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Artificial intelligence and the changing sources of competitive advantage

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Abstract

Research Summary: We apply a resource-based view to investigate how the adoption of Artificial Intelligence (AI) affects competitive capabilities and performance. Following prior work on using chess as a controlled setting for studying competitive interactions, we compare the same players' capabilities and performance across conventional, centaur, and engine chess tournaments. Our analysis shows that AI adoption triggers interrelated substitution and complementation dynamics, which make humans' traditional competitive capabilities obsolete, while creating new sources of persistent heterogeneity when humans interact with chess engines. These novel human-machine capabilities are unrelated, or even negatively related, to traditional capabilities. We contribute an integrated view of substitution and complementation, which identifies AI as the driver of these dynamics and explains how they jointly shift the sources of competitive advantage.

Managerial Summary: AI-based technologies increasingly substitute and complement humans in managerial tasks such as decision making. We investigate how such change affects the sources of competitive advantage. AI-based engines' adoption in chess allows us to investigate competitive capabilities and performance in human, AI, and hybrid settings. We find that neither humans nor AI in isolation explain performance differences in the AI and hybrid settings. Instead, a new decision-making resource emerges at the human-AI intersection, which drives performance but is unrelated or even negatively related to humans' original capability. Our results document how AI adoption changes the sources of competitive advantage and, in turn, requires managers to develop new capabilities to stay relevant in an AI-based competitive landscape.

KEYWORDS

artificial intelligence, competitive behavior, decision making, firm capabilities, resource-based view

1 | INTRODUCTION

Artificial intelligence (AI) enables machines to perform cognitive functions previously only associated with human minds (Rai, Constantinides, & Sarker, 2019). Management scholars surmise that AI changes the sources of competitive advantage (Daugherty & Wilson, 2018, p. 214; Davenport & Kirby, 2016, p. 204), but offer contrasting views on how this change occurs. Some assume that AI substitutes humans' cognitive capabilities (Balasubramanian, Ye, & Xu, 2021) when, for example, machines replace bankers in equity investment (Noonan, 2017), stand in for managers in talent recruitment (Chamorro-Premuzic, Polli, & Dattner, 2019), and take over from physicians in medical treatment (Blakely, 2020). Others suppose that AI complements rather than substitutes humans' cognitive capabilities (Murray, Rhymer, & Sirmon, 2021) when bankers, managers, and physicians collaborate with machines on equity investments (Marriage, 2017), talent recruitment (Hook, 2017), and medical treatments (Topol, 2019).

The resource-based view (RBV) describes the theoretical mechanisms through which resources are associated with competitive advantage (Barney, 1991). It depicts humans' cognitive capabilities as an important source of advantage because these capabilities are heterogeneously distributed, limited in supply, and difficult to imitate. Such capabilities thus lead to performance differences when managers use them for strategic decision making and problem solving (Helfat & Peteraf, 2015; Kunc & Morecroft, 2010). The RBV's predictions regarding how AI's adoption affects competitive advantage in decision making are, however, inconclusive. When AI substitutes humans' cognitive capabilities, the RBV expects the advantage that these capabilities provided to erode (Peteraf & Bergen, 2003). This is because, as a technology resource, AI has close to zero marginal reproduction costs and few imitation barriers (Brynjolfsson & McAfee, 2014, p. 31). Conversely, if AI complements humans' cognitive capabilities, the RBV expects it to generate advantages (Argyres & Zenger, 2012), because, as a widely applicable technology, AI enables the creation of unique bundles of previously unrelated resources—such as physicians' expertise and AI's machine prediction (Agrawal, Gans, & Goldfarb, 2018, p. 108).

These inconclusive predictions emanate from AI's unique characteristics. Contrary to prior technologies, AI enables machines to learn and act autonomously (Balasubramanian et al., 2021), which, in turn, allows these machines to interact with humans in decision making and problem solving (Murray et al., 2021). Consequently, AI has the potential to *both* substitute *and* complement humans' cognitive capabilities (Raisch & Krakowski, 2021). Prior RBV research has documented the co-occurrence of substitution and complementation when organizations use both familiar and new technologies (Stadler, Helfat, & Verona, 2021). In the case of AI, however, the technology and its novelty remain constant but substitution and complementation are still expected to co-occur. This raises pressing questions about the interrelations between substitution and complementation, drivers of these interrelations, and possible outcomes. In this article, we address these lacunae by exploring how AI is associated with the substitution and complementation of humans' cognitive capabilities through technology resources and assess the impact on the sources of competitive advantage.

Since we have no clear a priori theoretical guidance, we take a question-based approach (Berry, Kaul, & Lee, 2021) to juxtapose the theoretical cases for AI-driven substitution and complementation. We explore these dynamics abductively in the context of chess competitions, which provides a controlled setting for studying cognitive capabilities and competitive interactions (Bromiley, 2005; Knez & Camerer, 1994; Powell, 2003). This setting offers the unique possibility to clearly identify and directly compare the sources of competitive advantage across conventional (i.e., humans play against humans), centaur (i.e., humans with engines[1] play against other humans with engines), and engine chess (i.e., engines play chess autonomously, but humans select, tune, and govern these engines) while keeping the context (i.e., the chess rules and the tournament formats) stable. This limits the risk of confounding, which is high in real-world business settings where contexts are unstable, and emerging substitution and complementation alter competitive interactions and their outcomes.

On analyzing the chess data, we find that, in a previously human-only strategic decision context, AI adoption triggered interrelated substitution and complementation dynamics between humans and machines. First, we find evidence for substitution when chess engines enter the competition, which erodes the previously positive association between humans' chess playing capabilities and their chess performance. Chess engines show no corresponding performance effect, since they lack supply restrictions and face few imitation barriers. Second, complementation emerges when humans interact with engines while playing centaur chess, and when selecting, tuning, and governing engines in both centaur and engine chess. These human capabilities to complement machines create new persistent performance differences, but are unrelated, or even negatively related, to humans' traditional chess playing capabilities.

Our explanation of these findings is that AI has a dualistic effect that shifts the sources of competitive advantage. Although AI substitutes humans' traditional domain-related cognitive capabilities with machines' abundant computational capabilities, thus eradicating the extant sources of competitive advantage, it simultaneously enables complementation when humans use previously domain-unrelated cognitive capabilities to augment machines' capabilities, thus creating new persistent sources of competitive advantage.

We contribute to the strategy literature by moving beyond the discussion of either substitution as an act of destroying advantage (Peteraf & Bergen, 2003) or complementation as an act of creating advantage (Argyres & Zenger, 2012) toward an integrated view of these two acts occurring together. Moreover, we identify AI as the driver of these interrelated resource dynamics. Developing these insights is important, not only because they help integrate previously disparate RBV perspectives, but also because they are practically relevant. If substitution through AI provides opportunities to create new advantages from complementary human–machine capabilities—as was the case in our chess sample—then firms might survive disruption and realize superior profits nurturing these

[1]Engines are AI-based machines that analyze chess positions and determine the best possible moves.

"augmentation skills" (Raisch & Krakowski, 2021, p. 202). We therefore conclude our article by discussing our findings' applicability in business contexts and their practical implications.

2 | CONCEPTUAL BACKGROUND

We draw on prior RBV research focusing on new resources' emergence and their relationship with existing resources (Argyres & Zenger, 2012; Levinthal & Wu, 2010; Peteraf & Bergen, 2003; Polidoro & Toh, 2011). This work distinguishes between resource substitution and complementation, with substitution eliminating a competitive advantage when new resources with abundant availability replace traditional ones by providing the same functionality; and complementation creating a competitive advantage when traditional resources and new heterogeneous ones are integrated to form unique resource bundles.

When applying these insights to the AI context, we also rely on prior work describing AI as a new technology resource of strategic importance that can learn and act independently of humans (Agrawal et al., 2018; Brynjolfsson & McAfee, 2014; Choudhury, Starr, & Agarwal, 2020; Raisch & Krakowski, 2021). Humans and AI differ in the ways they process information to create domain expertise, since AI can process much larger quantities of information at a higher speed and accuracy, whereas humans rely on information processing shortcuts, which could cause potential errors or biases, but also make humans more versatile in scarce or complex information environments. From an RBV perspective, these different properties suggest interrelated substitution and complementation relationships, which we explore next.

2.1 | Substitution through AI

Substitution is an important RBV construct (Peteraf & Bergen, 2003; Polidoro & Toh, 2011), which centers on resources replacing others providing the same functionality (Levinthal & Wu, 2010). Resources with low fungibility are specific to one domain, whereas those with high fungibility can be applied widely. Furthermore, scale-free resources can be allocated across domains without additional costs, while those that are not scale free have opportunity costs. While humans' general cognitive capabilities have a high fungibility, advantage-generating resources, such as humans' domain-specific cognitive capabilities, have a low fungibility and are also not scale free (Helfat & Peteraf, 2015). This constrains these capabilities' use to related domains (Montgomery & Wernerfelt, 1988) because their application for substitution in unrelated domains would require extensive learning from experience, coming with significant economic costs that quickly exceed any potential benefits (Helfat & Peteraf, 2003).

The adoption of AI in a competitive domain could trigger substitution. Currently, AI is used widely to automate predictions regarding strategic decision making and problem solving tasks, which, traditionally, only humans could do by relying on their cognitive capabilities (Choudhury et al., 2020; Shrestha, Ben-Menahem, & von Krogh, 2019). Unlike humans, machines have quasi-unlimited information processing capacity, often providing better predictions than humans do (Raisch & Krakowski, 2021). This is evident, as AI-based machines now match or surpass physicians' cancer diagnosis and treatment recommendations (Jiang et al., 2017), human resource experts' prediction of candidates' future job performance (Chamorro-Premuzic et al., 2019), product developers' creation of design alternatives (Verganti, Vendraminelli, & Iansiti, 2020), and business angels' venture investments (Blohm, Antretter, Sirén, Grichnik, & Wincent, 2021). AI resources' accuracy and abundance are therefore likely to reduce human prediction capabilities' traditional value (Ahuja, Coff, & Lee, 2005), or even make these capabilities obsolete (Agrawal et al., 2018, p. 80).

While this prior work offers strong foundations, several open questions remain on how substitution occurs in an AI context. First, technical limitations hinder machines from taking over decision making or problem solving tasks entirely (Raisch & Krakowski, 2021). For example, prediction is only one component of decisions, which also require tasks like setting objectives, selecting data, exercising judgment, and taking action (Shrestha et al., 2019). While substitution through AI may occur, it is unlikely to capture AI-driven dynamics exhaustively. Second, the nature of substitution may differ when machines replace humans. For example, prior studies described the substitution of resources between related domains (Levinthal & Wu, 2010; Peteraf & Bergen, 2003), because humans' domain-specific cognitive capabilities are difficult to transfer to unrelated domains. While these arguments apply to humans and their cognitive capabilities, they may not apply to machines' corresponding capabilities, which AI scholars suggest are widely applicable across domains (Agrawal et al., 2018, p. 2) and scale free (Brynjolfsson & McAfee, 2014, p. 31). Extant research has little to report on how substitution might occur across previously unrelated domains, such as AI technology versus medical care, talent recruitment, product design, and venture capital. Consequently, the first question to explore is whether and how AI substitutes humans' advantage-generating cognitive capabilities.

2.2 | Complementation through AI

The RBV also explores how complementation creates a competitive advantage by developing unique resource combinations (Newbert, 2007). Actors with "the intent of creating a new competitive advantage" (Sirmon, Hitt, & Ireland, 2007, p. 282) integrate existing resources and new ones into resource bundles that are "uniquely complementary" (Argyres & Zenger, 2012, p. 1648). Complementary refers to resources that are supermodular in the sense that given two resources, A and B, more of A makes B more valuable (Milgrom & Roberts, 1990). To be *uniquely* complementary, these resources not only have to be supermodular, but also unrelated. Such unrelatedness ensures that the resulting resource bundles are novel and scarce, providing a foundation for sustainable heterogeneity (Argyres & Zenger, 2012). Conversely, resources within a competitive domain's reach may be complementary, but their proximity usually results in resource abundance and few supply restrictions.

Extant work provides different views of how AI adoption leads to complementation. One view describes the partitioning of tasks into subtasks, which are partly taken over by AI-based machines and partly remain with humans (Brynjolfsson & McAfee, 2014, p. 92; Raisch & Krakowski, 2021). For example, physicians delegate medical diagnosis to AI-based machines, while focusing on patient treatment (Talby, 2019). Another view suggests human–machine interaction in the same tasks (Agrawal et al., 2018, p. 66; Metcalf, Askay, & Rosenberg, 2019). For example, physicians can complement machines' medical diagnosis by using their contextual understanding to spot machine biases (Talby, 2019). Both views stress humans' and machines' distinctive capabilities, with their complementary strengths and weaknesses. Specifically, humans can complement machines' superior prediction capability by relying on their unique capabilities, such as creative ideation, large-scale contextualization, and social interaction (Brynjolfsson & McAfee, 2014, p. 202). For example, human resource experts can do so by assessing candidates' cultural fit and convincing them to work for their firms (Hook, 2017), while product designers do so by making sense of customers' problems (Verganti et al., 2020), and portfolio managers by providing creative investment ideas and selling them to investors (Marriage, 2017). Davenport and Kirby (2016, p. 204) therefore speculate that such human augmentation capabilities, which complement AI-based machines' capabilities, could be a new source of competitive advantage.

While providing valuable insights, this prior work still leaves questions on complementation in an AI context unanswered. First, prior RBV studies described how humans purposefully acquire new capabilities to complement their existing ones (Argyres & Zenger, 2012). However, AI as a novel technology with the ability to learn and act independently might not follow these predictions. For example, Shrestha et al. (2019) warn that combining human and machine capabilities in an AI context could also lead to negative complementarities. Second, prior research studied substitution and complementation in different contexts (Hess & Rothaermel, 2011; Stadler et al., 2021), providing little insight into how they are interrelated. In the case of AI, scholars described these resource dynamics as occurring in the same context (Brynjolfsson & McAfee, 2014, p. 134f; Raisch & Krakowski, 2021). For example, Talby (2019) showed that AI-based machines both substitute and complement physicians. Two additional questions to explore are therefore whether and how AI complements human capabilities with technology resources; and how such complementation relates to substitution effects.

3 | EMPIRICAL CONTEXT, DATA, AND METHODS

We embrace the variety of prior theoretical accounts and anecdotal observations by utilizing an abductive approach (Sætre & van de Ven, 2021). Specifically, we examine how the adoption of AI in chess competition is associated with the substitution and/or complementation of human capabilities through technology resources, and assess its impact on the sources of competitive advantage. Prior RBV studies used chess competition as a metaphor (e.g., Bromiley, 2005; Wernerfelt, 1995) and as an empirical context (e.g., Knez & Camerer, 1994; Powell, 2003). Building on seminal studies of chess competition (Chase & Simon, 1973; de Groot, 1946), these researchers explored how human capabilities, as heterogeneously distributed cognitive resources, contribute to performance differences. Since other resources (such as the time and the chess pieces) are distributed equally, the differences between competitive actors' chess playing capabilities largely explain performance heterogeneity. Chess is, therefore, a relatively "clean" and well-observable context for competitive interactions, which is often used to provide insight into strategic actions and outcomes that extends beyond the chess context (Gobet & Simon, 1996).

Studying competitive strategy in a chess context has certain limitations. The most important of these is that chess is a well-defined game with a lower degree of uncertainty than most strategic actions in business settings (Bromiley, 2005). However, similar to business settings, chess exposes humans to problem situations under uncertainty in which their cognitive limitations prevent them from exploring alternative courses of action comprehensively (Bromiley & Rau, 2018). The advantage of chess is that it provides a controlled context in which actors' capabilities, as well as the quality and sequence of their actions, are consistently identifiable and comparable (Cowen, 2013, p. 69f; Simon, 1972, p. 165ff). Such a controlled context is generally unavailable in business contexts, where each strategic action is essentially unique. Furthermore, the high levels of noise, as well as imprecise identification, limit researchers' ability to derive valid and generalizable theoretical insight from these contexts.

We use the controlled chess context to compare the same players' capabilities and performance across conventional, centaur, and engine chess tournaments. In conventional games, human players rely exclusively on their chess playing capabilities, whereas in centaur games they may consult a chess engine at any time during the game to evaluate the board positions and moves, and in engine games, in turn, the engine plays chess without a human player's involvement (Cowen, 2013, p. 77ff). In centaur and engine games, humans also intervene by selecting, tuning, and governing the chess engines (Ensmenger, 2012; Suba, 2010, p. 29f).

3.1 | Data sources and sample

We collected data in 2017 from chess tournament organizers' databases covering all the official centaur and engine tournaments that had been held at this time.[2] We therefore have full population level data. Chess players identified as participants in these tournaments constitute our sample's focal players. We identified players by their names or, if they used aliases, conducted extensive research to reveal their identities. Subsequently, we focused on *Fédération Internationale des Échecs* (FIDE) members, which allowed us to gather additional player data. We then collected data on all the official conventional chess tournament games involving these players between 2000 and 2017, using the *ChessBase Mega Database 2018*.[3] We therefore observe the same chess players across the three tournament formats, having initially identified them through the centaur and engine formats. This sampling procedure yields a sample of 112 unique players from 39 chess federations participating in 3,281 tournaments.

3.2 | Dependent variables

Our primary measure of chess performance is the *game result*, namely a win, loss, or draw from the focal player's perspective (with a draw as a baseline outcome).[4] Our secondary measure is the ply[5] quality, which we assessed using the chess engine *Stockfish 10* as a benchmark.[6] Two count variables, *positive plies* and *negative plies*, denote the respective sums of positive and negative plies that the focal player made in each game (Matanovic, 2008).[7] Finally, we conducted supplementary analyses, using the propensity for games to end in a *draw* as a binary variable, and assessing the *game length*, a count variable that measures the total number of plies in a game.

[2]Free Internet Correspondence Games Server ("FICGS") games downloaded from http://www.ficgs.com; Infinity Chess games downloaded from http://www.infinitychess.com; PAL Computer Systems ("PAL") and Computerschach & Spiele ("CSS") games downloaded from https://en.chessbase.com.

[3]*ChessBase Mega Database*, http://shop.chessbase.com/en/products/mega_database_2018.

[4]For an overview of the dependent, independent, and control variables' descriptions and measures, please see Table S1.

[5]In chess terminology, "ply" denotes a turn taken by one player, while a "move" refers to two consecutive turns or plies made by White and then Black (Charness, 1977). For a glossary of chess terms, please see the Appendix S1.

[6]The optimal choice was determined using *Stockfish 10*, the strongest available chess engine at the time of data collection (Cilento, 2019). This engine, and consequently its level of analysis, were not available to players during our observation period (2000–2017). Amazon's cloud-computing platform, which includes the Elastic Compute Cloud (EC2) application for parallel processing, enabled us to benchmark any decision for a given board combination against an optimal choice.

[7]The chess players in our sample are highly skilled and their plies are consistently considered excellent compared to those of non-professional players. Consequently, the benchmarking only identifies plies that are particularly close to the theoretical optimum as "positive," and those that are disproportionately below this optimum, as "negative."

3.3 | Independent variables

To capture *human chess playing capabilities*, we follow prior studies (e.g., Chassy & Gobet, 2011) and use Elo ratings (Elo, 1978) to measure *player capabilities* and *opponent capabilities*. This measure predicts the players' relative capability levels based on their previous tournament performance.[8] In addition, *player capabilities difference* captures the absolute difference in the focal player and the opponent player's chess playing capabilities.

Like human players, chess engines have Elo ratings that are predictions of their relative capability levels based on their prior tournament performance (Haworth, 2007). We use this *machine capabilities* measure as an indication of the focal player's machine chess playing capabilities, which is broadly (albeit not perfectly) comparable to human chess playing capabilities (Regan & Haworth, 2011). Accordingly, *machine capabilities difference* denotes the absolute difference between the focal player and the opponents' engines' chess playing capabilities.

Similar to the conceptualization of humans' and machines' Elo ratings (Haworth, 2007), we predict human–machine capabilities based on the focal players' prior performance in centaur or engine tournaments. Human–machine capabilities capture players' capabilities when interacting with chess engines in the respective tournament formats. *Human–centaur capabilities* denote this capability in centaur chess, and *human–engine capabilities* in engine chess. We also use the alternative measure *human–engine scope*, which refers to the cumulative number of unique chess engines that a player has used in centaur and engine tournaments.

Additionally, we designate the *tournament format* by using a categorical indicator of conventional (i.e., baseline), centaur, and engine tournaments. In analyses that exclude conventional games, this measure becomes a binary variable with centaur as the baseline.

3.4 | Control variables

We include control variables, such as the focal *player gender*, *player federation*, *player age*, *player members* (i.e., the number of members on the team), and *player set*, which indicates whether the focal player plays White (and thus makes the first move) or Black, with White as the baseline category. We also measure the cumulative numbers of previous centaur or engine tournament games that the focal player has played (i.e., *centaur games played*, and *engine games played*) to capture any learning effects from playing these tournaments. At the game level, we include *time controls*, which indicate the time available for players to reflect on and complete their plies,[9] *tournament system* controls, which indicate how a tournament winner is determined, and *tournament round* controls, which indicate the round in which the game is played. Finally, at the macro level, we control for unobserved time effects by using dummy variables for the current *year* and *quarter*. In some analyses, we substitute these time dummies with a *time count* variable to control for potential general learning effects (e.g., engines' improved

[8]As in many RBV studies, one could voice tautology or path dependency concerns (Priem & Butler, 2001) regarding Elo ratings (i.e., past chess performance affecting future chess performance). We nevertheless believe that such concerns are limited in our study, given that the Elo ratings' construction does not build directly on players' past game results but incorporates multiple and partially asymmetrical adjustments to account for the chess game's particularities. For more information, see our detailed explanations on the Elo ratings' construction in the Appendix S1.

[9]The normal time controls are 60 min per game and player for games with a "classic" time control (i.e., our baseline), between 10 and 60 min for "rapid" games, and below 10 min for "blitz" games (FIDE, 2020).

performance over time). When applicable, we include player fixed effects and, in these models, exclude the time-invariant variables.[10]

3.5 | Descriptive statistics

The players in our sample have an average Elo slightly above 1,800, making it highly comparable to the global FIDE average. This suggests that our player selection via centaur and engine tournament participation does not seem to introduce selection effects into our sample. The players use engines rated at 3,155. On average, games last 85 plies, with players making about 1 disproportionally positive and 0.6 disproportionally negative plies per game. Please see Table S2 for the main variables' descriptive statistics.

On analyzing the main variables' relative frequencies in respect of conventional games (see Table S3), we observe patterns in line with prior research: White's has a first-mover advantage over Black (35% compared with 26% of games won) (Ribeiro, Mendes, Lenzi, del Castillo-Mussot, & Amaral, 2013), and men are vastly overrepresented (Maass, D'Ettole, & Cadinu, 2008). In centaur and engine games, new patterns become apparent. Compared with conventional games, an increasing share of games with machines end in a draw (increasing from 39% of conventional to 54% of centaur, and 77% of engine games). These games also last longer in terms of the average number of plies (increasing from 80 in conventional to 100 in centaur, and 140 in engine games), and are characterized by fewer disproportionately positive and negative plies, whereby the decrease in negative plies is much higher. This suggests a convergence in game outcomes, with centaur and engine chess allowing less heterogeneity in relative player performance than conventional chess does.

We also analyze the main variables' pairwise correlations (see Table S4) to assess whether multicollinearity is a possible source of endogeneity. The correlations do not exceed the conventional cut-off of 0.70 between variables in the same econometric model (Dormann et al., 2013), although the correlations between *human–engine capabilities* and *engine games played* (0.80) were a notable exception. Since this problem only concerns a post hoc test, we address it later. We also calculate the collinearity diagnostic factors (see Table S5): Given a mean variance inflation factor (VIF) of 2.19 and a maximum of 8.07, all below the conventional threshold of 10, there is no major multicollinearity concern (Salkind, 2007, p. 639f).

3.6 | Methodology

In keeping with prior studies that used competitive game data (e.g., Cea et al., 2020), we apply a multinomial logistic model (Powers & Xie, 2008) to estimate the factors contributing to the likelihood of one of the three possible game results (i.e., win, draw, or loss). Although an ordered logistic regression would yield a more parsimonious model, modeling *game result* as an ordinal variable yields biased results if the proportional odds assumption, that is, that the coefficients will be equal across outcome pairs (win vs. draw, loss vs. draw), is violated (Fullerton, 2009). We therefore tested the proportional odds assumption by using Wolfe and Gould's (1998)

[10]Due to our unbalanced data structure and sparse variables, we were unable to include individual-level fixed effects in the multinomial logistic regressions, making estimation infeasible. Nevertheless, we estimated the models once more, clustering standard errors on the *player federation* level, given that chess players spend most of their time developing their capabilities in domestic federation contexts. Our findings are replicated across models, with results remaining robust in terms of comparable magnitude and significance.

omodel Stata command, followed by a Brant (1990) test based on Long and Freese's (2006, p. 199f) *brant* Stata command. The test statistics from both tests indicate that the assumption is unlikely to hold, leading us to proceed with a multinomial logistic model (Fullerton, 2009).

4 | ANALYSIS AND FINDINGS

4.1 | Human–machine resource substitution

In conventional chess competition, humans use their chess playing capabilities in order to make superior chess plies (Charness, 1977), which is the critical resource functionality (Peteraf & Bergen, 2003). The emergence of AI-based chess engines led to the creation of centaur and engine chess competitions. While these competitions are played in separate competitive niches (i.e., with their own tournaments), they belong to the same domain (i.e., chess competition), because the same players compete across these formats, and the same tournament organizers and audiences assign their attention and other scarce resources to them. We explore next whether and how the adoption of engines with their own chess playing capabilities substitutes humans' corresponding capabilities and assess the relevant impact on the performance differences.

4.1.1 | Human capabilities in conventional chess

Table 1 provides the results of a regression analysis that predicts the focal chess player's game result as a function of player and opponent capabilities, as well as the control variables' vector, in order to establish a baseline for human capabilities' role in conventional chess. As expected, player capabilities are associated with increased (decreased) chances of winning (losing) a conventional game, while the inverse is true of opponent capabilities. The raw coefficients in multinomial models are notoriously difficult to interpret. We illustrate them by calculating the average marginal effect (AME) of changing an independent variable's value with respect to the probability of observing an outcome, maintaining the other independent variables' observed values, and then calculating the average across the observations. A one standard deviation higher player Elo (i.e., 182.75), ceteris paribus, increases the chances of winning by roughly 22% (with an AME of 0.0012), and decreases the chances of losing by roughly 16% (0.0009).

From a theoretical perspective, the RBV describes humans' domain-specific decision making capabilities as an important source of competitive advantage (Kunc & Morecroft, 2010). In our domain, human chess playing capabilities are valuable and rare (Barney, 1991): Valuable, because they allow players to make better chess plies, therefore ultimately increasing their chance of winning (Chassy & Gobet, 2011), and rare, because humans must endure a long learning process to develop this expertise, which creates capability differentials (Castanias & Helfat, 2001) and supply restrictions (Levinthal & Wu, 2010). Human chess playing capabilities' tacit nature also means they cannot be easily imitated or traded (Miller & Shamsie, 1996).

4.1.2 | Human capabilities after AI adoption

We proceed by investigating what happens to human chess playing capabilities when we examine games played by the same players in centaur and engine chess tournaments. While it is

TABLE 1 Effect of player capabilities in the conventional, centaur, and engine tournament formats

Independent variable	Conventional games		Centaur games		Engine games	
Outcome	Win	Loss	Win	Loss	Win	Loss
Player capabilities	0.0048 (.0000)	−0.0040 (.0000)	0.0001 (.7955)	−0.0009 (.0371)	−0.0208 (.6025)	−0.0273 (.7848)
Opponent capabilities	−0.0060 (.0000)	0.0030 (.0000)	−0.0006 (.0341)	0.0003 (.3669)	−0.0039 (.0700)	−0.0013 (.5343)
Player set	−0.5302 (.0000)	0.2149 (.0059)	−0.5059 (.0048)	0.6635 (.0004)	−1.6524 (.0279)	1.2560 (.0912)
Player members			0.1637 (.5206)	−1.3012 (.0255)		
Player gender	−0.3650 (.0217)	−0.1877 (.2861)	−2.1446 (.0553)	−1.1781 (.1490)		
Player age	−0.0206 (.0119)	−0.0040 (.6355)	−0.0004 (.9710)	0.0070 (.5683)	−0.9920 (.1230)	−0.2492 (.6615)
Tournament system						
K.O.	0.1807 (.1359)	0.3012 (.0229)	−1.8134 (.0038)	−1.3638 (.0387)		
Round-Robin			−0.5858 (.1999)	−0.0325 (.9448)		
Scheveningen	−0.0928 (.7713)	0.3885 (.2428)				
Simultaneous	1.3296 (.1211)	−14.2804 (.9811)				
Tournament round	−0.0179 (.0900)	0.0241 (.0388)	0.0321 (.2354)	0.0526 (.0702)	−0.1422 (.0771)	−0.0835 (.2885)
Time controls						
Rapid (<60 min; >10 min)	0.6822 (.0000)	0.7238 (.0000)	−0.0019 (.9969)	0.1362 (.7858)		
Blitz (≤10 min)	1.1115 (.0000)	1.2022 (.0000)	1.6001 (.1972)	1.9390 (.1247)		
Constant	−10.5301 (.9903)	1.8149 (.1078)	−17.6551 (.9971)	0.3667 (.8500)	77.9088 (.9213)	62.0155 (.7279)
Controls (coefficients omitted)	Player federation, year, quarter					
Pseudo R^2	12.78%		14.21%		29.35%	
N	4,929		905		122	

Note: Multinomial logistic regression. Base outcome: draw. *p*-values in parentheses.

intuitive that human chess playing capabilities promote wins and prevent losses in conventional games, it is less clear if, and to what extent, these capabilities play a role in determining performance in the other tournament formats. The centaur and engine game results presented in Table 1 suggest that the player capability effects largely vanish after the adoption of AI, with the one remaining effect being a negligible prevention of losses in centaur games (with an AME suggesting a slight decrease of 0.01% in the risk of losing rather than drawing). Traditional chess playing capabilities' overall negligible effects provide evidence that the machine's computational capabilities substitute human cognitive capabilities.

To investigate this substitutive effect more directly, we replace the game results with the numbers of positive and negative plies as alternative outcome variables by using Poisson models. In respect of centaur games, we find that compared with conventional games, the expected log count of the number of positive plies decreases by 0.8684. The incident rate ratio (IRR) of $e^{-0.8684} = 0.42$ suggests that the positive plies' incident rate in centaur games is, ceteris paribus, 0.42 times that of conventional games. Furthermore, negative plies' incident rate is 0.16 times that of conventional games. In terms of engine games, there is no change in the number of positive plies, but a large decrease in the number of negative plies. Overall, these findings indicate that centaur and engine games reduce negative and/or positive plies (see Table S6).

We explore this tendency toward convergence further by estimating two fixed-effects panel models with standard errors clustered at the player level, using a draw outcome (logistic model) and the number of plies per game (Poisson model) as dependent variables in our full sample that comprises all three tournament formats. The logistic model shows that, compared with conventional games, centaur games increase the log odds of a draw by 1.0680 or a factor of $e^{1.0680} = 2.91$, while the engine games do so by a factor of $e^{1.6522} = 5.22$. The Poisson model shows that, compared with conventional games, the total number of plies is 1.26 times higher in centaur and 1.65 times higher in engine games. These findings show that tournaments with machines yield more draws and longer games, which is further evidence that the adoption of AI-based machines eliminates performance differences (see Table S7).

We proceed by discussing our findings regarding AI's substitution effects. As a general-purpose resource (Brynjolfsson & McAfee, 2014, p. 31), AI has a high fungibility, which prior RBV research associates with great potential for substitution across domains (Levinthal & Wu, 2010). In the chess domain, AI-based engines can, like humans, provide the functionality of making high-quality chess plies, although it is based on a different type of underlying resource, which describes a typical substitution scenario (Peteraf & Bergen, 2003). Given their superior computational capacity, chess engines process information far more comprehensively and rapidly than humans.[11] Machines are never tired or emotional, and their calculations are accurate. This means that the way machines play chess differs from the way humans do, because humans have imperfect memories, are highly selective in the options they consider, and make blunders when they are tired or emotional (Cowen, 2013, p. 104). With superior functionality in terms of identifying high-quality chess plies (Collins, 2017; Silver et al., 2018), chess engines can substitute human chess playing capabilities completely, rendering this resource obsolete (Polidoro & Toh, 2011). Consequently, human chess playing capabilities no longer fulfill the RBV's criteria as a valuable and rare resource (Barney, 1991) in centaur and engine chess competitions.

[11]For example, the chess engine *Stockfish* (TCEC, 2020) is capable of searching 60 million board positions per second when suggesting the best chess plies for a given position (Silver et al., 2018).

4.1.3 | The role of machine capabilities

To assess the role of machine chess capabilities, we include a control variable for these capabilities in centaur and engine games. The results in Table 2 provide no evidence of a relationship between machine capabilities and chess performance. This suggests that the substitution that occurs due to machines' introduction not only effectively ousts the previous human-derived performance differences, but also that the machine capabilities do not introduce new differences.

One of our analysis' limitations is that the absence of empirical relationships between human or machine chess playing capabilities and chess performance does not demonstrate that there is a non-relationship. Unlike the standard regression testing that we used, Bayesian analysis allows us to glean evidence of absence, rather than mere absence of evidence (Keysers, Gazzola, & Wagenmakers, 2020).[12] We therefore conduct a Bayesian analysis to explore the potential non-relationships further. The results of the Bayes factors (BF), the relevant Bayesian Information Criteria (BIC), and the R^2 values suggest strong (BF > 20) to very strong (BF > 150) evidence of the absence of non-trivial effects regarding the relationships presented in Sections 4.1.2. and 4.1.3.[13] In other words, human and machine chess playing capabilities have no material impact on chess performance in centaur and engine tournaments.

We also used alternative variables for supplementary analyses in order to address potential identification and measurement issues. Chess engines do not only differ in terms of their capabilities, but also in their underlying architecture. Among other factors, different engines vary in how they search and evaluate chess plies in a game's different stages (Cowen, 2013, p. 77ff). We therefore tested a model that replaces *machine capability* with dummy variables for *player machine* indicating the chess engine types (i.e., *Stockfish*, *Komodo*, etc.). The findings do not suggest a relationship between *player machine* and game results in terms of wins or losses.[14] Our results also hold when we substitute time dummies with the *time count* variable in order to control for general learning effects that could originate from sample-wide learning among engines over time. For instance, engine-specific weaknesses could become known and exploited by other engines. However, this variable's inclusion does not affect our results meaningfully.

Finally, the number of observations varies across the three tournament formats (see Tables 1 and 2). We ascertained that this variance does not affect our results by using random samples, equal in size to the engine chess sample (i.e., the smallest of the three subsamples), for the conventional and the centaur tournament formats. Apart from the obvious reduction in power, such random selection does not affect our results materially (see Table S9).

We conclude this section by discussing our findings regarding machine capabilities. There are many chess engines, whose chess playing capabilities vary (Wilkenfeld, 2019). Several state-of-the-art engines, such as *Stockfish*, are free, open-source programs (Cilento, 2019), while other

[12]Bayesian analysis compares competing models, usually a null hypothesis and an alternative one, to evaluate the change in the odds from their prior to their posterior distribution in the observed data (Wagenmakers, 2007). The *Bayes factor* captures this change by means of the ratio of the two competing hypotheses' marginal likelihood (Jeffreys, 1961, p. 30ff). A Bayes factor test yields evidence indicating whether, given the observed data, the null hypothesis or alternative hypothesis is more likely to be true, and, if so, what its probability is (Andraszewicz et al., 2015). For further discussion of Bayesian methods in management research, we refer the interested reader to Zyphur and Oswald (2015).

[13]In line with prior research, we use the widely accepted Raftery classification scheme (Kass & Raftery, 1995; Raftery, 1995). See Table S8 for the Bayesian analysis results and further explanations of the classification scheme.

[14]We conducted similar tests to investigate the effects of other potential sources of machine heterogeneity, such as engine programming language (i.e., C++, C, Pascal/Delphi, or asm/other), legal attribute (i.e., open source, commercial, or private), and vendor organization (i.e., ChessOK, ChessBase, or independent), which did not have a material impact.

TABLE 2 Effect of machine capabilities in the centaur and engine tournament formats

Independent variable	Centaur games		Engine games	
Outcome	Win	Loss	Win	Loss
Player capabilities	−0.0003 (.5762)	−0.0016 (.0085)	0.0577 (.5857)	−0.0228 (.8412)
Machine capabilities	0.0004 (.8480)	−0.0004 (.8417)	−0.0696 (.2845)	−0.0048 (.9201)
Opponent capabilities	−0.0006 (.1392)	0.0005 (.2793)	−0.0094 (.1425)	−0.0020 (.6463)
Player set	−0.3997 (.1026)	0.9537 (.0010)	−21.0781 (.9966)	−0.3694 (.7723)
Player members	−0.0675 (.8433)	−26.1369 (.9874)		
Player gender	−2.2525 (.1103)	10.6006 (.9928)		
Player age	−0.0058 (.7382)	0.0205 (.2844)	5.5582 (.3011)	1.3977 (.6342)
Tournament system				
K.O.				
Round-Robin	−0.5498 (.3236)	−0.5481 (.4706)		
Scheveningen				
Simultaneous				
Tournament round	0.0582 (.0943)	0.0612 (.1198)	0.0390 (.8586)	−0.2414 (.0779)
Time controls				
Rapid (<60 min; >10 min)	−0.2975 (.6450)	0.2186 (.7701)		
Blitz (≤10 min)	2.3335 (.1239)	2.3355 (.1851)		
Constant	−0.3896 (.9416)	26.6596 (.9872)	−115.9203 (.9928)	−4.1883 (.9850)
Controls (coefficients omitted)	Player federation, year, quarter			
Pseudo R^2	18.43%		51.01%	
N	499		74	

Note: Multinomial logistic regression. Base outcome: draw. *p*-values in parentheses.

engines, such as *Komodo* and *Houdini*, are commercial, but can be downloaded from the Internet at a relatively low price.[15] There are also private engines, such as IBM's *Deep Blue* (Campbell, Hoane, & Hsu, 2002) and DeepMind's *AlphaZero* (Silver et al., 2018), which sometimes introduce new technologies allowing superior performance. However, these engines' advantages tend to be short-lived, because open-source solutions quickly adopt similar technologies.[16]

Developers can offer AI-based chess engines for free or at a low price, since these digital resources are scale free, which means they can be infinitely copied and used without being depleted (Levinthal & Wu, 2010). Since chess engines are widely available, and players can choose freely among them, this resource has few supply restrictions and mobility barriers (Barney, 1986;

[15]At the time of writing, these chess engines' professional versions are available for roughly USD 60.

[16]For example, IBM's *Deep Blue* introduced heuristics into chess engines, but non-proprietary chess engines surpassed its chess-playing capabilities rapidly (Campbell et al., 2002). DeepMind's *AlphaZero* was the first to use neural networks in its chess engine, which allowed it to beat *Stockfish* in laboratory tests (Silver et al., 2018), but just months later an open-source version, called *Leela Chess Zero*, became available for chess tournaments (Wilkenfeld, 2019). While *Leela Chess Zero* won the engine-chess world championship in 2019, a new *Stockfish* version incorporating a neural network regained the title in 2020 (TCEC, 2020).

Peteraf, 1993). Furthermore, chess engines use general purpose AI technologies (Brynjolfsson & McAfee, 2014, p. 31), which competing engines can also adopt, therefore eroding new engines' initial performance advantages rapidly. In keeping with prior RBV assumptions (Barney, 1991; Levinthal & Wu, 2010), we conclude that technological solutions, even advanced AI-based engines, do *not* fulfill the criteria regarding sustaining resource heterogeneity.

4.2 | Human–machine resource complementation

Our results thus far indicate substitution, with traditional chess playing capabilities rendered obsolete in terms of determining game results in the centaur and engine chess tournament formats. Having focused on the erosion of these previously valuable capabilities, we next investigate whether there is also evidence of complementation (Argyres & Zenger, 2012) between humans' and machines' capabilities.

4.2.1 | A new source of performance differentials

After chess engines' introduction into tournaments in the mid-2000s, centaur chess received most of the attention (Collins, 2017). Kasparov (2017, p. 246) commented on a 2005 chess tournament during which centaur teams had beaten the strongest machines, "Human strategic guidance combined with [the] tactical acuity of a computer is overwhelming." Further technological progress shifted attention from human–machine chess playing to other forms of complementation between humans and machines. Humans can influence centaur and engine game outcomes by selecting a chess engine, tuning its parameters, and developing the databases that the engine uses (Ensmenger, 2012; Suba, 2010, p. 29). This influencing occurs when humans draw on their unique human capabilities, such as their creativity, which enables them to tune their engine in ways that exploit an opponent machine's weaknesses; their large-scale contextualization, which enables them to select engines or parameters that surprise their opponents; and their social interaction within the chess community, which allows them to develop an arsenal of possible strategies to interact with chess engines.[17]

We next examine the potential role of these novel human–machine capabilities. Table 3 shows the results of estimating the impact of *human–centaur capabilities* (for centaur chess games) and *human–engine capabilities* (for engine chess games) in terms of determining the focal player's *game result*. The results in Table 3 show that these human–machine capabilities have new, significant effects on game results. These effects are asymmetric, with the capabilities leading to wins in centaur games and preventing losses in engine games. To illustrate, a one-standard deviation increase in human–machine capabilities (i.e., 19.60) increases the likelihood of winning a centaur game by 7.6% (AME of 0.0039), and decreases the likelihood of losing an engine game by 8.4% (−0.037). Overall, the findings suggest the presence of new domain-specific human capabilities that, like traditional chess playing capabilities, have supply and imitation restrictions.

We ensure the validity of our findings by conducting supplementary analyses of our new measures of human–machine capabilities. These measures could contain noise relating to

[17]These illustrative examples of human-machine capabilities are taken from machine chess forums (such as https://forum.computerschach.de) and tournament reports (such as http://www.infinitychess.com/tournaments/reports).

TABLE 3 Effect of human–machine capabilities in the centaur and engine tournament formats

Independent variable	Centaur games		Engine games	
Outcome	**Win**	**Loss**	**Win**	**Loss**
Player capabilities	0.0001 (.7947)	−0.0008 (.0479)	−0.0208 (.6128)	−0.0636 (.6332)
Human–centaur capabilities	0.0216 (.0001)	−0.0084 (.1515)	0.0667 (.8067)	0.0870 (.8826)
Human–engine capabilities	−0.0311 (.6485)	0.0029 (.9705)	0.0366 (.7649)	−0.4232 (.0351)
Opponent capabilities	−0.0006 (.0298)	0.0003 (.3812)	−0.0039 (.0761)	−0.0018 (.4255)
Player set	−0.5127 (.0049)	0.6757 (.0003)	−1.5609 (.0404)	1.1697 (.1565)
Player members	0.0261 (.9206)	−1.3321 (.0269)		
Player gender	−2.1547 (.0565)	−1.1561 (.1654)		
Player age	0.0018 (.8864)	0.0051 (.6841)	−0.9301 (.1619)	−0.4571 (.4928)
Tournament system				
K.O.	−1.4675 (.0224)	−1.3885 (.0368)		
Round-Robin	−0.6279 (.1718)	−0.0029 (.9950)		
Scheveningen				
Simultaneous				
Tournament round	0.0310 (.2560)	0.0562 (.0550)	−0.1431 (.0771)	−0.0806 (.3248)
Time controls				
Rapid (<60 min; >10 min)	−0.1640 (.7443)	0.1435 (.7754)		
Blitz (≤10 min)	1.4772 (.2367)	1.9550 (.1228)		
Constant	−18.0122 (.9966)	0.5923 (.7614)	71.1444 (.9773)	138.4705 (.5567)
Controls (coefficients omitted)	Player federation, year, quarter			
Pseudo R^2	15.90%		32.58%	
N	905		122	

Note: Multinomial logistic regression. Base outcome: draw. *p*-values in parentheses.

higher-order effects, notably experience or learning in the relevant tournament formats. We investigate whether this possibility could be an alternative explanation for our findings by controlling for centaur and engine experience (i.e., the number of games played in the corresponding formats using the relevant *centaur games played* and *engine games played* variables). This alternative model specification leaves our findings largely unchanged, suggesting that our measures capture the underlying capabilities rather than mere experience effects (Anand, Mulotte, & Ren, 2016). Interestingly, the variables *centaur games played* and *engine games played*, do not affect the game results. This is logical, given that chess players, inter alia, acquire their chess capability outside official tournaments, especially by practicing in domestic club tournaments or private competitions. In addition, we address the relatively high correlation between (and, relatedly, high VIFs for) *human–engine capabilities* and *engine games played*, which we mentioned in our earlier discussion of descriptive statistics. In an analysis without the *engine games played* variable, the estimates remain stable in terms of magnitude and *p*-values (see Tables S10 and S11).

To address potential path dependency (or tautology) concerns (i.e., estimates based on past performance affecting future performance) associated with our new human–machine capability measures, we search for a different construct that captures the same underlying effects (i.e., players' proficiency with the respective engines) without being directly associated with previous game outcomes. We select *human–engine scope*, which is defined as the number of distinct engines a focal chess player used in prior centaur and engine tournaments. We find that *human–engine scope* has a positive effect on centaur game results in terms of preventing losses, which supports our main findings (see Table S12).

In addition, we include *machine capabilities* in the estimation, which we had initially omitted to enable comparison with conventional games. Overall, this variable's inclusion provides further corroborative evidence despite a high correlation between *machine capabilities* and *human–engine capabilities* (0.67). We do not expect this high correlation to translate into a collinearity issue for the following reasons: First, the VIFs are still within an acceptable range (3.45 and 7.73) in models containing the two variables; second, while including *machine capabilities* in the engine games' estimation renders the human–engine capabilities coefficient insignificant, additional analysis shows that this is due to the decreased sample size and not to collinearity. Running the regression for the same 74 observations without *machine capabilities* as a covariate also renders the coefficient insignificant, therefore yielding a highly comparable result in terms of magnitude and *p*-values (see Tables S13 and S14).

Finally, similar to the prior analyses (see Tables 1 and 2), the number of observations varies across the tournament formats (see Table 3). We again use random samples for the conventional and the centaur tournament formats, equal in size to the full sample for engine chess (i.e., the smallest of the three subsamples). Our results remain substantially unchanged, apart from an expected reduction in statistical power (see Table S15).

We next discuss our findings regarding AI's complementation effects. In both centaur and engine chess competitions, humans can create new, uniquely complementary resource bundles (Argyres & Zenger, 2012) by integrating the machine capabilities with their own capabilities. These resource bundles are heterogeneous, because humans learn to interact with machines through personal experience. Such experience creates persistent capability differentials across individuals (Castanias & Helfat, 2001). Furthermore, limited understanding of how exactly humans add value to machines in centaur and engine chess should create causal ambiguity, which makes transferring or imitating these capabilities difficult (Miller & Shamsie, 1996).[18] When actors compete like chess players do, their adversarial relationship and the resulting lack of motivation to share practices are additional barriers to knowledge transfer (Szulanski, 1996). Furthermore, human capabilities' domain specificity imposes limits on the new complementary capabilities' mobility (Helfat & Peteraf, 2015). Overall, the new human–machine capabilities are valuable (for winning games), while simultaneously imposing supply and imitation restrictions.

4.2.2 | The relationship between traditional and new capabilities

Finally, we turn our attention to the relationship between traditional and new advantage-generating chess capabilities. Table 4 provides the results of estimating focal chess players' *human–centaur capabilities*, measured in centaur games, and their *human–engine capabilities*,

[18]Despite an extensive search, we could not find a single reference explaining how exactly human players add value in engine chess tournaments, which illustrates the causal ambiguity argument. We did, however, find highly idiosyncratic comments on machine chess forums and in tournament reports (see Footnote 17). A reason for this apparent lack of explicit knowledge could be that players do not disclose the parameters of the specific machine implementations that they use during tournaments.

TABLE 4 Relationship between chess-playing capabilities and human–machine capabilities

Dependent variable	Human–centaur capabilities	Human–engine capabilities
Player capabilities	−0.0331 (.3355)	−0.0602 (.0632)
Opponent capabilities	0.0003 (.8326)	0.0014 (.5347)
Player set	−0.2432 (.8301)	−0.8868 (.2762)
Player members	0.5035 (.7473)	
Player gender		
Player age	−1.2465 (.0216)	−0.6224 (.4822)
Tournament system		
K.O.	−8.7749 (.2336)	
Round-Robin	2.0230 (.3289)	
Scheveningen		
Simultaneous		
Tournament round	−0.0139 (.8934)	0.0179 (.8260)
Time controls		
Rapid (<60 min; >10 min)	1.2877 (.6925)	
Blitz (≤10 min)	2.9914 (.5754)	
Constant	147.9460 (.0668)	160.1268 (.0520)
Controls (coefficients omitted)	Player federation, year, quarter	
R^2 (within subjects)	3.47%	12.92%
N	905	84

Note: Fixed-effects panel regression. *SE*s clustered at the player level. *p*-values in parentheses.

measured in engine games as a function of *human chess playing capabilities*. The estimates of a fixed-effects panel model indicate a negative relationship between traditional chess playing capabilities and human–machine capabilities in engine games (with a *p*-value of .0632), and no such relationship in centaur games.

We conducted another Bayesian analysis to explore this non-finding. The results confirm our initial estimations by providing evidence of the absence of a non-trivial relationship between traditional and new capabilities regarding centaur games (BF > 3; see Table S16).

Player self-selection could provide an alternative explanation of the non-relationship or negative association (i.e., the best players do not select themselves into centaur/engine chess). A closer look at the average player capability by year and tournament format reveals that in 2005 (the first year of centaur chess tournaments), the average player's Elo rating was 2,462 for centaur chess compared with 2,487 for conventional chess, while in 2014 (the first year of engine chess tournaments), it was 1,947 for engine chess compared with 1,928 for centaur chess. These similar capability levels do not suggest ex ante selection. However, the Elo ratings increasingly diverge across tournament formats in subsequent years, indicating ex post selection (see Table S17). We therefore analyzed the effects of chess playing capabilities and human–centaur capabilities in the early years after the centaur tournament format's introduction (i.e., 2005–2008). The results show that the findings still hold for this subsample (see Tables S18 and S19).[19] Overall, these additional findings suggest that selection occurs ex post due to traditional chess playing capabilities' eroding value in centaur and engine tournaments, and that this ex post selection does not bias our results.

These results indicate that the new human–machine capabilities are unrelated, or even negatively related, to humans' traditional chess playing capabilities–the capabilities that machines substitute (see Section 4.1.2). In respect of centaur chess, Kasparov (2017, p. 246) reported on the above-cited 2005 chess tournament that, "The surprise came at the conclusion of the event. The winner was revealed to be not a grandmaster with a state-of-the-art PC but a pair of amateur American chess players (…). Their skill at manipulating and "coaching" their computers to look very deeply into positions effectively counteracted the superior chess understanding of their grandmaster opponents." Paradoxically, centaur chess players must *not* rely on their chess playing capabilities, which are inferior to those of the machine, but use other capabilities that allow them to complement the machine's capabilities. Leading players are therefore often not highly rated chess players, but computer engineers with modest chess capability, who approach the game from a computational point of view (Cassidy, 2014). Similarly, the ability to select and tune chess engines in both centaur and machine chess is associated with general data science and creative capabilities rather than with specific chess playing capabilities (Cowen, 2013, p. 86).[20]

To develop new complementary resource bundles, humans must have a flexible ability to go beyond domain-specific expertise when structuring, bundling, and leveraging resources (Sirmon et al., 2007). Since humans develop their expertise in a path-dependent learning process (Helfat & Peteraf, 2015), domain experts, who have focused their limited attention and resources on building domain-specific capabilities, usually have little general data science or augmentation capabilities (Davenport & Kirby, 2016, p. 189). Applied to our domain, this means that computer engineers initially have, and—due to their path-dependent learning—continue to have, an edge over traditional chess players with regard to human–machine capabilities. Conventional chess players are therefore likely to experience motivational problems when, as beginners, attempting to develop these capabilities in a new community (Lave & Wenger, 1991, p. 96). Although some of them may make the transition, acquiring new capabilities once again requires learning through experience, which is time consuming (Kogut & Zander, 1992). As our findings show, it is therefore unlikely that actors who outperform in terms of traditional domain-specific capabilities are also able to do so in changed contexts where new and unrelated capabilities determine competitive advantage.

5 | DISCUSSION

In the context of chess competition, we find that AI adoption has a dualistic effect that shifts the sources of competitive advantage: Although substituting humans' traditional, domain-specific cognitive capabilities with machines' abundant computational ones destroys the existing advantage, complementation between previously domain-unrelated human and machine

[19]We would like to point out that a corresponding analysis of engine chess is superfluous, given that our sample only comprises 3 years (2014–2016) in which such tournaments took place.

[20]We obtained background information on 12 of the 20 centaur and engine chess tournament winners in our sample: 10 of the 12 studied computer science, data science, and/or software engineering and are currently employed in one of these domains. Only 6 of the 12 have an official chess rating, and these players have a modest Elo average of 1,994, therefore not even reaching the 2,000 threshold required for chess's "expert" status (US Chess Federation, 2004).

capabilities creates new, persistent advantages. We now argue that these findings from chess competitions are generalizable to business contexts, but also acknowledge the limitations of such a generalization.

5.1 | AI substitution and complementation in chess versus business contexts

With regard to substitution, machine capabilities have also become an alternative to humans' decision making and problem solving capabilities in business contexts such as consumer products, finance, healthcare, and insurance. This trend is likely to continue, "since [the] human/machine performance gap will only increase" (Davenport & Kirby, 2016, p. 20). In line with our results, AI experts also do not expect this new technological resource's abundant availability to provide a sustainable advantage. For example, Davenport and Kirby (2016, p. 204) expect companies' cost advantages from cognitive task automation to erode quickly, since competitors could simply imitate these automation strategies.

However, there are also notable differences between substitution in the chess and business contexts. For example, chess players can choose to remain in a legacy niche that is no longer competitive (i.e., conventional chess), which is difficult in a market context. Firms that fail to realize the benefits that machine substitution affords, risk losing their competitive edge, which could cause their decline. While these differences strengthen the tendency toward substitution even further, others constrain it. Machines perform well under uncertainty (Ghahramani, 2015), but need clear objectives and constraints to operate. While the goals and rules are clear and stable in chess, business contexts can be subject to goal conflicts (Cyert & March, 1963), leading to negotiations and the breaking of rules (Williamson, 1975). Machines also have limitations when there is little data, or when constant change makes using past decision patterns to predict future outcomes impossible (Raisch & Krakowski, 2021). In these situations of high uncertainty, companies must continue relying on human intuition (Huang & Pearce, 2015).

These machine limitations imply that humans still have a role to play in the AI age (Murray et al., 2021; Raisch & Krakowski, 2021). Our findings show the importance of human–machine capabilities as a new source of advantage, even in chess competitions' controlled environment. In business contexts, AI experts also associate competitive advantage with human augmentation capabilities that complement machine capabilities, such as creative ideation, large-scale contextualization, and social interaction (Brynjolfsson & McAfee, 2014, p. 202). Consistent with our results, business actors with deep domain-specific capabilities may not be the ones with superior augmentation capabilities, which require both advanced data science capability and strong social or creative capabilities (Davenport & Kirby, 2016, p. 189). Brynjolfsson and McAfee (2014, p. 194ff) similarly conclude that neither of these capabilities is commonly found in business actors whose education centered on acquiring domain-specific expertise, while building these capabilities now would require a long learning process.

Despite these similarities, there are also differences. Some companies make large-scale investments to develop their employees' augmentation capabilities (Davenport & Westerman, 2021) and design supportive organizational contexts for augmentation (Daugherty & Wilson, 2018, p. 105f). These investments, as well as similar governmental programs (Future of Life Institute, 2021), increase the chances of human experts acquiring augmentation capabilities more so than those of chess players lacking similar supportive measures. Furthermore, the substitution of traditional domain-specific capabilities may not always be as comprehensive in business contexts as in chess competitions. For example, Raisch and Krakowski (2021) describe how some perfumers remain involved and collaborate with data scientists after AI's introduction into the fragrance industry. While machines substitute perfumers regarding certain problem solving activities, they are unable to match the perfumers' unique ability to smell fragrances and predict the human emotions they trigger. This example illustrates that AI is likely to substitute some, but not all of complex business tasks' activities. This difference increases the likelihood that certain traditional domain-specific capabilities remain valuable and, in turn, provide additional opportunities for combining them with machine capabilities to create unique complementarities.

5.2 | Theoretical implications

The ways sources of competitive advantage change over time have received substantial research attention (Argyres & Zenger, 2012; Levinthal & Wu, 2010; Polidoro & Toh, 2011). This literature has tended to treat a new resource as either a substitute or a complement, informing a contingency view (Hess & Rothaermel, 2011; Stadler et al., 2021): The resource is either related, thus providing the potential to substitute rather than complement, or it is unrelated, therefore enabling complementation rather than substitution. In contrast, our findings show substitution and complementation as interrelated effects. Therefore, unlike prior RBV research with its contingency view of substitution as an act of destroying advantage (Peteraf & Bergen, 2003), and complementation as an act of creating advantage (Newbert, 2007), we propose an integrated view of these simultaneously occurring acts that shift the sources of competitive advantage.

We further identify AI as the driver of these new resource dynamics. RBV scholars traditionally described substitution as occurring between resources from related domains (Levinthal & Wu, 2010; Peteraf & Bergen, 2003). The latter was due to their focus on humans' domain-specific cognitive capabilities, which lose their value in unrelated domains (Montgomery & Wernerfelt, 1988).[21] In contrast, we observe that, as a general-purpose resource, AI enables substitution across previously unrelated domains, such as technology and chess competitions. For example, DeepMind outperformed the competition with no prior domain-specific chess expertise by exclusively relying on its AI-based capabilities (Silver et al., 2018). Such substitution across unrelated domains is possible, because AI-based machines' general-purpose capabilities are widely applicable across domains, their scale-free nature allows substitution across multiple domains, and the use of machine learning reduces the need for domain-specific expertise.

Combining these unrelated domains' heterogeneous resources could provide unique complementarities (Newbert, 2007), which are scarce when substitution occurs between related domains. Such AI-based complementation differs from the RBV's traditional perspective. In prior complementation accounts, domain experts purposefully explored a new unrelated resource that they integrated into their existing bundle of domain-specific resources (Argyres & Zenger, 2012).[22] Such complementation extends a once chosen development path and preserves the traditional domain-specific capabilities' value. In the AI context, however, we observe that

[21]For example, Peteraf and Bergen (2003) describe how *Quaker Oats*, a maker of hot cereals, uses its grain-based capabilities to move into the ready-to-eat cereals industry. The new industry domain (ready-to-eat cereals) is closely related to the existing one (hot cereals), and the domain-specific capabilities that *Quaker Oats* transfers are described as highly similar to those they substitute.

[22]For example, Argyres and Zenger (2012) describe how media managers at *The Walt Disney Company* created competitive advantage by integrating new animation capabilities with their existing bundle of complementary entertainment capabilities.

non-experts, or those with modest chess expertise, use their general augmentation capabilities to create new competitive advantages. This type of complementation breaks the domain's current development path by shifting attention to its augmentation capabilities, while AI-based machine capabilities substitute traditional domain-specific capabilities. Consequently, and as our findings show, human experts who have enjoyed competitive advantage in the past are no longer the ones to generate it in the future competitive landscape that AI creates.

Our findings also have wider implications for the RBV debate. In their influential review article, Kraaijenbrink, Spender, and Groen (2010, p. 350) summarize the RBV as follows:

> The RBV assumes firms are profit maximizing entities directed by boundedly rational managers operating in distinctive markets that are to a reasonable extent predictable and moving towards equilibrium (…). It accepts that information about the future value of a resource is asymmetrically distributed. If the firm's managers can estimate the future value of a resource better than their competitors—or when they are simply lucky—this provides their firm with ex ante sources of sustainable competitive advantage. Subsequently, the development of isolating mechanisms that prevent other firms from competing their above-normal-profits away provides the firm with ex post sources of sustainable competitive advantage.

Our findings relate to key elements of this statement. First, the strategic factor market concept (Adegbesan, 2009; Barney, 1986) suggests that there is, in predictable environments, heterogeneity in managers' ability to estimate resources' future value, providing ex ante sources of sustainable advantage. Our findings (Section 4.1.2) inform this debate by suggesting that, in competitive prediction contexts (like chess), AI-based capabilities have the potential to substitute human foresight (Csaszar & Laureiro-Martínez, 2018). Given AI-based capabilities' abundant availability, one of the RBV's most prominent *ex ante* sources of advantage (i.e., scarce managerial prediction capabilities) could be subject to equilibrium tendencies, which make creating or acquiring resources at a lower price than their subsequent value in use increasingly difficult.

Second, our findings corroborate the RBV's traditional assumption (Barney, 1986; Peteraf, 1993) that technological resources do not provide the isolating mechanisms that characterize human resources as *ex post* sources of competitive advantage (Helfat & Peteraf, 2015). This statement even holds for sophisticated AI-based machines that assimilate humans' cognitive functions. Our findings show that humans remain sources of sustainable advantage by combining and integrating their capabilities with machine capabilities into uniquely complementary bundles (Argyres & Zenger, 2012). These insights inform a central RBV debate about whether the locus of sustainable advantage lies in non-human resources or in the characteristics of the humans comprising the firm (Kraaijenbrink et al., 2010; Mahoney, 1995). Ironically, our study of AI-based technology suggests it is humans, because the locus of sustainable advantage is neither human nor machine capabilities, but what humans do with these capabilities.

5.3 | Limitations and future research

We have offered a perspective on how AI triggers resource dynamics that change the sources of competitive advantage. Our research has a significant limitation in that we have provided empirical evidence from just one domain—chess competitions—in which complete substitution occurs. While this scenario applies to certain business domains, the substitution may be partial in other domains, which means that traditional domain expertise is still required (Raisch & Krakowski, 2021). In these domains, experts' capabilities retain some value, but additional augmentation capabilities are also required.

Furthermore, consistent with prior RBV studies conducting within-level analysis, chess players compete primarily at the individual level. Consequently, our study associates individual-level substitution and complementation with individual-level performance. While we believe that such within-level analysis provides a strong foundation for studying AI's impact on individuals and their capabilities, some RBV studies have also explored multilevel relationships (see Nyberg, Moliterno, Hale, & Lepak, 2014). Specifically, these studies show that organizational-level human capabilities, such as those provided by corporate functions, can substitute or complement individual-level human capabilities (Crocker & Eckardt, 2014; Stadler et al., 2021). Moreover, the strategic human capital literature describes organizational-level human resources practices that promote and leverage individuals' capabilities (e.g., Gerhart & Feng, 2021; Ployhart, 2021; Shaw, 2021). Building on these insights, future research could study AI-driven substitution and complementation in multilevel settings, for example, by investigating how AI-driven substitution and complementation yields positive and/or negative outcomes across levels.

When implementing such multilevel work, we encourage scholars to conduct field experiments that will allow them to manipulate the functioning and/or implementation of AI in specific industries and decision making or problem solving domains. Such experiments have several advantages: First, they enable insight into AI's effects in real-life business contexts, including those characterized by high uncertainty and incomplete information. Second, manipulating contextual variables could provide valuable insight into the future division of labor between humans and AI within and across organizational levels, and the associated sources of advantage. Third, unlike our stable chess context, experiments could provide insight into the behavioral changes that occur during substitution and complementation through AI. Finally, given their experimental nature, these approaches could provide causal insight into these resource dynamics. While field experiments are likely to play a key role in future research, exploring the complex, yet increasingly pervasive, AI-driven resource dynamics also warrants the use of other methods that provide complementary insight. In order to empirically capture the nuances at play in AI-related substitution and complementation dynamics, future research requires approaches ranging from qualitative studies and ethnographies to simulations and observational studies.

5.4 | Practical implications

Managers need to increasingly deal with AI in their business domains. This requires knowledge of AI's impact on their competitive position. The arguments and evidence presented in this article suggest that substitution will increasingly originate from domains outside firms' related spheres. AI-driven substitution across unrelated domains has emerged as a new competitive threat that erodes firms' competitive advantages. However, our findings also suggest possible ways for companies to deal with this challenge. They highlight the importance of companies acquiring augmentation capabilities that complement and substitute their traditional domain-specific capabilities as sources of competitive advantage. Companies could invest in capability building initiatives to increase their employees' AI literacy and develop their complementary cognitive and social capabilities. Alternatively, they could hire human resources with these augmentation capabilities and deploy them in teams that also include domain experts, which will allow them to combine their complementary capabilities in unique ways that generate competitive advantage.

6 | CONCLUSION

At the outset of our research, we posed the question of how AI adoption affects the sources of competitive advantage. By exploring this question, we expanded our understanding of the resource dynamics that AI triggers. A key insight is that people still matter, which confirms the RBV's traditional focus on human cognitive capabilities' continued relevance. Another key insight is that AI substantially changes the ways in which people make a difference. These changes imply that the RBV should also evolve and continue to challenge, revise, and extend its theoretical assumptions to defend its competitive advantage as a leading management theory.

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NA

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