Journal of Go Studies
Volume 20, No. 1
2026

바둑학연구

2026

국제바둑학회

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인쇄일: 2026년 5월 31일
발행일: 2026년 5월 31일
인 쇄: 인쇄와 디자인 (02-957-7744)
편 집: 도서출판 안북스 (02-923-5930)

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Introduction

In closing our previous issue, we observed that 2026 would mark the tenth anniversary of the Google DeepMind Challenge Match, and promised to keep our readers informed as our commemorative plans took shape. That year has arrived.

Ten years ago, in March 2016, five games played in Seoul drew the eyes of the world to a board that most people had never seen before. AlphaGo's victory over Lee Sedol was reported, above all, as a milestone in artificial intelligence — and so it was. But for those within the Go community, the event carried a different, more intimate weight. Something familiar had been rendered suddenly strange. The game's internal logic, its aesthetics, its very conception of strength and creativity, were thrown open to question in ways that have not been fully resolved since.

Ten years, it turns out, is long enough to begin to see clearly, but short enough to still feel the force of that displacement. When we asked, in our last issue, whether the intelligence of the biological brain and body can truly be approached through technological advance — through deep learning, generative AI, or whatever comes next — we left the question deliberately open. The papers gathered in this issue do not close it. But they do something perhaps more valuable: they show how a discipline responds when its foundations are shaken.

The first paper, by Kim Jaeyun, addresses a question that has lingered since 2016 without a rigorous answer: not *whether* traditional joseki are inferior to AI recommendations, but *by how many points*. Using a purpose-built program—Joseki Analyzer—integrated with the KataGo engine, the study measures the efficiency gap across seventy moves from twenty pre-AlphaGo fuseki patterns. The overall mean Δ Score of −0.28 points per move is modest, but the typological contrast is sharp: corner-enclosure and pincer-response patterns diverge most from AI, while contact-play sequences show near-perfect alignment. The study's most consequential finding may be its simplest—KataGo consistently prioritizes claiming empty corners over consolidating established positions, a preference that runs directly counter to one of classical Go theory's foundational axioms.

The special feature closes with a paper by Bae Incheol, which offers a critical interrogation of Lee Sedol's 2025 *Memoir*—published, pointedly, a decade after the Match. Where Kim's paper measures the gap between human intuition and AI computation in points, Bae's measures it in memory. The paper's central target is Lee's 'bug-triggering theory': the retroactive claim that Move 68 in Game 4 was a calculated gambit to induce a system error, and that the celebrated Move 78—the *Divine Move*—was its dependent effect. Drawing on Bourdieu's theory of symbolic power and Ranganath's cognitive science of memory reconstruction, the paper argues that this narrative exemplifies the Orwellian memory hole: not a solitary act of myth-making, but a co-production between a dominant narrator and a society eager to consume a hero-narrative at the cost of intellectual honesty.

The third paper, by Arthur Mary, takes as its starting point a belief wide-

ly shared among Go players: that you can truly come to know a person by playing against them. Rather than dismissing this as romantic intuition, the study subjects it to formal investigation, asking whether statistically detectable correspondences exist between a player's strategic style—measured by Moudřík's four GoStyle indices (aggressiveness, orthodoxy, territoriality, thickness)—and their Szondi drive-profile scores. Based on a sample of 21 players who each submitted game records and completed three administrations of the Szondi test, the analysis identifies two statistically supported correspondences: stylistic aggressiveness is negatively associated with the percentage of null responses, and a more orthodox style is positively associated with the hy− factor. The paper is scrupulous in its epistemological framing: these are not causal claims, nor measurements of underlying psychological magnitudes, but structural correspondences between two distinct coding systems—a distinction the author maintains throughout with admirable rigor.

Does Go experience predict sustained attention in young adults — and if so, does it matter how long or how well one has played? The fourth paper, by Daniela Trinks and María Teresa Martínez García, addresses these questions with 99 Korean university students divided into experienced and minimal-experience groups, administering the Sustained Attention to Response Task 2 (SART2) and finding that Go players outperform non-players in overall accuracy, with performance increasing incrementally with both proficiency level and years of exposure. The effect holds after controlling for gender composition and bilingual background, two variables that differed noticeably between the groups. The study's cross-sectional design precludes causal claims, but its findings extend earlier clinical and developmental

evidence — most of which focused on children or older adults — to healthy young adults, and offer a cognitive rationale for introducing Go as an enrichment activity in formal educational settings.

Half a million games played on Fox Go Server between 2013 and 2019 form the empirical backbone of the fifth paper, by Quentin et al. Using a dual methodology — expert-informed pattern recognition and a purely data-driven clustering approach — the study maps which opening strategies amateur players actually favor across fourteen rank levels, from 10 kyu to 9 dan. Nirensei and hoshi+34 emerge as dominant across all ranks, while deeper openings such as Sanrensei, Chinese, and Kobayashi each peak at distinct rank bands. The study's most timely finding concerns the post-AlphaGo period: among players ranked 4 dan and above, the frequency of Nirensei openings rose sharply after 2016, whereas lower-ranked players show no comparable shift as of 2019 — a divergence the authors interpret as reflecting either stronger AI-awareness among higher-ranked players or a delayed adoption effect that more recent game records, currently unavailable, may yet reveal among lower ranks.

Rounding out the volume's second section, Marc Oliver Rieger draws on data from the PANDA survey — 2,510 university students across six countries (China, Taiwan, Japan, Vietnam, Germany, and Estonia) — to shed light on a population that has so far received little empirical attention: casual Go players. The study yields two headline findings. First, the casual player base is larger than expected even outside East Asia, with Vietnam and Estonia recording recent-play rates comparable to the traditional Go nations. Second, among the predictors examined — demographics, Big Five

personality traits, Hofstede cultural dimensions, and cognitive reflection — competitive orientation (masculinity index) is the most consistent predictor across both learning and continued play, while cognitive reflection, paradoxically, is negatively associated with sustained casual engagement, a result the author interprets as reflecting the cognitively restless tendency to move on to new challenges rather than persisting with a single game.

The volume closes with a book review by Park Woosuk, assessing Han Jeong-gyu's *AI and Consciousness* (CommunicationBooks, Inc., 2025). Written in a distinctly personal register — part critical appraisal, part intellectual memoir — the review situates the book within a broader argument: that Korea's academic world was slow to anticipate the AI turn precisely because neuroscience, rather than AI research, absorbed the lion's share of scholarly attention for three decades. Against that backdrop, the reviewer finds Han himself a rare and welcome exception: a neuroscientist with genuine credentials who takes consciousness seriously as both a scientific and philosophical problem. The book's ten chapters move from the historical and cinematic treatment of consciousness through its philosophical underpinnings and major theoretical frameworks, arriving finally at the question AI researchers themselves are now compelled to ask. For a journal appearing in the tenth anniversary year of AlphaGo, the pairing of this review with the preceding six papers feels less like coincidence than quiet necessity.

The six studies presented here — ranging from the quantitative analysis of AI-influenced joseki to the social geography of casual play, from the psychological architecture of playing style to the politics of how a historic defeat is remembered — collectively map a field in motion. A decade on from the

Match, Go studies is neither the discipline it was before AlphaGo nor a mere satellite of artificial intelligence research. It is something in between, and something genuinely new: a field alert to technology's transforming pressures, yet anchored in questions that no algorithm has yet learned to ask. We trust that readers will find in these pages not only answers, but reasons to keep asking.

June 2026
Bae Incheol, Editor-In-Chief

바둑학연구, 제20권 제1호, pp. 11-50
Journal of Go Studies
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Quantitative Comparative Analysis of Traditional Go Joseki and AI-Recommended Moves

A Study of Twenty Fuseki Patterns Using KataGo Expected Score

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Abstract

AlphaGo's landmark victory over Lee Sedol in March 2016 triggered an unprecedented paradigm shift in the game of Go, prompting widespread re-valuation of joseki sequences—locally optimal opening patterns refined over centuries of human tradition. Despite this upheaval, systematic *quantitative* research into precisely how inefficient traditional joseki are—measured in concrete point (目) differentials—remains scarce in the academic literature. Most existing discourse has operated at the level of qualitative judgment ("this move is good/bad") without rigorously measuring the numerical stakes.

This study addresses that gap by extracting approximately **70 key moves from 20 fuseki patterns** widely used in the pre-AlphaGo era and quantifying the efficiency difference between traditional sequences and AI-recommended moves using KataGo's Expected Score metric. A central contribution is the independent design and development of **Joseki Analyzer**—a purpose-built program integrating a FastAPI backend with the KataGo engine—enabling automated, large-scale, reproducible analysis under standardized conditions

(1,000 visits, Chinese rule set, komi 7.5). The core metric **Δ Score** is defined as the Score Lead of the AI's top-recommended move minus the Score Lead of the traditional move at the same position; a negative value indicates that the traditional move is less efficient by the corresponding number of points.

Results show an **overall mean Δ Score of approximately −0.28 points** across 20 patterns, indicating that traditional moves incur an expected-score loss of roughly this magnitude per move relative to AI recommendations. The largest divergences occur in the *Komoku Approach–Pincer Response* (II) (−1.20 pts), *Komoku Approach–Aggressive Response* (−0.68), *Hoshi One-Space Pincer–3-3 Invasion* (−0.60), and *Komoku Corner Enclosure Fuseki* and Komoku Approach–High Extension (both −0.53). The single largest move-level loss is −2.59 points. Conversely, four patterns achieve Δ Score = 0—*Hoshi Approach–Knight's-Move Response, Komoku Enclosure–Development Variation, Hoshi Approach–Contact-Play Joseki*, and *Komoku Approach–Contact Play* (II)—indicating perfect alignment with AI evaluation.

A consistent typological finding emerges: corner-enclosure and extension patterns show the largest divergence from AI, while contact-play (붙임수) patterns show the smallest. Across all patterns, KataGo systematically prioritizes claiming empty corners over reinforcing one's own established

positions—a finding that runs counter to a core axiom of classical Go strategy. This study represents the first systematic, tool-assisted effort to quantify the inefficiency of traditional fuseki joseki in point-based terms, offering both empirical findings and a replicable methodological framework for evaluating classical Go theory against modern AI computation.

Keywords: Go, joseki, fuseki, KataGo, Expected Score, quantitative analysis, AlphaGo, AI efficiency, Δ Score, Joseki Analyzer

1. Introduction

1.1 Research Background

In March 2016, Google DeepMind's AlphaGo defeated world champion Lee Sedol 9-dan by four games to one—an event that was widely recognized not merely as a technical milestone but as a fundamental challenge to centuries of accumulated human knowledge about Go (Silver et al., 2016). Subsequent AI systems, including AlphaGo Zero (Silver et al., 2017) and KataGo (Wu, 2019), have further eroded confidence in a substantial portion of the traditional joseki (定石) canon, revealing that many sequences humans once considered locally optimal are, from an AI standpoint, second- or third-best plays.

Joseki are locally optimal corner sequences—patterns in which both Black and White played what was considered their best response—that form the building blocks of fuseki (布石), the strategic opening phase of a Go game. Before the AI era, the joseki corpus represented the apex of human inductive reasoning applied to the game over centuries of competitive play and analysis. The AI revolution has put this corpus under unprecedented scrutiny.

Yet despite the upheaval, scholarly discourse has remained largely qualitative, offering assessments of "good" or "bad" moves without rigorously measuring the numerical point differential involved. The question "by exactly how many points is traditional joseki X inferior to AI's recommendation?" has, to the author's knowledge, not been addressed in a systematic, large-scale, quantitative study. This gap has two practical consequences: (1) Go educators lack data-driven guidance on which traditional patterns remain reli-

able and which require revision; (2) the historical moment—AlphaGo's tenth anniversary—calls for an empirical reckoning with the gap between human intuition and AI computation.

1.2 Research Objectives and Questions

This study aims to quantify the efficiency gap between traditional fuseki joseki and KataGo's AI recommendations by extracting approximately 70 moves from 20 patterns widely used before AlphaGo and measuring the difference in expected score in point (目) units. Three research questions guide the investigation:

RQ1. What is the mean difference in Expected Score (Δ Score) per move between traditional fuseki joseki sequences and AI-recommended moves?

RQ2. Does the magnitude of divergence from AI recommendations vary systematically by joseki type (corner enclosure, extension, contact play, pincer response, etc.)?

RQ3. How does AI evaluate traditional moves in terms of Prior probability, and what strategic characteristics does KataGo consistently prefer?

1.3 Originality of the Study

This study differentiates itself from prior work in three respects. First, **a quantitative metric:** the study uses Score Lead rather than Win Rate to measure efficiency in point units. Win Rate is a nonlinear indicator in which small differences may be amplified or compressed; Score Lead offers a directly

interpretable, linear measure of expected outcome. Second, **a purpose-built analysis tool:** the researcher independently designed and developed Joseki Analyzer, enabling automated analysis of 20 patterns and 70 moves under identical conditions—a scale of systematic comparison that was previously not feasible without dedicated tooling. Third, **cross-pattern comparison:** by applying a uniform measurement framework across 20 patterns, the study enables typological trend analysis that single-pattern studies cannot provide.

2. Theoretical Background

2.1 Joseki and Fuseki in Go

The opening phase of Go—the fuseki stage, typically the first 50 or so moves—is a contest for the most valuable territory. Classical theory holds that spatial value on a Go board follows a **corner → side → center** hierarchy: corners can be enclosed using only two board edges, yielding efficient territory with fewer stones; sides require one edge; the center requires no walls and is the hardest to convert into secure territory efficiently.

Within this framework, joseki are the locally agreed-upon optimal sequences in the corners, where both players played what was considered their best response, resulting in a locally balanced outcome. Fuseki is the art of combining these local joseki outcomes into a coherent global strategy. Before the AI era, the joseki canon—comprising hundreds of standard patterns—represented the highest level of human analytical achievement in Go theory. Players, coaches, and commentators treated joseki as a fixed reference system for understanding corner play.

2.2 The Rise of AI Go and KataGo

The development of AI Go can be understood in three phases. In the **first phase (2016)**, AlphaGo combined deep convolutional neural networks—building on advances in deep reinforcement learning (Mnih et al., 2015)—with Monte Carlo Tree Search (MCTS; Coulom, 2006; see Browne et al., 2012, for a comprehensive review), achieving superhuman performance against the world's strongest human players (Silver et al., 2016). In the **second phase (2017)**, AlphaGo Zero dispensed with human game records entirely, learning solely through self-play and rapidly surpassing its predecessor—in the process revealing that many canonical joseki were suboptimal (Silver et al., 2017). In the **third phase (2019–present)**, KataGo brought this technology to the open-source community, with efficient training algorithms and robust analysis tools making it the standard engine for Go research and education (Wu, 2019).

KataGo's Score Lead metric estimates Black's expected point advantage under Chinese counting rules, assuming optimal play from both sides. Positive values indicate a Black lead; negative values indicate a White lead. This metric provides a continuous, interpretable measure of positional efficiency appropriate for studying short-term move quality—the focus of this study.

Although the present study builds directly on the AI Go lineage outlined above, it differs from prior AI-driven revaluations of joseki in both scope and aim. AlphaGo Zero's self-play results (Silver et al., 2017) revealed that many canonical joseki are suboptimal, and subsequent discussions in the professional Go community broadly accepted this verdict at a qualitative level—new moves were adopted, certain sequences fell out of favor, and commentary literature shifted accordingly. However, these earlier revaluations were

largely demonstrative (showing that AI plays differently) rather than measurement-based (quantifying by how many points traditional moves diverge from AI). The present study extends this lineage in two specific directions: (i) it replaces qualitative endorsement of AI moves with a continuous, point-based metric (Δ Score in 目 units) that is directly interpretable in Go's own scoring system, and (ii) it applies a uniform analytical framework across 20 patterns to detect typological trends rather than commenting on individual sequences. In this sense, the study is best understood not as a contradiction of AlphaGo Zero's findings, but as their quantitative continuation—moving from "AI plays differently" to "AI plays X points more efficiently in this pattern type."

2.3 Operational Definitions

Table 1. Key terms and operational definitions

Term	Definition
Score Lead	KataGo's estimate of Black's expected point advantage under Chinese counting. Positive = Black leads; negative = White leads.
Win Rate	KataGo's estimated probability that Black wins the game from the current position (0–1).
Prior	The neural network's prior probability assigned to a candidate move during MCTS, reflecting the network's intuitive preference before deep search.
Δ Score	Score Lead (AI best move) − Score Lead (traditional move). A negative value indicates the traditional move is less efficient by that many points.
Joseki (定石)	A sequence of locally optimal moves in the corner, resulting in a locally balanced outcome for both players.
Fuseki (布石)	The opening phase of Go (~first 50 moves), in which players establish strategic frameworks across the whole board.
Visits	The number of MCTS simulations allocated to each candidate move. Higher visits yield more accurate evaluations.
Contact play (붙임수)	A tactical sequence initiated by placing a stone directly adjacent to an opponent's stone.

3. Methodology

3.1 Analysis Tool: Joseki Analyzer

The central methodological contribution of this study is the independent design and development of **Joseki Analyzer** (Kim, 2026), a purpose-built program that automates the collection and structuring of KataGo evaluation data for arbitrary joseki sequences. The system architecture is as follows:

> **Joseki Analyzer — System Architecture** ① **Backend:** Python FastAPI REST API server ② **AI Engine:** KataGo (open-source Go AI, integrated via GTP protocol) ③ **Database:** SQLAlchemy ORM for structured result storage ④ **Output:** Automatic collection of Score Lead · Win Rate · Prior for top-15 candidate moves at each position; automated generation of structured HTML visualization reports

The analysis workflow proceeds as follows: (1) the user inputs a joseki sequence in GTP coordinate format (e.g., B4, C3, D16 …); (2) Joseki Analyzer reconstructs each successive board position and calls KataGo; (3) KataGo returns Score Lead, Win Rate, and Prior for the top 15 candidate moves; (4) Joseki Analyzer records the rank and score of the traditional move and computes Δ Score against the AI's top recommendation; (5) results are automatically compiled into a structured HTML report. This automation made it feasible to analyze 20 patterns and 70 moves under identical, reproducible conditions.

3.2 Core Metrics

The primary metric of this study is defined as follows:

Δ Score = Score Lead (AI best move) − Score Lead (traditional move)

A Δ Score of 0 indicates that the traditional move and the AI's top recommendation achieve the same expected score. A negative value indicates that the traditional move is less efficient by that number of points. The *pattern-level mean Δ Score* is the arithmetic mean of Δ Score values across all analyzed moves within a pattern.

> ⚠ **Methodological caveat:** KataGo's Score Lead measures short-term expected efficiency, not absolute truth. The long-term strategic value of traditional joseki—particularly the exploitation of thickness (厚み) in the middle game, positional flexibility, and opponent-dependent variation—lies beyond the scope of this metric.
> Results should therefore be interpreted as evidence of short-term expected-score divergence, not a verdict on the overall value of traditional patterns.

3.3 Analysis Conditions

To ensure consistency and reproducibility, identical analysis conditions were applied to all 20 patterns. All analyses were conducted in February 2026.

Table 2. Standardized analysis conditions

Parameter	Setting	Rationale
Visits	1,000	Sufficient for systematic pattern-level analysis; consistent across all positions.
Rule set	Chinese	Area scoring; all stones and enclosed territory counted. Current international tournament standard.
Komi	7.5	Current official compensation for Black's first-move advantage.
Candidate moves	15	Top 15 moves reported per position, capturing the full competitive range.
Analysis mode	sequence	Moves reconstructed sequentially; each position analyzed independently.
Software	Joseki Analyzer v1.0	Custom-developed FastAPI + KataGo integration (see §3.1).

3.4 Pattern Selection

The 20 patterns were selected from Lee's (2007) *Joseki Selection* (정석 선택), published by Hyunhyungak Yangji—a widely used pre-AlphaGo reference textbook that systematically surveys fuseki joseki theory. Each pattern is identified using standard joseki nomenclature based on corner stone type (*hoshi / komoku*) and tactical method (approach, enclosure, pincer, contact play). Pure fuseki setup moves (where both players simply occupy corners without interaction) are excluded; analysis begins from the first interactive move in each sequence.

Table 3. The 20 analyzed joseki patterns

#	Standard Joseki Classification	Source Chapter Title (Korean)	Total moves	Analyzed
1	Komoku Corner Enclosure Fuseki	귀굳힘의 가치	9	4
2	Hoshi Approach–One-Space Pincer Response (Ⅰ)	협공에 대한 대응(Ⅰ)	10	4
3	Komoku Approach–Low Extension (3rd-line)	3선 돌의 가치	13	2
4	Komoku Approach–High Extension (4th-line)	4선 돌의 가치	21	6
5	Komoku Knight's-Move Enclosure Fuseki	날일자 굳힘의 가치	7	2
6	Hoshi Influence Fuseki – Side Extension	좌변 세력의 가치	21	2
7	Hoshi Approach–Knight's-Move Response	의문의 날일자	23	2
8	Komoku Enclosure – Development Variation	4선 돌의 발전성을 살려서	17	2
9	Komoku Approach–Context-Dependent Response	배석에 따른 변의 가치	21	2
10	Komoku Approach–Aggressive Response	적극적인 작전	20	2
11	Hoshi Contact-Play Stabilization Joseki	돌의 안정이 우선	13	2
12	Hoshi Approach–Contact-Play Joseki	붙임수 정석의 시기	13	7
13	Hoshi One-Space Pincer–3-3 Invasion Joseki	한칸 협공 이후	13	6
14	Komoku Approach–Contact Play (Ⅰ)	붙임수의 선악	15	3
15	Hoshi Approach–Contact Play	의문의 붙임수	16	3
16	Komoku Approach–Contact Play (Ⅱ)	붙임수의 선악은	18	4
17	Hoshi Approach–Contact-Play Timing	붙임수의 시기	21	7
18	Hoshi Approach–Contact-Play Direction	붙임수의 방향	16	6
19	Komoku Corner Development Fuseki	귀의 발전성과 변의 가치	13	2
20	Komoku Approach–Pincer Response (Ⅱ)	협공에 대한 대응(Ⅱ)	15	2
Total			335	70

Source: Adapted from Lee (2007), Joseki Selection (정석 선택), Hyunhyungak Yangji. Standard joseki classification names are based on corner stone type and tactical method; source chapter titles are the original Korean headings from the textbook.

4. Results

4.1 Overall Statistics

Metric	Value
Patterns analyzed	20
Total moves analyzed	70
Overall mean Δ Score (pts)	−0.28
Patterns with Δ = 0	4

Across 70 moves in 20 patterns, the overall mean Δ Score is approximately **−0.28 points**, indicating that traditional joseki moves incur a mean expected-score loss of this magnitude relative to KataGo's top recommendation. The pattern-level minimum is −1.20 points (*Komoku Approach–Pincer Response* II) and the maximum is 0.00 points (four patterns). The largest single-move loss recorded is −2.59 points (*Hoshi One-Space Pincer–3-3 Invasion*, move 9). Four patterns (20% of the sample) record a mean Δ Score of exactly 0, indicating full alignment between traditional sequences and AI evaluation.

4.2 Δ Score Across All 20 Patterns

Figure 1 presents the mean Δ Score for each of the 20 analyzed joseki patterns, sorted by absolute loss magnitude (descending). Detailed values and loss-category ratings are summarized in Table 4 below.

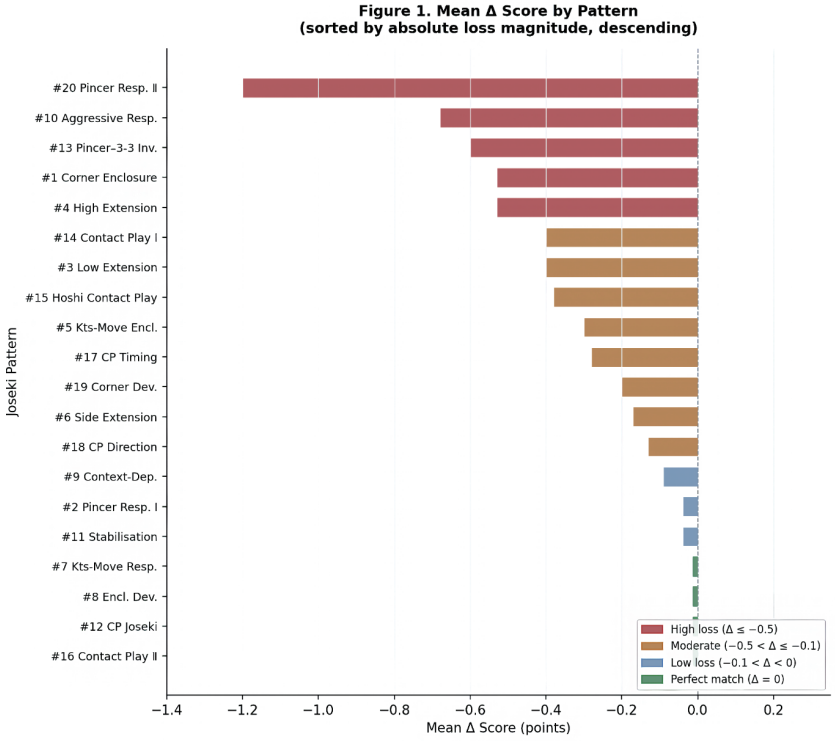

Figure 1. Mean Δ Score by pattern (points; sorted by absolute loss magnitude, descending). *Note: Negative values indicate the traditional move is less efficient than the AI recommendation by the corresponding number of points. Bar color indicates the loss-magnitude category as defined in Table 4 below (High loss / Moderate / Low loss / Perfect match).*

Table 4. Summary of Δ Score results across all 20 patterns

#	Standard Joseki Classification	Moves	Mean Δ	Min. Δ	Rating
20	Komoku Approach–Pincer Response (Ⅱ)	2	−1.20	−2.40	High loss
10	Komoku Approach–Aggressive Response	2	−0.68	−1.36	High loss
13	Hoshi One-Space Pincer–3-3 Invasion	6	−0.60	−2.59	High loss
1	Komoku Corner Enclosure Fuseki	4	−0.53	−1.46	High loss
4	Komoku Approach–High Extension (4th-line)	6	−0.53	−1.20	High loss
14	Komoku Approach–Contact Play (Ⅰ)	3	−0.40	−1.19	Moderate
3	Komoku Approach–Low Extension (3rd-line)	2	−0.40	−0.81	Moderate
15	Hoshi Approach–Contact Play	3	−0.38	−1.14	Moderate
5	Komoku Knight's-Move Enclosure Fuseki	2	−0.30	−0.59	Moderate
17	Hoshi Approach–Contact-Play Timing	7	−0.28	−1.26	Moderate
19	Komoku Corner Development Fuseki	2	−0.20	−0.40	Moderate
6	Hoshi Influence Fuseki – Side Extension	2	−0.17	−0.33	Moderate
18	Hoshi Approach–Contact-Play Direction	6	−0.13	−0.77	Moderate
9	Komoku Approach–Context-Dependent Response	2	−0.09	−0.18	Low loss
2	Hoshi Approach–One-Space Pincer Response (Ⅰ)	4	−0.04	−0.18	Low loss
11	Hoshi Contact-Play Stabilization Joseki	2	−0.04	−0.07	Low loss
7	Hoshi Approach–Knight's-Move Response	2	0.00	0.00	Perfect match
8	Komoku Enclosure–Development Variation	2	0.00	0.00	Perfect match
12	Hoshi Approach–Contact-Play Joseki	7	0.00	0.00	Perfect match
16	Komoku Approach–Contact Play (Ⅱ)	4	0.00	0.00	Perfect match

Patterns sorted by mean Δ Score (ascending). "Min. Δ»" denotes the largest single-move loss within each pattern.

4.3 Typological Trend Analysis

Grouping the 20 patterns by joseki type reveals a consistent and theoretically interpretable trend.

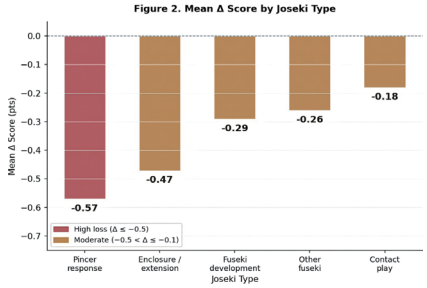

Figure 2. Mean Δ Score by joseki type. Pincer-response sequences exhibit the largest mean loss (−0.57); contact-play sequences show the smallest (−0.18).

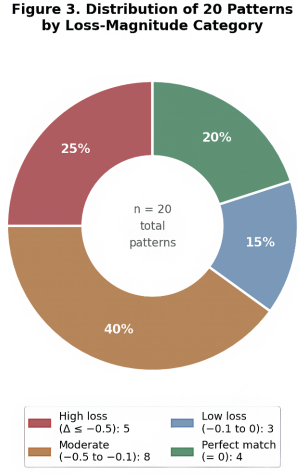

Figure 3. Distribution of the 20 patterns by loss-magnitude category, using the same Rating boundaries as Table 4: High loss ($\Delta \leq -0.5$) accounts for 5 patterns, Moderate ($-0.5 < \Delta \leq -0.1$) for 8, Low loss ($-0.1 < \Delta < 0$) for 3, and Perfect match ($\Delta = 0$) for 4.

Table 5. Mean Δ Score by joseki type

Joseki type	Patterns	**Mean Δ Score**	Patterns included
Pincer-response sequences	3	−0.57	#2, #13, #20
Corner-enclosure / extension sequences	5	−0.47	#1, #3, #4, #5, #6
Fuseki development variations	3	−0.29	#8, #9, #10
Other fuseki	2	−0.26	#7, #19
Contact-play (붙임수) sequences	7	−0.18	#11, #12, #14, #15, #16, #17, #18

Corner-enclosure and extension patterns (mean −0.47) and pincer-response patterns (mean −0.57) show the largest divergence from AI recommendations. Contact-play patterns show the smallest divergence (mean −0.18), with two achieving Δ = 0 across all analyzed moves. This trend suggests that AI and classical theory diverge most in situations where players have wide strategic freedom—choosing where and how to extend from an established corner position—and converge most when direct contact between stones narrows the locally feasible move space.

4.4 Deep Analysis: High-Loss Patterns

Four patterns share the largest mean Δ Scores in the dataset and are examined in detail below. They are ordered by mean Δ Score (descending in absolute value). Note that Pattern #4 (Komoku Approach–High Extension, mean Δ = −0.53) shares the same loss magnitude as Pattern #1 and belongs to the same typological category (corner-enclosure / extension); it is therefore represented in this section by Pattern #1 as a category exemplar.

① Pattern #20 — Komoku Approach–Pincer Response (II) | Mean Δ = −1.20 pts

The highest-loss pattern in the study. Of the two analyzed moves, the second (move 15, Black C7) incurs a loss of −2.40 points—the second-largest single-move loss observed. The traditional move C7 aims to claim a corner "territory" position in isolation; KataGo strongly prefers D5, a move that connects to neighboring groups and establishes a flexible, multi-purpose formation. KataGo's Prior for C7 is a mere 0.3%, compared with 52.9% for D5—a particularly large Prior gap that indicates the engine's learned intuition strongly disfavors the traditional choice even before deep calculation. Move 14 (White G3 vs. D3) records Δ = 0.00 in Score Lead, but still shows a Prior gap (0.9% vs. 25.9%), indicating that AI's overall strategic instinct points away from the traditional move even where short-term scores are identical.

② Pattern #10 — Komoku Approach–Aggressive Response | Mean Δ = −0.68 pts

Of the two analyzed moves, move 19 (Black F3) incurs −1.36 points; move 20 (White H3) achieves Δ = 0. The traditional Black F3 prioritizes speed and offensive pressure, but leaves adjacent groups inadequately connected, reducing overall positional thickness. KataGo prefers C3, which simultaneously secures solid thickness and strengthens the connection toward the center. The subsequent White H3, on which both tradition and AI agree, illustrates that moves satisfying thickness and connectivity simultaneously are consistently efficient.

③ Pattern #13 — Hoshi One-Space Pincer–3-3 Invasion Joseki | Mean Δ = −0.60 pts / Largest single-move loss: −2.59 pts

This pattern contains the largest single-move loss in the entire study: −2.59 points at move 9.

Across six analyzed moves, four achieve Δ = 0 and two record negative values, with high internal variance. This structure—where traditional moves initially align with AI and then sharply diverge at specific junctures—suggests that the traditional sequence is locally sound for several moves before committing to a strategic direction that AI evaluates as significantly suboptimal. The pattern has the widest per-move range of any pattern studied.

④ Pattern #1 — Komoku Corner Enclosure Fuseki | Mean Δ = −0.53 pts

Four analyzed moves yield losses at moves 7 and 9 (−0.67 and −1.46 respectively) and equality at moves 6 and 8. AI consistently responds to corner-enclosure positions by prioritizing empty-corner occupation elsewhere over reinforcing the enclosure already in progress. This is perhaps the most direct empirical illustration of the AI vs. classical divergence: what traditional theory treats as consolidating an advantage, AI treats as ceding initiative.

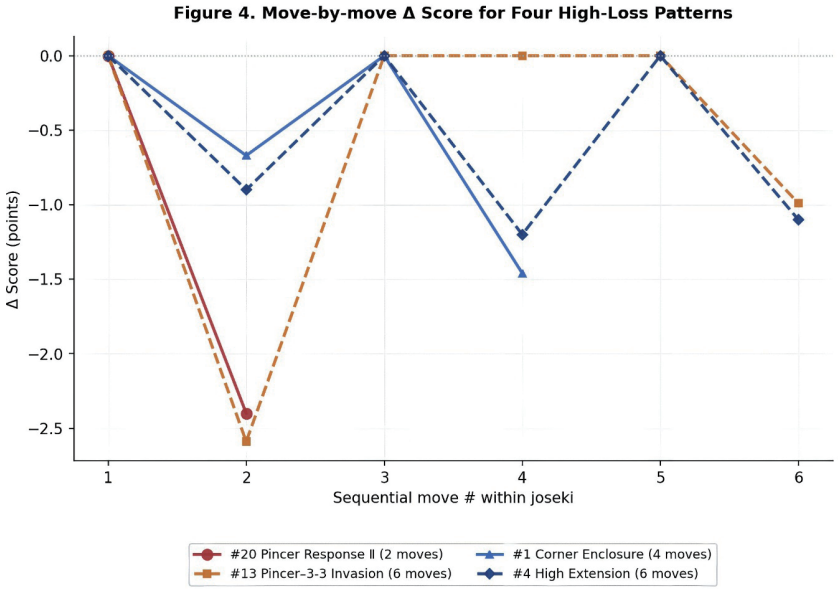

Figure 4. Move-by-move Δ Score for four representative high-loss patterns: #20 Pincer Response II, #13 Pincer–3-3 Invasion, #1 Corner Enclosure, and #4 High Extension.

Note: x-axis represents sequential analyzed move number within each pattern (not absolute game move number). Color encodes typological category — warm tones (red, orange) for pincer-related patterns, cool tones (blue) for enclosure/extension patterns. Pincer patterns exhibit sharp early losses at move 2 (−2.4 to −2.6), whereas enclosure/extension patterns show their largest losses at move 4 (−1.2 to −1.5).

4.5 Perfect-Alignment Patterns

The four patterns achieving Δ = 0 across all analyzed moves share a com-

mon structural characteristic: their locally optimal sequences are constrained enough that centuries of human analysis and AI computation arrive at the same conclusion. Patterns #12 (Hoshi Approach–Contact-Play Joseki, 7 moves) and #16 (Komoku Approach–Contact Play II, 4 moves) are the largest perfect-alignment sets, involving extended post-contact exchanges where both players have limited alternatives. Patterns #7 and #8 involve choice-restricted direction decisions following enclosure or approach moves.

Table 6. Characteristics of perfect-alignment patterns ($\Delta = 0$)

#	Classification	Moves	Structural characteristic
7	Hoshi Approach–Knight's-Move Response	2	Directional choice post-approach; locally constrained
8	Komoku Enclosure–Development Variation	2	Enclosure development; limited alternatives
12	Hoshi Approach–Contact-Play Joseki	7	Post-contact formalized exchange sequence
16	Komoku Approach–Contact Play (Ⅱ)	4	Post-contact formalized exchange sequence

This finding is consistent with the broader typological trend: divergence between AI and traditional theory is smallest when the move space is narrowest. When human intuition is guided through a constrained, locally forced sequence, it tends to converge with AI computation. Divergence is largest precisely when human intuition must choose among a wide range of strategically plausible options—where AI's global pattern recognition and exhaustive search create an advantage over human heuristic reasoning.

5. Discussion

5.1 AI Strategic Preferences

The most consistent finding across all 20 patterns is that **KataGo systematically prefers claiming empty corners over reinforcing one's own established position**. In every corner-enclosure or extension pattern studied, AI's top recommendation is to play elsewhere—most often in an unoccupied corner—rather than continue the local sequence. This contradicts a foundational classical principle: that the purpose of a corner approach is to develop that corner, and that the responding player should prioritize local stability before moving elsewhere.

The Prior analysis reinforces this finding. In corner-enclosure patterns, the traditional move typically receives a Prior of 1–3%, while AI's preferred alternative—often a distant empty-corner play—receives 20–30%. This large Prior gap indicates that KataGo's trained neural network, before any deep search, strongly encodes the preference for global initiative over local consolidation. The implication is not simply that individual moves are suboptimal, but that the underlying strategic framework of pre-AI corner theory systematically underweights the value of early global positioning.

A second AI preference, visible across contact-play patterns, is **the acceptance of locally formalized exchanges**. When both players are committed to a contact sequence with limited alternatives, KataGo's top move frequently coincides with the traditional move, suggesting that classical theory succeeded in identifying locally optimal plays precisely where the move space was constrained enough for human analysis to be thorough.

5.2 Reassessing the Value of Traditional Joseki

The results of this study do not support the conclusion that traditional joseki are "wrong." An overall mean Δ Score of −0.28 points per move is meaningful in aggregate over a full game of several hundred moves, but the interpretation requires important contextual caveats.

First, **educational value**. Traditional joseki sequences explicitly articulate strategic trade-offs—territory versus influence, corner versus side, speed versus thickness—in a pedagogically structured way. This function cannot be replicated by AI recommendations alone, which optimize outcome without articulating the trade-off. The tension illustrated in patterns like #10 (aggressive response) between a move that seeks immediate territory and one that builds thickness is precisely the kind of strategic decision that traditional joseki analysis was designed to teach.

Second, **the limits of the metric**. Score Lead measures expected outcome in the short term under the assumption of optimal play from both sides. This assumption is not a minor technical detail; it generates three distinct interpretive constraints that bear directly on how the present findings should be read.

The first is the thickness problem. In classical Go theory, thickness (厚み) denotes a wall or formation of stones whose immediate territorial value is small but whose latent power—projected influence, attacking potential against future invasions, and resilience under complex fighting—can decide games hundreds of moves later. Score Lead at the joseki stage cannot observe this latent power: it evaluates the position assuming both sides continue optimally, but the realized value of thickness depends critically on whether the resulting middle game contains the fighting situations in which thickness pays off. A traditional move that builds thickness at a Δ Score cost of −0.3 points

may, in practice, return several points in a complex middle-game exchange that the local evaluator does not see.

The second is the *flexibility problem*. Some traditional moves are favored not because they are locally optimal but because they preserve multiple follow-up options against unknown opponent responses. KataGo's Score Lead, computed under the assumption of optimal play from both sides, systematically undervalues this kind of optionality: a move with three reasonable continuations against three different opponent plans may appear inefficient against a single best-line opponent yet outperform the AI-preferred move in the broader space of realistic games.

The third is *opponent-dependent variation*. AI evaluation assumes a symmetric optimal-opponent model. Human players, however, choose joseki partly to steer the game toward positions that exploit known weaknesses of specific opponents or styles. This strategic dimension is invisible to Score Lead by construction.

These three constraints do not invalidate the −0.28 mean Δ Score finding, but they constrain its interpretation. The finding should be read narrowly: under the assumption of optimal play from both sides and at a 1,000-visit search depth, traditional joseki moves incur this short-term expected-score loss. Translating this measured quantity into a broader verdict on the overall value of traditional joseki—across thickness deployment, flexibility against varied opponents, and full-game outcomes—requires evidence that this metric cannot, by construction, provide.

Third, **practical implications**. The study's results offer a data-driven guideline: **AI consultation is most valuable in corner-enclosure, extension, and pincer-response positions**, where divergence is large and consistent. In contact-play sequences, traditional joseki shows higher alignment with AI

and can be followed with greater confidence.

5.3 Limitations

Five limitations constrain the generalizability of this study's findings. (1) **Analysis depth:** 1,000 visits, while sufficient for systematic pattern-level comparison, is substantially fewer than the hundreds of thousands of visits used in professional-level AI analysis; some evaluations may be inaccurate at this depth. (2) **Short-term metric:** Δ Score captures only short-term expected efficiency; long-term strategic value and opponent-dependent variation are not measured. (3) **Sample size:** 20 patterns and 70 moves represent a small subset of the several-hundred-pattern joseki corpus, and the present findings should therefore be read as evidence of trends within this sample rather than as conclusive claims about the joseki corpus as a whole. In particular, the typological pattern observed in § 4.3—largest divergences in pincer-response and corner-enclosure sequences, smallest in contact-play sequences—is a hypothesis generated from this sample; confirmation requires a substantially expanded analysis corpus, which is identified as a primary direction for future work (see § 6). (4) **Single source:** all patterns are drawn from a single textbook (Lee, 2007); other schools of joseki theory are not represented. (5) **KataGo's own limitations:** KataGo does not provide absolute ground truth; its evaluations reflect the biases of its training data and self-play regime, which cannot be fully controlled for in this study.

6. Conclusions and Future Directions

This study used a purpose-built analysis program—Joseki Analyzer—in

conjunction with the KataGo AI engine to quantify the efficiency of 20 traditional fuseki joseki patterns (70 moves total) in point-based terms. Four principal conclusions emerge.

First, the overall mean Δ Score of approximately −0.28 points per move indicates that traditional joseki moves incur a measurable, consistent expected-score loss relative to AI recommendations. This is the first systematic, large-scale evidence of this magnitude in the academic literature.

Second, divergence varies significantly by joseki type. Pincer-response (mean −0.57) and corner-enclosure/extension (mean −0.47) patterns show the largest gaps; contact-play patterns (mean −0.18) show the smallest, with two achieving Δ = 0 across all moves. This typological finding has practical implications for educators and players deciding where to incorporate AI insights into traditional training.

Third, four patterns achieve complete alignment with AI across all analyzed moves, all sharing a common structural feature: locally forced sequences with limited alternatives. This finding supports the hypothesis that traditional joseki theory achieves its highest accuracy precisely where human analysis is guided by narrow choice spaces.

Fourth, AI consistently prioritizes global initiative—particularly the occupation of empty corners—over local consolidation. This finding, evident in both Score Lead and Prior data, represents a fundamental departure from a core axiom of pre-AI classical strategy.

Future research directions include, as the primary priority, (1) substantially expanding the analysis corpus to additional joseki textbooks, professional game records, and mid-game transition positions, in order to test whether the typological trends identified here generalize beyond the present 20-pattern sample. Further directions include: (2) incorporating multiple traditional sources beyond a single textbook to capture cross-school variation; (3) increasing visit counts for higher-precision evaluations; (4) tracing move-sequence efficiency curves to identify the precise juncture at which traditional and AI sequences diverge; (5) developing a quantitative framework for measuring the exchange ratio between influence (thickness) and territory; and (6) tracking changes in joseki adoption rates in professional games before and after the AlphaGo era.

On the occasion of AlphaGo's tenth anniversary, this study offers a concrete, point-based reckoning with the gap between human intuition and AI computation in Go—contributing both empirical findings and a replicable methodological framework to the emerging field of AI-assisted Go research.

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Received: 3 May 2026
Accepted: 7 May 2026

Appendix

Go Board Diagrams: All 20 Joseki Patterns

Traditional Moves vs. AI-Recommended Moves

Source data: Joseki Analyzer + KataGo (1,000 visits · Chinese rule set · komi 7.5) · February 2026

Legend

Symbol	Meaning
T (orange circle)	Traditional move (only)
A (green circle)	AI best move (only)
Move # (blue circle)	Both agree (same move)
●	Black setup stone
○	White setup stone

How to read the boards: Each board shows the full 19×19 board, with the analyzed moves typically concentrated in one corner or side region. Markers indicate the analyzed moves: an orange circle with "T" denotes a traditional move only, a green circle with "A" denotes the AI's best move only, and a blue circle containing the move number indicates that the traditional move and AI recommendation coincide. When the AI recommends a distant tenuki—a move played elsewhere on the board, away from the local sequence—the move is listed in the table and is shown at its actual position on the full-board view. Setup stones are shown as standard black and white stones, representing the position before the analyzed sequence begins.

Note on Korean titles: The Korean titles provided for each pattern are descriptive labels for the standard joseki classification, not the original chapter titles in Lee (2007); see Table 3 of the main paper for the source chapter titles.

#1 — Komoku Corner Enclosure Fuseki

소목 귀굳힘 포석 · Δ avg = −0.53

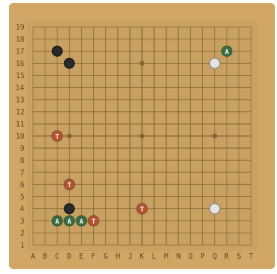

Figure A1. Board diagram for Pattern #1.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
6	○ W	F3	C3	0.00	1.7%	26.7%
7	● B	D6	E3	−0.667	3.4%	3.0%
8	○ W	K4	D3	0.00	1.4%	3.2%
9	● B	C10	R17	−1.455	0.8%	20.5%

#2 — Hoshi Approach–One-Space Pincer Response (I)

화점 날일자 걸침 한칸 협공 대응 (I) · Δ avg = −0.04

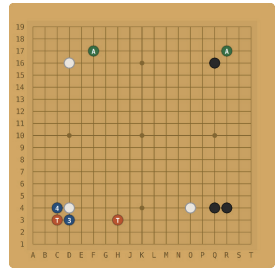

Figure A2. Board diagram for Pattern #2.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
7	● B	H3	R17	−0.178	2.4%	19.1%
8	○ W	C3	F17	0.00	23.7%	1.5%
9	● B	D3	D3	0.00	87.0%	87.0%
10	○ W	C4	C4	0.00	90.8%	90.8%

#3 — Komoku Approach–Low Extension (3rd-line)

소목 날일자 걸침 3선 벌림 · Δ avg = −0.40

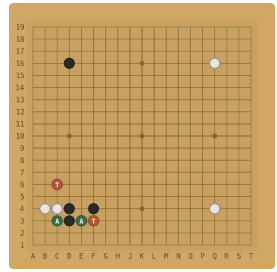

Figure A3. Board diagram for Pattern #3.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
12	○ W	F3	C3	0.00	1.9%	36.1%
13	● B	C6	E3	−0.806	2.3%	5.5%

#4 — Komoku Approach–High Extension (4th-line)

소목 날일자 걸침 4선 벌림 · Δ avg = −0.53

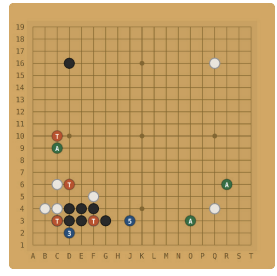

Figure A4. Board diagram for Pattern #4.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
16	○ W	F3	C3	0.00	1.6%	35.6%
17	● B	D6	C9	−0.900	4.1%	0.4%
18	○ W	D2	D2	0.00	25.9%	25.9%
19	● B	C3	O3	−1.200	15.2%	4.8%
20	○ W	J3	J3	0.00	27.9%	27.9%
21	● B	C10	R6	−1.096	0.3%	1.9%

#5 — Komoku Knight's-Move Enclosure Fuseki

소목 날일자 굳힘 포석 · Δ avg = −0.30

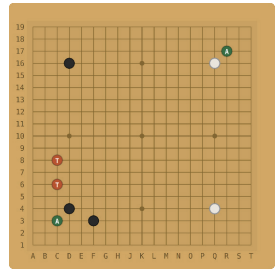

Figure A5. Board diagram for Pattern #5.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
6	○ W	C6	C3	0.00	1.0%	29.2%
7	● B	C8	R17	−0.593	3.1%	16.0%

#6 — Hoshi Influence Fuseki–Side Extension

화점 세력 포석 벌림 · Δ avg = −0.17

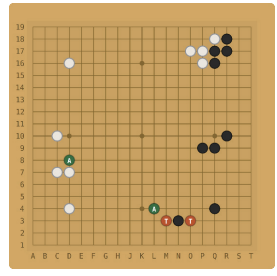

Figure A6. Board diagram for Pattern #6.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
20	○ W	O3	D8	0.00	1.2%	19.2%
21	● B	M3	L4	−0.334	12.1%	15.4%

#7 — Hoshi Approach–Knight's-Move Response

화점 날일자 걸침 후 날일자 응수 · Δ = 0.00

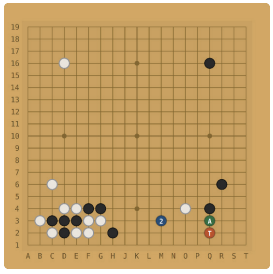

Figure A7. Board diagram for Pattern #7.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
22	○ W	Q2	Q3	0.00	15.7%	4.9%
23	● B	M3	M3	0.00	17.4%	17.4%

#8 — Komoku Enclosure–Development Variation

소목 날일자 굳힘 발전형 · Δ = 0.00

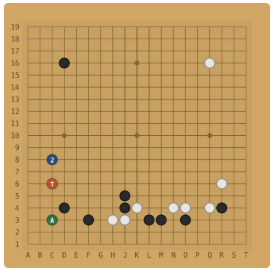

Figure A8. Board diagram for Pattern #8.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
16	○ W	C6	C3	0.00	1.9%	33.9%
17	● B	C8	C8	0.00	16.9%	16.9%

#9 — Komoku Approach–Context-Dependent Response

소목 날일자 걸침 배석별 응수 · Δ avg = −0.09

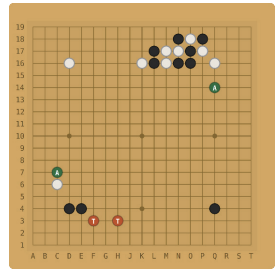

Figure A9. Board diagram for Pattern #9.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
20	○ W	F3	Q14	0.00	5.1%	1.3%
21	● B	H3	C7	−0.181	2.0%	8.1%

#10 — Komoku Approach–Aggressive Response

소목 날일자 걸침 적극 응수 · Δ avg = −0.68

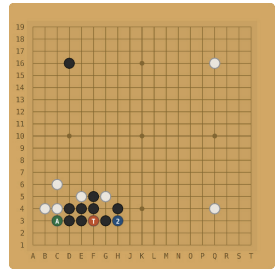

Figure A10. Board diagram for Pattern #10.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
19	● B	F3	C3	−1.364	3.1%	31.0%
20	○ W	H3	H3	0.00	52.0%	52.0%

#11 — Hoshi Contact-Play Stabilization Joseki

화점 붙임 안정형 정석 · Δ avg = −0.04

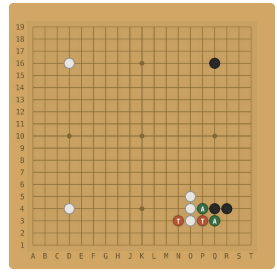

Figure A11. Board diagram for Pattern #11.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
12	○ W	P3	P4	0.00	36.1%	8.8%
13	● B	N3	Q3	−0.073	26.0%	23.3%

#12 — Hoshi Approach–Contact-Play Joseki

화점 날일자 걸침 붙임수 정석 · Δ = 0.00

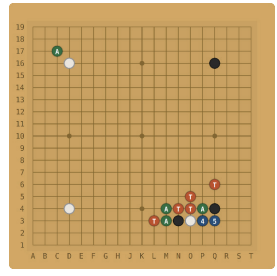

Figure A12. Board diagram for Pattern #12.

Mv#	Turn	Traditional	**AI Best**	**Δ Score**	T.Prior	AI.Prior
7	● B	O4	C17	0.00	1.1%	20.0%
8	○ W	N4	P4	0.00	51.8%	20.5%
9	● B	O5	P3	0.00	11.6%	62.9%
10	○ W	P3	P3	0.00	60.1%	60.1%
11	○ B	Q3	Q3	0.00	93.6%	93.6%
2	○ W	L3	M3	0.00	4.9%	10.9%
13	● B	Q6	M4	0.00	0.0%	14.5%

#13 — Hoshi One-Space Pincer–3-3 Invasion Joseki

화점 한칸 협공 3-3 침입 정석 · Δ avg = −0.60

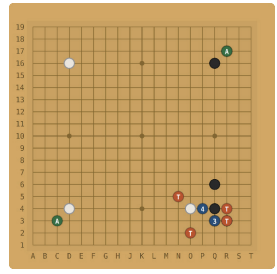

Figure A13. Board diagram for Pattern #13.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
8	○ W	R3	R17	0.00	30.1%	21.0%
9	● B	R4	Q3	−2.586	1.9%	86.1%
10	○ W	Q3	Q3	0.00	97.7%	97.7%
11	● B	P4	P4	0.00	84.5%	84.5%
12	○ W	O2	R17	0.00	0.2%	5.0%
13	● B	N5	C3	−0.986	29.6%	10.3%

#14 — Komoku Approach–Contact Play (I)

소목 날일자 걸침 붙임수 (I) · Δ avg = −0.40

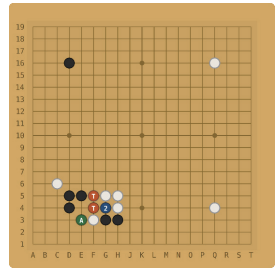

Figure A14. Board diagram for Pattern #14.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
13	● B	F4	E3	0.00	0.0%	19.7%
14	○ W	G4	G4	0.00	19.0%	19.0%
15	● B	F5	E3	−1.191	0.8%	66.8%

#15 — Hoshi Approach–Contact Play

화점 날일자 걸침 붙임수 · Δ avg = −0.38

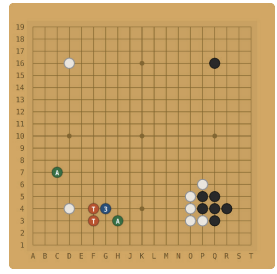

Figure A15. Board diagram for Pattern #15.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
14	○ W	F3	H3	0.00	5.8%	26.7%
15	● B	F4	C7	−1.139	0.2%	5.0%
16	○ W	G4	G4	0.00	57.9%	57.9%

#16 — Komoku Approach–Contact Play (II)

소목 날일자 걸침 붙임수 (II) · Δ = 0.00

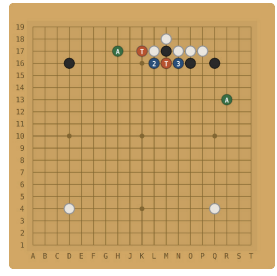

Figure A16. Board diagram for Pattern #16.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
15	● B	M16	H17	0.00	0.1%	2.8%
16	○ W	L16	L16	0.00	56.4%	56.4%
17	● B	N16	N16	0.00	13.9%	13.9%
18	○ W	K17	R13	0.00	62.7%	0.7%

#17 — Hoshi Approach–Contact-Play Timing

화점 날일자 걸침 붙임수 시기 · Δ avg = −0.28

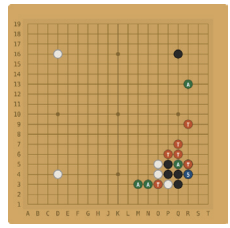

Figure A17. Board diagram for Pattern #17.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
15	● B	Q6	R13	0.00	0.3%	2.6%
16	○ W	Q7	Q5	0.00	60.4%	17.0%
17	● B	P6	R5	−1.255	2.2%	57.9%
18	○ W	R5	R4	0.00	33.1%	16.7%
19	● B	R4	R4	0.00	89.8%	89.8%
20	○ W	R9	N3	0.00	0.2%	6.0%
21	● B	O3	M3	−0.686	1.0%	17.3%

#18 — Hoshi Approach–Contact-Play Direction

화점 날일자 걸침 붙임수 방향 · Δ avg = −0.13

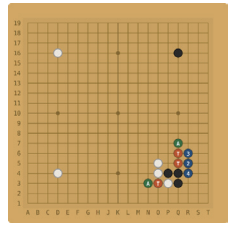

Figure A18. Board diagram for Pattern #18.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
11	● B	Q5	R5	0.00	7.5%	45.9%
12	○ W	R5	R5	0.00	17.4%	17.4%
13	● B	R6	R6	0.00	47.1%	47.1%
14	○ W	R4	R4	0.00	84.6%	84.6%
15	● B	Q6	Q7	−0.773	9.7%	62.7%
16	○ W	O3	N3	0.00	27.1%	25.6%

#19 — Komoku Corner Development Fuseki

소목 귀 발전 포석 · Δ avg = −0.20

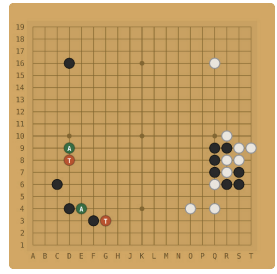

Figure A19. Board diagram for Pattern #19.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
12	○ W	D8	D9	0.00	2.3%	2.8%
13	● B	G3	E4	−0.402	0.9%	37.4%

#20 — Komoku Approach–Pincer Response (II)

소목 날일자 걸침 협공 대응 (II) · Δ avg = −1.20

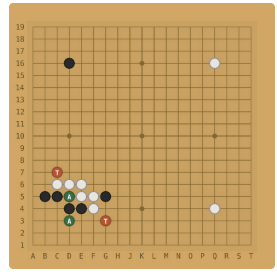

Figure A20. Board diagram for Pattern #20.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
14	○ W	G3	D3	0.00	0.9%	25.9%
15	● B	C7	D5	−2.397	0.3%	52.9%

Δ Score = Score Lead (AI best move) − Score Lead (traditional move). T.Prior = neural-network Prior for the traditional move. AI.Prior = neural-network Prior for the AI's top recommendation.

바둑학연구, 제20권 제1호, pp. 51-78
Journal of Go Studies
20263. Vol.20, No.1. pp. 51-78

Rewriting God's Move: Narrative Revisionism and the Memory Hole in Lee Sedol's *Memoir*

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Abstract

This paper presents a critical analysis of Lee Sedol's 2025 *Memoir*, published a decade after his historic match against AlphaGo. Unlike Garry Kasparov's *Deep Thinking* (2017), which seeks the truth behind defeat, Lee's narrative is characterized by 'narrative revisionism' and memory reconstruction designed to provide a post-hoc justification for a heroic myth. By retroactively framing Move 68 as a pre-planned gambit to justify the *Divine Move* (Move 78), Lee's account exemplifies the cognitive distortions Charan Ranganath warns against and instantiates the logic of the Orwellian memory hole. Drawing on Pierre Bourdieu's theory of symbolic power, this study examines how Lee's authority as a dominant narrator neutralizes public critical distance and entrenches an unverified narrative. Ultimately, the paper argues that the replacement of criticism with myth leads to a profound intellectual poverty in discourse on human-machine relations in the AI era and calls for a correction

of this constructed and subversive narrative that has taken hold amid collective social silence.

Keywords: Lee Sedol, AlphaGo, narrative revisionism, bug-triggering theory, memory hole

1. Introduction

In August 2025, nearly a decade after his landmark match against AlphaGo, Lee Sedol published a retrospective *Memoir*.[1] This work invites immediate comparison with Garry Kasparov's *Deep Thinking* (2017), which analyzes the chess grandmaster's defeat by IBM's Deep Blue. Both texts open with remarkably similar declarations of revealing unprecedented truths:

"The match against Google's artificial intelligence AlphaGo in March 2016 ended with a final score of 1–4, a victory for AlphaGo. In this book, I am publicly disclosing for the first time the detailed circumstances and feelings I recorded immediately after the match."[2]

"There are many books about Deep Blue, but this is the first one that has all the facts and the only one that has my side of the story. Painful memories aside, it has also been a revealing and rewarding experience."[3]

While both authors promise unvarnished revelations, a critical divergence emerges in their foundational philosophies regarding defeat. Kasparov follows the advice of his trainer, Mikhail Botvinnik, "to seek **the truth in the heart of every position**,"[4] delivering an unsparingly objective analysis. He concedes his own psychological missteps and acknowledges that immediate confusion had obscured a more vital inquiry into human-machine collaboration.

This paper argues that Lee's *Memoir* exemplifies a form of narrative revisionism driven by two interconnected mechanisms: memory distortion and symbolic power. Drawing on Charan Ranganath's cognitive science of mem-

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1) Lee described the book as 'autobiography-like' in a public lecture. Lee Sedol (2026).

2) Lee Sedol (2025), 82.

3) Kasparov, Garry (2017), 14.

4) Ibid. 14. Emphasis added.

ory, it demonstrates how Lee retroactively constructs Move 68 as a calculated gambit to justify the celebrated *Divine Move* (Move 78)—a claim that is both internally contradictory and empirically unsupported by contemporaneous evidence. Through the lens of Pierre Bourdieu's theory of symbolic power, the paper examines how Lee's authority as the sole human victor over AlphaGo neutralizes public critical distance, allowing an unverified narrative to harden into historical consensus. Crucially, the paper contends that this revisionism is not merely an individual psychological defense mechanism, but the product of a collective Orwellian memory hole—sustained by a public that, eager for a human champion in the age of AI, became a silent accomplice to an engineered myth. The displacement of critical scrutiny by heroic mythology, it ultimately argues, imposes a profound intellectual poverty on discourses concerning human-machine relations.

To systematically deconstruct this narrative invention, the remainder of this paper proceeds as follows. Section 2 establishes the technical context surrounding Moves 68 and 78 and identifies the foundational contradictions in Lee's revisionist account. Section 3 traces the evolution of Lee's public discourse over the past decade, establishing the baseline of his shifting attitudes toward AI. Section 4 critically dissects the 'bug-triggering theory' surrounding Moves 68 and 78, exposing the profound causal disconnect at the heart of his strategic claims. Section 5 broadens the comparative lens, contrasting Lee's narrative regression with Garry Kasparov's evolutionary adaptation to algorithmic supremacy. Finally, Section 6 situates this individual revisionism within a broader sociological framework, exploring how the public and the professional Go community acted as silent accomplices in cementing this constructed narrative into an Orwellian memory hole. The paper closes with a Conclusion that consolidates the key findings and situates them

within the broader challenge of sustaining honest intellectual discourse about human-machine relations in the AI era.

2. A Revisionist *Memoir*

Does Lee's *Memoir* similarly confront the objective reality of his match? Although the structural parallel is superficially plausible, the analogy ultimately fails. Lee's account of the celebrated Move 78 in Game 4 is structurally compromised by internal contradictions. Evaluating these claims requires a brief review of the technical context surrounding this move.

Following AlphaGo's loss in Game 4, the DeepMind team found no conventional system bugs. As team member Ioannis Antonoglou remarked, "the bug was Lee Sedol finding a brilliant move."[5] This raises a technical dichotomy: did Move 78 expose a standard algorithmic bug, or an inherent failure mode?

In June 2016, DeepMind's Aja Huang disclosed that the logical vulnerability exposed in Game 4 had been patched, implying a correctable software defect.[6] Conversely, analyst David Ormerod and Go journalist Kim Su-gwang argued that AlphaGo's subsequent errors reflected an intrinsic computational limitation typical of Monte Carlo Tree Search (MCTS) architectures.[7] Kim emphasized that Go AI does not exhaustively calculate all possible moves but relies on computationally realized intuition, rendering Lee's assumption that AlphaGo would simply "calculate all possible moves and err" a fundamental misconception.[8]

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5) Metz, Cade (2016).
6) Zastrow, Mark (2016).
7) David Ormerod's analysis is discussed in Metz, Cade (2016).
8) Kim Su-gwang (2026).

Whether classified as a specification-based bug or a fundamental algorithmic limitation, one empirical fact remains undisputed: throughout the five-game match, the only phenomenon plausibly characterizable as a computational failure occurred *after* Move 78 in Game 4.

However, Lee's narrative conflates verifiable algorithmic defects with subjective 'pseudo-bugs'.[9] The word 'bug' appears fifteen times in the *Memoir*'s Special Essay. Lee claims that his overarching strategy across multiple games was strictly dedicated to triggering these errors. Because only one verifiable instance of computational failure was recorded, Lee's account manufactures a series of technical anomalies that never actually occurred. The promised revelation thus devolves into narrative distortion.

More critically, Lee's bug-triggering theory—the assertion that Move 68 was a calculated mechanism to force a computational failure—subverts the established historical consensus. Move 78, universally celebrated as the 'Divine Move', was widely perceived as the apex of human intuition. In Lee's revisionist framework, however, it is relegated to a mere subordinate effect of Move 68.[10]

Trailing 3–0 against an opponent with unknown vulnerabilities, Lee's initial defensive stance was entirely rational. Yet, the *Memoir* translates this positional uncertainty into a masterfully engineered trap. The Special Essay constructs a narrative of performed self-deprecation—a superficial pose of helplessness that functions structurally to validate a newly fashioned claim of strategic genius.

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9) The term 'pseudo-bug' is introduced here to distinguish between the engineering definition of a bug and the looser usage in which any outcome contrary to a user's expectations is labeled a bug. Lee's own expressions—"bug-like sequence" (p. 95), "bug-like progression" (p. 100), and "a kind of bug pattern" (p. 112)—exemplify this conflation. See Lee Sedol (2025).

10) Lee Sedol (2026), cited above, n.1.

This narrative revision yields immediate internal contradictions. To substantiate his account, Lee cites neurosurgeon Iwatate Yasuo, who analyzed Move 78 as an exemplar of uniquely human intuition.[11] However, framing Move 78 as the predictable, dependent variable of a calculated strategy initiated ten moves prior is fundamentally incompatible with celebrating it as a spontaneous explosion of unconscious intuition.

3. The Anatomy of Inconsistency: Dissecting Lee Sedol's View of Go

Prior to his defeat, Lee conceptualized Go as an inviolable art form. In a 2024 *New York Times* interview, he characterized the psychological trauma of the loss as a sensation that his "entire world was collapsing."[12] To Lee, algorithmic efficiency shattered not merely his professional standing, but the ontological status of Go itself. This existential anxiety became the governing lens for his subsequent public discourse. Internalizing this trauma, Lee reduced the human-AI relationship to a rigid dichotomy: human creativity versus machine calculation. This epistemological reduction necessitates a critical reconstruction of his current rhetorical positioning.

"People used to be in awe of creativity, originality and innovation. But since AI came, a lot of that has disappeared."[13]

This statement illustrates Lee's primary logical maneuver: projecting a domain-specific trauma into a universal declaration on AI's cultural impact.

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11) Iwatate Yasuo (2024), 259–260.

12) Wakabayashi, Daisuke and Jin, Yu Young (2024).

13) Ibid.

The triad of 'creativity, originality, and innovation' exactly mirrors the attributes that epitomized his unconventional playing style. Whether analyzing the realm of professional Go or labor market dynamics, Lee systematically employs the fallacy of overgeneralization. His recent rhetorical efforts to disavow the 'doomsayer' label by characterizing AI as 'a god' function merely as a performative pivot from defeated grandmaster to technological evangelist—a posture riddled with internal contradictions.

A similar strategic plasticity informs his assertion that AI has fundamentally altered the essence of Go. Lee argues that because contemporary players strictly emulate AI from the opening moves, individuality has disappeared.[14] This constitutes a significant logical fallacy: conflating the sociological influence of AI on human training patterns with an intrinsic transformation of the game itself.

Analytically, the artistry Lee mourns may merely be a heuristic label for human cognitive wandering in the absence of computable optima. His lamentation that discovering the 'right answer' equates to the 'death of art' paradoxically reveals that his cultivated aesthetic value was a fragile construct, predicated entirely on human cognitive limitations. Elevating Go to an absolute aesthetic standard was arguably an illusion sustained by the boundaries of unassisted human computation. Lee remains confined within this obsolete ideological framework:

"I learned to play Go as an art … But after AI appeared, Go became simply a game of finding the right answer. There is no longer any room for human creativity."[15]

Lee perceives AI as an algorithm that eradicated artistic ambiguity by generating definitive computational optima. This determinism contrasts sharply

14) Yim Jeong-u (2026).

15) Wakabayashi, Daisuke and Jin, Yu Young (2024).

with the pragmatic framework of Shin Jin-seo, the current world number one player. Shin conceptualizes AI not as an oracle of absolute truth, but as a collaborative utility.

"If you only follow the recommended moves, the blue spots that AI points out, your study will become limited. True AI study is about imagining and calculating moves that go beyond those recommendations, constantly evolving your own ideas. It's about aiming for an answer beyond the answer… There's no clear answer. However, from my perspective as someone who's actively competing, I believe it's more productive to look for positive ways to use AI rather than worry about its impact."[16)]

This divergence illustrates that a player's conceptualization of Go now reflects their broader technological orientation. Analogously, the transcription of a Beethoven symphony into formal notation does not nullify its artistry; the structural execution remains a crystallization of human deliberation. Science fiction author Ted Chiang provides a compelling theoretical counterpoint by redefining the locus of artistic agency:

"What I'm saying is that art requires making choices at every scale; the countless small-scale choices made during implementation are just as important to the final product as the few large-scale choices made during the conception. It is a mistake to equate 'large-scale' with 'important' when it comes to the choices made when creating art; the interrelationship between the large scale and the small scale is where the artistry lies."[17)]

Chiang's framework dismantles Lee's dichotomy. If creativity manifests through the continuous execution of micro-decisions, algorithmic recommendations do not eradicate human agency; they merely shift the parameters of

16) Shin Jin-seo (2024), 72-73.
17) Chiang, Ted (2024).

choice. Yet, in his *Memoir*, Lee abruptly adopts a discordant, artificially optimistic register:

"What is clear is that while artificial intelligence can overwhelm humans in terms of skill, the power to create the essence of Go resides in human beings… I believe this is the time to collaborate wisely with it to maximize our strengths."[18]

Contrasted with his prior existential dread, this rhetoric constitutes a facile, manufactured paradigm shift. AI simultaneously operates as the desecrator of his artistic sanctuary and a collaborative utility for maximizing human potential—positions that are structurally irreconcilable.

A critical ideological inversion occurs at this juncture. The same narrator who laments the algorithmic destruction of Go's artistic sanctity paradoxically adopts a highly mechanistic, engineering-driven rationale—the bug-triggering theory—to validate his most celebrated intuitive achievement. As the following section demonstrates, retroactively classifying Move 68 as a calculated exploit to trigger a system error exposes the profound ambivalence and logical fractures at the core of Lee Sedol's narrative revisionism.

4. Move 78: Hail Mary Move[19] or Engineered Gambit?

The spring 2016 five-game match between Lee Sedol and AlphaGo concluded in a 4–1 algorithmic victory, conventionally framed as a human

18) Lee Sedol (2025), 8.

19) This coinage of mine draws on the historical event, 'Hail Mary pass'. It originated from a 1975 NFL playoff game when Dallas Cowboys quarterback Roger Staubach threw a desperate, last-second 50-yard touchdown pass to Drew Pearson to defeat the Minnesota Vikings 17-14. Afterward, the devoutly Catholic Staubach told reporters, "I closed my eyes and said a Hail Mary". Thus a 'Hail Mary Move' can be described as a last-ditch attempt with an extremely low probability of success in Go.

defeat. However, collective memory disproportionately elevates a single anomalous event: Move 78. Although post-match analysis revealed this decisive move in Game 4 to be structurally unsound—succeeding only due to an incorrect algorithmic response—it was universally celebrated as a triumph of human intuition. By forcing AlphaGo into a tactical domain beyond its computational reach, Move 78 induced a systemic failure, solidifying Lee's historical status as the sole human victor over this AI architecture.

While this remains the established historical consensus, Lee's *Memoir* introduces a revisionist narrative. With the benefit of hindsight, he defines his disposition across the series not as desperate defense, but as a deliberate hunt for software vulnerabilities. While acknowledging a waiting strategy in Games 2 and 3 to "increase the probability of a bug"[20], he elevates Game 4 to a masterclass in engineered exploitation:

"The strategy for Game 4 was: minimize variation in the opening and decide everything in the middle game… Move 68 was an extremely composed move, but it was in effect the decisive move… I moved in the direction more likely to produce a bug in AlphaGo rather than the orthodox move. Based on this move, the moment I had been waiting for arrived. White 78, Black 79: a fatal bug occurred in AlphaGo."[21]

This narrative framework suffers from two critical structural flaws. The first is profound internal illogic. As illustrated in Figure 1, White's Move 68 is a demonstrably conservative placement; establishing a causal mechanism between this move and the fierce central battle that followed is analytically impossible. Contemporaneously, Move 68 was universally classified as a standard, orthodox regulating move (*jeong-su*). A decade later, however, Lee

20) Lee Sedol (2025), 99, 104.
21) Ibid., 109-111.

retrofits this orthodox placement into the bug-triggering theory. Psychologically, this constitutes a textbook manifestation of hindsight bias, structurally consonant with retrospective teleology: a generalized anticipation of algorithmic error motivated conservative play, and upon the coincidental occurrence of an error, the preceding passivity was retroactively designated as a calculated tactic.

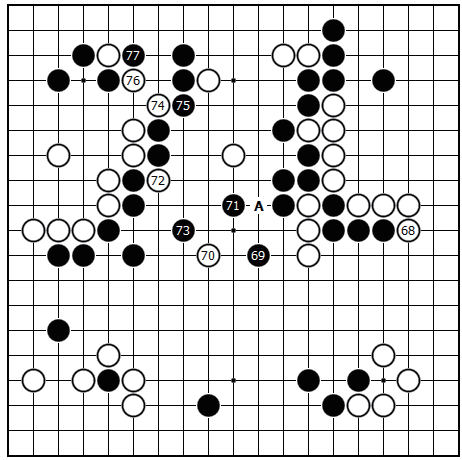

Figure 1

Lee systematically fails to articulate the specific causal mechanics linking Move 68 to Move 78, merely positing that the sequence was “already decided and connected”[22]:

“Move 78 was a sequence that was already decided and connected at the moment Move 68 was played… Move 68 stands as the decisive move because it worked; but had it not worked, it would have been the losing move of this game. It was a move played with the single-minded intention of pro-

22) Lee Sedol (2026).

voking AlphaGo's bug."[23]

This rhetoric of the omniscient strategist appears all the more striking when juxtaposed with the documented reality of 2016. Synthesizing immediate post-match analyses, Benjamín Labatut's *The MANIAC* provides an accurate reconstruction of the prevailing consensus—Move 78 was an uncalculated flash of inspiration. Lee's own 2016 press conference testimony firmly established this:

"At that point in the game, it was the only move I could see. There was no other placement. It was the only option for me, so I put it there. I am quite humbled by all the praise I am getting for it."[24]

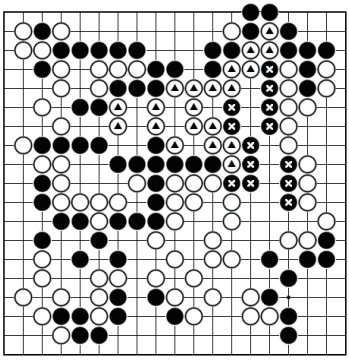

Figure **2**

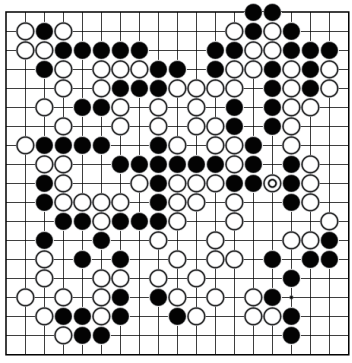

Figure **3**

This impromptu, non-calculated nature was universally accepted. In professional Go discourse, such phenomena are conceptualized as instantaneous manifestations of intuition—the subconscious distillation of accumulated ex-

23) Ibid.

24) Labatut, Benjamín (2023), 340.

pertise. The moniker 'Divine Move' functioned less as a technical evaluation and more as a symbolic tribute to human resilience in extreme adversity.

A comparative example clarifies this operational definition of intuition. Figures 2 and 3 illustrate an online match between professional players, culminating in a critical endgame capturing race. Under severe time constraints, White instantaneously identified the sole winning variation—a wedge move (◎) in Figure 3. The critical distinction between this intuitive brilliance and Lee's Move 78 is empirical soundness: White's move is analytically flawless. Conversely, Move 78 was structurally unsound, succeeding only due to AlphaGo's subsequent algorithmic failure. Nevertheless, its historical value remains undisputed, validating Labatut's assessment:

"As it turned out, AlphaGo's networks agreed with Gu Li… it truly had been divine, a touch from God's hand—only one in ten thousand human players would have considered it. That was the reason AlphaGo had been incapable of dealing with Lee's wedge move: it was too far from human experience, and past even where AlphaGo's seemingly boundless capabilities could reach."[25]

Notably, the DeepMind development team conceptualized Move 78 in parallel with AlphaGo's universally acclaimed Move 37 from Game 2. Google co-founder Sergey Brin observed that the architecture generated aesthetically "beautiful" moves exceeding human cognitive capacity.[26] The paradigm that deep neural networks can synthesize computational approximations of intuition is now canonical. OpenAI researcher Noam Brown summarized this epistemological shift: "AlphaGo definitively showed that neural networks

25) Ibid., 190.
26) Sergey Brin, quoted in Zastrow, Mark (2016).

can perform pattern recognition better than humans. Neural networks can essentially have intuition that surpasses human beings."[27] Technology journalist Cade Metz documented that the match profoundly transformed human understanding of Go, suggesting that AlphaGo's brilliance pushed Lee to find 'God's Touch': "The machine that defeated him had also helped him find the way."[28]

Why was this 'meticulous strategy' concealed for a decade? The contradiction between the humbled protagonist of 2016 and the omniscient strategist of 2025 is irreconcilable. It is highly probable that the contemporaneous narrative served to preserve his status as a surrogate for human intuition, whereas the current revision aims to establish his authority as a master tactician who dismantled a computational architecture. This reversal critically undermines the epistemic reliability of his narrative construction.

The claim of having a 'pre-planned strategy' stands as a jarring contradiction within the otherwise sentimental narrative of the day. Fundamentally, this narrative implicitly premises that the abandonment of one's core competitive philosophy is justified when confronting a non-biological opponent.

Even when accounting for the psychological weight of the 2016 defeat, the compulsion to manufacture the bug-triggering theory remains analytically perplexing. It is highly probable that this narrative construction is inextricably linked to his structurally ambivalent conception of AI. The profound irony is that the same narrator who mourns the algorithmic death of Go's artistic sanctuary now reframes his magnum opus as a mechanical exploit—a rudimentary hack of a system vulnerability. By validating the intentional triggering of computational errors as a legitimate tactic simply because the opponent is a machine, Lee systematically erases the very artistic dimension of Go he pur-

27) Wilkins, Alex (2026).
28) Metz, Cade (2016).

ports to defend. He effectively volunteered to become a mechanical gambler in order to defeat a machine.

By framing Move 68 as the calculated genesis of a 'divine' strategy, Lee consigns the uncalculated reality of the match to an Orwellian memory hole[29]. Through this mechanism of *ex post facto* justification, the documented history of a profound human struggle is quietly overwritten by a meticulously concocted myth. What, then, was the path taken by another genius who suffered the same defeat?

5. Two Paths: Lee Sedol and Garry Kasparov

The bug-triggering theory presented in Lee Sedol's *Memoir* serves as the antithesis to the trajectory of another genius who confronted a similar algorithmic defeat: Garry Kasparov. Kasparov's *Deep Thinking* (2017), published two decades after his 1997 loss to IBM's Deep Blue, perfectly contrasts with Lee's narrative. While both grandmasters share the trauma of machine subjugation, their subsequent conceptualizations of defeat diverge into two distinct archetypes: the evolutionary strategist and the fallen artist.

Initially, their trajectories aligned. Convinced that Deep Blue's anomalous Move 37 (Be4) in Game 2 was computationally impossible without human intervention, Kasparov publicly insinuated that IBM had cheated, famously likening it to Maradona's "Hand of God".[30] This initial denial closely parallels Lee's contemporaneous mystification of AlphaGo's unfathomable moves.

However, their subsequent paths radically diverged. Through rigorous

29) The specific sociological context and implications of the 'Orwellian memory hole' are discussed in detail in Section 6.

30) Kasparov, Garry (2017), 22.

post-match analysis, Kasparov systematically dismantled his own suspicions, concluding after twenty years of self-reflection that Deep Blue had not cheated.[31]

Conversely, Lee's *Memoir* and recent interviews demonstrate a retreat into narrative distortion. Despite the absence of contemporaneous evidence, he retroactively frames Move 68 in Game 4 as a calculated tactic:

"If you run the 68th move through an AI, I come out worse. It's not the jeong-su [the correct move]… **With the sole intention of inducing a bug**, I played an extremely strange move."[32]

Lee's contemporary justification rests solely on AI analysis verifying the move's objective disadvantage. However, numerical disadvantage does not constitute empirical evidence of intent to trigger a system error.

Figure 4 illustrates a simulation generated by KataGo, indicating that strong resistance at Move 68 was optimal. The difference in win rate for Lee's actual move is merely 2.4 percentage points. While this quantifies a minor positional disadvantage, it provides zero evidentiary basis for the claim that the move was a calculated tactic to trigger a bug. Furthermore, this AI-recommended variation portends a fierce battle, directly contradicting Lee's assertion that he avoided standard play because he "believed AlphaGo had the advantage in combat."

31) Ibid., 352.

32) Lee Sedol et al. (2026), 25. Emphasis added.

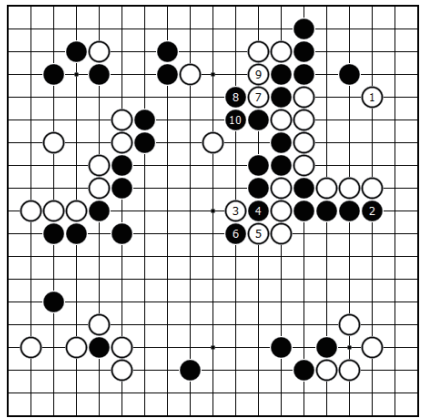

Figure **4**

Why persist in propagating this logically flawed bug-triggering theory? The psychological impetus driving this narrative revisionism is the necessity to restore the historical event to his locus of control. Establishing this narrative—framing the Game 4 victory as a calculated strategy rather than an uncalculated, serendipitous anomaly—is necessary for Lee to claim total intellectual ownership of the historical event. Humans inherently prefer outcomes generated by calculated agency over victories born of desperation. Lee seeks to reconstruct memory into a controllable scenario to mend his fractured professional esteem.

In sharp contrast, Kasparov demystified Deep Blue, conceptualizing it not as an infallible oracle but as a specialized algorithmic tool. Moving beyond mere capitulation, he pioneered Advanced Chess, investigating how algorithmic integration could maximize human creativity. Kasparov viewed AI not as a replacement for human intelligence, but as a utility liberating humans to pursue higher-order creativity. Quoting Pablo Picasso—"Computers are

useless. They can only give you answers"—Kasparov posits that authentic creativity manifests when human strategic discernment (the "power of the question") is integrated with mechanical precision.

Lee, however, remains trapped in his dichotomy, equating algorithmic mastery with the erasure of human creativity. While he formally retired, claiming AI eradicated his capacity to enjoy the game, his rhetoric collapses into contradictory ambivalence. He simultaneously mourns the loss of Go's "philosophical depth" due to AI study[33] and vaguely hopes for the "birth of a new aesthetic" through AI collaboration.[34] Lacking a logically consistent framework, he conflates the evolution of computational tools with the extinction of essential human value.

In attempting to reclassify a miraculous anomaly as a controlled intellectual triumph, Lee paradoxically reduces the sublime artistry of Go to a mechanical exploit targeting a software vulnerability. While Kasparov utilized his defeat as a blueprint for the future, Lee committed to rationalizing and distorting history to preserve his defeat as a relic of past glory. The silhouette of a hero who refuses to evolve, opting instead to guard a defunct sanctuary, appears increasingly tragic.

However, the story of Lee Sedol transcends the self-contradiction of a single grandmaster. The fact that these glaring internal inconsistencies have remained uncontested by the public and the media for an entire decade is the truly uncomfortable question that we, as a collective, must now confront.

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33) Lee Sedol (2025), 286.

34) Lee Sedol et al. (2026), 28.

6. The Orwellian Memory Hole: Selective Remembering and Reconstruction

"But it was all right, everything was all right, the struggle was finished. He had won the victory over himself. He loved Big Brother." (George Orwell, *1984*, 1949, Part 3, Chapter 6)

In George Orwell's *1984*, the 'memory hole' functions as the ultimate instrument of narrative control—an incinerator where any record contradicting the Party's shifting reality is turned to ash. This erasure, however, is not merely a top-down imposition; it is sustained by the collective 'Doublethink' of a society that finds the comfort of a sanctioned myth more palatable than the friction of objective truth. Just as Winston Smith finds hollow peace in submitting to Big Brother, contemporary society has sought comfortable refuge in the hero-narrative of Lee Sedol. Lee's narrative fabrication is not merely an individual defense mechanism; it is the byproduct of a collective memory hole, sustained by a society that, hungry for a human champion, became a silent accomplice to this engineered myth.

This mechanism aligns with Charan Ranganath's thesis in *Why We Remember* (2024): memory functions not as a passive archive, but as an adaptive utility serving present psychological needs. We selectively reconstruct the past to support current identities and goals. Consequently, the collective silence regarding the glaring causal disconnect between Move 68 and Move 78 is not a mnemonic failure, but a functional choice. This 'social remembering' prioritizes the preservation of human triumph over the uncomfortable reality of algorithmic supremacy. Society collectively incinerated the evidence of a computational exploit to protect the illusion of an inviolable sanctuary of human creativity.

This collective acquiescence stems from three primary factors. The first is psychological solace. The public and the professional Go community strongly desired Lee to remain a symbolic bastion, and maintaining his status as the sole human to defeat AI mitigates the collective existential anxiety of the algorithmic era. To challenge his narrative is to threaten that comfort directly.

The second factor is structural marketability. Institutions frequently deploy Lee as a symbolic asset, and his legacy functions as an unparalleled tool for attracting audiences. To preserve the marketability of this national hero, the establishment has systematically ignored his self-contradictions. Rigorous verification is an inconvenient friction; silence is a profitable commodity.

The third, and perhaps most troubling, factor is professional complicity. Despite recognizing the technical inconsistencies, experts within and outside the Go community have largely refrained from public verification. By choosing to assimilate into an established power structure rather than resist it, they appear to have allowed the name 'Lee Sedol' to solidify into a near-unquestionable institutional authority.

The convergence of these factors activates what sociologist Pierre Bourdieu terms 'symbolic power'. Lee's linguistic capital derives from his decade-long dominance in the professional Go world (*champ*) and the profound symbolism of Game 4. When these capitals converge, his discourse becomes virtually irrefutable in the broader public sphere:

"It is true that the definition of the symbolic relation of power … can be the subject of negotiation … But it goes without saying that the capacity to manipulate is greater the more capital one possesses, as is shown by the strategies of condescension."[35]

Lee strategically exploits the intimate nature of the *Memoir* format. He ap-

35) Bourdieu, Pierre (1991), 71.

pears deeply immersed in his self-contrived bug-triggering theory, exporting private reminiscence as historical testimony. When his claim of executing a deliberate tactic to trigger a bug is accepted as fact without critical scrutiny, the profound value of uncalculated human intuition—symbolized by Move 78—is systematically erased. He reinforces this during public appearances:

"… the true seung-bu-su [decisive gamble] of this match was actually move 68 … Did I have to compromise my philosophy and convictions just to win this game? It was, of course, a human decision. I was cornered at the time… Had I thought of it as my personal defeat alone, I likely would not have played move 68." (Lee Sedol, 'OhMyForum 2026') [36]

Here, unverified assertions acquire absolute authority solely through the speaker's identity. By framing a mechanical exploit as a heroic sacrifice made for humanity ("Had I thought of it as my personal defeat alone…"), it may be argued that Lee's address functions, at least in part, as an emotional appeal that deflects critical scrutiny. According to Bourdieu's field theory, this symbolic authority manifests dangerously on two levels.

First, the over-generalization of singular experience. Lee frequently projects his personal trauma onto universal AI discourse, oscillating between lamenting the death of Go's creativity and espousing vague AI optimism. Ranganath warns that each time a memory is recalled, it is "subject to edits and updates, so that, over time, our memories can drift further and further from that initial event." [37] When such distorted memories are recurrently voiced by a dominant authority figure, they contaminate public perception. As Ranganath notes, collective memory is not random; it becomes "especially skewed toward those of the loudest voices in the room", allowing the most

36) Lee Sedol (2026).
37) Ranganath, Charan (2024), 177.

confident speakers to overwrite shared history.[38]

Second, the transgression of epistemic boundaries. Lee extends his symbolic capital into domains where he lacks professional expertise, such as AI ethics and the philosophy of writing. Audiences suspend critical distance due to the "trap of familiarity"—where fame provides an unearned aura of trust and expertise.[39] Because humans are highly susceptible to inheriting memory errors from trusted figures, Lee leverages this familiarity to bypass critical scrutiny, making his distortions incredibly difficult to root out from the shared narrative.[40]

Just as the protagonist in *1984* found twisted solace in surrendering his memory to Big Brother, contemporary society has grown accustomed to the artificial sweetness of unverified hero narratives. Lee Sedol's distorted narrative is a co-constructed product of a society eager to indulge in that very sweetness.

The core issue transcends Lee as an individual. An individual's psychological desire to reconstruct defeat into myth is comprehensible; however, the societal failure to challenge this narrative fabrication for an entire decade is profoundly disturbing. In a space where the intersection of AI and humanity demands rigorous contemplation, unverified narratives have been elevated to credible testimony. Where criticism vanished, myth moved in; and where myth solidified, questioning was branded as sacrilege.

The subversiveness of Lee's narrative lies not merely in its factual distortion, but in the collective silence that legitimized it. When the discourse on human-machine interaction is monopolized by the most assertive, rather than

38) Ibid., 229-230.
39) Ibid., 142.
40) Ibid., 234.

the most accurate, voice, the resulting intellectual poverty burdens the entire society. Ultimately, this paper serves as a critical intervention, seeking to correct an engineered myth that has masqueraded as history amid collective social silence.

7. Conclusion

This paper has sought to demonstrate that Lee Sedol's 2025 *Memoir* is not merely a personal recollection but a strategically constructed revisionist narrative—one that retroactively recasts a contingent historical outcome as a premeditated strategic achievement at the expense of documentary accuracy. Through close analysis of the internal contradictions surrounding Moves 68 and 78, it has shown that Lee's 'bug-triggering theory' is both empirically unsupported and logically incoherent: Move 68 cannot simultaneously constitute a deliberate gambit and a spontaneous response to AlphaGo's anomalous behavior. The cognitive distortions Charan Ranganath identifies—whereby memory is reconstructed to serve the narrator's present needs—offer the most parsimonious explanation for this revisionism.

Yet the paper has also argued that Lee's narrative could not have hardened into consensus without structural complicity. Drawing on Pierre Bourdieu's theory of symbolic power, it has traced how Lee's authority as the sole human victor over AlphaGo effectively foreclosed critical scrutiny, while the professional Go community and a public hungry for a human champion colluded in silence. The result is an Orwellian memory hole: a manufactured account that has displaced the documented record and now risks calcifying into the authoritative version of events.

The contrast with Garry Kasparov's response to his defeat by Deep Blue is instructive. Where Kasparov's Deep Thinking (2017) models a form of intellectual accountability—honestly confronting the reality of machine superiority while extracting genuinely productive lessons for human-AI collaboration—Lee's *Memoir* retreats into self-serving mythology. This retreat, as the paper has argued, is not merely an individual failure but a symptom of a broader cultural anxiety: the difficulty of sustaining honest discourse about human-machine relations when the stakes of human dignity feel impossibly high.

The displacement of criticism by myth carries real intellectual costs. As AI systems continue to reshape domains of human expertise—not only Go but creative, analytical, and professional fields of every kind—the frameworks we develop for understanding these encounters matter enormously. Narratives that subordinate historical truth to consolation impoverish those frameworks and foreclose the more rigorous reckoning that the AI era demands. This paper calls for a critical re-examination of the revisionist narrative that has consolidated under collective social silence: one that honors the genuine complexity of the AlphaGo matches, acknowledges what they revealed about both human and machine intelligence, and resists the temptation to resolve that complexity through the consoling fiction of retrospective strategic mastery.

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Received: 1 May 2026

Accepted: 26 May 2026

바둑학연구, 제20권 제1호, pp. 79-128
Journal of Go Studies
20263. Vol.20, No.1. pp. 79-128

Exploring Structural Correspondences Between Go Playing Style and Szondi Drive-Profile Scores

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Abstract

This article investigates whether recurrent formal structures in Go gameplay can be statistically related to structured configurations derived from the Szondi test. Rather than treating psychological constructs as directly observable entities, we approach both playing style and drive organization as constructed systems of indices, each governed by internal regularities. The study examines inter-domain correlations between quantified stylistic dimensions of play (territoriality, orthodoxy, thickness, aggressiveness) and drive-based variables (acting index, symptomatic response rates, factor-level distributions), based on a shared participant corpus. Statistical analyses test linear and non-linear associations across domains. The results suggest non-random correspondences between specific stylistic tendencies and particular drive-related configurations. These findings do not warrant psychological reductionism; instead, they suggest that strategic behavior in Go may function as a structured expressive field in which latent organizational constraints become

formally instantiated. From an epistemological perspective, the study argues that correlations between heterogeneous index systems do not validate underlying constructs directly, but rather suggest structural compatibility between distinct formalizations of human behavior.

Keywords: Go game analysis; Szondi test; playing style metrics

The aim of this study is exploratory, abductive and heuristic: we investigate whether statistical regularities emerge between two formally structured coding systems (Go style metrics and Szondi-derived scores), with the goal of discussing hypotheses about possible structural correspondences. Cognitive psychology has used Go as a field of investigation for sequential memory, pattern recognition, and complex problem-solving, positioning the game as a fertile model for exploring cognitive styles (Burmeister, 2000). Nevertheless, our aim here is to approach the matter from a different angle: Do the players' deep psychological particularities (drive-related and unconscious) find expression in their playing style on the goban? This line of research ultimately aims to confirm or invalidate the popular belief that one can genuinely encounter a person by playing Go with them, or more broadly, by confronting them within a dynamic of competitive engagement.

The game of Go can be viewed as a structured, non-verbal semiotic medium through which certain dimensions of our humanity (and animality) find avenues of expression. In particular, issues of aggressiveness and territoriality can be readily observed in the course of a game. To explore these dimensions, we analyzed Go games and administered a projective test (Szondi's Experimental Diagnostic of Drives). This projective instrument is based on an affective choice standardized procedure involving series of modified photographs depicting psychiatric patients associated with extreme clinical forms. The subject is invited to select the portraits that evoke attraction and rejection, allowing the construction of a profile of drive tendencies organized into factors and vectors. Interpretation consists in treating these choices as projective indicators of the dynamics of drive needs, their modes of satisfaction, their conflicts, and their censorship. The test is administered repeatedly (never twice on the same day) in order to assess both the stability and the variations

of drive organization, as well as certain global indices (acting, variability, disorganization). For a more comprehensive presentation of the test, its testological specificities, and its limitations, we refer the reader to Legrand's critical work (1979). It should be noted that the question of its validity remains empirically open rather than conclusively resolved (Káplár et al., 2012; Thiry & Parete, 2015). Nevertheless, some studies suggest partial validity in specific domains (e.g., Garcia Siso, 2008; Gonçalves et al., 2014; Garcia Siso, 2024). Research suggests good reliability when compared to personality tests such as the MMPI (Káplár et al., 2012) or the FIP (Mello Schivitz et al., 2008). Mosso-Gautier (2023) highlighted the test's high intra-individual sensitivity and incremental and pragmatic validity, within the framework of a reflection on the construct validity of the test material. His PhD dissertation offers an epistemological perspective on the test, highlighting the theoretical stakes and interpretative precautions required for its contemporary use.

Despite reservations regarding the validity of this instrument, several reasons justify its use in the present study:

1. The Szondi test is one of the very few projective instruments explicitly designed to operationalize drive-related configurations of psychic life. While instruments such as the Thematic Apperception Test or the Rorschach may also access this dimension, they do not allow for the same level of formal differentiation between drive factors;
2. It is one of the rare projective tests that incorporates a test–retest logic (multiple administrations), making it possible to assess intra-individual stability and variability of configurations over time (e.g., indices of variability and disorganization);

3. Its highly standardized administration procedure allows for controlled empirical research (e.g., pre/post comparisons, see Máté et al., 2012);
4. Its ipsative format (forced-choice) is associated with better operational validity than Likert rating-scale item formats (Bartram, 2007).
5. Importantly, the present study does not rely on the Szondi test as a diagnostic or predictive instrument, but rather as a structured coding system (enabling investigation of structural correspondences with other devices such as Go games' metrics). It is only in a second step, once structural correspondences may be identified, that an interpretation can be proposed, strictly consistent with the theory underlying the psychometric instrument;
6. Other widely used instruments, such as the MMPI or Big Five inventories, primarily assess trait-level personality constructs, which are conceptually distinct from the dynamic configurations targeted in the present study. In addition, their practical (lengthy administration), psychometric (e.g., social desirability bias, partial non-orthogonality of factors), and cultural limitations are well documented, and may constrain their use in research design.

Ontological hypotheses and status of the variables

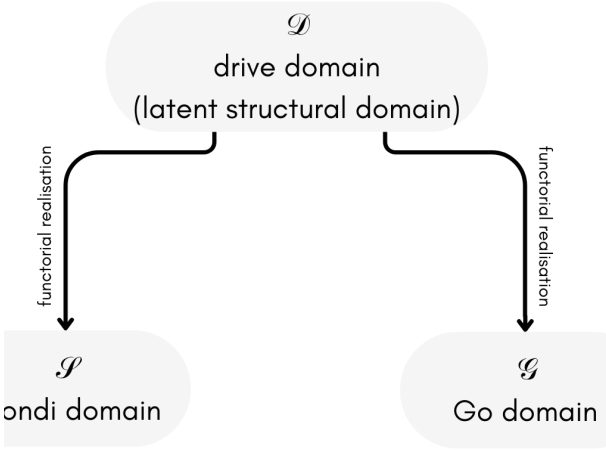
We situate ourselves within a psychoanalytic (psychodynamic) paradigm, in which the drive has an axiomatic status. Following Freud (1915, 1920), we define it as a psychically represented pressure of somatic origin whose satisfaction lies in the circuit accomplished around a partial object rather than in the object itself. Within this framework, any act may involve the partial

satisfaction of a drive demand whose origin remains partly unconscious. Applied to Go, this implies that a move and its execution on the goban may constitute such a circuit; the same assumption underlies the Szondi test as a reproducible semiotic support for apprehending drive organization. This postulate is theoretical rather than directly testable. The drive thus remains a construction, a "useful mythology" (Freud, 1933), not an observable entity. This obviously does not prevent us from indirectly measuring the manifestations of drives, rather than drives themselves.

The game of Go is conceived as a formal semiotic device (Mary, 2024b) in which strategic configurations may function as structural indices of drive orientations independently modeled by the Szondi test. A semiotic device is a structured system that organizes and constrains the interpretation of signs according to a set of internal rules and conventions. It generates interpretable configurations of signs that require theoretically informed decoding within a given framework (Eco, 1975; Greimas, 1976).Thus, whenever one attends a game commentary in which phrases such as "this move was telling you" are uttered, these translations into ordinary language – which intentionalize moves and even attribute a form of psychology to them (e.g. "this stone is sad") – attest to the existence of an implicit coding/decoding system sufficiently shared for such statements to circulate among players.

We distinguish three structural domains: (i) the psychic apparatus, (ii) the drive organization scores derived from the Szondi test, and (iii) the Go style derived from Moudřík's analyses. Rather than postulating identity or direct causality between these domains, we propose to consider them as distinct structures potentially maintaining partial correspondences. In a sense inspired by categorical thinking (Mac Lane, 1978; Grothendieck, 1986) – that is, an approach focusing on relations between structures rather than on the intrinsic

nature of the entities involved –, the aim would be less to identify objects than to examine the possible preservation of certain structural relations between drive configurations and strategic configurations. Kramer's (2021) work, proposing a Galois connection between a personality indicator (MBTI) and the Szondi test, shows that it is mathematically possible to provide a pair of computable, interpretive translations between two psychological assessment devices. Such a research program is ambitious, and the present work has only a preliminary scope within it. We are at the fuseki of a research program.



Rather than positing an identity between drives and moves, one may conceive their relation in terms of realizations (Connes & Gauthier-Lafaye, 2022): a latent drive-based structure is accessible only through local manifestations, whose coherence depends on their compatibility across successive situations. By "realizations," we mean observable configurations through which relational constraints are expressed within a given system. In this perspective, the drive dimension is treated not as a substantial object but as a

structural constraint. The drive retains an axiomatic status, yet it is no longer an ontological or energetic axiom (as in the early psychodynamic conception of the Freudian paradigm); it becomes a structural axiom (closer to a Lacanian orientation). It is not posited as an internal substantial force, but as a regulatory constraint on the forms of coherence that observable configurations may assume.

1. Presentation of the Szondian factors and vectors

Szondi's drive system describes eight factors (h, s, e, hy, k, p, d, m) grouped into four vectors, each corresponding to a structural domain of psycho-affective existence: S (sexual/objectal vector: h, s), P (paroxysmal/crisis vector: e, hy), Sch (ego vector: k, p), and C (contact vector: d, m). Each factor is assigned a sign indicating a modality of drive positioning: + and − designate unidirectional tendencies (acceptance/identification versus refusal/censorship, depending on the factor), whereas 0 and ± are classically considered "symptomatic" responses, in the sense that they signal either discharge/absence of manifest tension (0) or ambivalence/inner conflict (±).

From a dynamic perspective, these signs do not describe traits in a dispositional sense, but rather the momentary form of the subject's relation to drive needs, a relation liable to vary depending on context and internal reorganization (Deri, 1949). The factors may be summarized as follows: h (need for union/erotic attachment), s (aggression, struggle, domination/submission), e (paroxysmal register of tension and critical discharge, including the relation to prohibition and violence), hy (self-staging, expressivity/exhibition versus modesty/inhibition), k (modalities of control/repression and integration, ego constraint functions), p (modalities of elaboration and structuring of the psy-

chic field, ranging from more open symbolization to more projective tendencies), d (attachment/conservation and relation to loss), and m (dependence/anaclitic orientation versus autonomy/detachment).

This vectorial structuring makes it possible to reason both at the factorial level (signs of the eight factors) and at the vectorial level (configurations such as S++, P±−, Sch−+, C−+, etc.), the latter providing a synthetic reading of inter-factorial balances and conflicts.

In a Szondian perspective, a drive organization is a structure of fundamental relations (charge/discharge, active/passive, seeing/being seen, introjecting/projecting, etc.). Here, we consider a drive organization as a minimal structural signature.

2. Presentation of Moudřík's scores

Shirsat (2026) has shown that strategic styles are not arbitrary artifacts but exhibit a structure that can be computationally exploited. The Go game analysis program developed by Moudřík, Baudiš and Neruda (2015) extracts four synthetic indicators of playing style from SGF databases.

- **Territoriality:** an index measuring the propensity to secure clearly defined territories early, through closed, localized sequences with stable returns. A high score reflects an orientation toward early spatial consolidation rather than diffuse influence.
- **Orthodoxy:** an indicator of conformity to established sequences (classical joseki). It is based on the frequency of standardized variations as opposed to personal innovations. A high score signals a conventional style; a low score indicates a preference for rare or novel lines.
- **Aggressiveness:** measures the frequency and intensity of local fighting (di-

rect attacks, invasions, tactical confrontations). It is computed from contact events and conflict sequences.

- Thickness: refers to the construction of global influence and solid positions without immediate territorial gain, reflecting a strategy of long-term pressure.

These four outputs aim to operationalize stylistic dimensions that can be objectified from game traces. The four synthetic indices are normalized on a bounded 1–10 scale (with decimals), constructed through the player's relative positioning within a reference distribution (a comparative base derived from a large corpus). These scores are quasi-continuous. Although a strictly linear metric cannot be guaranteed (since these scores are composite indices dependent on a reference corpus) they rely on a series of measures extracted from Go games (SGF format): spatial distribution of moves; rate of standard joseki usage versus innovative variations; proportion of moves in direct contact (attacks, ataris, invasions); frequency and length of local fighting sequences; number of invasions into opponent territory; density of constructed groups (solidity versus dispersion); number of connecting or defensive reinforcement moves; early territorial exchanges versus development of global influence; local initiative (tenuki versus immediate response); and temporal distribution of conflicts.

We are aware that the validity of Moudrik's GoStyle has not been established, although it is used in academic research contexts. Its outputs appear structured and seem to differ from random distributions; however, it has not yet been demonstrated that its scores genuinely correspond to players' styles. Despite these limitations, the tool is used here as a structured descriptive system, under the assumption that its outputs capture non-random regularities in

playing styles, without implying that they constitute validated measurements of underlying stylistic constructs.

3. Metric status of the variables: scoring conventions vs. measured quantities

Although psychological research often claims to "measure" psychological realities, it rarely measures psychic processes directly (Deri, 1949; Vautier & Mazet, 2020). As in much quantitative research, the present study does not measure latent constructs but assigns scores: the numerical variables used here are indices produced by coding and calculation rules, not demonstrated measurements of psychological magnitudes. The reported correlations therefore concern structural correspondences between conventional indices rather than relationships between measured quantities.

A drive, being unobservable, can only be inferred from its effects (Freud, 1920; Lacan, 1973), and similar epistemological limits apply to the notion of "measuring" a Go playing style. The stylistic scores (orthodoxy, territoriality, aggressiveness, thickness) are constructed from measurable features (e.g., counts of ataris or contact events) but do not themselves constitute measurements of underlying entities. Both Szondi-derived variables and GoStyle outputs are thus treated as approximate ordered indicators within structured coding systems.

Within this framework, Pearson correlations and linear regressions are employed as pragmatic metric approximations, treating these scores as quasi-continuous across their observed range. This does not imply that the underlying constructs are quantitatively measurable; rather, these statistical tools are used heuristically to explore patterns of covariation between two

structured systems. The resulting coefficients should therefore be interpreted as indicators of structural correspondences within a given coding framework, not as estimates of relationships between latent variables, nor as supporting causal or population-level claims.

To assess robustness under different assumptions, these analyses are complemented by non-parametric correlations (Spearman) and uncertainty estimates (bootstrap). More generally, quantification here serves a comparative function rather than an ontological one: the correlations describe structural covariation between coded systems within this sample and should be interpreted as heuristic relational findings rather than evidence of measurable psychological forces.

Operational Hypotheses

Five a priori hypotheses (H1, H2a, H2b, H3a, H3b) were formulated prior to any analysis of the data. Under the global null hypothesis (absence of any true association), testing five hypotheses at $\alpha = 0.05$ yields an expected number of false positives of 0.25. However, the probability of obtaining at least one significant result purely by chance is approximately 22.6%. Thus, even a single significant finding among these tests cannot be taken as strong evidence without further corroboration.

Subsequently, exploratory correlations (not predicted a priori) were examined (H4 hypotheses family). Under the global null hypothesis, for 16 tests the expected number of significant results at the threshold $p = 0.05$ equals $16 \times p$, that is 0.8 expected false positives. The probability of obtaining at least one significant result by chance is then $1 - (0.95)^{16} = 0.56$. Exploratory

findings must therefore be interpreted with caution and regarded as hypothesis-generating.

H1: Aggressiveness and drive conflictualization

We hypothesize that a more aggressive playing style (calm–fighting axis) is associated with a lower percentage of null responses in the Szondi test (%0), a global indicator of reduced immediate discharge and greater conflictualization/elaboration of drive tendencies. We therefore expect a negative association: as stylistic aggressiveness increases, the percentage of null responses should decrease.

H2: Orthodoxy and the expression of singularity

Based on clinical observations conducted in therapeutic contexts, we claimed that the semiotic field of Go is sensitive to the expression of subjective singularity (Mary, 2024). Therefore, we hypothesize that a more orthodox playing style (Moudřík's classic–novel axis) is associated with the hy and p factors. The hy factor reflects expressive modulations of the self and forms of self-staging in social interactions, whereas the p factor reflects expressive projections of drive needs. We therefore expect to observe

- H2a: a correlation between orthodoxy score and the hy factor.
- H2b: a correlation between orthodoxy and the p factor.

H3: Territoriality and ego boundaries

We hypothesize an association between territoriality and the Ego vector (Sch).

- H3a: A more territorial style (moyo–territory axis) should be associated with more negative values of the p factor
- H3b: A more territorial style should be associated with the k factor (H3b).

These hypotheses are consistent with the idea that territorialization on the

goban may function as a formal analogue of the constitution of ego boundaries. We assume that indicators of territoriality in Go are associated with drive dimensions involving the relation to space or to the structuring of the relational field. This hypothesis is rooted in prior clinical observations conducted in psychiatric settings, where territorial configurations in Go appeared to articulate with modalities of subjective boundary formation (Mary, 2025).

H4: Duration of practice and drive organization

Taking advantage of the data collected, we sought to examine whether years of practice or playing strength are statistically associated with constructed variables derived from the Szondi test. No correlation was found between, on the one hand, the number of years of Go practice, and on the other hand, the playing level estimated by GoStyle (Moudřík et al., 2015), with the percentage of symptomatic responses, the acting index, the disorganization index, the variability index, etc. If an effect exists, it is too small to be detected in a sample of N = 21. On the basis of this sample, there is therefore no evidence to support the claim that long-term Go practice (without specification of frequency or intensity) has a psychological effect.

Sample and data corpus

The sample consists of 21 Go players: 20 men (95.2%) and 1 woman (4.8%). Two additional participants (a woman and a man) could not be included in the study due to incomplete data (non-exploitable SGF files). The mean age is 39.7 years (SD = 12.9), ranging from 28 to 71 years. Participants are primarily from France (n = 11), with others from the United States (n = 3), Italy (n = 2), and Spain, Colombia, Hungary, New Zealand, and Taiwan (n = 1 each).

Regarding playing strength, the average rank is 4.1 kyu, according to the estimation provided by the analysis software developed by Moudřík et al. (2015) (SD = 4.8). The distribution ranges from 13 kyu to 4 dan, with the majority of players ranked kyu (81%) and four players ranked dan (19%). Average playing experience is 14.5 years (SD = 9.3), ranging from 3 to 38 years of practice.

Each participant provided .sgf files of recent online 19×19 games (without handicap). The number of games analyzed per participant is relatively homogeneous (M = 37.7; SD = 8.2), ranging from 18 to 48 games. The games were analyzed using an online application described by Moudřík et al. (2015). The software generates, for each participant, four output values computed from the game corpus: an orthodoxy score (classic–novel axis), an aggressiveness score (calm–fighting axis), a thickness score (safe–shinogi axis), and a territoriality score (moyo–territory axis).

Finally, each participant completed three administrations of the Experimental Diagnostic of Drives (Szondi test). A quantitative analysis of each participant's test protocol makes it possible to compute an acting index, the percentage of negative and symptomatic responses, and numerical values for each of the eight drive factors measured by the test. The sample included participants with diverse personal histories, including self-reported psychiatric or neurological conditions. No subgroup analysis was conducted due to sample size limitations. Despite the potential insight that consideration of these diagnoses might have provided, we deliberately refrained from discussing them for ethical reasons, particularly due to the risk of participant identification.

All data were collected online (three videoconference sessions per participant) between March 14, 2025 and April 10, 2025. All participants provided informed consent and expressed their wish to be informed of any potential

publication of this work. The total time devoted to data collection, scoring, analysis, and recording is estimated at approximately 26.5 hours (i.e., an average of 75 minutes per participant).

The sample was recruited online (with the criteria to be more than 18 years old and having a minimum 15 kyu rank) and is unfortunately strongly unbalanced in terms of gender (20 men, 1 woman) and culturally heterogeneous. These characteristics limit the external validity of the findings. First, the distributions of style scores (derived from online games) and Szondi scores may depend on unmeasured selection variables (level of engagement in online Go, format preferences, self-selection of participants interested in a psychological study), which may produce associations that do not generalize to other player populations (for example, women or players who reject online Go). Second, the gender imbalance prevents examination of possible moderation effects or structural differences in associations by gender; it is therefore impossible to conclude that the observed correspondences extend beyond a predominantly male subgroup. Third, playing practices, valued strategic styles, and modes of reception of a projective device may vary across sociocultural contexts. The diversity of represented countries may thus introduce systematic variability that is difficult to isolate in a small sample.

However, it should be emphasized that the instruments used (the game of Go and the Szondi test) are strictly non-verbal semiotic devices structured as formal semiotic systems. While this may protect against linguistic bias, it does not eliminate the cultural coordinates surrounding each player's relationship to the game of Go. Consequently, the reported associations must be interpreted as specific to this exploratory sample and require replication in more diverse and better-balanced samples (particularly in terms of gender) before any generalization can be made.

Associations were quantified using Pearson correlations and, under weaker metric assumptions, monotonic correlations (Spearman). Given the sample size, interpretation prioritizes effect sizes (r, R^2, slopes) and their uncertainty: confidence intervals were estimated by bootstrap (5,000 replications). Sensitivity to individual observations was examined through influence analyses (jackknife leave-one-out and regression diagnostics) and, where relevant, through composition analyses (leave-two-out) in order to identify potential dependence on peripheral cases. Reported tests are distinguished between a priori hypotheses and post hoc explorations.

Descriptive vectorial distributions and modal profile

Table 1. Most frequent vectorial responses: observed proportions vs. expected probabilities under random model

	S		P		Sch		C	
1	+-	15,15 % *expected probability: 11,15%*	--	21,21 % *expected probability: 7,80%* *χ^2=3,40, p=0,065*	±0	16,67 % *expected probability: 4,46%* *χ^2=10,00, p=0,0016*	-+	34,85 % *expected probability: 11,15%* *χ^2=12,36, p=0,0004*
2	-0	12,12 % *expected: 7,10%*	-0	12,12 % *expected: 7,10%*	--	12,12 % *expected: 7,80%*	++	13,64 % *expected: 7,80%*
3	+0	12,12 % *expected: 7,10%*	0±	10,61 % *expected: 4,46%*	-+	9,09 % *expected: 11,15%*	0+	12,12 % *expected: 7,10%*

We present the most frequent vectorial responses observed in our sample. (Table 1) We report, beneath the observed percentages in the sample, the theoretical percentages expected under a random probability model. A theoretical profile emerges from the data: S +- ; P -- ; Sch ±0 ; C -+. It outlines

a globally coherent organization, characterized by a strong relational orientation tempered by inhibition of aggressiveness and paroxysmal affects. The sexual vector (+-) suggests a significant investment in relational bonds and an idealization of the object, accompanied by an avoidance of direct conflict and a contained form of aggressiveness. The paroxysmal vector (--) indicates marked emotional control, restrained expressiveness, and an aggressive tension (e-) that is internalized rather than discharged.

At the level of the ego (Sch ±0), the presence of k± reflects a structural tension between self-assertion and self-restraint: the subject may alternately withdraw into a position of internal mastery (k+) or submit to normative and critical demands (k-), without either position becoming durably dominant. Finally, the contact vector (-+) reveals a strong, conservative, and at times dependent attachment, with difficulty detaching from invested objects.

Overall, this theoretical profile points to affectively engaged yet not demonstrative individuals, capable of control and self-regulation, who privilege continuity and fidelity in relationships, and whose drive tensions appear more frequently internalized than converted into acting out.

Such a general profile is ultimately not very surprising in a population of individuals engaged in a form of serious leisure practice that lends itself to intellectualization and sublimation, and that displaces interpersonal conflict onto the pacified arena of a game board. Comparisons with normative data remain delicate, given the influence of cultural factors and gender composition. The interpretation of this theoretical drive profile should not lead us to overlook its constructed (that is, fictive) character. It constitutes a first approximation and certainly not an authentic psychology of the Go player.

For comparisons, we constructed a sample of 10,000 random profiles. Among the nine most represented vector configurations in our sample, the

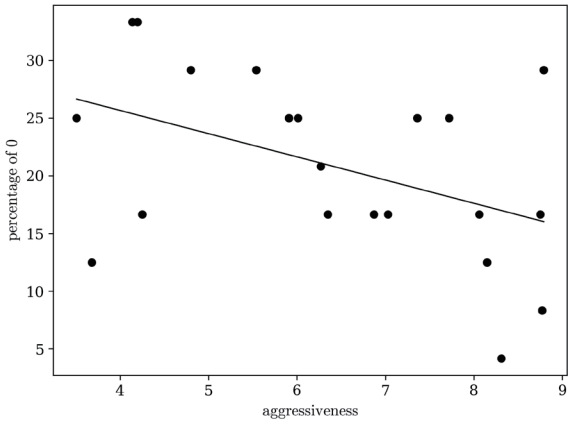
configuration C-+ in particular appears to be significantly overrepresented (approximately three times more frequent than expected by chance) relative to the constrained random model (p = 0,006). A global non-randomness score computed across these nine configurations indicates that their combined pattern significantly departs from their occurrences in our randomly created sample (Monte Carlo p = 0,0056). This suggests that human responses are not distributed as mere combinatorial noise, but exhibit a degree of structured organization, here especially marked in the contact vector. This observation provides a modest argument in favor of minimal construct validity (i.e., the test produces a structured object that is not reducible to randomness).

Results

1. Correlation between stylistic aggressiveness and percentage of null responses

A simple linear regression shows a moderate negative association between stylistic aggressiveness and the percentage of 0 responses (%0), $r = -0.45$, $R^2 = 0.21$, p = 0.039. The estimated slope (−0.020) has a 95% confidence interval of [−0.039; −0.001]. With $R^2 = 0.205$, approximately 20.5% of the variance is explained by the aggressiveness score. The monotonic correlation (Spearman) is borderline ($\rho = -0.43$, $p = 0.053$).

%0 = 0,337 – 0,020 x AGR



The negative association observed between aggressiveness and the percentage of neutral responses (%0) should be interpreted cautiously. The Pearson correlation reached nominal significance. Although the bootstrap confidence interval did not include zero, it remained wide. A jackknife influence analysis further revealed moderate sensitivity of the coefficient to individual observations, with the correlation ranging between –0.38 and –0.58 depending on the case removed. The effect size appears moderate but unstable, which is consistent with the limited sample size (n = 21).

2. Correlation between stylistic orthodoxy and the hy factor

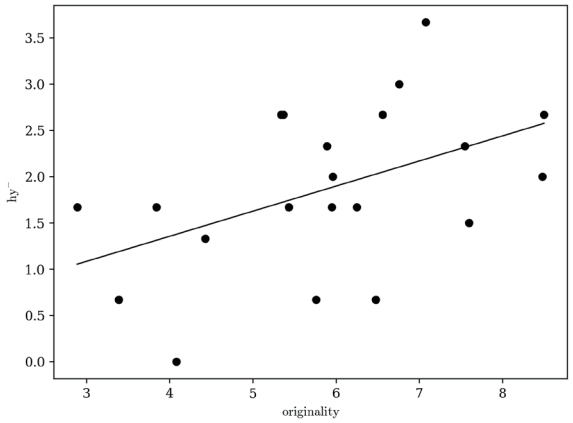
Based on the 21 available observations, the linear correlation between orthodox style and the hy− score was estimated using Pearson's coefficient. The obtained coefficient is $r = 0.470$, corresponding to $R^2 = 0.221$. Thus, within a simple linear model, stylistic orthodoxy accounts for approximately 22.1%

of the variance observed in hy− in this sample. The associated significance test yields $p = 0.032$, below the predefined threshold of 0.05, indicating a statistically significant association.

To assess the robustness of this estimate, a non-parametric bootstrap procedure (5,000 replications) was performed by resampling paired observations with replacement. The 95% percentile confidence interval for the correlation coefficient is [0.165; 0.699]. This interval does not include zero, confirming the statistical significance of the association. However, its relatively wide range reflects non-negligible estimation uncertainty due to the modest sample size.

A jackknife analysis (successive deletion of one observation) yields an approximate 95% confidence interval of [0.201; 0.739], also entirely positive. No single deletion reverses the sign of the coefficient, indicating that the effect is not driven by an isolated case or a major influential point. The directional stability of the coefficient therefore strengthens the internal reliability of the estimate.

From a statistical standpoint, the association can be described as moderate ($|r| = 0.47$). The significance level ($p = 0.032$) is compatible with a linear association hypothesis within this sample. Given the limited number of observations ($n = 21$) and the fact that the model accounts for only a limited portion of the variance, with approximately 78% remaining unaccounted for, conclusions must be drawn cautiously. The observed effect constitutes an empirically coherent signal that is statistically robust to resampling procedures, but it would benefit from replication in an independent sample or within a longitudinal design.



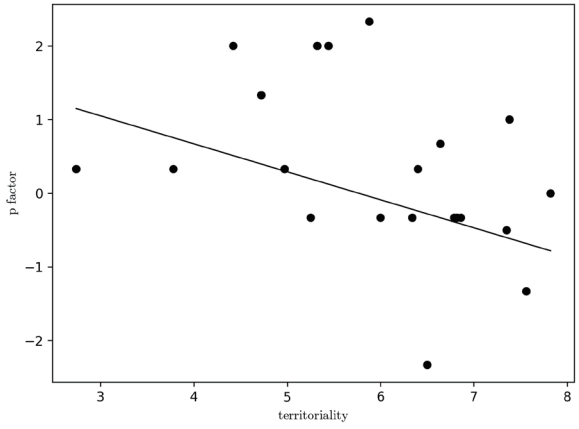
3. Correlation between stylistic territoriality and the p factor

The analysis reveals a moderate negative linear correlation between territorial style and the p factor. Pearson's correlation coefficient is $r = -0.40$, corresponding to an R^2 of approximately 0.16. However, the association does not reach the conventional threshold for statistical significance ($p = 0.076$). The linear regression model corresponds to the equation: $p = 2.40 - 0.35 \times$ TER.

The robustness of this association was examined using resampling procedures. The bootstrap (5,000 replications) yields a 95% confidence interval for r ranging from −0.67 to −0.16, suggesting directional stability of the effect, although the exact magnitude of the coefficient shows notable variability. The jackknife analysis further indicates that successive removal of each observation does not alter either the sign or substantially the strength of the correlation (r varying approximately between −0.48 and −0.34), suggesting that the observed effect is not attributable to a single influential data point.

Overall, these results suggest the presence of a negative trend between

territoriality and the p factor in this sample, while inviting caution in interpretation given the modest sample size and the absence of statistical significance at the conventional threshold.



To assess the sensitivity of the relationship between territoriality and the p factor to sample composition, we conducted a systematic influence analysis consisting of successively removing all possible combinations of two participants (leave-two-out) and recalculating the correlation at each iteration. Among all tested configurations, only one combination yielded a correlation crossing the conventional significance threshold ($p < 0.05$): the removal of the two observations with the lowest territoriality values (TER = 2.74 and TER = 3.78; participants 9 and 16). In this case, the correlation becomes significant and increases in magnitude ($r = -0.543$; $p = 0.016$). This result indicates that the low-territorial style scores in these two observations introduce substantial heterogeneity into the overall relationship and contribute to attenuating its statistical significance in the full sample. These two extreme cases will be discussed below. (Table 2 summarizes all hypothesis results)

Table 2. Summary of a priori and exploratory hypotheses: effect sizes, confidence intervals, and robustness analyses

hypotheses	r or ρ	IC95 %	R^2 or ρ^2	p	Tests	Robustness analysis	Conclusion
H1: Agr~%0	-0.45	[−0,775 ; −0,103]	0.255	0.039	Pearson	Jackknife, bootstrap	moderate, worth following up
	-0.486	[−0,768 ; −0,073]	0.236	0.026	Spearman		
H2a: Orth~hy-	0.471	**[0,030 ; 0,771]**	0.222	0.031	Pearson	Jackknife, bootstrap	suggestive evidence of moderate association, worth following up
	0.452	[0,015 ; 0,756]	0.204	0.039	Spearman		
H2b: Orth~p	0.048	[−0.383 ; 0.479]	0.002	0.836	Pearson		no evidence of association
H3a: Ter~p	-0.402	[−0.708 ; 0.052]	0.162	0.076	Pearson	Jackknife, bootstrap	effect of moderate size with insufficient power, the estimate remains uncertain, worth following up
	−0.368	[−0.685 ; 0.097]	0.135	0.102	Spearman		
H3b: Ter~k	0.071	[−0.378 ; 0.487]	0.005	0.756	Pearson		no evidence of association
H4a: years~%Symp	-0.433	[−0.723 ; −0.006]	0.187	0.049	Pearson		no clear evidence of association after removal of the influential case (38 years)
H4b: years~Acting	0.249	[−0.206 ; 0.618]	0.0262	0.276	Pearson		no clear evidence of association (neither with Spearman)
H4c: rank~%Symp	-0.353	[−0.664 ; 0.096]	0.125	0.116	Pearson		no clear evidence of association (neither with Spearman)
H4d: rank~Acting	-0.214	[−0.585 ; 0.229]	0.046	0.351	Pearson		no clear evidence of association (neither with Spearman)

Statistical Limitations

Our use of quantitative statistical methods is intended to be cautious and informed by the major problems raised by probabilistic tools in the human sciences (Ioannidis, 2005; Amrhein, Greenland, & McShane, 2019; Mary, 2024a). We employ standard statistical procedures while recognizing that they constitute descriptive instruments rather than epistemic guarantees. We adopt a critical stance toward statistical approaches and assess them at their proper value – acknowledging the pre-scientific character of statistics in the human sciences, including inferential statistics (Bernard, 1865; Skinner, 1990). We emphasize rigorously that statistics alone can never establish causal relationships without additional structural assumptions. Indeed, causal inference always requires a theory of mechanisms and interventions (D'Agostino McGowan et al., 2024). Such a theory cannot be derived from statistical results alone, but must rely on other approaches: experimental, hypothetico-deductive, speculative, hermeneutic, etc. Strictly speaking, the correlation analyses conducted here do not test any psychological mechanism. The observed associations are compatible with a plurality of rival explanations. Rather than making a causal claim, we argue that the observed correlations – if they are not mere probabilistic artifacts – are compatible with our general theory of a structural correspondence between drive organization and playing style in Go.

The sample size ($N = 21$) limits statistical power. For associations of moderate magnitude (≈ 0.45), the expected power is approximately 0.60–0.65, below the conventional threshold of 0.80, implying substantial uncertainty in the estimates and an increased risk of failing to detect real effects. The sample size would indeed be problematic in a confirmatory study; however, an N

= 21 sample remains legitimate for mapping a space of correspondences.

The dataset mobilized in the present study is extensive. In this respect, it is important to keep in mind the reservations associated with the "Bonferroni criterion," according to which the multiplication of statistical inference tests increases the probability of obtaining correlations with $p < 0.05$ by chance alone. The analysis plan includes 16 statistical tests (mostly grouped under H4 hypotheses family). At a threshold of p = 0.05, the expected number of significant results under the null hypothesis is approximately 0.8, and the probability of obtaining at least one false positive approaches 56%. The reported *p*-values should therefore not be regarded as confirmatory evidence (Ioannidis, 2005). The observed associations constitute exploratory signals motivating a pre-specified replication study, ideally pre-registered, with a larger sample (approximately 35–50 participants, depending on the targeted effect size).

This study adopts an explicitly non-metric stance regarding its variables. The indices derived from both the Szondi test and GoStyle analyses are treated as constructed scores rather than measurements of latent quantitative attributes. Nevertheless, Pearson correlations and linear regressions are employed as pragmatic *metric approximations*, used here as heuristic tools to explore patterns of covariation between structured coding systems.

This methodological choice implies a specific form of rigor: rather than assuming the measurability of psychological constructs, we explicitly limit the epistemic status of the statistical operations performed. Consequently, the reported coefficients should not be interpreted as estimates of relationships between underlying continuous variables, nor as supporting population-level generalizations or causal claims. Instead, they are intended to highlight potential structural correspondences within the present dataset, in an explorato-

ry perspective.

This approach differs from standard inferential frameworks commonly used in psychological research, which often rely on implicit assumptions about measurement and generalization. By contrast, the present study prioritizes the explicit characterization of these assumptions and their limits. This comes at the cost of reduced inferential scope, but aims to avoid stronger interpretative commitments that would not be warranted given the nature of the data and the sample size.

Extreme Cases

Our sample includes participants presenting extreme scores on the variables under study. It is appropriate to examine these cases, not only to capture their descriptive singularity, but also to assess whether the observed association depends on extreme configurations. From the perspective of an internal stress test of the correlational model, the analysis of influential observations is a necessary step in evaluating the stability of the estimated relationship.

Participant No. 9

We selected this case because it displays the lowest territoriality score in the sample (2.74). He is also among the participants with a highly aggressive style (8.77).

Participant No. 9 (TER = 2.74; p factor = 0.33) occupies a clearly peripheral position on the territoriality axis. Standardized relative to the sample (N = 21), his score corresponds to a z-score of −2.45 for territoriality, exceeding the conventional threshold of $|z| \geq 2$ and indicating a statistically atypical

value. By contrast, his score on the p factor ($z = +0.02$) is strictly central and presents no extreme character. In terms of distance from the median, his territoriality score lies 3.60 points below the sample median, whereas his p value coincides exactly with the median (distance = 0). The atypical character of Participant No. 9 therefore concerns exclusively the territorial dimension.

Influence analysis shows that this case acts as an attenuation point in the linear association. With all participants included, the Pearson correlation between territorial style and the p factor is $r = -0.40$, $p = 0.076$, with an estimated slope of −0.38. After removal of Participant No. 9 ($N = 20$), the correlation remains stable ($r = -0.475$, $p = 0.034$), and the slope increases in magnitude (−0.51). The direction of the association remains negative. The position of Participant No. 9 thus tends to reduce the steepness of the regression line without reversing the relationship. In a small sample, this configuration illustrates the sensitivity of estimates to the distribution of horizontally extreme points. His drive protocol is shown in Table 3.

Table 3. Szondi drive protocol – Participant No. 9 (three administrations)

	S		P		Sch		C	
	h	s	e	hy	k	p	d	m
1st administration	+	-	±	-	-	+	+	+
2nd administration	+!	-	-	0	-	+	+	+
3rd administration	+	-	-	-	-	0	+!	+

The acting index Σ0 / Σ± = 2 falls within the statistical norm [1; 3] and indicates a satisfactory balance between drive discharge and conflictualization (repression, inhibition, etc.) of drive demands. The percentage of symptomatic responses is 12.50%, which is below the statistical norm [20%; 30%],

suggesting that such discharges and inhibitions occupy relatively little place in the participant's psychic economy. The general disorganization index (0) indicates perfect coherence of the psycho-drive organization; the general variability index (4) is low and may reflect a relatively stable psychic organization, not readily disposed to internal rearrangements.

Drawing on classical interpretative frameworks, the p+ score of Participant No. 9 suggests identification with the need to affectively control the environment. Processes of sublimation and symbolization appear to be operative. The s− factor generally indicates that ordinary aggressiveness is poorly accepted, insufficiently assumed, or rejected. It is often displaced into an overinvestment in the intellectual dimension. With s−, one withdraws from conflict rather than confronting it; s− is one index of a superego configuration. One may hypothesize that Participant No. 9 finds in Go (a game readily intellectualized) a modality for avoiding overly direct aggressiveness, sublimated (p+) in his relation to the game, while his actual games display a particularly aggressive style. The overall profile suggests a neurotic drive organization structured around repression (hy−, k−) of aggressiveness (s−).

The C++ vector, constant across the three administrations, suggests a dispersed mode of contact, deployed through scattered investments in a multiplicity of objects. Among all participants, he is the only one to present this vectorial configuration consistently. One might be tempted to relate this C++ configuration to the particularly low territoriality score (the lowest in our sample), insofar as the C vector is classically interpreted as reflecting the relation to (pre-objectal) space and thus, indirectly, to territoriality. However, this interpretation must be cautiously qualified: several participants (11, 12, 16, and 20) displayed a C++ vector in one or two administrations, yet their territoriality scores were above the sample mean, except for Participant 16

(territoriality: 4.42). The correspondence between territorial style and contact vector therefore appears neither one-to-one nor deterministic.

Participant No. 16

We selected this case because he presents the highest aggressiveness score (8.79).

With z(AGR) = +1.34 and z(%0) = +1.04, Participant 16 does not constitute a univariate outlier (|z| < 2), but he functions as an influential point. His removal substantially increases both the magnitude and the statistical significance of the correlation between aggressive style and percentage of null responses (r increasing from −0.45 to −0.56; p from 0.042 to 0.0097; slope from −2.01 to −2.58). He therefore contributes to attenuating the observed relationship, without altering its direction. His drive protocol is shown in Table 4.

Table 4. Szondi drive protocol – Participant No. 16 (three administrations)

	S		P		Sch		C	
	h	s	e	hy	k	p	d	m
1st administration	0	-	-	-	0	+!	±	+
2nd administration	0	0	-	-	0	+	±	±!
3rd administration	±	0	-	±	+	0	-	±

His general drive profile differs markedly from that of Participant 9. This contradicts any naïve isomorphism between a behavioral variable and drive organization and, more broadly, challenges strictly behaviorist conceptions according to which observation of behavior would suffice to infer psychic in-

teriority.

The acting index Σ0 / Σ± = 1.4 falls within the statistical norm [1; 3] and reflects a satisfactory balance between drive discharge and conflictualization (repression, inhibition, etc.) of drive demands. However, the percentage of symptomatic responses is 50%, far above the statistical norm [20%; 30%]. The general disorganization index (0) indicates perfect coherence of the drive organization; yet the numerous null and ambivalent responses in Participant 16's test protocol substantially increase the general variability index (7).

Drive discharges are located in the S and Sch vectors. Interestingly, they concern the domain of aggressiveness: with s0, we would be dealing with a subject for whom aggressiveness does not constitute a latent conflict and is not refused as such. (Notably, examination of the background profile of Participant 16 reveals s−!! when the s factor is discharged (s0) in the foreground.) It is therefore unsurprising to observe this aggressiveness expressed in his playing style; however, this aggressiveness may be more spontaneous, less mediated by the playful detour of the game. The e− factor, persistent across all three administrations, is characteristic of aggressive, irritable, and impulsive personalities. It is hardly incidental to find it in the player exhibiting the most aggressive style in our sample.

Comparison of Participants No. 9 and No. 16

With these two participants, we have the most aggressive playing styles in the sample, whose percentages of null responses lie markedly off the regression line identified for the sample. We examine their formal influence on the linear regression observed between aggressive style and percentage of null responses. These two cases are of particular interest because they exhibit a

strong contrast in the influence they exert on the correlation observed within the sample. They therefore provide an opportunity to stress-test the model. Influence diagnostics are presented in Table 5.

Table 5. Influence analysis: comparison of Participants No. 9 and No. 16 on the aggressiveness–%0 association

		Participant 9	Participant 16
aggressiveness		8.77	8.79
Percentage of null responses		0.08	0.29
Leverage		0.136 (<0,19)	0.137 (<0,19)
Cook's D		0.101 (<0,19)	0.294 (>0,19)
DFBETA (slope)		-0.36 (<0,44)	**+0.67 (>0,44)**
Effect of removal:			
r	-0.45	-0.38	-0.56
p-value	0.042	**0.097**	**0.0097**
slope	-2.01	-1.68	-2.58

The thresholds used (for leverage, Cook's D, and DFBETA) follow classical heuristics and are intended for descriptive purposes.

Participant No. 9 appears to align with the overall trend of the sample (high aggressive style and low percentage of 0), whereas Participant No. 16 runs counter to this trend (high aggressive style and high percentage of 0). Removing Participant No. 9 from the sample weakens the relationship. Participant No. 16, by contrast, exerts a statistically substantial influence on the slope; removing him from the sample markedly strengthens the association.

The association between aggressive style and percentage of null responses is therefore not produced by a single favorable case (No. 9). On the contrary, it is attenuated by a discordant influential case (No. 16). The model thus

appears structurally coherent, albeit sensitive to peripheral configurations, which is not surprising given $N = 21$. This pattern suggests structural consistency of the trend, even though the magnitude of the effect remains sensitive to peripheral cases. If the correlation were an artifact driven by a favorable extreme case, its removal would eliminate the effect. This is not what is observed.

Participant No. 20

We chose to examine this participant in detail because he presents a striking extreme value: his acting index reaches 8, whereas the statistical norm lies within the interval [1; 3], and this is the only value significantly outside that range in the sample. Such a value is generally interpreted as indicating immediate discharge of drive needs, with little tolerance for temporal delay or diversion and reduced capacity to sustain intrapsychic tension, leading to a short-circuiting of conflictual elaboration. The singular organization of the Contact vector does not directly indicate a manic or hypomanic structure in a nosographic sense, but rather suggests a mode of existence in which contact is maintained at a distance while drive tension is discharged through action. In a Schotte-Szondi perspective, such a configuration may give rise, at the phenomenological level, to what could be described as a hypomanic tone – not as a disorder, but as a style of being characterized by mobility, reduced dependence, and limited tolerance for internal tension (we wish to clarify that, from our Schotte-Szondi perspective, situated midway between psychoanalysis and psychiatric phenomenology, mania is never the name of an "illness" of the mind, but rather refers to an existential style, an orientation of existence along one of the directions made possible by our humanity.) He is

the only participant in the sample whose Szondi protocol shows such an alteration of the Contact vector. His drive protocol is shown in Table 6.

Table 6. Szondi drive protocol – Participant No. 20 (three administrations)

	S		P		Sch		C	
	h	s	e	hy	k	p	d	m
1st administration	+!!	0	-	-	±	-	0	0
2nd administration	+!!	0	-	+	-	-	0	-
3rd administration	+!!	+	-	-	0	0	0	-

He has been playing Go for more than ten years. Certain stylistic scores are noteworthy: his play is highly territorial (7.56, the second highest value in the sample) and highly orthodox (his score of 2.89 is the lowest in the sample). His territorial style may plausibly be understood in relation to p−, reflecting a drive need to structure a defensive space in order to protect oneself from the influence of the other's thoughts.

The P vector highlights a significant anxious background. The P−− configuration evokes an internal oppression, a free-floating anxiety not crystallized around a specific object (Legrand, 1979).

This profile suggests a man in whom internal anxiety (P−−) and projective tendencies (p−) are contained through massive recourse to action (high acting index, Sch±−, Sch00) or adaptive discipline (Sch−−), while contact is kept at a distance (C0−), at the cost of a detachment that may take on a hypomanic tone. Drives are neither massively repressed nor extensively mentalized: they are discharged.

The protocol is organized around a marked imbalance of the peripheral vectors (S and C), reflecting an unequal distribution of drive investment. The

m− factor (C vector) signals refusal of reliance and distancing from the environment as an affective support. Conversely, drive investment is concentrated in the S vector of object relations, with repeated and intense accentuation of the need for union (h+!!). This configuration reveals a structural tension: on the one hand, withdrawal from anaclitic attachment; on the other, an insistent push toward the object. The need for relationship is strongly invested, yet dependence is refused.

From this perspective, the highly territorial and highly orthodox playing style may constitute a formal solution to this difficulty of being-with-the-other. High territoriality suggests spatial ordering, a reassuring delimitation of boundaries within the space of encounter. Orthodoxy indicates a preference for established and culturally validated forms (notably joseki), rather than a singular invention of strategic relation. Whereas a non-orthodox style (classic-novel axis) might reflect affirmation of singularity within the exchange, recourse to established forms implies adherence to shared knowledge – perhaps even the introjection of an impersonal Other (Mary, 2024b) – to an impersonal normativity, as if the relationship to the opponent were mediated through a pre-constituted symbolic framework. The goban thus becomes a space in which the bond is intensely invested (h+!!), yet contained within collectively stabilized forms (k−, p−). The use of orthodox patterns might function as a structural substitute for interpersonal negotiation, allowing the bond to be maintained while minimizing the uncertainty inherent to direct interaction.

Discussion

The observed correlations should not be understood as causal relationships between measured psychological magnitudes, but as structural correspondences between two distinct systems of notation: on the one hand, a system describing strategic regularities in the game of Go; on the other, a system formalizing drive tensions according to Szondi's model. Within the drive paradigm, these correspondences may nevertheless receive a coherent interpretation. While the data do not allow for a strict empirical adjudication between competing theoretical interpretations, they may nonetheless render some readings more coherent or plausible than others within a given framework. The interpretations of Szondi factors and indices are not derived from the statistical analysis itself, but follow established manuals and classical guidelines associated with the instrument. They are proposed at a second level, as a way of rendering the observed correspondences intelligible within this framework. Particular care was taken to remain within the bounds of these conventional interpretative frameworks, without extending beyond what is supported in the literature. The Szondian interpretations are theoretically guided readings rather than empirical conclusions. They provide a coherent framework for understanding the observed patterns. This approach is consistent with the most rigorous uses of statistics (see D'Agostino McGowan et al., 2024): statistical analysis never permits inference without a theoretically coherent interpretative intervention.

1. Aggressive style and percentage of null responses (%0)

In the Szondian model, the null reaction (0) corresponds to a form of discharge or absence of drive need. A high percentage of 0 responses reflects lower internal conflictual tension and greater immediacy of drive response.

Conversely, a lower percentage of 0 suggests more marked conflictualization and a greater degree of symbolic detour.

The finding that stylistic aggressiveness is associated with a lower percentage of null responses may thus be interpreted as follows: the aggressiveness observed on the board would not necessarily be the expression of raw drive discharge, but might instead signal mediation, elaboration, or symbolization within the playful space. It may be of interest to consider this interpretation alongside studies suggesting that Go practice may have an inhibitory effect on impulsivity in children with ADHD (Kim et al., 2014). We emphasize that the conclusions of this study, conducted within a neurocognitive paradigm, appear to find a form of convergence with our work conducted within a distinct paradigm. Interestingly, a participant (with rather few null responses) who self-reported a diagnosis of ADHD indicated that he experiences a certain sense of calming in his everyday life, which he attributes to his practice of Go.

A combative playing style might correspond to an aggressiveness that does not discharge directly in immediate psychic life or in the somatic apparatus, but instead finds, within the formal plan of the game, a circuit of partial satisfaction. The board would then function as a symbolic stage where aggressive tension can be structured, deferred, and strategically invested. This pattern, however, is not consistent with a simple reinforcement model in which increased engagement in aggressive play would linearly increase drive manifestations.

This interpretation is consistent with the Freudian idea that the drive does not aim at the object as such, but at the circuit it accomplishes around it. Strategic combat in Go would constitute such a circuit, a deviation or deferral of satisfaction.

2. Stylistic orthodoxy and the hy− factor

We observed a positive correlation between stylistic orthodoxy and hy−. Within the Szondian framework, hy− is associated with restraint in exhibition, repression, or inhibition of self-staging. The subject has a need to show him-/herself, but this need is not consciously assumed. It may therefore be displaced onto a less directly exposing stage.

A non-orthodox style in Go – understood as deviation from classical sequences, strategic risk-taking, and non-conventional choices (Moudřík et al., 2015) – may be interpreted as an indirect mode of expressing a tension related to recognition, visibility, or subjective affirmation. Orthodoxy (classic-novel axis) could function as a detoured path toward singularization. From this perspective, the hy− player does not necessarily put himself forward in a spectacular manner, but may affirm his singularity within the formal space of the game through atypical strategic choices. Deviation from classical sequences thus becomes a stage on which identity is enacted without direct exhibition.

We suggest that a single structural tension concerning self-staging and conformity to stylistic orthodoxy may find convergent modes of expression within two distinct semiotic plans. Playing Go may provide an opportunity to satisfy the human need for self-display through the unveiling of an original style. It is important to emphasize the complex and dialectical character of this human need: the detour through Go (and likely through other media) would simultaneously allow the satisfaction of a refusal to exhibit oneself directly (hy−, repression of the scopophilic drive) and the mediated fulfillment of the need to exhibit (the return of the repressed drive demand). Such a reading is compatible with the observed correlation.

3. Territoriality and the p Factor

The negative correlation between stylistic territoriality and the p factor invites an interpretation centered on the relation to control and organization of the field. Recall that the p variable is derived from the scores p+ and p− (p = p+ − p−). The p factor is constitutive of the Ego vector and concerns the question of ego boundaries. The p factor designates the Ego's need to give meaning to the world and to organize it affectively and cognitively. It is also linked to processes of sublimation. Classically, it is associated with issues of mastery, positional affirmation, and environmental control. A high p factor value (p+) may correspond to strong investment in authority or structuring functions. The psychoanalytic paradigm invites us to consider the player's territory as potentially symbolizing the player's ego boundaries, drawing on Anzieu's (1974) conceptualization of the "skin-ego" (Mary, 2024b). When a player utters a phrase such as "he is attacking me" (where, strictly speaking, what is being attacked are the boundaries of a territory on the board), this abuse of language reveals a common latent identification of the player with their stones and the territory they delimit. In Go, high territoriality implies progressive stabilization of zones, controlled spatial organization, and structured closure of the field. Conversely, a weakly territorial style (moyo-oriented, diffuse potential) privileges openness and indeterminacy. Territory is realized later and remains longer in a virtual state, as a project under construction.

In Susan Deri's (1949) terms, p+ refers to an Ego capable of flexible appropriation of reality, whereas p− implies a more projective, more distrustful, or more self-centered relation. The p factor of the Ego vector thus appears to articulate with the spatial style adopted on the board. In our sample, players

presenting p− tend to privilege territorial structuring characterized by closure and delimitation. Conversely, players presenting p+ tend to favor open influence configurations (moyo), relying on dynamic participation in the global field of the game. The hypothesis that the constitution of territory on the board constitutes a spatial analogy of the constitution of ego boundaries appears to find support in this correlation. Once again, this is not a term-to-term equivalence, but a possible preservation of structural relations between two registers.

Drawing on five years of psychotherapeutic workshops centered on Go in psychiatric settings, I observed that patients with a distrustful paranoid register (p−) tended to construct early, rigid, and overprotected territories, whereas those with a more expansive or megalomaniac orientation (p+) more often diffused influence across the goban, with less concern for stable boundaries. These observations led to the hypothesis of a relation between territoriality and psychotic organizations (Mary, 2024). Psychosis can be understood as a particular mode of relating to space and boundaries (Raballo, 2025), and Go, as a structured Euclidean space, may bring these spatial modes into tension (Mary, 2025): certain territorial configurations appear as attempts at stabilization in the face of porous internal limits. Without implying any deterministic correspondence, these observations support the hypothesis that territorial styles in Go may maintain structural relations with modalities of ego-boundary constitution.

The moyo-oriented player appears capable of investing the field without immediately enclosing it. This presupposes confidence in the dynamics of play. The territory-oriented player actively participates in reducing the initial indeterminacy between the space of the self and the space of the non-self (which is indeed a movement described by the p− factor). One may hypoth-

esize that extremely territorial styles express, through playful mediation, an anxious need to materialize the boundary between ego and non-ego; whereas moyo-oriented styles presuppose having accepted the deferral of boundary between ego and non-ego to a later stage (possibly even to the yose).

One plausible alternative account was that a low degree of territorial structuring in Go might reflect a form of psychic "invasion" or boundary instability, such that intrusion-related drive markers (p–) would be associated with reduced boundary construction on the board. In this view, difficulty maintaining a clear inside/outside distinction at the experiential level would be mirrored by a tendency to leave regions open, unclosed, or weakly delimited in play. However, the direction of the observed association does not support this straightforward "boundary-instability" model. Rather than aligning low territoriality with higher intrusion-related drive markers, our results suggest that the relationship is more complex than a simple mapping from intrusion anxiety to reduced boundary building. We rather interpret this correlation as suggesting that Go may offer a structured space in which defensive boundaries, required to contain experiences of intrusion or influence by the Other, can be enacted on the board.

4. Absence of one-to-one correspondence and plurality of configurations

The analysis of extreme cases shows that similar playing styles may correspond to different drive organizations. This non-biunivocality is essential, as it rules out any naïvely reductionist interpretation. Within the drive paradigm, a given behavior does not correspond to a single structure: acts are sites of partial satisfaction, which may be supported by distinct drive circuits. Thus,

similar aggressive styles may reflect either repressed aggressiveness sublimated within the game or relatively non-conflictual aggressiveness directly expressed through it.

Rather than treating a game of Go as the expression of drives—an ontologizing postulate that presupposes a subject identified with a somato-psychic substance—it is more parsimonious to consider it as a locally constrained realization of a structure of relations (the drive organization), shaped by game rules, physical constraints, and the player's dispositional subjectivity. A correlational approach cannot adjudicate between these models, but the structural account is preferable insofar as it explains the same observations with fewer ontological commitments.

Observable playing style is therefore insufficient to infer the full underlying drive economy. This limitation does not refute the structural approach but highlights its complexity. While playing style may inform cognitive tendencies (Burmeister, 2000; Rieger, 2021; Samano, 2023), it does not allow a complete inference of deep psychic organization, although it may still support hypothesis generation.

Finally, the question of whether realizations from the drive domain to the Szondi and Go domains are "faithful" must be treated cautiously. In categorical terms, faithfulness would require that distinct transformations in the drive domain systematically produce distinguishable variations in their observable realizations. The observed associations suggest only that variations in drive-related scores are not randomly distributed with respect to strategic parameters. Given the small sample and wide confidence intervals, this indicates limited empirical sensitivity: the mappings cannot be considered injective, nor do observable domains fully preserve structural distinctions. At best, these realizations are partially informative and potentially lossy repre-

sentations.

5. Limitations

The gender imbalance observed in our sample constitutes a major limitation to the external validity of the findings. This bias partly reflects the broader demographic composition of the Go community. According to data from the International Go Federation (IGF, 2016), fewer than 20% of amateur and professional players are women in most countries, often with proportions below 15%. In South Korea, the proportion has increased from 4% in 1994 to 21.7% in 2023, but remains a minority (Kang, 2024). In our online recruitment, launched through calls disseminated on Go-dedicated platforms (forums, social media), the majority of responses came from men, aligning with this community dynamic. To mitigate this bias, we encouraged initial participants to relay the announcement to potentially interested female players, adopting a snowball sampling approach. Two women were recruited in this way, but one had to be excluded due to incomplete data (SGF files not provided), further reducing female representation. Consequently, it is impossible to examine gender-related moderating effects or structural differences in the observed associations, limiting generalization beyond an essentially male sample.

To address this bias in future research, several strategies may be implemented, inspired by recommendations for reducing gender bias in scientific recruitment. These include targeted recruitment toward underrepresented groups, such as associations or forums dedicated to female Go players, in partnership with organizations promoting diversity in Go.

A correlational design does not allow us to exclude the influence of third

variables that may simultaneously affect both drive configuration scores and Go playing style. Possible confounders include level of expertise, age, years of practice, cultural exposure to specific schools of play, and broader personality traits not directly captured by the Szondi model. Future studies should explicitly model such variables and test whether the observed associations remain when statistically controlling for these factors.

The displacement of the Szondi test from a clinical interpretative framework to a quantified correlational framework raises important questions. Does our use of it in this study remain faithful to the psychoanalytic paradigm from which it originates? Certainly, situating the Experimental Diagnostic of Drives within a quantitative framework drastically attenuates its epistemic value (Mosso-Gautier, 2023). The full interest of the test is best appreciated within a monographic approach. The limitations of the present study should encourage the development of heuristics grounded in single-case studies, for instance through in-depth analysis of a particularly significant player.

Conclusion

The observed associations are compatible with theoretical interpretations derived from the drive paradigm: Go playing style can function as a stage for the partial satisfaction of structural tensions, and certain strategic orientations may maintain correspondences with particular drive organizations independently formalized.

Nevertheless, these correspondences are neither causal, nor one-to-one, possibly nor exhaustive. They constitute structural indices within a specific theoretical framework. Statistical caution does not invalidate theoretical interest; it simply delineates its scope. The small sample size does not undermine

the theoretical plausibility of our prior hypotheses (generated from theoretical speculation and clinical observation), but it considerably limits the precision of the estimates and the evidential strength of the observed associations.

No conflict of interest. To preserve participant confidentiality, individual profiles are not described in a way that would allow indirect identification through combined rare characteristics.

Acknowledgments

The article was initially written in French and then translated into English using ChatGPT (5.2) under my supervision. I would like to acknowledge Stéphane Vautier, whose courses I attended nearly twenty years ago and which ultimately bore fruit; as well as Josef Moudřík and his colleagues, whose work constituted an essential pillar of this research.

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Received : 26 February 2026

Accepted : 14 April 2026

바둑학연구, 제20권 제1호, pp. 129-158
Journal of Go Studies
20263. Vol.20, No.1. pp. 129-158

Association between Go Experience and Sustained Attention in Young Adults

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Abstract

Due to increasing digital distractions, maintaining attention has become essential for effective learning and work performance. This cross-sectional study examined whether experience with the strategic board game Go is associated with enhanced attentional control in young adults. Ninety-nine university students (49 with substantial Go experience and 50 with minimal experience) completed the Sustained Attention to Response Task and a background questionnaire. Participants with extensive Go experience demonstrated higher overall accuracy than those with minimal experience and performed better on response trials than on withhold trials. Accuracy further increased with both Go proficiency and years of exposure. These results suggest an associa-

tion between Go experience and sustained attention and inhibitory control in young adults, with implications for educational contexts.

Keywords: Go game, attentional control, sustained attention, inhibitory control, executive function, cognitive enhancement

I. Introduction

In learning environments, students must sustain attention amid constant distractions, multitasking, and short-form digital media, raising concerns about the capacity to maintain focus during instruction and independent learning. Mark (2023) reported evidence from her empirical work that the average time people spend on a single screen has decreased from approximately 2.5 minutes in 2004 to around 47 seconds by 2020. Educators likewise report that students often struggle to maintain attention for extended periods across all educational levels (Bunce et al., 2010; Hlas et al., 2019; Godwin, 2025; Cueto, 2025). Since attentional control and inhibitory control support key learning behaviors such as following instructions, resisting distraction, and completing extended tasks, there is renewed interest in activities and instructional approaches that may help strengthen these skills.

Digital and board games offer diverse cognitive demands, and their increasing popularity has motivated research on how games influence human behavior and cognitive functions. A common approach compares players with non-players. Recent studies have reported that players tend to exhibit superior cognitive performance compared to non-players (Martinez et al., 2023; Choi et al., 2020; Noda, Shirotsuki, & Nakao, 2019). However, evidence varies by game genre, outcome measure, and study design, and the mechanism behind the benefits remains under debate.

The strategic board game Go (also known as Baduk in Korea) provides a relevant context for studying attentional control. It requires prolonged focus, continuous monitoring, anticipation of the opponent's next moves, and refraining from impulsive responses. Recent review articles agree on the view that Go is associated with a broad range of cognitive benefits. Kim (2025)

surveyed cognitive and neural lifespan evidence and reported intervention findings that suggest improvements in working memory, attention, strategic decision-making, and emotion regulation. Long-term Go training is associated with structural and functional brain adaptations, whereas short Go programs show rapid, domain-specific gains, particularly among individuals with ADHD, mild cognitive impairment, and dementia. The author notes methodological heterogeneity as a key limitation and calls for larger, longitudinal, and cross-cultural studies. Rieger and Wang (2021) similarly summarized neurobiological and psychological research linking Go play to enhanced general intelligence, attention, creativity, emotional intelligence, and personality, as well as its potential use as a treatment for patients with ADHD. Wu (2025) reviewed board-game research and empirical studies on Go, describing existing evidence that supports benefits for executive function, working memory, attention, and reasoning of children and older adults. She argues that introducing Go in early elementary education could be a promising innovation for fostering cognitive skills. Wu also addresses methodological flaws, such as small sample sizes, a lack of reporting effect sizes, and the small number of studies.

Building on these findings, the present study examines whether experience with Go predicts attentional control in non-clinical young adults. Specifically, we investigate whether Go experience relates to sustained attention and inhibitory control, and whether proficiency level and years of exposure contribute to individual differences. We assess these abilities with a standard sustained-attention task (SART). Our pre-specified hypotheses were: (H1) students with Go experience would show higher SART accuracy scores than Go novices, and (H2) attentional performance would be positively associated with both proficiency and years of exposure. Understanding the link between

Go experience and attentional control may provide new insights into the educational benefits of learning and playing Go and inform pedagogical practices.

II. Literature Review

1. Attentional Control and Games

The relationship between traditional games, modern games, and attentional control can be understood through their respective cognitive demands and effects on attentional processes. Most research to date has focused on modern digital games, particularly action video games, and their influence on attention and executive control. Comparatively fewer studies directly examine traditional games, but their cognitive impact can be inferred from shared features such as rules, competition, and strategy. A review of the aspects of attention enhanced in digital game players suggests changes in the mechanisms that control attention allocation and efficiency (Hubert-Wallander, Green, & Bavelier, 2011; Shahmoradi, Mohammadian, & Rahmani Katigari, 2022; Wiley, Robinson, & Mandryk, 2021).

Research on modern digital games shows consistent evidence of a direct relationship between playing them and having better measures of attentional control. Action video games have been found to enhance both the ability to select relevant information and the ability to respond efficiently to it (Chisholm & Kingstone, 2015). In all the studies reviewed, players typically demonstrate faster reaction times, greater resistance to distraction, and more efficient task-switching compared to non-gamers (Cain et al., 2012). These

improvements appear to be related to enhanced top-down attentional control: frequent players show fewer involuntary shifts of attention toward irrelevant stimuli, indicating better suppression of distractions (Cain et al., 2014). Neurocognitive evidence suggests that these attentional advantages are linked to strengthened activation of frontoparietal networks involved in executive control (Bavelier et al., 2012).

Importantly, the benefits of digital games are not restricted to a single sensory domain. Studies report cross-modal attentional improvements, showing that video game training positively affects both visual and auditory attention, indicating a supramodal effect on alerting and executive control (Wu et al., 2021). Beyond action games, real-time strategy games have also been shown to improve visual attention and reactive control, and these effects appear stronger when accompanied by background music that promotes proactive control (Zhang et al., 2016). In educational contexts, serious games have demonstrated measurable improvements in attention, especially in students with ADHD and learning disorders, indicating that attentional gains are not limited to entertainment-focused game design (García-Redondo et al., 2019).

Although empirical data on traditional games are more limited, existing evidence reveals that they also engage and develop attentional mechanisms. Turn-based board games such as chess or Go require sustained and selective attention, as well as working memory, functioning similarly to non-action digital games in terms of attentional demands. Traditional physical games (such as tag or ball games) train divided attention and motor coordination through real-time monitoring of multiple moving targets (Bavelier & Green, 2024), which parallels the attentional benefits associated with action video gaming.

Research has consistently found that both traditional and modern games

contribute to attentional development, but they do so through different mechanisms. Traditional games tend to promote attentional endurance, planning, and perseverance, whereas modern digital games more efficiently train rapid attentional shifts, executive control, and distraction suppression across multiple sensory modalities. Together, they provide complementary pathways for strengthening attention management. However, merely playing a game may not be sufficient to produce observable effects. Variables such as length of use (i.e., years spent playing) or level of proficiency (regular practice vs. sporadic play) could yield very different findings.

2. Attentional Control and Go

Go provides a natural setting to train attention: players need to stay focused while monitoring a gradually developing position, evaluate local fights while estimating the whole-board position, and resist impulsive moves. These features support sustained-attention skills. The two components (sustained focus and inhibition of prepotent responses) mirror the demands of the Sustained Attention to Response Task (SART) used in the present study.

Developmental and clinical studies align with this view. In a six-month kindergarten program, Kim and Cho (2010) reported gains in performance IQ, problem-solving, and delay of gratification relative to a control group. In children with ADHD (7–12 years), an intensive 16-week Go program (10 hours/week) was associated with reduced inattention, better working memory, and prefrontal electroencephalography (EEG) changes compared to a matched non-ADHD group (Kim et al., 2014).

EEG studies with primary-school children also report attention-related benefits of Go training. A three-month pre–post study found improvements in

EEG-based indices of attention but lacked a control group (Ahn, 2008). In a follow-up study, 20 children received intensive Go instruction (80 minutes/day, five days/week for one year) and outperformed a control group on measures of mental activity and emotional stability (Ahn et al., 2010).

In later life, a 15-week program with residents of Japanese care homes diagnosed with mild to moderate dementia, weekly Go lessons improved attention and working memory relative to controls (Iizuka et al., 2018). Subsequent work reported better visual-memory span test results, with stronger effects for face-to-face than tablet-based instruction (Iizuka et al., 2019). Together, these findings across childhood and ageing suggest that Go training engages cognitive processes relevant to attention regulation throughout the lifespan, yet the effects during early adulthood (a period of high cognitive plasticity) remain largely unexplored.

Neuroimaging research in Go experts complements these findings. Early work linked Go to the activation of brain areas involved in attention and visuospatial processing (Chen et al., 2003), while Ouchi et al. (2005) implicated dorsal parietal and frontoparietal networks during Go problem-solving, with efficiency differences observed between experts and novices. Diffusion-tensor imaging also suggests structural adaptation with long-term Go practice: young Go experts with 12 years of experience showed increased white matter connectivity in networks for attention, working memory, and cognitive control (Lee et al., 2010). Additional structural and resting-state work points to adaptations in networks supporting monitoring and decision-making (Jung et al., 2013; Sohn et al., 2017), and during non-Go working-memory tasks, experts showed superior parietal activation and stronger frontoparietal and frontotemporal connectivity (Jung et al., 2018). In number-estimation tasks, Go professionals exhibit greater cerebellar engagement that is linked to complex

cognitive processes and fast, intuitive decision-making (Lee et al., 2025). Furthermore, Wojtasinski and Francuz (2019) found that Go expertise correlates with visuospatial ability and pattern recognition in young male adults (18–26 years). Overall, these neuroimaging results converge on the idea that Go expertise involves adaptations in neural systems responsible for monitoring, decision-making, and top-down attentional control.

Compared to other frequently studied board games such as chess, Go may place distinct demands on attentional and executive processes. While chess often relies on piece-specific rules, discrete move sets, and relatively constrained decision trees, Go involves a larger board, more uniform rules, and a substantially higher number of possible configurations. This may place greater demands on sustained attention, global monitoring, and the integration of local and global patterns over extended periods of time. In addition, the absence of clearly defined piece hierarchies in Go may reduce reliance on rule-based processing and instead emphasize distributed attention and strategic flexibility. Furthermore, games of Go usually last longer than games of chess. In other words, players need to focus on a single game for longer until the outcome is decided. These characteristics suggest that Go may engage attentional control mechanisms in ways that differ from other board games, potentially leading to distinct cognitive profiles.

Despite these encouraging findings, the cognitive benefits of Go for healthy young adults remain understudied. Much of the literature targets children, older or clinical populations, and the few young-adult samples are male-only. Most intervention studies are short-term, except for a one-year study on children. Existing evidence nonetheless suggests that Go may enhance attention control, but effects are likely to vary with individual experience. The present study, therefore, tests whether Go experience relates to sustained attention and inhibitory control in young adults and examines

whether these outcomes depend on individual factors such as length of exposure and proficiency in the game.

III. Methodology

1. Participants

This cross-sectional study included 99 Korean undergraduate students (aged 18–28) enrolled at two private universities in South Korea. Participants were recruited through a course participant pool between March and December 2023. Participation was voluntary, and all participants provided written informed consent. Data from a small number of non-Korean participants were excluded from the analyses.

Participants were divided into two groups: a group with substantial experience playing Go (hereafter, the Go Group) and a group with minimal experience (the No-Go Group), with the demographics shown in Table 1. The Go Group consisted of 49 participants (13 were females and 36 males), with an average age of 21.88 years (SD = 2.35). This group demonstrated a diverse range of proficiency in their second language (L2, English), with the majority indicating intermediate (or lower) proficiency (81.63% of the participants). Their experience with Go was notable, with all members possessing extensive knowledge of the game. On average, they began learning Go at the age of 6.94 years (SD = 1.93) and accumulated significant experience, with an average of 14.94 years (SD = 3.30) of playing the game. They reported currently spending an average of 4.80 hours per week (SD = 7.98) on Go-related activities (learning, playing, or teaching Go).

The No-Go Group consisted of 50 participants (35 females and 15 males), with an average age of 21.38 years (SD = 2.50). Unlike the Go Group, all participants in this group had experience with an L2 (English), with most of them rating their proficiency as intermediate or higher (82%). Only 36% of the participants had any proficiency in Go. On average, they started learning Go later in life, at the age of 8.61 years (SD = 1.94) and had minimal experience, with an average of 0.65 years (SD = 1.25). Furthermore, they reported currently spending a negligible time of 0.01 hours per week (SD = 0.07) on Go activities.

As shown in Table 1, groups differed significantly in gender distribution, $\chi^2(1) = 17.02$, $p < .001$, and knowledge of Go, $\chi^2(1) \approx 45.00$, $p < .001$. No significant differences were observed for age, $t(97) = 1.02$, $p = .31$, or self-reported attention, $t(97) = 1.97$, $p = .052$. As expected, all Go-related variables differed significantly between groups (all $p < .001$), reflecting the criteria used to define group membership.

Table 1. Participant demographics

	Go Group	No-Go Group	Test	p-value
Gender	13 female, 36 male	35 female, 15 male	$\chi^2(1) = 17.02$	< .001
Age	21.88 (2.35)	21.38 (2.50)	$t(97) = 1.02$	.31
Knowledge of Go	100%	36%	$\chi^2(1) \approx 45.00$	< .001
Age starting to learn Go	6.94 (1.93)	8.61 (1.94)	$t \approx 4.30$	< .001
Years of experience with Go	14.94 (3.30)	0.65 (1.25)	$t \approx 27.00$	< .001
Current hours per week playing Go	4.80 (7.98)	0.01 (0.07)	$t \approx 4.20$	< .001
Go Level (0-5, see Table 2)	4.86 (0.35)	0.78 (1.15)	$t \approx 20.00$	< .001
Self-reported attention	72.33 (14.36)	66.59 (14.65)	$t(97) = 1.97$	.052

The aim was to compare individuals with significant Go experience to those with little or none. However, because Go is culturally widespread in South Korea and commonly perceived as educationally beneficial (TNO, 2024), recruiting a completely naïve control group was not feasible. Accordingly, while the between-group analyses used the categorical distinction above, analyses of individual differences in Go experience were conducted at the participant level, irrespective of group (Table 2).

The primary outcome variable was SART2 accuracy. The experimental design incorporated three independent variables: (a) group (Go vs. No-Go), (b) Go proficiency level (0-5; 0 = no experience; 5 = expert), and (c) years of exposure to Go. Gender and L2 proficiency were considered potential moderating factors.

Table 2. Participants' Go Proficiency

	Female	Male	Total
Go proficiency (0-5) [1)]			
0=non-player	23	9	32
1=beginner	2	2	4
2=basic	6	1	7
3=intermediate	4	3	7
4=advanced	3	4	7
5=expert	10	32	42
Total	48	51	99

1) Non-player = Does not know how to play Go. Beginner = weaker than 20 kyu. Basic = 19−11 kyu. Intermediate = 10−1 kyu. Advanced = 1−4 dan. Expert = stronger than 4 dan.

2. Tasks and Procedure

Participants completed two tasks: a background questionnaire and the Sustained Attention to Response Task 2 (SART2).

The background questionnaire (presented bilingually in English and Korean) aimed to gather demographic information such as age, gender, language proficiency, and familiarity with the game of Go. Additionally, it included questions regarding participants' self-reported attention levels and other relevant factors, for which we adapted the questions of the Attention Control Scale (ATTC or ACS), a widely used self-report instrument designed to assess individuals' ability to maintain focus and flexibly shift attention between competing stimuli or tasks (Derryberry & Reed, 2002). The scale captures two complementary dimensions of attention control: focusing, or the capacity to resist distraction and sustain attention on a task, and shifting, or the ability to redirect attention efficiently when required. Higher scores indicate greater perceived control over attentional focus and flexibility.

The SART2 (a newer version of the SART that provides visual feedback when the participant presses the button correctly and an error message after each mistake) was implemented using the online PsyToolKit software (Stoet, 2010; 2017). We adjusted the tool by creating a Korean version of the instructions. The instructions for the SART2 were translated into Korean to ensure participant comprehension. This adaptation was limited to the instructional component, while the task structure, stimuli, and timing parameters remained identical to the original validated version (Stoet, 2010, 2017). Given that the SART2 is a non-verbal task relying on simple digit recognition and response inhibition, the translation of instructions was not expected to affect the underlying cognitive processes assessed.

The test sessions were conducted either individually or in small groups

within a designated lab area. During the SART procedure, a total of 225 single digits, comprising 25 of each of the nine digits, were visually presented over a 3.2-minute period. Each digit appeared for 149 milliseconds, followed by an 899-millisecond mask. Participants were instructed to respond by pressing the space bar to each digit (henceforth, "response condition") except for the 14 occasions when the digit "3" appeared, prompting them to withhold their response (henceforth, "withhold condition"). Performance in the response condition reflects sustained attention and response consistency, whereas accuracy in the withhold condition indexes inhibitory control, that is, the ability to suppress an automatic response.

Participants used their preferred hand to respond. The target digit was distributed randomly throughout the 225 trials. The time interval between digit onsets was 49 milliseconds. Participants were instructed to give equal priority to accuracy and response speed during the task. The digits were displayed in one of five randomly assigned font sizes, ranging from 37 to 109 points, to increase the cognitive demand for processing numerical value rather than relying on peripheral features for identifying the no-response target. Both digits and masks were presented in the middle of the screen in white against a black background. The screen was positioned at a typical viewing distance of approximately 40-50 cm from the participant's eyes, following standard SART protocols (Stoet, 2010; 2017). Each session began with a practice period involving seven-digit presentations, two of which were targets.

The SART and its updated version, the SART2, have been widely employed to assess sustained attention and inhibitory control (Alloway & Alloway, 2012; Ralph et al., 2015; Robertson et al., 1997). By combining these measures, the present study aimed to examine how attentional control relates to individual differences in Go experience and proficiency.

3. Statistical Analysis

A range of data analyses were conducted using R (R Development Core Team, 2009), depending on whether a group comparison was made or the effects of individual differences with respect to experience with Go were analyzed.

For the group comparison, a Two-Way Analysis of Variance (ANOVA) was conducted using R (R Development Core Team, 2009) to compare the effects of Group (Go, No-Go) and Condition (Response, Withhold) on accuracy in the SART2 task. All effects were statistically significant at the 0.05 significance level.

Although experience with Go is inherently a continuous variable, its distribution in the present sample was highly uneven, with minimal-experience participants showing very limited exposure and no active engagement at the time of testing. In addition, exploratory correlation analyses treating experience as a continuous predictor yielded inconclusive results. Therefore, for the primary analyses, a categorical distinction (Go vs. No-Go) was retained to allow for more robust and interpretable group comparisons. Analytical decisions were guided by prior literature on attentional control and game-based cognitive engagement, with a focus on a limited set of theoretically motivated variables (group, condition, proficiency level, and years of exposure). Additional variables were explored but not retained in the final models to preserve parsimony and avoid issues related to collinearity and overparameterization, mostly given the exploratory nature of this study.

Potential covariates, including age and gender, were examined in preliminary analyses to assess their association with SART2 accuracy. These variables did not show consistent or statistically meaningful relationships with the outcome measure and were therefore not included in the primary models. Additional covariance analyses were conducted to determine whether gender

distribution and bilingual proficiency significantly influenced attentional-control performance. Although the groups differed descriptively in both variables, neither gender ($F(1, 86) = 0.59$, $p = .446$, $\eta p^2 = .007$) nor bilingual proficiency ($F(1, 86) = 0.55$, $p = .459$, $\eta p^2 = .006$) emerged as statistically significant predictors of SART2 accuracy after controlling for group membership. Importantly, the main effect of Go experience remained significant after inclusion of these covariates ($F(1, 86) = 15.19$, $p < .001$, $\eta p^2 = .15$). Furthermore, given the sample size and the focus on theoretically motivated predictors, excluding additional covariates helped preserve model parsimony and avoid overparameterization.

After examining the accuracy results separately for both groups (Go, No-Go) and the two conditions (Response, Withhold), we conducted two additional analyses on individual differences related to participants' experience with Go. The first analysis, a Two-Way ANOVA, was conducted to compare the effects of Condition (Response, Withhold) and level of Go (coded numerically, ranging from 0 for individuals without knowledge of Go to 5 for participants at an expert level) on SART2 accuracy. Finally, the effect of years of learning Go was examined using Pearson's linear correlation analysis in R (R Development Core Team, 2009). The value representing years of learning Go was calculated by subtracting the age at which participants started learning Go from their current age (unless they explicitly stated in the questionnaire that they had stopped playing the game earlier).

Reaction-time measures were examined during the preliminary stages of analysis. However, the present study ultimately focused on accuracy-based outcomes for several methodological reasons. First, participants were instructed to prioritize accuracy over speed during task performance. Second, data collection took place across different testing locations and hardware configurations, and variables such as monitor refresh rates and keyboard re-

sponse latency were not systematically controlled. Finally, the withhold condition of the SART2 paradigm does not generate meaningful reaction-time data for successful trials because accurate responses involve inhibition rather than overt motor responses. Accordingly, accuracy was considered the most reliable and interpretable measure of sustained attention and inhibitory control in the present dataset.

IV. Results

1. Group Comparison

The results of comparing the two groups are shown in Figure 1. Accuracy in the response condition is represented in dark grey, and that for the withhold condition in light grey for the Go and No-Go groups, respectively.

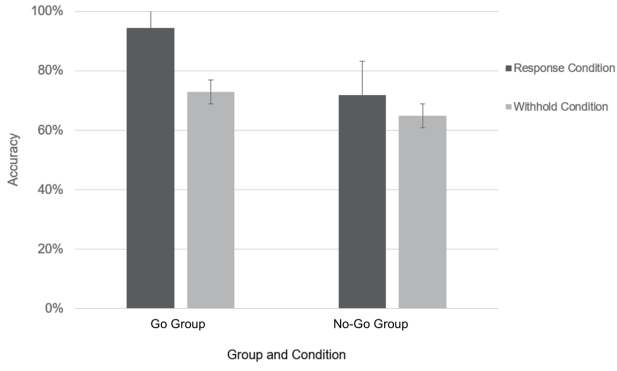

Figure 1. Accuracy in the attention-control task of the two groups across the two conditions

A Two-Way Analysis of Variance (ANOVA) was performed to analyze the effects of Group (Go, No-Go) and Condition (Response, Withhold) on accu-

racy in the attention-control measure. A main association of Group showed that participants in the Go group were statistically more accurate than participants in the No-Go group ($F(1, 98) = 35.43$, $p < .001$, $\eta p^2 = .27$). A main association of Condition showed that participants were more accurate in the response condition than in the withhold condition ($F(1, 98) = 78.49$, $p < .001$, $\eta p^2 = .44$). Finally, there was a marginal interaction between Group and Condition ($F(1, 98) = 3.90$, $p = .052$, $\eta p^2 = .04$), revealing that participants in the Go group were statistically more accurate in the response condition than in the withhold condition, compared with the No-Go group.

2. Impact of Go Strength

Accuracy as a function of level of mastery in Go is shown in Figure 2. The horizontal axis displays levels of proficiency in Go ranging from 0 (individuals without experience) to 5 (individuals with expertise). Accuracy in the response condition is depicted in dark grey, and accuracy in the withhold condition in light grey.

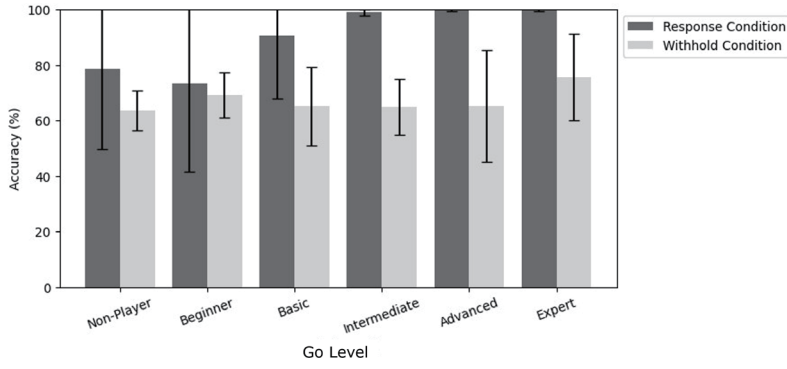

Figure 2. Accuracy in the attention-control task by Go level for both conditions

A Two-Way Analysis of Variance (ANOVA) was performed to analyze the effects of Go strength (six proficiency groups: Non-player, Beginner, Basic, Intermediate, Advanced, Expert) and Condition (Response, Withhold) on individuals' accuracy results in our attentional control measure. A main association of proficiency level showed that participants at higher levels of expertise were statistically more accurate than those at lower levels ($F(1, 194) = 34.44$, $p < .001$, $\eta p^2 = .15$). A main association of Condition showed greater accuracy in the response condition than in the withhold condition ($F(1, 194) = 77.69$, $p < .001$, $\eta p^2 = .29$). Finally, there was a significant interaction between proficiency level and Condition ($F(1, 194) = 2.53$, $p < .001$, $\eta p^2 = .01$), indicating that participants were better in the response condition than in the withhold condition as their mastery in Go increased.

3. Impact of Years of Exposure to Go

The correlation between years of exposure to Go and accuracy in the SART2 task is shown in Figure 3.

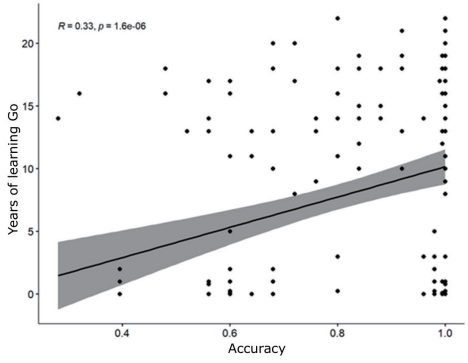

Figure 3. Accuracy in the attentional control task as a function of years of learning Go

The results of the correlation analysis showed a significant, moderate, positive correlation between years of exposure to Go (learning and playing the game) and participants' accuracy results in the attention-control task ($r = 0.33$, $p < .001$). According to Cohen's (1988) benchmarks, this represents a medium effect size, suggesting a practically meaningful association between accumulated Go experience and attentional-control performance.

V. Discussion

The present study examined whether learning and playing Go are associated with attentional control in young adults and which factors modulate this relationship. Young adults with Go experience outperformed minimally experienced peers on the Sustained Attention to Response Task (SART) accuracy. Moreover, higher Go level and more years of exposure predicted better performance, implying a graded, experience-related association with sustained attention and response inhibition.

These results align with previous developmental (Kim & Cho, 2010) and clinical studies (Kim et al., 2014; Iizuka et al., 2018) that have reported attention-related benefits from Go instruction, and extend those findings to a non-clinical, young-adult population. Playing Go naturally requires prolonged monitoring of board positions, suppression of impulsive candidate moves, and strategic evaluation at local and global levels, skills that plausibly overlap with those required in the SART2 task employed in the current study. Comparable findings have been observed in other cognitively demanding games, such as chess and certain video games, where structured practice is linked to gains in working memory and executive control (Choi et al., 2020). For chess, evidence suggests that transfer to other domains is most likely

when it is learned for at least 25-30 hours (Sala & Gobet, 2016). Neuroimaging evidence of activation in frontoparietal and visuospatial networks among Go experts (Chen et al., 2003; Ouchi et al., 2005) and structural white-matter adaptations linked to attentional control (Lee et al., 2010) offer a convergent neural explanation for these behavioral associations. Importantly, our findings indicate that not only familiarity with Go, but also proficiency and accumulated experience, are associated with attention-control performance.

Gender differences may have partially influenced the results. Evidence on gender effects in attention is mixed and often task-specific. Some studies report that females outperform males on tasks involving information inhibition and episodic memory (Hasher, Zacks, & May, 1999; Herlitz, Nilsson, & Bäckman, 1997), while others report minimal or inconsistent effects in sustained-attention tasks. For instance, Riley et al. (2016) found that males responded faster but with more commission errors on a continuous performance task, whereas Chan (2001) reported no gender differences in SART performance. In the present data, male participants appeared to perform slightly better than females, but this difference was not statistically significant. Nevertheless, because the Go group was 73.5% male compared with 30% in the No-Go group, some degree of confounding by gender composition cannot be ruled out. At the same time, additional covariance analyses did not identify gender as a significant predictor of attentional-control performance after controlling for group membership, suggesting that the observed Go-related associations are unlikely to be fully attributable to gender composition alone. Future work should further clarify potential gender-specific mechanisms in sustained-attention tasks.

Another relevant variable concerns bilingualism. Many participants reported proficiency in a second language, most often English or Chinese, and bilingualism was particularly common among those with minimal Go

experience. Since bilingualism has been associated with enhanced attentional control and inhibitory processing (Bialystok, 2009), this factor could have attenuated the between-group differences observed here. However, additional analyses did not reveal a statistically significant association between bilingual proficiency and SART2 accuracy in the present dataset. In other words, if bilingualism indeed confers an advantage in attention control, the contrast between Go-experienced and minimally experienced participants might have been even larger under stricter control of language background. Nevertheless, this overlap highlights an interesting intersection between two potential sources of attentional enhancement—bilingual experience and Go practice—both of which merit closer examination. Future studies should incorporate validated proficiency measures to clarify whether the effects of Go experience and bilingualism are additive, overlapping, or interactive in shaping attentional performance.

Several broader limitations should be noted. First, the cross-sectional design precludes causal inference. It remains unclear whether Go experience strengthens attentional control or whether individuals with naturally stronger attention are more likely to engage in and persist with Go from an early age. Nonetheless, the association between SART accuracy and both Go proficiency and years of exposure to Go suggests that the relationship extends beyond a simple player–non-player contrast. Longitudinal and intervention studies are therefore needed to confirm causality. Second, the sample consisted exclusively of Korean university students, for whom Go is culturally familiar and socially valued. The generalizability of these findings to other cultural contexts remains to be established.

Despite these limitations, the results carry potential educational implications. The findings suggest that engagement with Go may provide a valuable

context for the development of attentional control. Specifically, (1) playing Go is associated with improved sustained attention and inhibitory control; (2) this association appears cumulative, increasing with practice intensity and duration; and (3) higher mastery is linked to greater attentional benefits. Together, these results indicate that opportunities to engage with Go may support the development of attentional skills in educational settings. In this context, our findings are consistent with the view that Go could be a promising enrichment activity for fostering attentional skills, and they provide a potential cognitive rationale for Wu's (2025) proposal that Go may be particularly valuable when introduced in early elementary education.

In conclusion, Go experience in young adults is associated with enhanced sustained attention and inhibitory control, and performance increases with both proficiency and years of exposure. These findings support the view of Go as a promising, accessible means of training attention control, while emphasizing the need for longitudinal, intervention, and cross-cultural research to establish causal mechanisms and broader applicability.

Acknowledgements

This research received no specific grant from any funding agency. The authors gratefully acknowledge the institutional support of the Max Planck Institute for the History of Science (Germany), the University of Valladolid (Spain), Myongji University (South Korea), and the University of Utah Asia Campus (South Korea). We are deeply grateful to all participants for their time and contributions, to our assistants who helped conduct the study, and to the colleagues and reviewers who provided valuable feedback on earlier drafts of this manuscript.

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Received: 5 May 2026

Accepted: 8 May 2026

바둑학연구, 제20권 제1호, pp. 159-182
Journal of Go Studies
20263. Vol.20, No.1. pp. 159-182

Popular openings amongst amateur online Go players: insights from data-informed analysis

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Abstract

Starting from an empty board, the number of legal positions in a Go game grows exponentially as the number of moves increase. During the early moves, a very large subset of the possible positions have balanced win rates. This suggests that the choice of the opening is not crucial to decide a Go game. Nevertheless it is important for players to know what kind of openings they will most frequently face. To answer this question, we collected half a million games played on Fox Go server from 2013 to 2019 amongst players ranked between 10 kyu and 9 dan. A data-informed methodology was developed to classify and compute the frequency of the different openings before and after the introduction of AI. The most popular first moves are nirensei and hoshi+34. Deeper openings popularity depends on rank. Sanrensei fre-

quency decreases with rank, Chinese opening is most popular below 5 dan and Kobayashi between 3 dan and 7 dan (Fox Go Server ranks). The results also show a change in opening playstyle for players ranked above 4 dan after the rise of Go AI. Up to 2019, a similar change is not observed amongst lower ranked players.

Keywords: Go opening, Data-informed, Fox Go dataset

I. Introduction

As with other strategy games, the opening stage of Go has been the subject of active study. Opening styles have evolved through time, notably in the early and mid 20th century with the Shinfuseki, a revolutionary change brought by Go Seigen and Kitani Minoru (Rapley, 2025). In the end of the 20th century, Takemiya Masaki contributed to the popularity of 4-4 move and Sanrensei opening, while Cho Chikun and Kobayashi Koichi contributed to the rise of the so-called Chinese openings (Beheim, 2025). More recently the value of 3-3 point invasion during opening has been re-evaluated after being frequently chosen by AI (Silver et al., 2017). All in all, the preferences of moves during opening is affected by the player's rank and playstyle, as well as the historical context.

Using computers to find the best Go openings is not a recent topic. A winning opening strategy has been found on 5x5 boards as early as 2003 (van der Werf et al., 2003). Recently, catalogues of most likely optimal opening variations using AI scoring have been compiled for 6x6 up to 9x9 boards (https://katagobooks.org/). However, no such study can be envisioned on the standard 19x19 board due to the sheer complexity of the possible openings. Moreover, to the authors knowledge, there has not been a review of modern opening strategy from the perspective of amateur players and across skill ranks.

Thanks to the popularity of online Go play, large datasets of Go games are made available. In this work, two methods have been developed to evaluate popularity of Go openings amongst amateur players across ranks and time using a database of 500,000 games. The first method is based on expert knowledge of traditional openings such as Sanrensei, Kobayashi or Chinese

opening, while the second-one is purely data-driven. By spanning the years before and after the development of AlphaGo, one can address the influence of AI on opening popularity. Since the advent of open source AlphaGo-like AI software for Go games analysis, it became popular to obtain feedback about one's own games thanks to AI. One question addressed in this work is to evaluate if the use of AI changed the opening playstyle of human players of different ranks.

In section II, the database and the two methods are described. The expert driven approach studies established openings while distinguishing moves that are required from moves that are possible variations. The data-driven approach searches for identical openings up to rotations and reflections to identify the most popular opening up to 8 turns deep. In section III, the results about the most popular opening patterns are presented across the player's rank and time.

II. Methods

1. Data

A source dataset of online Go games played on Fox Go Server is used in this study. It contains more than 20 million Go games played between 2013 and 2019 (Featurecat, 2019). The dataset includes every rank from 18k to 9d. Data curation was conducted by selecting evenly matched games of at least 100 moves terminated by scoring or resignation. No games were discarded because of unorthodox openings. 14 ranks are investigated in this work, namely 10k, 8k, 6k, 4k, 2k, 1d, 2d, 3d, 4d, 5d, 6d, 7d, 8d, and 9d. This re-

sults in a curated dataset of half a million games.

2. Expert-informed pattern search

Two approaches were conjointly used to identify the most popular openings. The first approach, called expert-informed, consists in choosing a *priori* a set of common openings, such as Nirensei, Chinese or Kobayashi opening among others. Each opening stone is determined to be intentional or flexible by the expert. An opening thus includes intentional moves, such as moves 1 and 3 in Figure 1a, and patches, represented as transparent black and white rectangles in Figure 1a. The intentional moves are mandatory, they are the essence, the skeleton of the openings. The patches represent areas where a specific opening move could reasonably be placed. Patches allow to include variants of an opening. For instance, move 5 in Figure 1a can be placed at P10 (high Chinese opening), or at Q9 (classical Chinese opening). The variability of the opponent's move can also be modelled by a patch. For instance, move 4 in Figure 1b can be anywhere between 3-3 and 5-5 points without modifying the opening. An additional constraint is applied for openings with several patches of the same player colour: each patch must contain one, and only one, stone.

3. Data-driven pattern search

A second approach, called data-driven, consists in a clustering of the available openings. The clustering procedure is iterative and goes as follows. For a given number of moves starting with the first, all the games are parsed one by one up to a maximum depth of 12 moves. If an opening sequence ending

in a Black player stone placement has not yet been observed, it is added to the Black player opening list and given a count of 1. If the sequence is already in the opening list, its count is incremented. The same is done on the sequences that end in White player stone placements. By ordering the opening list by games count, one obtains the k most popular openings played by Black or White. As an example, the 5 most frequent 8 moves Black and White openings at 1d rank in 2019 are plotted in Figure 2.

Notice that the order of moves is not taken into account and only the final position after a given number of moves is considered for increasing a count. In both expert-informed and data-driven approaches, the rotations and reflections (when the pattern is not chiral) have been accounted for.

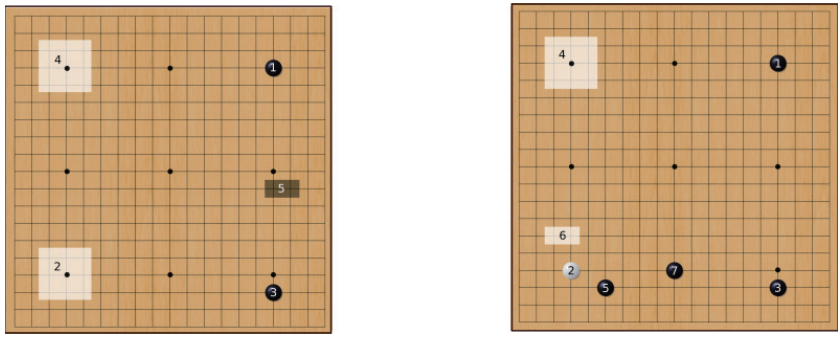

Figure 1: Illustration of the patterns for Chinese (left) and Kobayashi (right) openings. Intentional moves are depicted as stones whereas patches are represented as transparent areas (move order is not considered for analysis, the numbers shown here are only for illustration)

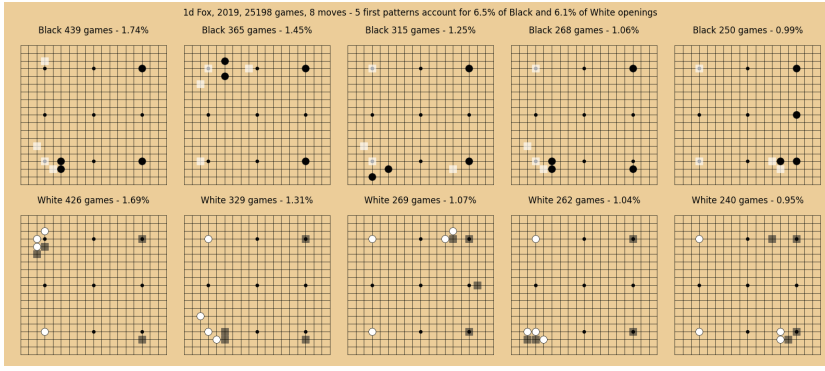

Figure 2: Most frequent Black and White 8 moves openings for 1d players in 2019 (the identified patterns are represented as solid stones, the transparent rectangles show one possible sequence for the opponent).

4. Statistical analysis and uncertainty quantification

In order to study the effect of rank and year on the opening frequency, the dataset is divided into subsets with homogeneous rank and year. Most of the subsets contain between 10,000 and 40,000 games, although the smallest ones contain only a few hundreds of games. Amongst these games, some patterns are very frequent (e.g. ~ 40% for white Nirensei across all ranks), whereas some others are rare (e.g. ~ 0.4% for Kobayashi amongst 1d players). Such discrepancies in sample sizes can lead to large uncertainties. In this subsection, the method to estimate opening frequency (and uncertainty) is presented and validated.

For a subset of Ng games, among which α games exhibit a given opening, the observed frequency of the opening is α/Ng. This value can be considered as a point estimate in a frequentist framework. A common way to evaluate

the uncertainty of this estimate is bootstrapping. Bootstrapping is achieved by resampling b times with replacement Ng games from the original subset. Higher value of b gives a smoother estimation at a larger computational cost. The histogram of expected frequency is shown in Fig.3 for b=10,000 (1d games from 2019, Ng=25,198). On top of the mean value, which is close to α/Ng, these histograms give an estimation of the uncertainty of the expected frequency. For instance, using Fig.3, the Sanrensei opening expected frequency computed 95% confidence interval is [5.5%-6.1%].

This method gives very satisfactory results, but it is computationally expensive. Given the large dimensionality of our study (~15 opening patterns x ~15 ranks x ~5 years), a faster method is preferable. In this work, an analytical Bayesian approach using Beta distributions is used to increase the computational efficiency. The methodology of the proposed Bayesian approach is given in the next paragraph.

Several openings can be present in a single game, for instance Kobayashi is a sub-opening of hoshi+34 (see Fig.4). However, each opening is either present or not in each game, which means only two outcomes are possible. Moreover, the presence of an opening in a given game is independent of its presence in the other games. A sequence of events satisfying these two conditions is called a Bernoulli process. In this study, the parameter π of the Bernoulli process is the expected frequency of a given opening. Beta distributions are conjugate priors for the Bernoulli process, making them a very efficient choice to model π. Before seeing any games, all the values of π are equally probable. This is reflected by using the uniform prior Beta(1,1). The likelihood of finding the opening α times out of Ng games is given by

Beta(α,Ng-α). The posterior distribution of π is the product of the prior and the likelihood, which is equal to Beta($\alpha+1$,Ng-$\alpha+1$). The posterior distribution of π is reported in Fig.3 on top of the histograms obtained using bootstrapping. There is a very good agreement between both predictions, showing the ability of Beta distributions to predict the expected frequency and its uncertainty. The computational cost is much lower: the Bayesian approach is on average 2000 times faster than bootstrapping.

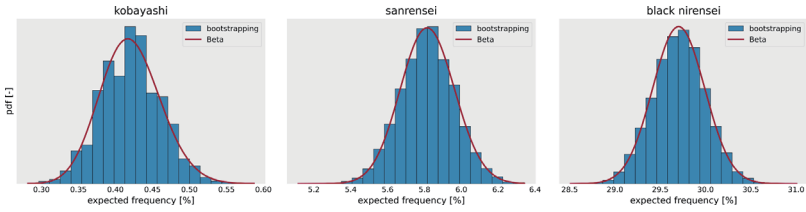

Figure 3: Comparison of bootstrapping (b=10,000) and analytical Beta distributions for three opening patterns using 25,198 games played between 1d Fox players in 2019

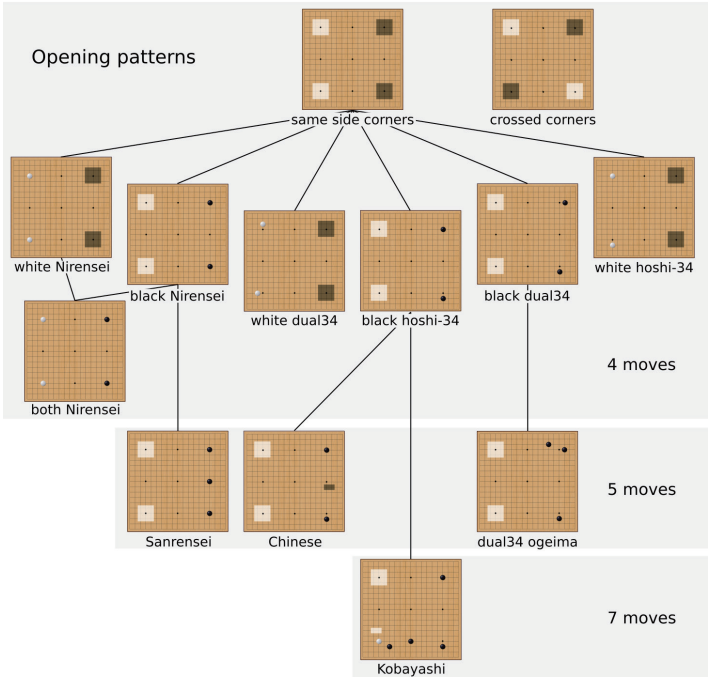

Figure 4: Expert-informed opening patterns - Intentional moves are depicted as stones whereas transparent areas indicate the range of the opponent's possible moves

III. Results

1. Corner is gold (4 moves openings)

One of the first proverb a beginner might hear about Go opening is "corner is gold, side is silver, center is grass" (金角银边草肚皮). Thus, it is not a surprise to observe that the very large majority of 4 moves opening consist of

a stone played in each corner. When looking more closely, 5 patterns represent 86% of Black openings across all ranks. These patterns, shown in Fig.5 amongst 1d games, are:

- Nirensei, two 4-4 points on the same side
- hoshi+34, one 4-4 point and one 3-4 facing the 4-4
- hoshi+43, one 4-4 point and one 3-4 facing the opponent's side
- dual34, two asymmetric 3-4 points
- crossed Nirensei, two 4-4 points in diagonally opposed corners

Looking at Fig.5, notice that these patterns are not equally popular, Nirensei and hoshi+34 being roughly 10 times more popular than crossed Nirensei. The expected frequency of each pattern depends on the players' rank and is plotted in Fig.6 for games played in 2019. At low amateur level, the most popular Black opening is Nirensei, which appears in more than 35% of games, followed by hoshi+34 (15%). The popularity of hoshi+34 rises steadily with the players' rank, while Nirensei popularity decreases. Amongst 1d players, both openings are equally popular (~ 30%), and hoshi-34 is the most popular amongst 6d players (almost 35% vs 25% for Nirensei). Interestingly, the trend reverses for players ranked 7d and above. The opening dual34 is less frequent, starting around 7% at 10k and increasing steadily until around 10% at 9d. Crossed corners is more frequent amongst lower ranked players, with a frequency around 10% below 1k and around 5% above.

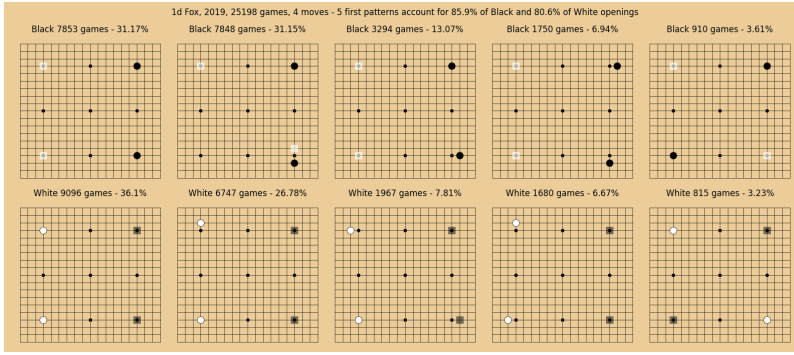

Figure 5: Five most frequent Black and White 4 move openings for 1d players in 2019 (the identified patterns are represented as solid stones, the transparent rectangles show one possible sequence for the opponent).

Looking at White perspective openings, the five most frequent patterns at 1d fox level is the same than for Black, as can be seen in Fig.5. These five openings account for 81% of White 4 moves opening, a slightly lower figure than for Black. But when looking more closely, one can see that the frequency of each opening differs. Nirensei is 5% more frequent for White than for Black. Hoshi+34 and hoshi+43 openings are 4% less frequent for White than for Black.

As these results are only valid at 1d Fox level, the frequency of the five most popular openings is plotted across rank in Fig.7. The frequency of Nirensei follows the same shape for White and Black: it is higher at ranks lower than 1d and higher than 7d than between 1d and 7d. However, while it is competing with hoshi+34 as Black's most popular opening, Nirensei is always White's most popular opening, reaching a maximum of 55% at 9d Fox

level. Hoshi+34 is always the second most popular opening, reaching a maximum of 30% frequency between 3d and 6d Fox levels. The three remaining openings follow a decreasing trend when rank increases. This results in a lower diversity of openings at high ranks compared to low ranks, whereas the diversity of Black openings was more or less constant across rank.

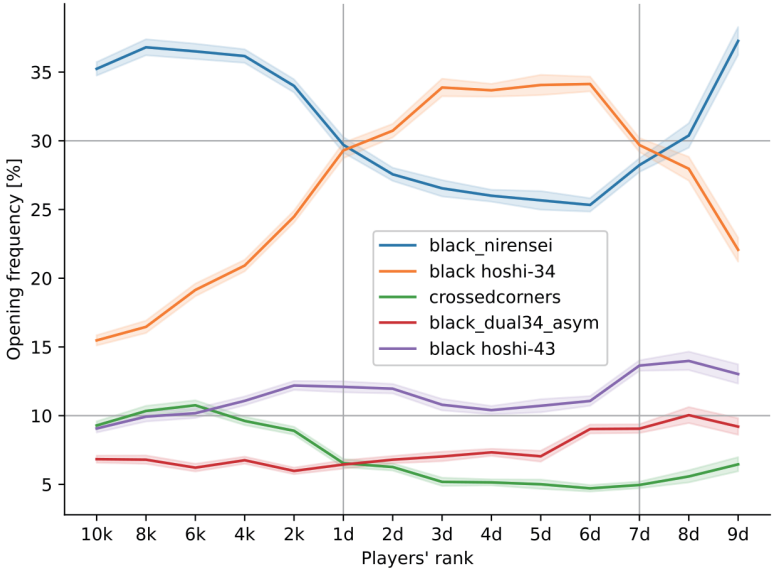

Figure 6: Frequency variation of five Black 4 moves openings (games played in 2019 on Fox Go server)

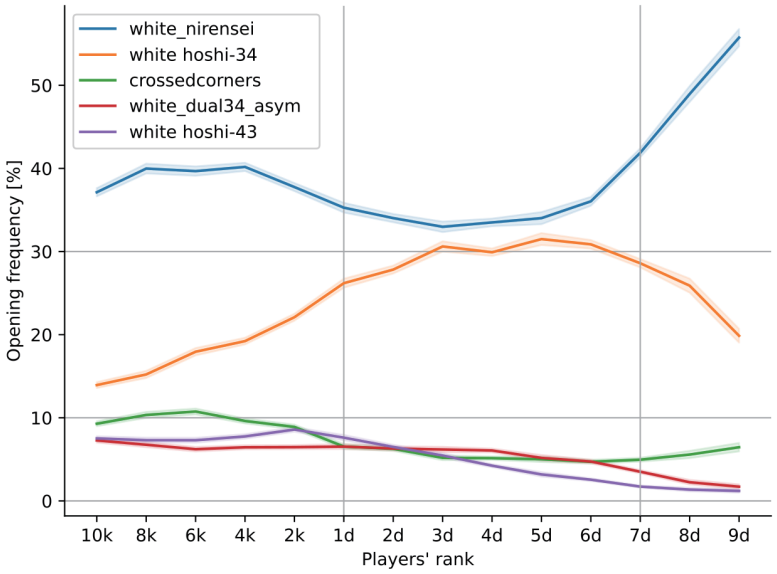

Figure 7: Frequency variation of five White 4 moves openings (games played in 2019 on Fox Go server)

2. Side is silver (5+ moves openings)

Within the next two moves (5 and 6 moves openings), two specific openings appear, both focusing on side development: Sanrensei and Chinese opening. Sanrensei consists of occupying the three hoshi on one side (4-4, 4-10, and 4-16). Sanrensei is a possible follow-up of the Nirensei opening. On the other hand, Chinese openings are possible follow-ups of the hoshi+34 opening. Several variants exist, in this study we considered the two most frequent ones: the low and high Chinese openings, represented on the left side of Fig. 1. Although Sanrensei is sometimes played by White, only the Black openings are studied in this section. Another 5 move opening, called here

dual34ogeima, consists of a dual34 opening followed by a corner enclosure, in this particular case an ogeima in the direction of the opponents' stones (see Fig.4).

Within two more moves (7 and 8 moves openings), the Kobayashi opening appears, a deeper hoshi+34 follow-up than the Chinese opening. The mandatory stones and the possible opponent's response for the Kobayashi opening are plotted on the right side of Fig. 1. The frequency of Sanrensei, Chinese, dual34ogeima and Kobayashi openings are plotted across rank in Fig. 8. Sanrensei is very popular amongst 10k to 4k players (8% opening frequency), but its popularity decreases sharply with rank for players above 4k. At 8d level and above, its opening frequency is well below 1%. Chinese, dual34ogeima and Kobayashi openings all show a bell-shaped curve, with a maximum frequency close to 3% around 2k-1d for the Chinese opening, 2% around 7d-8d for the dual34ogeima and almost 4% around 5d-6d for the Kobayashi. Notice that the Chinese opening's bell curve is quite wide, reaching a larger pool of players' ranks. Kobayashi's maximum frequency of 4% is remarkable given that it is a 7 moves opening, in contrast with Sanrensei, Chinese and dual34ogeima which are 5 moves openings (see Fig. 4).

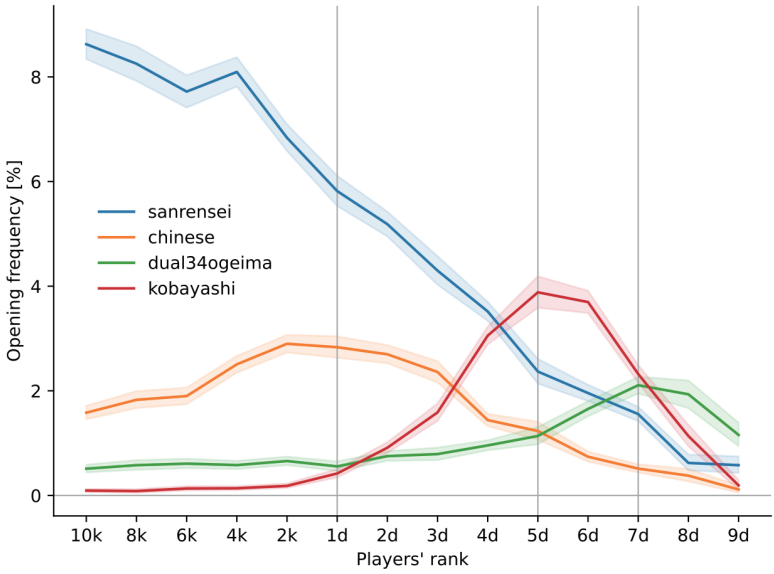

Figure 8: Frequency variation of four Black 5+ moves openings (games played in 2019 on Fox Go server)

3. Influence of AI on popular openings

The rise of AI after the match of Lee Sedol and AlphaGo in 2016 (Silver et al., 2016) saw a change in Go opening practice. One of the most striking features of this change is the early san-san invasion which was considered a bad move before but was frequently played by AlphaGo Master (Silver et al., 2017). These AI expert systems are now available to all players thanks to the release of open source software for AI analysis of Go games. Two examples are Leela Zero initially released in 2017 and KataGo initially released in

2019. The question we are addressing in this section is whether the rise of AI influenced the popularity of Go openings.

A first analysis is performed for 9d Fox players since we have a large dataset of game records across all years from 2013 to 2019. Four different openings are considered: crossed corners and Nirensei played by Black, White, or both players. The resulting opening frequencies are plotted in Fig.9. White Nirensei has always been popular over the studied period, ranging between 25 and 40% before 2017, and between 30 and 55% after 2017. On the other hand, Black Nirensei was a rare sight before 2015, accounting for less than 3% of openings, whereas it reached 37% of openings in 2019. Games with both sides playing Nirensei also saw a large increase, from less than 1% before 2015 to 24% in 2019. On the other hand, crossed corners opening, which is neither favored nor unfavored by AI, saw a relatively constant opening frequency across the years. These results clearly demonstrate a sudden change in Go openings popularity amongst the highest ranked players after the advent of AI.

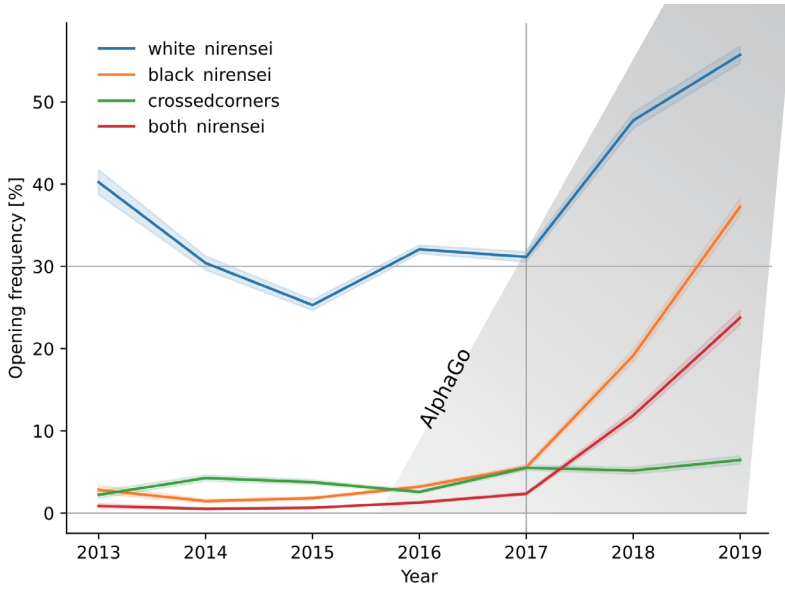

Figure 9: Black and White Nirensei and crossed corners opening frequency from 2013 to 2019 for 9d Fox players (the grey shaded area is a qualitative representation of the increase in AI usage since AlphaGo demonstration games in 2016 until the release of open source software such as Leela Zero in 2017 and Katago in 2019)

A natural follow-up question is to know if the AI also influenced the opening popularity amongst amateur players of lower ranks. While it is clear that playing the best opening can lead to a significant advantage at professional level, we have shown that the opening has a weaker impact on the game outcome at lower ranks (Rendu, 2023). The database is more sparsely populated for games played before 2019 at lower ranks, hence only games played in 2015 and 2017 are collected. The opening frequency of Black Nirensei is plotted across players' rank in Fig.10. In 2015 and 2017, Black Nirensei

frequency decreased almost linearly with players rank. In 2019, it first decreases, then shows a plateau and finally increases again for players above 6d. Overall, the frequency is the same across all years for players below 4d, slightly higher for 2019 games between 4d and 6d, and largely superior for players above 6d in 2019.

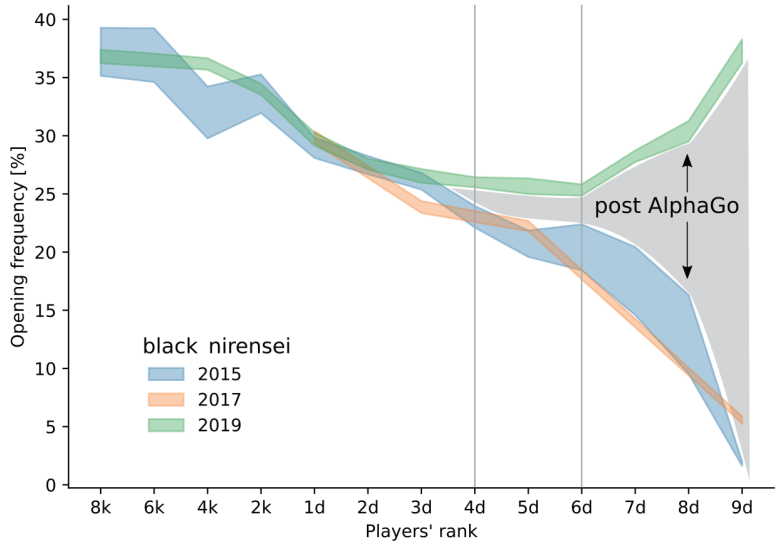

Figure 10: Frequency of black Nirensei opening across rank for games played on Fox Go server before (2015, 2017) and after (2019) the widespread use of AI Go analysis software

These results indicate a change in opening frequency only for the strongest players. Two hypotheses can explain this behavior. The first one relies on the link between score in the opening and game outcome. A previous study

showed that a given score advantage translates into higher winning rate for stronger players (Rendu, 2023). Hence lower ranks might not benefit from an optimised opening strategy. A second hypothesis relies on the time lag between the availability of AI and the change in Go openings. As shown in Fig.9, the rise of Black Nirensei popularity is spread across three years for the strongest players. One could argue that the strongest players have a higher awareness about AI's influence on Go opening, as well as a faster ability to change their style of playing. Under that hypothesis, lower ranked players might also experience a change in opening strategy but across a longer timeframe. This hypothesis could be evaluated by analysing more recent games, unfortunately not available in the current source dataset.

IV. Discussion

Our findings show that the vast majority of games follow a small diversity of openings, with 5 openings accounting for 80% of the games after 4 moves. Amongst these, Nirensei is very popular across all ranks. Although Nirensei popularity feels natural today, it was seldom played a century ago, before the Shinfuseki revolution (Rapley, 2025). This demonstrates the fluctuating popularity of Go openings through time. A recent study (Beheim, 2025) investigated the frequency of the first two moves from 1600 to 2024. It could be extended to deeper openings such as Nirensei, Sanrensei, Chinese and Kobayashi openings to evaluate their popularity over time.

Until 2016, changes in opening popularity have been driven by professional Go players experimenting with new strategies. One recent example is

the Sanrensei opening, part of Takemiya Masaki “natural style” (also termed “cosmic style”), which is now one of the most popular openings amongst low rank amateur players. Since 2016, the rise of superhuman-level AI Go engines led to a more objective evaluation of moves value, improving human understanding of the game (Choi et al., 2025 ; Kim et al., 2021). The re-evaluation of openings and common sequences such as 3-3 invasion impacted the style of professional go players. This is clearly seen in our results on the frequency of Nirensei vs Nirensei opening amongst 9 dan Fox players, which accounted for less than 1% of the games in 2015 and for around 24% in 2019.

An open question is whether and how the rise of AI will affect the popularity of Go openings amongst lower rank players. On the one hand, an advantage of a few points in the opening is not decisive for lower rank players (Rendu, 2023). On the other hand, from the first author’s own experience, openings involving 3-3 moves and 3-3 invasion have been very popular amongst lower rank players in the last few years. Go AI also confirmed that midgame is the decisive stage of a Go game, and that most moves are good moves in the opening (Rendu, 2025). Rather than limiting our options, AI might have revealed a large uncharted territory for creative playstyle in Go openings – a territory yet to be explored.

V. Conclusions

Go opening patterns of games played by amateur players on Fox Go Server were analyzed using a data-informed framework. The games were played

from 2013 to 2019 across ranks ranging from 10 kyu to 9 dan. Standard opening Go theory which favors the development of corners in the first moves and then the sides is observed across all ranks. In the first four moves, 5 openings account for 80% of the game, with Nirensei and hoshi-34 being the most popular openings across all ranks for both Black and White players.

Considering famous opening strategies, Black Sanrensei is the most popular one but its frequency decreases with the player's rank. Chinese openings are most popular amongst 1 dan players and then decrease with rank. Above 1 dan, Chinese openings are roughly twice less frequent than Sanrensei. Kobayashi is the most popular opening for players between 4 dan and 7 dan, showing a significant frequency given that it's a deeper opening.

When comparing games played before and after the introduction of AlphaGo, a large increase in the frequency of Nirensei openings is observed for players ranked 4 dan and above. This indicates a significant impact of AI on professional Go players' opening style. Lower ranks are not affected as of 2019, but could be in more recent games. Alternatively it could be that lower rank players benefit minimally from an advantage in the opening strategy due to larger mistakes in midgame and endgame.

These results could be of use to customize training of Go openings depending on the student rank. We hope it will be relevant for players and educators of Go, as well as for readers interested in the impact of AI on players' decisions.

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Received : 3 May 2026
Accepted : 4 May 2026

바둑학연구, 제20권 제1호, pp. 183-196
Journal of Go Studies
20263. Vol.20, No.1. pp. 183-196

Casual Go players among university students in Europe and East Asia: Numbers and Characteristics

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Abstract

Little is known empirically about casual Go players. Their numbers are difficult to estimate and there are no systematic studies about their characteristics (demographics, personality, intelligence etc.). We use data from an international survey among university students including all major Go nations besides Korea (China, Taiwan and Japan) and additional three other countries (Germany, Estonia and Vietnam) to estimate the size of the casual player base and their main characteristics. We find a surprisingly large number of casual players also in countries where Go is not traditionally played. Moreover, we find high masculinity as the strongest predictor for casual Go players while demographic and personality variables are not significant.

Keywords: Go, Baduk, Weiqi, international players, survey

1. Introduction

The board games Go (also known as *weiqi or baduk*) and chess are among the most widely played strategic games, with long histories and large player communities. Go originated in China and remains especially popular in China, Korea, Japan and Taiwan. Precise global participation numbers are difficult to establish, surveys and academic studies suggest that Go has a substantial but regionally concentrated player base. Estimates indicate that the global number of Go players is around 100 million (Rieger and Wang, 2021), including both regular and occasional players, mostly located in China, Korea and Japan.

In contrast, chess shows a much broader global diffusion. According to the Fédération Internationale des Échecs (FIDE), approximately 600–605 million people worldwide know how to play chess, based on YouGov survey data (FIDE, 2012). Among them, around 1.64 million players are registered on the FIDE rating lists (Friedel, 2025). Chess federations and online platforms provide organized structures for play across almost every country, making it a useful benchmark for comparative studies of strategic game participation.

In East Asia, Go coexists with other traditional strategy games. Xiangqi (Chinese chess) is widely played in China, with market research reports estimating around 300 million people familiar with the game (PMarketResearch, 2021) and approximately 10 million active enthusiasts (XiangqiWu.com, 2023). Shogi (Japanese chess) is similarly embedded in Japanese culture. Estimates of the number of shogi players in Japan range from about 6.2 million (Tansey, 2021) to roughly 10 million playing at least annually (Japan Policy Forum, 2016), with survey-based participation rates suggesting around 3% of the Japanese population plays shogi (Statista, 2022). Historical data indicate

that the number of players has fluctuated between 8.4 and 16.8 million over the past decades (Japanese Productivity Center, 2006).

Despite these broad figures, quantitative comparisons of board game engagement among specific demographic groups remain limited. University students are a particularly important population for such research because they represent the young generation whose cultural preferences and leisure activities may reflect broader trends in strategic game participation. Estimating the size of the Go-playing population among university students in selected East Asian and European countries, and comparing it with chess participation within the same cohorts, can provide insight into patterns of game adoption, cultural diffusion, and cognitive engagement in competitive strategy games.

There is another difficulty that is noticeable in the wide ranges of estimates stated above: The difficulty of defining what constitutes a "player" of a game like Go. This can be seen from an older comprehensive and representative survey in Germany from the year 2004 (Grootenhuis, 2004): It indicates that around 20 million Germans had heard about Go, 3 million Germans have played Go at least once, 750,000 play it "from time to time". At the same time, only around 2000 persons were members of the German Go Association or one of its sub-organizations. Depending on how we define a "Go player", their numbers can therefore vary easily by a factor of more than 1000. There is no reason to assume that the differences in other countries or other comparable games would be smaller.

Numbers of Go players, particularly of young ones, are informative as they can help to predict the future potential for the game in certain countries. There are, however, other interesting details to know about Go players than only their total numbers. In particular, there is a severe lack of empirical data on demographic characteristics and typical properties of Go players (e.g.,

regarding their personality, their intelligence, etc.). Rieger and Wang (2021) studied some of these properties for European tournament players and found that they excel particularly in cognitive reflection, even compared to chess players that had previously been found to have large values (Campitelli and Labollita, 2010). When it comes, however, to the big majority of Go players who are not participating in tournaments and are not members of a Go association, there is even less known. Our study tries to shed some light on this by using data from a large-scale survey among university students.

2. Method

We used data from the PANDA study (Preferences, Attitudes, Norms and Decisions in Asia), conducted in the years 2018 and 2019 in several countries of East Asia (China, Taiwan, Japan and Vietnam) and Europe (Germany and Estonia). While three of these countries are traditional strongholds of Go, the three others have a much smaller Go tradition and community.

The survey was advertised at several universities and in total $N = 2510$ subjects participated in it and answered the questions about Go. Most of the participants were university students. More about the methodology of this survey can be found in Tian et al. (2021) and Wang et al. (2023).

The survey contained the following items relevant to this study regarding games:

· To measure participants' familiarity with and recent engagement in mind games, respondents were asked to indicate which of the following **games they had ever learned the rules of** and which they had **played in the past 12 months**. Options included Chess (changed to Xiangqi in Chinese and

Shogi in Japanese), Go, and an open-ended category for other similar mind games.

· To assess cognitive reflection, we administered a set of free-response questions adapted from the classic Cognitive Reflection Test (CRT) and extended items used in prior research. The original CRT was developed to capture the tendency to override an intuitive but incorrect response in favor of a more deliberative one (Frederick, 2005). In this study, participants responded to the six CRT items as follows:

1. A pen and an eraser cost 1.10 Euro in total. The pen costs 1.00 Euro more than the eraser. How much does the eraser cost?
2. If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?
3. In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?
4. If you're running a race and you pass the person in second place, what place are you in?
5. A farmer had 15 sheep and all but 8 died. How many are left?
6. Laura is 10 years old. Her father has three daughters. The first two are named April and May. What is the third daughter's name?

(For Chinese and other language versions, gendered proper names in item 6 were adapted to culturally appropriate equivalents.)

The first three items are direct adaptations of the original CRT developed by Frederick (2005), which has been widely used as a measure of reflective versus intuitive thinking in judgment and decision-making research. The latter three items are structurally similar "intuitive lure" problems commonly used in extended CRT batteries and alternative forms (Thomson et al., 2016),

each eliciting an intuitive but incorrect response unless reflective processing intervenes. These items were presented in free-text response format to allow for open coding of answers.

- The classical Hofstede cultural dimensions Individualism (IDV), power distance (PDI), masculinity (MAS) and uncertainty avoidance (UAI), see Hofstede (2011).
- The Big5 personality dimensions, measured as in Rammstedt and John (2007).

3. Results: number of players

Table 1: Percentage of students answering "Yes" to learning and playing board games by country

Category	JAP	CHN	TWN	VNM	GER	EST
Learned chess (%)	77	74	85	56	84	69
Learned Go (%)	29	35	42	23	10	18
Learned other abstract board games (%)	26	26	14	53	23	24
Played chess in past 12 months (%)	65	53	56	40	59	50
Played Go in past 12 months (%)	16	17	18	13	5	15
Played other board games in past 12m (%)	34	41	36	59	40	40

Table 1 summarizes the proportion of university students who reported having learned and played chess, Go, and other abstract board games across the six countries. As expected, chess (or its regional variant xiangqi and shogi) was the most widely learned and played game in all surveyed countries, with particularly high learning rates in Taiwan (85%), Germany (84%), and Japan (77%).

In contrast, Go showed substantial cross-country variation: While in the classical Go countries China, Taiwan, and Japan 29%–42% reported having learned Go before, in Vietnam 23%, in Estonia 18%, and in Germany only 10% had. The differences, however, are less clear-cut than one might have expected previously. In particular, the fairly high percentage among university students in Vietnam and Estonia is surprising.

Recent playing behavior showed similar trends. While Go was played by a smaller share of students than chess in all countries, recent Go play was reported by 13–18% of respondents in Vietnam, China, Taiwan, Japan, and Estonia, compared to only 5% in Germany. Again, Vietnam and Estonia stood out, as their rates of recent Go play were comparable to those observed in East Asian countries.

It is interesting that the gap between "having learned" and "played within the recent 12 months" was much wider in the classical East Asian Go nations. A reason is probably that there it is more common that children learn Go early on and then might eventually drop it if they do not like it, whereas, e.g., in Europe many encounter Go first at university when they are older and might therefore have a better ability to assess whether the game will be interesting for them before learning it.

4. Results: characteristics of Go players

In this section, we study how persons who have played Go at least once and persons who regularly play Go differ from the rest of the sample. To this end, we conduct regression analyses where we use the Go playing status as dependent variable and as independent variables gender, age, bachelor degree, Hofstede cultural dimensions, cognitive reflection score, and the Big5 personality dimensions.

Table 2: Dependent variable: Has learned Go

Independent Variable	Standardized β	p-value
Bachelor degree	0.014	0.532
Age	-0.011	0.591
Female	-0.026	0.212
Hofstede dimensions:		
Individualism Index	0.025	0.226
Power Distance Index	0.000	0.997
Masculinity Index	0.065**	0.002
Uncertainty Avoidance Index	-0.077***	<0.001
Cognitive reflection score	0.021	0.327
Big Five Personality Dimensions:		
Extraversion	-0.034	0.097
Agreeableness	-0.016	0.439
Conscientiousness	-0.039	0.062
Neuroticism	-0.006	0.763

Openness	0.053**	0.009
Country controls	yes	

*Notes: Standardized coefficients reported. p < 0.01, *p* < 0.001.

Table 3: Dependent variable: Played Go in the past 12 months

Independent Variable	Standardized β	p-value
Bachelor degree	0.026	0.267
Age	-0.014	0.527
Female	0.001	0.981
Hofstede dimensions:		
Individualism Index	-0.001	0.944
Power Distance Index	-0.037	0.096
Masculinity Index	0.086***	<0.001
Uncertainty Avoidance Index	0.002	0.926
Cognitive reflection score	-0.066**	0.003
Big Five Personality Dimensions:		
Extraversion	-0.003	0.893
Agreeableness	-0.028	0.199
Conscientiousness	-0.004	0.853
Neuroticism	-0.028	0.200
Openness	0.015	0.467
Country controls	yes	

*Notes: Standardized coefficients reported. p < 0.01, *p* < 0.001.

The two models capture two sequential stages of engagement with Go: first, learning Go, and second, continued engagement, as indicated by having played Go in the past 12 months. All cultural dimensions are measured at the individual level, reflecting respondents' personal cultural orientations rather than country-level averages.

At the first stage (learning Go), basic sociodemographic characteristics (education, age, and gender) are not significantly associated with the likelihood of learning Go. Among individual-level cultural orientations, masculinity is positively related to learning Go, while uncertainty avoidance is negatively related. Given that the masculinity dimension partly reflects competitiveness and achievement orientation, this finding suggests that individuals with a stronger competitive orientation are more likely to take up Go in the first place, whereas individuals who are more averse to uncertainty are less likely to do so. Among personality traits, only openness is positively associated with learning Go, consistent with the idea that openness facilitates initial exploration of complex and unfamiliar activities.

At the second stage (continued engagement, i.e. having played Go in the past 12 months) masculinity again shows a strong positive association, indicating that competitive orientation remains important not only for entry into Go but also for sustained participation. In contrast, the other cultural dimensions and all Big Five personality traits are not significantly related to continued play.

Notably, cognitive reflection is negatively associated with recent Go play, suggesting that individuals with higher cognitive reflection may be less like-

ly to remain active players once the initial learning phase is completed. This result seems at first in contradiction to Rieger and Wang (2021) who showed that tournament Go players with higher playing strengths also had higher cognitive reflection scores, and in general the cognitive reflection scores of tournament Go players were exceptionally high. One potential reason for the findings among casual Go players might be that individuals with high cognitive reflection could be more curious and thus starting more often different activities, instead of sticking to one. A hint into this direction is that subjects who had learned not only Go, but also chess and other similar games tend to have a *higher* cognitive reflection than others (4.85 versus 4.40, t-test $p = 0.002$).

Across both stages, gender shows no significant effect, indicating that men and women are equally likely to learn Go and to play it casually, as measured in this survey. This finding is noteworthy given the continued underrepresentation of women among tournament-level Go players, and suggests that gender disparities observed in competitive settings likely emerge after the casual participation stage rather than at the level of initial or informal engagement.

5. Conclusions

This article is one of the first that aims to study the broader demographic of casual Go players, instead of focusing solely on professional or amateur tournament Go players. In this way, it provides interesting insights into the approximate size and demographics of this player population.

The results highlight the importance of individual-level cultural orientations -- especially competitiveness-related masculinity -- across both stages of engagement, while demographic characteristics and most personality traits

play a limited role once cultural orientations and country controls are taken into account.

It would be interesting to broaden the analysis in future studies in order to include broader populations (not only university students). A more nuanced view on casual playing could distinguish the different types of casual players (e.g. players who only play online or those who only play within their families etc.). Finally, more direct evidence on the effect of cognitive reflection on the formation of casual players would be interesting as well.

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Received : 4 February 2026

Accepted : 4 May 2026

바둑학연구, 제20권 제1호, pp. 197-218
Journal of Go Studies
20263. Vol.20, No.1. pp. 197-218

서평

한정규, 『인공지능과 의식』, 서울: 커뮤니케이션북스, 2025.

박우석

가지 않은 길과 무덤으로 가는 길

범한서적과 종로서적을 잇는 직선이 1970년대 후반, 그러니까 한창 젊은 시절, 나의 고정 산책로였다. 교보와 영풍이 존재하지 않던 시절이라 외국어 원서를 구경하려면 누구나 피할 수 없는 길이었다. 중간 지점의 범문사에서 출발해서 광화문 쪽으로 가면 이공계 서적만 전문적으로 취급하던 책방과 비록 좁지만 썩 괜찮은 원서 전문 헌책방도 들릴 수 있었다. 혹한의 칼바람을 맞으며 비장한 마음으로 걷던 산책로가 어느 순간 사라졌는데, 사지도 읽지도 못할 아리스토텔레스 전집 앞에서 서성대다 호되게 구박을 받았기 때문인지, 계산대 위에 키 높이로 구입할 책들을 쌓아놓던 은사 박동환 교수님을 질시하지 않으려는 결단 때문인지는 확실히 기억나지 않는다. 그러나 전략도 무기도 없이 우연 배후의 신탁에 의지하여 나서던 사냥에서 오스틴이 영역한 프레게의 『산수의 기초』 독영 대역본을 전리품으로 챙긴 것은 나로서는 잊지 못할 무용담이다.

종이책을 살 필요를 느끼지 않을 젊은이의 마음을 훔치기 위해서는 꼰대의 체취를 가능한 한 숨기며 짧게 하고 싶은 이야기를 하는 편이 현명했겠다 싶다. 이제라도 그렇게 하자. 장시간에 걸친 인터넷 서핑 끝에 쌈박한 책을 성공적으로 사서 읽고 행복했다. 이 책은 마치 저자가 나만을 위해 맞춤형으로 제작한 듯하다. 혼자 읽기 아까워서 이 글을 쓰고 있는데, 왜 그런지 설명하고 깔끔하게 마무리 짓기 위해서는 다시 꼰대 모드로 돌아갈 수밖에 없다.

저자와의 만남은 언제나 운명의 장난인가?

이제 와서 돌이켜 보면 알파고 충격이 충격이었다는 사실 자체가 인공지능 시대의 도래에 우리 모두가 얼마나 둔감했었는지를 단적으로 보여준다. 나중에 알파폴드로 노벨상까지 받은 구글 딥마인드의 데미스 허사비스경이 뇌과학자라는 사실도 뼈아프다. 지난 30년 동안의 한국의 학계나 도서출판 시장을 돌아보면 뇌과학은 인공지능보다 훨씬 더 각광받은 인기 종목이라 여겨지기 때문이다. 뇌과학 분야 석학들이 넘쳐나는데 어떻게 이런 결과가 초래되었을까? 그들 중 상당수가 사이비 뇌과학자였기 때문이라는 진단은 과연 지나치게 폭력적인 것일까?

일면식도 없는 이 책의 저자를 페이스북을 통해 알게 된 것은 100 퍼센트 우연은 아니겠지만 그에 가까운 행운이었다. 문외한이 전문가를 어찌 감별할 수 있겠느냐만, 이 분이 진짜 뇌과학자라는 느낌은 단번에 왔다. 평소에 사이비 뇌과학자라고 의심하며 혐오했던 인물에 대해 이 분이 단호하게 취하는 준엄한 태도 때문이었다. 진짜 과학자라면 사이비 과학자에 대해 의당 그런 태도를 보여야 마땅하지 않은가? 이 분이 해외 유수 학술지에 게재하신 논문이나 박사학위 논문을 읽고 이해한다는 것은 실질적으로 불가능한 일이므로 페이스북에 올리시

는 글들을 통해 감질나지만 기본 개념들을 배우고 또 최신 학계 동정에 관한 유용한 정보를 얻곤 했다. 그런데 마침내 이 분이 일반 대중을 위한 교양서를 내셨다. 이렇게 반갑고 고마울 데가 없다. 모처럼 왕년에 밤새워 무협소설 독파하던 실력으로 독서삼매경에 푹 빠졌다.

이 책의 구성

이 책은 어쩌면 커뮤니케이션북스의 인공지능 총서가 지금까지 낸 632권의 인공지능 관련 저서들 가운데서 가장 주목할 만한 책일지도 모른다. 이 시리즈는 "인공지능 문고"로 이름을 바꾸어 계속 출간되고 있는데, 거기서 나온 책들까지 포함해도 사정은 다르지 않을 것 같다. 이 총서의 집필 원칙에 따라 친절하고 상세한 머리말에 이어 저자가 추린 열 개의 핵심 단어를 주제어 삼아 열 장의 내용이 펼쳐지고, 그 단어들을 선정한 이유와 책의 전체 구조는 머리말에서 명쾌하게 설명되고 있다. 1장은 의식 문제의 중요성을 역사적 맥락 안에서 이해하고자 한다. 2-3장은 영화와 드라마에서 다뤄진 의식 개념을 분석한다. 4-5장은 철학적 관점에서 의식의 본질과 정의를 재고한다. 6-7장에서는 의식과학의 이론적 배경을 설명하면서 주요 의식 이론을 정리한다. 8-9장은 인간이 아닌 다른 생명체의 의식 가능성을 고찰한다. 그리고 에필로그인 10장은 현재 인공지능 연구자들이 의식에 대해 고민하는 지점을 소개한다.

문제를 도입하는 머리말과 제1장

저자가 이 책을 쓰게 된 배경, 동기, 구상, 그리고 목표에 관한 이야기는 특히 졸저 『AI 로봇공학의 철학적 뿌리』(서울: 커뮤니케이션 북스, 2025)에서 이미 논의한 바보다 더 낫게 서술할 자신이 없으므로 재탕하는 데 대해 너그러운 이해를 구한다.

<한정규는 “인공지능의 등장과 함께 의식 연구는 더욱 중요한 문제로 떠오르고 있다”고 본다(한정규, 2025, p. vii). 왜, 어떤 근거에서 그렇게 볼 수 있을까? 그 이유 또는 근거를 그는 이렇게 제시하는 것으로 보인다.

> 지금 우리는 단순한 신경 신호의 집합체에 불과한 존재인지, 아니면 보다 깊은 본질을 지닌 존재인지에 대한 근본적인 물음 앞에 서 있다. 인공지능과 의식의 문제는 단순히 기술 발전에 따른 도전이 아니라 인간이 자기(self)를 이해하는 문제이기도 하다(같은 곳).

그 결과 그는 의식 연구와 인공지능 연구는 “서로 영향을 주고받는 수준을 넘어”, “함께 수행”해야 하고, 궁극적으로는 “하나로 융합되는 방향으로” 나아가리라고 예상한다(같은 곳). 그리고 이런 사고의 흐름 기저에는 의식 연구와 인공지능 연구를 함께 수행한다는 것은 “의식을 물리적 현상으로 전제하고, 과학적 탐구의 대상으로 삼는 접근 방식”이라는 그의 신념이 자리하고 있다(같은 곳). 한정규는 신경과학자이자 실험과학자로서의 정체성을 유지하면서도(같은 책, p. x), 인지신경과학 연구가 활발해져 “의식이 작동하는 메커니즘을 연구하는 흐름이 강화되면서 정작 의식이란 무엇인지 밝히려는 치열한 철학적 논쟁이 점차 사라졌다는 사실”을 아쉬워한다. (같은 책, pp. x~xi) 이러한 내면의 긴장 또는 갈등을 그는 “신경과학 연구자의 좌충우돌”로 묘사하기도 하고, 의식 연구를 “오래된 (그러나) 깨고 싶은 금기”로 특정하기도 한다(같은 책, p. 2, 5) [박우석 (2025), pp. 68-69].

저자 자신의 학자로서의 정체성에 대한 치열한 반성 외에도 머리말에서 독자가 건질 바는 상당히 많다. 예컨대 저자는 머리말에서 “‘박쥐가 된다는 것’ 이해하기”와 “‘박쥐가 된다는 것’ 이해하기 2”라는 소제목을 단 두 개의 독립된 절에서 오늘날 의식 과학이 정립되기까지의 전사를 간략하면서도 요령 있게 서술했

다. “박쥐가 된다는 것은 무엇인가?(What is it like to be a bat?)”는 저명한 미국 철학자 토머스 네이글(Thomas Nagel)의 1974년 논문 제목이고, 그 논문에서 네이글은 의식이 ‘무엇 같은 느낌(what it is like)’이라는 주관적 특성을 지닌다고 주장했다고 한다. 초음파를 이용한 반향정위(echolocation)로 세상을 인식하는 박쥐의 주관적 경험을 인간은 결코 완전히 이해할 수 없다는 것이 한 단적인 예다. 저자의 설명에 따르면, 네이글 이후 학자들 중에는 설사 박쥐의 마음을 완전히 이해할 수는 없더라도 “무엇 같은 느낌”을 이해하는 것은 가능할지도 모른다고 본 이들이 있었다. 미국 철학자 알바 노에(Alva Noë)와 영국 심리학자 케빈 오레건(Kevin O’Regan)이 감각-운동 이론(Sensory-motor Theory)을 주창하며 “의식을 환경과의 능동적 상호작용 속에서 이해하려 한” 것이 한 사례다. 또 미국 신경생물학자 안토니오 다마지오(Antonio Damasio)가 “의식이 신체적 감각과 감정에 깊이 뿌리박고 있다”고 주장하면서 의식을 원초적 자아(Proto-self), 핵심 의식(Core consciousness), 그리고 확장된 의식(Extended consciousness)의 세 가지 층위로 구별한 것이 또 다른 예이다. 의식을 단순히 뇌의 내부 기제로 취급하지 않고 신체와 환경의 상호작용 속에서 이해하려는 이 이론들은 “의식에 대한 전통적인 표상주의적 접근과는 다른 관점을 제시하며, 체화인지(embodied cognition) 패러다임과 연결된다”고 한다. (pp. xiv-xv)

1장에서 저자는 의식 문제의 중요성을 강조하기 위해 그것이 왜 오랫동안 금기시되었는지를 반성하는 일견 대단히 위태로운 전략을 취하고 있다. 얼핏 의식 연구를 알게 모르게 기피하는 현상이 자칫 사이비 과학에 빠질까 두려워하는 신경과학자들에게 국한된 것으로 여길지도 모르지만, 이런 조심스러움은 심리철학자들에게서도 마찬가지로 발견되기 때문이다. 다시 말해서, 저자는 의식 연구가 금기시된 원인을 추적한 결과 그 자신도 설득되어 의식 연구를 기피하게 될 가능성이 있다는 점을 충분히 인식하고 있다. 전문가는 물론 아니지만 심리철학의 다양한 분야에서 제기되는 문제들을 다루는 데 별다른 부담감을 느끼지

못하는 나부터도 의식의 문제에는 감히 도전할 용기가 나지 않는다는 점을 상기할 때, 이 문제와 정면으로 대결하려는 저자의 결단에는 비장감마저 느껴진다.

실제로 저자는 "의식 과학 연구를 더 이상 금기시해서는 안 된다"는 대단히 강한 결론으로 1장을 마무리한다. 그러나 역설적으로 이 결론의 논거가 충분히 제시되었는지에 대해서는 상당히 의구심이 든다. "왜 의식은 그토록 오랫동안 금기였을까?"라는 질문에 대한 저자의 답변은 두 가지로 요약된다: "첫째로, 인공지능 연구에 대한 높은 기대가 실망으로 변했던 점을 들 수 있다"; "둘째, '골상학(phrenology)'과 '내성법(introspection)에 대한 깊은 의심이다". (p. 3) 첫째 논점과 관련하여 저자는 인공 신경망 개발이 제대로 평가받기까지 인공지능 연구가 인고의 세월을 감내하면서 "'의식'이라는 개념이 'C-word'로 불리며, 언급 자체를 꺼리는 분위기가 형성되었다"고 설명한다. 인공지능 연구가들이 인공 신경망 개발 과정에서 인간의 고차원적 인지를 구현하려 했기 때문에 "높은 기대가 실망으로 변했다"는 이야기 같다. 20세기 중엽 이래 관련된 여러 분야에서 일어난 일들에 관해 저자의 시각에서 이해한 바를 피력하는 것인 까닭에 서술이 불가피하게 애매모호하다는 느낌을 받지만, 매우 중요한 단서들이 제공되고 있다는 점은 부인하기 어렵다. 아마도 그 단서들로부터 유의미한 탐사가 이어지기 위해서는 구체적인 시기가 적시되고 거론한 사실들과 더불어 저자가 염두에 둔 인물들이 특정되어야 하리라고 본다.

영화와 드라마에서 다뤄진 의식 개념을 분석하는 2장과 3장

"대중매체에 등장한 의식 문제"라는 제목을 단 2장과 "대중화된 의식 과학 연구"라는 제목을 단 3장은 의식이 왜 철학과 과학에서 문제가 되는지 잘 이해하기 어려운 일반 대중들을 보물섬으로 유혹하는 신비스럽고 오묘한 지도다. 저자가 의식을 주제로 강좌를 정기적으로 개설할 행운을 누렸을지 여부는 확인할

길이 없지만, 영화 감상에서 출발해서 깊이 있는 문제로 나아가도록 정교하게 설계된 내용을 볼 때 오랜 기다림 끝에 마침내 얻은 수강생들 면전에서 열강하는 저자의 모습이 생생하게 그려진다.

2장은 TV 시리즈 <웨스트월드(Westworld)>와 두 편의 영화, <2001: 스페이스 오디세이(2001: A Space Odyssey)>와 <그녀(Her)>에서 다뤄진 의식 개념을 분석함으로써 아주 자연스럽게 독자를 의식이라는 주제에 빠져들게 만든다. 다행스럽게도 이 세 작품을 모두 즐겁게 관람했었기 때문에 저자의 해설을 통해 이해를 심화하는 기쁨이 쏠쏠하다. 유능한 평론가라면 당연히 <웨스트월드>가 마이클 크라이튼(Michael Crichton)의 소설을 기반으로 제작되었고, 그 스스로 만든 동명의 영화가 흥행에도 성공했으며, 2016년 방영된 TV 시리즈는 그 작품의 리메이크라는 정보를 어김없이 제공할 것이다. 그러나 "2016년 작 <웨스트월드>는 단순한 리메이크를 넘어, 줄리언 제인스(Julian Jaynes)의 저서 『양원적 마음의 해체와 의식의 기원(The Origin of Consciousness in the Breakdown of the Bicameral Mind)』(1976)에서 많은 영감을 받았다는 해설은 상당히 뛰어난 평론가에게서도 듣기 어려운 이야기일 것 같다. 더구나 역사와 고전 문헌학 연구를 통해 "인간 의식을 진화의 필연적 산물이 아니라 문화적·언어적 발달의 결과"로 본 줄리언 제인스의 양원적 마음 이론이 현대 심리학에서는 사실로 받아들이지 않지만 "의식, 사고, 인지 작용에 대한 탐구에 상당한 영향을 미쳤다"는 정보는 아마도 평론가가 의식과학자가 아닌 한 제공이 불가능할 것이다. 고대인들은 자각이나 내면 독백을 하지 못했고 문자 발명 등 "사회문화적 변화가 뇌의 두 반구를 연결해 의식을 언어로 표현할 수 있도록 만들었다"는 제인스의 양원적 마음 이론의 아이디어도 흥미롭지만, 이 개념이 "로저 스페리(Roger Sperry)와 그의 제자 마이클 가자니가(Michael Gazzaniga)가 1967년 발표한 분리뇌(Split-brain) 실험을 바탕으로 한다"는 것, 그리고 <웨스트월드>에서 호스트가 "내면의 목소리를 듣게 되면서 자의식을 갖게 된다"는 설정이 양원적 마음 이론을 활용한 것이라는 해설

에 이르러서는 저자를 TV 교양 프로그램 고정 출연자로 적극 천거하고 싶어진다. (pp. 13-14)

3장을 구성하는 세 절은 각각 “뇌 읽기”, “뇌 쓰기”, “뇌 바꿔치기”라는 흥미진진한 제목을 달고 있다. “뇌 읽기”는 초능력자가 미래의 범죄를 사전에 예측해서 범죄자 체포를 돕는다는 “2002년 개봉한 스티븐 스필버그(Steven Spielberg) 감독의 SF 스릴러 영화 <마이너리티 리포트(Minority Report)의 설정”을 거론하는 데서 시작해서 “뇌 활동을 해석해서 인간의 생각을 읽을 수 있다는 개념은 기능적 자기공명(fMRI)이나 뇌전도(EEG, Electroencephalography) 같은 뇌 영상 기술이 등장하면서 꾸준히 제기되어 왔다”는 관찰로 이어진다. (pp. 22-23) 한편 “뇌 쓰기”는 “2010년 크리스토퍼 놀란(Christopher Nolan) 감독의 SF 액션 스릴러 영화 <인셉션(Inception)>의 주요 줄거리”에 기대어 논의를 전개한다. 그 영화에서 주인공은 ‘추출’이라는 기술로 타인의 꿈에 침투해서 생각을 훔치는 전문가인데, 추출이 아니라 ‘인셉션’, 즉 아이디어를 심어 달라는 의뢰를 받게 된다. 저자는 “타인의 생각을 조작하는 방법으로, 꿈속에서 정보를 훔치는 기술을 활용한다는 점”이 이 영화가 보여준 “참신한 발상”이라 여긴다. 실제 의식 연구가 “꿈, 수면 각성 등 다양한 의식 상태를 탐구”하므로, 이 영화의 설정과 전제된 개념이 “인간의 의식의 경계와 공유 가능성에 대한 철학적 질문을 불러일으킨다”는 저자의 지적에 공감하지 않을 수 없다(pp. 24-25). 마지막으로 “뇌 바꿔치기”는 중국 민간 설화에서 실제 사례들에 이르기까지 장기 이식과 관련된 이야기로 운을 뗀 다음 “뇌를 마음의 장기로 인식하기 시작한 이후, 역사적으로 극히 드물지만 뇌 이식이 시도된 적이 있다“는 사실에 독자의 주의를 환기시킨다. 개와 원숭이를 대상으로 머리를 몸통에 이식하는 실험을 했을 뿐만 아니라 2015년에는 인간 뇌 이식 수술 계획이 발표되었고, ”2017년에는 카데바(시신)를 이용한 뇌 이식 수술 리허설을 진행했다”고 한다(pp. 26-27).

철학적 관점에서 의식의 본질과 정의를 재고하는 4장과 5장

4장과 5장은 저자가 마지못해 억지로 쓴 부분일지도 모른다. 물론 그런 생각은 이 부분을 별로 꼼꼼히 읽고 싶지 않기 때문에 떠올랐을 수도 있다. 의식의 사전적 정의에 문제가 많고, 의식의 본질을 규명하고자 철학자들이 오랜 기간 동안 다양한 이론들을 제시해 왔지만 우리는 여전히 오리무중 상태에 있다는 것이 저자가 하고자 하는 이야기 아니겠는가? p. 35에서 저자는 ”이처럼 다양한 사전적 정의를 종합해보면, 의식이란 깨어 있는 상태에서 자신과 외부 세계를 인식하고, 생각·감정·의지를 통해 주변을 이해하며 반응하는 정신적 작용이라 할 수 있다“고 쓰고 있다. 저자의 지적대로 이런 정의에는 문제가 많다. 그래서 저자는 “의식을 제대로 정의할 수 있을까? 나아가 정의가 반드시 필요할까?”라고 자문하기도 했는데, 그러는 저자에게 독자들은 이미 충분히 공감하고 있다. 불가사의한 점은 대동소이한 정의가 p. 23, p. 27, p. 36에도 등장한다는 사실이다. 특히 의식이 복잡하고 복합적인 현상이라는 생각은 저자의 사고를 철저히 지배하고 있는 것으로 보인다. 여기서 혹시 저자가 의식의 이론적 정의를 추구하는 지난한 여정에 오르기 전에 이미 뭔가 선결문제 요구의 오류를 범하고 있지는 않은지 우려되기도 한다. 마찬가지로, 단 하나의 장에 철학사 전체 또는 현대 심리철학 전체를 적절하게 요약하는 일을 저자에게서 기대할 독자는 단 한 명도 없기 쉽다. 불가능한 일이기도 하고, 그 일은 당연히 철학사나 심리철학 책들에게 맡기면 된다.

하룻밤 자고 나서 생각이 많이 바뀌었다. 꿈속에서도 계속 툴툴대며 의식을 정의하는 문제와 심리철학의 근본 문제들과 씨름했나 보다. 저자가 이 부분을 쓰기 싫어 원고지 매수만 억지로 채우는 모습을 상상한 것은 그 어려운 문제들이 왜 그토록 중요한지를 전혀 이해하지 못하는 나 자신에게 분통이 터졌기 때문이었던 것으로 여겨진다. 사실은 저자 자신이 의식의 정의로 제시된 것들에 대해 불만을 느끼고 더 나은 정의를 모색하면서 겪어 온 과정을 있는 그대로 보여주

려는 의도가 이 부분의 서술에 그대로 반영된 결과일 가능성이 높다. 현대 심리철학에서 필수 종목이라고 할 기능주의, 환원주의, 다중 실현 가능성(Multiple realizability), 감각질(qualia), 존 설(John Searle)의 중국어방 논변 등이 주마간산격으로 소개된 것도 몇 줄로 그것들을 다 소화할 수 있다고 믿어서가 아니라 겹겹이 쌓인 난제들과 씨름하다 좌절하고, 포기했다가는 다시 어느 틈에 그것들의 해결에 고심하고 있는 저자의 일상이 생생하게 독자들에게 중계되기를 바랐기 때문인 것으로 보인다. 의식의 문제는 고사하고, 심리철학의 상투적 문제들에 관해서도 A4 용지 열 장 남짓의 소위 연구논문을 써서 SCI급 학술지에 게재하는 일은 상상 이상으로 어렵다. 그러나 학계에서 살아남으려면 연구논문 편수를 어떻게든 채워야 한다. 어쩌면 의식 문제와 심리철학의 다양한 문제들에 관해 논문을 써볼 생각을 단념했던 것은 생존을 위한 불가피한 선택이었던 것 같다. 용서받을 수는 있을지 몰라도 대단히 비겁한 선택이었다는 점을 부인하기는 어렵다. "페르마의 마지막 정리"라는 난제를 풀기 위해 수년 간 다른 일을 전혀 하지 않았다는 앤드류 와일즈(Andrew Wiles) 흉내를 내지는 못하더라도 최소한 저자처럼 의식의 문제와 심리철학의 문제들과 정면으로 대결했어야 하는데, 나는 그러지 못했다. 또 하룻밤 자고 나면 어떻게 생각이 바뀔지 모르지만, 이 책의 독자들은 현실을 직시하되 불굴의 자세로 한 걸음씩 전진하기를 바란다.

의식과학의 이론적 배경을 설명하면서 주요 의식 이론을 정리하는 6장과 7장

이 책의 핵심은 6장과 7장일지 모른다. 아니 반드시 그래야 하는데, 왜냐하면 그 부분에서 무엇인가 배울 수 있으리라는 기대 때문에 이 책을 펼쳐 읽게 되었기 때문이다. 머리말에서 저자가 스스로 이 책에 대해 "깊이 있는 설명이 부족하다"고 고백하면서도 (p. xviii) 독자들의 "확장된 독서와 연구에 도움이 되도록" 기획했다는 점을 명시했다는 점도 (p. xvii) 모두 이 부분에 관한 이야기라

야 앞뒤가 맞는다. 저자의 의도와 독자의 관심이 이만큼 일치하기도 쉽지 않으리라 여겨진다. 저자가 안내하는 대로 확장된 독서를 열심히 하면 과연 연구라고 할 만한 활동을 통해 가시적인 성과를 낼 수 있을까? 나는 기꺼이 실험에 자발적으로 참여하는 모델 생물의 역할을 맡고 싶고, 언젠가는 부족하더라도 그 실험 결과를 보고하고 싶다.

저자는 "과학 문제로서의 의식"이라는 제목의 6장에서 현재 의식 과학 연구에서 취해지는 두 가지 접근법으로 데이터 기반 접근법과 이론 기반 접근법을 소개한다. 그러나 저자는 실험심리학과 신경과학이 취하는 전자가 현재 의식 연구의 주류라고 보고, 의식을 물리적 대상으로 보고 물리 법칙 내에서 탐구하는 후자는 소개하는데 그치고 논의의 거의 전부를 전자에 집중하고 있다.

그러나 이 두 접근법을 논의하기에 앞서 그것들 양자 모두 저자가 이해하듯 "의식에 대한 엄밀한 정의를 잠시 보류한 채" 데이비드 차머스(David Chalmers)가 '쉬운 문제'라고 부른 문제들을 해결하는 데 집중하고 있는지를 확인할 필요가 있다. 흥미롭게도 저자는 그 소위 쉬운 문제들을 차머스를 인용하여 나열한 다음 그것들을 설명하는 데 6장의 논의 거의 전부를 할애한 반면 '어려운 문제'에 관해서는 실질적으로 침묵하고 있다. 물론 저자는 1장에서 이미 차머스의 쉬운 문제와 어려운 문제 구별을 간략하게 소개했다: "'어려운 문제'는 의식의 본질과 같은 철학적 문제로, 과학적으로 해명하기 어려운 수준의 난제를 의미한다. 반면, '쉬운 문제'는 인지신경과학에서 다루는 뇌 연구와 행동의 상관성을 규명하는 과학적 문제를 가리킨다". (p. 6) 곧 이어 저자는 차머스가 그의 유명한 1995년 논문 "의식 문제와 마주하기(Facing up to the problem of consciousness)"에서 우리가 의식 문제를 정면으로 마주해야 한다고 주장했다는 점을 상기시키기까지 했다. "깨고 싶은 금기"라는 제목의 절 안에서 "새로운 프레임이 학문의 판도를 바꾼 사례로 차머스의 기념비적 논문을 거론했으므로 문맥상 차머스는 의식의 쉬운 문제뿐만 아니라 어려운 문제까지도 정면으로

마주해야 한다고 주장한 것인가?

어쨌거나 저자는 6장에서 우선 차머스가 '쉬운 문제'라고 부른 것들을 다음과 같이 열거한다: "1. 환경적 자극을 구별하고 범주화하며 반응하는 능력, 2. 인지 시스템에 의한 정보 통합, 3. 정신 상태를 보고할 수 있는 능력, 4. 시스템이 자신의 내적 상태에 접근할 수 있는 능력, 5. 주의 집중, 6. 신중한 숙고를 통한 행동 조절 메커니즘, 7. 깨어 있는 상태와 잠든 상태의 차이. 그리고 이 문제들 하나하나에 대해 많이 쓰이는 연구 기법들을 친절하게 소개해준다. 예를 들어, 1과 관련하여 자극-반응 능력의 관점에서의 연구 방법이 "19세기 구스타프 페히너가 확립한 정신물리학적 실험 방법론에 뿌리를 두고" 있고, "이후 신호 탐지 이론(Signal Detection Theory)으로 발전"했다거나 2와 관련하여 사용되는 다양한 방법 중에 "기능적 자기공명영상을 이용한 기능적 연결성 분석", "뇌전도를 활용한 정량적 분석", 그리고 "멀티모달 통합 실험" 등이 있다는 설명을 통해 독자는 언젠가 들어본 적이 있는 이야기들이 퍼즐 맞추듯 연결되는 데서 배우는 기쁨을 만끽할 수 있다. 한편 3과 관련하여 "의식적 지각의 동적 특성을 연구하는 강력한 도구"로 소개된 "양안 경쟁(binocular rivalry) 패러다임"처럼 처음 들어보는 신기한 이야기도 있다. 각각의 눈에 서로 다른 이미지를 제시하면, "두 이미지가 동시에 망막에 투사됨에도 불구하고, 의식적으로는 한 번에 하나의 이미지만 지각된다"니 참 신기하다. 당연히 나머지 문제들에 대한 논의에서도 독자는 다양한 연구기법들에 관한 유용한 정보를 얻고 개안의 기쁨을 맛볼 수 있을 것이다.

앞서 지적했듯, 문제는 6장과 7장의 내용이 어떻게 연결되는지와 관련하여 석연치 않은 점들이 있다는 데 있다. 소위 쉬운 문제들은 당연히 모든 의식과학자들이 해결하기 위해 부심하는 공통의 과제들이다. 이 문제들 각각에 대해 대표적으로 널리 사용되는 연구기법들도 아마도 의식과학자라면 누구나 사용하는 것들이기 쉽다. 그렇다면 7장에서 소개한 의식과학의 네 가지 주요 이론들은 쉬운

문제들과는 상관이 없고 오직 어려운 문제에만 관련되는 것인가? 아니면, 혹시 어느 한 의식과학자는 자신이 추종하는 의식과학의 이론에 따라 의식과학의 쉬운 문제를 연구하는 데서도 특정 연구방법에 대한 의존도가 높다든가 특정 연구기법은 금기시한다든가 하는 차이를 보이는가? 소개된 일곱 가지 쉬운 문제들은 또한 서로서로 긴밀하게 연결되어 있으리라 짐작된다. 그렇다면 추종하는 의식 이론의 차이에 따라 문제들에 접근함에 있어서 순서가 달라진다거나 문제의 중요성을 전혀 달리 파악한다든가 하는 차이를 보이는가? 일곱 문제 중 어느 하나에 관해서는 현재 경쟁 중인 의식 이론들 중 어느 한 이론이 다수설의 지위를 누리고 있고 다른 하나에 관해서는 또 다른 어느 이론이 선두주자의 역할을 하고 있다든가 하는 개관을 제공할 수는 없는가?

7장 "의식 과학에 대한 주요 이론"에서 저자는 광역 작업 공간 이론, 통합 정보 이론, 예측 이론, 그리고 재귀 처리 이론의 네 가지를 지목하고 각각에 대해 간결하면서도 풍부한 내용을 전달한다. 이 지점에서 독자는 저자가 자신의 입장을 분명히 밝히고 있지 않다는 인상을 받게 된다. 의식의 어려운 문제까지 정면으로 마주해야 한다는 것이 차머스의 주장이고 저자가 이에 공감한다면, 7장에서의 논의는 의식의 어려운 문제와 정면으로 대결하고 있는 대표적 이론들을 소개한 것으로 이해해야 할 것 같은데, 저자는 그 점에 관해서 속 시원히 갈래를 잡아주지 않고 있다. 아래에서 다시 거론하겠지만 이는 그 자체로 중대한 누락일 소지가 있고, 저자가 의도적으로 누락시킨 것이 명백하다는 점에서 좀 더 심각한 문제일 가능성을 지니고 있다.

현재 스타니스라스 드앤(Stanislas Dehaene) 등에 의해 확장되어 대표되는 광역 작업 공간 이론[Global (Neuronal, 신경 중심) Workspace Theory]에 따르면, "작업 공간에서는 수많은 정보가 무의식적으로 처리되지만, 특정 정보만이 광역 작업 공간으로 올라와 의식적으로 인식된다"고 한다. (p. 64) "의사 결정과 같은 합리적 사고를 위해 뇌에 저장된 정보 중 일부만이 사용 가능하다는

개념을 기반으로"하는 이 이론은 "의식과 인지 처리 가정을 설명하는 중요한 이론적 틀"이며 뇌 영상 연구를 통해 상당 부분 실험적으로 지지된다고 한다 (p. 65).

통합 정보 이론(Integrated Information Theory: IIT)는 정신과 의사이자 수면 신경과학자인 줄리오 토노니(G Tononi)가 스승 제럴드 에델만(G. M. Edelman)과 함께 발전시켜 온 의식에 대한 수학적 이론이다. 의식이 "뇌의 특정 영역이나 기능에서 발생하는 것이 아니라, 다양한 신경 네트워크가 서로 통합되고 상호작용하는 과정에서 형성된다"는 것이 이 이론의 핵심 주장이다 (p. 66). 데이터 기반의 실험 증거에서 출발하는 기존의 이론과 달리 순수한 이론적 작업을 추구하는 이 이론의 특징은 "의식을 주관적 경험으로 정의하며, 경험의 필수 속성에서 다섯 공리(axiom)를 도출한다"는 데서 단적으로 드러난다 (같은 곳).

예측 이론(Predictive Processing)은 뇌가 "끊임없이 감각 입력을 예측하고, 실제 감각 정보와의 차이를 최소화하는 방식으로 작동"한다고 주장하는 현대 인지과학 이론이고, 저자는 뇌가 상향식(bottom-up) 및 하향식(top-down) 처리를 동시에 수행한다는 생각이 이 이론의 핵심이라고 본다. 제이콥 호위(Jakob Hohwy), 앤디 클라크(Andy Clark) 등 철학자들과 아닐 세스(Anil Seth), 칼 프리스턴(Karl Friston)을 비롯한 다수의 신경과학자들이 이 이론을 지지하고 있지만, 저자는 이 이론이 "의식을 직접적으로 설명하는 이론"이라기보다는 "의식 연구를 위한 하나의 패러다임"으로 파악한다 (p. 68-69).

마지막으로, "재귀적(recursive) 신호 전달의 중요성을 강조하는" 재귀 처리 이론은 "시각적 의식의 핵심 메커니즘을 설명하는 유력한 이론 중 하나"다. "시스템 내 요소의 출력이 다시 입력으로 활용되는 피드백 루프(feedback loop)"가 핵심 개념인 이 이론은 "특정 자극이 의식적으로 지각되는 과정"이 "단순한 무의식적 정보 처리 과정"과 어떤 차이를 갖는지를 규명하는 것을 목표로 한다. 저

자는 이 이론이 “비선형적이고 복잡한 시스템에서 나타나는 반복적 패턴과 순환적 프로세스를 연구하는 이론적 프레임워크로, 그 응용 범위가 매우 넓다”는 데 주목하지만, 그것이 “모든 형태의 의식을 설명할 수 있을지”에 대해서는 논쟁의 여지가 있다고 보는 신중한 태도를 견지한다 (pp. 69-70). 유독 이 이론에 대해서는 대표적 이론가를 소개하지 않아 아쉽다.

애당초 기대했던 바 이상으로 저자는 의식 문제에서 주요 이론들을 명쾌하게 소개하는 데 성공했다고 판단된다. 어쩌면 저자는 이 이론들에 관해 더 자세하게 논의하고 싶었을지 모른다. 예컨대, 저자는 통합 정보 이론(IIT)이 의식을 주관적 경험으로 정의하며, 경험의 필수 속성에서 내재성(Intrinsic experience), 구성성(Composition), 정보성(Information), 통합성(Integration), 배타성(Exclusion)이라는 다섯 공리를 도출한다는 점을 설명하고 나서 이것들 하나하나에 대해 깊이 있는 논의를 하고 싶었을 것이다. 4장과 5장을 한 데 묶고 그 대신 네 가지 의식 이론들 사이의 경합 양상을 신바람 나게 중계하는 데 하나의 독립된 장을 할애할 수는 없었을까? 이쯤에서 불현듯 저자가 머리말 말미에서 1990년대가 오늘날까지 이어지는 주요 의식 과학 학회들이 설립된 시기이고, “노벨 과학상 수상자들이 제2의 연구 분야로서 의식 과학에 적극적으로 뛰어든 시기”라는 점을 강조했던 것이 상기된다. 저자는 특히 “1972년 항체 구조 발견으로 노벨 생리의학상을 수상한 면역학자 제럴드 에델만(Gerald Edelman)”을 거론하면서 그의 신경 다윈주의(Neural Darwinism)나 그가 저술한 다수의 의식 과학 연구서들이 아니라 줄리오 토노니, 칼 프리스턴, 아닐 세스 등 오늘날 의식 과학 연구를 주도하는 인물들을 길러냈다는 것을 그가 남긴 가장 중요한 유산으로 손꼽았었다 (pp. 6-7). 이 점이 상기된 까닭은 당연히 저자가 통합 정보 이론의 개척자로 토노니와 에델만을 지목한 반면, 프리스턴과 세스는 예측 이론 진영의 수뇌부에 포함시켰다는 데서 찾을 수 있다. 다시 말해, 통합 정보 이론과 예측 이론은 같은 뿌리에서 나온 것으로 보인다. 여기서 “왜 갈라졌을까?”, “설사 갈라졌다고 하더라도 다른 의식 이론들과의 싸움에서는 공동

전선을 구축할 가능성이 높지 않은가?" 등등 꼬리에 꼬리를 물고 궁금증이 증폭된다. 실제로 다수의 공동연구자들이 참여한 최근 네이처 논문은 현재 의식 이론 분야에서 주도권 싸움을 벌이고 있는 광역 작업 공간 이론가들과 통합 정보 이론가들이 어떻게 비판을 통해 서로서로 배우면서 함께 성장하고 있는지를 여실히 보여준다 (Cogitate Consortium et al., 2025).

인간이 아닌 다른 생명체의 의식 가능성을 고찰하는 8장과 9장

제목만 보고서 이 부분은 현재 의식 과학자의 "실전 맛보기"라고 할 수 있으리라 예상했다. 이 예상은 반쯤은 맞고 반쯤은 틀린 것으로 판명되었다. 우선 "비인간 모델과 의식"이라는 제목을 단 8장은 뇌 연구의 발전에 따라 동물의 의식에 대한 관심이 높아진 상황에서 저자 역시 동물 심리철학 연구에 투신할 준비를 착실하게 하고 있다는 점을 짐작케 해준다.

저자는 우선 오랫동안 유지되어 온 "뇌는 어류, 양서류, 파충류, 조류, 포유류, 인간의 순서로 진화하며, 뇌간(brainstem), 중뇌(midbrain), 전뇌(forebrain)가 차례대로 형성되고 층층이 쌓이는 방식으로 발전했다"는 믿음이 현대 진화생물학에 의해 산산이 깨어졌다는 사실을 보고하는 데서부터 논의를 시작한다. 동물의 뇌는 "단계적 축적이 아니라, 세 영역을 모두 갖춘 공통 조상에서 분기된 결과"로 설명되고, "어류 역시 뇌간만 가진 것이 아니라 중뇌와 전뇌까지 포함하고 있었으며, 인간의 경우 단지 전뇌의 비율이 상대적으로 커졌을 뿐"이라고 한다 (p. 74). 저자는 이런 사실이 무엇을 의미하는지를 묻고, 이에 대한 성찰이 인간 중심 사고에 의문을 제기하는 계기가 될 수 있다고 본다. 나아가서 저자는 2012년 7월 7일 의식을 연구하는 신경과학자, 심리학자, 철학자들이 영국 케임브리지 대학에서 발표한 "인간이 의식을 생성하는 신경학적 기질을 지닌 유일한 동물이 아니라는 사실"을 핵심적 내용으로 하는 선언문과 2024년 4월 19일 뉴욕 대학에서 의식을 연구하는 신경과학자, 심리학자, 철학자들이 발표한 "다른 포유류와

조류에게 의식적 경험이 있다는 것에 대해 강력한 과학적 근거가 있(다)"는 요지의 선언문의 원문과 우리말 번역문을 전재하고 있다 (pp. 76-79).

나 자신이 동물의 가추적(abductive) 인지에 관해 몇 편의 논문을 쓴 적이 있는 까닭에, 2024년 뉴욕 선언문의 제1 저자가 동물 심리철학 분야의 선도적 연구자 중 한 사람인 크리스틴 앤드류스(Kristin Andrews)라는 사실이 너무나 반갑고, 저자가 참고문헌에 철학 분야에서 최고 수준의 학술지인 *Synthese*와 *Philosophical Studies*에 게재된 논문들을 포함시킨 것을 보며 머지않아 저자의 철학 논문이 국제적으로 논의되리라는 확신에 가슴 설레게 된다.

"특이한 의식"이라는 제목의 9장은 존재론 분야에서 다시 저자와 조우하게 되리라는 예감을 갖게 해준다는 점에서 큰 기쁨을 준다. "공유된 의식"이라는 제목을 단 소절에서 저자는 지금까지 "의식에 대한 논의가 주로 하나의 개체를 중심으로 이루어졌다"는 데 주목하고, 그런 관행에 대해 샴쌍둥이 사례가 심각한 도전이 된다는 점을 지적한다 (p. 84). 실상 샴쌍둥이 사례는 개체화 문제로 박사 학위 논문을 쓸 때뿐만 아니라 생명의료윤리학 강의를 하면서도 마주쳤던 아주 어려운 문제다. 어디서부터 실마리를 얻어 풀어나갈지 난감한 주제인데, 저자의 공유된 의식에 관한 신경과학자로서의 관점과 이해가 많은 시사점을 제공해준다.

"2006년 캐나다에서 두개골이 연결된 샴쌍둥이로 태어(난)" 타티아나와 호간의 사례는 "시상이 연결되어 있어 감각과 생각의 일부를 공유한다"고 하며, 저자가 지적하듯, 이는 기존 의식 이론과 달리 "개별적이면서도 연결된 의식의 가능성을 보여준다"는 점에서 매우 소중한 사례로 보인다 (pp. 84-85). 그 반면, "1990년 미국에서 태어난 샴쌍둥이로, 하나의 몸통을 공유하지만 각각 독립된 머리와 뇌를 가지고 있(던)" 아비게일과 헨젤의 사례는 ("의식이 신체적 경험에 의해 형성된다"고 가정할 때) "하나의 신체를 공유하면서도 두 개의 독립적 의

식이 존재한다는 것이 어떻게 가능한지 의문이 제기된다" (p. 85). 계속해서 저자는 "1911년 태국 시암에서 태어났(고)" "샴쌍둥이"란 용어가 그들로부터 유래된 창과 엥 벙커의 사례를 소개한다. 흉골 부위가 연결된 채 태어났지만, 그들은 각각 독립적인 머리를 가지고 있었고, 협력하면서 일상생활을 영위했을 뿐만 아니라 "미국으로 이주한 후 각각 결혼해 가정을 꾸렸으며, 일정한 시간 동안 서로 다른 가족과 지내는 방식으로 생활 패턴을 조정"했다고 하는 놀라운 이야기를 소개한다 (p. 86). 저자가 지적하듯, 이 사례는 자아(self)의 독립성과 행위 주체성(agency)의 범위에 관해 중대한 질문을 제기한다.

저자는 이에 그치지 않고 "뇌 없는 사람"이라는 제목의 그 다음 소절에서 좀 더 충격적이고 도전적인 문제를 소개한다. 2007년 의학 저널 《란셋(Lancet)》이 보고한 "대뇌 피질 영역이 거의 없는 것으로 확인"된 한 44세 남성의 사례와 2014년 의학 저널 《브레인(Brain)》이 보고한 소뇌가 없는 24세 여성의 사례는 너무도 놀랍다. 후자의 경우 메스꺼움과 구토 증상으로 병원을 찾았다가 소뇌가 없다는 것이 밝혀졌다고 하는데, "약간의 보행 불안정을 제외하면 전반적으로 건강한 상태"였다고 하니 문외한으로서는 이 사례를 어떻게 이해해야 할지 어안이 벙벙할 따름이다. 신경과학자들은 이런 사례들에서 인간 뇌의 "놀라운 가소성"에 주목한다고 하는데, 아마도 그것들은 인간의 삶과 죽음의 정의와 기준에 대해서도 심각하게 재고해야 할 필요성을 깨닫게 해주는 것으로 보인다.

현재 인공지능 연구자들이 의식에 대해 고민하는 지점을 소개하는 10장

마지막으로 10장은 책에서 다루어진 내용을 반추하고 남은 문제들에 대한 전망하는 결론이자 에필로그라고 할 수 있다. 참고문헌이 대단히 부실하고, 저자는 (아직은) 한 인공지능 연구자로서 현재 인공지능 연구자들 대부분이 의식에 대해 고민하는 지점을 대변할 만한 위치에 있다고는 믿어지지 않는 까닭에 이 장

의 전반부는 실망스러운 면이 있다. 조금 더 겸손하게 외부자 내지 관찰자의 관점에서 주류 인공지능 연구자들이 언제 어디서 무엇 때문에 의식과 관련된 문제들에 관심을 보이는지 포착해서 보고했어야 하리라고 본다. 최소한 인공지능 연구와 의식 연구를 동시에 함께 하고자 하는 저자의 야심 내지 목표가 아직은 구체적으로 결실을 맺었다고 보기 어렵다. 그렇다면 이 장의 백미는 후반부에 제시한 SF 소설 구상일 수밖에 없고, 그것을 품평하는 즐거움은 독자들에게 남겨두어야 마땅할 것이다.

사족

저자가 참고문헌으로 소개한 논저들은 모두 다 의식과학의 역사에서 중요한 위치를 차지하게 된 소중한 자료들이고, 그것들로부터 출발해서 저자가 권면하는 확장된 독서에 몰입하는 즐거움은 위에서 이미 충분히 예증했다고 본다. 한 가지 아쉬운 점은 국내에서 이미 번역된 책들의 경우 서지사항을 알려주는 친절함이 저자에게 결여되어 있다는 사실이다. 물론 저자에게 그 많은 책들을 다 구입해서 검토해야 할 의무를 지울 수는 없다. 번역서들의 질적 수준에 대해 저자는 상당히 회의적이라 짐작되고, 아마도 그런 이유로 알면서도 침묵하는 결단을 내렸다고 여겨진다. 그럼에도 불구하고, 확장된 독서를 열망하는 독자들이라 해도 그 많은 자료들을 원서로 독파할 가능성은 거의 없고, 또 그럴 결심을 한 열혈 독자들의 짐을 덜어주기 위해서라도 번역서의 존재는 알려주는 편이 나았으리라고 본다.

앞에서 누차 강조했듯이, 이 책은 가지 못한 길에 대한 회한을 일깨우는 동시에 무덤으로 가는 길을 두려움 없이 걸어 나가게 해준다. 저자에게 깊이 감사하면서 사족에 사족을 하나 더 덧붙인다. 광역 작업 공간 이론가들과 통합 정보 이론가들 사이에 과학적 논쟁뿐 아니라 철학적 논쟁이 점점 더 치열해지고 있는

현재 상황에서 저자는 “의식이 작동하는 메커니즘을 연구하는 흐름이 강화되면서 정작 의식이란 무엇인지 밝히려는 치열한 철학적 논쟁이 점차 사라졌다는 사실“을 아쉬워한다 (p. xi). 저자의 이런 소회를 앞에 두고 두 가지 차원에서 복합적 가정을 느끼지 않을 수 없다. 첫째, 전세계적으로 의식 연구의 현황을 조감할 때, 저자의 느낌은 대체로 정확하리라 본다. 그러나, 그렇다면, 저자는 비록 극소수이기는 하지만 20세기말 의식 문제에 관해 최소한 단행본 저서를 냈던 심리철학자들의 사상을 좀 더 진지하게 다뤘어야 마땅하지 않을까? [Carruthers, P. (2005); Dennett, D. C. (1992); Lycan, W. G. (1987)] 물론 저자가 암암리에 가정하듯 20세기 후반과 21세기 초에 이루어진 철학자들의 의식 논의가 차머스의 비판에 의해 일거에 무색해졌다고 볼 수도 있다. 그러나, 설사 그렇다고 하더라도 차머스 이후 심리철학자들이 전적으로 침묵을 지키고만 있지는 않을 것이고, 최소한 차머스에 의해서라도 의식의 어려운 문제에 대한 철학자들의 논의는 명맥을 이어가고 있을 것이다. 특히 차머스의 경우 지속적으로 활발한 저술활동을 벌이고 있을 뿐만 아니라 (유튜브만 보더라도) 논의의 상당 부분에서 의식 과학자들의 최근 연구에 초점을 두고 있다고 여겨지므로, 저자가 그의 최근 사상에 관해 거론하지 않은 것은 자못 서운하다. 최근 우연히 발견한 한 논문은 명백히 의식 과학자가 쓴 것인데 놀랍게도 의식 철학이나 심리철학에 국한하지 않고 과학철학자 마이클 프리드만(Michael Friedman)의 칸트 해석을 통합정보 이론에 접목시키는 시도를 보이고 있었다 [Chis-Ciure (2025); 프리드만 (2012)].

그리고 이런 생각의 흐름은 다시 저자가 머리말에서 고백한 바로 되돌아간다: ” 필자는 의식에 대한 관심을 내려놓을 수 없어 사비를 들여 의식 과학 학회에 참석해 왔다. 공적 연구비 지원을 받을 수는 없었다. 2014년부터 참여한 학회에서는 주요 이론 간의 대립이 첨예하게 펼쳐졌으며, 한 분야에서 권위자로 인정받는 대가일지라도 의식 문제를 다루는 데는 서툴 수 있다는 점을 직접 목격하며 배웠다. 약 10년이 흐른 뒤, 학회의 성격은 더욱 과학적인 방식으로 의식을 연구

하는 방향으로 발전했다. 이는 인지신경과학 연구가 활발해진 영향인지도 모른다“ (p. x-xi). 짧지만 이 고백 내지 보고는 대단히 함축적으로 국내에서의 의식 연구의 산 역사를 보여준다. 사이비 뇌과학자들이 출판시장을 교란하고 대중을 혹세무민하는 사이 진짜 의식 과학자와 철학자들은 가시밭길을 걸어왔다는 말이다. 차머스의 1995년 논문이 실렸었고, 그 후 의식 과학 연구에서 빼놓을 수 없는 매체가 되어 온 *Journal of Consciousness Studies*를 카이스트 도서관이 구독하지 않고 있다는 사실을 극히 최근에 알게 되었는데, 너무도 믿어지지 않는 일이라서 내가 검색에 서툴러 찾지 못했으리라 믿고 있는데, 가부간에 저자의 고백의 진실성과 그것이 의미하는 바는 가감 없이 충분히 전달된다. 페북 활동을 통해 거론된 학회의 활동에 대해 잘 알고 있었고, 차마 학회에 가입할 용기를 내지 못했을 뿐 멀리서 계속 응원해 왔고, 이제 학회 회원들이 탐스런 결실을 맺는 모습을 목격하며 아낌없는 찬사를 보내게 된다. 이제 국내에서 벗어나 전 세계의 의식 연구를 선도하는 학회로 거듭나기를 학수고대한다.

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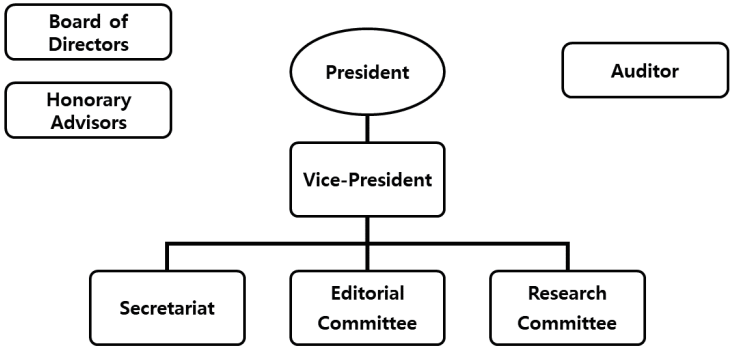

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논문투고 규정 및 작성요령

1. 논문투고자는 본 학회의 회원에 한한다. 단, 비회원은 공동연구자로 참여할 수 있다.
2. 논문은 본 논문지에 투고하기 전에 공개 출판물에 발표되지 않는다.
3. 투고 규정에 위배되는 원고는 접수하지 않는다.
4. 논문은 연중 수시로 접수하되, 학회지 발행 예정일 2개월 전에 해당호에 게재할 논문을 마감한다.
5. 논문의 심사는 전문가 심사과정(peer review processor)에 따라 진행하며, 본 학회의 심사규정에 따른다.
6. 논문의 채택여부는 본 학회지 편집위원회의 결정에 따르며, 논문의 부분적 수정을 요구할 수 있다.
7. 논문투고자는 1부를 작성, 투고신청서와 함께 사무국장의 공식 이메일로 제출한다.
8. 논문 첫 쪽에 제목, 성명, 소속기관 (모두 영문 포함), 연구분야, e-mail 등을 기입한다.
9. 논문은 영문초록(주제어 포함), 본문, 참고문헌의 순으로 한다.
10. 논문의 영문초록은 500단어 이내로 한다.
11. 논문은 [별첨1] 국제바둑학회지 투고논문 편집지침에 맞추어 제출한다.
12. 논문은 [별첨1] 을 기준으로 A4 20장 내외로 한다.

[별첨1] 국제바둑학회지 투고논문 편집지침

1. 한국어 논문은 한글과컴퓨터사의 한글로 작성하는 것을 원칙으로 한다.

2. 형식 지침

제출하는 논문의 형식은 아래와 같은 형식을 권고한다.

- 제목은 한글 함초록바탕 18, 굵은체, 그 다음 줄에 영문 제목은 Times New Roman 18, 굵은체, 중간 정렬로 한다.
- 저자 이름은 한글 함초롱바탕 12, 그 다음 줄에 영문 이름은 Times New Roman 12, 우측 정렬로 한다.
- 저자 소속은 한글 함초롱바탕 12, 그 다음 줄에 영문 소속은 Times New Roman 12, 우측 정렬로 한다.

3. 논문의 저자가 2인 이상인 경우, 논문 작성에 대한 참여 정도에 따라 책임저자(제1저자), 공동저자(제2저자) 등으로 공동 저자의 순위를 정하고 참여 정도가 동등한 경우 공동저자라고 밝히고 저자들을 '가나다' 또는 'ABC' 순으로 기재한다. 영문인 경우 책임(1st author), 공동(Co-author, 2nd author, 3rd author…) 등으로 명기한다. 모든 논문은 교신저자(Corresponding author) 표기를 해야 하며, 단독 저자 논문의 경우 단독 저자를 교신 저자로 표기하는 것을 원칙으로 한다.
4. 한글의 경우 본문은 함초롱바탕, 글자크기 10, 장평 100, 자간 0%로 한다.
5. 원고 중 장에 해당되는 번호는 로마자(Ⅰ, Ⅱ …)로, 절에 해당되는 번호는 아라비아자(1, 2, 3,…)로 표시한다.
6. 그림과 표의 제목은 아래에 써넣고, 본문에서 그림과 표에 대한 언급은 괄호를 사용하지 않고 언급한다.
7. 참고문헌에서 문헌 나열은 한글을 먼저 '가나다' 순으로 나열하고 그 다음에 외국어 문헌을 언어별로 분리하여 알파벳순으로 나열한다.

[별첨2] 연구윤리확약서

1. 저자(들)는 본 논문이 창의적인 것이며, 위조, 변조, 표절, 부당한 저자 표시, 중복 게재 등의 연구부정행위를 하지 않았음을 확인합니다.
2. 저자(들)는 본 논문에 실제적이고 지적인 공헌을 하였으며 논문의 내용에 대하여 책임을 함께 합니다.
3. 본 논문은 과거에 출판된 적이 없으며, 현재 다른 학술지에 게재를 목적으로 제출되었거나 제출할 계획이 없습니다.

Regulations for Submission
Journal of Go Studies

1. All submissions to the *Journal of Go Studies* should be limited to members of the International Society of Go Studies; Non-members are allowed to participate as joint authors.
2. Authors must not submit their manuscripts that have already been published in a domestic/foreign journal without disclosing the fact. Also, the same manuscript shall not be submitted to more than one journal at the same time.
3. The manuscripts that violate the submission rules will not be accepted.
4. Author(s) may submit manuscripts at any time of the year. However, the manuscripts to be published in the upcoming volume should be submitted no later than two months before the due date of publication.
5. The manuscript shall be reviewed according to the peer review process and the regulations of this society.
6. Whether or not to accept a manuscript is subject to the decision of the editorial committee of the journal, and partial revisions of the manuscript may be requested.
7. Author(s) shall submit the manuscripts together with the submission application form via the official e-mail of the Secretary General.
8. All author(s) should also include the title, the author's name, and the details of their affiliation, and e-mail address on the first page of the manuscript.
9. The manuscripts should be written in the following order: abstract, keywords, body text, and references.

10. The abstract should be approximately 500 words.
11. Author(s) should conform to the guidelines in appendixes 1 and 2 in submitting manuscripts.
12. The length of the manuscript should not exceed A4 20 pages.

Appendix 1. General Guideline

1. File Format

In principle, the manuscript shall be written in MS Word (.doc or .docx).

2. Specifications for Manuscripts

All manuscripts should be formatted for publication according to the style notes below;

- The title of the article: Times New Roman 18 bold, not indented, centered
- Author's name: Times New Roman 14, line space above
- Author's workplace or affiliation, nation: Times New Roman 12, italicized

3. Authors' Names & Corresponding Author

If there are more than one author, their names should be listed sequentially, beginning with the author who has made the greatest contribution to the article followed by the other writers in descending order, the Primary author (1st author), Co-author, 2nd author, 3rd author, etc. If equal contributions to the article were made, names of co-authors should be provided in alphabetical order. Every article should have a corresponding author. Therefore, in the case of a single author article, he/she should be designated as the corresponding author.

4. Body of the Article

   In the case of English manuscripts, the font shall be Times New Roman, font size 11, 100% character spacing, and single line spacing.

5. Headings

   The level 1 headings shall use Roman numerals (I, II…), while other heading levels shall use Arabic numerals (1, 2, 3…).

6. Figures and Tables

   The title of the figures and tables should be placed below, and the in-text references mentioned without using parentheses.

7. In the reference list, the references should be sorted in the languages as following order; English and then the others in the alphabetical order.

Appendix 2. Research Ethics Guideline

1. The author(s) confirm that this manuscript is original and did not commit research misconduct such as forgery, falsification, plagiarism, unfair indication of authorship, or duplicate publication.
2. The author(s) have made practical and intellectual contributions to this paper and share responsibility for the contents of the paper.
3. The author(s) have never published the manuscript or translations of it in the past, they have not submitted it, and have no plans to submitted it for publication in other academic journals.

국제바둑학회 (International Society of Go Studies)

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