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The Dual Edges of AI: Advancing Knowledge While Reducing Diversity

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Abstract.
We study how the interaction between human professionals and artificial intelligence (AI) in advancing knowledge, using professional Go matches from 2003 to 2021. In 2017, an AI-powered Go program (APG) far surpassed the best human player, and professional players began learning from AI. Such human-AI interaction paved a new way to reassess historical Go knowledge and create new knowledge. We analyze *standard patterns* (defined as a sequence of the first eight alternating moves) in 15,023,212 moves by 1,714 players in 69,996 professional Go games and find that, after APG, professional players significantly changed how they adopted different sets of moves. However, new knowledge catalyzed by AI comes at the expense of a reduced diversity in moves. Further, AI's impact on knowledge creation is greater for highly skilled players; since AI does not explain, learning from AI requires the absorptive capacity of the top professionals.

Keywords.
Artificial Intelligence (AI); Knowledge Creation; Knowledge Diversity; Professional Go Players

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Significance Statement.

Knowledge is a key driver of competitive advantage, innovation, and economic growth, yet creating new knowledge is inherently challenging. By analyzing 15 million moves from professional Go matches, we explore *standard patterns*—the first eight alternating moves within a quadrant—that have a long history and represent a strategically important knowledge base for establishing balance early in the game. Our findings reveal that AI catalyzes the creation of new knowledge by enabling players to reassess and innovate these time-honored patterns. However, AI simultaneously increases the concentration of standard patterns and reduces their diversity, particularly among highly skilled players. This dual-edge impact highlights AI's complex role in the tradeoff between advancing new knowledge and fostering its diversity.

Acknowledgments.

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Data and Code Availability.

Since the primary data was obtained through purchase or private sources, we do not distribute the raw data. Instead, we make available both the data and the code used to generate the main figures and regression tables.

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Introduction

New knowledge[2] boosts productivity and innovation (3, 4). Scholars have long examined how to explore and create new knowledge (5-7). As knowledge advances, however, humans reach a limit in their ability to generate new knowledge due to heuristics and routine (8). The path-dependency view suggests that human rationality is limited when it comes to knowledge creation because humans are unaware of all relevant information, often do not have the capacity to process vast information sets, and may choose to settle for suboptimal outcomes (9, 10). The difficulty of generating new knowledge has worsened in recent years (11, 12). As low-hanging fruit is collected, the effort required to acquire new knowledge escalates over time and becomes prohibitively expensive (13, 14). This is also due in part to the burden of knowledge (12)—that is, the need to accommodate a greater body of accumulated knowledge to push the knowledge frontier forward.

The latest advancements in computer science signal a potential paradigm shift in the creation and discovery of new knowledge. This transformative phase is predominantly driven by the rapid progress and integration of artificial intelligence (AI). AI stands out for its remarkable predictive accuracy combined with cost-efficient utilization (15). For example, new AI algorithms can help researchers to discover previously unidentified protein structures (16) and novel materials (17), thereby aiding in the development of new drugs and the application of innovative materials (18-20). Such AI algorithms have been widely adopted in a variety of scientific domains such as material science and mathematics and are expected to rapidly expand their application cases across fields (21-23).

Despite the burgeoning use of AI, little is known about whether it catalyzes pushing the knowledge frontier, what its unintended consequences might be, and what heterogeneous effects it might have. Empirical evidence remains scarce—particularly due to the difficulty in identifying and quantifying the utilization of AI and the consequent creation of unprecedented knowledge. The game of Go offers a unique opportunity to measure AI usage and the creation of new knowledge, as players in the early stages rely on *standard patterns,* known as *joseki*, which have been accumulated over the long history of the game. These patterns represent a deeply ingrained and systematically structured knowledge base for achieving balance when setting the stage early in the game. In this context, we investigate whether AI facilitates the creation of new knowledge, particularly through the development of these standard patterns, the role of different human skill levels, and the potential pitfalls of the reliance on AI in knowledge creation.

[2] We define knowledge as a form of awareness and understanding among individuals—arising both from systematic scientific methods and from socially constructed norms, conventions, or paradigms that guide behavior within specific domains. (1, 2). For a more detailed discussion, please see Supplementary Information (Section B.1).

AI and standard patterns in Go games

The game of Go, a two-player 19×19 board game known to exist since B.C. 2300, provides an ideal testbed to investigate how AI pushes the frontiers of knowledge that humans have accumulated for thousands of years. First, Go players have developed a set of standard patterns (i.e., opening moves that constitute the sequence of first eight alternating interactions by two players in each quadrant (or corner); see Figure 1, panels A and C, for examples). These patterns, developed over thousands of years, play a significant role in setting the stage for the rest of the game. As they lay the groundwork for subsequent engagements, standard patterns constitute a fundamental knowledge in Go. An important feature of a standard pattern is that it provides an equivalent (balanced) exchange of stones, leaving both players with the same probability of winning as they leave the initial stage of the game; standard patterns that give one player with a lower chance of winning compared to their opponent eventually become obsolete. Through repeated gameplay over time, players can identify standard patterns that place them at a disadvantage and continuously refine their strategies.

Professional players have done thorough research on the standard patterns to the best of human cognitive capabilities (24-26). In this sense, "good" standard patterns constitute a valuable knowledge set, and players use them not only to teach Go learners but also to play in high-stake professional matches (see SI Appendix, section B.1 for more detailed explanation). Still, it had not been possible to quantitatively assess the balance and fairness of the standard patterns before the emergence of AI.

Second, an AI-powered Go program (henceforth, APG) has far exceeded the performance of the best professional Go player since the historical match between AlphaGo and Sedol Lee in 2016 (27). Professional players quickly began to rely extensively on an APG to assess the quality of moves (i.e., the winning probability associated with each move) and to learn from it (28). Third, accurate and detailed records of gameplay are available for all professional games in the past decades.

Importantly, an APG provides the opportunity to quantify the prior knowledge—i.e., hundreds of standard patterns accumulated over thousands of years—assess whether it provides the optimality (best response) for both players, and develop new standard patterns that achieve better balance by evaluating the effectiveness of each move that an APG suggests.

Several studies have analyzed the quality or novelty of *individual* moves by comparing them with AI's suggestions or historical moves (28-30). However, this approach overlooks a crucial distinction: while individual moves might represent tactical choices, it is *the sets of standard patterns* that embody strategic knowledge through their interaction with and consideration of others. These patterns are not merely sequences of moves; they are systemic frameworks designed to achieve balance between players, meticulously developed and refined over time by the Go community. Standard patterns therefore represent a deeper level of strategic thinking, and the highest refinement of human knowledge accumulated over time.[3]

Data and methods

We empirically analyze all documented professional Go games from 2003 through 2021. We focus on games by full-time professional players (leading players earn upwards of $100,000 through prize money) and do not consider games by amateur players or hobbyists. We gather granular data on Go games and players from *Go4Go* and *Go Ratings*. The Go4Go database, previously used in Go research such as (28) and (31), provides information on 15,023,212 moves by 1,714 players in 69,996 professional Go games from 2003–2021. The data contain exhaustive details on each game, such as player name, Komi (the amount of bonus points provided to the second mover), notations (the sequence of all moves in the game) (32), and the outcome of the game. We obtain additional player-level information from *Go Ratings*, which offers each player's age, gender, country, and annual ranking.

We compare the outcomes before and after the first public release of an APG, *Leela*, in February 2017.[4] Although we do not explicitly consider a comparison group for the counterfactual, Go has been played for thousands of years, and the usage of standard patterns had been remarkably stable before the advent of APG (33). We carefully document and illustrate the trends of standard patterns for the pre-APG (January 2003 through February 2017) and the post-APG (March 2017 through December 2021) periods.

Our primary outcome of interest concerns the share of a standard pattern i in year t, $Share_{it} = N_{it} \,/\, N_t$, with which we can track the discovery and emergence of new standard patterns and the decline of existing ones around the introduction of APG. The standard patterns are defined as the sequence of first eight alternating interactions by two players in each quadrant.[5] We identified 80,952 standard patterns in 52,507 games played by 1,454 professional players during 2003-2021. A comprehensive account of the data and methodology employed is available in the supplementary materials.

[3] The distinction between this study on *standard patterns* and the analysis of individual moves (30) is detailed in Supplementary Information E.

[4] Although the AlphaGo vs. Sedol Lee match was held in March 2016, AlphaGo was not an open software and not available to Go players. Leela provided the first opportunity for professional players to learn from an APG since 2017.

[5] We focus on the first quadrant where the battle occurs because the subsequent battles in the remaining quadrants are substantially affected by the existing stones in other quadrants. We drop non-alternating cases. As a robustness check, we use alternative definition with the first ten alternating interactions in Supplementary Information D.

Results

AI facilitated the creation of new standard patterns

APG helps professional players quantitatively assess the optimality of the existing pool of standard patterns and discover better alternative moves with higher winning probabilities, thereby creating a new set of standard patterns and achieving the better balance (fairness) for both players.

Figure 1B shows the changes in the share of the five most frequently played standard patterns from the pre-AI era. The standard patterns that dominated previously rapidly became obsolete after the introduction of APG.[6] Figure 1D illustrates the same for the top five standard patterns identified from the post-AI era. All but one pattern had been rarely played pre-APG but emerged as dominant patterns post-APG. The notations of the top 1 standard pattern from the pre- and post-AI eras are illustrated in Figure 1A and C, respectively (see SI Appendix, section B.1 for detailed discussion). Notably, the top 1 standard pattern had almost never been played pre-APG (0%), but its share surged up to 18.7% shortly after the introduction of APG (see SI Appendix, section C.2 for formal regression analysis). The emerging patterns post-APG indeed achieve a much better balance, evidenced by the standard deviation and the sum of squared differences of winning probability associated with each move (Table S1). These findings suggest that AI facilitated not only the deterioration of historically accumulated, knowledge that Go players have consistently relied on and deemed optimal but also the creation and discovery of superior knowledge. This was achieved through its ability to quantify the quality of each move, which had been not possible due to humans' limited capacity to process all the relevant information, often resulting in reliance on suboptimal knowledge.

AI decreased knowledge diversity and increased concentration

That professional players can stand on the shoulders of AI and create new, superior standard patterns has yet another important implication for human knowledge. As players rely more on APGs that provide one particular metric of the quality (i.e., winning probability) (28), the set of knowledge and its utilization may rapidly converge, eventually shrinking the effective set of knowledge humans draw from. To tackle this question, we examine two prominent measures of concentration and diversity, concentration ratio 4 (CR4) and Herfindahl-Hirschman Index (HHI), based on the annual usage share of standard patterns. Figure 2A shows that the sum of top four standard patterns (CR_4), that had been low and stable around 8–13% for 15 years pre-APG, surged three-fold immediately after APG up to 37%. The low and stable value prior to APG means that (1) players utilize a variety of standard patterns based on their strategies and preferences and (2)

[6] The first public APG, *Leela*, was released in February 2017. In all figures that illustrate yearly outcomes, we draw a vertical line between 2016 and 2017 to indicate APG's release.

factors other than AI (e.g., non-AI computer software or the emergence of superstar players) had not been able to shift this pattern. It is only after the introduction of APG that players suddenly changed how they play standard patterns that they had kept for decades. Likewise, in Figure 2B, the HHI of all standard patterns dramatically increased from around 0.005 to 0.05, exhibiting a ten-fold increase shortly after APG.

These findings suggest that, although AI helped players create new and better standard patterns, they have quickly converged to a very small set of dominant ones that AI deemed optimal. Players put AI's quantification and suggestion over individual characteristics and preferences, at least in the early stage of the game. Consequently, concentration increased among a small number of standard patterns in games, and diversity declined significantly.

Importantly, if standard patterns have become established knowledge post-APG, players may spend less time utilizing these patterns. This is because they have already acquired detailed insights using APG prior to the game. Supporting this argument, our empirical findings show that players indeed allocated less time to executing standard patterns. Conversely, they spent more time in the later, non-standardizable stages of the game, where play diverges unpredictably and cannot be effectively prepped with APG. For a more detailed analysis of time allocation, please refer to SI Appendix Table S2 and Figure S4.

Heterogeneity: High Skilled players exhibited greater effects

An important factor that could affect how players play standard patterns is their skill level. As such, we conducted subgroup analyses comparing players in the top versus bottom decile in terms of skill level based on the yearly ranking of players by Go Ratings (www.goratings.org) who initiates the standard pattern. Figure 3 illustrates how the share of the most played standard pattern from the pre-AI era and the post-AI era evolved over time across different skill levels, in response to the release of APGs. The magnitude of change in the top 1 standard pattern from the post-AI era following the release of APG, as shown in Panel B, is greater among top decile players than among bottom-decile players. Conversely, while the difference appears marginal, the top 1 standard pattern in the pre-AI era, as depicted in Panel A, seemed to be utilized less by players in the top decile than by those in the bottom decile following the release of APG. We further examine how knowledge concentration varies by skill level. In Figure 4, the dynamic pattern of knowledge concentration is not distinguishable for the top and bottom decile players prior to APG. This suggests that other factors did not disproportionately shift the concentration pattern during this period. After the release of APG, both groups exhibit a substantial increase, but the gap becomes substantially larger.

To better illustrate the changes for each standard pattern, we present the alluvial plots in Figure 5. Panel A shows the changes in the share of standard patterns for all players. Panel B then contrast the pattern for players in the top and bottom deciles in their skills. The effects of AI on knowledge creation and concentration were particularly pronounced for players with high skill levels. In Panel B, the top ten standard patterns in 2021 account for 66.8% of the patterns used by players in top decile (from 4.02% in 2003), while the top ten hold a 52.6% share (from 2.48% in 2003) for players in bottom decile. This pattern reinforces the idea of differential learning from AI, highlighting a heterogeneous and potentially unequal effect of AI even among professionals.

These results suggest two important aspects of human-AI interaction. First, top players could better utilize AI and benefit from it with a deeper comprehension of new knowledge. Current AI algorithms can better predict each move but cannot explain *why* certain standard patterns are better. Players with high skill levels can better comprehend the meaning of AI's suggestions and figure out how to play subsequent moves. Second, top players, because of their advanced knowledge and skill levels, have no one who can instruct them in improving their play. Now that AI has emerged as the very best player (or grandmaster), top human players could learn from it and improve their skills. They thus use AI-facilitated knowledge more actively. These findings about skill levels diverge from prevailing views in the literature, which often suggests that AI enhances the productivity or performance of low-skilled workers (e.g., 28, 34, 35). The key difference is that, unlike routine tasks or AI-assisted work in previous studies, standard patterns in Go consist of a sequence of alternating moves that require a comprehensive understanding of how each move interacts with possible alternative moves, necessitating more expertise in Go. The top players have the capacity to absorb—and thus more effectively leverage—the new knowledge offered by AI.

This insight into how humans with different skill levels interact with AI provides important implications for when and for whom AI's superior performance could help. The SI Appendix provide a comprehensive complement to our empirical findings, featuring robustness checks such as (1) a statistical test for validating our results (SI Appendix Tables S3 to S4, and SI Appendix Figures S5 to S6), (2) a heterogeneity test considering variations in opponent players' skill levels (SI Appendix Figure S7), and (3) a sensitivity analysis to assess the effects of altering the range of standard patterns (SI Appendix, section D).

Discussion

The rise of AI has drawn attention from both the public and from academics. Using the Go context, this study provides a new understanding of AI as the catalyst for human knowledge creation. Our empirical findings indicate that AI has the potential to significantly contribute to knowledge creation, potentially leading to new inventions and innovation. However, our study also uncovers a tendency to favor the new knowledge generated by AI, risking reduced its diversity. This trend becomes more intriguing upon discovering that individuals with higher skill levels are more adept at utilizing this knowledge. It may be that those with higher skills have a better understanding of the AI-generated knowledge and be more adept at grasping the “why” behind this knowledge so that they can more effectively integrate it, facilitating a more effective integration of this knowledge into their work.

This study also provides a new perspective on AI-human interactions. First, a notable consequence of human-AI interaction in knowledge creation is that the application and utilization of this knowledge have become significantly concentrated toward a smaller set of AI-suggested knowledge. Although AI has pushed the frontier of knowledge space, humans tend to utilize new knowledge generated by AI. This concentration may reduce the variety of human knowledge and might challenge the preservation of human characteristics and preferences. This finding raises a crucial question about the trade-off between the creation of knowledge and its diversity.

Second, we demonstrate that not all players learn from and utilize AI at the same level. The utilization of new knowledge catalyzed by AI are dependent on the human professional’s skill level: the better you play, the more you can leverage new knowledge offered by AI. Learning from AI requires that human professionals possess a high level of skill and understanding to maximize AI’s benefits. Our research indicates that even among professionals, top-performing workers (“superstars”) exhibit greater ability to utilize the complex knowledge created by non-explainable AI.

Third, our paper reveals implications for scientists in effectively utilizing AI, particularly in the realm of “artificial superintelligence”—an area where AI’s capabilities surpass human performance in complex cognitive tasks (28-30, 36). Our analysis of professional Go games shows AI’s transformative impact on domain-specific knowledge, reshaping historical strategies and fostering new insights, albeit with reduced diversity. The creation of unprecedented standard patterns illustrates AI’s role in evolving specialized (or biased) knowledge, particularly for skilled players. In conjunction with the rapidly expanding role of AI in scientific discovery (17, 22, 37), our study offers insights into how scientists can harness the power of AI in their research endeavors.

While our study offers insights into how AI-facilitated knowledge creation and human-AI interaction within professional Go games, we recognize certain limitations that suggest directions for future research. Our focus on professional Go matches provides a clear, quantifiable context for analysis but may not encompass the full range of human-AI interactions in other fields. Additionally, while our method of analyzing quantitative patterns in the game is effective for this study, it might not fully capture the entirety of knowledge creation, particularly the qualitative aspects of cognitive processes and interactions.

Furthermore, the specialized skills required for professional Go may differ from those typically demanded in other industries, particularly service sectors.[7] As a result, AI's impact on existing knowledge—and whether it boosts productivity or exacerbates inequality—could vary across these different contexts. In some fields, AI may bring substantial productivity gains, while in others, barriers to adoption or skill gaps could limit its benefits. Future research could therefore investigate how varying skill requirements and differences in knowledge distribution across sectors influence both productivity and income inequality, offering more insight into the broader welfare implications of AI adoption and use.

References

1. P. L. Berger, T. Luckmann, *The Social Construction of Reality: A Treatise in the Sociology of Knowledge* (Anchor Books, 1966).
2. T. S. Kuhn, *The nature of scientific revolutions* (University of Chicago Press, Chicago, 1962).
3. R. R. Nelson, S. G. Winter, *An evolutionary theory of economic change* (Harvard Business School Press, Cambridge, 1982).
4. P. M. Romer, Endogenous technological change. *J Polit Econ* **98**, S71-S102 (1990).
5. D. Dougherty, D. D. Dunne, Digital science and knowledge boundaries in complex innovation. *Organ Sci* **23**, 1467-1484 (2012).
6. L. Fleming, Recombinant uncertainty in technological search. *Manage Sci* **47**, 117-132 (2001).
7. A. Hargadon, R. I. Sutton, Technology brokering and innovation in a product development firm. *Adm Sci Q*, 716-749 (1997).
8. D. Kahneman, Thinking, fast and slow. *Farrar, Straus and Giroux* (2011).
9. J. G. March, H. A. Simon, *Organizations* (Wiley-Blackwell, 1958).
10. S. G. Winter, The satisficing principle in capability learning. *Strategic Manage J* **21**, 981-996 (2000).
11. N. Bloom, C. I. Jones, J. Van Reenen, M. Webb, Are ideas getting harder to find? *Am Econ Rev* **110**, 1104-1144 (2020).
12. B. F. Jones, The burden of knowledge and the "death of the renaissance man": Is innovation getting harder? *Rev Econ Stud* **76**, 283-317 (2009).
13. T. Cowen, *The great stagnation: How America ate all the low-hanging fruit of modern history, got sick, and will (eventually) feel better: A Penguin eSpecial from Dutton* (Penguin, 2011).
14. R. Gordon, *The rise and fall of American growth: The US standard of living since the civil war* (Princeton university press, 2017).
15. A. Agrawal, J. Gans, A. Goldfarb, *Prediction Machines: The Simple Economics of Artificial Intelligence* (Harvard Business Press, 2018).

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[7] Unlike Go's rule-based, head-to-head competition with an enormous branching factor (i.e., a vast number of possible moves at each turn), many industries (e.g., healthcare, finance, or service sectors) may require broader, less-structured skills—such as handling regulatory requirements, customer interactions, and diverse problem-solving contexts.

16. K. Tunyasuvunakool *et al.*, Highly accurate protein structure prediction for the human proteome. *Nature* **596**, 590-596 (2021).
17. A. Merchant *et al.*, Scaling deep learning for materials discovery. *Nature* **624**, 80-85 (2023).
18. A. Trafton (2022) Analyzing the potential of AlphaFold in drug discovery. in *MIT News*.
19. R. F. Service, AI-driven robotics lab joins the hunt for materials breakthroughs. *Science* **380**, 230 (2023).
20. F. Wong *et al.*, Discovery of a structural class of antibiotics with explainable deep learning. *Nature* **626**, 177-185 (2024).
21. A. Fawzi *et al.*, Discovering faster matrix multiplication algorithms with reinforcement learning. *Nature* **610**, 47-53 (2022).
22. B. Romera-Paredes *et al.*, Mathematical discoveries from program search with large language models. *Nature* **625**, 468-475 (2024).
23. R. Van Noorden, J. M. Perkel, AI and science: what 1,600 researchers think. *Nature* **621**, 672-675 (2023).
24. Wikipedia Contributors, Go professional. Wikipedia. Available at: https://en.wikipedia.org/wiki/Go_professional.
25. J. v. d. Steen, GoBase.org - Joseki Dictionary. GoBase.org. Available at: https://gobase.org/joseki/.
26. J. Prokop, Waltheri's go pattern search. Available at: https://ps.waltheri.net/.
27. C. Burton-Hill (2016) The superhero of artificial intelligence: can this genius keep it in check? in *The Guardian*.
28. S. Choi, H. Kang, N. Kim, J. Kim, How does artificial intelligence improve human decision-making? Evidence from the AI-powered Go program. *Strategic Manage J*, in press (2025).
29. F. Gaessler, H. Piezunka, Training with AI: Evidence from chess computers. *Strategic Manage J* **44**, 2724-2750 (2023).
30. M. Shin, J. Kim, B. Van Opheusden, T. L. Griffiths, Superhuman artificial intelligence can improve human decision-making by increasing novelty. *P Natl Acad Sci* **120**, e2214840120 (2023).
31. T.-R. Wu *et al.*, Multilabeled value networks for computer Go. *IEEE Trans Games* **10**, 378-389 (2018).
32. Wikipedia Contributors, Komi (Go). Wikipedia. Available at: https://en.wikipedia.org/wiki/Komi_(Go).
33. S. J. Kim, *A Dictionary of Modern Fuseki: The Korean Style* (Kiseido, 2000).
34. E. Brynjolfsson, D. Li, L. R. Raymond, Generative AI at work. *NBER Work Pap* (2023).
35. S. Noy, W. Zhang, Experimental evidence on the productivity effects of generative artificial intelligence. *Science* **381**, 187-192 (2023).
36. N. Bostrom, *Superintelligence: Paths, Dangers, Strategies* (Oxford University Press, 2014).
37. J. Jumper *et al.*, Highly accurate protein structure prediction with AlphaFold. *Nature* **596**, 583-589 (2021).

Figures and Tables

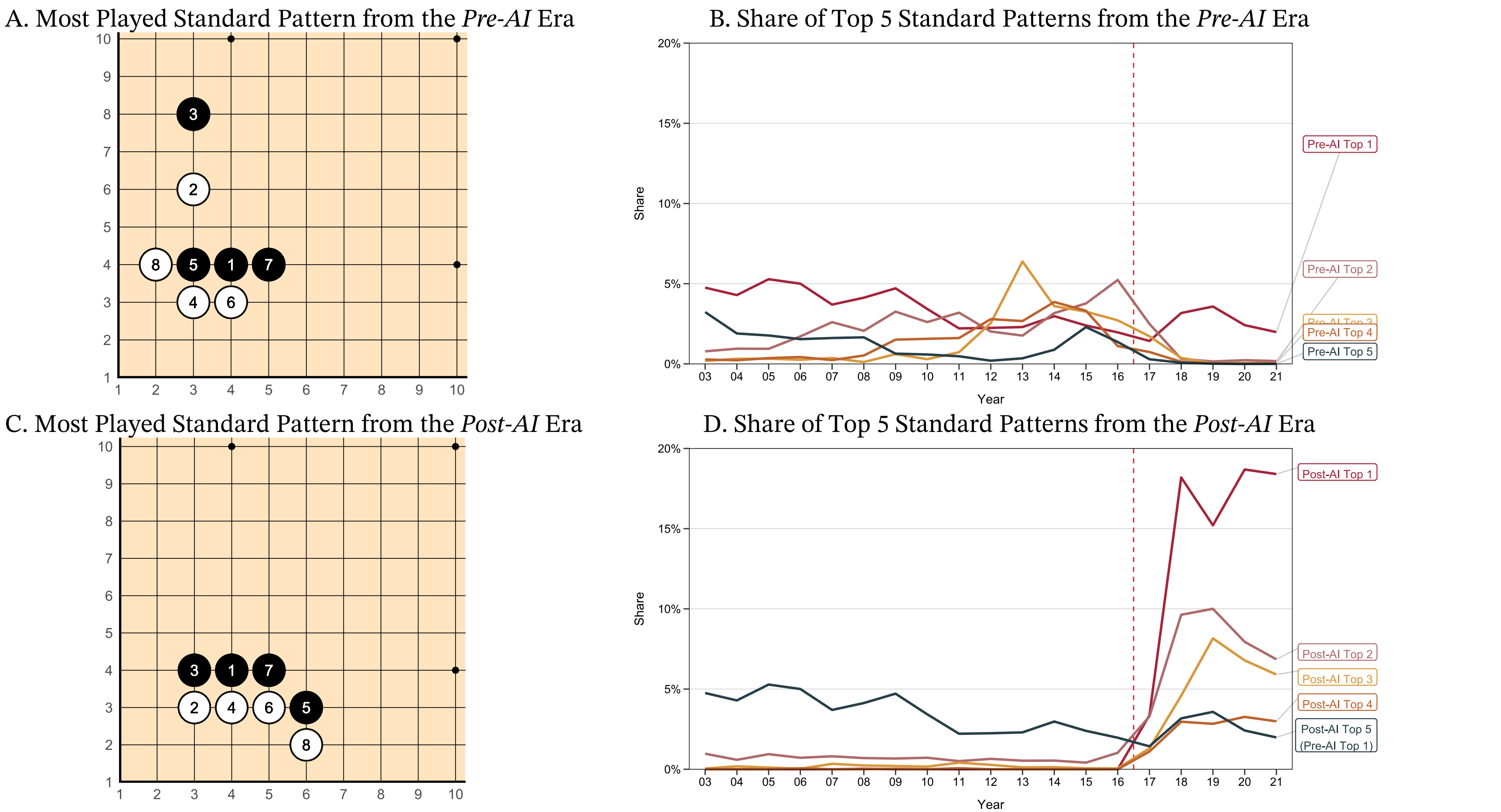


Figure 1. AI and knowledge creation: The share of top standard patterns before and after APG. This figure illustrates the yearly change in the proportion of top five most frequently played standard patterns from 2003 to 2021. The red vertical dashed line drawn between 2016 and 2017 indicates the first public release of APG in February 2017. Pre-AI top five standard patterns show consistent results when analyzed one or two years before APG's release *(SI Appendix Figure S13)*.

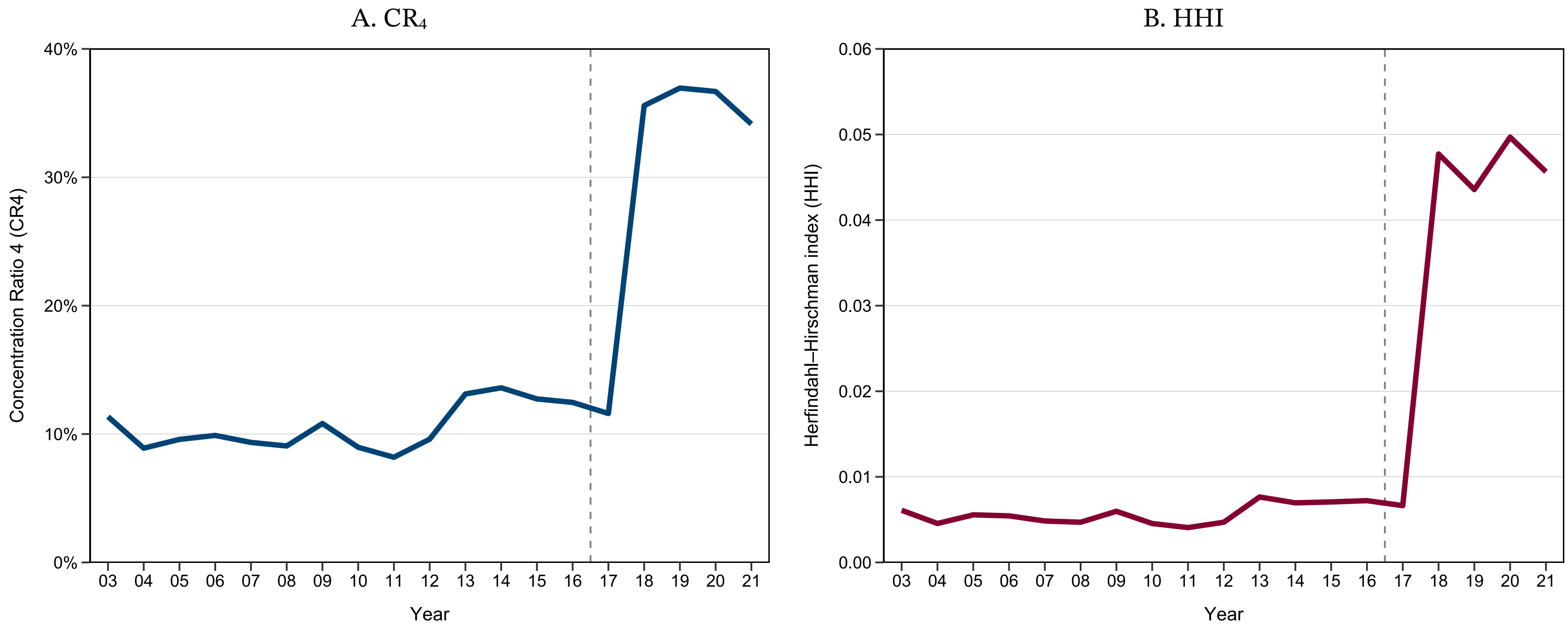


Figure 2. AI and knowledge concentration: CR$_4$ and HHI. This figure illustrates the yearly change in the concentration of standard patterns played from 2003 to 2021. In this figure, we employ two concentration measures: concentration ratio 4 (CR$_4$) in Panel A, and Herfindahl-Hirschman Index (HHI) in Panel B. The grey vertical dashed line drawn between 2016 and 2017 indicates the first public release of APG in February 2017.

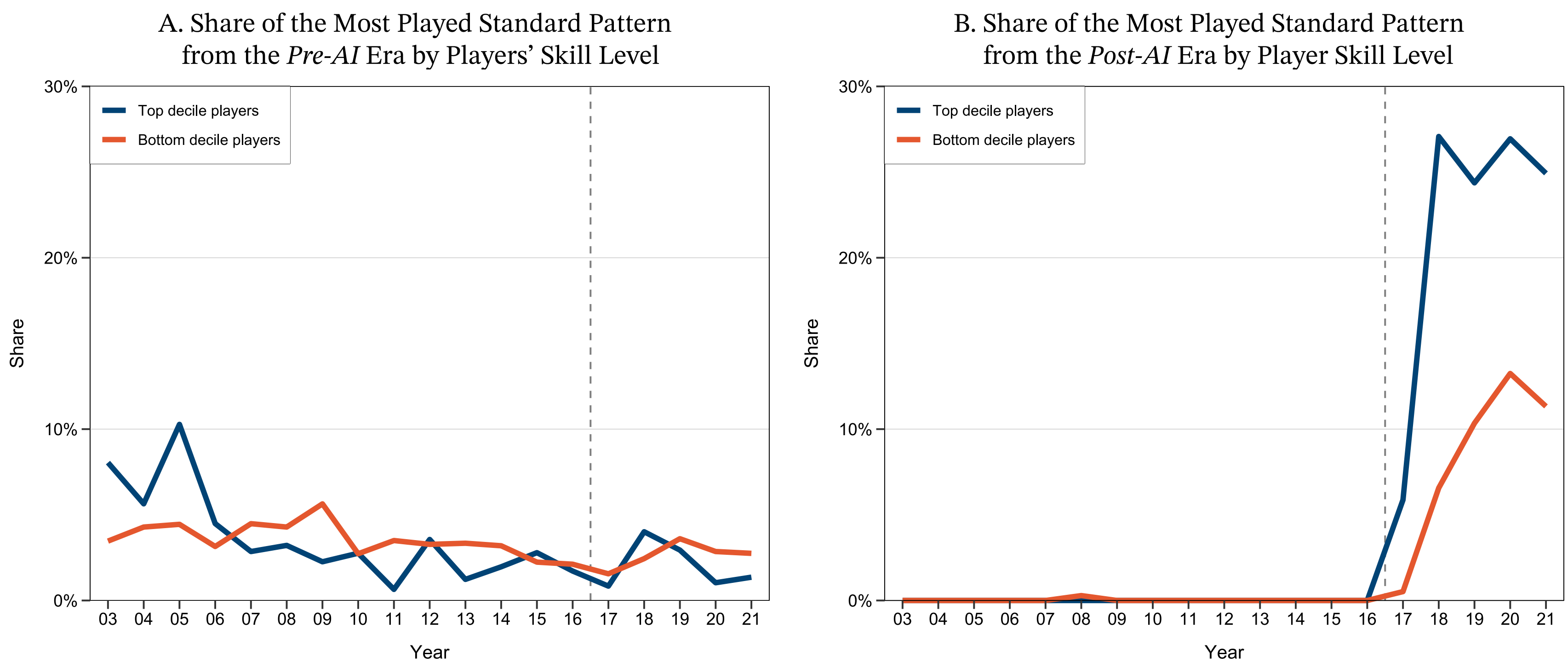


Figure 3. The heterogeneous effect of AI on knowledge creation by players' skill level. The figure illustrates the changing share of two distinct standard patterns by player skill level from 2003 through 2021. Panel A tracks the share of the most frequently played standard pattern in the pre-AI era across the entire period. Panel B shows the share of the most frequently played standard pattern in the post-AI era over the entire period. Together, the panels illustrate how the dominance of top patterns from the pre- and post-AI eras evolved in response to the public release of APG. We divide players by skill levels into deciles using an annual ranking of players who initiate the standard patterns, and the top and bottom decile groups are used in this study. The blue lines in both figures denote the share for the top decile group, while the orange is for the bottom. The grey vertical dashed line drawn between 2016 and 2017 indicates the first public release of APG in February 2017.

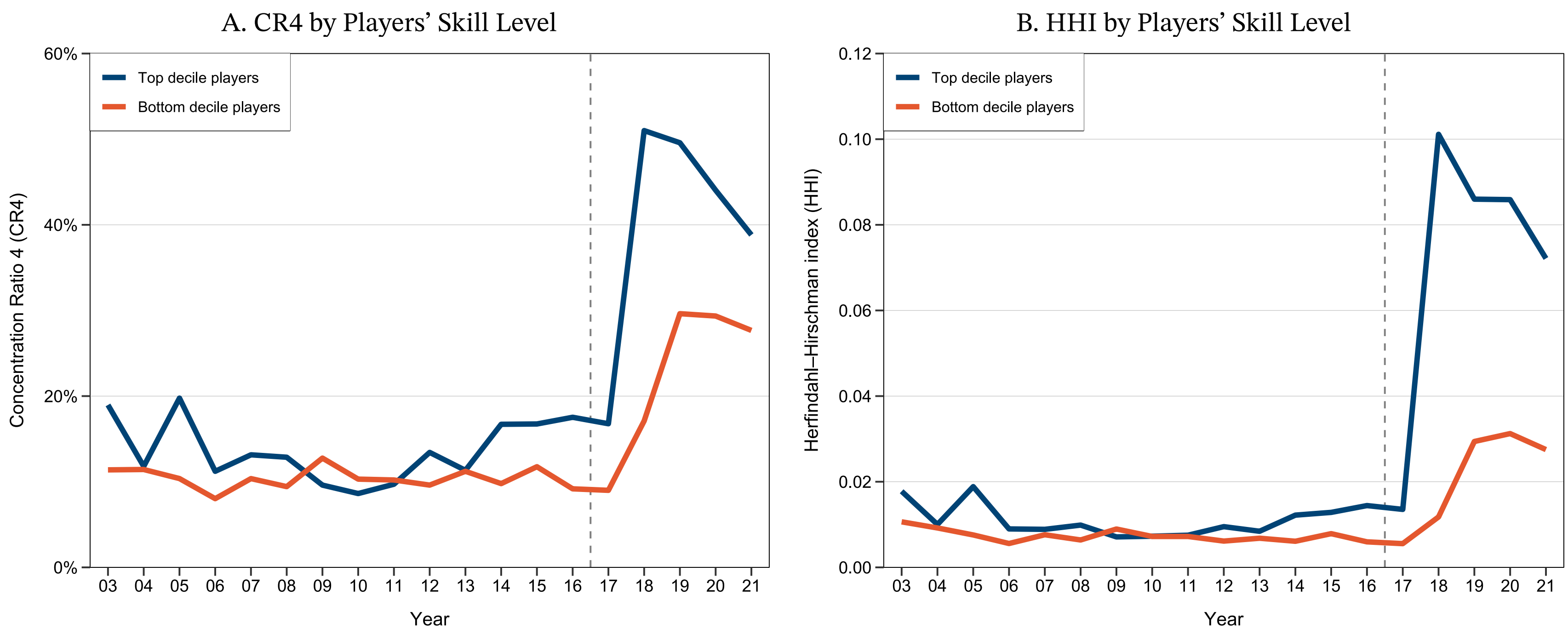
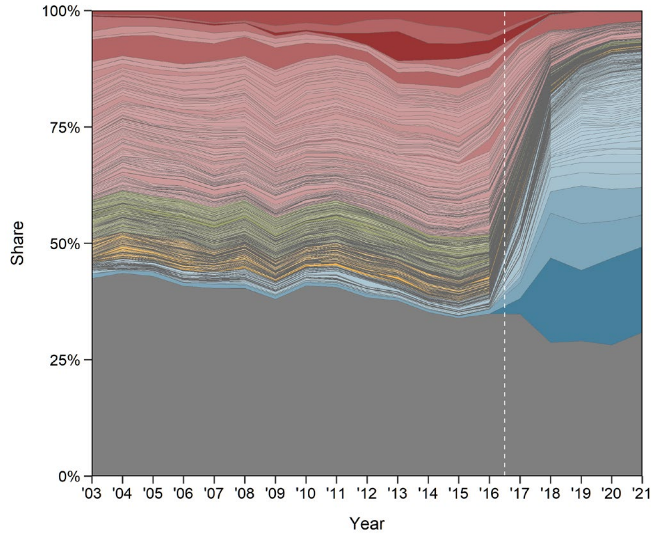


Figure 4. The heterogeneous effect of AI on knowledge concentration by players' skill level. This figure illustrates the differences by players' skill levels in the concentration of standard patterns played from 2003 to 2021. Players are divided by skill level into deciles using an annual ranking of players who initiate the standard patterns, and the top and bottom decile groups are used in this study. In this figure, we employ two concentration measures: concentration ratio 4 (CR_4) in Panel A, and Herfindahl-Hirschman Index (HHI) in Panel B. The blue lines in both figures denote the concentration for the top decile group, while the orange is for the bottom. The grey vertical dashed line drawn between 2016 and 2017 indicates the first public release of APG in February 2017.

A. All players



B. Players by Skill Levels: Top vs. Bottom Decile Players

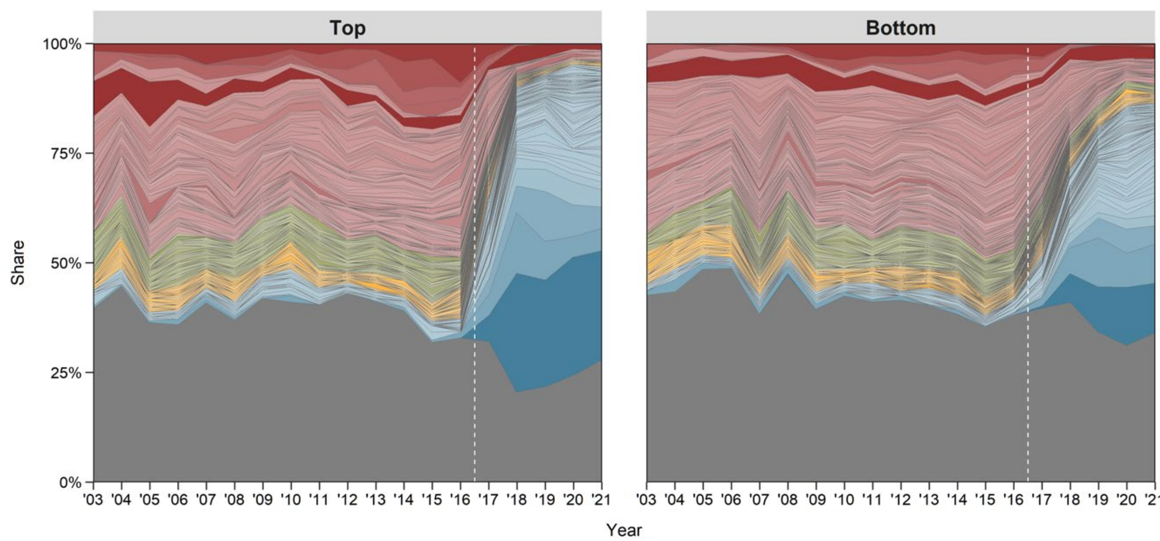


Figure 5. The heterogeneous effect of AI by players' skill level. This figure illustrates the yearly proportions of overall standard patterns played by players' skill levels during the sample period. Players are divided by skill levels into deciles using an annual ranking of players who initiate the standard patterns, and the top and bottom decile groups are used in this study. In this figure, yearly proportions of overall standard patterns for all games are depicted in Panel A, while that of the top and bottom decile groups are depicted in Panel B. We categorized the change in standard patterns before and after February 2017 into four quartiles, ordered and represented by the colors blue, yellow, green, and red, respectively. Blue denotes patterns used more frequently after the release of APG, while red indicates decreased usage. If a pattern is played on average at least once per year during the sample period, it is assigned one of these colors; otherwise, we sum the frequencies of such patterns and depict them in grey. The color gradient visually represents the relative changes in absolute values of pattern usage before and after APG within the quartile, and lighter shades indicate smaller changes. The black dashed lines illustrate the relative proportions of standard patterns within the quartiles, indicating a higher frequency of use, while the white vertical dashed line drawn between 2016 and 2017 indicates the first public release of APG in February 2017.