Singularity and the Seniority in the Knowledge Economy: Evidence from Japanese Chess Hierarchy

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Abstract

This study examines how digital revolutions shape the seniority premium among knowledge workers, using move-level game data from 40 years of professional Japanese chess (Shogi) league. We use two measures of productivity: a relative measure based on annual Grandmaster League rankings and an absolute measure based on the optimality of players' moves as evaluated by an AI engine. We find that the AI revolution in the 2010s shifted peak performance to older ages, whereas the ICT revolution in the 1990s shifted it to younger ages, according to both measures. These results suggest the AI can reduce age-related disadvantages among knowledge workers by democratizing access to high-quality learning.

JEL Classification: J24, O33, Z22

Keywords: technological change, human capital, seniority

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1 Introduction

Throughout history, technological innovations have always transformed the labor market, causing significant changes in the way workers work and their work environment. From the time of the Industrial Revolution to the present day, the introduction of new technologies has contributed significantly to improving worker productivity. However, the rapid pace of technological change presents challenges, particularly for those who find it difficult to adapt.

For older workers, adapting to new technologies can be particularly challenging. Age makes adapting to new systems and technologies increasingly difficult, often leading to generational disparities in occupational choices and workplace status. Young workers, who adapt more quickly to new technologies, secure their competitive edge in the labor market. Conversely, older workers' slower adaptation may compel them to prematurely exit the market.

This paper empirically examines the impact of technological innovation on younger and older workers. Our analysis focuses on the Japanese chess called Shogi, and using approximately 40 years of professional grandmaster league panel data, we investigate the impact of two technological innovations that have occurred on the tools used by players. The first is the ICT revolution: since 1992, the Shogi Federation has introduced a database containing past game records, which professional players can use to study tactics. The second is the AI revolution: when AI began to outperform professional players in 2016, professionals began to incorporate AI to explore new game tactics.

There are five advantages to using board game data to study worker adaptation to technological change. First, Shogi is a competitive board game, and the outcomes of wins and losses, as well as the moves, are recorded in the game records, implying that objective worker performance data are available. Second, because the rules are standardized and the institutions within the community have changed little, it is possible to compare the player performance across different eras and identify the impact of technological change. Third, we can construct a panel dataset comprising approximately 130 full-time players, ranging in age from 14 to 76, over a 40-year period from 1978 to 2020, allowing us to observe changes in life-cycle pattern while controlling for unobservable abilities. Fourth, professional players receive monetary rewards for each game, which varies widely by rank. Thus, we can analyze the heterogeneity of economic incentives for adaptation to technological change. Finally, using Shogi AI, we can obtain an objective performance indicator, namely the consistency rate, which measures how closely professionals' moves align with the AI's optimal moves.

Additionally, the following features of the Shogi Grandmaster League bring three distinct advantages over sports and other board games. First, the clear timing of technological innovation allows us to accurately capture the impact of new technology on workers. Second, there are fewer sample selection concerns in the Grandmaster League, since there are very few player exits. This contrasts with regular chess, where only a small fraction of players can earn a stable income. Third, by focusing on the Grandmaster League in professional shogi, we can observe the distinct impact of technological innovations on its organizational structure. Unlike professional go, which typically employs a tournament system where only the strongest players advance, shogi includes all professional players in a pyramid-style league. In this league, 'class' indicates the tier or level to which a player belongs, while 'ranking' refers to the annual position of each individual player, with both aspects determined through annual league matches.

We find that during the ICT revolution, the younger cohort is achieving long-term success. Furthermore, when examining relative performance based on grandmaster league, the peak age of players shifts to younger years. However, the AI revolution appears to slightly delay this peak age of player performance. Conversely, in terms of absolute performance, we employ the consistency rate—the degree to which a player's moves match those recommended by AI—as a key metric. We observe that after the AI revolution, the peak age for this consistency rate shifts to older age.

This study contributes to the recent literature on technology shocks and labor demand. There are many empirical studies that examine the impact of skill-biased technological change (SBTC) on the wage gap (Katz and Murphy, 1992; Krueger, 1993; Acemoglu and Autor, 2011, for example). These studies discuss how technological change affects the wage gap between high-skilled and low-skilled workers. On the other hand, our study is more related to the study of "skill altering technical change" (Macdonald and Weisbach, 2004), which discusses how technological shocks can make the skills of experienced workers obsolete. The study by Fillmore and Hall (2021) is also related to ours. They examine the impact of changes in tennis racquets on the age structure and the entry and exit of younger and older players in professional tennis.

Also relevant in the context of AI innovation is the study by Kanazawa et al. (2022). They show that the productivity gap between high-skilled and low-skilled workers narrows when taxi drivers use AI navigation to drive along designated routes based on demand forecasts. Their results are like ours in that older players have also seen absolute performance gains due to the AI revolution, but they differ in that the relative performance gap between younger and older players has widened.

Yamamura and Hayashi (2024) also employed shogi data to examine the effects of technological innovation on player performance. There are two main differences between their study and ours. Firstly, we used the absolute performance of players calculated by AI engine to investigate the age curve of shogi players. Secondly, our study demonstrated that the relationship between players' performance and age is characterized by an inverted-U shape. In contrast, they found a linear relationship indicating a decline in performance with age.

This study is organized as follows. In Section 2, we develop a discussion of the background of Shogi. Section 3 examines the impact of two types of technological innovations on players using data from Shogi ranking games. Section 4 analyzes the impact of the technological innovations on the relative and absolute performance of players. Section 5 presents our conclusions.

2 Background

This section describes the income structure of professional chess players in the Shogi game and the two types of technological innovations (ICT revolution and AI revolution) that have occurred in the Shogi world.

2.1 Income Structure of Players

Japanese professional chess players primarily earn their income from seven major tournaments, which has recently expanded to eight. Their earnings heavily rely on the grandmaster league, one of these seven events. Intriguingly, around 70% of a player's annual salary is dictated by their class in the grandmaster league.[1] This class system serves as a steady source of income, akin to a fixed salary.

The grandmaster league is divided into five classes, with promotion and demotion determined by annual performance in league matches within each class. For instance, if the basic monthly salary for a player in the top class, Class A, is 1 million yen, the salaries for Classes B1, B2, C1, and C2 are 700,000 yen, 500,000 yen, 350,000 yen, and 250,000 yen, respectively.[2] The classes form a pyramid hierarchy, with the highest class at the top. Regarding the number of players in each class, approximately 10 players belong to Class A, 13 to Class B1, 20 to Class B2, 40 to Class C1, and 50 to Class C2. In the grandmaster league, the rate of demotion varies by class. In the higher tiers, such as Class A and Class B1, approximately 20% of the players face demotion each year. However, in the lower tiers, specifically Classes C1 and C2, less than 10% of the players are demoted annually. Each year, around four players enter Class C2, and similarly, about four players exit this class.

2.2 The ICT Revolution

Since 1990, the spread of personal computers and the Internet has accelerated in Japan. This technological innovation has significantly impacted the world of Shogi. Particularly notable is the Shogi Federation's introduction of a game record database, which has revolutionized how professional players prepare for games and plan their strategies. The digitization of game records, previously only available in paper form, now allows professionals to access these records from home, greatly reducing the search cost. This change has facilitated more efficient and in-depth game analysis by providing easy online access to a vast archive of past game records and various early-game strategies.

Since the late 1980s, the Shogi world has been dominated by the 'Habu Generation,' a group of professionals centered around Yoshiharu Habu. The Habu Generation typically refers to players who

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1 Top professionals earn most of their income from prizes won in other tournaments.

2 Aono (2016) Puro Kisi to iu sigoto (in Japanese). Sougensya

are a year older or younger than Yoshiharu Habu. According to Amahiko Sato, one of the current top players, the long-term success of the Habu Generation is attributed to their use of databases, advanced study of the game's opening phases, and development of new standard moves.

Furthermore, professional Shogi player Yoshiharu Habu has testified about the ICT revolution as follows: Before this revolution, emphasis was placed on how players would deal with unknown situations on the spot, and reliance on data was seen as a sign of lacking confidence. However, with the introduction of the database, past games and specific positions can be easily searched and referenced. The digitalization of information management has significantly improved data collection efficiency. Initially, the benefits of these advancements were not immediately apparent in individual games, but over time, as players engaged in more matches, the accumulated research and data analysis began to impact game outcomes. In this study, 1992 is marked as the year when the Shogi Federation database was introduced (Okawa, 2016)

2.3 The AI Revolution

Since 2010, Shogi AI has made remarkable progress, surpassing even the top professionals; in October 2015, it was officially declared by the Information Processing Society of Japan that AI has surpassed the playing strength of the top professionals in Shogi. In May 2015, the Shogi AI software "Apery" was also released free of charge, and Shogi players began to actively use it for their research.[3] Similarly, in the Go world, the study suggest that professional Go players began to use AI in 2016 (Shin et al, 2023).

In parallel with these developments, this study also observed a marked improvement in consistency rates in 2016. The above suggests that it is highly likely that professional players began to incorporate AI into their everyday learning from this year, and we consider 2016 to be the year in which the AI revolution took place.

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[3] For example, Shota Chida, a professional player who is called "the poster child of AI Shogi", has actively used Apery to improve his skills (Ookawa, 2016).

3 Data

We use two types of data for our analysis. The first is the match history data from the grandmaster league between 1968 and 2020, including each player's age, debut age, training period before turning pro, date of each match, wins, losses, total number of moves, and final ranking. The second data includes the consistency rate, an indicator that indicates how often a player's moves match the optimal moves recommended by a Shogi AI. To calculate this rate, we used the 2020 Shogi AI to retrospectively analyze game records from 2011 to 2020. For each turn in these games, the AI determined what the best move would be. The consistency rate is then defined as the percentage of moves in each game where the player's move matched the AI's recommended move. Detailed descriptive statistics for these variables are provided in the Appendix.

In Section 3.1, we use the match history data to descriptively examine the impact of the ICT revolution on the age structure of players, and in Section 3.2, we use the consistency rate data to examine the impact of the AI revolution on player performance.

3.1 The ICT Revolution

Using the match history data, we examine the relationship between the introduction of the shogi database by the Shogi Federation, the ages of the players, and the length of the games.

First, we examine how the length of games changed before and after the technological innovation. The longer the total number of moves, the better the losing player fights, suggesting a decrease in one-sided games due to information gaps. Longer games may also increase the chances of reversals by lengthening the middle and endgame development and by increasing the number of steps beyond standard moves. Figure 1 illustrates the yearly trend in the total number of moves made in A class matches, the highest class in the grandmaster league. The vertical axis shows the moving average of total moves, while the horizontal axis indicates the year. Two dot lines mark the years of technological advancements: 1992, the year of the ICT revolution, and 2016, the year of the AI revolution. The figure reveals a downward trend in the total number of moves by players following the ICT revolution. Initially, the integration of databases into players' research led to shorter length of the game. However, since 2000, there has been an upward trend in the total number of moves. This increase might coincide with the widespread use of databases for game analysis, potentially leading to more complex gameplay and extended sequences of moves before the conclusion of the game.

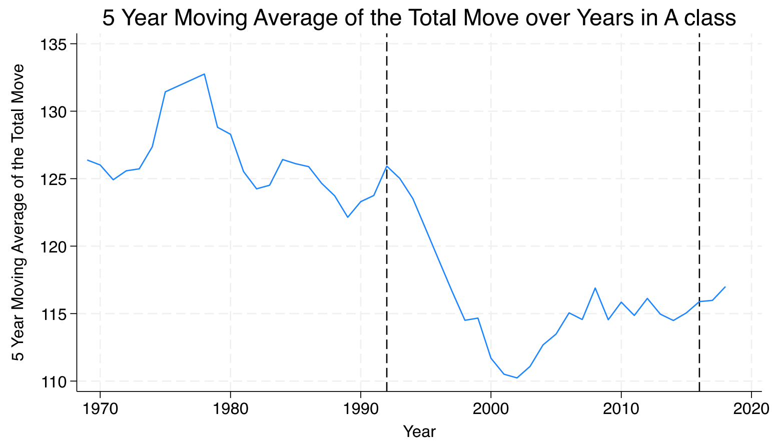
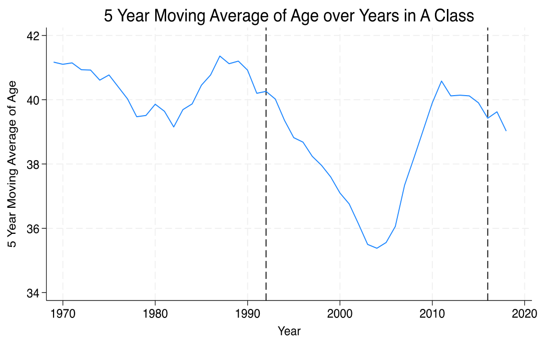


Figure 1: Average of the total move in A class

Notes: This graph is based on grandmaster league data spanning from 1968 to 2020. The average of the total moves in Class A is calculated as a moving average over a five-year period, encompassing the two years preceding, the year in question, and the two years following it.

Figure 2-a shows the trend in the average age of players in A class. According to the figure, following the ICT revolution, the average age of players decreased until 2005. This trend reflects younger players adapting to the technological changes and advancing to the A class, while older, veteran players were more likely to be demoted. However, post-2005, the average age began to increase, indicating that younger players who reached A class tended to maintain their position for longer durations. Figure 2-b categorizes players into two groups: those in classes A and B1, and those in other classes. It illustrates the transition in median age for each group. After the ICT revolution, the median ages of the higher and lower classes reversed. This suggests that younger players have been promoted to higher classes due to the technological shock.



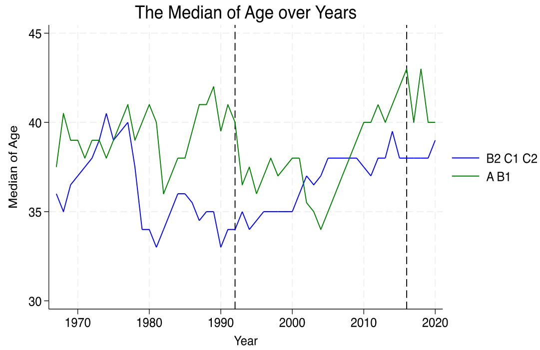
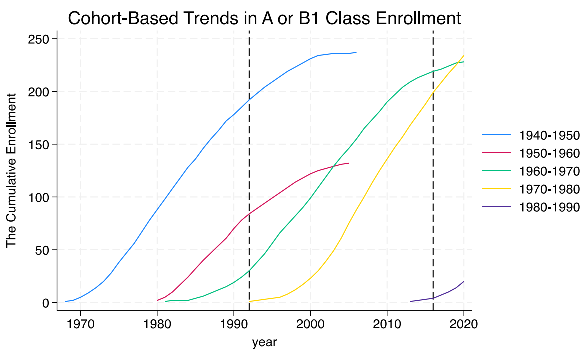


Figure 2-a: Average of the age in A class

Figure 2-b: Median age of above and below average players over time

Notes: Both graphs are based on grandmaster league data. For the Figure 2-a, the average age of players in A class is calculated as a moving average over a five-year period, encompassing the two years preceding, the year in question, and the two years following it. For the Figure 2-b, the median of Age in each group is shown.

Figure 3 focuses on the A and B1 ranks, known for their high demotion rates, and compares the cumulative number of enrollments by birth cohort. The vertical axis represents the cumulative number of times players have been in these top tiers, while the horizontal axis indicates the year. The figure reveals that players in their thirties in 1992 had a lower cumulative enrollment compared to other cohorts. This suggests that older players struggled to adapt to the technological changes, making it challenging for them to maintain their positions in the upper ranks.



Cohort	Age when 1992
1940-1950	42-52
1950-1960	32-42
1960-1970	22-32
1970-1980	12-22
1980-1990	2-12

Figure 3: The enrollment in A or B1 class by birth cohort

Notes: Due to the absence of ranking data from 1968 to 1977, this graph uses data from the years 1978 to 2020.

In summary, the ICT revolution has increased the speed of the game because of advances in game analysis and research, and has encouraged the rise of younger players, while older players have struggled to adapt to these changes.

3.2 The AI Revolution

To assess the impact of the AI revolution, which began post-2016, on players, we use consistency rate data for the five years before and after the AI revolution to examine the relationship between the AI revolution and player performance.

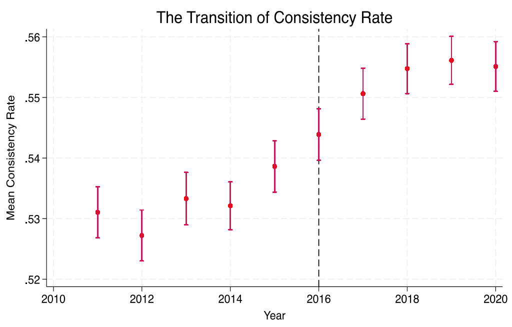
Figure 4-a shows the average consistency rate of players in games. A higher consistency rate indicates that the player's moves are more consistent with the AI's best moves. The figure shows that the consistency rate increased in 2015 and leveled off in 2018. This confirms Watanabe's statement that some players started using AI in 2015, and by 2018 at the latest, most players had begun using it.[4]

Figure 4-b shows the consistency rate over cohorts. The older generations born before 1960 has the lowest consistency rates, while younger generations tend to have higher consistency rates. Additionally, compared to the generation born before 1960, the youngest generation born after 1990 exhibits a higher growth rate in consistency, suggesting the potential benefits of learning with AI.

Figure 4-c shows the trend of consistency rates by class. The A and B1 classes with high demotion rates show a sharp increase in consistency rates in 2016, while the C1 and C2 classes with low demotion rates do not show such a trend. This suggests that in classes with higher competitive pressure, professionals in these classes were quicker to adopt AI into their learning strategies. We also examined the evolution of the total number of moves to confirm that the incorporation of AI into their learning has advanced early-stage game analysis and accelerated game pace. For the higher classes, a decrease in the total number of moves was observed in 2016, while this was not the case

[4] Diamond Online. (2022) https://diamond.jp/articles/-/293924. Accessed January 24, 2023.

for the lower classes.



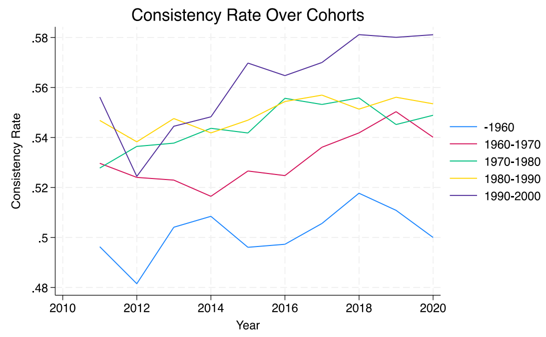


Figure 4-a: Trends in Consistency Rate

Figure 4-b: Consistency Rate over Cohorts

Figure 4-c: Consistency Rate and Game Length by Class

Notes: We used consistency rate data from the years 2011 to 2020. 90% confidence intervals are shown in Figure 4-a.

In summary, the trends in consistency rate and total number of moves indicate that the AI revolution began to make its presence felt around 2016, particularly in the higher classes, and by 2018, many professionals had already incorporated AI into their learning.

4 Empirical Analysis

In this section, we analyze the impact of technological innovation on the age composition and performance of players. Section 4.1 examines how technological innovation has affected the age curve of players, using the relative performance indicator of players' initial ranking. In Section 4.2, we assess the impact of the AI revolution on the performance of both young and old players. Here we use data with an absolute measure, the consistency rate calculated by Shogi AI engine, to examine the changes brought about by the AI revolution in the relationship between player performance and age.

4.1 Effects of Technological Innovation on the Age Structure

In a situation where the hierarchical structure of the organization remains unchanged, we examine how technological innovation alters the relationship between players' rankings and ages.

First, we examine the relationship between the ranking's percentile value (which ranges from 0 to 1, with 1 indicating the highest rank) and age using Locally Weighted Regression and Smoothing Scatterplots for each of the three periods: the period without technology shocks, the ICT revolution period, and the AI revolution period (Figure 5). In all three periods, the relationship between the percentile value of the ranking and age is an inverted U-shaped curve. Compared to the period without technological shocks, the peak age occurs earlier and shifts to the left during the ICT revolution. However, during the AI revolution period, the peak age shifts to the right and tends to be later compared to the ICT revolution period.

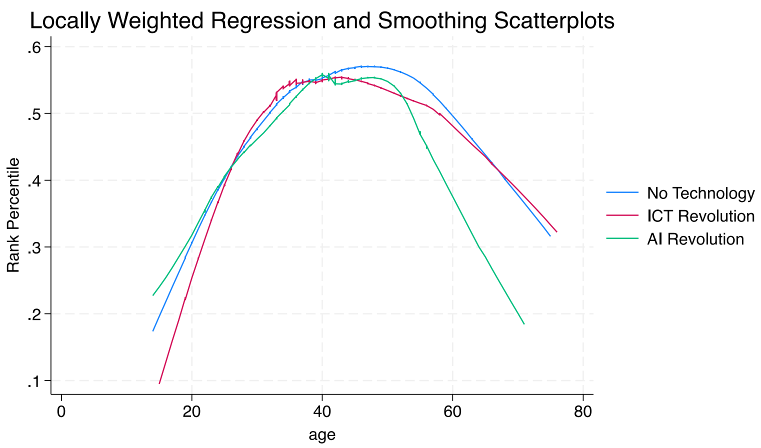


Figure 5: A Lowess-fitted curve showing the relationship between ranking percentiles and age

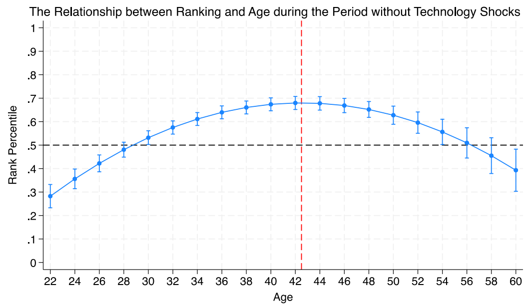
Notes: A bandwidth of 0.8 is used, indicating that 80% of the data is used to smooth each point.

Next, we divide the sample into three periods and show the relationship between ranking and age using the following estimation equations.

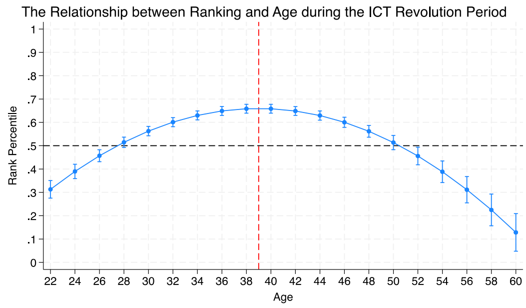
$$Rankpt_{it} = \alpha_i + \beta_1 Age_{it}^2 + \beta_2 Age_{it} + \epsilon_{it}$$

$Rankpt_{it}$ represents the percentile ranking of player i at the end of year t. Age_{it} represents the player's age, and α_i denotes player fixed effects. The estimation results are detailed in Table A.2.

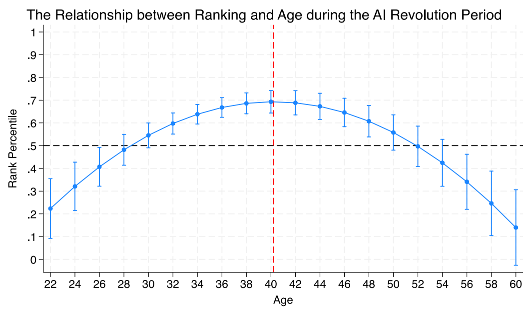
Figure 6 displays the predicted age curves of players from the estimation, including the 90% confidence intervals. From the table A.2, the peak ages are calculated to be approximately 42.6, 39.2, and 40.2 years for the period without technological shocks, the ICT revolution period, and the AI revolution period, respectively. The ICT revolution period accelerated the peak age of professionals compared to the period without technological shocks, while the AI revolution period delayed the peak age of professionals.



The Period without Technology Shocks



The ICT Revolution Period



The AI Revolution Period

Figure 6: Relative Performance by Age

Notes: Based on the estimation results in Table A.2, the figure plots the relationship between the predicted value of the percentile of the ranking and age, including 90% confidence intervals. The red dashed line represents the vertex of the quadratic function, while the black dashed line represents the line with a ranking percentile value of 0.5.

4.2 Effects of the AI Revolution on the player's performance

Next, we examine the change in the relationship between player performance and age before and after the AI revolution using the consistency rate of players.

$$CR_{ijt} = \alpha_i + \boldsymbol{A}_{ijt}\boldsymbol{\beta} + \boldsymbol{AI}_{ijt}\boldsymbol{\gamma} + \boldsymbol{W}_{ijt}\boldsymbol{\delta} + \epsilon_{it}$$

CR_{ijt} represents the consistency rate of player i against opponent j during the year t. $\boldsymbol{A}_{ijt}$ includes the player's age, including the squared and cubic terms. We use two dummy variables to represent the AI transitional period (2016~2017, referred to as $Transit_t$) and the AI establishment period (post-2018, referred to as $Establish_t$), and those variables are included in $\boldsymbol{AI}_{it}$. $\boldsymbol{AI}_{it}$ also includes the interaction terms of the player's age with the dummy variables. $\boldsymbol{W}_{ijt}$ includes player i's class in year t, and a dummy variable for playing black, since the player moving first typically has an advantage in games. The estimation results are presented in Table A.3.

Figure 6 illustrates the empirical relationship between the consistency rate and age, after netting out the class and individual fixed effects. Compared to the pre-AI revolution and AI transitional periods, the peak of the age curve shifts rightward during the AI establishment period. This shift suggests that the AI revolution has altered the age curve, with older players experiencing significant benefits.

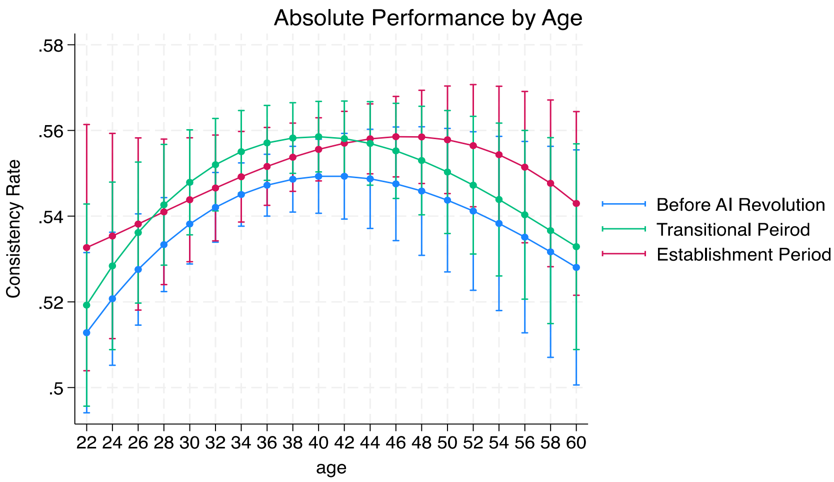


Figure 6: Absolute Performance by Age

Notes: Based on the estimation results in Table A.3, the figure plots the relationship between the predicted value of the consistency rate and age, including 90% confidence intervals.

In conclusion, technology shocks have significantly impacted the relationship between relative performance and age in the professional chess world. Specifically, while the ICT revolution advanced the peak age for professionals, the AI revolution has had the opposite effect, postponing it. Furthermore, the AI revolution has also delayed the peak age in terms of absolute performance, demonstrating that professionals have successfully adapted to and benefited from reskilling opportunities.

The acceleration of peak ages during the ICT revolution and their delay during the AI revolution can be attributed to the alignment of technological advancements in the chess world with broader societal changes. Initially, in 1992, the introduction of game record databases coincided with a low computer penetration rate of only about 10%.[5] Young professionals, eager to leverage new technologies, saw their careers peak earlier. Conversely, by the time of the AI revolution in 2016, the widespread acceptance of computers and smartphones—with penetration rates around 77% and 72%, respectively—facilitated the integration of AI into professional practice.[5] This accessibility allowed

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[5] Cabinet Office, Government of Japan. "Consumer Trends Survey."

players of various ages to enhance their performance and extend their career peaks.

This shift is also closely tied to the evolution of user interfaces. Initially, tasks like keyboard operation on personal computers posed challenges for those unaccustomed to them. However, the advent of smartphones made operations more intuitive and user-friendly, enabling even senior players to adopt new AI tools and thus prolong their active careers.

Lastly, utilizing AI has allowed for a more precise identification of the "correct" answer, providing a significant advantage over the ICT era, when problem-solving largely relied on personal analysis or discussions with others. During the ICT era, especially in post-game feedback sessions, younger players often found it difficult to express their opinions, consequently limiting the opportunities for older players to learn new techniques and strategies.

5 Concluding Remark

This study provides unique insights into the impacts and dynamics of technological innovation on the workers, with a particular focus on younger and older workers. Using the Japanese chess as a case study, it analyzes the introduction of the ICT and AI revolutions in this context and presents several key findings.

The findings reveal that while technological innovation generally improves performance, its impact is not uniform across all workers. Specifically, during the ICT revolution, younger workers tend to benefit significantly from these technological shocks. In contrast, during the AI revolution, older workers experience improvements in their relative and absolute performance

The study highlights the critical importance of continuous learning and adaptation to technological changes in today's labor market. The ability to quickly adapt to and effectively utilize new tools is a key survival factor, especially for older workers.

However, there are some limitations in this study. While the grandmaster league system offers a clear and controlled environment to observe the impact of technology, generalizing these results to a broader labor market context has its limitations. Future research should explore similar impacts across different industries and cultural contexts to further elaborate on the findings of this study.

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Appendix

Variable	Obs	Unit of Observation	Mean	Std. dev.	Min	Max
Age	5,222	Player-Year	37.341	11.851	14	76
Debut Age	5,222	Player-Year	21.038	3.414	14	41
Training Year	4,679	Player-Year	6.856	3.150	1	27
Tenure	5,222	Player-Year	16.303	11.756	0	62
Rank Percentile	5,222	Player-Year	0.5004	0.291	0	1
ICT Dummy	5,222	Player-Year	0.583	0.493	0	1
AI Duumy	5,222	Player-Year	0.104	0.305	0	1
The Number of Moves	20,226	A match	114.309	29.186	25	390
Consistency Rate	13,222	A player in a match	0.543	0.093	0.097	0.889

Table A.1: Summary Statistics

Notes: This table shows the summary statistics using grandmaster league data from 1968 to 2020 which includes consistency rate data from 2011 to 2020.

	No Technology	ICT	AI
Age	0.080***	0.094***	0.114***
	(0.008)	(0.007)	(0.018)
$Age^2/100$	-0.094***	-0.120***	-0.141***
	(0.010)	(0.009)	(0.022)
Individual FE	Yes	Yes	Yes
N	1755	2905	535
adj. R-sq	0.829	0.804	0.926

Table A.2: Effects of the Technological Innovations on Organizational Structure

Notes: We used grandmaster league data from 1978 to 2020. Robust standard errors are clustered by individual level, and cluster robust standard errors in parentheses. We split the samples into 3 periods: the period without technological shocks, the ICT Revolution period, and the AI revolution period. * p<0.1, ** p<0.05, *** p<0.01.

	CR
$Transit$	-0.033
	(0.070)
$Establish$	0.189**
	(0.080)
Age	0.012*
	(0.006)
$Age^2/100$	-0.0215
	(0.016)
$Age^3/1000$	0.001
	(0.001)
$Transit \times Age$	0.003
	(0.005)
$Transit \times Age^2/100$	-0.007
	(0.012)
$Transit \times Age^3/1000$	0.001
	(0.001)
$Establish \times Age$	-0.014**
	(0.006)
$Establish \times Age^2/100$	0.032**
	(0.013)
$Establish \times Age^3/1000$	-0.002**
	(0.001)
$Black\ Dummy$	0.007***
	(0.002)
Class FE	Yes
Individual FE	Yes
N	13222
adj. R-sq	0.104

Table A.3: Effects of the AI Revolution on the Player's Absolute Performance

Notes: We used grandmaster league data from 2011 to 2020, including information on consistency rates. Standard errors are clustered by player level. Clustered robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.