understanding gender bias in leadership. *Leadersh. Q.* **2007**, *18*, 370–390. [CrossRef]
63. Mai, M.Y.; Jalaluddin, M.B. High order thinking skills of level two orang asli students in rompin district, pahang. *Ejser Eur. J. Soc. Sci. Educ. Res. Artic.* **2015**, *5*, 25. [CrossRef]

64. Galloway, C.M. *Analysis of Theories and Research in Nonverbal Communication*; ERIC Clearinghouse on Teacher Education: Washington, DC, USA, 1972.
65. Verbal and Nonverbal Classroom Communication: The Development of an Observational Instrument. Available online: https://files.eric.ed.gov/fulltext/ED040957.pdf (accessed on 9 March 2022).