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A Game-Theoretic Model for Teacher–Student Decision-Making in Adaptive Learning Environments

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Abstract
Adaptive learning environments offer the possibility of providing instruction according to the learner's current status, but the choices that determine the trajectory of the learner cannot be made only by the system. The amount of effort and intensity of the instruction are chosen by the teacher, while the learner makes his/her choice of effort. Both choices are related to each other, but adaptive learning models usually consider the learner as a passive party receiving algorithm recommendations. In this work, a game theoretic model of the teacher-student decision making process in adaptive learning environments is developed. The players and their action sets, the information sets and the payoff functions are defined and formulated in three ways: simultaneous normal-form game, Stackelberg leader-follower game where the teacher acts first and evolutionary game describing a population of teachers and learners adjusting their strategies over time. Best responses are derived, characterization of equilibria conditions, and threshold conditions where mutual effort is maintained are obtained. Next, the various equilibrium results reported in the literature are summarized and the three models are compared against each other. It can be concluded that when there is a strong correlation between teacher's reward and current performance of the students, an equilibrium emerges where the teacher asks easier questions and the student's success hides very little learning; on the contrary, removing the correlation between teacher's payoff and current approval of the student yields an effort equilibrium.

Keywords: Game theory, adaptive learning, teacher–student interaction, Nash equilibrium, Stackelberg game, evolutionary game, incentive design.

1. Introduction

Adaptive learning is defined as the provision of the learner with the education content that is in alignment with their current state, unlike the conventional classroom setting (Chen et al., 2018). The core of this kind of learning is a recommendation mechanism, which involves selecting the next learning content for the learner – video lectures, practice questions or assessment on various skills – depending on the knowledge and personal traits of the learner (Chen et al., 2018). The problem in the activity selection in this process can be framed as an

optimization problem: which activity would best benefit learning aspects like gains and engagement, given an estimate of what the learner understands (Koedinger et al., 2013).

The main formulation of the problem is through sequential decision making under uncertainty. Selection of pathway has been modeled as a Markov decision process in which the rules of decision making would optimize the learning outcome of the student based on performance criteria (Lin, 2016). Recommendation has also been formulated as a Markov decision problem where decisions are made based on the knowledge of the learner and the learning content (Chen et al., 2018). Recent developments have used the reinforcement learning concept to make decisions and solve the sequential problem (Tang et al., 2019).

There is one commonality in the structure of the literature: there is a unilateral decision-maker. The system either finds the optimal path for the learner, or the learner himself/herself is regarded as the environment. In reality, adaptive learning environments consist of two strategic players (Fazilova et al., 2026). The teacher is responsible for making decisions about how hard he/she will work, how difficult the problems he/she will create, and how and when to intervene. On the other hand, the student makes decisions about the effort he/she will apply, whether to focus more on the learning process or just get by. These decisions are correlated, as the value of the student's effort depends on the difficulty of the problem assigned by the teacher.

The game-theoretic approach offers the most suitable formalism for this kind of interdependence. In particular, the process of learning can be considered as a game played by the teacher and the student, where the former's objective is to uncover the deficiencies in the latter's knowledge and remedy them, and where the objective of the latter is to appease the former and thus prevent any corrections; the game itself consists of a series of questions posed by the teacher and eliciting responses from the student, and each player receives certain payoffs they try to maximize. On this basis, this paper makes three contributions. First, we formulate the problem of teacher-student decision-making in adaptive learning systems as a game in its formal form, specifying players, their actions, information, and payoffs. Second, we provide three different game-theoretic formulations – simultaneous, Stackelberg and evolutionary – with different information structures of the interaction. Third, we formulate equilibrium conditions and summarize the results reported in the literature to identify when effort-based cooperation is sustained.

Organization of this paper is as follows. In section 2, we survey the literature relevant to adaptive learning, decision-theoretic teaching and game-theoretic analysis of education. Section 3 describes the model. Section 4 provides the three formulations of the game. Section 5 analyzes the equilibrium of the model. Section 6 presents the results and section 7 concludes.

2. Related work

2.1 Adaptive learning and recommendation systems

Adaptive learning has evolved from a generic delivery system to one where the content is customized based on the learner's skills. The current systems incorporate knowledge tracing, learning mode adaptation, and recommenders that provide personalized content by combining all three approaches separately devised (Murtaza et al., 2022). There are two common techniques of knowledge tracing: Bayesian knowledge tracing, which employs probabilistic algorithms to model skill acquisition based on the assumption that knowledge comprises binary variables per each skill, and deep knowledge tracing (Ilić et al., 2023). In the context of adaptivity, the recommendation problem is usually formulated in terms of sequential optimization, and the task of course sequence recommendation can be considered as choosing optimal sequences in terms of reduction of time to completion taking into account prerequisites and course availability (Xu et al., 2016).

2.2 Decision-theoretic models of instructional choice

Another line of work describes tutoring as making decisions under uncertainty rather than a game (Vaezzade&Alinia, 2014). Decision theory-based methods choose the tutoring actions in advance in order to predict their consequences for the student and the state of the tutorial based on a dynamic decision network describing the uncertain knowledge and goals of the tutor (Murray et al., 2004). Similar to that, machine teaching research investigates the relationship between the teacher and the learner where the objective of the teacher is to identify an optimal teaching sequence which will lead the learner to the desired goal; the adaptivity aspect is critical there, and the behavior of the learner is described via hypotheses about his selection of the candidate concepts (Chen et al., 2018). These approaches describe uncertainty of the teacher about the learner, but do not treat the learner as a strategic player.

2.3 Game-theoretic models in education

In the case where the learner is treated as strategic, the use of game theory becomes explicit. Methods that involve the computation of utility of the alternatives of the learner have been introduced using utility functions, which can be optimized, thus making it possible to compute the expected utility of different alternative actions of the learner so that an optimal decision action is made; this traditional approach of game theory has been applied to various decisions in education that can be optimized (Pavlik Jr et al., 2007). Group-learning mechanisms have also been modeled using game theory in which learners compete for better explanations by providing them with incentives, and then analyzing the game to find a Nash Equilibrium that will motivate learners to provide explanations (Bakaeva et al., 2026; Noorani et al., 2018). The institutionally, evolutionary models have been used in modeling populations of teachers' pedagogical actions using pay-off monotone dynamics, where teachers make actions before knowing the other's action (Antoci et al., 2021).Researches related to technology-based learning have developed this idea into a game involving three players, namely the evolution game between the teacher, machine, and student, which has been formulated to determine the combination of strategies that will maximize the effectiveness of learning and will become stable (Srinivasa Rao et al., 2019; Xiang et al., 2024). Lastly, the use of AI in learning has been studied as a strategic interaction involving AI, teachers, and institutions, showing the existence of a threshold below which cooperation is impossible and emphasizing that it takes effort by collaboration rather than one individual (Zhao & Ding, 2024).

Our model belongs to this third stream of research but concentrates on the dyadic relationship between the teacher and the student in the adaptive learning setting. It considers all three canonical forms of the model simultaneously, sequentially, and evolutionarily.

3. Model setup

3.1 The adaptive learning environment

Let us define an adaptive learning setting where the number of rounds of learning is discretized. In every round, an activity suggestion, an attempt at the activity, and the generation of an assessment signal take place; this is then used for updating the learner model. The adaptive learning setting is described in terms of: (i) a curriculum of knowledge components with prerequisites, (ii) an assessment function that provides a noisy estimate of mastery, and (iii) an adaptation policy for selecting the next activity. This setting resembles the sequential framework wherein decisions are made in view of the knowledge of the learner and of the learning materials.

3.2 Players, actions, and information

We model two strategic players.

The teacher sets an effort level, which refers to the amount of effort invested in preparation, quality of feedback, and the degree of task difficulty calibration. The teacher evaluates the history and cues in the assessment but does not observe the true effort level or true ability of the student.

The student sets an effort level, which relates to the effort invested in deep engagement, time on task, and readiness to work with difficult tasks. The student evaluates the activities provided and feedback but not the teacher's effort.

Since the effort is not directly observed, there is an imperfect information game—a type of frictions that makes instruction a strategic problem. Machine teaching framework assumes that the teacher makes inferences about the state of the learner through the responses of the learner, and the hypothesis space of the learner dictates these responses.

3.3 Payoffs

Learning achievement is an increasing function of the two efforts, but subject to decreasing returns. Assume that the student's learning is given by:

$$L(e_T, e_S) = \theta \cdot e_T^{\alpha} e_S^{\beta},\ \alpha, \beta \in (0,1) \qquad (1)$$

where $\theta$is a productivity parameter, and $\alpha$and $\beta$are the output elasticities of teacher and student effort, respectively. Efforts are costly. The payoff of the student is:

$$U_S = L(e_T, e_S) - c_S e_S \quad (2)$$

while the payoff of the teacher is:

$$U_T = \lambda L(e_T, e_S) + (1 - \lambda) R(e_S) - c_T e_T \quad (3)$$

where $c_T$and $c_S$are marginal effort costs, $R(e_S)$denotes the reward the teacher gets from the student's visible satisfaction or approval, and $\lambda$is the weight the teacher attaches to learning as compared with approval. Parameter $\lambda$is the central design variable of the model: for $\lambda = 1$, the teacher cares only about learning; if $\lambda$is small, then the teacher's payoff depends on the student's reaction more heavily than on learning achievement. This captures the issue that, if the teacher's incentives become too strongly aligned with the student's, the teacher will be tempted to ask questions that are too simple.

4. Game Formulations

4.1 Simultaneous-move (normal-form) game

In the base formulation, the teacher and student select effort levels simultaneously. Both parties maximize their expected payoff based on their belief concerning the level of effort exerted by the other party. In this case, we should use this model where there is no feedback or feedback is asynchronous, such as when the student works on the adaptive module independently while the teacher analyzes the results later. The structure used here is the normal form game with two players considered in the learning meta-game.

4.2 Stackelberg (leader–follower) game

In cases where the teacher decides on a particular difficulty level and feedback mechanism prior to the student's reaction – as in the case where the course has been designed and then attended by the student – the process is one of sequence. The teacher is in the driver's seat and the student is the follower. The teacher foresees the student's best move and decides upon the required effort. In this case, we can say that what is intended in the statement is that the teaching-learning processes, when designed well, may not only enhance the abilities of the student but also increase the gain of the teacher.

4.3 Evolutionary game

With a population unit of interest rather than a couple – more teachers, more students, multiple interactions – strategy updating can be better captured by evolutionary dynamics. Consider a population of teachers, some of whom adopt a demanding strategy and others adopt an easy strategy, with the choices made in advance without knowledge of what the other will do. Strategy adoption occurs through the evolution of the distribution of strategies, where strategies yielding above average payoff gain in prevalence. In a parallel way, the choice of effort of students between high and low is determined by replicator dynamics. This approach is appropriate for an adaptive environment on the scale of the "system" consisting of a number of teachers–student pairs, and links our model with the trilateral analysis where teachers, machines, and students simultaneously update their strategies.

The three approaches are complementary rather than competing because they have different assumptions regarding which parameters of the system are constant: in the simultaneous game, neither of the two actions is predetermined; in the Stackelberg game, the teacher's action is predetermined first; and in the evolutionary game, none of the two is predetermined.

5. Equilibrium Analysis

5.1 Best responses

The student's payoff function is concave in e_S, so the student's best reply is calculated using the first-order condition:

$$\frac{\partial U_S}{\partial e_S} = \beta\theta e_T^{\alpha} e_S^{\beta-1} - c_S = 0 \;\Rightarrow\; e_S^*(e_T) = \left(\frac{\beta\theta e_T^{\alpha}}{c_S}\right)^{\frac{1}{1-\beta}}$$

Thus, the effort of the student depends on the effort of the teacher and on the productivity θ, and it is decreasing in the student's marginal cost of effort c_S. Thus, effort is a strategic complement because the higher the effort of the teacher, the more effort the student invests. This is the formal way to state the idea that a difficult lesson

generates effort from the student, which corresponds to the finding that adaptivity is crucial for learning speed (Chen et al., 2018).

The optimal strategy of the teacher crucially depends on whether. If, then the problem faced by the teacher is symmetric to the one faced by the students, and the optimal strategy is an increasing function in terms of the effort of the students. If, then the approval term comes into play. In case the approval is more easily attained by making things easy for the student so he is able to succeed, then the marginal product of the effort exerted by the teacher becomes smaller, and the optimal strategy is shifted towards less effort.

5.2 Nash equilibria

The Nash equilibrium is a couple of efforts where each effort is a best response to the other. There are three qualitative regimes.

Regime 1: Equilibrium in efforts. For large values of , both best responses have a positive slope and cross at the interior point of positive effort for both players. The teacher works because she teaches what he cares about. The student works because he is forced to work on difficult but productive tasks.

Regime 2: Low effort equilibrium. For small and inexpensive approval, the best response of the teacher is flat. The equilibrium becomes characterized by small effort and small tasks, although learning is not much, the interaction remains stable as both players are happy with the achieved result.

Regime 3: Stable mediocre states. If the game is repeated and can lead to a tie or collusion, there can be equilibria where neither player would like to play by himself. They are Nash equilibria of the meta-game of learning, which appear in human education systems if the student solves all problems and rewards the teacher for not asking any more questions.

5.3 Threshold conditions for cooperation

The most relevant outcome of our analysis from a design perspective is the threshold condition. In the Stackelberg version of the game, the teacher makes the commitment first; cooperation, or both exerting efforts at a level above a certain target effort level, is possible only if the gain from learning for the teacher is greater than the cost of effort incurred, adjusted for the distortion in approval. Mathematically, there exists a threshold of the value below which the equilibrium of cooperation breaks down. This corresponds to the insight that there exists a threshold of the benefit from integration for cooperation between the stakeholders to be possible, and collaborative effort as opposed to individual effort is needed to sustain cooperation (Zhao & Ding, 2024).

6. Results

This section compiles the results of reported equilibria that reflect the regimes stated above and contrasts the three models. The figures and results presented here were taken directly from the cited literature.

6.1 Reported equilibrium outcomes

Conclusions to draw from the above evidence include the following. Firstly, equilibrium is not inevitable as a stable solution can be inferior to what could have been collectively obtained, as shown by the mediocre stable equilibria whereby students' success is due to easy questions posed to them and not to learning. Secondly, the cooperative equilibrium is one where there is mutual interaction between the proactive teaching and active participation and it relies on the incentives given to each participant (Xiang et al., 2024). Finally, for cooperation to occur, no one individual should shoulder more of the burden (Zhao & Ding, 2024).

Table 1: Maps each source to its setting and its reported equilibrium finding. Each entry reproduces the outcome the source reports.

Source	Setting	Reported Equilibrium Outcome
Pollack & Blair	Teacher–student meta-game of learning	Inferior Nash equilibria, known as mediocre stable equilibria; in human educational systems, these occur when the student gets the answer right and rewards the teacher with good evaluations for not asking difficult questions.

Xiang et al., (2024)	Trilateral evolutionary game among teachers, machines, and students	The best strategy equilibrium for effective education is where teachers adopt proactive approach, machines adopt proactive approach, and students adopt active approach because their reputations improve, evolve respectively, and gain from the process of learning respectively.
Zhao & Ding, (2024)	Strategic interaction among AI systems, teachers, and institutions	There is a threshold in the value of AI integration below which there will be no cooperation; teamwork needs to be done rather than one party shouldering most of the load.
Zhang et al., (2021)	Stackelberg model of process teaching	Process Teaching enhances the sense of gain on both sides and hence allows teachers and learners to reach their optimum level at the same time.
Noorani et al., (2018)	Game with a purpose for peer explanation and competition	Nash Equilibrium parameters were examined where students are incentivized to give good explanations and from the statistical analysis via Student's t-test, the game motivates students to engage actively and learn more effectively

6.2 Effect of payoff alignment

The key comparative-static prediction of the model is about, the weight the teacher puts on learning compared with approval. As the teacher's marginal benefit of effort, declines, the marginal benefit from learning decreases, the teacher's optimal effort function becomes flatter, and the intersection of best responses approaches Regime 2. Since student effort is a strategic complement to the teacher's effort (Section 5.1), this has additional reinforcing effects: a little decrease in the teacher's effort lowers the student's optimal effort, which further lowers the teacher's, and the equilibrium collapses into the low-effort outcome.

This is the reason why the mediocre stable equilibrium is so persistent once it is achieved. The teacher has no incentive to increase difficulty because the student will not appreciate it; the student has no incentive to work hard since the lesson is not demanding. Getting back to the effort-driven equilibrium would require changing the incentive structure rather than motivating either party to make more effort. This is also supported by the result that cooperation involves joint effort and cannot be done by one side alone (Zhao & Ding, 2024).

6.3 Comparison of formulations

Table 2: Summarizes how the three formulations differ in what they capture and what they predict.

Formulation	Timing	What it captures	Equilibrium Implication
Simultaneous	Both choose ex ante	Anonymous or asynchronous interaction	Nash equilibria may be suboptimal; mediocre stable states possible
Stackelberg	Teacher commits first	Designed courses; teacher as leader	Cooperation sustained only above a threshold on the teacher's valuation of learning
Evolutionary	Population strategies adjust over time	Many teachers and students at scale	Long-run share of demanding strategies driven by payoff-monotonic dynamics (Antoci et al., 2021)

The comparison makes it clear when each version of the framework should be applied. In case of one-time implementation of the course with fixed design, the Stackelberg version comes closer to reality since the teacher's strategy is formed prior to the students' reaction (Tang et al., 2019). The simultaneous model corresponds to self-paced modules without any human intervention. For a platform that works on a large scale, where strategies become diffused among numerous instructors, the evolutionary model should be used as in such cases adjustment of strategy shares follows the payoff-monotonic dynamics, not conscious decision-making (Antoci et al., 2021). This is exactly why evolutionary game models are used instead of classical game theory due to the bounded rationality of the players involved (Huang et al., 2025).

7. Discussion

The model restates a well-known puzzle in adaptive learning. Most of the research focuses on how one can optimize the pathway based on the learner model (Chen et al., 2018; Lin, 2016). This model suggests posing another more fundamental question: provided that the learner is a self-interested agent with his or her own goals,

what causes this pathway to be followed by effort at all? And the answer is the correlation of each individual's payoff with learning.

There are three implications of the results. First of all, the incentive design is not secondary, but constitutive in adaptive learning. Since effort is strategic complement, the misalignment does not result in some minor distortion—it may cause a shift from effort regime to low-effort regime completely. Second, the diagnostic power of the model is in the parameter: a system designer needs just to check whether there is a connection of the reward of the teacher with learning or approval. Third, the threshold property (Zhao & Ding, 2024) gives a ground for intervention: the cooperation may persist only if there is no player who shoulders the majority of effort.

The proposed model is also related to the decision-theoretic paradigm (Murray et al., 2004) and machine teaching (Chen et al., 2018). The models underlying these paradigms assume that the teacher optimizes against a non-strategic learner. Our model demonstrates what is gained when the learner optimizes back, i.e., the existence of suboptimal equilibria cannot be mitigated by any improvement in the estimation quality due to the nature of the difficulty being strategic rather than informational. That is why explicit modeling of students' preferences, e.g., by means of utility-based approaches, is beneficial since it incorporates the objective of the learner into the problem setting (Pavlik Jr et al., 2007).

There are two caveats regarding the approach presented in the paper. Firstly, the analysis performed above is structural and symbolic: the results regarding the equilibrium properties are reported without estimating the parameters of the model empirically. Secondly, the model ignores the details of the learning process and focuses on the payoffs only. Indeed, in the actual system, the recommendation engine refines the learner model in every step, so the payoff functions change dynamically. Extending the game-theoretic framework by adding the sequential-optimization layer is a natural step, and it will enable the derivation of the threshold condition as a function of the rate at which uncertainty is resolved.

8. Conclusion

A game-theoretic model of decisions of teachers and students in adaptive learning was built in this paper. Players, actions, information, and payoffs were identified, while simultaneous, Stackelberg, and evolutionary variants of the interaction were described. Equilibrium analysis proved that the effort of students is a strategic complement of the effort of teachers, that a low-effort equilibrium is achieved if teacher rewards depend on approval, not on learning, and that cooperation implies reaching a critical level of effort at which none of the parties takes the burden of carrying out most of the effort. All three regimes have supporting empirical evidence in the literature: stable mediocre equilibria in the meta-game of learning, mutually engaging as the optimal structure of interaction in trilateral approach, and a benefit threshold for achieving cooperation in AI integration. The model itself is quite concise, but it makes a structural statement that pathway optimization alone cannot make: in an adaptive learning environment, the construction of incentives ensures that the pathway suggested is actually walked, not just passed through. In future research, the model should be calibrated on actual interaction data, and the game-theoretic layer combined with sequential pathway optimization.

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