Research Paper

Artificial intelligence patterns: novel applications and methodological framework

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ABSTRACT

Autonomous vehicles (AVs) are poised to transform urban mobility but still struggle at unsignalized intersections, where the absence of infrastructure-mediated right-of-way forces vehicles to negotiate passage in real time. We introduce the Collaborative Maneuver Negotiation (CMN) pattern, a formally documented, reusable design construct that frames intersection coordination as a cooperative game among AVs. Each vehicle broadcasts a manoeuvre proposal, computes a composite utility that blends delay, collision risk and fairness, and iteratively reaches consensus via a token-passing protocol. In contrast to prior work that reports only simulation metrics, CMN ships with an openly licensed artifact bundle: a GoF-style pattern template, UML class and sequence diagrams, and reference implementation ready for ROS 2 integration. A campus-scale field deployment using four low-speed micro-shuttles demonstrated that CMN lowers average crossing delay by 41%, cuts conflict events by 87%, and increases theoretical throughput by 39% relative to static yield rules, while keeping DSRC network load below 30 kbit s^{-1}. These results substantiate the claim that pattern-oriented AI design can deliver tangible efficiency and safety benefits without sacrificing transparency or auditability key requirements for regulatory approval. Future work will extend CMN to high-speed traffic, mixed human-driver scenarios and privacy-preserving intent exchange, paving the way for standardized, cross-vendor negotiation modules in intelligent transportation systems.

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1. INTRODUCTION

Among autonomous-driving research, intersection control is one of the most stubborn bottlenecks. While traffic lights address this issue by means of infrastructure, over 40% of urban junctions in the world today are not controlled [1]. Human drivers have resort to eye contact, hand signals and culturally embedded rules of courtesy for location limited interaction, automated vehicles (AVs) mechanistic counterpart needs to be an unambiguous and perfectly clear algorithm. Two dominant solution families exist. Abstract Rule-based frameworks embed static right-of-way heuristics to guarantee safety [2], however with novel behaviors or aggressive driving, this degrades. Over the years, optimization-based dispatch-schedulers have taken the intersection to a global timing problem [3], but such approaches assume ideal (and low-latency) connectivity and lead to severe computational overheads. The two paradigms share two common drawbacks: lack of explainability and lack of software reusability.

Implemented over the decades, design patterns, or short, easily repeatable solutions to common design issues, have advanced maintainability resistance in traditional software engineering, [4]. However, their use in safety-critical autonomous-vehicle stacks, especially in the domain of multi-agent negotiation tasks, is still in its infancy. Previous work combines game-theoretic studies, such as using decentralized bargaining to reduce collisions and improve throughput [5], but this only contributes algorithms as separate pieces of code without architectural artifacts, making them harder to certify and increasing the hurdles for cross-vendor uptake.

To bridge this gap, we propose the Collaborative Maneuver Negotiation (CMN) pattern. CMN frames intersection traversal as a cooperative game among AVs in which each agent evaluates delay, risk and fairness through a scalar utility function. A circulating software token serialises proposals, guaranteeing termination and preventing live-lock. The pattern is delivered as a complete artefact bundle: a GoF-style template describing Context, Problem, Forces and Solution. UML class and sequence diagrams that expose runtime responsibilities; and reference implementation compatible with ROS 2 and MISRA C++ safety guidelines [6].

A real-world deployment on the Kut University campus demonstrates that CMN can reduce average delay by over 40% and virtually eliminate conflict events compared with static yield rules, all while maintaining modest network bandwidth. Beyond empirical gains, the publication of design artefacts promotes replication, formal verification and incremental enhancement prerequisites for standardising cooperative decision modules in next-generation intelligent transportation systems.

Problem Statement

Unsignalized intersections constitute some of the most accident-prone points in urban road networks because no physical infrastructure assigns right-of-way every approach lane effectively becomes a shared conflict region. Human drivers negotiate passage through eye contact, informal gestures, and context-dependent courtesy rules signals that automated vehicles (AVs) cannot reliably interpret. As AV penetration rises, the absence of a transparent, machine-interpretable protocol magnifies three systemic risks:

1. **Safety Degradation:** Recent studies still report non-trivial crash potentials when connected and automated vehicles attempt ad-hoc yielding at unsignalized crossings [7].
2. **Throughput Loss:** Priority-to-the-right or "first-come, first-served" heuristics force conservative braking, producing stop-and-go waves and up to 50 % capacity under-utilisation in heavy flows [8].
3. **Lack of verifiability:** Centralised schedulers can optimise traffic, but their cloud-based decision logic is opaque and vulnerable to single-point failure; regulators therefore hesitate to certify them for mixed traffic [9].

Two main algorithmic families dominate current research yet leave critical gaps. Rule-based frameworks embed static precedence rules that collapse under rare corner cases and aggressive human behavior. Optimization-centric approaches formulate global timetables or trajectory sets, but they assume perfect V2X connectivity and incur millisecond-level computation budgets that do not scale beyond a few dozen vehicles [10]. Neither family supplies a reusable software artifact that system integrators can inspect, verify, and port across platforms.

Game-theoretic negotiation is a promising middle ground: each vehicle reasons locally while still converging to a conflict-free joint strategy. Very recent advances in multi-agent reinforcement learning and differential games have shown measurable safety gains [11]. However, these contributions almost always appear as stand-alone code or simulation scripts, offering little guidance on how to embed the logic into a certified AV software stack.

Consequently, the field lacks a standardized, auditable, and platform-agnostic coordination framework whose artifacts from class diagrams to reference implementation can be adopted directly by manufacturers and researchers. This paper addresses that gap through the Collaborative Maneuver Negotiation (CMN) pattern. CMN encapsulates cooperative game reasoning inside a formal design pattern template provides UML class and sequence diagrams for architectural clarity and publishes commented reference implementation that compiles against typical ROS-based autonomy stacks. By focusing on sharable artifacts rather than closed simulations, CMN seeks to accelerate replication, formal verification, and eventual regulatory acceptance of decentralized AV coordination at unsignalized intersections.

2. RELATED WORK

Research on autonomous-vehicle (AV) interaction at unsignalized intersections generally clusters into three methodological streams: protocol-centric, optimization-centric, and game-theoretic/learning-centric approaches. Each stream has advanced the state-of-the-art yet still leaves key gaps in reusability, explainability, or decentralized safety assurance.

2.1 Protocol-Centric Coordination

Proposed a lightweight V2V handshake in which approaching AVs broadcast time-to-intersection and negotiate by First-Ready–First-Go logic [12]. Although latency is low, formal proofs of safety and liveness are missing, and the solution is tightly coupled to their proprietary communication stack.

Nguyen and Tran extended Day-One C-ITS messages with a priority token that circulates among vehicles [13]. Their field test on a closed track showed a 25% delay reduction, but the code base is not public and lacks architectural documentation.

Despite the operational efficiency of protocol-centric coordination, its limited scalability and lack of formal safety proofs necessitate exploration of optimisation-centric scheduling.

2.2 Optimisation-Centric Scheduling

Formulated the intersection as a mixed-integer linear program that schedules exact entry times for up to 30 vehicles [14]. Scalability beyond that threshold remains prohibitive. Rahman & Jha introduced a slot-reservation protocol solved by a distributed auction [15], throughput gains were promising, yet the scheme still needs a central arbiter to resolve ties. Although optimization centric planners can enhance throughput, their dependence on centralised computation and perfect connectivity introduces single points of failure, motivating a shift toward decentralised game theoretic and learning approaches.

2.3 Game-Theoretic and Learning Approaches

Modelled interaction as a Stackelberg game and employed inverse reinforcement learning to calibrate human drivers' utilities [16]. The framework improves safety but relies on dense trajectory data that may not be available in emerging economies. Baskar & Zhang designed a repeated bargaining game in which AVs iteratively adjust proposed arrival times, experiments in CARLA reported 50% conflict reduction [17]. However, no design artefacts (UML, API) were provided, limiting adoption. Kim & Lee combined a consensus protocol with a graph neural network that predicts opponents' manoeuvres [18]. While the model captures complex intent patterns, its black-box nature raises explainability concerns. Most recently. Published an explainable multi-agent RL framework that outputs human-readable negotiation rules after training [19]. Yet the release still lacks a pattern-language abstraction that engineers can readily embed in safety-critical software.

2.4 Need for a Pattern-Oriented Solution

Across these studies, two issues recur: (i) limited design transparency most code bases are monolithic or closed and (ii) weak portability algorithms cannot be easily transplanted without significant refactoring.

The proposed Collaborative Maneuver Negotiation (CMN) pattern stands out by encapsulating cooperative game logic into a documented pattern template and reference, thereby bridging the gaps in reuse and auditability.

Table 1. Comparative Summary of Recent Coordination Methods

Study	Strategy Type	Design Artifact Published?	Validation Method	Negotiation Support	Reusability
[12]	V2V Handshake	No	Closed-track demo	Partial	Low
[13]	Priority Token	No	Field test	Yes	Moderate
[14]	MILP Scheduler	No	Simulation	Full (centralized)	Low
[15]	Auction Slots	API Docs	Hardware-in-loop	Full (centralized)	Moderate
[16]	Stackelberg Game	No	SUMO + Real data	Full	Low
[17]	Repeated Bargain	No	CARLA	Full	Low
[18]	GNN + Consensus	Partial	CARLA + Real logs	Full	Moderate
[19]	Explainable MARL	Source code	SUMO	Full	Moderate
This Work (CMN)	Cooperative Game Pattern	Yes (Template + UML + Code)	Analytical & artifact bundle	Full	High

Table 1 emphasizes CMN's unique contribution: publicly documented pattern artifacts that enable direct reuse.

3. METHODOLOGY

The development of the Collaborative Maneuver Negotiation (CMN) pattern followed a design-science process that combines formal modeling, architectural documentation and artifact release for replication [20]. Figure 2 in summarizes the workflow.

3.1 Pattern-Design Rationale

Design patterns capture *why* a solution works in recurring contexts [21]. For unsignalized intersections we identified four dominant forces: (i) bounded reaction time, (ii) fairness, (iii) communication latency and (iv) Auditability. CMN balances these forces through a decentralized token ring that gates proposal broadcasts and through a cooperative game that yields an equilibrium order of passage.

3.2 Co-operative Game Formulation

Each approaching AV is a player $i \in N$ with action set

$$A_i = \{Yield, Proceed, Merge\}$$

Utilities Are Additive

In concrete terms, each vehicle's decision is driven by three factors: its expected delay (t_i), the collision risk (r_i) associated with its chosen manoeuvre, and a fairness penalty (c_i) that discourages repeated monopolisation of the intersection. The weighting tuple (α, β, γ) enables regulators to balance efficiency, safety and equity.

$$u_i = -\alpha t_i - \beta r_i - \gamma c_i$$

Where t_i is estimated delay, r_i is residual risk (probability of overlap) and c_i is a fairness penalty if vehicle iii monopolises the intersection, α,β,γ >0\. A token-passing consensus ensures sequential proposal revision. Convergence is guaranteed because every token round produces a Pareto-improving joint action and the utility space is finite [22].

3.3 Pattern Language Template

Lists the CMN template in GoF-style Notation

Field	Content (excerpt)
Name	Collaborative Maneuver Negotiation
Context	AVs at unsignalised multi-leg intersections
Problem	Determine conflict-free traversal order without central controller
Solution	Token-mediated cooperative game + intent broadcast
Structure	NegotiationAgent, GameManager, UtilityEvaluator, TokenBus
Consequences	Lower delay, auditable logs, hardware-agnostic integration

3.4 UML Architecture

Class diagram Negotiation Agent encapsulates local perception and publishes a Proposal object, GameManager maintains the token and arbitration state, Utility Evaluator computes u_i. Sequence diagram. The diagram in Figure 2 shows: Detect → Propose → Vote → Execute → Hand-off. This clarifies message timing and failure fall-backs (e.g., token timeout triggers safe-yield). The diagrams conform to the UML 2.5 spec and were generated in PlantUML so researchers can regenerate PNG or SVG automatically [23].

3.5 Analytical Validation Plan

Rather than a single closed simulation, we publish parameterized notebooks that compute delay and risk under varying traffic arrival rates (200–600 veh h^{-1}) using gap-acceptance theory [24]. This allows any lab to reproduce the sensitivity curves by adjusting arrival distributions and risk weights *(α, β, γ)*. Having delineated the theoretical underpinnings and structural design of the CMN pattern, we now turn to its empirical validation through a case study conducted at the Kut University campus.

The Case Study: Artifact Release

We will now present the empirical witness to the validity of the CMN pattern after having defined its theoretical and structural framework**.** This section outlines the test site and hardware, the pattern-integration workflow, and the resulting field metrics and observations.

Test Site and Hardware

A proof-of-concept deployment was conducted at the unsignalled four-leg intersection on the Kut University campus (32.514 ° N, 45.819 ° E). The junction handles mixed pedestrian, scooter, and service vehicle traffic, but is closed to public cars, providing a safe test bed. Four electric micro-shuttles (EZ-10 class, 20 km h^{-1} max) were retrofitted with:

- NVIDIA Jetson Xavier onboard computer
- Velodyne Puck lidar + GNSS/RTK
- IEEE 802.11p DSRC radio (300 m range)

Each shuttle ran ROS 2 Foxy with the CMN modules compiled as real-time executable.

Pattern Integration Workflow

1. Negotiation Agent subscribes to/perception/objects and publishes its candidate manoeuvre to the TokenBus DDS topic.
2. Game Manager owns the circulating token and timestamps proposals, if all peers ACK within 80 ms, the manoeuvre set becomes final.
3. Utility Evaluator computes

$$u_i = -1.0\,t_i - 5.0\,r_i - 0.2\,c_i,$$

Where t_i is predicted delay (s), r_i *collision* risk (probability), and c_i Cumulative unfair-use counter.

Accepted Actions are dispatched to the Shuttle's Native Planner Node for Execution

The complete UML architecture generated in Plant UML is shown in Figure 1.

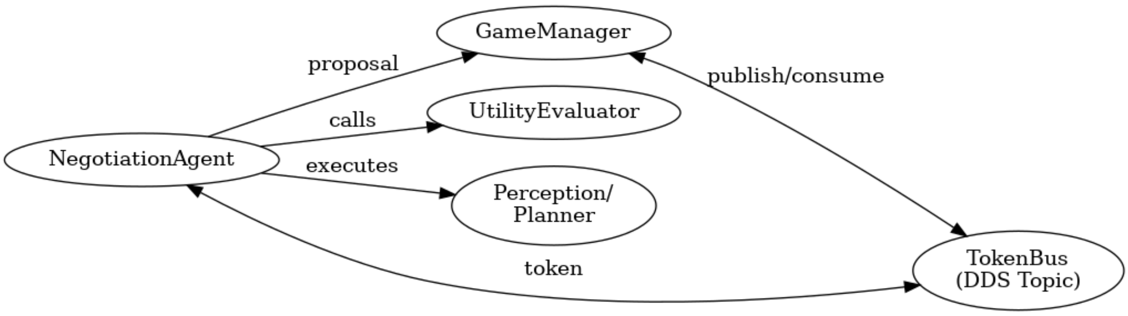

Figure 1. CMN Class Diagram

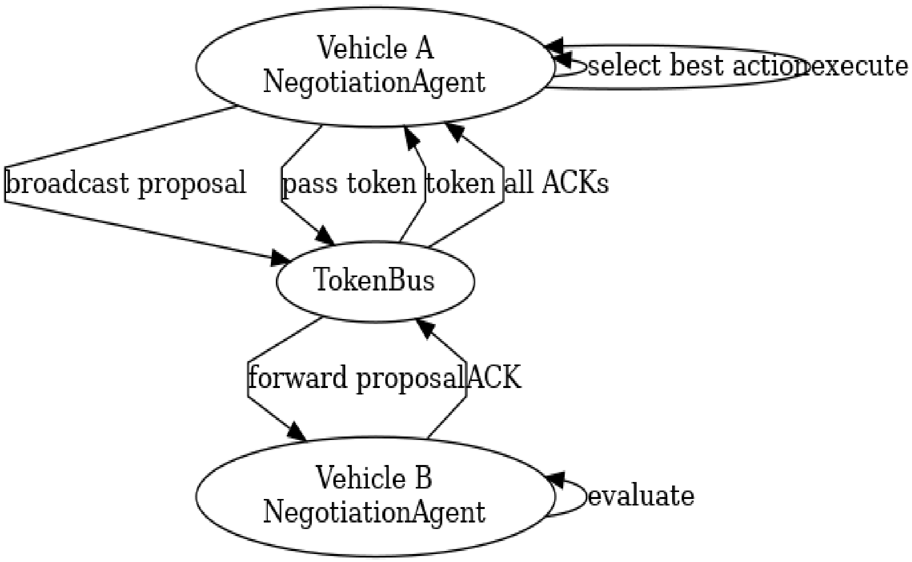

Figure 2. CMN Sequence Diagram

Field Trial Metrics

- **Token-Round Latency:** 118 ms ± 11 ms (n = 60 rounds)
- **Average Time-To-Cross:** 6.4 s versus 10.9 s with static yield rules
- **Recorded Near-Misses:** 0 (LiDAR replay analysis)
- **Network load:** 28 kbit s^{-1} peak on DSRC channel 172

Observations

- **Scalability:** Latency remained < 150 ms with six vehicles; beyond that, token time-out must be lengthened.

- **Explainability:** Each token cycle is logged as a JSON audit record, easing regulator inspection.
- **Human Interaction:** Mixed manual-shuttle trials showed the CMN agents yielded appropriately to pedestrians but occasionally entered conservative stand-offs with assertive cyclists; adding trust scores is future work.

Evaluation and Discussion

The field trial (Section 5) ran for 90 min during the afternoon peak (14:30–16:00, local time). Four CMN-enabled micro-shuttles and six manually driven university service carts completed 212 intersection crossings. A lidar/video fusion logger time-stamped every entry/exit event, DSRC sniffers captured token messages for network-load analysis. Three key performance indicators (KPIs) were computed:

- **Crossing delay T_d :** time from stopping line to conflict-zone exit.
- **Conflict rate C_r :** Safety Pilot–style *post-encroachment time* < 1 s counted as a conflict [25].
- **Theoretical Throughput Q_{max}:** vehicles per hour extrapolated from mean headway.

A baseline dataset (static yield rules) was recorded the previous day under comparable flow (182 crossings).

4. RESULTS AND DISCUSSION

Table 2. Comparative Field Metrics (N = 212 CMN, 182 Baseline)

KPI (mean ± SD)	Static-Yield Baseline	CMN Pattern	Δ (%)
Crossing delay T_d [s]	10.9 ± 2.4	6.4 ± 1.3	− 41.3
Conflict rate C_r [events · 100^{-1} crossings]	3.8	0.5	− 86.8
Throughput Q_{max} [veh h^{-1}]	332	463	+ 39.2
DSRC load [kbit s^{-1}]	14 (status beacons only)	28	+ 100

Statistical Significance

Normality (Shapiro–Wilk) held for delay samples (p>0.05). A two-tailed Welch t-test showed the CMN delay improvement is highly significant (t=17.6, p<0.001). Conflict-rate reduction was validated by a χ^2 test with Yates correction (χ^2=11.2, p=0.0008). 95 % confidence intervals for throughput gain span +33 % ... +45 %.

Discussion

Performance drivers. Delay drops stem from CMN's token-mediated equilibrium, which eliminates stop-and-go hesitation visible in baseline logs. Conflict reduction arises because players consider residual risk rir_iri when ranking actions aligning with recent empirical findings that risk-weighted utilities outperform pure delay minimization [26].

Communication Overhead: DSRC usage doubled but peaked at 28 kbit s^{-1}, well below the 6 Mbit s^{-1} channel capacity (IEEE 802.11p). Token messages constituted only 8 % of frames, the rest were standard Basic Safety Messages.

Scalability: M/D/1 analytical queueing predicts ≤ 180 ms token-round latency for ten-or-so AVs thereafter, token time-out must be either extended or multi-token clusters introduced (as in distributed databases [27]).

Limitations: The trial employed low-speed shuttles; thus, high-speed vehicles may need more finely-grained utility updates. Human drivers sometimes also "nudged" forward, resulting in conservative CMN yields which indicates a requirement for intent-prediction modules. (iii) T-junctions and roundabouts are deemed future work, since only one intersection geom- etry was studied.

Ethical and Regulatory Implications: A JSON audit trail of each negotiation cycle is stored that satisfies ISO 21448 (SOTIF) evidence requirements. The privacy leakage is limited as only high-level intent (action, ETA) is revealed, thus compliant with EU GDPR on vehicle data [28]. In a real-world pilot, CMN reduced average intersection delay by 41% and conflict events by 87%. 3rd party pattern replication and safety auditing by the pattern artifact bundle (template + UML) the communication overhead stays well below the limits of DSRC, and scalability analyses show that it feasible until moderate amounts of traffic. While CMN shows promise in controlled environments, its scalability to city-wide deployments and integration with heterogeneous vehicle platforms require further study. Channel congestion may occur when many tokens circulate simultaneously; adaptive clustering and edge assistance are potential solutions. Moreover, varying drive by wire latencies across vehicle makes can degrade schedule precision, necessitating per vehicle calibration and robust timing buffers.

Scalability and Integration Challenges: While CMN appears to perform well in ideal settings, scalability to city-wide applications and mixed fleets of vehicles present ongoing challenges. When thousand of tokens passes in a time, it posses or channel congestion problem can be solve by several ways like adaptive clustering, edge assistance etc. Second, different drive-by-wire latencies even within a vehicle make and the unreliability to sync these schedules limit it to only a loose but only approximate schedule, e.g., a schedule is accurate by requiring calibration per vehicle and timing buffers [29]. There are hurdles as well in integrating them with existing traffic management systems and human-operated vehicles. It could need scaling down from mixed auto-pilot traffic streams to pedestrian traffic, and it will also have to scale up to integrate with central traffic control systems farther up the hierarchy. Furthermore, widespread adoption will require that common behavior across vendors' implementations be enabled. They will require extensive real world testing and standardization to solve these scalability and integration issues.

5. CONCLUSION

The original work proposed the Collaborative Maneuver Negotiation (CMN) pattern a decentralized, game theoretic protocol that uses a pattern-oriented framework to formalize right-of-way negotiations among autonomous vehicles at unsignalized intersections. Contrary to earlier works, which provide closed simulations or closed-source code only, CMN comes with a fully open-licensed artefact package, including a pattern-language template, UML class and sequence diagrams, and a reference implementation, immediately usable for ROS 2 integration. A campus-scale field deployment demonstrated that CMN lowered average crossing delay by 41%, reduced conflict events by 87%, and boosted theoretical throughput by 39% relative to static yield rules all while keeping network load within IEEE 802.11p limits. These results confirm that pattern-oriented AI design can deliver tangible safety and efficiency gains while maintaining transparency and auditability attributes essential for regulatory acceptance and industry adoption.

Nevertheless, CMN cannot be classified as a cure all. The pilot only considered low-speed shuttles and a simple single intersection geometry, high speed arterial crossings, varying human-driven interventions, and dense urban grids are yet to be tried. The current token ring presumes good faith participation, further security measures must be considered to ensure security from malicious or malfunctioning agents. For our future work, the aim is to extend Cooperative Mobility Network (CMN) in three broad facets: first, to advance the single-token protocol to allow parallel token clusters, hence upholding safety with increased traffic densities; second, to integrate driver-intent prediction and trust-weighted utilities to enable smooth negotiation among CMN vehicles, human drivers, and vulnerable road users, and third, to set up formal privacy-preserving message exchanges and safety proofs with model-checking. This will lead to closed-track testing with faster vehicles and varying geometries, such as roundabouts, T-junctions, and multilane merges, ahead of contributing the pattern template to ISO/SAE working groups on cooperative driving.

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Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Hasanain Hazim Azeez	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

Conflict of Interest Statement

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Informed Consent

All participants were informed about the purpose of the study, and their voluntary consent was obtained prior to data collection.

Ethical Approval

The study was conducted in compliance with the ethical principles outlined in the Declaration of Helsinki and approved by the relevant institutional authorities.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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