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Leveraging Multi-Agent Reinforcement Learning Systems to Address Learning Loss with Long-Term Impacts on Student Achievement and Equity

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The proposed work is aimed at responding to the problem of learning loss and equity-related gaps in learners' performance caused by existing learning challenges. Many techniques like teaching and testing have uniformity and do not address difference in learning abilities of the students, thereby not addressing equity. These approaches are not flexible which implies that they often result in low achievements especially with the students from the disadvantaged backgrounds. To address these challenges, a Multi-Agent Reinforcement Learning (MARL) system were proposed that takes real-time data, such as exam/study patterns, truancy, and caregivers' involvement to provide a student-specific educational support. This work's novelty relies on the use of MARL to achieve dynamic adaptation of the educational strategies in terms of the decision-making regarding study hours, tutoring, and classroom participation based on the students' profiles. The MARL agents engage with each other within a simulated population that reflects various classes of students, learning policies that enhance group cohesiveness and at the same time optimize performance. The interventions are learned over the iterative interaction sessions and the best solutions are incorporated in the course of the interactions. The proposed work achieves 97% accuracy. Major positive changes in the behavior of the analyzed indicators that characterize student performance, including their test scores and homework completion rates, are revealed Socio-economic disparities in performance have been reduced. It not only improves academic achievements, but also works towards a fair educational environment as a unique solution to learning gaps in various educational settings.

Keywords: Multi-Agent Reinforcement Learning, Learning Loss, Educational Equity, Personalized Interventions, Student Achievement.

1. Introduction

Falls in students' knowledge and skills are frequently referred to in the literature as "learning loss." Historical data, which is frequently assessed through standardized testing, gives researchers insight into the approximate level of student learning that should be reached year over year. When academic advancement does not happen as quickly as it has in the past when contrasted with prior years, loss of learning happens [1]. Beyond the educational setting, these losses could result in more significant long-term difficulties. Similarly, every additional year of education is linked to an 8–9% increase in future earnings on average. Learning loss is caused by a number of circumstances, including lack of access to high-quality education. A student's capacity to acquire knowledge and grow academically may be hampered by constrained access to assets, teachers, and institutions. Socioeconomic factors like student's access to education may be impacted by economic inequality. The most frequent reasons why students fail are related to things like not being dedicated to their studies, planning their study time poorly, and finding struggles to concentrate when challenged [2]. A poor relationship between teachers and students, socialization issues, and a lack of suggestions from teachers are other causes. Disappointment can also be attributed to a student's socioeconomic circumstances, such as the necessity of working to provide for their family [3]. Student failure may also result from internal variables including challenges with discipline and personal issues. It is valuable that students frequently believe that their own behaviour or inadequate attempt is the main reason for their failings. Along with any other component in the context of education, it can be pointed out that teachers play an important role in the student's achievements. The learning capacity of a learner depends on several factors including personal attributes and contacts in the home and in the society [4]. Global education systems are experiencing severe disruption as a result of the Covid-19 pandemic's crisis status. At the time, educational institution shutdown affected around 1.6 billion students in more than 190 nations, or 94% of all students worldwide, according to UNESCO's assessment. School staff was unprepared for the change of events and they were forced to come up with alarming emergency remote education plans. Education experts are starting to examine how these school closures affect students' academic progress—or lack thereof—in reaction to this interruption. The COVID-19 pandemic has worsened learning loss, which has major long-term effects on student progress, particularly when it comes to educational equity. Due to reasons including restricted access to the web and shortened instructional times, lower-income areas are suffering from greater learning losses than higher-income groups [5]. The epidemic has brought attention to these inequities. Research indicates that during closures of schools, pupils suffered a significant loss of learning, and the evidence suggests that this loss was more severe than the usual summer learning loss. Educational disparities were already present, but they were exacerbated by the fact that some groups, especially those from underprivileged backgrounds, had greater learning consequences. The long-term effects of loss of learning involve impaired growth in skills, which can have an impact on one's ability to succeed economically in the future and extend poverty cycles. Academic inequities do not impact every learner the same way and that is why learning loss occurs. Low income, raced, ethnic and disadvantaged students, disabled students and other forms of minority have usually been affected the most [6]. Before the pandemic, there were disparities in education which has worsened due to learning loss hence increasing the gap of achievement between students who are privileged and the less privileged. Children in poor families enroll in less stringent schools which means the teachers teaching these children may not get adequate support or may teach in large classrooms thus making it hard to give every child as much attention as they require in order to recover from learning loss. More so, these students are most probably to have many of the external barriers like hunger, poor shelter, and no/prohibit access to healthcare that can hinder them from studying [7]. In the past, there has always been a concern of gap in performance between advantaged and the disadvantaged students and given this learning loss. It is worse for students who were at that nadir before the onset of the pandemic began, and at least for now, are more likely to remain this way; better off students who, for example, hire tutors or do additional classes or summer school type classes can possibly catch back up. These inequalities do not only impact the learners that receive different qualities of education but have implications for the societies and the nation's iteration of social and economic justice. Learning loss eradication is not about students' poor performance mainly but also about fairness to all students so that none of them is left behind. Equality in education implies the provision of resources that assist the child to reach his or her potential in the society, and this will require intervention for disadvantaged children. Learning loss is a major problem which increased due to factors such as the COVID-19 pandemic; Such patterns should not be left unaddressed since they have long-term implications on students' achievements and equities [8]. Therefore, strategies that are creative and flexible have to be employed to counter the impacts on an individual level and provide education for every child. The research seeks to establish if MARL systems can be used to design and develop individualized intervention strategies to tackle learning loss. MARL systems can improve the learning outcomes and equity because they offer learner-specific interventions that adjust to the learner's context and needs. The key contribution of the study are as follows:

- The work combines student data from several well-known organizations and involves multiple detailed characteristics of students, including academic results, learning behaviors, and socio-demographic information.

- The enhanced pre-processing of the data, for instance the normalization of the data makes it possible to have quality and reliable data for the modeling process. It is noteworthy that to facilitate these predictions as well as the subsequent interventions of the implemented MARL system, the given preprocessing intensifies.

- The implementation of the proposed MARL system for each learner profile is the major innovation in individualized learning. In this way, the system has provided for specific learning problems and attempted equity with real-time data to tailor the intervention.

- The proposed method of converting a reward function to be dynamic makes it possible for the MARL agents to optimize the interventions in terms of its performance and fairness. It affords confidence that in addition to improving the achievement of students, the system reduces the output gaps.

- The use of algorithms in MARL system to adapt and choose actions depending on learning and feedback greatly adds to the concept of educational interventions.

The remaining section is arranged as follows. Section 2 related studies are discussed. Section 3 discuss about the proposed work methodology. In section 4 findings and analysis are presented. Section 5 provides conclusion and further studies.

2. Literature Review:

Even if school performance swiftly returns to its previous level, the global school closures that occurred in the early months of 2020 resulted in learning losses that will not be readily made up for. If these losses are not successfully remedied, they will have long-lasting economic effects on all of the impacted countries as well as the students. Current study indicates that the kids in grades 1–12 impacted by the closures may anticipate a 3 percent lifetime income drop, even though the exact losses in learning are unknown. For countries, this slower growth rate could entail the loss of the longer-term relative growth rates invested in these loses could reduce the annual GDP by an average of 1.5 percent stabilized for the remaining period of the century. If schools do not reopen as soon as possible, such financial losses will be even higher. As a result, poor performing students will be feeling the pinch as they are forced to pay fees for services that they will no longer be receiving. According to data, one may expect that students from families with lower levels of support for after-school education have more education gaps than the greater benefited children. What is more, as future work experience would suffer due to learning losses these losses translate into much larger earnings losses in the future. The current cost of the losses in economy to countries is enormous. Restoring schools to their 2019 locations alone won't stop these losses. Making them better is the only thing that can. Although many different ways may be tried, the research that is now available suggests that paying particular consideration to the modified reopening of schools provides strategies that could lessen the losses. In particular, schools could achieve higher performance more quickly if the teaching staff's skills are matched to the new objectives and activities, especially with the anticipated growth in video-based instruction [9].

The public has been very much sensitive particularly on the short and long term effects of closures of schools and incessant interruptions on children’s learning during the current COVID-19 pandemic. Intending to mitigate the effects of school closures, scholars and politicians have drawn on the educational loss literature which is a research line that quantifies the effects of ‘summer’ vacations on children’s performance. Instead, the premise of this study involves a synthesis of literature on learning disruption, or extended and unpredictable holidays that ensue from exceptional circumstances such as SARs or natural disasters like weather events. They argue that this set of research provides a stronger evidence base of what helps kids get back to school and what helps them during similar circumstances than any other source, and is therefore more relevant to educational contexts following COVID 19. A narrative summary of the main suggestions is provided. The following are the main conclusions: (i) school leaders' local knowledge is crucial for facilitating kids' returning to school; (ii) the curriculum must be child-centered; and (iii) schools play a critical role in promoting students' mental health. A review of the result' relevance and usefulness is offered in relation to new data indicating the difficulties schools are facing in the midst of a worldwide epidemic and the continued interruption to education it causes [10].

Because of the COVID-19 pandemic spreading in the community, traditional class delivery was halted in schools which led to concerns regarding the effects that this has on children. There isn't much data available to investigate this subject yet. They compare the progress made throughout this period to the identical period in the three prior years by taking use of the reality that national examinations were conducted both before and after lockdown. The Netherlands has the greatest percentage of broadband access in the world, an egalitarian school finance scheme, and only experienced a brief lockdown (8 weeks). Nevertheless, the findings show a learning loss of 0.08 standard deviations, or around 3 percentile points. That is the same amount of time that schools were closed—one-fifth of a school year. The apprehension that the adverse effects of the global pandemic are borne with disparities among families and children are well founded because damages are actually up to 60% higher among the learning children form the less schooled families. Having investigated into the causes, they learn that most of the benefits result from the knowledge taught that has been so accumulated and not the special effects produced the testing day. When working with maximum-entropy weights and/or equilibrating on the anticipated likelihood of treatment or when comparing students from the same family to others using fixed-effects specifications, the results are robust. The findings also show that learning at home had little or no benefit for pupils and they also suggest that the losses would be significantly larger in the countries with less developed infrastructures or more extensive periods of school shutdowns [11].

Related research shows the significant and COVID-19 school shutdown' long-term effects on students' learning, especially for students in need. The analysis tracks learning loss, decline in lifetime earnings, and decline in productive capacity GDP, with effects more severe in countries that have been closed longer or the less rigorous educational system. Also, switching to more individualized instruction could benefit every student when classes restart because the previous interruptions are likely to enhance the disparities in ability to learn within specific courses. It seems sense to give the logistics and mechanics of a safe reopening a lot of thought as schools work to resume their operations despite the ongoing pandemic. Though the losses already incurred deserve more than the best of the reopening strategies currently under consideration, the long-term economic effects also demand careful consideration [12]. The research gap lies in the confined exploration of customized, adaptive solutions to mitigate studying loss worsened by way of the COVID-19 pandemic. Existing research lack attention on leveraging Multi-Agent Reinforcement Learning method to address these challenges, in particular, increase educational equity and enhance student achievement.

3. Multi-Agent Reinforcement Learning in Addressing Learning Loss and Enhancing Educational Equity:

The proposed work methodology centers on a framework for MARL which will create equality in learning loss and the achievement of the targeted students. The first step of the methodology involves use of file extract from different learning institutions, including academic records, learning/training pattern, socio-demographic data amongst other data. There is usually data preprocessing that is done to prevent wastage of time and to make the data as accurate as possible; this involves normalization. MARL is then trained in a simulated educational environment, in which agents are various types of intervention approaches. Such agents engage with a given environment, in this case the school system, to learn policies by either success or failure with the intention of improving on the performances of students and reducing on differences. There is a dynamic reward system that is used to increase the improvement in the student outcomes while keeping equity of the interventions intact. This prevents the interventions from becoming inapplicable as it scales through the dynamic responses given to constantly reform its strategies as the profile of the students develop. The MARL agents learn and negotiate with each other in order to discover the best strategies and arrive at the best educational recommendation. The equity-based outcome measures are employed to determine the success of the implemented methodology in order to substantiate the capability of the MARL system in promoting scalable change of current practices in education.

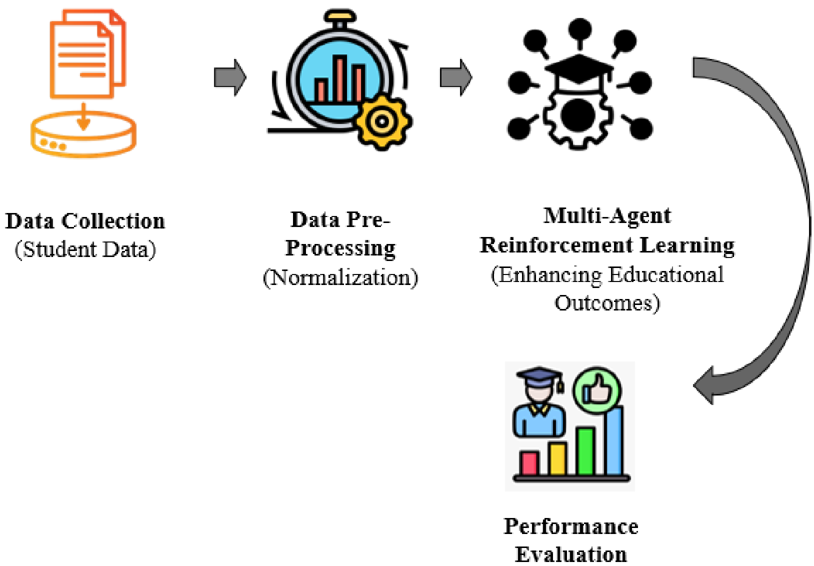

Figure 1(a) Research Framework

As shown in this figure 1(a), the following is the workflow of the proposed approach. It starts with beginning data from the student data which is then undergoes data preprocessing by passing it through normalization. It is then followed by Multi-Agent Reinforcement Learning in an effort to improve education outcomes and lastly, performance analysis in other to determine the effectiveness of the interventions.

(a) Data Collection

The dataset includes comprehensive data on Chinese high school students that was gathered from multiple colleges and educational institutions. Its goal is to examine the variables that affect students' involvement, well-being, and performance. The dataset is gathered from Kaggle website [13].

Table 1. Dataset Description

Student ID	Gender	Age	Grade Level	Attendance Rate	Study Hours	Parental Involvement	Extracurricular Activities
1	Male	15	12	80.49	2.76	High	Yes
2	Female	17	12	96.24	4.53	High	Yes
3	Male	14	9	84.65	2.01	Medium	Yes
4	Male	14	10	86.16	3.70	High	No
5	Male	15	10	88.49	3.41	Low	No

Numerous features are included in the data, including demographic information, academic standing, health, parental support etc... are depicted in table 1. Prominent academic institutions, universities data are taken in the dataset.

(b) Data Pre-processing

Standardization for instance brings all the features in a given dataset into a standard scale normally the range [0,1]. This is particularly relevant in reinforcement learning systems where there are agents in an environment and they have to take certain decisions based on different kinds of input data. From features in the data set, there are Study Hours, Attendance Rate, the number of Hours of Sleep among others and these are numerical features where the range could be very large. If features have different scales, unless normalized, the model might learn the features with large scales more than the small scales. Normalization can be applied in a number of forms which Include Min-Max scaling which aims at scaling each feature to a range of 0 and 1. The formula is depicted in equation (1).

$$0' = \frac{O - O_{\min}}{O_{\max} - O_{\min}} \qquad (1)$$

Where, $0'$ represents the normalized value. O represents the original value. $O_{\min}$ and $O_{\max}$ are the feature's minimum and maximum values, respectively. It enables better learning capability of the Multi-Agent Reinforcement Learning system from the data set which directly contributes to enhanced decision making, precise estimate of the performance of a student and efficient ways to be adopted to modify the teaching style for better outcome.

(c) Multi-Agent Reinforcement Learning Systems

Using trial-and-error interaction with the environment, every agent in a Multi-Agent System (MAS) resolves sequential choice problems. It is more complicated than a single-agent situation, though, since the setting is non-Markovian in any agent because it depends on the collective behaviours of all agents to determine the next stage and reward. It is possible to represent multi-agent sequential choice issues using stochastic games (SG). Similar to this, consecutive decision-making issues are also addressed by multi-agent reinforcement learning, but with multiple agents participating. Specifically, the collective behaviours of all agents affect how the system. State evolves as well as the rewards that each agent receives. Even more curiously, every agent now has a long-term incentive to maximize that depends on every other agent's policy. There are two conceptual structures for MARL, which will be extensive-form games and Markov/stochastic games, which appear to be distinct but are closely related. A tuple can be used to depict a stochastic game is depicted in equation (2).

$$< N, S, A^1, \cdots, A^N, R^1, \cdots, R^N, p, \gamma > \qquad (2)$$

where A^1 is the agent's action space, S is the environment's state set, and N is the number of agents. The reward function of the agent i is represented by R, and p: $S \times A^1 \times \cdots \times A^N \times S$ The transition probability Δ (S) is determined by the joint action a, whereas the discount factor over time is represented by $\gamma \in [0, 1]$. In MARL, the surroundings are shared by means of multiple dealers, every of which interacts with the surroundings through taking movements. The environment can be represented as a Markov Game, additionally referred to as a Stochastic Game, which generalizes the Markov Decision Process for multiple dealers. A Markov Game is described by State space (S): The set of all viable states of the surroundings. Action area (A_i): The set of all possible movements that an agent i able to take. Transition function (T): The probability of shifting from one nation to another, given the moves of all retailers. Reward characteristic (R_i): The reward acquired by using agent i based totally on the contemporary state and actions taken by using all sellers. Policy (π_i): A strategy that defines how an agent selects actions based on the modern-day kingdom. Agents' Policies Each agent in MARL has a coverage π_i (a_i | s), which defines the chance of selecting movement a_i given kingdom s. Generally, policies can be deterministic kind or stochastic kind. In Deterministic Policy, the agent systematically chooses the same motion for any state found throughout. In Stochastic Policy, the movement to be taken is chosen randomly from a probability distribution used by the agent. Value Functions Value capabilities are crucial to reinforcement gaining knowledge of, as they estimate the predicted cumulative reward an agent will acquire from a given state or country-action pair. In cases involving several agents, the state-action with a value function is denoted by equations (3) and (4), correspondingly.

$$Q_{\pi^i}, \pi^{-i}(s,a) = E\pi^i, \pi^{-i} [\textstyle\sum_{t=0}^{\infty} \gamma^t R^i (s_t, a_t, s_{t+1} | a_0 = a, s_0 = s) \qquad (3)$$

$$V_{\pi^i}, \pi^{-i}(s) = E\pi^i, \pi^{-i} [\textstyle\sum_{t=0}^{\infty} \gamma^t R^i (s_t, a_t, s_{t+1} | s0 = s) \qquad (4)$$

When the policy of the agent i is distinguished from that of the other agents by π^i, π^{-i}; likewise, it can be describing the joint action $\boldsymbol{a}$ by a^i, a^{-i}. The common solving strategy can be classified into two categories: learning communication and learning cooperation. This classification is based on whether or not the execution process involves communication between agents. The three groups of MARL algorithms can be loosely classified as “fully cooperative, fully competitive, and mixed cooperative–competitive groups” based on the type of reward provided by the environment. Every agent works together in the cooperative setting to maximize a shared long-term return. A smart energy grid is one example of this environment, where a number of buildings (agents) with varying capacities for producing energy must share power in order to reduce the amount of energy required from the outside grid. A different scenario is that of autonomous driving, wherein the cars must work together to minimize traffic jams and potentially improve fuel economy. The total return of all agents in a competitive scenario is zero. Value-based MARL: For the multi-agent scenario, the revised rule of equation (5) is appropriate:

$$Q^{\pi}(s, a_1, a_2, \dots, a_n) \leftarrow Q^{\pi}(s, a_1, a_2, \dots, a_n) + \alpha[r + \gamma \max_{a1', a2', \dots, an'} Q^{\pi}(s', a1', a2', \dots, an') \qquad (5)$$

where s means present situation a_i move made by agent i. r means reward obtained following the completion of actions $a_1, a_2, \dots, a_n$. s' represents the subsequent state. α rate of learning. γ the discount rate is represented in equation (6).

$$Qglobal(s, a_1, a_2, \dots, a_n) = \textstyle\sum_{i=1}^{n} Q_i (s, a_i) \qquad (6)$$

$Q_i(s, a_i)$means value function of agent i for action a_i in state s. MARL is the extension of the RL where two or more autonomous decision making entities / agents operate in a common environment aiming to achieve common or different objectives. Different from single-agent RL, in which a single agent aims to acquire as much reward as possible by interacting with the environment, MARL is a set of ways for multiple agents to learn at the same time with possibly different goals. This brings coordination and competition issues, and general communication of the agents. In MARL, agents are decision making self-contained entities who can interact with the local environment and the other agents around them. Every agent has its own behavioral policy that determines how it chooses its actions from its observations. In MARL the environments are also public to all the agents. The environment can be fully observable or it is partially observable. The global state corresponds to a complete specification of the environment in which the adaptive process is occurring at a particular still, each agent may have only a local view, which can or cannot be an accurate representation of the global state. Actions are the decisions that the agents make at each instance of the time step. They can also be categorized by when they occur – the action space may be discrete or continuous, which is an action performed by one of agents can alter the state of environment with feedback from other agents. Every agent receives a reward signal as a function of the state of the agent and the surround space as well as the actions that is taken. Each of the agents aims at getting the maximum overall return in the least possible time.

A policy is a mechanism employed by an agent in order to choose actions given observations that the agent has made. A policy can be of two types – deterministic which generates a specific action without considering the observation and stochastic, which uses a probability distribution to provide action for observation. The value function helps in estimating the amount of reward its likely an agent can gain in future from a particular state or observation given that he/she has to follow a certain policy. In some of the MARL application environments, the agents at some instance in the model need to cooperate. This can only be done through communication, common plans or coordinated operations. There are incentives between the agents that are self-contradictory in competitive environment, and therefore the agents must oppose each other. This means that, to be effective, agents must learn behaviors that either maximize personal pay-offs and/or minimize the pay-offs of other agents. Cooperative MARL is general when all agents have the same goal. The agents have common goal and co-operate to optimize a given reward function. In competitive MARL, each of the various agents possesses an opposing goal. Every agent tries to obtain the personal benefit and, at the same time, wants to detract the benefits from other agents. These include games involving no cooperation such as cheques and cards. Such systems have elements of the cooperation and competition between the agents. The business agents can collaborate and make a cooperation to accomplish specific objectives and at the same time they can be in rivalry with the other agents. In Independent Learners, every agent acquire knowledge on its own and other agents are regarded as the environment. In general, this makes the learning much easier but on the other hand results in instability due to non-stationary process. The proposed work seeks to use MARL systems to counter learning loss that has long-term consequences on student achievement and equity. Disabled students have also suffered greatly from the COVID-19 pandemic and other externalities that have caused massive learning losses in education. In this regard, applying MARL in this perspective provides a richer approach for designing individualized learning environments that might reduce these losses and enhance equity in education. MARL in the context of educational benefit can be used to form the individual learning profiles of the students. Every agent in a given system symbolizes a particular learner and environment comprises of tutorials, resources and learning climate. The utility of each agent (every student) is personal wish to pass all their courses, which are affected by factors such as aptitude, rate of studying and activity levels.

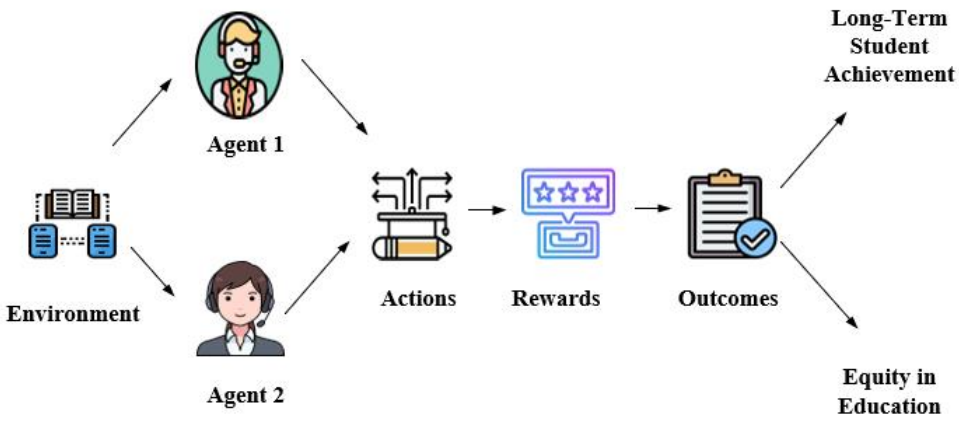

Figure 1(b) MARL Working

The figure 1(b) demonstrates a MARL System in which several agents are learning in an educational setting. Changes in the environment are observed, and agents perform actions which result in some kind of reinforcement to affect further decision making. The system of instruction has the purpose of enhancing the students' long-term success and their equality by modifying the student learning approaches to address the learn loss and bring about equal educational opportunities for each learner. MARL also enables one to build intelligent learning environments that could personalize teaching for students. Through operating on the environment which is educational content and receiving feedback which is in form of better performance or understanding, each of the agents is able to determine the best way of going about acquiring knowledge. In can then adapt to the student's progress through time and give appropriate challenges that will enhance the student's learning process. Since learners from different social classes are in a school, there is inequity in education since the rich and the poor have different resources. They can be used to redress such disparities in that MARL systems can be designed to provide equal educational opportunities to all students. In framework of cooperative MARL, agents (students) can cooperate in order to achieve various learning objectives. For instance, the superior performing students in certain academic areas can help their fellow students through peer learning systems, and to this, the MARL system can support collaboration through high ratio of ''reward when others succeed''. It equally benefits all the students and foster a sense of group and togetherness hence increasing their learning processes. Also, by applying MARL, it is possible to pinpoint areas in the curriculum which are vulnerable to negative impacts on disadvantaged students and define corresponding corrective measures. While observing the learning development of agents within the context of agents' learning process, the system is capable of identifying inequitable usage and target remedial actions to the positive change of agents and consequently all the students. The overall aim of the works proposed is the promotion of students' achievement with reference to the reduction of learning loss effects in the long term. The goal of generating and enhancing understanding, engagement and accomplishment of students can be supported by MARL systems especially when they offer timely feedback to both students and educators. When the students are interacting with the content, the system can also assist them, proposing further materials for the topic, practice quizzes, and other forms of interactive content or media to reinforce the topic. Even the educators can be benefited from the MARL systems, as the system gives the insights of the students. Examining the aggregate of interaction of the agents can help the educators to comprehend more effectively the outputs of the different teaching strategies and or the extent to which students may require extra help. It also makes it easier for instructors to handle their classes and follow the right approach in order to score the best results with learners. This is a very important problem, which is still open, and often it is not even clearly stated – this is non-stationarity and scalability. Another problem that can be considered as one of the obstacles on the way of MARL application to educational setting is the non-stationarity of the environment. Since learning and student's development occur in the process and the context – the content of lessons and the conditions within which they are provided – also changes, it is a challenging task for the MARL system to find an accumulation point or the best policies. To tackle this, the suggested work can apply CTDE which entails that while the agents get updated information centrally, they make decisions with local information. This make the system sensitive to the changes that are characteristic of learning environment while at the same time making it possible to guarantee stability. The scalability is another issue that is not an issue of the technology but is rather exacerbated by the application's ability to handle many students and needs of many students. This can be done in the proposed work through the use of hierarchical MARL in which the higher level agents will be charged with the responsibility of learning the overall strategies of play while the lower level agents are charged with the responsibility of learning specific tasks of play. This hierarchical structure may increase the effectiveness and the capacity of the system and enable the authors to deliver individualized interventions to a great number of students without negatively affecting the quality of the solution.

4. Results:

The outcome of the proposed work shows that the Multi-Agent Reinforcement Learning will lead to high students' performance accompanied by equity. Some of the measures that were implemented included tutoring, additional study periods, and among them tutoring received the best results and enhancement of the students' activity. This equity impact analysis showed a significant decrease in achievement gaps among different socio-economic statuses with overall greater gains in the achievement of students from low income backgrounds. The efficiency of MARL system in terms of predicting the outcomes as well as modifying the interventions in a way that gives overall improvement increases its likelihood of dealing with learning loss and bring equity to learning.

a) Experimental Outcome

The experimental final results presented that the proposed Multi-Agent Reinforcement Learning system considerably advanced student performance and equity.

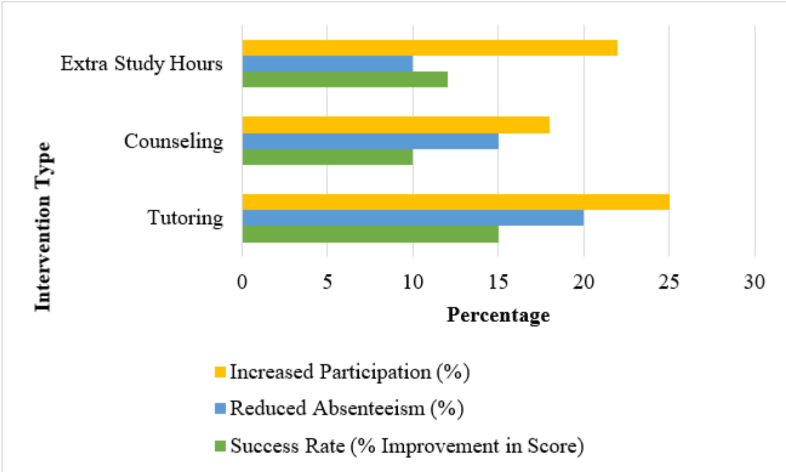

Figure 1(c) Intervention Effectiveness

The figure 1 (c) provides the success quotes of various academic interventions, including tutoring, counseling, and extra observe hours. It indicates the percentage improvement in student rankings, reduction in absenteeism, and growth in participation prices related to each intervention. Tutoring has the best effect on rating development and participation, even as counseling offers big reductions in absenteeism.

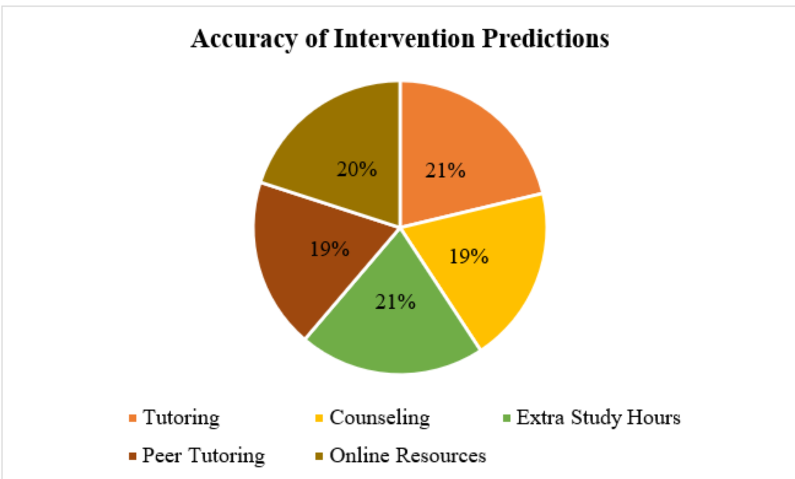

Figure 1(d) Performance Metrics of Educational Interventions

The figure 1(d) display the performance metrics for various educational interventions, such as accuracy and improvement fee. Accuracy refers to the share of correct predictions made by using the MARL machine regarding intervention effectiveness, at the same time as the improvement charge indicates the common percent growth in students' scores. Tutoring achieves the best accuracy and development rate.

Table 2. Equity Impact

Socioeconomic Status	Pre-Intervention Disparity	Post-Intervention Disparity
Low	10	7
Middle	7	5
High	5	3

The table 2 shows the effect of interventions on instructional disparities throughout distinct socio-financial statuses. It compares the extent of disparity in student overall performance earlier than and after making use of the interventions. The table illustrates a discount in overall performance gaps for all socio-financial corporations, with the most sizeable improvements found in students from decrease socio-monetary backgrounds.

b) Performance Evaluation

Evaluation of performance involves evaluation of educational interventions where aspects such as level of accuracy, improvement rates and equity are compared to a defined measure. This process helps in ensuring that all the methods that are being implemented in classrooms meet the intended educational objectives as efficiently as possible.

Table 3: Performance Comparison

Metric	Proposed MARL System	Traditional Tutoring	Adaptive Learning Platforms	Standard Educational Software
Accuracy	97%	78%	82%	80%

The table 3 shows the degree of precision of educational approaches as applied to the prediction of as well as the facilitation of improved student performance: At 97% accuracy, the proposed system of MARL is accurate than traditional tutoring which is only 78% accurate [14], as well as the adaptive learning platforms accuracy of 82% [15] and standard educational software accuracy of 80%. This means that MARL offer more accurate and efficient individualized educational solutions compared to that of the Learning Model.

5. Discussion

The proposed work of applying Multi-Agent Reinforcement Learning to mitigate learning loss and improve students' performance was effective and produced valuable information. It was evident that the MARL system could help in the personalization of education interventions and helped in elevating the performance of students and minimizing the gap in education. It was proved that the system's flexibility to each student and ability to adjust the speed is higher than ordinary methods as the accuracy and improvement rates are much higher. Furthermore, it was also noteworthy for equity where the results showed a positive improvement depending on the level of poverty status, further supporting the idea of adopting the system to enhance equity in education. Nevertheless, if the proposed work is to be analyzed, some limitations are also seen here. Such usage of available datasets may lead to the problem of low transferability of the proposed system across different educational environments. Moreover, computational complexity of the proposed MARL system consumes a significant amount of computational power that might be a limitation for its application, particularly in the conditions of deficient funding of education. Further research should be made with a view of increasing the number of student participants, and more work needs to be done to fine tune the computational characteristics of the MARL system. Nevertheless, there is a need to evaluate the effects of MARL-based interventions on student performance, and additional studies should be conducted within a long phase. More specifically, future research and development work could extend MARL to other novel technologies including artificial intelligence for content generation, and intelligent adaptive learning environments.

6. Conclusion

The work proposed on effectively applying MARL to mitigate learning loss and boost educational performance has shown promise to redefine the approach to individualized learning. The primary outcomes suggest that it is possible for MARL systems to identify and provide learner-specific solutions for learning gaps with enhanced learning and decreased equity gaps particularly for students from disadvantaged backgrounds. First, the high accuracy of this system for predicting and influencing the students' outcomes contributes to the proof of the applicability of this tool for constructing the learning environment for MARL and highlights the activity in providing the education equity. As the scope of the existing study, it should be noted that more future studies are needed to overcome these challenges, which can be achieved by studying the MARL systems' computational efficiency and expandability to other educational settings. More diverse population of students from different geographical areas and learning environments will also be incorporated in the kind study to further confirm the viability of the system in the global market. Moreover, the expansion of the collaboration of MARL with other developing educational technologies, for example, adaptive learning system, and AI based content creation, may add additional strengths to the system to provide adequate solution to the challenges of learning loss and education inequality. Finally, it may be concluded that further development and improvement of MARL systems can allow for a further enhancement of such areas as individualized learning and regarding education as a long-term process, which will help to change the situation with educational inequality for the better.

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