教育向けの情報推薦手法：パズルゲーム分析を通じた学習スタイル特定の新アプローチ

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Doctor’s thesis

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Enhancing Educational Recommendation: A Novel Approach to Identify Learning Styles through Puzzle Gameplay Analysis

Graduate School of Engineering,
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A Doctor's Thesis

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Abstract of Doctor's Thesis of Academic Year 2023

Enhancing Educational Recommendation: A Novel Approach to Identify Learning Styles through Puzzle Gameplay Analysis

Each learner has a distinct approach to learning, known as their "learning style." Understanding one's learning style can significantly improve their learning process. Advancements in technology and innovations in data analytics have led to a significant increase in educational researchers applying learning styles into information technology systems and applications. These developments enable educational support systems to swiftly identify and analyze each student's information such as academic profile and behavioral profile. Based on the outcomes of a systematic literature review on the educational support system applying learning style, it is clear that the Felder-Silverman model is the main learning style theory applied in educational technology. In fact, it's used in over 71.8% of all studies. Furthermore, the use of questionnaires stands out as the most commonly used method for identifying individual learning styles, with a majority of 72.97%. However, the traditional method of identifying the Felder-Silverman model learning styles using the Index of Learning Styles (ILS) questionnaire has several limitations such as misunderstanding of a question and language barrier. Educational games are becoming more popular research topic for educators because they make learning any topic enjoyable and comfortable. They are especially good at showing how one action can affect another, and playing games can often help learning stick better in student' minds. Because games feel more like play than work, students were persuaded to spend more time learning by playing instead of just reading books or doing homework. This can help understanding a student's unique learning style better. Plus, games can make learning more exciting, which is really important for a good learning experience. With this in mind, this study introduces a novel approach to figure out how a student learns best by analyzing how they play a puzzle game. The experiment was conducted with Thai high school students and undergraduate engineering students, each given the ILS questionnaire to assess their styles. Then, their gameplay was recorded, the video was processed, and a machine learning model was trained on the processed gameplay data to identify their learning styles. The results show that a puzzle game is a promising approach for identifying Felder-Silverman learning styles. The findings suggest that the utilization of a puzzle game constitutes a promising methodology for determining Felder-Silverman learning styles. The introduction of this approach is ground-breaking, and the discovery of this research provide encouragement for future studies to incorporate gaming within the learning style framework.

Keywords:

Learning Style, Systematic Literature Reviews, Felder-Silverman Model, Game, Machine Learning

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Chapter 1
Introduction

1.1 Background

Learners possess different learning styles indicating their individual preferences in processing and comprehending information. For example, some learners prefer working with factual information, such as experimental data and facts, whereas others prefer working with abstract information, for example, theories, mathematical models, and symbolic information. Visual presentation of information might be more effective for some learners, whereas verbal explanations might more beneficial for others. Certain learners prefer to learn through analysis and experimentation, whereas others prefer to reflect on what they plan to do before attempting it. Learning styles refer to specific attitudes and behaviors linked to the learning context [1]. Over 70 studies have been published on learning style theory in recent years, demonstrating its considerable importance and relevance in education [2]. Recognizing one's learning style can offer various advantages, including personalizing the learning process to enhance efficiency, [3],[4],[5] which benefits not only the learners themselves but also other stakeholders within the educational field, such as educators. By comprehending their learning style, learners can achieve success and confidence in their educational pursuits. For educators, this knowledge assists in the development of academic courses, instructional materials, and teaching strategies. However, failing to recognize the style might cause discomfort, disinterest, inattentiveness in class, poor test results, discouragement, and, in severe cases, switching curricula or giving up altogether [6].

Advancements in technology and innovations in data analytics have led to a significant increase in educators and researchers incorporating learning styles into information technology systems and applications. These developments enable computer systems to swiftly identify and analyze each student's data and information. For decades, recommender systems have been recognized as applications capable of satisfying user preferences through personalization. By considering relevance, these systems select and offer the most appropriate services or items for users with similar profiles. Numerous studies have applied learning style theory to recommender systems. The most common approach involves selecting and offering the most suitable class environment, teaching methods, hints, and guidelines for individual students [7]. For instance, Latham [8] developed a personalized conversational tutoring system utilizing learning styles, while Limongelli [9] created a recommender system under the LecomP5 framework, providing courses of action, including resource selection and learning sequences that best align with students' learning styles.

After conducting a systematic literature review on the subject of recommender systems incorporating learning styles, the study found out that the Felder & Silverman learning style model [10],[11] is the most extensively researched and applied model in the area of advanced learning technologies among various learning style models proposed [12],[13],[14] and is commonly assessed using the Index of Learning Styles (ILS) [15],[16],[17]. which is a 44-question survey designed to measure the preferences of the four dimensions of the model. Multiple studies have adopted and validated this questionnaire [18],[19],[20],[21],[22],[23],[24]. However, the survey items are only presented in a text format, which might result in errors. For instance, respondents might respond without careful consideration or misunderstand the questions, which leads to misidentification of their learning styles and the learning tasks/activities suiting their preferences.

Numerous techniques have been suggested to identify the Felder & Silverman learning style. Typically, these methods observe the learner's behavior in an academic setting and extract specific details regarding their interaction [25],[26],[27],[28],[29],[30],[31]. This information includes exam scores, preferred material types, chat and forum participation, and exam revision duration. Accordingly, these approaches categorize learners by their learning styles. The use of automatic detection for learning styles presents multiple benefits compared to the ILS. Firstly, it removes the requirement for extra effort by students, like completing surveys or offering direct input about their learning inclinations, since data is acquired through their engagement with the educational platform. Moreover, this automated method collects data over an extended duration instead of a single point in time, allowing for the tracking of shifts in learning traits over time.

Educational games have become increasingly popular [32],[33]. as they provide captivating and flexible approaches to instructing nearly any topic. Their efficacy in illustrating cause-and-effect connections is particularly notable, and the immersive aspect of games frequently results in a more enduring educational impact [34]. Games also have the advantage of being perceived as play rather than work, which may encourage learners to spend more time playing games than reading related materials or completing end-of-chapter problems [35]. This makes games an effective tool for automatically detecting learning styles. Additionally, games enhance learning motivation [36], which is a critical element for improving the learning experience in the learning environment [37],[38],[39],[40],[41],[42] Finally, previous research has encountered difficulties in identifying learning styles among students who have minimal exposure to online courses [26]. Nonetheless, gaming does not necessitate previous experience, making it less probable for students to display behavioral alterations during gameplay, as they acquire the skills by engaging in the game itself [42].

1.2 Objective

The objective of this thesis is to present a novel approach to identifying a learner's learning style by tracking and analyzing how they play a puzzle game, as a game-based approach is a promising option for the automated identification of learning styles.

1.3 Goal

The goal of this thesis is to propose an innovative and pioneering methodology that could inspire future research to incorporate gaming within the framework of learning styles. This study presents an opportunity for a more engaging, efficacious, and personalized form of education by identifying an individual's learning style through gameplay. Should this approach prove to be dependable, it has the potential to amplify the customization of learning materials and strategies, an aspect that is increasingly acknowledged in the educational field as beneficial for student performance.

This study not only merges the usage of games in education but also contributes significantly to the domain of gamification, thereby adding an entertaining and engaging layer to the learning process and, specifically, to the identification of learning styles. This could potentially enhance student involvement and motivation.

Moreover, this study broadens the scope of machine learning applications within the field of educational studies, enriching the growing body of work that explores the utilization of machine learning in less traditional fields. This extension could potentially stimulate further research and advancements, promoting a more comprehensive integration of machine learning into educational strategies and methodologies.

1.4 Construction of the thesis

The rest of the thesis is organized as follows. Section 2 introduces the topics related to learning styles and games in education and the systematic literature review process on the topic of the educational support system applying learning style. Section 3 describes the methodology for assessing learning styles by using a puzzle game. Section 4 presents and explains the experimental results. Finally, Section 5 concludes the thesis and discusses future work.

Chapter 2
A Systematic Literature Review on the Educational Recommendation Utilizing Learning Styles

This chapter systematically provides various topics of educational recommendations, starting with personalized learning, achieved by understanding each student deeply and designing tailored learning experiences. This approach is enabled via recommender systems, which further facilitate educational recommendations. The chapter progresses to discuss the evolution of these systems, emphasizing their use of learning styles and integration of student psychological profiles, learning styles, for enhanced personalization. The concluding part provides the process of the systematic literature review process, which contextualizes the discussion within existing research.

2.1 Personalized Learning

According to Ashman [43], personalized learning may involve identifying learning or teaching preferences by examining student or teacher profiles. Nevertheless, since no single teaching strategy is suitable for every learner, the success of the teaching and learning process largely depends on its adaptability to individual differences and the degree of personalization. Two approaches to personalize learning can be identified: user-centered [44] and technology-centered [45], [46], [47]. In the user-centered approach, personalization focuses on specific procedures [48], [49]. Conversely, the technology-centered approach emphasizes systems, such as course management systems or e-learning platforms [16],[50].

Numerous findings from previous research demonstrate that learners engaged in personalized e-learning systems exhibit increased motivation [51]. For instance, the outcomes of a study [52] exploring the adoption of a learner-centered approach system reveal that the majority of participants found the learning experience to be more effective than traditional teacher-centered methods. This effectiveness is attributed to learners feeling a sense of ownership as the teacher's role transitions to that of a coach providing recommendations rather than dictating all aspects of the learning process [53].

The examples mentioned above highlight advancements in education, suggesting that students can acquire knowledge not only through the direct transfer of information from teachers but also as a result of effective recommendations from an educational coach. In terms of technology utilization, teachers' guidance remains a crucial component of the learning process, as it can significantly enhance learner motivation [19], [54].

2.2 Educational Recommendation by the Recommender System

Recommender systems can provide learners with suitable learning resources and guidance among an extensive array of educational materials [55], thereby enhancing the likelihood of successful knowledge acquisition [56], [57]. The primary beneficiaries of educational recommendations generated by such systems are students who may lack prerequisite knowledge or expertise in a specific domain or those who do not have the time to assess the multitude of available learning materials. Several examples of recommender system capabilities in education are outlined below: [58], [59]

1. The system is able to provide proper knowledge to learners in collaborative study group settings based on respecting roles, tasks, and degrees of expertise.
2. The system can aid students in arranging their learning schedule by

identifying courses that correspond with their choices and imposed regulations.

3. The system can propose instructional materials and resources.

As stated by Shute [54], an educational recommendation constitutes constructive guidance, conveying information to a student with the objective of modifying their specific behavior to improve learning outcomes. This conclusion suggests that recommender systems are the most suitable technology for facilitating educational recommendations. The types of educational recommendations can be categorized listed below:

1. Attribute-based recommendations: These address the qualities of the target concept or taught skill, such as suggestions for learning materials.
2. Topic-dependent recommendations: These are relevant to the subject being studied, such as course recommendations that depend on the specific topic.
3. Response-contingent recommendations: These focus on the learner's individual response, discussing why an incorrect response is wrong and a correct response is right without utilizing error analysis.
4. Hints/cues/prompts recommendations: These advises the learner in the proper direction, such as a strategic tip on what to do next.
5. Error-focused recommendations: These encompass error analysis and diagnosis, providing explanations of what is incorrect and why.
6. Comprehensive tutoring suggestions: These recommendations combine elements from the categories mentioned above.

2.3 Recommender Systems Utilizing Learning Style

The user model serves as the foundation for personalization systems and has been referred to as "the core of all automated personalization systems" [60]. In the context of education, the user model primarily comprises learner-specific information, including prior knowledge, learning experience, educational background, learning objectives, and learning styles. The challenge for researchers lies in identifying the optimal learner model structure for a particular application. Learning style is considered to be the most significant factor influencing e-learning and academic performance [61].

According to Kurilovas [62], learning styles can be defined as "strategies, or regular mental behaviors, habitually applied by an individual to learning, particularly deliberate educational learning, and built on her/his underlying potentials." Various theories have proposed different descriptions and classifications of learning styles [63], often referred to as "Learning Style Models," such as Felder-Silverman's Learning Style Model. Coffield [2] officially recognized 71 learning style models, which have since become the standard for numerous studies. Different learning style theories have been the focus of considerable recent research. For example, between 1985 and 1995, 2,000 papers were written about the Myers-Briggs Type Indicator Learning Style Model [64], while more than 1,000 articles referenced the Kolb Learning Style Model [65] and the Dunn and Dunn Learning Style Model [66].

Numerous studies [67], [68], [69], [70] have investigated the relationship between learning styles and various components of learning scenarios. Kurilovas [62], for example, identified correlations between learning styles and preferred learning activities, types of learning objects, and appropriate teaching/learning approaches in his research. However, evidence suggests that an individual's learning style may vary depending on the activity or learning material. As a result, it seems counterproductive to confine a student to a fixed learning style profile based on the initial evaluation. In terms of utilizing learning style data for system adaptation design, several unresolved questions remain. These include inquiries about how learners with different learning styles respond to assessment tests, exercises, activities, and the like; the navigation patterns followed by learners with varying styles; common characteristics shared by learners with the same style; and evidence demonstrating how learners of a specific learning style select and utilize educational resources considered beneficial for their particular style [71].

Phase 1: Planning

- Identification the needs for the reviews
- Specifying the research questions
- Developing the review protocol

↓

Phase 2: Conducting

- Searching strategy
- Study selection criteria
- Study quality assessment
- Data extraction plan
- Data analysis

↓

Phase 3: Reporting

- Structure the extracted results
- Discuss the results

Figure 2.1: systematic literature review process

2.4 Systematic Literature Review

This review study adopted the systematic literature review procedures from the Guidelines for Performing Systematic Literature Reviews in Software Engineering [72]. The procedures consisted of three phases which are shown in Figure 2.1.

2.4.1 Planning

2.4.1.1 Identification of the Objectives of the Review

The initial step in the planning phase involved determining the research objectives (RO) to serve as guidelines for the systematic review. Each RO is listed below:

- RO1: Research Objective
- RO2: Research Methodology
- RO3: Educational Recommendation
- RO4: Learning Styles Theory
- RO5: Learning Styles Identification
- RO6: Recommendation Algorithm

2.4.1.2 Specifying the Review Research Questions

The review research questions (RQ) were specified to clarify the RO. Each RQ explains each RO listed below:

- RQ1: What is the most common procedure for utilizing a learning style in a recommender system?

  This research question (RQ) addresses RO1: Research Objective, RO2: Research Methodology, and RO3: Educational Recommendation. Although learning styles have been applied to various applications, including recommender systems wherein classes are organized, and teaching methods, hints, and guidelines are tailored to individual students [7], recommender systems have not been the most prevalent application for systems utilizing learning styles in recent years. Consequently, to comprehend the research progress, this question guides the review to analyze and synthesize information about the procedures of the reviewed studies, encompassing the objectives, methodologies, and applied educational recommendations.

- RQ2: What is the recommender system's most commonly utilized learning style theory?

  This research question (RQ) addresses RO4: Learning Styles Theory and RO5: Learning Styles Identification. Focusing on applied theory as a detailed aspect following the research procedure, this question guides the review to analyze and synthesize information about the employed learning theories in the reviewed studies, encompassing both the theory and the identification of the particular style.

- RQ3: What is the recommender system utilizing learning styles' most commonly used algorithm for recommending?

  This research question (RQ) addresses RO6: Recommendation Algorithm. Another aspect to consider after the research procedure is the algorithm the system employs to generate recommendations. This question offers additional insight into recommender systems that utilize learning styles, focusing not on how to use the learning style but on how to create a recommendation system based on it. The review is directed to analyze and synthesize information about the algorithm that leverages the identified learning style to make recommendations.

2.4.1.3 Developing the Review Protocol

The review protocol adopted from the guideline [72] was used for structuring the procedure. The protocol is shown in Figure 2.1.

2.4.2 Conducting

2.4.2.1 Search Strategies

The studies under review were sourced from two reputable academic libraries, IEEE Xplore and Science Direct, utilizing advanced search features with various keyword combinations.

Table 2.1: search keywords

Topic	Set of keywords		
Learning Style	learning style(s) OR	mind styles(s) OR	cognitive style(s) OR
	type indicator OR	motivational style(s) OR	brain dominance OR
	study skill(s) OR	thinking style(s)	
Recommender System	recommender system(s) OR	recommendation system(s) OR	recommendation
	recommender		

2.4.2.2 Search Keywords

The search strategy for this study was developed by adhering to the research objectives and refining the research questions to filter the reviewed studies. Initially, search keywords were identified and categorized into three groups based on thematic relevance. Most keywords were extracted from prior research. Synonyms, plural forms, capital forms, and alternative spellings were then manually identified. Finally, search strings were created by combining each group of keywords. The Boolean operator 'OR' included synonyms and alternative spellings, while the Boolean operator 'AND' was used to connect the keywords. The search keyword combinations are presented in Table 2.1.

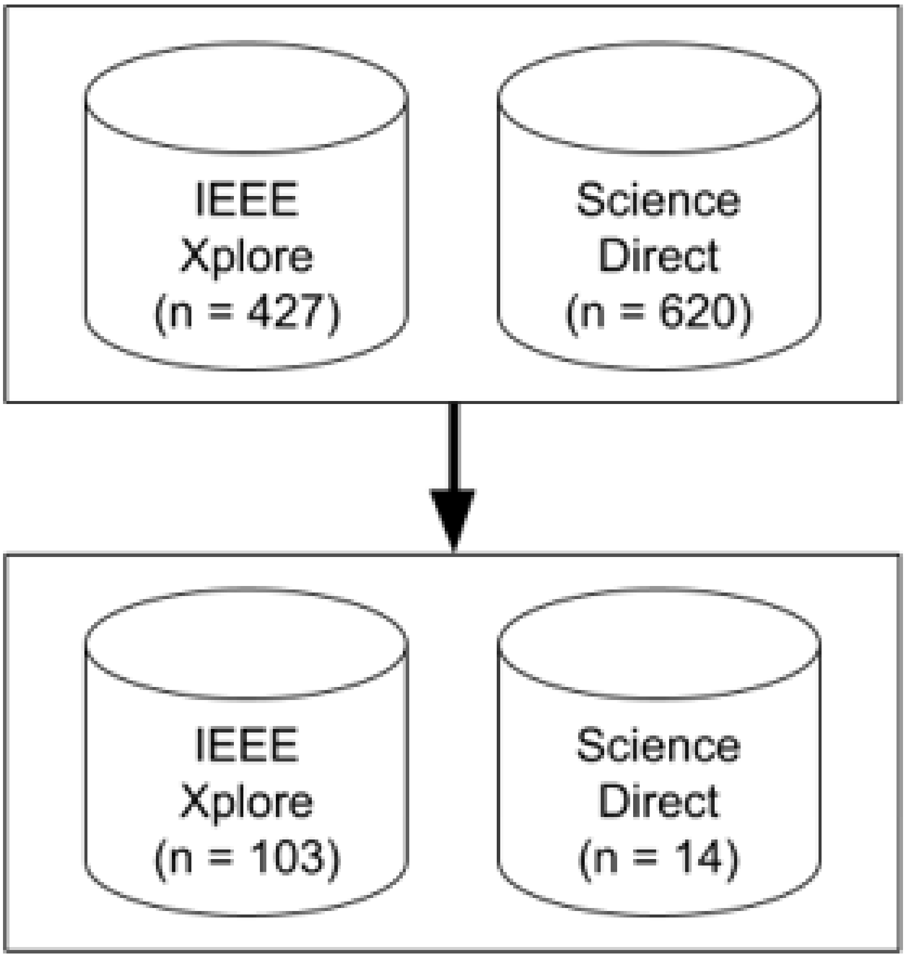


Figure 2.2: process of study selection criteria

2.4.2.3 Study Selection Criteria

A multitude of papers identified using the search strings in Table 2.1 was selected based on specific criteria to ensure their relevance and capacity to address all research questions. Relevant studies were those that met all inclusion criteria, including aspects such as title, abstract, and keywords. The inclusion criteria are outlined below:

- Studies that are written in English
- Studies that were published between 2011 and 2020
- Studies that presented the learning style theories
- Studies that presented the recommender or recommendation system
- Studies whose title, keywords, and abstract do contain the following words: "recommend," "system," "learn," and "style."

Studies that met any exclusion criteria were excluded. The exclusion criteria are outlined below:

- Course
- Encyclopedia
- Book chapters
- Editorials
- Correspondence
- Others (type of literature except for article)
- Articles whose full text was not accessible
- Duplicate articles that reported the same study from different academic databases

Table 2.2: quality assessment (QA) checklist

Item	Assessment criteria	Description of checklist
QA1	Does this article clearly describe the aim of the studies which propose the recommender system for usage in the field of education?	No, the aim is described but was not for the usage in the field of education.
		Partially, the aim is described as proposing the system for usage in the field of education but not the system that can give the recommendation.
		Yes, the aim is clearly described as proposing the recommender system for usage in the field of education.
Item	Assessment criteria	Description of checklist
QA2	Does the article clearly present the usage of learning style theory?	No, the usage of learning style theory is not clearly presented.
		Partially, the usage of learning style theory is not clearly presented and described.
		Yes, the usage of learning style theory is clearly presented and described.
QA3	Does the article clearly present the development of the recommender system?	No, the recommender system was not developed or there is no evidence of the system being developed.
		Partially, the developed system can give recommendation, but it is not actually the recommender system.
		Yes, the recommender system was clearly developed.

Table 2.2 (cont.): quality assessment (QA) checklist

Item	Assessment criteria	Description of checklist
QA4	Does the article present the implementation of the proposed system?	No, the proposed system was not implemented or there is no evidence of the system being implemented.
		Partially, the proposed system was tested or simulated by feeding the created data.
		Yes, the proposed system was clearly implemented.
QA5	Has the article been cited by other authors?	No, not at all.
		Partially, 1-5 other articles cite this article.
		Yes, more than 5 articles cite this article.

2.4.2.4 Assessment Criteria for Study Quality

Studies filtered through the inclusion-exclusion criteria will be assessed based on quality evaluation criteria. The quality evaluation checklist for this study was adapted from Papamitsiou's research [73], owing to the similarities between the studies, as it was employed to evaluate articles included in a systematic literature review of technology utilization in education. The adopted checklist will be modified to evaluate and describe studies more accurately, as displayed in Table 2.2. Each question on the quality evaluation checklist was rated on a three-value Likert scale with varying descriptions, and the results were used to summarize and characterize the included study.

2.4.2.5 Data Extraction Plan

This study utilized a standard information form, derived from Kitchenham's research [72] to gather the necessary data for analysis from a selection of publications. The Mendeley software was employed to extract essential information and publication characteristics, while a manual examination of each individual study was conducted to collect the remaining data.

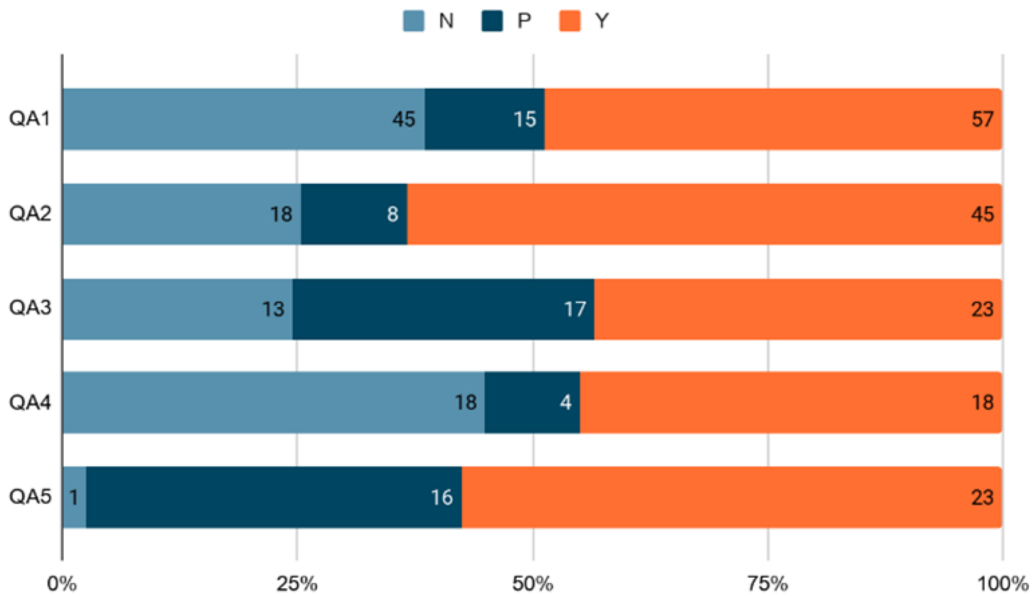


Figure 2.3: result of quality assessment

2.4.2.6 Data Analysis

Not all selected studies were deemed suitable for analysis; only those that met the assessment criteria were considered, as these criteria were employed to filter out irrelevant studies, such as those not intended for application in the field of education. The results of the quality assessment are illustrated in Figure 2.3.

In the first criterion (QA1), the objective of each selected study was evaluated. Among the 117 selected studies, only 57 were found to clearly describe the objective of proposing a recommender system for use in the field of education. Fifteen studies partially propose a system for use in the field of education but are unable to provide recommendations. Although 45 studies include the words "recommend," "system," "learn," and "style" in their titles, keywords, and abstracts, their aims were not for application in the field of education. For instance, the study titled "Clothing Recommendation System based on Visual Information Analytics" contains the words "recommend" and "system" in the title and "style" and "learn" in the abstract and keywords, referring to fashion style and deep learning. However, this article is not intended for use in the field of education. Consequently, these 45 studies were excluded from the review.

Upon assessing the applicability of the studies in the field of education, the second criterion (QA2) examined whether the studies presented or described the utilization of learning style theory. Eighteen studies did not present or describe the use of learning style theory and were consequently excluded. Conversely, eight studies did present the use of learning style theory but did not clearly describe its application, such as how to identify each individual's learning style. Nevertheless, these studies were deemed acceptable for the analysis.

Pertaining to the third criterion (QA3), the analysis revealed that 13 articles were excluded, as this review study focused on the development of recommender systems or systems capable of providing recommendations. Examples of excluded articles include "Developments in Educational Recommendation Systems: A systematic review," which involved a recommender system for use in the field of education but did not align with the focus of this review study. Conversely, 17 articles were deemed acceptable, as they proposed systems capable of offering recommendations, even though they were not explicitly recommender systems.

The fourth criterion (QA4) assessed whether the studies implemented the proposed system. Merely 18 studies explicitly implemented and evaluated the suggested system, whereas the remaining articles focused on the development of a framework or a prototype system.

The single study that fulfilled all acceptable requirements out of a total of 40 was assessed based on the fifth criterion (QA5), which examines the number of citations in other articles. The citation count was verified using Google Scholar (citation check conducted on March 3, 2021). According to Google Scholar, out of the 40 selected studies, 23 were cited more than five times by other research articles, 16 were cited infrequently (1-5 times), and only one had no citations as of the date of citation verification. Due to the dynamic nature of citation counts, the results of QA5 may vary at different points in time.

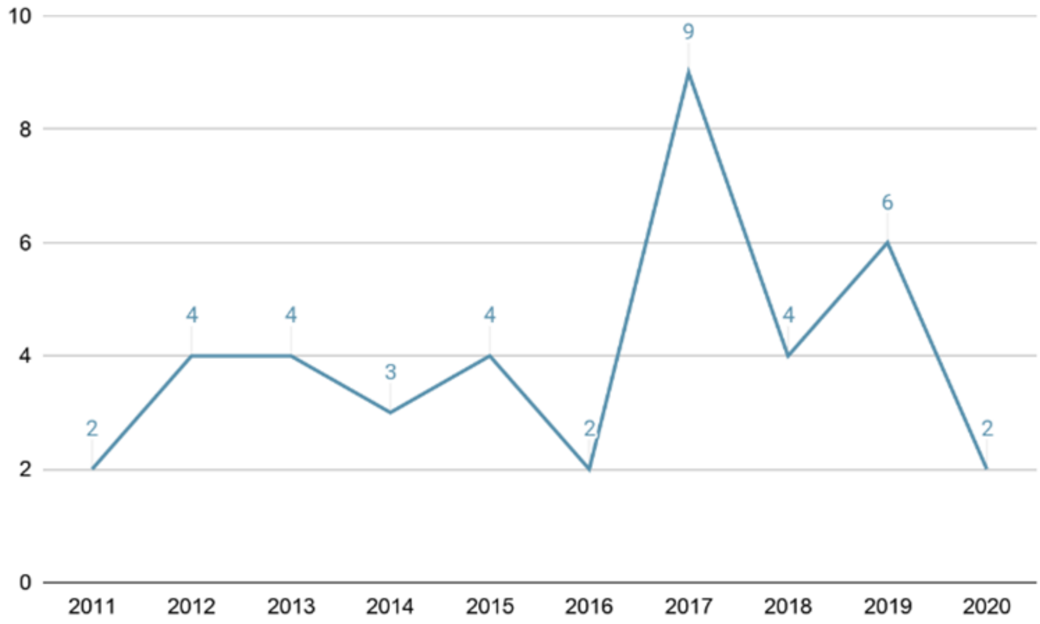


Figure 2.4: distribution of articles based on publication year

2.4.3 Reporting: Structure the extracted results

2.4.3.1 Research Objective Analysis

The distribution of findings in the analyzed studies based on research objectives is presented in Table 2.3. Among the 40 studies, there are only two primary objectives. A majority of the selected studies, 90%, propose to design a system that takes into account the learner's learning style to provide educational recommendations. Klanja-Milievi [68] described a suggestion module in 2011 for the "Protus" programming tutoring system, which can automatically adapt to a learner's interests and knowledge levels by identifying patterns of learning methods. This study is the most well-known research on educational recommender systems and has become a reference for numerous subsequent studies in this field. Many later studies adopted its system architecture and design, such as learner and recommender modules. The remaining 10% of the studies offer detailed insights into personalizing learning to enhance learning quality and efficiency. Kusumawardani's enhanced idea mapping between student traits and categories by Felder-Silverman Learning Style Model and relevant material inside Moodle-based e-learning was the most referenced study [74]. This research produced a set of ideas that form the foundational definition of learning styles and e-learning material, as well as several rules used to integrate content suggestions from the foundational definition.

Table 2.3: overview of the studies' objective

Research objective	Number of studies	%	References
System that considers the learning style to give educational recommendation development	35	90%	[68], [70], [76-89], [91-104], [106-110]
Research to provide insights into detail for personalizing learning	4	10%	[74], [75], [90], [105]

2.4.3.2 Research Methodology Analysis

The distribution of findings in the analyzed papers based on research methodologies is presented in Table 2.4. Among the 40 studies, the majority of the methodologies, 97.50%, involve studies that actually develop a system or plan to develop a system. This is distributed between studies that developed a system with evaluations, 52.50%, and studies that developed a system without evaluations or merely proposed a system framework, 45%. The most cited study that developed a system was "Protus" [68]. The most recognized research for the creation of a framework was "Protus 2.0" [70], which suggested a new version of the system framework for the "Protus" tutoring system that relies solely on Semantic web standards and technologies. The primary objective of this type of study was to present the advantages and new functionalities of the system. The implementation of the framework system is typically presented as future work.

Table 2.4: overview of the studies' methodology

Research methodology	Number of studies	%	References
Discussion or experiment about techniques, methods, or algorithms to improve or acquire knowledge	1	2.5%	[74]
Developing the system to conduct an experiment or deploy a prototype system then evaluate its performance	20	52.5%	[63], [79], [80], [84-87], [89], [91], [93], [97], [98], [100], [101], [103-107], [109]
Design the system framework for an experiment or a prototype system	17	45%	[75-78], [81-83], [88], [90], [92], [94-96], [99], [102], [108], [110]

2.4.3.3 Educational Recommendation Analysis

Following the analysis of objectives and methodologies, the final analysis was conducted to answer the RQ and explore challenges and opportunities in the utility or value of the proposed system in the field of education. As discussed in the related work section, formative feedback refers to information communicated to the learner with the intent to modify their thinking or behavior to enhance learning. Six types of formative feedback have been identified as "Educational Recommendations" and are described below:

1. Attribute-related
2. Topic-contingent
3. Response-contingent
4. Hints/cues/prompts
5. Bugs/misconceptions
6. Tutoring recommendations

The proposed system aims to deliver one of these educational recommendations, enabling it to be beneficial in the field of education. Table 2.5 displays the distribution of results for the reviewed studies concerning educational recommendations.

Among the 40 reviewed studies proposing a system, a majority of 75% were attribute-related, primarily because most of the systems aimed to recommend learning materials using recommender system algorithms that mainly calculated user preferences for items, making it the most convenient to build. The most cited article, Protus 2.0 [74], is also the most renowned in the field. Systems providing tutoring educational recommendations represent the most advanced ones, and many researchers are eager to explore and develop these systems further. Kurilovas's work [87] is the most cited paper that presents the results of employing the adaptive ant colony optimization approach to identify suitable learning paths for students based on their learning styles. This research focused on creating a novel approach for customizing learning units by modifying and expanding the Ant Colony Optimization (ACO), making it an ideal source for generating innovative methods or algorithms.

Table 2.5: overview of the studies' educational recommendation

Topic	Number of studies	%	References
Attributed-Related	27	73%	[74], [76], [79-82], [84], [86], [88], [89], [91-94], [96], [98-102], [104-110]
Response-Contingent	2	5%	[85], [103]
Hints/Cues/Prompts	2	5%	[83], [95]
Tutoring Recommendations	6	17%	[75], [77], [78], [87], [90], [97]

2.4.3.4 Learning Styles Theories Analysis

The initial stage in developing or constructing an adaptive system involves selecting a learning theory, which can pose a challenge for researchers as it dictates the data collection method and recommender algorithm utilized. The landscape of learning styles and theories is diverse and multifaceted. Over the past three decades, nearly seventy hypotheses have emerged, with some potentially overlapping. For example, Felder-Silverman's model [2] shares similar dimensions with those proposed by Kolb and Riding. Furthermore, as Coffield [2] highlights, the majority of theories describing learning styles face issues related to validity and/or reliability.

Consequently, no single theory is inherently superior to others. In the context of modified recommender systems, only a few hypotheses have been implemented. Table 2.6 presents the results of the content analysis of the reviewed studies based on the learning style model applied. A significant 72.5% of the reviewed studies employed the Felder-Silverman model [111]. This model differentiates learning styles into four dimensions: perception (Sensory/Intuitive), information input (Visual/Verbal), information processing (Active/Reflective), and understanding (Sequential/Global). Other theories, such as Kolb's Learning Styles Inventory [112] and Honey and Mumford's Learning Styles [113], also categorize styles into four dimensions, which might be considered alternatives to the Felder-Silverman model if researchers seek to explore different approaches. According to Germanakos et al. [114], theories like Kolb's are complex and closely related to personality theories, making them neither sufficiently comprehensive nor easily quantifiable.

The Felder-Silverman model, which comprises a discrete scale corresponding to different aspects of the learning process, is strongly advocated by the majority of reviewed studies. Feldman [115] justified their choice to focus on the perception style of the Felder-Silverman model, arguing that it is closely connected with other essential factors such as career preferences, aptitudes, and management styles. Dorca et al. [116]

contended that the Felder-Silverman model stands out because it encompasses numerous key learning styles and concepts. The fact that customized theories ranked second, at 10%, suggests that several studies continue to explore the development of a new theory capable of delivering optimal performance by combining various existing theories.

Table 2.6: overview of learning styles theories applied in adaptive learning system

Theory	Number of studies	%	References
Felder-Silverman	28	71.8%	[73], [74], [77], [79], [80], [82-84], [86], [88], [90-92], [94-98], [100-108], [110]
Honey & Mumford	2	5.1%	[87], [99]
Kolb	2	5.1%	[75], [89]
Reid Perceptual Learning Style Preference	1	2.6%	[81]
GRLSS	1	2.6%	[85]
VAK	1	2.6%	[93]
Custom	4	10.3%	[63], [76], [78], [109]

2.4.3.5 Identification Techniques Analysis

Table 2.7 displays the distribution of results for the reviewed studies concerning learning style identification techniques. The most prevalent method, accounting for 73%, involves using questionnaires associated with the applied theories. For instance, studies employing the Felder-Silverman model also utilize the Index of Learning Styles (ILS) questionnaire to analyze Felder-Silverman's learning styles, as it is considered the most convenient and accurate method for data collection. Another approach involves data mining to analyze learners' data logs or stored transaction data. While this method appears to be less intrusive for learners and does not require substantial effort on their part, it necessitates a significant amount of stored data for analysis. Most studies employing this technique have developed educational systems already in implementation.

Table 2.7: overview of identification technique applied in adaptive learning system

Topic	Number of studies	%	References
Questionnaire	27	72.97%	[74], [76-78], [80], [81], [83-88], [90], [92-94], [96-100], [103-108]
Data Mining	7	18.92%	[75], [79], [82], [91], [95], [109], [110]
Rule-Based	2	5%	[89], [101]
Fuzzy C Mean	1	2.7%	[102]

2.4.3.6 Recommendation Algorithms Analysis

Table 2.8 presents the distribution of results for the reviewed studies on recommender strategies. The recommendation algorithm serves as the engine that empowers recommender systems to generate recommendations. However, the recommendation algorithms employed in educational data exhibit considerable diversity, as this field is still in its early stages, and an optimal base algorithm has yet to be determined.

The most prevalent approach in 42.5% of the analyzed studies is the appropriateness method. Appropriateness refers to applying the most effective learning method for a learner based on their learning style description. Kolekar's study [102] is the most cited work that describes a method for identifying learning styles by adopting the Felder-Silverman Learning Style Model; each learner with a specific learning style is then assigned a corresponding theme and component. This recommendation concept may appear limited since it relies solely on learning style theory; however, it is the most popular approach because it is the most convenient way to provide personalized recommendations based on learning style. Collaborative filtering represents the second most common method for recommender systems, accounting for 27.5% of the cases.

Table 2.8: overview of the article's recommendation algorithm

Topic	Number of studies	%	References
Suitable	17	44.7%	[74], [75-78], [81], [82], [89], [90], [92], [95], [99], [101], [102], [104], [108], [110]
Collaborative-Filtering	9	23.7%	[79], [83], [84], [86], [88], [97], [98], [106], [109]
Hybrid	4	10.5%	[80], [91], [100], [107]
Rule-Based	2	5.3%	[96], [105]
Other	6	15.8%	[63], [85], [87], [93], [94], [103]

2.4.3.7 Discuss the Results

The data extraction analysis produced multiple outcomes, addressing each research question comprehensively. A systematic examination of the literature unveiled several notable advancements, opportunities, and challenges in the field. Upon analysis of educational recommendations, it became evident that numerous well-established educational recommender systems provided an extensive understanding of how learning styles can be incorporated into recommendation processes. This information directly addresses RQ1: What is the most prevalent method for incorporating learning styles into recommender systems? The analysis of research objectives and methodologies demonstrated that, while various types of educational recommendations have been offered by recommender systems, the majority of systems were designed to deliver attribute-related recommendations. This is primarily because the fundamental objective of a recommender system in the education sector is to suggest items or attributes; hence, the most direct and straightforward adaptation is the attribute-related recommendation.

The investigation of recent trends highlighted that research in the domain of educational recommendations is still in its early stages and necessitates further exploration and development. Moreover, the methodological analysis identified a secondary concern: not all assessed publications include evaluations of their respective systems. Consequently, these publications are classified as framework studies and are unsuitable for use as references in future research.

The analysis of learning style theories yielded insights that addressed RQ2: Which learning style theory is most commonly employed in recommender systems? The Felder-Silverman model emerged as the predominant theory utilized in these systems. The extensive body of research employing this model enables comparative evaluations of its effectiveness. However, recommender systems that incorporate alternative learning theories remain underexplored, necessitating future research to develop models that integrate and measure these theories effectively. By examining the impact of various theories on student learning outcomes, it is possible to compare their performance with that of the Felder-Silverman model. To ensure efficiency, it is crucial to recognize and compare the strengths and limitations of the chosen theory with those of other theories. Ocepek [63] suggests that combining learning style theories may offer complementary benefits, thereby enhancing the flexibility and recommendation capabilities of the system.

The analysis of identification techniques yielded results that further addressed RQ2. This analysis revealed a complex interplay between a learner's learning style and their actual behavior. Although the underlying concepts may remain consistent, the methods for identifying learning styles can vary across studies. Notably, no studies were found that evaluated the performance of questionnaires in comparison to alternative methods. Nevertheless, questionnaires emerged as the most prevalent approach. In addition to questionnaires, the analysis uncovered intriguing evidence that data mining from log data could also be utilized to identify learning styles. This discovery warrants further investigation, potentially through the integration of multiple algorithms, with each model contributing an equal vote. The resulting probability of a learner belonging to a specific style would then be determined by aggregating the proportions derived from all algorithms.

It can be concluded that an examination of forty papers and evaluation of data extracted from diverse aspects of studies on recommender systems integrating learning styles offer valuable insights into the current state of development and research, as well as opportunities and challenges. The systematic literature review process encompasses a structured discussion and analysis of topics in order to address research objectives and questions. Ultimately, findings from these analyses are consolidated to explore recent trends, challenges, and opportunities in the field.

Chapter 3
A Novel Approach to Identify the Felder & Silverman Model Learning Styles using Puzzle Gameplay Data

This chapter presents a comprehensive overview of the methodology employed to identify the Felder-Silverman Learning Style Model. First part delves into a broad discussion of learning styles, followed by an in-depth analysis of the Felder-Silverman Model, to enhance the reader's comprehension of the psychological theories implicated in this study. The subsequent part is dedicated to the Index of Learning Styles, explaining its practical application, and exploring alternative approaches. The next part offers an examination of educational games, with a specific emphasis on how they can involve to learning styles. The last part represents methodology of this study.

3.1 Learning Styles

According to a widely accepted definition by leading theorists [117], a learning style is "the composite of characteristic cognitive, affective, and psychological factors that serve as relatively stable indicators of how a learner perceives, interacts with, and responds to the learning environment." The concept was introduced by Kolb, who created the first learning style instrument in the U.S. [118]. Since then, the number of studies using learning styles has grown dramatically, with 71 different styles and instruments identified in one review of post-16 education [119]. Moreover, thousands of papers related to learning styles were reported in another paper [79]. Although some authors have expressed criticism [120], learning styles have seen extensive use in educational technology, yielding encouraging outcomes [26],[28],[121],[82]. A key point of contention revolves around the implementation of learning styles once they are determined, either manually or through automation. A notable debate concerns the appropriate method for tailoring learning materials to individual styles within adaptive educational systems [122].

3.2 Felder & Silverman Model

This research focuses on the widespread use of the Felder--Silverman model in engineering education. The learning style model, introduced by Richard Felder and Linda Silverman in 1988, aims to capture essential differences in learning styles among engineering students and provide a reasonable basis for engineering instructors to address the learning needs of all students [2][123]. The model classifies students according to their preferences in each of the four dimensions listed below:

1. Perception: relates to the type of information a student prefers to perceive.
    - Sensitive learners: prefer facts, data, and experimentation.
    - Intuitive learners: prefer principles and theories.
2. Processing: describes how perceived information is converted into knowledge.
    - Active learners: learn better in situations requiring active participation.
    - Reflective learners: learn better by themselves or with at most one other person.
3. Input: considers how students prefer to receive external information.
    - Visual learners: remember best what they see.
    - Verbal learners: remember much of what they hear and say.
4. Understanding: describes the way students progress toward understanding.
    - Sequential learners: follow linear reasoning processes.
    - Global learners: make intuitive leaps and may require help understanding partial information.

The ILS questionnaire is the traditional method to obtain Felder & Silverman learning styles. Despite the criticism about how learning styles are applied after their acquisition, these styles have shown promise in the educational technology field. [26],[28]

3.3 Index of Learning Styles (ILS)

The ILS is an assessment tool consisting of 44 questions for evaluating preferences on the four dimensions of the Felder & Silverman model. It was first created in 1991 by Richard Felder and Barbara Silverman of North Carolina State University. In 1994, the responses to Version 1 were collected and underwent factor analysis; items that did not load significantly on single factors were replaced by new items to create the current version. A pencil-and-paper version was made available on the World Wide Web in 1996, with an online version added in 1997. [124]

After finishing the ILS, participants instantly receive a profile containing scores for all four aspects, along with descriptions of their significance and connections to resources that offer further insight on the appropriate and inappropriate interpretations of these scores.

The ILS is accessible to individuals who wish to assess their preferences or to instructors or students who wish to use it for classroom instruction or research. Each dimension has 11 forced-choice items, with each option corresponding to one category of the dimension. For statistical analyses, a scoring method that counts "a" responses ranging from 0 to 11 is used, with each range indicating a different preference level. This method emphasizes that learning style dimensions are continua, not categories. This scoring method is used in all the statistical analyses to be reported. However, the method used to score the pencil-and-paper and online versions of the instrument subtracts the "b" responses from the "a" ones to obtain a score between -11 to 11.

3.4 Uses and misuses of learning styles and the ILS

Keefe's definition [117] can be used to describe the learning style preferences that the Felder & Silverman model and the ILS assess. The ILS scoring method also reflects this concept. The learning style profiles indicate behavioral tendencies rather than infallible predictors of behavior. Although sensitive and intuitive learners are often presented as distinct and contradictory traits, in reality, learners exhibit characteristics of both styles in varying situations. Preferences for a particular learning style do not necessarily indicate strengths or weaknesses in associated tasks. Educational experiences can affect learning style preferences, with exposure to different teaching styles potentially altering a learner's preferences. The purpose of identifying learning styles is not to label students and modify instruction to fit their labels. Rather, it is optimal to balance teaching styles that accommodate all students' preferences while challenging them to develop skills in their less preferred categories. Studies have shown that teaching styles that match learning styles may result in more significant learning [2],[125],[126],[127], but teaching exclusively to accommodate learning style preferences is not recommended [2],[128].

3.5 Automatic learning styles detecting

Felder & Silverman's learning styles are traditionally obtained through the application of the ILS [129]. However, various approaches for detecting learners' learning styles have been proposed recently; they automate the process by tracking how students interact with educational environments. Technological advancements in computer science have also led to the application of machine learning techniques, such as neural networks [130],[131] Bayesian networks [5],[26], decision trees [25],[30],[132] genetic algorithms [133],[134], and rule-based methods [27],[28] to learning style detection. These techniques involve feeding the learner's actions into the algorithm and training it to classify new students based on their learning styles.

Despite the range of machine learning techniques employed, a common limitation in these works is the need to process vast amounts of data obtained from student interactions within the educational environment. For example, Graf et al. [20] examined 27 behavioral patterns, which required gathering information from six system attributes. In another study by Hj Ahmad and Shamsuddin [29], interaction data were stored as attributes in a student profile, with 20 attributes and values identified, such as the number of exercises accessed, forum views/reads, example usage, exam preparation, and PowerPoint slide engagement. This study simulated data within Moodle for a Data Structures course. Özpolat and Akar [30] utilized decision trees to identify learning styles by analyzing student queries submitted to web search engines like Google and mapped keywords to Felder & Silverman learning styles. Lastly, García et al. [26] employed SAVER, an e-learning platform, to assess 27 computer science students during an Artificial Intelligence course. The interaction data used for constructing user profiles included 10 student actions in the educational environment, with each action represented by variables such as reading materials, example access, answer modifications, exam submission time, and forum participation.

3.6 Games and Education

Numerous studies explored the relationship between games and education. For example, collaborative learning was facilitated through multiplayer online games, as noted in [135]. Additionally, the design and gameplay of modern games were analyzed to determine how they support learning styles [136]. One feature distinguishing games from other learning technologies is their high-level interactivity. Moreover, in [137], the captivating qualities of video games for learners were described and examined.

Educational games have been demonstrated to offer numerous advantages. By presenting abstract ideas within real-world contexts, games capture students' attention and inspire them to apply learned concepts to practical situations [37],[38]. Games are also well-liked among today's students, which boosts their motivation to learn while playing [42]. In terms of automatically detecting learning styles, students are more inclined to engage with a game than an unpersonalized educational platform.

According to [138], video games serve as valuable instruments for learning specific strategies and acquiring knowledge. A related study [139] assessed the impacts of educational video games on learning, motivation, and class dynamics. These research findings underscore the appealing features of games in education, such as distinct objectives, suitable complexity, rapid pace, integrated instructions, and sustained engagement. These traits can help overcome some limitations in existing learning style detection approaches. For instance, well-defined goals and instructions enable players to comprehend the game without prior experience. Moreover, games are engaging and motivating, as they present challenges necessitating continuous interaction and testing learners' skills.

3.7 Games and Learning Styles

The value of learning through games will not be discussed herein, but it is indisputable that games can facilitate learning. According to [140], computer games that are considered "good" (i.e., highly rated and popular) present information in various formats (such as visual, textual, auditory), with visual aids being the most common. Thus, players can choose a style that suits their preference and develop skills in other styles as well, often without even realizing it.

Malone's and Malone and Lepper's work on intrinsic motivation provides a framework for engaging learners [141],[128]. Games that meet Malone's criteria for engagement are likely to be effective for learners with different learning styles. Game developers strive to design games that attract a wide range of players, regardless of whether they consider a particular learning style during the process. Effective games have a learning curve that supports players while they learn but also changes as players advance through the game. Designers achieve this in various ways, such as providing hints to players, offering different modes of support, and adjusting the game's difficulty level as players' skills improve. Games rarely provide straight answers but instead use various forms of communication such as images, text, narrative, or sounds to give players hints. Successful games allow players to have direct control over the amount of support they receive, providing options for beginner and expert players. This is why a commercial game was used herein instead of a developed game that has the only objective of identifying learning styles.

The extent to which playing games influences individuals' learning styles remains to be explored, but some styles appear to be better supported in games than others. This idea has implications for how children learn to learn as games are increasingly popular and serve as a training ground before and throughout their schooling. Prensky suggested that engaging in a certain activity for a prolonged time inevitably alters the brain, as with gaming [142], indicating that playing games may impact some aspects of an individual's learning style.

Figure 3.1: a screenshot of the game

3.8 Methodology

3.8.1 HELLTAKER, the puzzle game

HELLTAKER is an indie puzzle-adventure game that includes dating-sim elements, developed by Lukasz Piskorz, a Polish game developer known as vanripper. The game was released in May 2020, and it is available for Microsoft Windows, macOS, and Linux platforms. The game's description emphasizes its focus on elegantly dressed demon girls. To advance in the game, players must solve a series of puzzle stages to reach a demon girl, provide the correct response to her question, and add her to their demon harem. Each puzzle stage involves moving stones and skeleton soldiers around a two-dimensional top-down grid, reminiscent of Sokoban, within a specific number of turns while avoiding spike traps and collecting necessary items. Once the player reaches the goal, the demon girl of that stage will ask a question, and the player must provide the correct response on the basis of her personality. An incorrect answer may lead to an undesirable outcome, such as death, which will force the player to restart the stage. The final level includes phased bullet-hell-like mechanics with chains that traverse the screen and feature the demon "Judgement, the High Prosecutor." Figure 3.1 depicts a screenshot of the game HELLTAKER.

HELLTAKER is a one-way maze puzzle game with specific rules that must be followed to solve the puzzle.

- The game interface displays the number of available steps, which decreases with each move the player makes.
- The hero can move rocks by kicking them, and the rock moves one square in the chosen direction. However, the hero remains in the same position, and rocks cannot be destroyed.
- Enemies follow the same movement rule as rocks but will be destroyed upon collision with a wall.
- Traps do not block the hero's movement but reduce the number of available steps by one if stepped on.
- At times, treasure chests may block the hero's path, and the player

must find a key to unlock them.

- From the 10th stage onward, the game switches to an action-oriented mode, where the player must move and attack objects according to specific conditions.
- Each level has only one set of movements that represent the solution to the puzzle.

For instance, Figure 3.2 represents the solution to the first-level puzzle. Puzzle games are a suitable tool for assessing learning styles because of their proven ability to foster skills associated with the Felder & Silverman learning style model [143]. Such games offer a challenging environment where players need to apply their critical thinking skills to grasp abstract concepts and solve difficult problems.

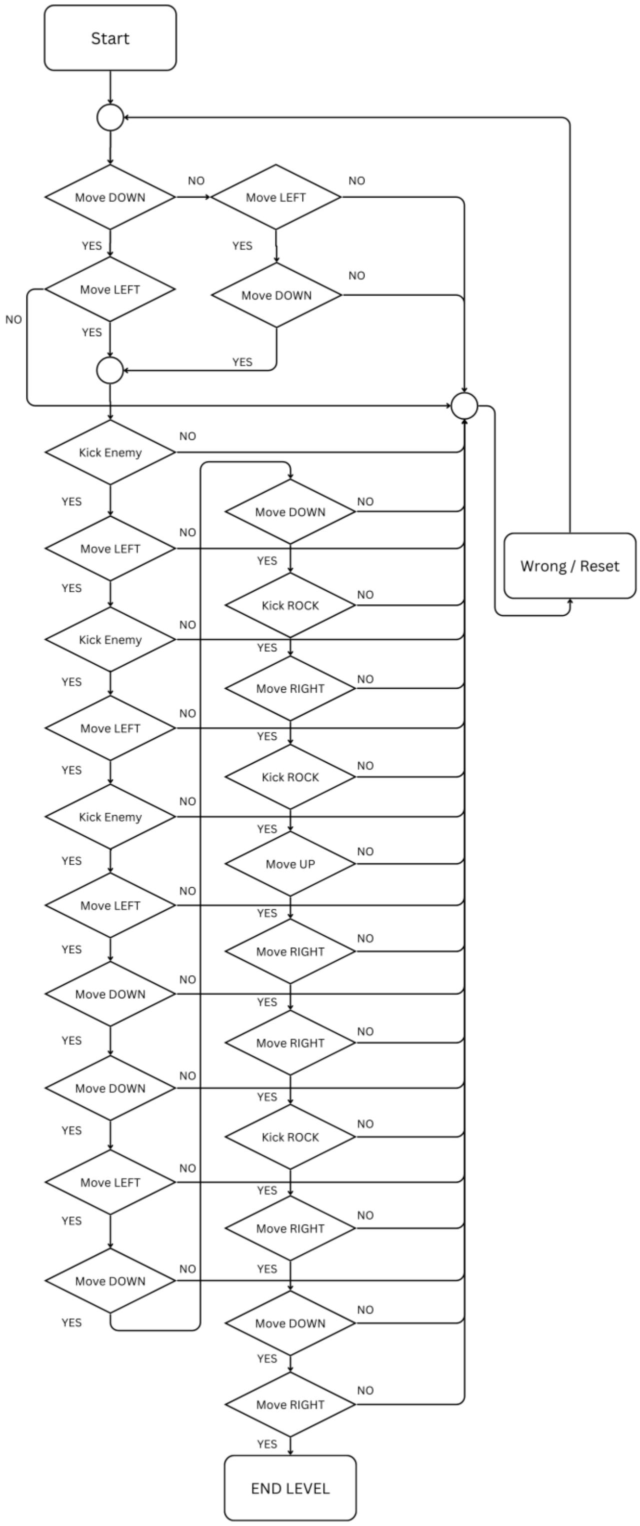


Figure 3.2: the level one puzzle solution

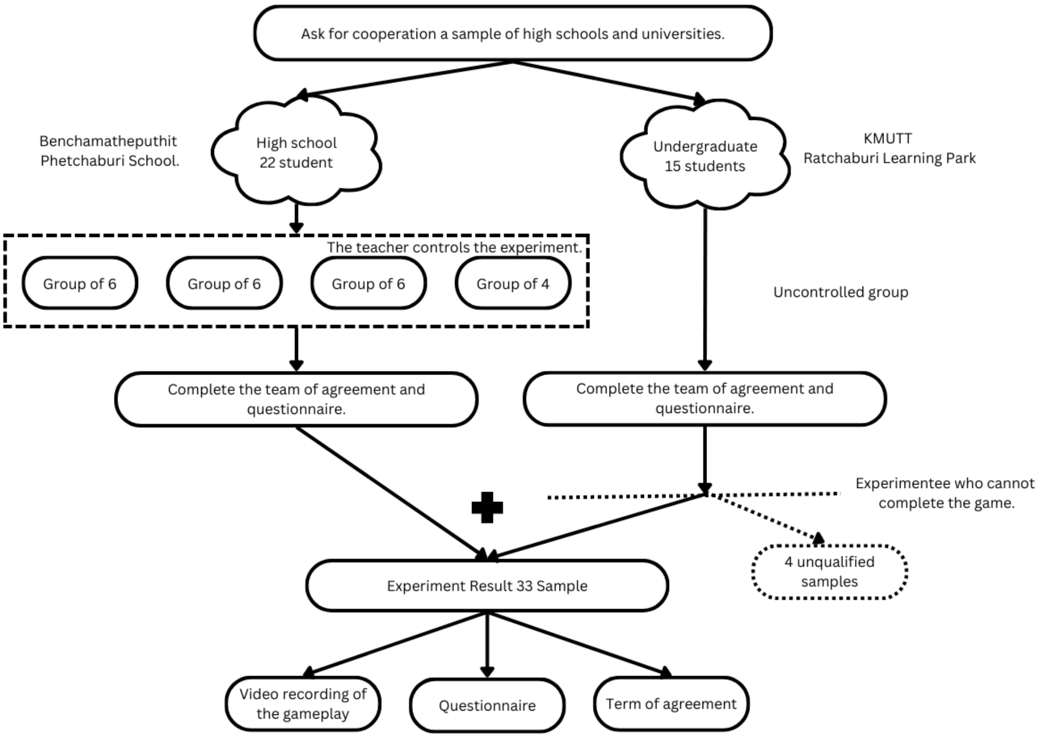


Figure 3.3: a detailed overview of the experiment

3.8.2 Tracking how a student plays the game

3.8.2.1 Experiment Design

The experiment was conducted on a group of 37 Thai students attending two colleges: Benchamatheputhit Phetchaburi School and King Mongkut's University of Technology Thonburi Ratchaburi Learning Park. The experiment was specifically tailored to suit each college's distinct environmental and situational factors. The experiment was conducted separately for two groups of students. The first group comprised 22 high school students from Benchamatheputhit Phetchaburi School and was supervised by a single teacher. The experiment was divided into four stage, each lasting for three hours, spread over two days, with one session held in the morning and another in the afternoon. On the other hand, the second group consisted of 15 undergraduate students from the Engineering Faculty at King Mongkut's University of Technology Thonburi Ratchaburi Learning Park. These undergraduates were from the first and second years of the Intelligent System Engineering, Computer Engineering, and Mechanical Engineering courses. Participation in the game was voluntary for the undergraduates.

Before playing the game, all participants were required to sign a terms-of-agreement form and complete the ILS questionnaire. A detailed overview of the experiment is presented in Figure 3.3. The participant's gameplay was recorded on-screen during the experiment to facilitate the subsequent video processing step.

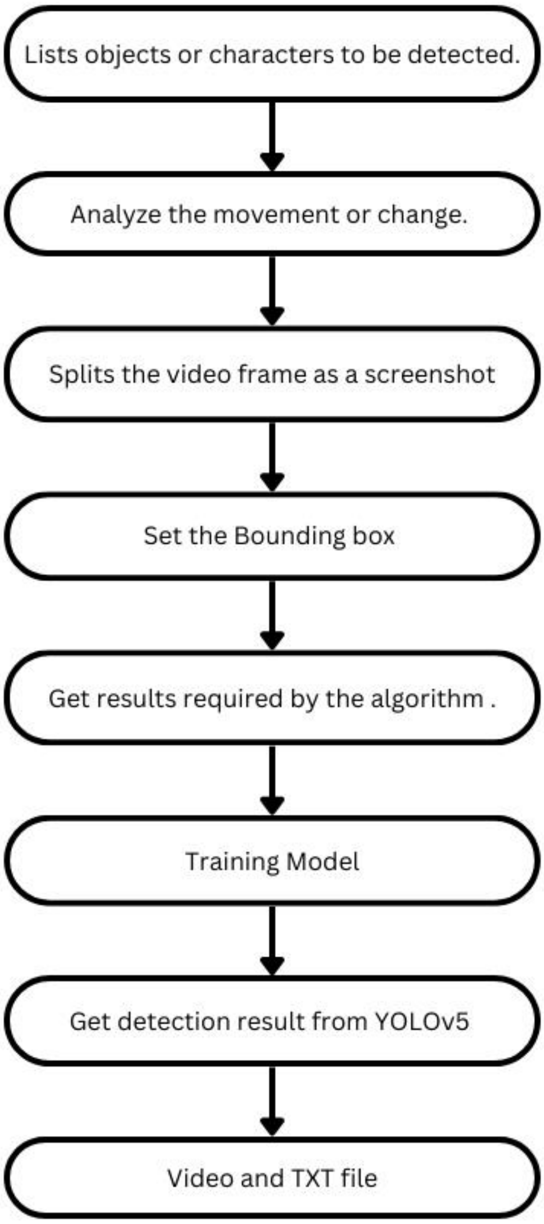


Figure 3.4: a detailed overview of the process

3.8.2.2 Video Processing

For detecting character-type objects within a game, such as those present in the video captured during gameplay, a dataset should be created to train the model to classify them. This is due to the unique nature of such objects compared with people, animals, or other objects commonly found in detection tasks. Consequently, data need to be generated for character classification in the game. Furthermore, to represent the algorithm results in terms of the position and type of objects detected in each frame, researchers should understand how the character progresses at each level. Herein, the fifth version of the "You Only Look Once" algorithm, known as YOLOv5 [144][145] ,was employed. A detailed overview of the process is given in Figure 3.4.

Upon collecting the data, the first step involved listing the characters, level markers, and objects that indicate in-game level transitions to be detected throughout the experiment. Then, patterns in the movements or transformations of game characters or objects were identified. Contextual information of the objects or characters during transition scenarios was captured by splitting the video frames into screenshots. These images were subsequently brought to match the label after defining the bounding box. A total of 311 images, divided into 890 objects, were used to build an image database to classify objects into 15 different items, which are shown in Table 1. The algorithm requires the classification of objects into classes, their positions in the x- and y-coordinates, and the width of the bounding box object. The data output was recorded in a .txt format file with the same name as the detected object. The YOLOv5 model training can be configured with five different training modes, depending on the time and precision required for the task. YOLOv5m (YOLOv5m medium) was selected for this experiment as it is both fast and accurate. Five hundred epochs were required to train the data, and the process took 31 hours, yielding a data efficiency of over 99%. This enabled the model to objectively and efficiently identify objects. The YOLOv5 training results were saved as PyTorch (.pt) files, which can be used to identify objects in the video. Figure 3.5 depicts a screenshot of the video processing with YOLOv5

YOLOv5 was used for video processing to detect objects, and the output is shown in Table 3.2. The results can be interpreted as follows. The filename "user2_2599" indicates that this file contains the detection results for the 2599th frame of the video recorded while user2 was playing the game. Each row of data comprises information regarding the detected object, represented by the values in Table 3.1, followed by the x-coordinate, y-coordinate, and width and height of the bounding box enclosing the object.

Figure 3.5: a screenshot of the video processing with YOLO5

Table 3.1: list of detected objects in HELLTAKER

Item	Object
0	Hero
1	Level 1
2	Level 10-1
3	Level 10-2
4	Level 10-3
5	Level 10-4
6	Level 2
7	Level 3
8	Level 4
9	Level 5
10	Level 6
11	Level 7
12	Level 8
13	Level 9
14	Cutscene

Table 3.2: the output of the video processing using YOLOv5

user2_2599				
1	0.894531	0.775694	0.109375	0.106944
0	0.603516	0.707639	0.0539063	0.0986111

3.8.3 Training machine learning model to assess learning styles

3.8.3.1 Data Preparation

Based on the results obtained from the video processing, the video frame files in .txt format were reformatted into a data frame, where an array of x- and y-coordinates was assigned as the corresponding values. Furthermore, data wrangling procedures, such as removing missing values, were also carried out during this process.

3.8.3.2 Data Understanding

According to the Felder & Silverman model, distinct traits describe each learning style. Consequently, the questions included in the ILS were categorized by semantic similarities. Table 3.3 illustrates the semantic groups and questions associated with each learning style. A question may be listed twice in the table if its answer points to two different semantic groups.

Table 3.3: The semantic groups and questions associated with each learning style.

Style	Semantic Group	ILS Questions (Answer A)	Style	Semantic Group	ILS Questions (Answer B)
Active	trying something out	1, 17, 25, 29	Reflective	think about material	1, 5, 17, 25, 29
Sensing	existing ways	2, 30, 34	Intuitive	new ways	2, 14, 22, 26, 30, 34
	careful with details	22, 42		not careful with details	42
Sequential	sequential progress	20, 24, 32, 36, 44	Global	non-sequential progress	24, 32

The data frame produced from the video processing results is composed exclusively of x- and y-coordinate values. This raw data, in its current form, is unsuitable for direct implementation in the training of a machine learning model. However, interpreting sequential positional changes as movement information, represented by vector values, enables a transformation of this data into a more utilizable format. For example, a shift from the initial position (0,0) to a subsequent position (1,0) is interpreted as the vector X1, (1,0), while a leftward movement from position (1,0) to (0,0) is designated as the vector X2, (-1,0). To derive meaningful information for training a machine learning model, an interpretive method, as referenced in [146],[147], was utilized. This method is predicated on the distinct characteristics that define each learning style. The semantic group associated with each question guides the interpretation process. Similarly, the interpretation of in-game interactions, which is equivalent to the question interpretation, is also conducted. Subsequently, a game log is designed based on the extracted data frame from the video processing results. The correlation between the created game log and learning styles is then evaluated to assess if the log has any predictive utility. The process is shown in Fig 3.6 and the methodological process is presented in detail as follows.

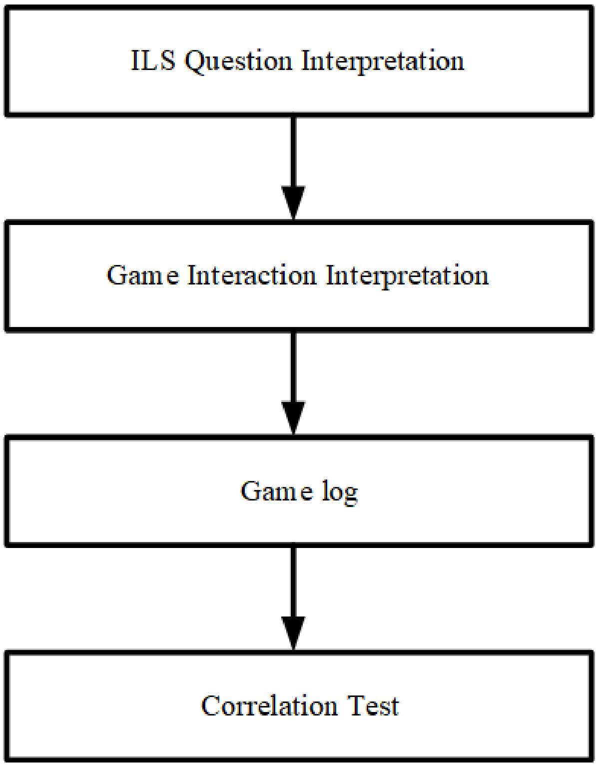


Figure 3.6: the interpretation process

3.8.3.3 Interpretation of Processing: Active / Reflective

- ILS Question Interpretation
  - An active learner who understands something better after trying it out tends to repeatedly move the hero character in a video game to try multiple solutions and is not dettered by the need for retires to solve a puzzle. On the other hand, a reflective learner, who understands something better after thinking it through, takes the time to strategize before moving the character to solve the puzzle. Consequently, reflective learners tend to have fewer movements of the hero character and retires than active learners,even playing at the same level of the game.
  - An active learner is more likely to start working on the solution immediately when starting a homework problem. Similarly, when starting a video game, they tend to make immediately move the hero character, resulting in multiple movements. In contrast, a reflective learner is more likely to try to fully understand the problem first when starting a homework problem. When starting a game, they take the time to contemplate a solution before making any moves with the hero characters. As a result, reflective learners require fewer hero character movements to solve a puzzle and retries than active learners, even when playing at the same level of the game.
  - An active learner who favors learning through trial and error tends to adopt a hands-on approach by repeatedly moving the hero character to solve a puzzle, resulting in numerous character movements before arriving at a solution. In contrast, a reflective learner who favors a more thoughtful learning process takes this time to strategize before moving the hero character to solve the puzzle. As such, reflective learners exhibit fewer character movement before successfully solving the puzzle and retries than other types of learners, even when playing at the same level of game.

- An active learner has a higher propensity for memory retention of experiential learning and thus tends to employ a trial-and-error approach in solving puzzles by repeatedly moving the hero character and not hesitating to retry, as this method enhances their recollection and understanding of the problem-solving process. Conversely, a reflective learner has a higher tendency for memory retention of cognitive learning and therefore prioritizes taking time to think and strategize before moving the hero character in solving the puzzle. In addition, by considering the problem, a reflective learner is more likely to remember and comprehend the process of problem-solving. Hence, reflective learners exhibit fewer character movement times and retries before solving the puzzle than other types of learners, even when playing at the same level of the game.

- Game Interaction Interpretation
    - The total number of times the character moves before successfully solving the puzzle or when retrying on a particular level in game.
    - The total number of game rounds played before successfully solving the puzzle or when retrying on a particular level in the game.
    - The total duration of time spent on a particular level in the game.
- Game Log
    - The number of hero character movements is equivalent to the number of movement vectors that occur at a given level in the game. For instance, the set of x-y coordinated values of the hero character before successfully solving the puzzle or when retrying level 1 can be presented as [(0,0),(0,1),(1,1)]. In level 1, two movement vectors occur, namely X1: (0,1), which represents the movement from the start position (0,0) to the first position (0,1), and X2:(1,0), which represents the movement from the first position (0,1) to second position (1,1).

- The number of game rounds played is equivalent to the number of sets of movement vectors that start from the initial position. At the beginning of each round of game play, the hero character's position always starts from the initial position of a given level. For instance, the set of positions of the hero character in particular level can be expressed as [(0,0),(0,1),(1,1),(0,0),(1,0),(1,1)]. This set of x-y coordinates can be split into two game rounds played in that particular stage, as there are two sets of movement vectors that start from the initial position (0,0). These sets are [(0,1),(1,0)] and [(1,0),(0,1)].
- The total duration of time spent on a particular level in the game is equivalent to the number of video frames that contain the object representing that specific level of the game.

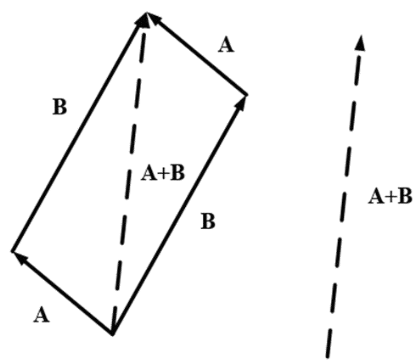
3.8.3.4 Interpretation of Perception: Sensitive / Intuitive

- ILS Question Interpretation
  - A sensitive learner, who prefers to master a particular method of performing a task, tends to focus on the solution that has the highest probability of solving a puzzle and continuously refines it until it succeeds. Although they may experiment with different movements, they adhere to a set of movements that have been proven effective. In contrast, an intuitive learner, who prefers to generate novel methods of performing a task, seeks to find alternative solutions when a previous one fails to solve the puzzle. As a result, they produce multiple sets of movements that are entirely distinct from one another.
  - A sensitive learner regards practicality as a key trait and thus prioritizes finding the solution that has the highest probability of solving a puzzle. Their approach involves continuously refining the most effective solution until it successfully solve the puzzle. Although they may experiment with different movements, they adhere to a set of movements that have been proven effective, as this is the most sensible course of action.

Conversely, an intuitive learner values creativity and innovation and therefore employs a more creative methodology by attempting multiple new solutions after a previous one fails to solve the puzzle. As a result, they generate multiple sets of movements that are entirely distinct from one another.

- A sensitive learner, who is known for their meticulous attention to detail, tends to refine the most promising solution to solve a puzzle. Their approach involves carefully preserving the details of the solution that has the highest probability of success and making slight improvements where necessary. In contrast, an intuitive learner, who is recognized for their creativity and innovation, employs a more creative methodology by attempting multiple new solutions after a previous one fails to solve the puzzle. As a result, they generate multiple sets of movements that are entirely distinct from one another.
- A sensitive learner is characterized by their propensity to repeat each step and meticulously check their work carefully. They tend to preserve the details of the solution that has the highest probability of successfully solving the puzzle and make slight improvements to refine the solution. As a result, their sets of movements tend to be subtly different from each other.

- Game Interaction Interpretation
  - The mean similarity between each set of hero character movements before solving the puzzle or retrying on a particular level in the game.
- Game Log
  - The degree of similarity between sets of hero character movements can be measured by the cosine similarity between the entire sets of movement vectors in each round of game play. To determine the similarity between these sets, the summation of movement vectors for each game round is calculated, followed by the cosine similarity between each summation vector of each game round.



$$\begin{aligned} \mathbf{A} &= (a_1, a_1, \dots, a_n) \\ \mathbf{B} &= (b_1, b_1, \dots, b_n) \\ \mathbf{A}+\mathbf{B} &= (a_1 + b_1, a_2 + b_2 \dots, a_n + b_n) \end{aligned}$$

$$cosine\ similarity = S_c(A,B) \coloneqq \cos(\theta) = \frac{\mathbf{A}\cdot\mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

Figure 3.7: the cosine similarity calculation

3.8.3.5 Interpretation of Understanding: Sequential / Global

- ILS Question Interpretation
  - A sequential learner progresses through learning at a steady, regular pace. As the difficulty of sub-levels in level 10 of the game increases progressively, a sequential learner tends to improve their performance on these sub-levels in relation to the difficulty of progress. In contrast, a global learner progresses through learning in irregular bursts. They may initially struggle to gasp the learning materials but then suddenly have a comprehensive understanding that allows them to play sub-levels in level 10 of the game independently.
- Game Interaction Interpretation
  - The total number of game rounds played before successfully solving the puzzle or when retrying on a particular sub-levels of level 10 in the game.
- Game Log
  - The number of game rounds played is equivalent to the number of sets of movement vectors that start from the initial position. At the beginning of each round of gameplay, the hero character's position always starts from the initial position of a given sub-levels of level 10. For instance, the set of x-y coordinates can be split into two game rounds played in that particular stage, as there are two sets of movement vectors that start from the initial position (0,0). These sets are [(0,1),(1,0)] and [(1,0),(0,1)].

3.8.3.6 Interpretation of Input: Visual / Verbal

- ILS Question Interpretation
  - Since HELLTAKER, the puzzle game does not convey data through sound, it cannot be directly utilized to assess the input dimension of the Felder & Silverman model. Nevertheless, the game can be employed to measure the learning progress of both visual and verbal learners. In the puzzle game, learning

progress refers to the degree of similarity between a player's solution in each game round and the correct solution to solve the puzzle at each level of the game. If the similarity of a player's solution in each game round steadily increase and approaches the correct solution, it indicates that the player has made learning progress.

- Game Interaction Interpretation
  - The mean similarity between each set of hero character movements made before solving the puzzle or retrying and the correct solution to solve the puzzle in a specific level of the game.
- Game Log
  - The degree of similarity between sets of hero character movements and the correct solution can be qualified using the cosine similarity between the entire sets of movement vectors in each round of game play and the entire sets of movement vectors of the correct solution. To calculate this similarity, the summation of movement vectors is computed, and then the cosine similarity is determined.

3.8.3.7 Correlation Test of Perception: Sensitive / Intuitive

- Analysis of the sensitive style

  According to the correlation heatmap in Figure 3.9, the following observations and explanations can be made:

  - The total time spent on level 2 in the game has the strongest positive correlation with the sensitive style.
  - The total number of game rounds played on sublevel 3 of level 10 has the strongest negative correlation with the sensitive style.
  - Sensitive learners tend to produce sets of movements that are relatively similar to each other because of their preference for mastering a specific method of task performance, prioritizing solutions with a high likelihood of puzzle-solving success, and continuously refining these solutions until they are effective. However, compared with other features, the features associated with the similarity between sets of hero character movements do not exhibit a strong correlation with the sensitive learning style. On the other hand, there is a strong positive correlation between the sensitive learning style and the similarity between each set of hero character movements and the correct solution.

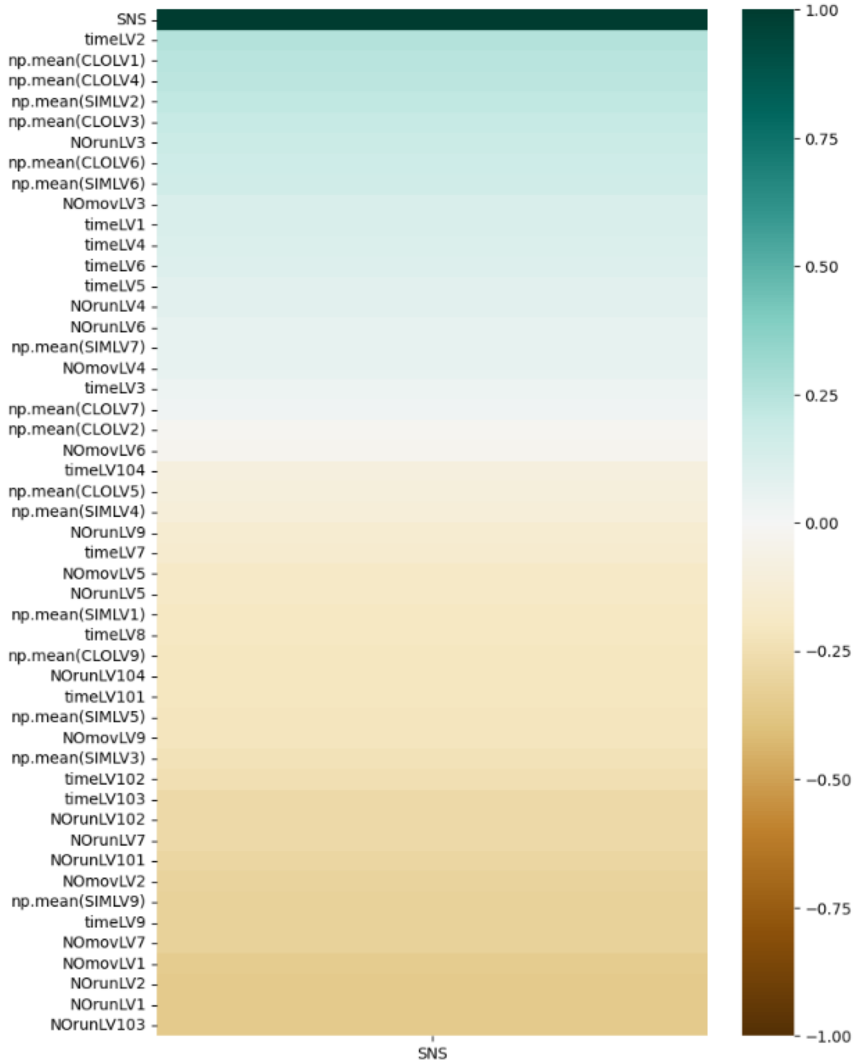


Figure 3.8: the correlation heatmap of the sensitive style and other features

- Analysis of the intuitive style

  According to the correlation heatmap in Figure 3.10, the following observations and explanations can be offered:

  - The total number of game rounds played on level 1 has the strongest positive correlation with the intuitive style.
  - The similarity between each set of hero character movements and the correct solution on level 1 has the strongest negative correlation with the intuitive style.
  - Intuitive learners prioritize innovation and tend to explore new solutions when a previous attempt fails to solve the puzzle. They tend to create multiple sets of unique movements. However, compared with other features, the features associated with the similarity between sets of hero character movements do not exhibit a strong correlation with the sensitive learning style. On the other hand, there is a strong negative correlation between the intuitive learning style and the similarity between each set of hero character movements and the correct solution.

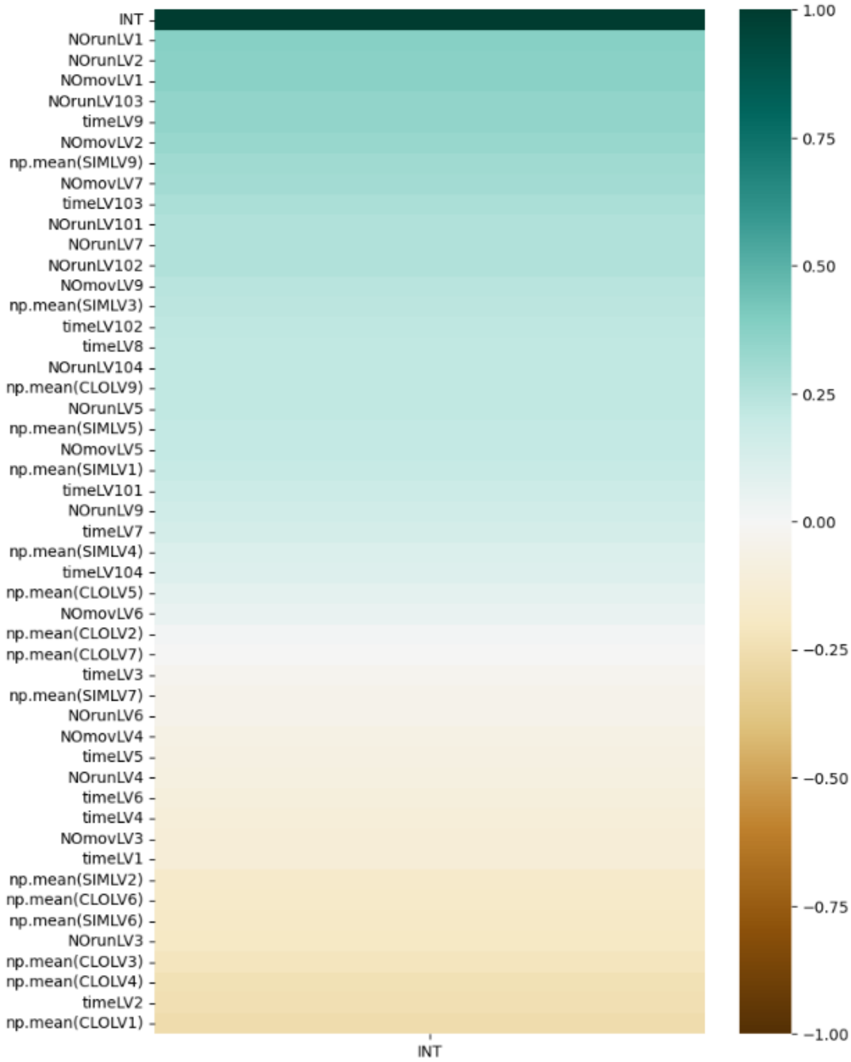


Figure 3.9: the correlation heatmap of the intuitive style and other features

3.8.3.8 Correlation Test of Processing: Active / Reflective

- Analysis of the active style

  From the correlation heatmap in Figure 3.11, the following observations and explanations can be derived:

  - The total number of game rounds played on sublevel 4 of level 10 has the strongest positive correlation with the active style.
  - The similarity between each set of hero character movements and the correct solution on level 4 has the strongest negative correlation with the intuitive style.
  - An active learner gains a better understanding of a concept through trial and error and, thus, tends to repeatedly move the hero character in a video game to experiment with multiple solutions, retrying and solving a puzzle without hesitation. Consequently, they tend to have a high number of hero character movements and retries. However, compared with other features, the features associated with the number of times the hero character moves and the number of game rounds played do not exhibit a strong correlation with the sensitive learning style. On the other hand, there is a strong negative correlation between the active learning style and the similarity between each set of hero character movements and the correct solution.

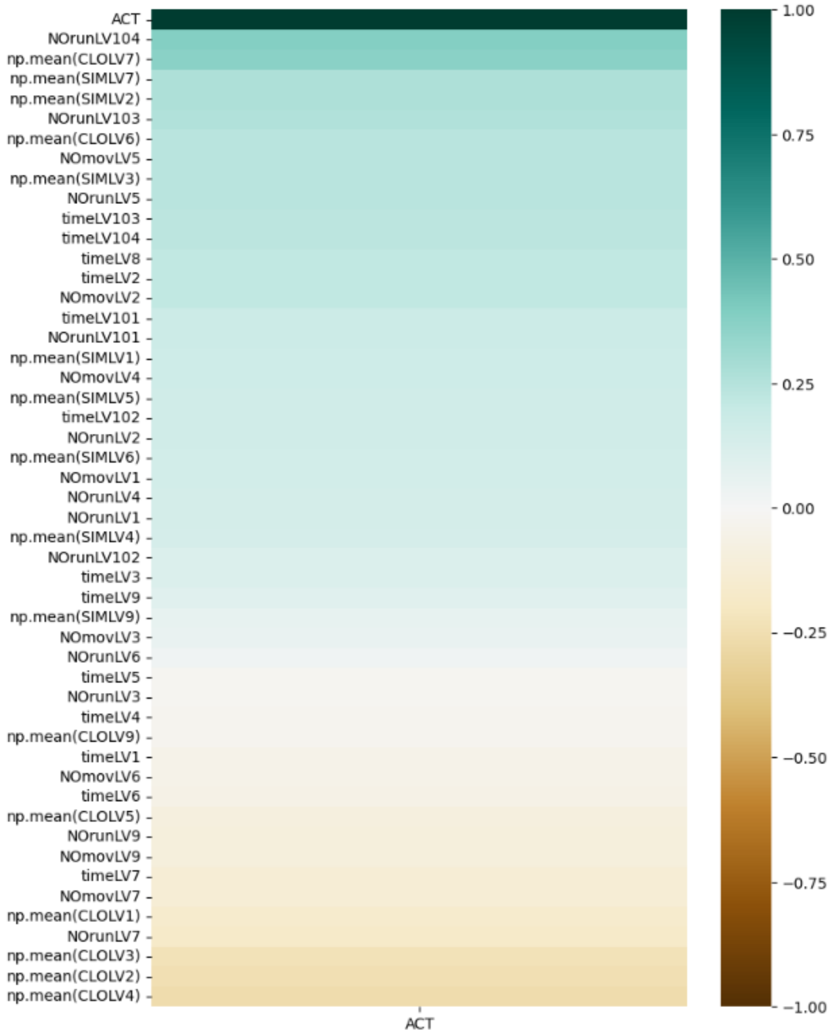


Figure 3.10: the correlation heatmap of the active style and other features

- Analysis of the reflective style

  On the basis of the correlation heatmap in Figure 3.12, the following observations and explanations can be provided:

  - The similarity between each set of hero character movements and the correct solution on level 4 has the strongest positive correlation with the reflective style.
  - The total number of game rounds played on sublevel 4 of level 10 has the strongest negative correlation with the intuitive style.
  - Intuitive learners tend to adopt an approach that contrasts with that of active learners. The correlation pattern between the reflective learning style and other features is opposite to that between the active learning style and other features.

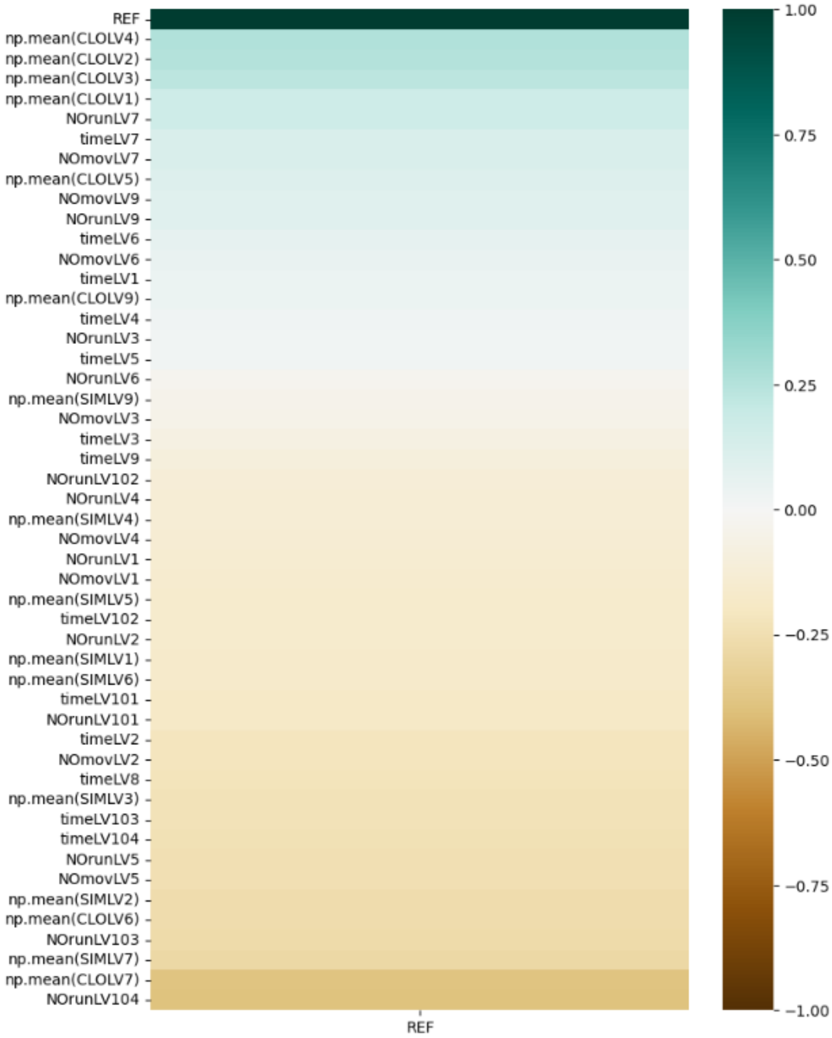


Figure 3.11: the correlation heatmap of the reflective style and other features

3.8.3.9 Correlation Test of Understanding: Sequential / Global

- Analysis of the sequential style

  According to the correlation heatmap in Figure 3.13, the following observations and explanations can be made:

  - The total time spent on sublevel 1 of level 10 has the strongest positive correlation with the sequential style.
  - The similarity between each set of hero character movements and the correct solution on level 5 has the strongest negative correlation with the sequential style.
  - Sequential learners advance in their learning at a consistent and steady pace. As the difficulty of the sublevels in level 10 of the game progressively increases, sequential learners tend to enhance their performance accordingly. Therefore, the features associated with these sublevels have a strong positive correlation with the sequential learning style.

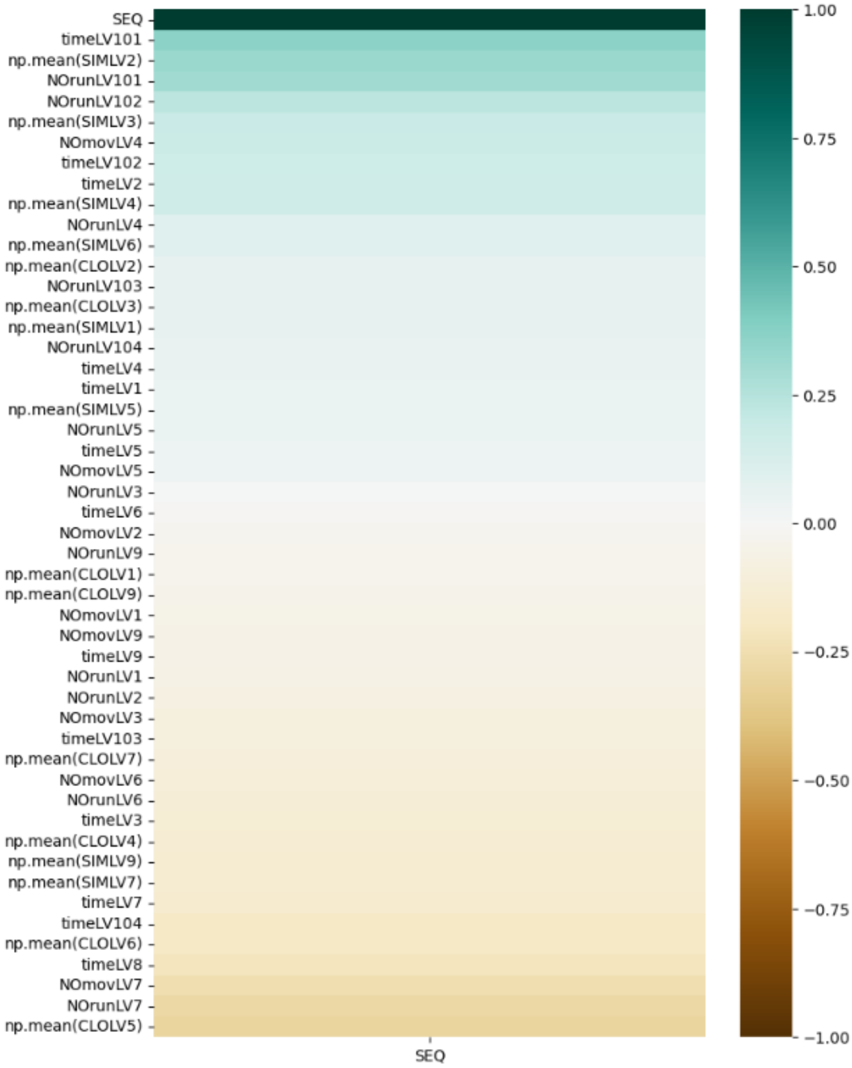


Figure 3.12: the correlation heatmap of the sequential style and other features

- Analysis of the global style

  The following observations and explanations are based on the correlation heatmap in Figure 3.14:

  - The total number of game rounds played on level 7 has the strongest positive correlation with the global style.
  - The total time spent on sublevel 1 of level 10 has the strongest negative correlation with the intuitive style.
  - Global learners advance in their learning through sporadic bursts, struggling initially to grasp the learning materials before suddenly attaining a comprehensive understanding that enables them to play the sublevels in level 10 independently. Therefore, the features associated with these sublevels have a strong negative correlation with the global learning style.

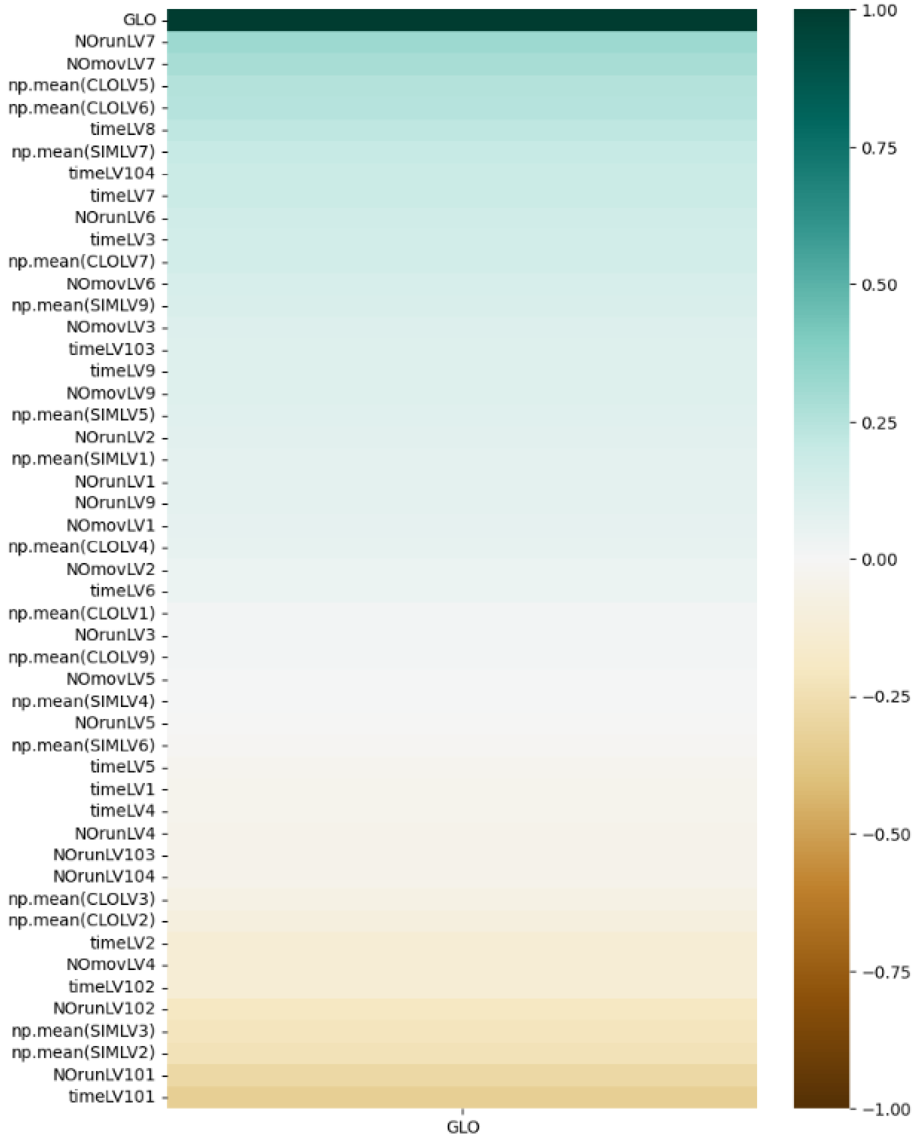


Figure 3.13: the correlation heatmap of the global style and other features

3.8.3.10 Correlation Test of Input: Visual / Verbal

- Analysis of the visual style

  From the correlation heatmap in Figure 3.15, we can deduce the following:

  - The similarity between the set of hero character movements of each game round on level 4 has the strongest positive correlation with the visual style.
  - The similarity between each set of hero character movements and the correct solution on level 5 has the strongest negative correlation with the visual style.
  - The features associated with sublevels of level 10 have a strong positive correlation with the visual learning style.

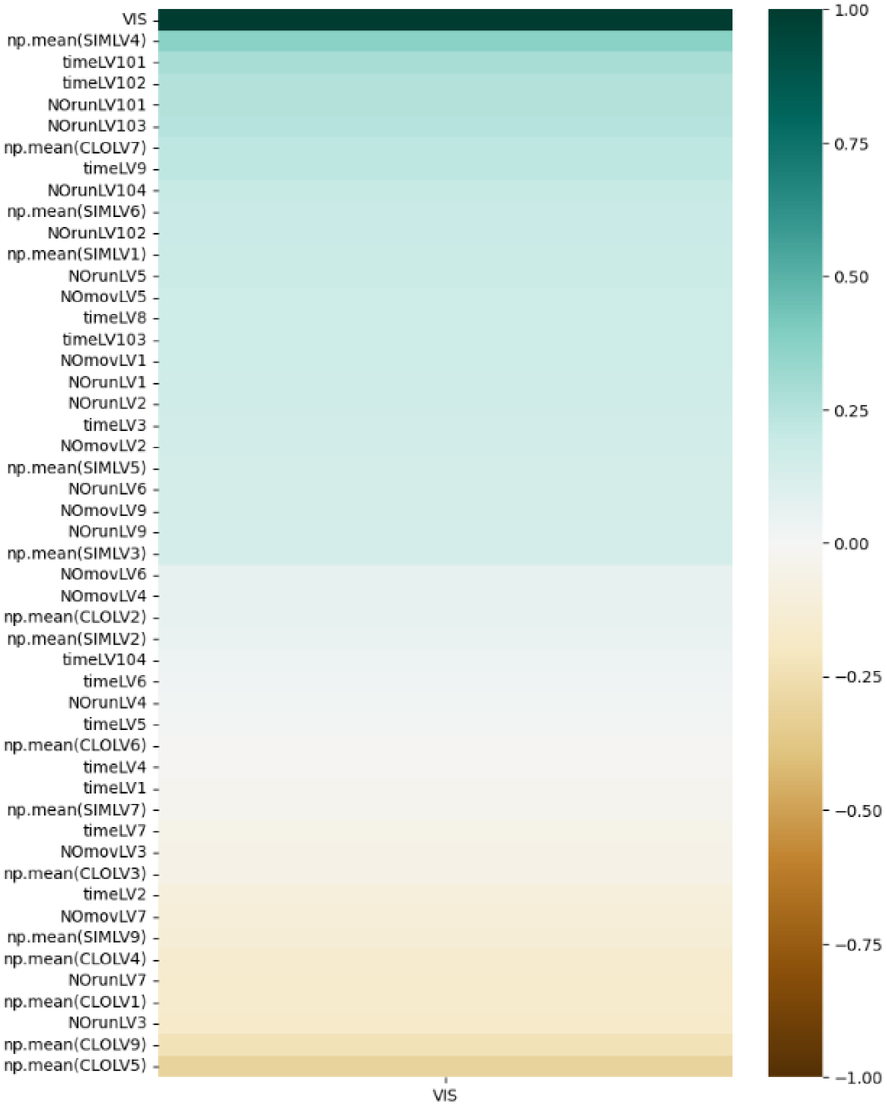


Figure 3.14: the correlation heatmap of the visual style and other features

- Analysis of the verbal style

  From the correlation heatmap in Figure 3.16, we can infer the following:

  - The similarity between each set of hero character movements and the correct solution on level 5 has the strongest positive correlation with the verbal style.
  - The similarity between the set of hero character movements of each game round on level 4 has the strongest negative correlation with the verbal style.
  - Verbal learners tend to adopt an approach that contrasts with that of visual learners. The correlation pattern between the verbal learning style and other features is opposite to that between the visual learning style and other features.

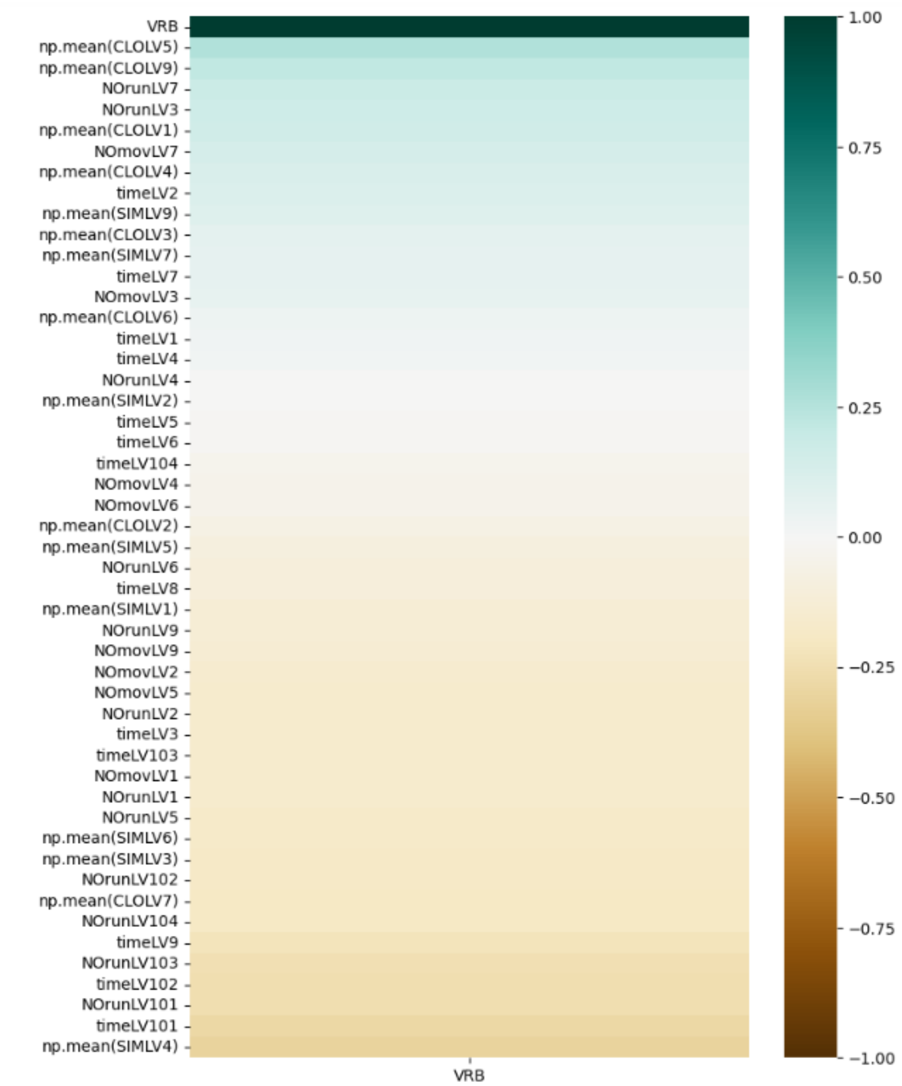


Figure 3.15: the correlation heatmap of the verbal style and other features

3.8.3.11 Modeling

AutoGluon was used to model the learning style prediction. AutoGluon [148] is an open-source AutoML library that automates deep learning and machine learning for tabular datasets.

In the past, achieving state-of-the-art performance in modeling machine learning algorithms was challenging and time-consuming. It required extensive expertise, background knowledge, and considerable human effort. Many tasks must have been completed, including data preparation, feature engineering, validation splitting, missing value handling, and model selection. Selecting hyperparameters was one of the most difficult tasks. Hyperparameters are the user's choices when building a model, such as the data processing steps, neural network architecture, and optimizer used during training. They significantly impact the model's performance, and as models become more complex, the number of hyperparameters increases. Even slight changes to hyperparameters can significantly affect model quality. Developers often have to manually adjust different aspects of their ML pipeline to achieve strong predictive performance, which can be time-consuming and iterative. [149],[150],[151]

AutoGluon utilizes the available computing resources to discover the most robust machine learning approaches within its designated runtime. Advanced tuning algorithms, such as Bayesian Optimization, Hyperband, and Reinforcement Learning, automatically select each task's hyperparameters. AutoGluon automatically adjusts all hyperparameters within predetermined ranges that are recognized to perform well for the given task and model. [152]

Chapter 4
Result Discussion

This chapter provides an analysis and a discussion of the results from the conducted experiment, segmented into two parts. The initial part focuses on the analysis of video processing designed to aim at the detection of in-game character movements in real-time as a player interacts within the game. The secondary part focuses on the modeling process designed to identify the most effective machine learning model capable of identifying Felder-Silverman learning styles, based on the information derived from gameplay analysis.

4.1 Video Processing with YOLOv5 Results

The YOLOv5 algorithm was utilized to train the model for object detection in images or videos, with a focus on accuracy, model size, and detection speed. However, in the context of gameplay recordings in time-controlled experiments, where the outcomes are not immediate, the detection of characters' or objects' behavior may not be instantaneous. Therefore, the primary objective of object detection and character positioning is to identify the object type in the video and determine its position in pixels in each frame. Furthermore, the order of frames is employed to compute the player's reaction time, thus reducing the missing frames that cannot detect objects or characters.

The YOLOv5 algorithm was chosen after a rigorous evaluation process, which included testing small, medium, and large models - YOLOv5s, YOLOv5m, and YOLOv5x, respectively. The selection criteria were based on their detection capability, ensuring that object capture was at least 99% regardless of the training time. However, during preliminary tests at 300 epochs, the desired 99% model accuracy was not achieved. Therefore, the number of epochs was increased to 500 during the training process, resulting in the highest possible accuracy and improved object detection performance in images and videos.

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Through the course of preliminary testing, it was noted that the YOLOv5s model reached an accuracy plateau of 93% following 230 epochs, demonstrating no subsequent improvement. Conversely, the YOLOv5m and YOLOv5x models were able to achieve a completion of training with an accuracy exceeding 99%. Upon evaluation, the YOLOv5m model demonstrated an optimal balance of model size, detection speed, and accuracy, positioning it as the most fitting choice aligned with the project's objectives. However, the YOLOv5x model also stands as a competitive alternative for contexts demanding heightened accuracy and expedient detection.

Being selected for object detection, the YOLOv5m model was used to process the sample video data. The results demonstrated that the model accurately detected all relevant objects within the video, including the player's character, with a consistent accuracy level above the desired 99% threshold. The detection speed was also impressive, with an average of only 27 ms per frame, which allowed processing the entire video in a reasonable amount of time. Another advantage of the YOLOv5m model was its reduced susceptibility to overfitting compared with the YOLOv5x model [153]. Overfitting can result in missed or false positive detection. With the YOLOv5m model, only 1.5% of the frame data were missing after filtering out irrelevant objects, so it significantly outperformed the YOLOv5x model as indicated in Figure 4.1.

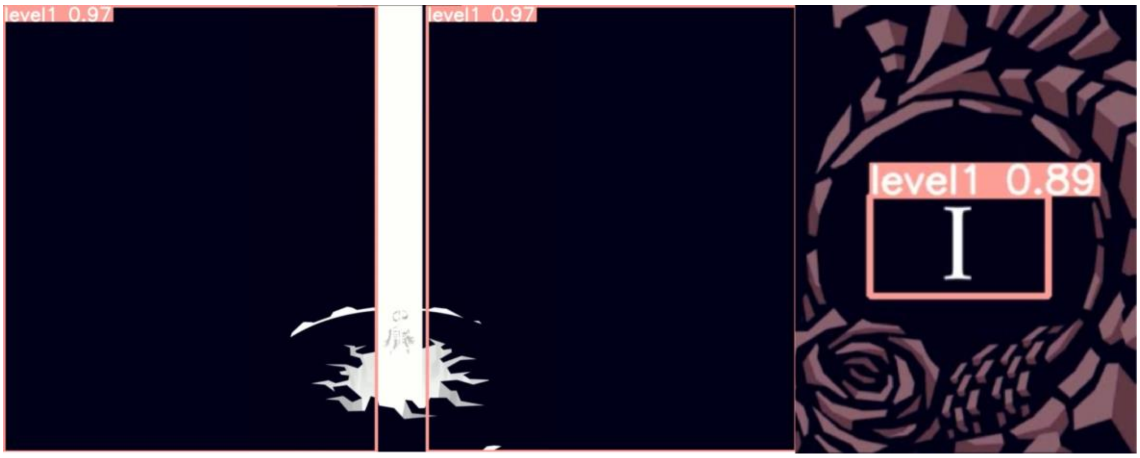

Figure 4.1: detection error with roman numerals at level 1

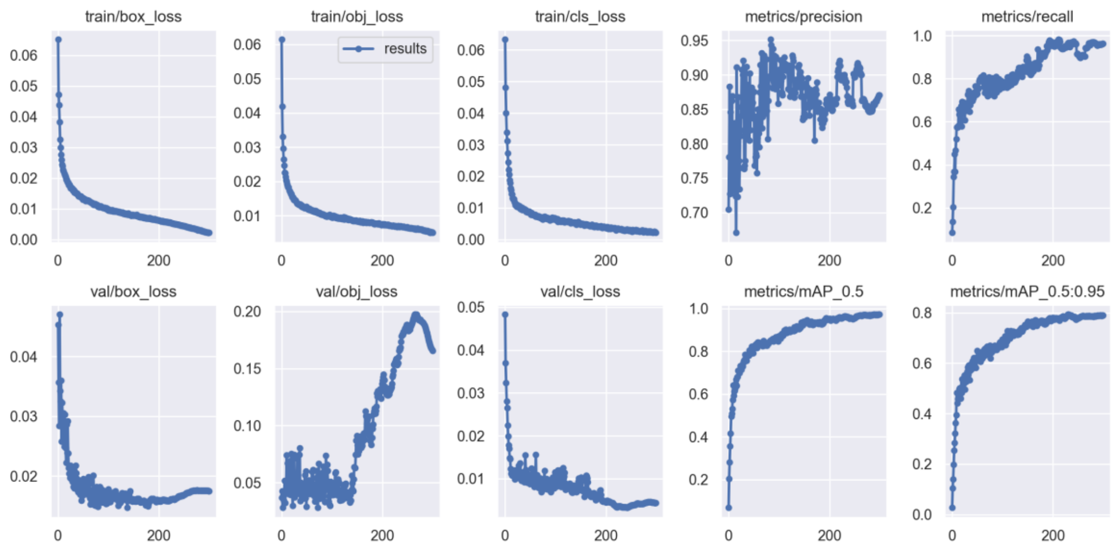

Figure 4.2: result of training model

The training data results after training for 500 epochs are illustrated in Figure 4.2 and listed below:

- The loss function, which calculates the error (train/box_loss) between the predicted and the ground-truth bounding boxes, had an average value of 0.0041586. A lower value of the loss function indicates better accuracy and performance of the model in detecting and localizing objects.
- The average object detection loss (train/obj_loss), which measures how well a model can detect and classify objects within the input data, was 0.0065045. A lower loss value indicates better object detection.
- The classification loss (train/cls_loss) is a measure of the difference between the predicted and actual class probabilities, and a lower value indicates higher accuracy in object classification. In the case of the trained YOLOv5m model, the classification loss was 0.0034207, indicating its efficacy in accurately classifying objects in the sample video.
- The precision score (metrics/precision) achieved by the model was 0.96857, indicating the model's ability to identify true positives among all optimistic predictions accurately. In other words, it represents the percentage of correctly detected objects in all the detected objects.
- The recall score (metrics/recall) measures the model's ability to identify all relevant objects in the video, regardless of whether it also detects some irrelevant objects. The selected model achieved a score of 0.99952, meaning that it correctly identified and detected 99.952% of the relevant objects in the video.
- The mean average precision (mAP) with an overlap of 0.5 (metrics/mAP_0.5) was evaluated. The model scored 0.99153, indicating its high accuracy in detecting objects within the video, with a precision of almost 99% at the overlap threshold of 0.5. The mAP for object detection with a confidence threshold of 0.5-0.95 (metrics/mAP_0.5:0.95) achieved a score of 0.87655, indicating that the model performs well in detecting objects in the sample video. However, there is still room for improvement in the model's

performance.

- The box loss (val/box_loss) is a metric used to evaluate the performance of object detection models by measuring the difference between the predicted and the ground-truth bounding boxes. A lower box loss value indicates that the predicted bounding boxes are closer to the ground-truth ones and, thus, the model performs better in object detection. The YOLOv5m model achieved a box loss of 0.014122 during validation, indicating that it detected objects well in the validation set.
- The objective loss (val/obj_loss) is a measure of how well the model can detect and locate objects within an image. It reflects the error between the predicted and the ground-truth bounding box coordinates. A lower objective loss indicates the model can better detect and accurately locate objects within images during validation. The YOLOv5m model achieved an objective loss of 0.07357 during validation.
- The classification loss (val/cls_loss) indicates the accuracy of the model in predicting the class of the detected objects in the validation dataset. The YOLOv5m model achieved a very low classification loss (0.00040696) during validation, showing good accuracy in classifying objects.

4.2 Modeling with AutoGluon Results

AutoGluon was utilized for training a regression model with various machine learning algorithms to predict the active learning style, and the outputs are presented in the following list:

Table 4.1: The AutoGluon leaderboard of the sensitive style prediction

Model	Score_test	Score_val
LightGBM	0.930246	2.083067
LightGBMXT	0.930246	2.083067
CatBoost	0.933415	2.085359
LightGBMLarge	0.934473	2.093178
ExtraTreeMSE	0.998750	2.097709
RandomForestMSE	1.051742	2.345731
KNeighborsUnif	1.163738	2.255406
KNeighborsDist	1.205548	2.293080
NeuralNetTorch	1.258755	1.789284
NeuralNetFastAI	1.433738	1.920734
WeightedEnsemble_1.2	1.665165	1.083467
XGBoost	1.827685	1.155839

- Prediction of the sensitive style

    According to the AutoGluon leaderboard result presented in Table 4.1, the following observations and explanations can be made:

    - The best model for the sensitive style prediction is the LightGBM algorithm.
    - The "score_test" value of 0.93 and "score_val" value of 2.083067 indicate that the LightGBM model was able to accurately predict the sensitive style with a low error rate. The lower the score, the better the performance, so these results indicate that the model performed better on the test set than on the validation set.

    The evaluation metrics for a sensitive style prediction model are listed below:

    - The RMSE value (herein 1.665) measures the average distance between the predicted and actual values of the target variable. A lower RMSE value indicates better prediction of the sensitive style.
    - The "mean_squared_error" value (herein 2.77) is another measure of the average difference between the predicted and actual values of the target variable. The “mean_absolute_error” value (herein 1.52) measures the average absolute difference between the predicted and actual values of the target variable. In both, lower values indicate better performance of the model.

    Overall, this result suggests that the LightGBM algorithm is an effective and efficient approach to predicting the sensitive style.

Table 4.2: The AutoGluon leaderboard of the intuitive style prediction

Model	Score_test	Score_val
LightGBM	0.919627	2.127597
LightGBMXT	0.919627	2.127597
CatBoost	0.922951	2.129640
LightGBMLarge	0.924944	2.136964
ExtraTreeMSE	0.986656	2.360181
RandomForestMSE	1.043434	2.469548
NeuralNetFastAI	1.114769	2.316832
KNeighborsUnif	1.131371	2.290560
WeightedEnsemble_1.2	1.140938	1.558577
NeuralNetTorch	1.140938	1.558577
KNeighborsDist	1.158691	2.334007
XGBoost	1.191726	2.633678

- Prediction of the intuitive style

According to the AutoGluon leaderboard result in Table 4.2, we can offer the following observations and explanations:

  - The best model for the intuitive style prediction is the LightGBM algorithm.
  - The "score_test" value of 0.92 and "score_val" value of 2.13 indicate that the LightGBM model was able to accurately predict the intuitive style with a low error rate.

The values of the evaluation metrics for an intuitive style prediction model are listed below:

  - The RMSE value is 1.14.
  - The MSE value is 1.3, and the MAE value is 0.94.

Overall, this result suggests that the LightGBM algorithm is an effective and efficient approach to predicting the intuitive style.

Table 4.3: The AutoGluon leaderboard of the active style prediction

Model	Score_test	Score_val
KNeighborsUnif	1.320173	1.939072
RandomForestMSE	1.368742	2.008384
KNeighborsDist	1.427100	2.005224
CatBoost	1.513000	1.845417
LightGBMLarge	1.519154	1.755456
ExtraTreeMSE	1.636057	2.034688
LightGBM	1.642298	1.968079
LightGBMXT	1.642298	1.968079
NeuralNetTorch	1.706167	1.881618
NeuralNetFastAI	1.849949	2.167170
WeightedEnsemble_1.2	1.995560	1.711959
XGBoost	2.228614	1.718379

- Prediction of the active style

  On the basis of the AutoGluon leaderboard result in Table 4.3, the following observations and explanations can be made:

  - The best model for the active style prediction is the KNeighborsUnif algorithm.
  - The "score_test" value of 1.32 and "score_val" value of 1.94 indicate that the KNeighborsUnif model was able to accurately predict the active style with a low error rate.

  The values of the evaluation metrics for an active style prediction model are as follows:

  - The RMSE value is 1.995.
  - The MSE value is 3.98, and the MAE value is 1.86.

  Overall, this result suggests that the LightGBM algorithm is an effective and efficient approach to predicting the active style.

Table 4.4: The AutoGluon leaderboard of the reflective style prediction

Model	Score_test	Score_val
KNeighborsUnif	1.330950	1.947648
RandomForestMSE	1.406384	1.938045
KNeighborsDist	1.441106	2.0115654
WeightedEnsemble_1.2	1.512895	1.752339
CatBoost	1.512895	1.752339
XGBoost	1.512895	2.171422
ExtraTreeMSE	1.635025	1.950528
LightGBMLarge	1.640216	1.889147
LightGBMXT	1.660123	1.984733
LightGBM	1.684276	1.984733
NeuralNetTorch	1.927036	1.92489
NeuralNetFastAI	2.179456	1.874700

- Prediction of the reflective style

From the AutoGluon leaderboard result in Table 4.4, we can deduce the following:

  - The best model for the reflective style prediction is the KNeighborsUnif algorithm.
  - The "score_test" value of 1.33 and "score_val" value of 1.95 indicate that the KNeighborsUnif model was able to accurately predict the reflective style with a low error rate.

The values of the evaluation metrics for a reflective style prediction model are presented in the following list:

  - The RMSE value is 1.51.
  - The MSE value is 2.29, and the MAE value is 1.27.

Overall, this result suggests that the KNeighborsUnif algorithm is an effective and efficient approach for the task of predicting the reflective style.

Table 4.5: The AutoGluon leaderboard of the sequential style prediction

Model	Score_test	Score_val
NeuralNetTorch	1.995624	1.439169
ExtraTreeMSE	1.998723	1.220524
LightGBMLarge	1.999664	1.2035584
CatBoost	2.003994	1.261134
LightGBMXT	2.036015	1.272465
LightGBM	2.036015	1.272465
RandomForestMSE	2.056160	1.263515
NeuralNetFastAI	2.203232	1.326889
KNeighborsDist	2.262714	1.058552
WeightedEnsemble_1.2	2.265266	0.972968
KNeighborsUnif	2.265266	0.972968
XGBoost	3.043232	1.842136

- Prediction of the sequential style

From the AutoGluon leaderboard result in Table 4.5, we can infer the following:

- The best model for the sequential style prediction is the NeuralNetTorch algorithm.
- The "score_test" value of 1.995 and "score_val" value of 1.44 indicate that the NeuralNetTorch model was able to accurately predict the sequential style with a low error rate.

The values of the evaluation metrics for a sequential style prediction model are given below:

- The RMSE value is 2.265.
- The MSE value is 5.13, and the MAE value is 2.00.

Overall, this result suggests that the NeuralNetTorch algorithm is an effective and efficient approach for predicting the sequential style.

Table 4.6: The AutoGluon leaderboard of the global style prediction

Model	Score_test	Score_val
ExtraTreeMSE	1.925936	1.290470
LightGBMLarge	1.928755	1.147919
RandomForestMSE	1.963994	1.415096
LightGBM	1.987730	1.306076
LightGBMXT	1.987730	1.306076
CatBoost	1.989530	1.308485
WeightedEnsemble_1.2	2.107301	1.127388
NeuralNetTorch	2.115964	1.226356
NeuralNetFastAI	2.143235	1.335202
XGBoost	2.157752	1.354412
KNeighborsDist	2.262714	1.155494
KNeighborsUnif	2.265266	1.137248

- Prediction of the global style

From the AutoGluon leaderboard result in Table 4.6, the following observations and explanations can be drawn:

  - The best model for the global style prediction is the ExtraTreesMSE algorithm.
  - The "score_test" value of 1.925 and "score_val" value of 1.29 indicate that the ExtraTreesMSE model was able to accurately predict the global style with a low error rate.

The values of the evaluation metrics for a global style prediction model are listed below:

  - The RMSE value is 2.11.
  - The MSE value is 4.44, and the MAE value is 1.9.

Overall, this result suggests that the ExtraTreesMSE algorithm is an effective and efficient approach for predicting the global style.

Table 4.7: The AutoGluon leaderboard of the visual style prediction

Model	Score_test	Score_val
LightGBM	1.129949	1.842779
LightGBMXT	1.129949	1.842779
NeuralNetTorch	1.271845	1.707917
CatBoost	1.309408	1.568827
KNeighborsDist	1.311554	2.039752
KNeighborsUnif	1.371131	2.004994
WeightedEnsemble_1.2	1.388979	1.474402
RandomForestMSE	1.569062	1.523666
ExtraTreeMSE	1.593835	1.727846
LightGBMLarge	1.613533	1.846102
NeuralNetFastAI	1.633405	2.121115
XGBoost	1.701893	2.131757

- Prediction of the visual style

The following observations and explanations are based on the AutoGluon leaderboard result in Table 4.7:

  - The best model for the visual style prediction is the LightGBM algorithm.
  - The "score_test" value of 1.13 and "score_val" value of 1.84 indicate that the LightGBM model was able to accurately predict the visual style with a low error rate.

The following list contains the values of the evaluation metrics for a visual style prediction model:

  - The RMSE value is 1.39.
  - The MSE value is 1.93, and the MAE value is 1.16.

Overall, this result suggests that the LightGBM algorithm is an effective and efficient approach for predicting the visual style.

Table 4.8: The AutoGluon leaderboard of the verbal style prediction

Model	Score_test	Score_val
NeuralNetTorch	1.114773	2.104422
LightGBM	1.129949	1.842779
LightGBMXT	1.129949	1.842779
KNeighborsDist	1.305179	2.025913
LightGBMLarge	1.340307	1.783606
CatBoost	1.351499	1.590156
KNeighborsUnif	1.364865	1.978215
ExtraTreeMSE	1.630687	1.715360
RandomForestMSE	1.655527	1.492990
WeightedEnsemble_1.2	1.658485	1.432436
NeuralNetFastAI	1.768681	1.676308
XGBoost	2.342321	1.724198

- Prediction of the verbal style

  On the basis of the AutoGluon leaderboard result in Table 4.8, the following observations and explanations can be made:

  - The best model for the verbal style prediction is the NeuralNetTorch algorithm.
  - The "score_test" value of 1.11 and "score_val" value of 2.10 indicate that the NeuralNetTorch model was able to accurately predict the verbal style with a low error rate.

  Following are the values of the evaluation metrics for a verbal style prediction model:

    - The RMSE value is 1.66.
    - The MSE value is 2.75, and the MAE value is 1.53.

  Overall, this result suggests that the NeuralNetTorch algorithm is an effective and efficient approach for the task of predicting the verbal style.

4.3 Result Conclusion

The results are divided into two sections. The first revolves around video processing, which aimed to detect in-game character movements while a player engaged in the game. The goal here was to extract attributes from the learning process that occurs during gameplay. To do this, the YOLOv5 model was utilized. The results affirmed the model's proficiency in detecting all necessary elements within the gameplay video, such as the player's character, maintaining an impressive accuracy rate above the targeted 99% mark.

The second section resolves around the modeling process, which aimed to determine the best machine learning model to identify Felder-Silverman learning styles based on the information extracted from gameplay. AutoGluon was used to uncover the optimal model and assess its predictive performance. The results indicated that AutoGluon was capable of identifying the most suitable model for every style using gameplay data. The KNeighborsUnif algorithm achieved root-mean-square error (RMSE) values of 1.995 for the active style and 1.51 for the reflective style. The LightGBM algorithm achieved RMSE values of 1.665 for the sensing style, 1.14 for the intuitive style, and 1.39 for the visual style. The NeuralNetTorch algorithm achieved RMSE values of 1.66 for the verbal style and 2.265 for the sequential style, while the ExtraTreesMSE algorithm achieved an RMSE value of 2.11 for the global style. These RMSE values suggest that the predictions are quite accurate, demonstrating the effectiveness of the selected machine learning model and the relevancy of the predictors chosen during the hyperparameter tuning process.

Chapter 5
Conclusion

5.1 Results

This study introduces a novel method for detecting the Felder & Silverman learning styles by analyzing the gameplay of a puzzle game. The YOLOv5 model was used for video processing, and the results showed that the model accurately detected all relevant objects within the gameplay video, including the player's character, with consistent accuracy above the desired 99% threshold. These findings indicate that puzzle games can provide valuable data to create learner profiles for training machine learning models to assess learning styles. Moreover, the information needed to predict learning styles using games is less than that required in other educational environments. Puzzle games provide a challenging environment where players are presented with complex concepts and difficulties, whereas the commercial game used herein was found to motivate players to learn while enjoying the gameplay.

In terms of modeling the prediction of learning styles, the results show that AutoGluon was able to predict every style using gameplay information. The KNeighborsUnif algorithm achieved RMSE values of 1.995 for the active style and 1.51 for the reflective style, whereas the LightGBM algorithm achieved RMSE values of 1.665 for the sensitive style, 1.14 for the intuitive style, and 1.39 for the visual style. The NeuralNetTorch algorithm achieved RMSE values of 1.66 for the verbal style and 2.265 for the sequential style, whereas the ExtraTreesMSE algorithm achieved an RMSE value of 2.11 for the global style. The acquired RMSE values suggest that the predictions are precise, utilizing the optimal machine learning algorithm model identified through model selection and the most relevant predictor derived from the hyperparameter tuning process.

The novelty and value of this research primarily stem from its unique approach to determining learning styles through an engaging and interactive process utilizing a puzzle game as a tool for identifying Felder-Silverman learning styles. Traditionally, identifying learning styles relies on the completion of a questionnaire, a process that can be influenced by biases, misunderstandings, and limited self-awareness. This new methodology is innovative in that it sidesteps these potential issues by analyzing the more objective behaviors exhibited during gameplay. The proposed method also harnesses the potential of machine learning to analyze the data, a modern technique that allows for robust and efficient data analysis, potentially providing more reliable and detailed results than a simple questionnaire. The value of this research can be identified in several key areas:

- Educational Technology and Personalized Learning: By determining an individual's learning style through gameplay, this study opens the door for a more engaging, effective, and individualized education. If the approach proves reliable, it could enhance the personalization of learning materials and methods, a trend that's been increasingly recognized in the education sector as beneficial for student outcomes.
- Gamification: The study integrates the use of games in education, contributing to the field of gamification. This adds a fun and engaging dimension to the learning process and, in this case, to the determination of learning styles. It could potentially boost student engagement and motivation.
- Machine Learning Applications: By applying machine learning to educational research, this study contributes to the growing body of work on machine learning applications in non-traditional areas. This could lead to additional research and innovations, further integrating machine learning in educational strategies and techniques.
- Cross-cultural research: The study's focus on Thai students may contribute insights to the understanding of learning styles in this specific cultural context, potentially enhancing the adaptability of the Felder-Silverman model to different cultural contexts.

Hence, the novelty of the research lies in its innovative method of identifying learning styles, and its value is found in its potential to revolutionize personalized learning, advance gamification, expand the application of machine learning, and enrich cross-cultural research.

5.2 Future Research Opportunities

One limitation of the proposed approach is the lack of sound as a data input in the selected puzzle game, HELLTAKER, which may limit its applicability in assessing the input dimension of the Felder & Silverman model. Additionally, not all question items of the ILS questionnaire were interpreted for this study, such as the item related to teamwork, as the game does not support cooperative play. Future research should focus on analyzing other games and variables that may affect the detection of learning styles, especially in cases where games use sound as a data input. For instance, we can investigate why some students do not play the game or how students' behavior changes as they learn to play, to expand the approach to detecting other learner behaviors using different types of games and additional variables in learner profiles.

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