TFL - Chess 101: Chess for Chumps

Ko Schoemaker (6021573), Ignacy Skrzeczek (0116408), Marre Slikker (6541364), Samuel Spithorst (5956684), Lukas Stemerdink (6217265)

November 12, 2023

Abstract

Chess is one of the most widely known sports on the planet. In this article, Chess for Chumps is presented: an adaptive e-learning system designed to teach the fundamental concepts of chess to absolute novices. It utilizes a combination of adaptive learning support methods, in both the inner and outer loop, providing personalization for each learner as they progress through the learning material. First of all, this article reviews related literature, and discusses relevance and potential contributions. Then the system design is presented. An experiment design is also proposed, to check the validity of the design, with a focus on learning outcomes and long-term knowledge retention. The results from this study might be used to improve existing educational systems for more effective and efficient knowledge transfer.

1 Introduction

Deep Blue's victory over former world chess champion Gary Kasparov in 1997 marked a start of a new era in chess history. From now on, professional players would be aided by computers to gain the upper-hand over their opponents. Computers were able to quickly evaluate the position that previously took whole teams of chess players to solve, computers were also able to show holes in chess theory. Soon anyone who owned a computer was able to install a chess engine and let it go through a game by entering moves. The introduction of these computer aiding systems, marked a new era of chess learning. A modern approach to learning of a timeless game.

Today, online chess platforms offer a multitude of learning opportunities; chess puzzles, online courses created by chess grand masters supported by machine learning, and many more. The proposed adaptive learning system *Chess for Chumps* is another addition into this domain of chess learning systems. While being focused on absolute novices, it extends the domain by providing adaptation techniques to the instructional content, such that each student follows a unique learning path towards mastering the basic concepts of chess. The system adaptation allows for different learning rates of individual students and more personal feedback.

It has been found that adding some methods of adaptation to intelligent tutoring systems can be feasible and useful, but can also come with problems (Verdu et al., 2008). To research whether the adaptiveness in *Chess for Chumps* has a positive effect on the knowledge gain of the student, the following research question is proposed:

> *To what extent does the adaptiveness in Chess for Chumps, an intelligent tutoring system aimed at teaching novices chess, contribute to learning and retaining chess knowledge?*

For this, the null hypothesis is that adaptiveness does not significantly contribute in long-term learning, while the alternative hypothesis is that adaptiveness does significantly contribute in long-term learning. This is split in sub-questions, one focusing on the inner loop of adaptiveness and the other is focused on the outer loop.

To answer this research question, this article is structured as follows; first, there will be a literature review, covering relevant literature, including the relevance and potential contributions. Then, the *Chess for Chumps* system design is discussed. An experiment design and (expected) results are presented. In the conclusion section, the research is summed up and limitations & future work are presented

2 Literature review

The main inspiration for the system design was a book, '*Bobby Fischer Teaches Chess*' (Fisher, 1966). It is one of the most popular chess books in history, teaching fundamentals of chess based on a programmed learning approach. It inspired the design of the system, the domain models reassemble each other. Moreover it ensured that there are no missing domain-related concepts. First the book introduces the movement of all the pieces. After that it goes over all the special moves and game ending conditions. Unlike our system it introduces all of the information about the game of chess first. It reinforces this learning by having reader solve a number of chess puzzles, where all the topics are mixed together. In our opinion this increases the difficulty of learning as all the rules have to be comprehended from the start.

When it comes to the importance of the topic, and possible applications, 'Chess for Educators: How to Organize and Promote a Meaningful Chess Teaching Program' (van Delft, 2021) shed light on the importance of the topic. The book attempts to promote chess as a part of the educational process of children, by highlighting the benefits of learning chess. Chess is described both as a social game and as a therapeutic tool. It mentions how people with different disabilities are capable of playing chess. A section of van Delft's book is dedicated to research, compiling information about the benefits of chess instruction.

2.1 Relevance

Chess can be quite a complex game to start learning, with many compound concepts and difficult topics, such as strategy and tactics (Morales, 1996). Chess learners easily feel overwhelmed, which makes it hard to get started in chess and to stay motivated. Besides that, people tend to learn at different paces and in different ways (Gobet and Campitelli, 2002), so making a one-size-fits all system for chess learning may be difficult. An adaptive chess learning system would overcome these problems.

An adaptive chess learning system can ensure that learners do not get overwhelmed in the beginning, get the right level exercises, and enhances their knowledge retention. Long-term knowledge retention is important in chess, because the game concepts are repeated throughout the whole game, which might be practiced best in an adaptive system that can provide you exercises or situations that the student hasn't seen in a while. Additionally, an adaptive chess learning system is able to provide targeted, personal feedback, whilst traditional chess learning often leaves the learners to figure out their mistakes on their own, which can be frustrating and inefficient. The experiment tests if the described adaptive chess learning system, indeed helps in staying motivated and provides an efficient learning path.

2.2 Potential contributions

There are a lot of (online) educational systems designed for teaching basic chess rules already, some learning systems more adaptive to the student than others. *Chess for Chumps* implements a mastery learning approach, using Bayesian Knowledge Tracing for measuring student knowledge, combined with unlockable levels based on a student's progress. In contrast, the basic lessons provided by chess.com[1] or Lichess[2] do not implement a mastery learning approach and have sequential lessons that are not locked away based on student knowledge. Similarly, the Dutch website Chessity[3] provides a static number of exercises for each knowledge component, but this system does lock away more advanced chess concepts until the student has completed prerequisite knowledge.

Our research will examine to what extend different levels of adaptiveness based on mastery learning & Bayesian Knowledge Tracing, adaptive feedback and locked exercises can contribute to long-term learning. Results from this study might be used to improve existing educational chess systems for more effective knowledge transfer.

Mastery learning in educational systems has been proven to be an effective strategy for teaching (Bloom, 1968). A system that is adaptive can provide a student with more relevant study material or help than a more static system.

[1] `https://www.chess.com/lessons`

[2] `https://lichess.org/learn`

[3] `https://www.chessity.com/chess/learn`, user needs an account to view and work on exercises

3 System Design

The core of the pedagogical model in *Chess for Chumps* is mastery learning, which ensures that students have a solid grasp of fundamental chess concepts before progressing to more advanced topics (Bloom, 1968). The system contains four levels, each with their own subset of knowledge components. The levels and their corresponding learning material are presented in 6. These levels were designed around prerequisite-outcome relationships between knowledge components, ensuring that each level contains prerequisite knowledge for the next. As such, mastery learning enables the student to move naturally through the levels, learning something new at each step. In the model, adaptation occurs in both the outer-loop and the inner-loop.

To create an accurate overview of all domain knowledge to be taught, a domain model was designed (see Figure 5). Due to our system being aimed at novices, only knowledge relating to the absolute basics was selected. Skills such as calculations, tactics and specific strategic openings & endgames are omitted, as it will make the system too large to cover in this project.

The proposed learning system employs mastery learning. Users are allowed to move through the learning system on their own pace, though they should not move on to the next set of objectives before having mastered the prerequisite set of objectives (Block and Burns, 1976). The relations between knowledge components in the model are labeled as a *prerequisite for* or *part of* relation. A *prerequisite for*-relationship means that a skill is a prerequisite for another skill to be learned, meaning the student must always understand this concept before advancing. An example of this relationship is fully comprehending *piece movement* before learning how *check* works. *Part of*-relationships are relationships where a skill is a part of another skill, for example *rook movement* is part of *basic moves*.

A distinction between the types of knowledge components in the domain model has been made as well, with declarative components being marked as yellow and procedural components being marked as purple. Components that are out of scope for this learning system are marked as gray. Procedural (or "how") knowledge covers skills and rules the player should know (Ten Berge and Van Hezewijk, 1999). The purple components cover the basic concepts of *Gameplay*, e.g., the basic rules in *Piece Movement*. As the purple components are a prerequisite for the declarative knowledge chunks, they are of high granularity - to make sure the user fully understands the rules about piece movement. Declarative (or "what") knowledge is conscious and can be verbalized, like knowing what specific *Game conditions* are. Being able to verbalize when there is a *Check*, *Checkmate*, or *Draw* in the current board setup can only be done when the player knows the piece movements. The declarative knowledge components are of lower granularity, as they cover more overarching chess concepts. For example, *Check* can be reached in many ways, the system should not have to cover all of these - the user only needs to understand the underlying rule for when check is reached.

Notation and specific draw conditions are regarded as out-of-scope for this learning system, as their knowledge is either not necessary to know by heart, or is difficult to translate to exercises.

For each of the defined knowledge components, learning material was designed. The content model defines the mapping between the learning material and the knowledge components. An illustration of the content model can be found in the Appendix, in Figure 6. Each of the *question type*s (colored green in the content model) contain learning material that is directly linked to the knowledge component. The learning material for one knowledge component is composed of one type of exercise, practiced in multiple different board set-ups to test if the student can apply the knowledge in different situation.

As described, the learning content is subdivided into 4 levels. The exact set-up of these levels is detailed in the next sections.

Level 1: Initial board setup, Basic moves

Initial board setup has two types of questions, 'place a piece' and 'correct a piece'. From an empty board state the student will place every piece on its starting position.

For each of the basic moves (pawn movement, rook movement, knight movement etc.), an exercise targeting that specific piece's movement exists. This would explain the basic movement of every chess piece. Pieces would move on an empty board until the student makes enough legal moves. In the appendix Figures 13, 14, 15, examples of what the learning material might look like, can be found.

Level 2: Special moves

After a student has learned the basic moves, it is possible to learn the special moves in chess.

A single exercise 'castle' exists that is applicable to both queen side castling and king side castling. To be able to castle, both king and rook on the chosen side must have not moved during the game. There can be no pieces between them and the king cannot be under check. During the king side castle, king ends up on g1 and your rook on f1. For queen side castle king is put on c1 and your rook on d1. This counts as one move. Student would be presented with several positions where castling is possible and one where it is illegal. An example of the exercises for castling can be found in Figure 18.

For promotion, an exercise 'promote a pawn' exists. Once the pawn reaches the end of the board it can be promoted to a different piece of a higher value.

For en passant, an exercise 'take a pawn en passant' exists. This quite unintuitive rule allows players to capture a pawn that has moved more than two squares on a previous move as if it has only moved one. Only pawns can capture en passant and only on the turn following the double movement. To be able to determine whether capturing en passant is a legal move, one has to know the previous move made on the chess board. Student will take with his pawn en passant.

Level 3: Check

For check, four types of exercise exist. 'How to put someone in check', 'King moves out of check', 'Take the piece that is checking' and 'A piece blocks the check'. A check is a situation in which, on the next move, a king could be taken. This would result in the end of the game but usually there is a way to avoid it. King can move to a square where they are no longer under threat. Sometimes it is possible to parry a danger with your own piece or simply take the piece that is threatening your king. Student have to respond to a check by applying all of those tactics. An example of one of these four types of exercises can be found in appendix 16.

Level 4: Checkmate, Draw

Only when all of the knowledge components in the previous levels have been mastered can a student start exercises in this fourth level.

For Checkmate, a single exercise 'Find a checkmate' exists. Checkmate is a check that the king cannot get away from, that would result in his capture. An example of an exercise for this is shown in Figure 17. For draws through move repetition an exercise 'three moves' exists and for draws by stalemate an exercise 'what to do then' exists.

3.1 Outer-loop support

In the outer-loop, the system provides adaptive learning support to the student based on the distinct levels defined in the content model, each comprising of specific knowledge components. Access to higher levels becomes available as learners demonstrate proficiency at lower levels, allowing users to build their chess knowledge incrementally. For each locked level, the learner can perform an optional summative assessment. This allows the learner to inform the system of prior knowledge, skipping the levels that the learner already knows. Passing the summative assessment will make the system update its mastery estimates on the lower levels. This enables a user who understands the chess concepts quicker is allowed to move through the program quickly, while users who are experiencing more difficulty can move at their own pace.

To achieve this, the system builds a model of each student's mastery of every individual knowledge component and updates this in real-time (after every completed puzzle). It does so through the use of Bayesian Knowledge Tracing (Pelánek, 2017; Corbett and Anderson, 1995; Van de Sande, 2013). In this approach, each knowledge component is modeled as being either a) not mastered, or b) mastered and learning is modeled by a discrete transition from the former to the later state.

The quality of the estimated θ relies heavily on the values of the four parameters ($P(i)$, $P(l)$, $P(g)$, $P(s)$). As such, ideally, they would be fitted based on empirical data, for example, through the methods mentioned by Pelánek (2017) such as the standard expectation-maximization algorithm, exhaustive search, or stochastic gradient. Unfortunately, it is out of our scope to build a prototype to gather this data. For now, we have attempted to estimate these probabilities ourselves as follows:

- $P(i)$: We have set this probability at 0.1 (10%) for the earlier (easier, lower-level), and 0.01 (1%) for later (more complex) knowledge components. Given our focus on absolute beginners, we anticipate that the chances of prior mastery for each knowledge component are very low. With slightly higher chances of prior knowledge for the very basic concepts, and very low chances for later concepts.

- $P(l)$: Beginners often require multiple attempts to grasp new concepts due to the nature of learning curves (Howard, 2018). As such, we have estimated this probability to be relatively low at 0.3 (30%) for all of the knowledge components.
- $P(g)$: The likelihood of guessing a puzzle correctly, without having mastered the knowledge component, is relatively low. This is due to the complex nature of chess puzzles and the vast action space involved in selecting and moving pieces. For earlier, more basic knowledge components, where puzzles have fewer pieces on the board or may explicitly guide the player to move a specific piece, we estimate this probability to be around 0.15 (15%). As concepts become more advanced, the action space becomes larger as such, we gradually lower the probability of guesses as concepts grow in complexity, all the way down to 0.05 (5%).
- $P(s)$: We expect the probability of slips to be low, at 0.01 (1%), as the possibilities within exercises are very restricted and the taught concepts are low-level.

The system's model of the student's knowledge is designed as an open learner model (Bull and Kay, 2007), meaning that it exposes its mastery estimates directly to students. This is done to enhance students' awareness of their learning and foster skills like self-regulation and self-assessment. In this system, the model is opened to the student in the form of skill meters, with each skill meter representing the student's mastery in a specific knowledge component, shown in Figure 1. The granularity of these knowledge components differs. Some skill meter bars represent a higher level knowledge component, such as basic moves, which represents the overarching mastery of its lower level children (Pawn movement, Rook movement, Knight movement, Bishop movement, King movement, Queen movement). Other bars such as Initial board setup, are based on a single atomic knowledge component. This was done to provide a clean overview to the student, instead of having to present them with a bar for each atomic knowledge component. The values of these skill meters are obtained simply from the Bayesian knowledge tracing model value for the probability of mastery of that component. If the bar represents multiple components (i.e., is a higher level knowledge component), the bar aggregates the values of its children.

In line with transparency and open learning, the student can also see the way the knowledge components are broken down into levels, allowing for an overview of what the student need to master in order to progress.

3.2 Inner Loop support

The inner-loop provides adaptive support to the student in the form of adaptive hints.

When a student chooses the learning component they would like to master, they are greeted with a tutorial page with explanation of the knowledge component, followed by an instruction of the exercise they should perform on the chess board.

The chess board is filled with different chess pieces, some of which are relevant to the puzzle and some which are irrelevant. In the example of an exercise on moving the pawn (see Figure 3), a student can either move the pawn one place forward (correct solution), move the pawn to an illegal location (incorrect) or pick a piece that is not the pawn and try to move with that piece (incorrect). In the incorrect situations, a distinction can be made between two different misconceptions: 1) the student does not know what legal moves a pawn can make or 2) a student does not know which piece is a pawn. When a student made a mistake, immediate minimal feedback is given "incorrect". The student can try again or click the hint button. If the hint button is clicked, based on the type of error that the student just made, an error-specific targeted feedback message is displayed on the topic of the functioning of the chess piece / move or board state. In the case of moving the wrong chess piece, a reminder hint is given with a picture of what the correct piece looks like. When an incorrect or illegal move is made, a small description of the correct behavior of a chess piece is displayed or the goal of the exercise is repeated.

After a player has requested a first hint, they can also demand another hint (progressive hints). This would be a bottom-out hint, a text describing exactly what the student should do to reach the correct solution.

The clearly demarcated exercises and progressive error-targeted hints contribute to the mastery learning strategy by addressing only a specific subset of skills and trying to get the student to master it through repeated exercises.

3.3 Interface design

3.3.1 Menu design

The application interface was created with simplicity in mind. The menu consists of two distinct layers each with their own design. Figure 1 describes the first layer of the interface design. The green bars inform how much is left until completion. The content is divided into levels that require progression to be made accessible. There are 4 sections with content of progressively higher complexity, highlighted by the differences in color. The student can clearly see what exercises are available to them, how far they have progressed in each exercise and what is locked behind the mastery level progression. This enforces mastery learning principles and groups concepts from relatively simple ones to the most difficult. Once a level has been chosen, the user is presented with various knowledge components between different subsections as shown in Figure 11.

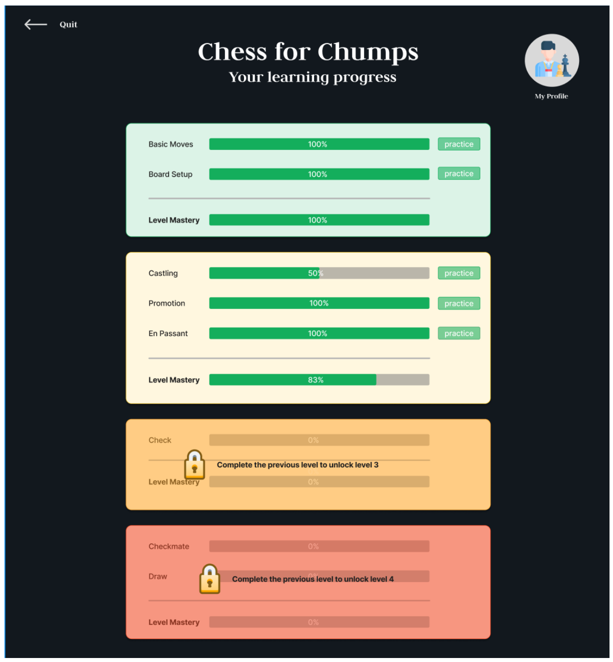

Figure 1: The design of the main screen, with some exercises being locked behind a progression system.

3.3.2 Exercise design

During exercises, the screen is split between a chessboard on the left, and an information box on the right. Figure 2 showcases how the tutorial page is being presented to the student. Concepts that could be considered difficult are highlighted, clicking on them offers information about them in a text box. Figures 3, 4 and 7 display how the task is presented and how the system responds to a correct and incorrect solution. In case the user is incapable of solving a problem on their own, a hint offers support. Figures 8 and 9 illustrate how hints help solve a chess problem. If a hint does not suffice, a solution can be accessed. Figures 9 and 10 show how a solution is presented. Once a solution is presented, the user still has to manually enter the right solution. Once a puzzle has been solved two new options appear on the screen, a red "Try Again" and a green "Try New Situation". Once a knowledge component has been mastered, a congratulation screen appears, offering gratification displayed on Figure 12.

4 Experiment Design

To sufficiently test the research question, four groups of users are created, each with the following characteristics: *1)* Absolute novice in chess, *2)* 18 years or older, *3)* English speaking, *4)* Able to see, *5)* Having completed the full *Chess for Chumps* system, *6)* ±40 participants, *7)* Fully randomized.

The four groups are:

- **Full Adaptivity Group**: Uses *Chess for Chumps* normally, with all adaptive features enabled

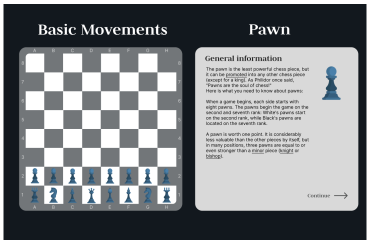

Figure 2: Information slide, before the task is given.

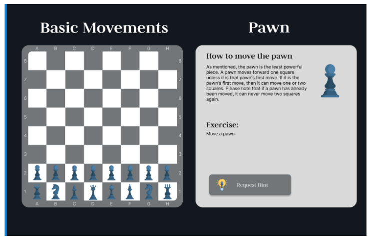

Figure 3: A task and additional information is presented.

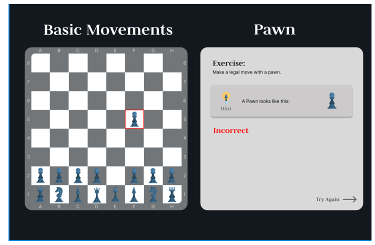

Figure 4: This task has been incorrectly solved.

- **Inner-loop Only Group**: Uses *Chess for Chumps* with only inner-loop adaptivity
- **Outer-loop Only Group**: Uses *Chess for Chumps* with only outer-loop adaptivity
- **No Adaptivity Group**: Uses *Chess for Chumps* without any adaptivity (baseline)

For the Inner-loop Only Group, the outer-loop mastery learning functionality will be disabled. This means that instead of the system inferring the user's mastery of knowledge components and locking/unlocking levels based on that, all levels and their knowledge components will be fully unlocked and accessible from the start. There will be no enforced sequence or gating based on inferred mastery. To replace the outer-loop mastery functionality, users will be able to freely select any level to study. For this group the inner-loop hint system will still provide adaptive hints based on the user's errors when working through exercises.

For the Outer-loop Only Group, the inner-loop hint system will be disabled. This means that when users work through exercises, no adaptive hints will be provided. Instead, all hints are put together in a sequence, with the final hint being the bottom-out hint. The student can freely request a hint, which will show them the first hint in the sequence. From there, they can manually navigate forwards (or backwards) through all the available hints. For this group, the outer-loop mastery learning system will still remain active. This means that knowledge components and levels will be locked until the system has inferred mastery of prerequisite concepts based on the user's performance on exercises.

The No-Adaptivity Group will have both inner and outer-loop adaptive functionality disabled and replaced with the non-adaptive counterparts used in the Inner-Loop Only and Outer-Loop Only groups

All of the knowledge components and related questions can be found in the appendix in Figures 5 and 6. With a total of 160 participants that have completed the *Chess for Chumps* system, there should be some significance in the numbers generated and their standard deviations, while the amount of participants is kept low to account for the intensiveness of needing to complete the full course. Ideally, each group of participants would be fully randomized, so that gender and academic level are irrelevant for the results on measured chess knowledge. Lastly, all of the groups are not allowed to practice chess outside of the adaptive system, to prevent potential knowledge gain from external sources, though they are allowed to go through the system on their own pace.

To assess the effect of the system compared to a defined baseline, data is collected at three distinct points in time: *Pre-test*: to establish baseline knowledge before using the system. *Post-Test*: Following the completion of the last knowledge component, participants are given a second test, to gauge short-term retention. This immediate post-test aims to measure the knowledge acquired during their engagement with the system. *Long-Term Post-Test*: To assess the system's impact on long-term knowledge retention, a third test is conducted approximately two weeks after participants have finished all knowledge components.

Each of the tests is randomized, yet isomorphic to each other, i.e., each test uses different variations of puzzles to test the same underlying knowledge. These puzzles are drawn from the collection of questions available to the system. The following puzzles will be used: *For level 1:* 2 questions of the 'initial board setup' component question set, 2 questions of the 'basic move' knowledge component question set. *For level 2:* 2 questions of the 'castling' knowledge component question set, 2 questions of the 'promotion' knowledge component question set, 2 questions of the 'en passant' knowledge component question set. *For level 3:* 2 questions of the 'check' knowledge component question set. *For level 4:* 2 questions of the 'checkmate' knowledge component question set, 2 questions of the 'draw' knowledge component question set. That means a total of 16 questions per quiz.

The questions are selected to be representative of all the knowledge components covered within the *Chess for Chumps* system and exclude any topics outside of what the system teaches the user. This ensures that the assessment is focused solely on the knowledge and skills gained through the use of the system.

5 (Expected) Results

Based on the experimental design, we expect the full adaptivity group to demonstrate the highest levels of learning and long-term retention. This group receives adaptive support in both the outer and inner loop, allowing them to progress through the system at their own pace while receiving personalized guidance.

In contrast, we anticipate the no adaptivity group will perform the worst overall. Without any adaptive learning components, these students could struggle master concepts, lose motivation, and not retain knowledge long-term because the student might not pace their learning as well as the adaptive system would.

The inner-loop only group should outperform the no adaptivity group, as the adaptive hints provide guidance during exercises even if concepts are not properly sequenced. The outer-loop only group should also exceed the no adaptivity group as the knowledge sequencing still enforces mastery learning. However, the lack of adaptive hints on exercises may frustrate some learners, limiting knowledge acquisition.

To test these hypotheses, we will conduct quantitative analysis on the test scores across the three time points. First, we will check that the pre-test scores do not significantly differ, confirming random group assignment. Next, we will compare post-test and long-term post-test scores using statistical tests to determine if there are significant differences between groups. We expect the full adaptive group will significantly outperform the others on the post-tests. If adaptiveness improves long-term retention as hypothesized, the full adaptive group's scores should show the smallest decrease between post-test and long-term post-test.

Additionally, we can quantitatively analyze metrics captured during system use, like time spent, attempts per exercise, hints requested, etc. This data could provide further insight into how the different groups engaged with the system. For example, we may find learners in the non-adaptive conditions require more attempts to master concepts.

6 Conclusion

In this study we have presented *Chess for Chumps*, an adaptive learning system designed to teach fundamental chess concepts to absolute novices. We designed a domain model, and based on it created interface. The system employs a combination of adaptive learning support techniques in both the outer and inner loop, providing personalized support to learners as they progress through the material. An experiment was proposed to check the validity of some of the design decisions. Our experimental design aimed to compare the effectiveness of full adaptivity, inner-loop only adaptivity, outer-loop only adaptivity and no adaptivity, with a focus on learning outcomes and long-term retention.

6.1 Limitations

First, *Chess for Chumps* focuses solely on teaching fundamental chess concepts to absolute novices. The scope of covered knowledge is limited compared to the full breadth and depth of chess knowledge. Advanced strategic concepts like specific openings, endgames, calculations, and tactics are not addressed. To expand the system to support intermediate or advanced chess instruction would require additions to the domain model, content model, and adaptive teaching techniques.

Additionally, the knowledge tracing relies heavily on its parameters, which are being set manually in this project. For better results these parameters could be made more reliable by using a data-driven approach to estimate them based on empirical learner data.

The experimental study is limited to short-term use of the system over a couple of weeks. Longitudinal studies evaluating the use and effectiveness of the system over months or years could provide stronger evidence. Additionally, the study sample is limited to English-speaking adults and may not represent diverse demographics of chess learners.

6.2 Future Work

This work provides a foundation for the *Chess for Chumps* system, but there are many opportunities to build on these concepts in future research and development. Some potential directions include:

Expanding Content and Knowledge Scope: As noted in the limitations, *Chess for Chumps* covers only fundamental chess knowledge targeted at novices. The domain model, content model, and adaptive teaching techniques could be extended to support more advanced strategic concepts like openings, endgames, tactics, calculations, and positional play. With that in mind, the implementation of the system does not necessarily transition or scale well with more advanced concepts. The domain model in this project allows for simple right or wrong puzzle, but as concepts get more advanced it becomes progressively more difficult, if not impossible, to create short puzzles with a dichotomous outcome. As such, with a broader scope, new forms of teaching material and puzzles would need to be designed and implemented.

Broader evaluation: The experimental methodology could be expanded to larger samples, longer duration, and more diverse populations. Additionally, evaluating perceptions, engagement, motivation, and usability would provide insights beyond learning outcomes alone. Comparisons to human tutors could also shed light on the pros and cons of automated adaptive instruction.

Expanding on adaptive support: To provide more adaptive and personalized learning support to students, various other adaptive support techniques could be implemented. One such opportunity would be to add large language model powered tutorial dialogs, as was recently done for example in Duolingo Max [4]. This would allow a student to engage in a conversation with the system, to receive explanations, feedback and guidance that are personalized on both a linguistical level (catering to the student's tone of voice, and vocabulary usage) and chess mastery level. These adaptive tutorial dialogs could be especially beneficial in the case that a student does not understand a piece of learning material, as it would allow them to ask follow-up questions until the misconception is clarified.

Expanding on content, evaluation and adaptive support hold promise for advancing adaptive learning in chess instruction. Exploring these elements could lead to a more engaging, personalized and effective chess learning experience.

[4] `https://blog.duolingo.com/duolingo-max/`

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A Models

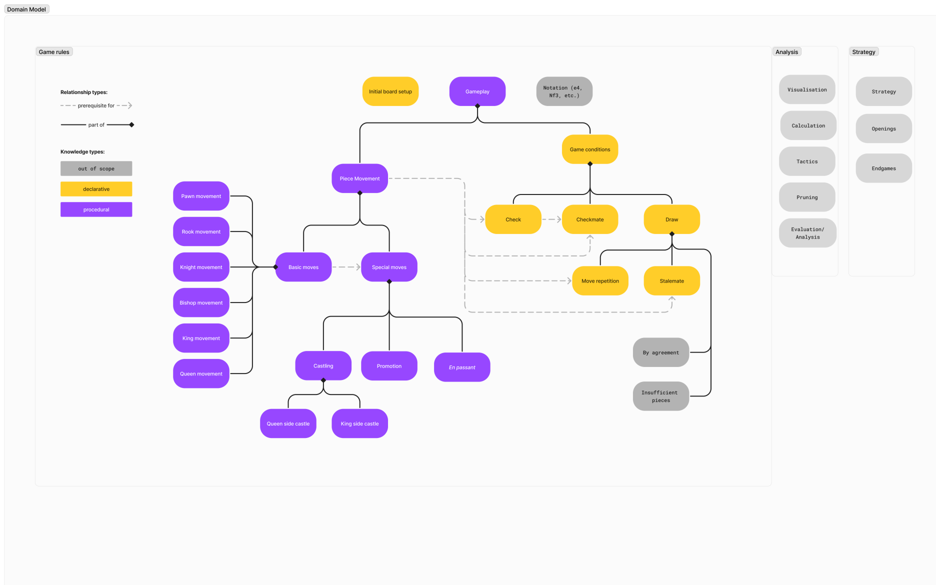

Figure 5: A domain model showing the three domains in chess. Only *Game Rules* has been expanded, showing relationship types and knowledge types between the knowledge components

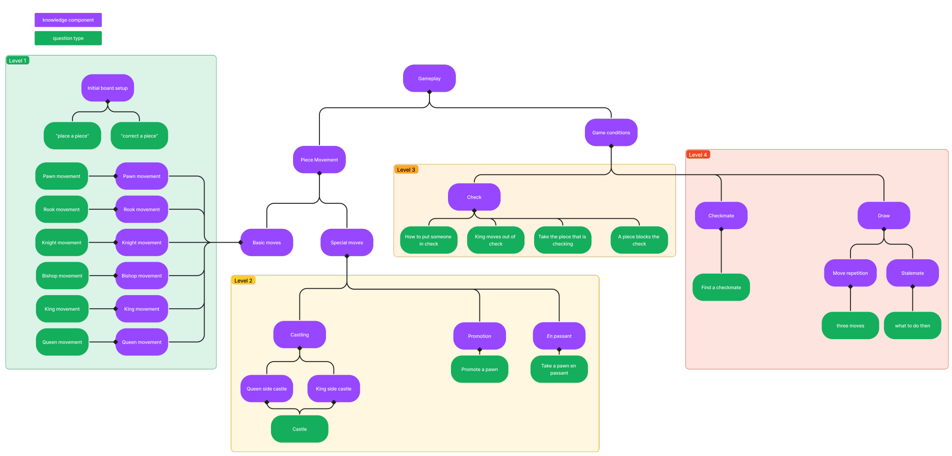

Figure 6: A content model showing how the knowledge components relate to the learning material (items). Green denotes a type of exercise, purple denotes a knowledge component.

B Interface design

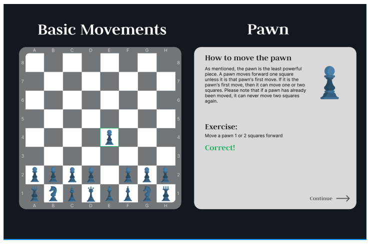

Figure 7: This task has been correctly solved.

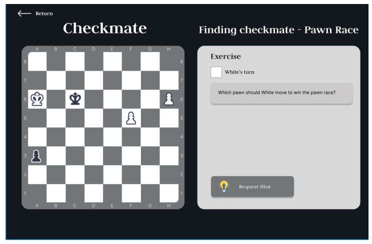

Figure 8: A task with a possible hint is presented.

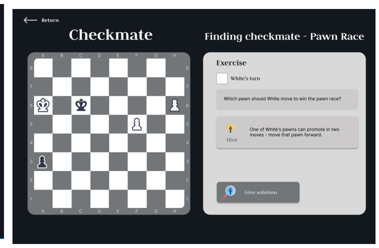

Figure 9: A hint has been given, additional solution is offered.

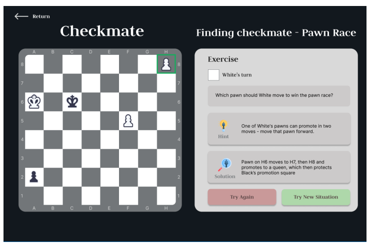

Figure 10: A solution is offered, student still has to input a move. Similar task will be offered if the student tries again.

Figure 11: The design of basic movement subsection, with several different tasks.

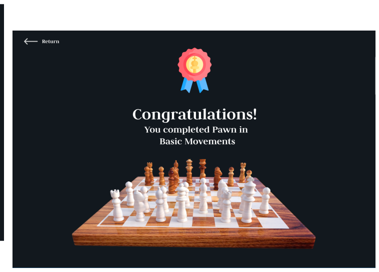

Figure 12: A successfully completed subsection.

C Basic moves

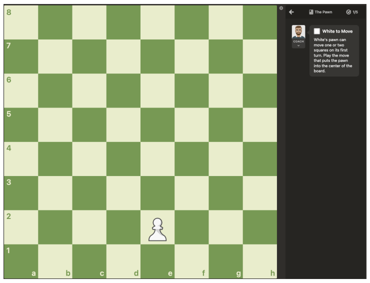

Figure 13: A board set up asking the player to move the **pawn**, image taken from Chess.com

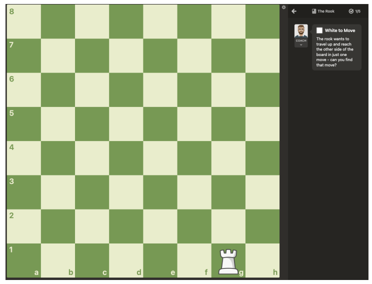

Figure 14: A board set up asking the player to move the **rook**, image taken from Chess.com

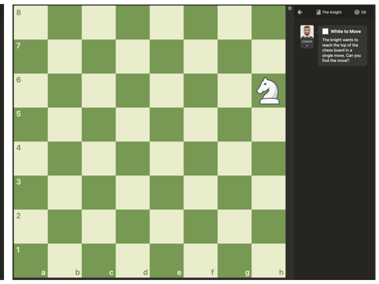

Figure 15: A board set up asking the player to move the **knight**, image taken from Chess.com

D Game conditions

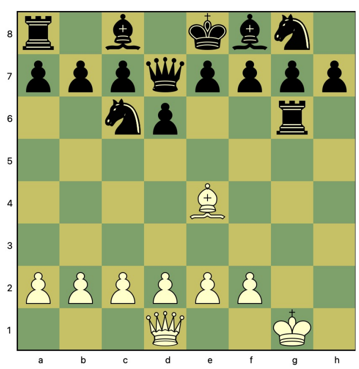

Figure 16: A board set up with three different ways to **protect from a check**, image taken from Next Chess Move

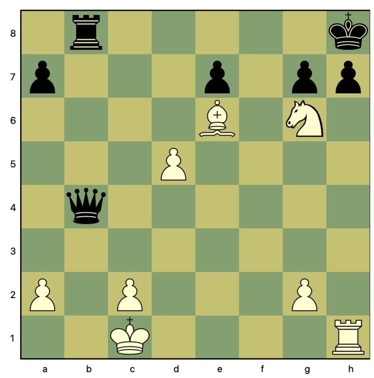

Figure 17: The black king cannot escape from being **checked**, image taken from Next Chess Move

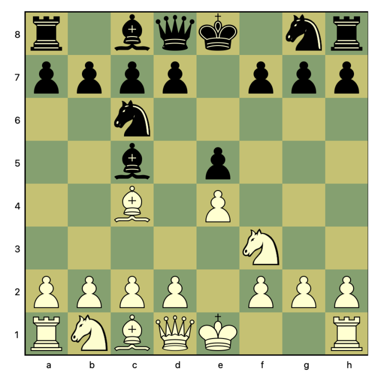

Figure 18: In this position the king can castle, image taken from Next Chess Move