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Fabian Anicker

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When machines take over: professional chess as a model case for the societal impact of superhuman AI

Fabian Anicker[1]

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Abstract

Once emblematic of human intellectual mastery, chess has become a domain where machines not only surpass human ability but fundamentally reshape the practice's social dynamics, meanings, and power structures. This paper examines the transformative impact of superhuman AI on professional chess, positioning it as an analytical model case for understanding AI's broader societal implications. Drawing on a corpus of 271 h of transcribed chess commentary, the analysis traces the shift from symbolic AI to deep learning systems, and the consequent reconfiguration of chess as a social practice. The study explores how this transformation alters the game's meaning, redistributes authority, reshapes power relations, and creates new social roles through AI's integration. These insights foreshadow challenges for fields, such as medicine or law, where AI's ascendancy may similarly redistribute authority, redefine purpose, and reshape agency.

Keywords Artificial intelligence · Agency · Transformation · Social field · Chess

In the *Perry Rhodan* pulp science fiction novel series that I read as a child, by the year 2000 humanity had colonized space and technologically modified their bodies. Computers had taken over most of the mundane tasks and surpassed humans in virtually every field. However, there was one exception: when Major Rhodan played chess against his spaceship's board computer, the power consumption skyrocketed, the systems overheated, and critical functions failed in the machine's attempt to overpower its human competitor—it was a tough battle, but Perry usually prevailed. In the better-known *2001: A Space Odyssey* from 1968, the board computer HAL-9000 demonstrates its superior intelligence by effortlessly checkmating a crew member with a sacrifice combination, showcasing its intellectual prowess but also foreshadowing later events when HAL decides to eliminate all crew members to preserve what it deems the mission's higher purpose.

These examples are illustrative of the twentieth-century imaginary of chess as a battleground between human beings and their smartest tools: computers. In the mid-century, chess was considered emblematic of human rationality, creative intelligence, and strategic foresight. As Ensmenger remarks, "a broad range of thinkers, from Goethe to Franklin, had made chess a metaphor for war, romance, politics, commerce, sports, and just about every other complex human cognitive and social activity" (Ensmenger 2012, 9; see also Reider 1959).

This high intellectual prestige of chess was one of the reasons why AI engineers imagined a chess-playing machine as an extraordinarily intelligent machine. Indeed, many of the most important figures in information technology were fascinated by making machines play chess at a time when this was mostly only a theoretical possibility: Konrad Zuse, Alan Turing, John von Neumann, and Claude E. Shannon were not only fathers of the modern computer and its information theoretical architecture but also wrote primitive algorithms for chess programs (Tomašev 2024; Keymer 2023). Another reason for the tight relationship between AI development and chess is to be found in the affordances of games, and chess in particular. Games provide a structured and calculable, yet complex environment that can be represented algorithmically. Unlike simpler games like tic-tac-toe, chess cannot be solved by calculating all possible outcomes due to its vast space of possible positions. Machines need to choose strategically which possible futures of the game they want to calculate and which ones to discard. This combination of cultural prestige, programmability of the rules,

✉ Fabian Anicker
f.anicker@hhu.de

[1] Department of Social Sciences, Heinrich Heine University Düsseldorf, Düsseldorf, Germany

and the complexity of the task made chess a central focus of AI research. Systems that were smart enough to be good at chess were imagined to be capable of doing all kinds of other tasks: "If one could devise a successful chess machine, one would seem to have penetrated to the core of human intellectual endeavor" (Newell, Shaw, and Herbert. A. Simon 1958, 320; see also Herbert A. Simon and Chase 1973; McCarthy 1990; Ensmenger 2012). It was, therefore, quite common in AI research to see the chess match of man vs. computer as an important focal point of the contest of mind vs. machine (Atkinson 1993, 85–102).

In hindsight, this idealization of chess as the pinnacle of human intellectual power and, therefore, as the ultimate frontier for what is now called "AI" seems slightly comical. Chess turned out to be one of the first complex human activities that is done better by machines without any human assistance. Currently, none of the elite players in the world could hope to win a single game against the best chess engine. At the same time, machines still struggle with more mundane tasks, such as understanding geometric relations or operating door handles. However, precisely these circumstances make chess an intriguing domain for the investigation of the effects of superhuman AI on social practices and social fields. Arguably, chess may serve as a *model case* (Krause 2021) for theorizing about the likely impacts of superhuman AI on society.

As I will show in the article, the social practice of chess was transformed thoroughly by AI. Important developments in AI like the paradigm shift from classical, symbolic AI to deep learning left profound traces not only in the technology of chess but also in the social practice of chess, its goals, its meanings, the network of recognized agents, and the distribution of power within the field.

The argument is based on a qualitative online ethnographic study of the transformation of chess. I have been interested in professional chess for approximately 10 years, and occasionally play chess online. For the last 3 years, I systematically collected information on the transformation of chess through AI, mostly by following chess forums and watching online videos on the topic. In addition to the academic literature, I draw on three types of sources:

- Forums, Interviews, and online videos on the impact of chess computers (often called "chess engines"), on the history of engines in chess, playing style, and impact of chess engines
- Presentations by grandmasters and AI developers on AI's impact on chess and on the transformation of chess through neural-net-based AI
- A text corpus of transcribed professional chess commentary on the most important tournaments—the chess world championship and the qualification "candidates tournament"—from 2013 to 2024

While most of the online ethnographic research was selectively focused on the topic of AI transformation, the corpus of chess commentary serves the purpose of getting an impression of the typical role of computers in professional chess, the role attributed to them, the typical ways to refer to them, to describe their actions and to negotiate with them about the 'right' judgment of a chess position. This serves the dual purpose to, firstly, give a diachronic overview of the transformation of chess through AI and, secondly, to examine the agency of machines in current professional chess. The selected tournaments are usually considered to be the most important ones in chess and are accompanied by capable teams of commentators (usually two or three titled players with commentary experience). For 2013, the coverage amounts to 14 h; from all other tournaments, 4 or 5 videos were randomly selected that amount to between 24 and 30 h of commentary. It was technically impossible to obtain the transcripts for the world championships of 2016 and 2017, but the other events were covered, in total covering 11 tournaments with 5 world championships and 6 candidate tournaments. The corpus amounts to approximately 271 h of transcribed video, resulting in a text corpus of 2.2 million words. The corpus was explored by doing word sketches (Kilgarriff et al. 2014) of important keywords (such as "engine", "computer", "human", "intelligent", and "machine") to see the typical grammatical and semantic function of these core concepts and to identify key passages for further analysis. The qualitative analysis of passages was oriented by two theoretical concepts to elucidate the shifting role of AI in chess: first, the conceptual difference of symbolic AI and socialized machines. This distinction refers to the way AI adapts to a human practice. Second, a theory of agency that aims to theorize the social status of chess engines in the social field of professional chess. Recent scholarship has developed a differentiated notion of "agency" to grasp the social–ontological aspects of AI emergence. In contrast to 'flat' conceptions of agency, which treat all entities on the same ontological footing (Latour 1996, 2005; Barad 2003) an increasing number of scholars has become interested in developing a more nuanced idea of agency to differentiate between different types of systems and different kinds of sociotechnical relations (Schreiber 2024; Rammert 2012; Rammert and Schubert 2023; Esposito 2022; Suchman 2023). These concepts of agency allow to conceptualize different kinds of agency and to inquire into the reconfiguration of sociotechnical relationships between humans and AI. I will especially build on a proposal by Anicker et al. that stresses the difference between weak agents, who lend themselves to an intentional interpretation (Dennett 1989; Forbes-Pitt 2011) and strong agents", who determine the agency of other systems (Anicker et al. 2024). In the following section, I will use this framework to reconstruct the developments in chess as a monopolization

of domain-specific authority by computers and thereby as a transition of chess AIs from weak to strong agency. The consequent section turns to the social repercussions of this social–ontological transformation. The third section analyzes chess as a model case to spark theory-building about the transformation of other social fields.

1 Shifting agencies: from deep blue to AlphaZero

In 1997, Gary Kasparov, by then chess world champion and widely recognized as one of the best chess players of all time, was not happy after his decisive game against Deep Blue. Indeed, he was enraged by what he deemed to be clear signs of cheating on the part of IBM. He was sure that some human player must have helped the room-filling supercomputer to choose the correct move. Did the computer cheat by taking recourse to human intuition? Was this a high-tech recurrence of the "Mechanical Turk"—a fake chess-playing automaton that impressed eighteenth-century salons by its ability to beat humans at chess (actually, it had a very talented chess player with dwarfism hiding under the table selecting the moves that the machine executed with its mechanical arm).[1] Kasparov could never prove his allegations, went on to lose his match against Deep Blue, and thereby became the first world champion to be beaten by a machine. Sociologically, the (in)correctness of the allegation is less interesting than the very fact that he could even make it. What made it plausible to claim that a computer may cheat by receiving human help?

Reflecting on this question brings out an interesting point about the architecture and the agency of late twentieth-century AI. In terms of their algorithmic architecture, chess engines at the time were what is now called "symbolic AI": computer programs that rely on explicit, human-coded algorithmic rules to achieve a desired outcome (Garnelo and Shanahan 2019). As already stated, brute force calculation is not sufficient; chess engines need some idea of what positions would be advantageous to achieve and which ones ought to be avoided, even if they are not able to calculate their way to a win. Decisions about what to discard and what to analyze further (so-called "pruning") need to be based on knowledge of what's desirable in chess.

This problem of chess's inexhaustible complexity is solved technologically by "evaluation functions". In symbolic AI, evaluation functions are carefully crafted, hard-coded algorithms. They are developed in close collaborations between professional players and software programmers. The chess masters share their knowledge about the value of pieces, the quality of certain pawn structures, and favorable strategies for attacking and defending, while the programmers translate this knowledge into algorithmic rules for assessing positions. In combination with the superior ability of machines to calculate possible states (a human grandmaster may calculate 100 positions, a machine more than 10.000.000 positions on each turn—(Tomašev 2024)), this made machines powerful enough to finally outperform even the best humans. However, the way these machines played, especially at the time of the Kasparov match, was awkward from a human perspective. Machines lacked an understanding of the deeper concepts that human chess masters internalize through pattern recognition. Certain pawn structures and piece configurations just "look bad" to experienced grandmasters, because they resemble other unfavorable structures they have seen before. Evaluation functions were continuously updated, but for a long time lagged behind human intuition due to the inability to make all the tacit knowledge that underlies intuitive judgments of humans explicit (Atkinson 1993). By the time of the Kasparov match vs. Deep Blue, computers were outcalculating human players, but not outsmarting them. The algorithmic architecture basically consisted of an imperfect representation of the parts of human chess knowledge that could be explicated and that was then supercharged with the calculative abilities of computers. Their play was often unattractive and materialistic, and because of their erratic, opportunistic style, difficult for humans to comprehend. They shone in chaotic positions that demand precise calculation while still being weak in static situations requiring long-term planning and strategic vision. This was far from a generalizable basis for intelligent behavior (Ensmenger 2012). This is why Kasparov's suspicion was perfectly plausible: adding human intuition to the IBM supercomputer could have tipped the balance in favor of the machine. Kasparov would, soon after his defeat, even try to popularize a chess variant ("advanced chess") in which teams of players and computers would play against one other, combining "human strategic guidance [with] the tactical acuity of a computer" (Baron 2023, 181). In spite of the early triumph of symbolic AI in chess, these limitations point to a fundamental problem. Symbolic AI is weak, where intuitive knowledge cannot easily be made explicit and where situations are too complex to capture the boundary conditions and success parameters in the form of explicit rules. Michael Polanyi's observation that we "know more than we can tell" (Polanyi 2009, 4) applies to chess, too. Many things excellent players know about chess cannot be translated easily into verbal or algorithmic form; as is illustrated by the following quote from the corpus: "Then you have these dark square weaknesses which maybe … I cannot

[1] Amazon's platform for online-contract work "Mechanical Turk" is aptly named as it hides real, frequently exploitative human labor under a shiny interface (see Geoghegan 2020; Crawford 2021, 63–69).

explain but still they're quite ugly just (.) on the eye" (Commentary WC 2024, game 10). The naïve underestimation of the importance of the tacit, non-explicable component of human cognition by symbolic AI optimists had precisely been the point of the philosophical and sociological critique of AI (Dreyfus 1976, 1992; Collins 2018). The success of symbolic AI in chess had mostly shown that humans are so bad at calculating chess positions that even computers with a very limited understanding of the game can beat them.

Due to this complementarity between human and computer strengths, the constellation of human and machine agency did not change dramatically after the first win of an engine over a world champion. On a social level, chess programs were pragmatically treated as agents even before they were surpassing human abilities—in fact, chess computers are the classical example of intentional systems (Dennett 1971). Intentional systems are systems that are best understood by attributing beliefs, desires and other mental states to them. Indeed, while playing against a chess computer to practically treat it as being able to have a goal (checkmate), develop "plans" (going for a kingside attack), and have "opinions" about positions (the computer evaluation) is almost the only feasible way. The contemporary chess world has broadly institutionalized the agentic nature of chess engines in the way chess players and commentators talk about chess computers. For the corpus data, according to the combined word sketches of "engine" and "computer" in the subject position, the most common linguistic construction to refer to computer evaluations is "the engine/computer says" (158 instances in the corpus)—a remarkable finding given that there is usually no linguistic output by the engines. Among the other subject–verb constructions in the text we find that the computer "thinks" (17), "suggests" (18), "shows" (25), "believes" (6), "likes" (16), or "wants" (8) certain things—for example, that certain moves or lines be played. This is clear evidence of the pragmatic attribution of agency through the imputation of mental states. This apparently wrongful anthropomorphization is simply the cognitively most efficient way of dealing with them—the vocabulary of mental states is completely justified (Dennett 1989; Forbes-Pitt 2011). The word sketches show that intentional vocabulary was consistently applied to chess computers throughout the corpus. However, a closer inspection of the context of the relevant passages reveals that, after the advent of deep learning, chess engines acquire a qualitatively different kind of agency in the chess world.

We jump to the year 2017. By now, human intervention could only make computers play worse. In the 20 years since the Deep Blue match, chess computers had great impact on chess, especially in the preparation of openings and tactical variants. Professional players routinely enter symbiotic relationships with their engines to test the soundness of their ideas and to prepare for matches against other humans. Yet, the basic principles of chess engines were still the same: they were still extremely powerful calculating machines based on explicit human knowledge. Then, after a long period of incremental change, the next big step in the history of AI in chess happened: a completely unknown team in the world of chess algorithms, DeepMind (now a part of Google), created a spin-off of its program AlphaGo (which had sensationally defeated the world's best Go player, Lee Sedol in the previous year). It had been impossible to solve Go with the method that had been so successful in chess—adding lots of brute force calculation to some explicable human knowledge about the game. This system, however, was no longer based on the paradigm of symbolic AI. Instead, the evaluation function was mostly based on deep reinforcement learning—a technique of machine learning that allows machines to generalize successful strategies by learning from previous play.

The program, named AlphaZero, had not been provided any explicit human knowledge for evaluating positions. Everything it knew about chess came from playing an enormous number of games against itself. It started with completely random moves, learning from wins and losses by adjusting its evaluation function (McGrath et al. 2022). Chess, like other games, is especially suited for deep learning, as self-play can generate the heaps of data needed for this method (Tomašev et al. 2022). Like in almost all other areas of AI, the advent of deep learning marks a watershed (Pasquinelli 2023; Cardon et al. 2018). A chess engine based on AlphaZero ("Leela Chess Zero") did not only manage to outperform the so-far best chess engine based on symbolic AI in 2019—it did so in a fashion that surprised many commentators. First, it was clearly not employing a brute force approach—calculating a thousand times *fewer* moves per minute than its competitor (Tomašev 2024). Due to its superior evaluative capacities, it was much better at choosing the variations worth calculating—a capability very similar to human intuition (Silver et al. 2018). Second, it was not bound by conventional human knowledge about chess. From a number of games played against itself that would require many human lifetimes, it extrapolated policies for finding promising candidate moves. This allowed its developers to circumvent the requirement to express human knowledge in algorithmic rules. While Deep Blue marks the superiority of computers over humans, Leela marks the superiority of deep learning over symbolic AI. AlphaZero can, therefore, be understood as a "socialized machine" (Airoldi 2022; Anicker 2023). Socialized machines adapt to an environment (in this case: the environment of chess) and learn appropriate reactions that are produced according to implicit rather than explicit rules. Just like in human socialization, machine socialization allows bypassing the bottleneck of explication: a sufficiently structured environment (and chess is, of course, highly structured) is enough to infer the optimal behavioral policies.

This independence from human chess knowledge showed in its playing style. Leela rediscovered many chess principles known to humans, but also played strategies that were completely unknown in professional chess (Sadler and Regan 2019; McGrath et al. 2022). Its style of play was less materialistic and focused on deep strategic concepts rather than tactical skirmishes. While conventional symbolic AI had proven to be the best way to automate the application of human knowledge about chess, the socialized machine AlphaZero created new knowledge about the game. It was almost immediately perceived as a "game changer" in the chess community (Sadler and Regan 2019), Garry Kasparov talked of a "knowledge revolution" (Kasparov 2019). Indeed, Leela's masterpieces could be studied just like the games of historic chess masters who had added new nuances to the understanding of the game (for the importance of chess history to the practice of chess see Fine 2013)—and humans could learn new strategic concepts by observing engine play.[2]

1.1 The monopolization of strong agency by chess computers

Since the arrival of socialized machines, there is arguably not a single aspect of chess, including the intuitive judgment of positions, in which a human could hope to compete with the best engines. Leela's and similar chess computers' human-like but far superior strategic knowledge ousted humans from their last niche of superior competence—intuitive judgment of positions and creation of long-term plans. A former world championship challenger remarks:

> "[The] computer is impossible to beat even if you use another computer against it – that's the nature of the game. I remember that like even 10 years ago I felt like if you give me just a laptop just a normal laptop and my knowledge and we can play against a supercomputer I'm absolutely not afraid. (…) nowadays even I feel like if I'm with a supercomputer I'm not sure that the supercomputer alone isn't more useful." (World championship commentary, 2024)

According to a current top-20 player, "engines cannot be corrected anymore by human players" (Keymer 2023). Players may discard engine lines that are not suited to their style or that are overly complex for humans, but they cannot objectively improve on an engine's analysis.

This shift can be conceptually grasped on a social theoretical level by observing that chess engines transitioned from being weak agents to strong agents. Early chess computers were practically interpreted in intentional terms, as being able to have plans or strategies, but enjoyed little authority over the domain of chess. Their assessments were only recognized as authoritative in very specific circumstances (e.g., positions that require lots of calculation ability). This amounts to what Anicker et al. (2024) consider "weak agency"—chess computers were objects of agency ascription rather than subjects, because engines alone only had a very limited say in which moves were socially accepted as good chess moves. However, if grandmasters and engines teamed up to analyze games, their judgment bore additional authority. However, by now this phase of complementarity (shared strong agency of humans and machines) has passed and computers are currently the only strong agents left when it comes to objective judgment of chess. Strong agents are not only recognized as actors, but they also have the power to recognize other actors' competence in a certain domain and thereby assign *domain-specific agency* to them (see Anicker et al. 2024, 315–317). Strong domain-specific agency shows itself in the capacity of an actor to recognize certain acts as adequate contributions to a domain—and exclude others. For example, usually only capable artists, art critics, and art collectors can decide what works ought to be considered "art" and who counts as an "artist", thereby controlling the ascription of agency in the domain of art. Humans will probably keep strong agency in judging what works count as art for some time, because the reasons for these judgements are in constant flux and can probably not easily be automated. In contrast, the stratification of strong and weak agencies is very pronounced in chess and clearly decided in favor of the computers. In chess, humans can of course still acknowledge other players as worthy human competitors—but they conceded all agency in the dimension of judging the quality of moves, positions, and strategy to the engines.

This has consequences for what it means for humans to play chess. The classical chess theoretician Siegbert Tarrasch could still see chess as a unity of different intellectual domains and placed it "on the borderline between game, art and science" (Tarrasch 1935, vii). Yet, the appropriation of strong agency in objective play means that human actors lose any leading role in the 'science'—part of chess, the systematic accumulation of chess knowledge. Historically, chess has partly been a battle of different 'schools' that brought forward different principles of good play and that competed under conditions of uncertainty. Chess knowledge was partially constituted through the chess public's collective memory of chess history (Fine 2013). Through the advent of engines, especially socialized machines, the professional

[2] For example, conventional chess wisdom held that it is most important to occupy the center with pawns and pieces and usually considered early flank pawn moves too slow and potentially weakening. Yet, AlphaZero and Leela loved squeezing their opponents on the flanks by pushing their pawns at the rim of the board (Sadler and Regan 2019)—a strategy that was almost immediately adopted by grandmasters and is now common practice in elite chess.

playing practice has changed dramatically. As the distance in playing strength between the best human players and the best engines is approximately the same as the distance between decent amateur players and the world champion,[3] computer preparation is essential for current professional chess: all human players become students of AI.

In current chess, competing schools have become basically irrelevant as all professional players have access to the same engines that easily surpass the collective human knowledge from the chess tradition—there is only one school left, and all the courses are taught by AI tutors:

> "(…) Just because someone's doing something that we haven't seen before or that we frown upon doesn't necessarily mean it's wrong (…). We're seeing so many new ways so many new avenues and we have to thank the silicon overlords for that one" (Candidates Tournament Commentary, 2024)

The reference to the AI systems as "silicon overlords" is only halfway ironic. Humans may be able to turn engines on or off, but once the engines are running, humans are immediately epistemically enslaved by the overwhelming superiority of the machines. This reconfiguration of agencies sidelines the epistemic matrix of traditional chess knowledge that is rooted in the study of classical playing styles and model games. One example for the devaluation of human expertise is opening play. For current professionals it has become vital to memorize as many opening lines and ideas from engine analysis as possible and take the opponent 'out of book' early. Players who are easy to predict, may see themselves confronted with "opening bombs"—like the French grandmaster who was surprised with a computer-prepared piece sacrifice 18 moves deep into his favorite opening (McGourty 2021). While some grandmasters with exceptional memory try to prepare deeper than their opponents, others deliberately play suboptimal moves just to start playing the human instead of the AI as soon as possible.[4] This is a promising strategy, as the opening skills of the computer are by now so advanced, that humans frequently only insufficiently understand their own, memorized computer preparation and make mistakes soon after the opponent deviates from the 'optimal' response:

> "It's a typical situation for [the] modern player. There is this disconnection between the (…) computer prep you have and your own understanding – and the disconnect is terrible. (…) This makes modern chess quite challenging because the preparation is really hard because your assistant, the computer, is far, far too strong for you" (Commentary, WC 2024, game 12)

Historical games by humans are, according to a top player, not "accurate" enough to be relevant to current practice anymore (Keymer 2023). "Accuracy" is a concept that was entirely unknown in chess a few years ago. The emergence of this concept is maybe the clearest indicator of the reversal of roles between humans and AIs. The accuracy of a game refers to the amount of deviation of humans from the preferred engine lines. A 100% accurate game of chess would be one in which both players do not deviate from the engines' preferences at all. The metric is used to determine how well particular games were played by human players. A "mistake" in chess is sometimes *defined* as a slight drop in the engine's evaluation, a "blunder" as a larger one. Human strength is measured by the degree of similarity with engine performance. Engine evaluations (that may change for a given position with each new generation of engines) have become the operative definition of objectivity in chess. Young players have been able to take advantage of the simultaneous devaluation of traditional human knowledge about chess (taking away some of the advantage of more experienced players) and the easy access to the most advanced chess knowledge compressed in engines. The grandmaster status is achieved by ever younger players (Bilalić et al. 2024, 5) and in 2024, 18-year-old Gukesh Dommaraju became the youngest chess world champion of all time. However, even his moves only count as objectively good, if they are confirmed by the strongest engines. To praise non-engine approved moves, commentators qualify their assertions by saying that they are good "practically speaking" (24 times in the corpus) or "from a human point of view" (5 times in the corpus). This language reflects a change of the social–ontological status of humans in chess—they no longer hold the status of epistemically relevant actors. AI systems are the only strong actors left. In the following, I will show how the social practice of chess absorbed these developments and what repercussions this had in the social field of chess.

[3] Chess playing strength is measured by Elo rating. A good amateur may have an Elo rating of 1800–2000. The highest peak rating ever achieved by a human (Magnus Carlsen) is 2882 while the estimated Elo rating of the best engine (Stockfish) is 3642 as of April 2025 (see https://computerchess.org.uk/ccrl/4040/, accessed April 2025).

[4] A study found that inexplicably to the authors elite players have tended to play *less* precisely in the past few years (Bilalić et al. 2024). This can most likely be explained by the players' strategic deviation from well-explored engine lines to confuse their human opponents with chaotic play.

2 The transformation of the social field of chess: digitization, platformization, AI integration

What happens to a social practice if AI systems systematically outperform the best humans in every aspect of this practice? How do these AI systems reshape the meaning of the practice, how are they incorporated into it, and who can take advantage of them? The developments in chess shed some light on these questions, but they also need to be taken with a grain of salt.

Chess is, from a human point of view, a fortunate environment for AI superiority. First, the game was not destroyed by AI, as no forced winning or drawing lines were found by the engines that could be easily memorized by players. Second, chess is not exhausted by its science-like epistemic aspect. Whatever human chess is about—after the advent of superhuman computers, it cannot be about playing 'the right moves' anymore. A comment from the World Championship 2024 is revealing:

> "Computers have gotten so much stronger now that they are basically flawless in all areas of the game but humans are still having fun with the game of chess fortunately, and that's why we love it" (from WC 2024)

Human players are valued for their capacity to fight, to suffer, to make mistakes, to live through tragedies—in other words: to entertain. The dramatic quality of chess as a battle of two human beings who may play brilliantly for almost the entire game, but may make a crucial mistake at any point, is a nondepletable source of dramatization. The whole field could, therefore, reorient to the emergence of AIs as the only strong agents in chess by emphasizing other aspects of the game—and has arguably even benefitted from it. The current interest in chess is very high, and recent years saw the emergence of more and more tournaments, formats, new streaming audiences and bigger prize funds. This blossoming of chess is strongly related to its digitization, the professionalization of live chess reporting and the increased dramatization of the forms of play and coverage.

2.1 The growing field of chess: AI-assisted live commentary and platformization

Traditionally, chess is not a game that is particularly suited for live coverage. A classical chess game that reaches the endgame phase can easily take 5–7 h of play with long periods of inaction when players are silently sitting at the board calculating variations. The largest part of the (small) chess public studied important games weeks after they were played by reading chess magazines that printed the moves accompanied by the annotations of a competent chess master. The intellectual enjoyment of reconstructing professional games from the printed move lists, just by calculating possible variations from a diagram position, was only open to a very select public, mostly consisting of advanced club players.

The emergence of video platforms such as YouTube or Twitch changed the playing field (see Taylor 2018). Commentators and chess players could provide video analyses of games (usually a few days after they were played), showing moves and comparing actual with possible lines on a digital board. This opened the enjoyment of elite chess games to a much wider audience. A pioneering moment in full-fledged live video streaming occurred during the 2013 World Chess Championship, which was widely broadcasted with professional live commentary.

In 2013, the commentary was done without any assistance from chess engines, even though they were already far stronger than humans in finding the best continuation. This left the commentators in a precarious position, as they were giving evaluations and possible lines that could immediately be refuted by anyone in the audience who had a machine running:

> Our primary intention with this live coverage is to reach the average player (…) but not trying to target those aficionados who [are] analyzing their games with the computer (…) what we're trying to give you is the human take and what we think at a first glance and trying to explain it in a way that hopefully most of you can understand (…) we are not uh using the engines here and we are trying to give the human perspective. (WCC 2013)

The reason for doing without engines and for emphasizing the human take was that the availability of computer assessments had a hypnotic effect on commentators and audiences alike: by broadcasting the apparently 'right' move alongside the games, chess coverage tended to become all about the ability of the players to find this move. This one-dimensionality of comparing human chess and computer lines is also pointed out in the commentary:

> if you're watching this game at your home I mean you know what is right because of your super computers (…) you can really understand what is going through these guys (…) heads you know by just switching all off your super computer (Commentary, WCC 2013)

However, a complete barring of AI in commentary frequently led to situations, where commentators, who were usually distinguished chess masters, were mis-evaluating positions or cluelessly trying to understand what was going

on, while everyone who had a machine running at home was much better informed. The 2014 chess world championship saw a solution to the problem of how to inject AI into chess coverage that became the standard solution. In a typical chess broadcast, human commentators and the audience are not shown the recommended moves by the engine. However, the video interface next to the chess board displays an "engine-bar" that shows by how much the engine prefers one side over the other—and that may swing violently when mistakes are made. Human commentators can still provide the "human stance" on a position, but are strongly guided by the computer evaluation and are prevented from going astray too far in exploring untenable ideas. This solution became the standard for chess commentary. Since then, it would be misleading to say that chess commentary is done by humans. The engine evaluation is usually the first clue commentators take to build their assessment of a position, and they immediately retract or relativize their interpretation, if the engine "disapproves" of a move. With this integration of AI into chess coverage, we have to conclude that commentary is neither done by AI nor by humans but effectively performed by a hybrid entity, the commentator-bar, that is composed of one unit that knows what's 'objectively' right but is limited to inconclusive signals, and the other that tries to decipher the board position and the computer signals to translate the game into humanly understandable categories. These increased possibilities for following elite-level chess opened chess to a much wider audience. Commentators can instantly give their engine-backed assessments and can point out mistakes or outright blunders by players. This allowed for an unprecedented dramatization of chess. Coverage, especially of larger tournaments, could easily identify critical games and react immediately to mistakes or blunders by players (including close-up shots of their faces).

The expansion of the audience of chess through visualization and the dramatization of chess coverage were driven and harnessed by newly emerging chess platforms. These typically combine an online-pairing system for players, proprietary online tournaments for elite players (with exclusive rights of coverage), and commentators who work for the platform. Especially the currently most important platform, Chess.com, has pushed for changing formats of chess to make it more adaptable to the viewing habits of an expanding audience that watches chess for entertainment purposes (see Majhi 2023). New tournaments with considerable prize funds were started that experiment with ways to mold chess into even more dramatic, viewer-friendly formats. Among these are:

- Shorter time controls (rapid and blitz chess), so that periods of inaction are as short as possible, more mistakes and, therefore, more decisive results happen
- Larger teams and different types of commentators—some elite player for the content, others for the dramatization and entertainment
- Tournaments without boards where elite players play chess on their computer—trying to position chess as "esports"
- Chess variants like Fischer Random chess that eliminate opening preparation and promise more entertainment due to more mistakes
- Additional features of dramatization like the provision of a "confessional booth" that players can enter during the game to broadcast their current evaluation of the game and their plans or live heart rate monitors, that visualize the inner tension of the players to the audience.

The success of these strategies and the growing audience for chess has led to an ongoing rivalry between newer actors like the platform Chess.com, other emerging organizations, including venture capital firms, and the traditional world organization for chess, FIDE. While FIDE has stuck to more conventional formats of chess, Chess.com has launched competing formats that have a prize fund comparable to the most important FIDE tournaments and even an alternate world championship (renamed to "global championship" after pressure from FIDE). The power struggle between the established chess organization and its new competitors is maybe best exemplified by the decision of the world No 1 player, closely affiliated to Chess.com, Magnus Carlsen, to not defend his title in the classical FIDE world championship after FIDE declined to change the rules (Carlsen had demanded more games and faster time controls).These developments closely align with a common field-theoretical hypothesis that incumbents will aim to preserve existing field structures, while challengers aim to transform the field to their advantage (Fligstein and McAdam 2015; see also Bourdieu 1996).

These new opportunity structures in chess due to the emergence of new platforms, a growing audience, and associated advertisement opportunities have for some professional players even tipped the balance, redefining themselves as "content creators" rather than chess professionals. Apparently achieving more income from streaming than from winning tournaments, one of the world elite players in the candidate tournament—the highly prestigious qualifying tournament for the world championship—even stated that he "would not play" if it were not for the possibility to do recapitulation videos for his audience after his games (Interview with elite player H.N., Candidates 2024, Round 4).

The possibility to achieve revenue from streaming and content creation (see Johnson and Woodcock 2019) allows for the emergence of new positions in the field: commentators who are not particularly capable chess players themselves but who specialize in the AI-assisted presentation of

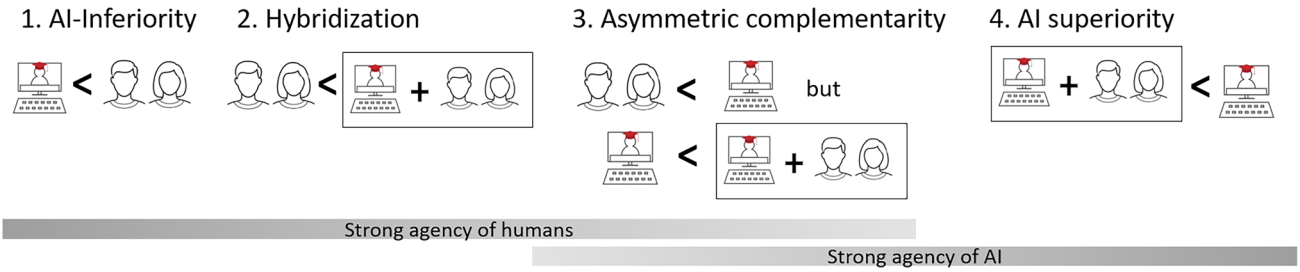

Fig. 1 Phase model of AI transformation

games. Their expertise is less in chess but rather in using engine analysis of games for dramatic storytelling. Due to AI, they can compensate for their lack of chess understanding and specialize in an entertaining and engaging presentation. For beginners and amateurs, all these developments have led to an abundance of easily available chess content and chess knowledge. Platforms provide quick access to human opponents in similar playing strength, online courses and postgame AI analyses of games that allow steeper learning curves.

If we take these different field positions and the resources of the actors into account it becomes possible to see why AI superiority is, for most practitioners of chess, not only subtractive story about the loss of human authority over a practice domain, but also a success story about an expanding field. Quite in line with typical arguments from field theory, this growth of the field and the economization of chess led to a higher relative field autonomy (more resources allow more people to live from doing chess), but simultaneously chess took up logics from marketization and entertainment to cater to an audience that is no longer almost exclusively composed of experts (see Bourdieu 1983, 335–339).

3 AI transformation of social practices and fields: some tentative generalizations

At first glance, it may be tempting to draw an optimistic conclusion from the transformation of chess. The arrival of superhuman AI has profoundly changed the game, but it did not lead to the sidelining of human actors that is sometimes feared. Chess seems to show how human actors can find new niches and invent new social roles even if they lose control over the apparent core competency of a domain. But is chess really a typical case—and if not: how can it serve as a model case for the transformation of society through superhuman AI?

A model case in my sense neither implies normative claims about how society *ought to* react to superhuman AI nor the oversimplistic assumption that the AI transformation in all other fields will look *similar* to chess. It is a case that is a seed for theory building, because it is central in understanding the larger picture of AI transformation. Regarding the central role of chess, I would like to defend two claims. First, chess is one of the first cases of thorough and socially established AI superiority in a practice domain. Studying chess helps us transform the topic of AI superiority from an object of futurological speculation to an area of empirical of study. We may observe stages of the process of AI transformation that are only rudimentary in other domains.

Second, I propose to see chess as a case that is not "representative" or "typical" for other social fields but rather a case that is especially informative for finding *theoretical relationships* (Small 2009, 17–19; see also Mitchell 1983, 194; Pacewicz 2022). Chess stands out as a striking example, because its transformation through AI is very deep and has clearly visible effects. Also, due to its special relation to AI research and its rapid AI adaption in each phase of AI, we can observe longer processes that led to its current state. This makes it easier to infer causal processes and establish functional relationships that may well hold in other domains. Not every field will be like chess but fields with similar conditions will probably see similar trajectories.

3.1 Some theoretical generalizations about AI superiority

The analysis of chess shows that AI superiority is not necessarily characterized by the displacement of human actors. It should rather be understood as a change in the relations of practical recognition, especially those authority relations that determine *domain-specific agency* (Anicker et al. 2024). This opens methodological avenues for the empirical research of AI transformations in other fields: AI's relation to the existing human and non-human actors in a field can be determined by tracking the type of agency it exerts in the field and the authority it has in judging other actors' performances. While early symbolic AIs had *weak agency*, because it was treated as an intentional agent but enjoyed very limited authority in judging human performances, after the advent of deep learning the chess world saw a monopolization of *strong agency* by AI. The new AI systems

overhauled the epistemic order of chess and monopolized the judgement over what counts as a good move and who counts as an accurate player. The following graph distinguishes four ideal-typical phases of the relation of human and AI agency that may be used to locate the state of the AI transformation in other fields (Fig. 1).

In the first phase, AI in a given field is so inferior in its competence that it is hardly useful. Only when humans using an AI achieve superior results to those that do not it starts to impact a practice and the social field embedding it. Chess entered this phase of *hybridization* already in the 1980s and 1990s when chess computers helped analyze openings or chaotic positions for players. From this point on, engines started entering the field of professional chess as a new type of actor that had to be accommodated into the practice. Thus, AI can already be transformative for a field without reaching general human-level competence (see also Gruetzemacher and Whittlestone 2022). While the 1997 match marked the transition to computers being superior to humans, the phase from then until the advent of deep learning may best be described as *asymmetric complementarity*. While computers were better at chess overall and their judgement counted, humans had enough intuitive and strategic knowledge that was not captured in the hard-coded algorithms of symbolic AI to contribute. The mere fact that machines are better at fulfilling core tasks of a certain practice domain does not lead to an immediate crowding out of human beings, as long as they can substantially augment the abilities of the computer (e.g., by providing types of know-how that cannot be automated easily). This is a phase of shared strong agency between humans and computers. Only with the emergence of self-socializing machines, the neural-net-based algorithms, chess left this phase and moved to a complete domination of AI. This phase of *AI superiority* is characterized by the fact that human interference in a machine's performance cannot improve its results anymore. In current chess, AIs remain the only recognized agents when it comes to playing correct chess and judging the objective merits of moves. In this phase, AI absorbs the core competencies of the practice and becomes the sole guardian for "doing things right". Human competence is devaluated and humans lose control over this objective dimension of the practice domain. Yet, if there are aspects of the practice that are still better done by humans, this can lead to a specialization and division of labor between humans and AI. AI monopolizes the core competence (in our case: the epistemic judgment what counts as objectively correct chess), while humans may successfully specialize in other aspects of the practice that are (also economically) valued by the audience (here: storytelling, dramatization and emotional relation to the game).

The phase model of AI superiority shows that the different phases of AI development and implementation can be analyzed as different *constellations* of human and machine agencies and conceptualizes AI superiority in sociological terms: as the monopolization of strong agency. This allows for a more fine-grained analysis of the emergence of AI superiority and allows to see that human participants in a practice are confronted with different challenges in each phase. A second theoretical concept that proved helpful in analyzing the AI transformation is the assumption that practices are embedded in social fields that provide different opportunities to actors. A differentiated analysis of the field positions of professionals (elite chess players), central organizations, semi-professionals (commentators), and the audience that forms the economic basis of the domain (wider chess public and amateurs) shows that actors are affected differently. A relative loss of power (viz machines) is compatible with absolute gains in resources and opportunities for most actors in the field. Whether this holds for other domains crucially depends on case characteristics. I will analyze some of the particular conditions of chess in the next section.

3.2 The (model) case of chess and careful abstraction

The theoretical generalizations about the transition to AI superiority in the previous section are mostly on a conceptual level, recommending a certain understanding of AI superiority and certain tools to investigate it empirically. Moving beyond these social–theoretic claims to expectations about the likely pathways of AI transformations in other practice domains is much riskier. Monika Krause warns us that many general theories in sociology are problematic, because they insufficiently reflect their being abstracted from quite peculiar cases (Krause 2023, 2021). There is always a danger of mistaking idiosyncratic case characteristics for general patterns. And, indeed, there is no reason to believe that chess is particularly "representative" or "typical" for other practice domains in a statistical sense (for the irrelevance of representativeness for case studies see Small 2009). Chess shows us some general dynamics of the process of AI transition *in conjunction* with contingent conditions of chess as a particular case. There is no mechanistic procedure by which we can tell general trends and contingent conditions apart. Yet, there is certainly a chance to generalize more carefully by taking the specific characteristics of chess as a model case into account and evaluate their likely impact on its particular transition to AI superiority.

First of all, the practice of chess is, as we have seen, highly conducive to automation. Its goals and skillsets are clearly defined, it offers a regular and rule-bound environment, and it provides an unlimited amount of high-quality data for machine learning. There is certainly room for reasonable scepticism whether other practices will see a similarly strong impact of AI. However, even though there is no

guarantee that other domains will follow chess in transitioning to AI superiority, this is generally expected within the AI research community (Gruetzemacher et al. 2020) and it seems reasonable to assume that AI will, in the near to medium future, play a significant role in various human practices that are far higher-stakes than chess, even if these fields may not reach full AI superiority (Acemoglu et al. 2022). One can think of medical fields, such as drug discovery, personalized medicine, cancer screening and predictive health analytics (Topol 2019; Kourou et al. 2015), healthcare (Silcox et al. 2024), stock trading (Hendershott et al. 2011), finance (Benedetti et al. 2019), traffic management, or data analysis (Davenport and Harris 2007). Given that AI transformation is already happening in these and other fields—will they look similar to the development of chess?

The answer depends crucially on certain core features of human practices. In chess, the mere fact of AI superiority did not lead to the displacement of human participants—but this finding should certainly not be generalized to other fields AI transformations. Chess is a practice in which human participation is valued for its own sake. Humans continue playing chess, because it is enjoyable, not because they are good at it. Its audience cares less about optimal play than about the dramatization of human effort—an experience that is even heightened by the real-time awareness of the difference between 'correct' and actual move. In other fields such as medicine or science, however, we would be much less willing to "let humans play", if this comes at the risk of inferior results. In radiology, what matters most is the accuracy of diagnosis, not whether the diagnostician is someone we can identify with. The key distinction appears to be whether human participation in a practice is valued for its own sake rather than for producing an outcome or product. More precisely, it depends on whether valuing a practice requires a *rich intentional interpretation* of its main actors. Professional chess players are unlikely to be replaced entirely by AI, because a significant part of the game's appeal lies in our cognitive and emotional identification with the human competitors—*we* care about their play, because we know and see that *they* care. In contrast, the intentionality we attribute to chess engines is rather thin: we acknowledge that they "want" to win and "know" how to play, but we do not believe it genuinely matters to them whether they win or lose. This importance of rich intentionality as an integral part of the practice may extend to fields, like art, sports, religion, friendship, or love. Practices that are structured by a cultural preference for rich intentionality can probably transition to AI superiority without human beings being sidelined. Practices and fields that are mostly valued for their outputs will find it much harder to find a central place for human agency.

A second characteristic that probably influenced chess's path of AI transition is the existence of *clear and socially recognized criteria for assessing skill*. There is no disputing the objective superiority of AI in chess, because the Elo-rating system tracks performance reliably and whoever has doubts can simply play against a computer and experience its dominance firsthand. Many other practices, however, lack such definitive performance criteria and thereby grant humans more space to resist the encroachment of AI—at least temporarily. While skill in chess (but also in stock trading) can be measured well, skill in journalism or software development is harder to evaluate objectively. In these more ambiguous domains, humans may benefit from a preference for human agency over artificial alternatives (Dillion et al. 2025; Aharoni et al. 2024). Consequently, the monopolization of strong agency by AI may tend to proceed more slowly, as people strategically emphasize AI's weaknesses and may redefine the meaning of the practice in ways that place human contributions at its center. Fields with fluctuating or very weak objective rules for performance assessment like poetry or other forms of high art may resist complete AI dominance permanently.

4 Conclusion

AI superiority has transformed the social meaning of chess and led to a reshuffling of actors and power. The AI-assisted removal of knowledge barriers that barred less capable chess players from enjoying chess games helped to grow the audience of chess and, therefore, the overall economic opportunities to support careers for chess players, chess streamers, and commentators. Professional chess players saw a devaluation of traditional chess knowledge by AI and ceded all epistemic authority to AI, but they benefit from increased economic opportunities and higher public interest in chess. While loosing its status as a symbol for the pinnacle of human intellectual achievement, chess commentators and streamers pushed an understanding of chess as an entertaining and dramatic sport that benefits from dramatizing the difference between 'objective' chances and actual human play.

As a theory-building model case, chess provides an example of a clear and thorough transition to AI superiority. It may work like a prism that sheds light on characteristic patterns of transformation in other social fields that may be confronted with superhuman AI in the future—e.g., stock trading, parts of medicine, certain branches of mathematics, computer programming, data analysis and many more. Those theoretical tools—the relational theory of agency, assumptions about practice characteristics, and field structure—that proved useful for analyzing chess may also be helpful for understanding other domains transformed by AI. It is futile to speculate which human practices will be affected by superhuman AI and how long this may take, but many are already in a stage, in which AI-assisted humans

outperform unaided competitors. That some will transition from human superiority to AI superiority in the medium to near future seems highly plausible given the rapid progress of AI in many fields.

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