Identifying Students' Learning Patterns in Online Learning Environments: A Literature Review

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Abstract—Digital learning environments have offered new opportunities to stream educational materials such as courses, educational videos, forums and provide learning outcomes, grades, engagement data, and learning patterns. These valuable educational data have emerged with the latest technologies and software tools to provide researchers and decision-makers with a better understanding of students' behaviours. Virtual learning environments can professionally aid struggling students by observing, learning, and identifying their different learning patterns. Many researchers have discussed that even if there are instructions and helping tools within these environments, some students may remain at risk of negative learning behaviours such as boredom, disengagement, and failure. Particularly when approaching complex or new educational content. Previous researchers have observed that the students exhibit high persistence levels when spending too much time on a particular task while they are learning remotely or too many tries to solve a specific task without reaching the success level. Students' persistence is identified as a prominent learning skill contributing to confirmed success while learning new education materials. Many works of literature recognised the value of persistence. They reached a fundamental fact that not all persistence is considered productive, especially when spending more time and effort without moving toward a state of mastery in learning new skills and topics. This scenario may eventually lead to frustration and disengagement; in the worst-case scenarios, the students will finally drop the course or just quit learning. By examining the most relevant literature, this paper discusses the main factors affecting persistence in digital learning. Different models performed at each learning opportunity are observed to categorise when involvements may be arranged to best aid the learners facing learning struggles.

Keywords—digital learning, educational data, engagement, behaviours, struggling students, persistence

1 Introduction

"A little more persistence, a little more effort, and what seemed hopeless failure may turn to glorious success." [1].

Throughout the years, researchers and educators have used different terms to define the students' persistence, regardless of their inclination towards the task. Persistence has been an essential element for reaching a successful level in any endeavour. Recent studies have proven that persistence is associated with creativity [2], academic achievement [3, 4], and success in the workplace [5]. Other researchers have a positive point of view about students' persistence. For instance, the researchers in [6] have shown that higher grades in Learning Management Systems (LMSs) are associated with the highest success levels, and the researcher in [7] has argued that the students' clicks-streams are highly correlated to their outcomes.

Grit, on the other hand, has been studied extensively. In general, it is highly associated with endurance, stressing the part of the energy, curiosity, and excitement in keeping focused on the objectives. In the academic field, grit is related to educational accomplishment or success. Girt ensures persistence over long periods, associated with long-term outcomes such as educational attainment and retention. Therefore, its benefits can span several years [4, 8].

Grit and persistence are essential to all educational fields and students' outcomes [4, 9]. With these benefits in mind, it becomes imperative to anticipate such behaviour before the student exhibits an unproductive persistence. In this context, the early identification of struggling students could help educators to take more advanced action to lessen the students' failure [10].

Other studies have shown that persistence is not always fruitful. Although, learners are encouraged to persist through the educational process obstacles [11]. While persistence is essential, the author in [12] has stated that persistence is not enough for students; it is the key to why and how they persist. A failure to understand these issues will trap the learners into a cycle of unproductive persistence, affecting long-standing productivity and enthusiasm [13, 14]. Further, recent works have demonstrated that once the learner's achievements become unproductive, they will block to move forward to productive outcomes and face struggles such as disengagement and quitting [15, 16].

According to the related works, several factors can affect students' struggles; such difficulties are related to learning software development and algorithms, difficulties in problem-solving, and the failure of detecting the early stage of these situations [17, 18]. Observing student learning patterns within sets of problems, especially those who show considerable perseverance, is considered a problem instead of achievement. For example, the word "wheel-spinning" [14] has been used to students' struggling behaviours, showing that a vast amount of persistence equals making no progress at all [19, 20]. The researchers in [14, 21] were the first researchers who gave the preliminary description of "wheel-spinning" when examining ASSISTments[1] and Cognitive Tutor systems[2] (CAT) platforms. They stated that wheel-spinning means any student who finished ten mathematical problems on one skill without mastering it.

Most of the previous wheel-spinning works did not distinguish students who persist and finally succeed from those who persist but never succeed [10, 14, 22]. From the same standpoint, other researchers went to develop this principle and study students'

[1] ASSISTments is an E-learning platform for teaching math, it has a predefined mastery criterion (3 problems solved correctly in a row) [49].

[2] Cognitive Tutor Algebra (CAT) is an interactive E-learning software that teaches algebra [51].

learning behaviors in a broader fashion. For example, the researchers in [23] have stated that even after spending ten tries on a single task, students' progress can still be noticeable. Other researchers in [24] argued that students should only be considered wheel-spinners if they are no longer making progress in terms of a knowledge model. Following previous researchers and their collagenous work, the researchers in [20] have another opinion on persistence, they defined productive persistence and separated it from unproductive persistence when persistence never leads to success.

Determining students' learning status in digital learning, specifically differentiating between fruitful persistence and passive persistence, did not stop at the detection in the early stages. In addition, the researchers went to develop certain mechanisms not only for examining the students' success or suffering but also how to develop effective remedies in cases of delays or backsliding. As will be viewed in the next section, the utilisation of advanced technologies like deep learning, machine learning, and educational data mining methods has produced outstanding educational achievements. These works specifically examined the struggling situations that hinder students' success in various online learning environments such as intelligent tutoring systems (ITSs), MATHia[3], formerly Cognitive Tutor (CT), ASSISTments, and Physics Playground[4] [10].

Ultimately, one of the most significant questions is how to build an effective learning environment with efficient software tools to expect learning achievements, trying to enable the direct involvement of teachers and decision-makers [25, 26]. By identifying how students' outcomes are related, the researchers, software designers, and developers will better highlight various trajectories of persistence and recognise possible considerations to encourage productive learning.

The results of the previous researchers can inform the educational platform designers and developers about what instructional strategy in these platforms need revisiting, updating, and enhancement. In addition, delivering an adaptive environment delivers just-in-time aid and involvement, potentially growing the area of smart learning, and encouraging students in developing their academic skills to extract knowledge and discover more important learning patterns. Many potentials are available to enable future studies to investigate students learning patterns with different online learning platforms using diverse educational datasets and investigation tools. Further work is needed to better understand how this structure correlates with more global measures of persistence. It is also clear that student interaction implies engagement, more engagement directs successful students.

The next sections of this paper are organised as follows: Section 2 reviews the most related work, while Section 3 draws a general conclusion.

[3] MATHia is for learning mathematics, it provides a web-based implementation of the Cognitive Tutor technology [53].
[4] Physical Playground game is based on a reward system [29].

2 Related works

Information and communication technologies (ICTs) have greatly reflected on the learning process, delivering rich learning experiences and content. It is known that students have unique learning styles, and their learning paths are affected by several factors, these factors are linked to diverse learning methods. In addition, it may be linked to hidden considerations that are revealed when students' behaviors are studied extensively for many academic years. Therefore, there has become an urgent need to develop interventions to promote persistence to understand the learning behaviors and learning strategies better. In this section, we focus on reviewing three main parts of related literature: (i) students' persistence, (ii) students' mastery level, (iii) students' wheel-spinning, and (iv) students' struggles as adopted by previous researchers in their extensive studies in digital learning environments.

2.1 Students' persistence in online learning environments

"Where the ability to work hard towards a goal – and not give up even in the face of serious challenge – appears to be a key part of life success" [20].

This part focuses on students' persistence, since it has significant importance in learning progress, it may be worthwhile to investigate which factors influence students' productive persistence from several online learning platforms. For instance, the researchers in [27] have studied students' persistence in the fashion of learning by playing a video game called Newton's Playground, which was later called physical playground (PP) a platform to learn physics. Several learning criteria have been established to study students' perseverance, such as log files, time, number of attempts, students' self-report, and Anagram Riddle Task (ART). Their results showed that learning by gaming was linked to constructive outcomes. Also, time spent on unanswered tasks was considered a struggle among the students. Additionally, they conclude that self-report may lead to incorrect measures than behavioural measures of persistence. One limitation was that the researchers did not reason how ART was associated with self-report nor related to GPA; this could be due to the smaller number of samples in the self-report measure. Additionally, this study only aimed to study several learning factors of dependability instead of overall learning measures.

In the same context of observing students' learning through playing video games, the researchers in [28] have explored the indicators of persistence with Physics Playground (PP) with the same principles implied by the previous researchers [27]. Furthermore, they laid a basic rule in this study: the more persistent a student has, the more likely he/she is to succeed in learning a task. The K-means algorithm was implanted with two clusters, time spent and several restarts' markers were the only differentiating factors. Although these findings may distinguish persistence, students may be wheelspin. The researchers have linked persistence with three types of badges gold, silver badges, and no badges received. Finally, the results indicated that time was negatively associated with both gold badges and no badges, with no significant difference among the clusters and silver badges.

In the light of their previous study, the researchers in [29] have produced another research within the same game (PP). Their study eliminates self-report measures and replaces them with behavioral and observational measures. They utilised predefined assessments (i.e., pretest and posttest, a performance measure of persistence, and demographic survey). Structural equation modelling (SEM) instigated the relation influencing all the features. Evidence has been found that pretest and students' performance inside the game can expect learning outcomes, frustration, and engaged concentration. Finally, they found no relation to either confusion or boredom predicted in-game progress. The researchers stated their limitations with the number of samples that might be inefficient to SME analysis also they focused on linear relationships while the data might have quadratic relation with other variables.

Moving from observing the macro-level measures to examining students' persistence at a more micro-level. the researchers in [30] have examined students' persistence within specific tasks in Assessment and Learning in Knowledge Spaces (ALEKS) by detecting the connection among persistence and learning outcomes using students' log files, attempts, and time. The researchers put several possibilities for each attempt, i.e., (1) correct answer, (2) wrong answer, (3) mastering a skill, and (4) failure. The participant students clustered into three types: (i) high persistence, where the students tend to put high to medium effort on their attempts and rarely switch to another skill before reaching mastery level, (ii) moderate persistence, where the students put medium effort on their attempts and moderate switching, and (iii) low persistence where the students put less effort and highly switch between the topics then gave-up after two or one attempts. The outcomes indicated no relation between academic achievement and persistence; instead, persistence was related to learning in ALEKS, specifically more challenging topics. One limitation of this system is that even though ALEKS provide feedback to the students when they are failed, in many cases, the students were wheel-spinning while the system was unable to stop them by giving "failed" feedback, instead, the system showed only 1% who failed, and the students kept struggling. Therefore, the real-time intervention was highly recommended by the researchers.

Studying the phenomenon of students' persistence was not limited to a single task or an entire course but it was extended to study the impact of perseverance in the pre-college stage when the researchers in [20] have measured the relations between students' persistence and their college enrollment through learning at middle school using ASSISTments dataset and college enrollment records. They defined three indictors of persistence as (i) Wheel-spinning, (ii) Productive persistence, and (iii) Quitting. Productive persistence related to constructive results, but wheel-spinning and quitting was linked to negative results. In addition to other situations like boredom, engagement, confusion, and frustration. they found that wheel-spinning was not related to college enrollment. Finally, they concluded that quitting was linked to a smaller possibility of college enrollment. One limitation is that the type of dataset used in this study to examine students' skill builders from ASSISTments was not related to the same students who enrolled in college.

2.2 Students' mastery learning in online learning environments

Mastery learning is a level that students reach while they are learning a specific task, mastery level motivates many learning technologies to investigate how and why students reach this level or fail to master a certain task, it gives valuable feedback on how students are making a progress while learning in the online based-learning environments. The idea of making a student reach a mastery level is by feeding him/her with just the proper amount of education based on their needs on that topic before moving forward to another. In recent years, mastery learning, positive persistence, and successful learning have been the goal of many learning technologies like Khan Academy, Duolingo, ASSISTments, ALEKS, and cognitive educators such as MATHia and CAT [31].

To effectively investigate mastering a skill in digital learning environments, most previous works focus on examining students' behaviors while learning a particular skill. Especially in learning cognitive problems such as physics or mathematics, requiring high practice and effective perseverance to master one skill.

Mastery learning is a strategy developed by the researcher in [32] that demands the learners to grasp a subject then move to an advanced subject. Mastery criterion is the key to measuring the mastery level at any topic; it is a rule or set of rules that can distinguish if the learners have achieved mastery level. One of the most popular online learning platforms is ASSISTments which defines the mastery criterion as a specific number of questions correctly solved in a row.

The researchers in [33] have examined various mastery levels to understand the behavior of already exhibited mastery learning criteria. Czech grammar and spelling programs along with an adaptive practice system for basic arithmetic were utilised with both actual and simulated data. Their theory involved many techniques for detecting mastery: (1) without assumptions about the students learning but counting the number of accurate answers and declaring mastery once the count reaches the threshold N. (2) Moving Average, with a threshold T. (3) Exponential Moving Average (EMA) with exponential weights. (4) Bayesian Knowledge Tracing (BKT). (5) Logistic function. One crucial conclusion declared by this research is that the source to decide the mastery level is more important than the learning mode. They argued that the EMA method was the most appropriate technique for mastery criterion. The limitation of this work was that they did not consider wheel-spinning learners, forgetting, and neglected potential preferences appearing in actual learning data.

The researchers in [34] have examined how many tries a student needs before reaching the mastery learning level to better understand distance education. ASSISTments, Bayesian knowledge tracing (BKT), and Performance Factors Analysis (PFA) were utilised to compare prediction correctness. PFA showed a promising result. BKT, however, performed poorly. They have realised that the used methods can only distinguish mastery level when it happens or after it has already happened.

Instead of the classical rule-based systems, the researchers in [35] have employed human judge to identify the patterns of students' behavior. The study was in an adaptive, game-based math skills software called Mastering Math (MM). The human evaluation starts from the moment that the students are acting. Also, the visual progress replay

(VPR) technique visualised the performance of each level that the student may reach. The researchers have defined student behaviors within different features, the analysing process started to extract the most relevant data to the behavior, they captured wheel-spinning as the minor game-play productivity in the system (great effort leads to lower progress in playing the game). Ultimately, CART algorithm produced the best model performance in predicting wheel-spinning.

In the light of choosing the best method for analysing mastery learning heuristic, the researcher in [31] has examined mastery learning from different types of educational datasets. The N-Consecutive Correct answers in a Row (N-CCR) heuristic, ASSISTments, and a simplified version of ALEKS mastery learning heuristic are ideal strategies for the Bayesian knowledge tracing model (BKT). BKT was utilised to determine when students have mastered a topic and to decide when to stop giving students more practice. Results showed that (N-CCR) is more optimal than the Bayesian knowledge tracing (BKT) model. In addition, further broad knowledge of mastery learning criteria will optimistically assist to guarantee that adaptive learning achieves mastery learning in many creative approaches.

2.3 Students' wheel-spinning in online learning environments

Although the online learning systems produced helpful instructions and intense multimedia content for different learning models, some students face challenges coping with these systems. In the sense that not all persistence is practical and not all students have fruitful outcomes in online learning environments, negative persistence was defined as the consecutive failures in solving a given task before mastery. Many researchers utilised various methods to distinguish unproductive behaviors in students' learning.

This part starts from the most famous definitions of students' suffering, called students' wheel-spinning, introduced by the researchers in [14, 21]. They have termed non-productive persistence as the wheel-spinning (WS) metaphor, which was inherited from the idea of persistence. They have shown that if a student didn't reach a mastery level, they are expected to struggle and will most likely never master that skill. They reached the fact that 38% of the students who had ten or more tries were possibly wheel-spinners; the observation indicated that the mean score of gaming the system is higher when the students are defined as wheel-spinners. At the same time, the mastery level gave a less mean score of gaming the system. The limitation of this study is that students' are defined as wheel-spinners after their tenth try regardless that some skills require more than ten tries to master. In 2015, the same researchers in [21] have investigated whether wheel-spinning is related to certain factors or a random phenomenon; the proposed wheel-spinning detector was constructed using generic features like the number of previous problems that the student has solved in one skill. Cognitive Tutor Algebra (CAT) and ASSISTment were both utilised, wheel-spinning in CAT was defined as the student who tries 15 opportunities on one skill and 10 for ASSISTments. Also the mastery level was defined as it is the three correctly solved problems sequentially at one skill. They claimed that the early detection of wheels-pinning helps the early solution and thus saves the students' time. The results showed that the student will wheelspin with the more problems they are solving without reaching mastery. The rates showed a promising result with 70% accurately classified as wheel spinning, but the recall is lower with over 50% in both cases. This drives the study to conclude that the proposed model has a weaker ability to distinguish WS from mastery which makes it in front of a limitation that the model overlooks more than half of WS behaviors.

To overcome the unproductive persistence, the researchers in [36] have utilised Cognitive Tutor Geometry[5] (GTA) taken from DataShop[6] to build an early detector of wheel-spinning. This work kept only the skills of the students who had five or more opportunities, fewer opportunities were defined as not enough data to determine wheel-spinning. The response sequence of the students is first given to Bayesian knowledge tracing (BKT) to calculate a number of the possibility of mastery at each applied skill. The model can differentiate the students who are more likely to wheelspin than those who are not. The limitation of this study is that although the results showed that the detector has extreme recall equal to (0.79) at the same time, it has low precision equal to (0.25) when combined with other detectors for mastery levels. Also, this model considered the students who are unsuccessful as WS students even if they are not, according to the human coders that they set to code the WS model.

Detecting wheel-spinning behavior in the game-based learning was produced by the researchers in [8] when they gave three classes of progress badges (silver: to those who completed a level in the proposed game, gold: to those who completed the level with an optimal solution, and bronze: to those who completed in medium-range), their attempt was not do classify the students who wheel-span from the successfully persistent student. Instead, they focused on distinguishing wheel-spinning from those who failed to reach a mastery level (non-wheel-spinning). They got a surprising result: the golden badge achievers may not necessarily achieve a silver one. On the other hand, wheel-spinning observation in this playground was defined as the student who failed to reach a golden badge after a silver one or the student who took more than 15 minutes to complete one attempt. Finally, they suggested that the best way to help the correct interventions and wheel-spinners detectors is by understanding how learners interact with the game.

A different opinion on the term wheel-spinning was proposed by the researchers in [23] they have introduced the process of (WS) detection as not to include the initial students' performance only but to comprehend all the skills that the students have learned during time duration with a delayed test. They suggested that timing is an important way to distinguish the student's learning path, and not all minor productivity students in the system are hopelessly struggling. They defined persistence as those who attempt ten or more problems in one set even if they did not reach a mastery level. The students were defined into two groups: wheelspin and positive persistence. Furthermore, the results showed that there are two groups of wheel-spinning students: (1) students who tend to wheelspin in the first group are those who did not request a hint in any problem but demand more than one bottom-out hint and (2) students who tend to wheelspin in the second group requested have fewer bottom-out hints, but they also

[5] Cognitive Tutor Geometry GTA [50]
[6] https://pslcdatashop.web.cmu.edu/ [52]

have less variation in the time spent between solving the problems that belong to one skill. These findings suggested that students' engagement is related to encouraging the students to request bottom-out hints to reduce the likelihood of wheel-spinning and shift their struggle to positive persistence. The results suggested that wheel-spinning and productive persistence can be separated.

In the next research, the researchers in [37] have offered different criteria of wheel-spinning, most influenced features, and models utilising various evaluations. The dataset was taken from an algebra learning environment called MATHia. The agreement on wheel spinning was generally less than 50%. To find a set of features for better prediction, it was found that the most convenient performance was produced by random forest model when detecting wheel-spinning early. The researchers hypothesised that three correct answers in a row criterion might not need complicated features to predict, so adding new features merely introduces noise for detectors. Another common issue, they found the models suffer from the "cold start" problem in every dataset, model, and operationalisation. Finally, the researchers suggested that it would be worthwhile to study agreement and disagreement of additional operationalisations of wheel spinning.

In the field of exploring unproductive persistence, the researchers in [10] have studied the relationship between unproductive student persistence criteria to build initial detectors. The researcher stated that it is preferred to stop the student when they struggle instead of remedy after their failure. They defined wheel-spinning and stop out behaviors as mutually exclusive. In addition, they defined stop out as it appears when the student stops learning after the 10^{th} problem. Assignment and across assignments criteria were both utilised to study students' behaviors. Long-Short Term Memory (LSTM) network, decision tree, and logistic regression models were conducted. The results showed that the stopout and wheel-spinning could be detected and generalised to forecast the other from across-assignment behaviours. One limitation is that the models are unsure of how the student will perform in the next problem set. Therefore, the predictive task is relatively more complicated.

Novice programmers were examined by the researchers in [22] they have employed five wheel-spinning methods all performed with a reasonable performance. They reviewed the pointers of wheel-spinning and measured each created model utilising the metrics from previous related works, wheel-spinning indicators were defined by this study as the relationship among three features (problems correctly solved, problems attempted, and total correct response). The results indicated that the number of problems correctly solved showed a negative correlation with (1) wheel-spinning, (2) the overall number of the attempted problems, and (3) the number of successive mistakes were expressed as wheel spinning, new features were discovered such as (average number of consecutive incorrect responses of the student and number of consecutive mistakes solved by the student) they justify these new features that the more attempts made by the student, the more mistakes he/she may do, and this could lead to wheel-spinning. In conclusion, the researchers concluded that it is crucial to reveal wheel-spinning to novice programmers early. The suggested future work may have the potential to obtain more characteristics built on other algorithms. In addition, utilising a larger dataset to test the performance of the conducted models is advisable since the applied dataset was relatively at a small scale.

2.4 Students' struggles in online learning environments

Students' have shown many forms of struggles when learning on online platforms, learning struggles can be defined when a student drop-out a course and/or fail to reach a successful end. Failure, Stop-out, and dropout can face any educational level. There has also been many works examining, searching, and detecting at-risk students and working on knowing the circumstances that may start these cases [20].

Similar issues of student distress in Digital learning environments have attracted the attention of o researchers, whose importance is like that of studying student behaviors related to passive persistence such as quitting [38, 39, 40], and at-risk students [41].

To assist the students in overcoming the difficulties and disengagement behaviors on their learning journey the researchers in [38] have investigated the environment of learning by gaming (PP), if the students' quit a level or not. The results suggested that the conducted model has an outstanding predictive implementation at one level. Given the model's level of accuracy, to justify whether the student is likely to quit, a proper threshold is given to the utilised model. One limitation of this study was that identifying all the given datasets in visiting the game as quitting. Therefore, quitting may be predicted before it may occur, leading to early unwanted intervention. Finally, it may produce an intervention with students' learning persistence.

To distinguish the standard situations where and why the students fail to progress during their learning the researchers in [40] have investigated students' programming behavior. Showing which test level measures the students may struggle to make further progress. Furthermore, the related learned tasks and progress were compared among subgroups of students. Their outcomes were in the following points (i) covering the idea of interaction networks to progress networks, (ii) offering a technique to equivalence progress networks crosswise groups and tasks, and (iii) delivering samples of analyses on a large-scale programming education dataset. The results indicated that the quantitative method primarily directs our interest to the number of specific programs to understand why students failed to make progress. The limitation of their analysis is that a quantitative amount of how characteristic a certain program is for a node or edge is not available yet.

A study to provide more understanding upon students' educational datasets and classification models was conducted by the researchers in [41] to find struggling students at the early stage using predictions at a programming course. Thirteen datasets are conducted with Moodle logs and five classification algorithms were used in the experiments, based on different aspects of student interactions, the researchers noted that any grade below 6.0 considered a struggling or at-risk student. The results indicated no variations between methods created from the different datasets. However, there was no progress in implementing these methods utilising those three elements: cognitive, social, and teaching presences. Finally, the questionnaire showed no improvement in performance. The limitation of the work was because of the minor number of cases studied from the utilised datasets.

3 Conclusions

The role of education is significant not only to the learning process and solving cognitive problems but answering the real-life challenges of a more experienced and well-educated generation. In this sense, education should never be underestimated in creating a brighter future for the educated students, promoting their social skills, and creative thinking hence providing them with successful life outcomes [54].

The technological revolution led to major changes in our daily life. Education, in turn, also responded to this revolution and shifted from being face-to-face to online learning separate from any spatial or temporal restrictions, which led to the multiplicity of students' roles in registration, communication, and networking [55].

The impact of technological development on education has led to the emergence of a variety of electronic learning platforms that provide educational content each for different learning materials and for all ages of students to serve the various educational institutions [56]. Previous studies have shown that the emergence of these learning platforms leads to an active learning experience in the information society [54].

Students' outcomes in online learning environments have been extensively studied. Previous works have examined several features related to student learning behaviors such as (positive persistence, mastery level, and negative perseverance/wheel-spinning). Each work has defined and categorised its own independent and dependent variables to study these behaviors. Accordingly, many relationships were recognized among students' learning patterns and their learning features (i.e., the number of questions answered correctly and incorrectly, the number of hint requests, the time required to answer questions, the total number of attempts on a particular skill, etc.…). Different algorithms and educational data mining and software tools were used to extract these patterns. Overall, it is interesting to note that most of the observations were made using Intelligent Tutoring Systems (ITS).

Previous studies have proven that the more diverse the samples were, the more accurate and successful the algorithms in predicting student behaviors. Although some researchers have tried to enlarge the size of their dataset by engaging students' demographic data, self-reports, and questionaries, some of these data did not have many benefits in comparing it with those extracted in real-time learning. In addition, the researchers proved that the platforms that provide students with educational content must be diverse in their content, providing more problems and questions so that they can provide students with quick solutions in case they were facing struggles in solving a set of specific issues, then the platform can direct them to other simple problem sets. This will make the student commit to the solution without feeling pressured or frustrated.

Therefore, researchers focused on linking learning with playing games to increase student participation and stimulate their desire to complete learning. Video games are utilised to expose learners to advanced problem-solving situations. In general, playing video games can develop skills to indicate the cognitive, emotional, educational, and social benefits [42]. These factors can influence persistence that involves the desire to work hard despite repeated failures. The researchers in [27] have stated that "*Learning through games is a way to increase student participation*". Therefore, Educational games are designed to keep students involved in an enjoyable understanding while aiming to advance their learning outcomes. Well-designed games improve create fundamental enthusiasm in players, which they support during the learning process by maintaining the learner deeply involved. Games let the developers and the researchers utilise performance-based measures of theories such as persistence and engagement, which are more dependable and effective than students' self-report measures [29]. Also, the results have shown that the learners who play more will persist more [27, 29].

The results of previous literature agreed upon students' perseverance since it plays an important role in supporting students' successful learning. However, despite the learning benefits of perseverance, a consistent effort may not always lead to academic success. For example, continuing with a task may not be beneficial if students struggle unsuccessfully with little or no progress in their learning. By investigating how these patterns relate to each other, a better understanding of the different pathways of student perseverance and distinguishing possible factors to encourage effective learning are studied.

The major concern was distinguishing between unproductive persistence and productive persistence—toward developing a motivational research-based procedure that boosts productive struggle and reduces the wheel-spinning phenomenon. This indicates that the key to successful learning does not necessarily depend on continuous effort but also on determining when the effort is not productive and when the strategy should be changed. In addition, understanding the key differences between these participation patterns can begin to bridge the gap in the literature and help teachers and knowledge builders identify and support students in their learning process.

In short, by identifying the ways that influence students' learning and interaction, persistence, and performance, we can learn how to effectively design and develop educational systems; not only for providing a better learning experience but to assess creating advanced learning technology. In addition, by extracting more educational datasets and revealing hidden factors that affect the entire learning process students' struggles can be aided greatly which will eventually lead towards successful learners. Therefore, successful lives.

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