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Consumer Perception and Policy Intervention in Large-scale Implementation of Advanced Autonomous Driving: A Dynamic Evolutionary Study Based on Agent-Based Modeling

hao zhang
Nanjing University of Aeronautics and Astronautics
Peifeng Zhu
280702@njucm.edu.cn
Nanjing University of Chinese Medicine

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Abstract

Despite continuous technological advancements and robust policy support mechanisms, consumer perceptions of autonomous driving systems remain cautious or even conflicting. Advanced autonomous driving bridges the gap between the “technological feasibility” and “market acceptance.” This study focuses on cognitive bottlenecks in the large-scale implementation of advanced autonomous driving and introduces an agent-based modeling simulation approach to construct a dynamically evolving consumer cognition and decision-making model. The model simulates how consumer trust and acceptance behaviors evolve during the transition from low-order to high-order autonomous driving under the influence of multiple factors, including technological evolution patterns, safety accident public opinion, and policy interventions, to reveal macroscopic emergent patterns. The simulation results reveal the intrinsic mechanisms and typical pathways of consumer cognitive evolution and further explore the optimal combination strategies for policy interventions. This study provides a reference for automobile manufacturers to optimize product launch strategies and for policymakers to design communication and regulatory measures.

1. Introduction

At present, China's autonomous driving industry is at a critical juncture as it transitions from technological verification to institutionalized implementation. On December 15, 2025, the Ministry of Industry and Information Technology officially granted market access to two models equipped with Level 3 conditional automated driving systems. This milestone marks the first time China has legally authorized high-level autonomous driving systems for road use and clarified corresponding liability subjects at the national level, thereby achieving a historic leap from “pilot demonstrations” to “mass production and commercial application.”[1]

Shortly afterward, the Shanghai Municipal Commission of Economy and Informatization, the Shanghai Municipal Transportation Commission, and the Shanghai Public Security Bureau jointly issued the *Shanghai High-Level Autonomous Driving Leading Zone “Smart & Efficient Mobility” Action Plan*. The plan explicitly aims to build a large-scale application ecosystem for Level 3 to Level 4 autonomous driving, covering urban core areas, expressway trunk lines, and port hubs, and to advance the coordinated development of technology, application scenarios, and regulatory frameworks as an integrated whole.[2]

This combined policy approach of national market access and local pioneering initiatives not only demonstrates firm support from national authorities for the commercialization of autonomous driving but also signals that China is accelerating its entry into a new phase of large-scale deployment of high-level autonomous driving technologies.

Nevertheless, the rapid advancement of policies and industrial development has not synchronously translated into stable consumer trust and active adoption of autonomous driving as consumers remain cautious and ambivalent about autonomous driving technologies. Recent media coverage of traffic accidents involving intelligent electric vehicles has triggered widespread public doubt about safety, introduced complex variables for public acceptance, and further hindered trust cultivation.[3]

Statistics indicate that 93% of respondents have at least one concern regarding autonomous driving (Bieber and Ramirez, 2024). The lag in public cognition and trust has become a core bottleneck restricting the large-scale industrial application of autonomous driving. Against this backdrop, establishing a social-cognitive foundation compatible with technological progress serves as the core proposition for the industry to overcome developmental bottlenecks and achieve sustainable growth.

This study argues that consumers’ current cognition of autonomous driving constitutes a complex dynamic system that is driven by multiple factors including technological evolution, accident-related public opinion, policy signals, and social interactions. Traditional cross-sectional surveys fail to capture nonlinear feedback and emergent characteristics, and cannot provide a forward-looking policy simulation tool to address the aforementioned cognitive bottlenecks.

From the perspective of technological evolution, this study adopts the agent-based modeling (ABM) method to construct a computational laboratory for simulating cognitive evolution. This study aims to answer two core research questions:

(1) How do technological evolution, safety accidents, and policy interventions interact dynamically to shape consumer risk perceptions and trust structures?

(2) What are the typical evolutionary paths of consumer cognition under the disturbance of multiple factors? What combined policy strategies can effectively break cognitive bottlenecks, rationally guide public attitudes, and accelerate the social integration and market popularization of autonomous driving?

This study intends to provide theoretical insights and decision-making support to understand the internal mechanism of consumer cognitive evolution and optimize policy intervention paths via simulation experiments. The remainder of this paper is structured as follows: first, a review of domestic and international literature is provided; second, the questionnaire design, data collection, and initial parameter setting for the first-stage research are presented; subsequently, agent modeling and simulation in the second stage are discussed; and lastly, management implications and targeted policy recommendations based on simulation results are discussed.

2. Literature Review

2.1 Autonomous Driving Technology Classification and Cognitive Implications

The SAE J3016™ standard (SAE International, 2021) defines six levels of driving automation (L0–L5), with human responsibility gradually diminishing from full driver control (L0) to fully autonomous operation (L5). This classification provides a common reference for both the engineering and behavioral science communities. However, for the purpose of modeling consumer cognition, the relevant distinction lies not in the technical specifications per se, but in the shifting human–machine role boundaries that each level entails.

Two transitional thresholds are particularly noteworthy. First, the shift from L2 to L3 alters the driver's role from active monitor to fallback-ready supervisor, introducing a takeover demand that creates substantial cognitive and temporal pressure (Bel & Coeugnet, 2024). Second, the progression from L3 to L4 transforms the system from conditional to full operational authority within defined domains, challenging consumers to trust system boundaries rather than moment-to-moment system performance. Unlike continuous technical improvements, these level transitions impose discontinuous cognitive demands on end-users, as the required mental models and trust calibration differ qualitatively across levels (Staab & Liebherr, 2024).

Prior acceptance studies have often treated autonomous driving as a homogeneous technology, focusing primarily on the idealized L5 scenario. This simplification overlooks the fact that consumers' actual exposure—and thus their trust formation—occurs sequentially from L2 assistance systems through L3 conditional automation to higher levels. As Kim and Rha (2025) noted, trust established at one level does not automatically transfer to the next; rather, each upward transition necessitates a recalibration of perceived risk and reliability. This path-dependent nature of trust evolution is central to understanding the cognitive bottlenecks that impede large-scale adoption.

Therefore, rather than providing a comprehensive technical review of each automation level, this study adopts the SAE taxonomy as the conceptual backdrop for a dynamic, stage-wise modeling approach. Specifically, the staged technology progression (L2+ → L3 → L4) is operationalized in our ABM as discrete milestone events that generate exogenous trust signals, which in turn interact with endogenous social influence and individual psychological traits to shape cognitive evolution over time.

2.2 Research Gaps in the Acceptance of Autonomous Vehicles

Over the past three decades, scholars have developed various theoretical models to explain individuals' acceptance of new technologies. Among these, the Technology Acceptance Model (TAM; Davis & Venkatesh, 1996), Theory of Planned Behavior (TPB; Ajzen, 1991), and Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) have been widely applied in the field of intelligent transportation. These frameworks are commonly adopted to investigate the public acceptance of advanced driver assistance systems (ADAS) and autonomous vehicles (Rahman et al., 2017, 2018; Zhang et al., 2019; Wang et al., 2024; Kim & Rha, 2025). Previous studies have identified core influencing variables including perceived trust, perceived risk, technology adoption motivation, social influence, and individual differences, which have substantially advanced the understanding of the underlying mechanisms driving autonomous vehicle adoption (Yuen et al., 2021; Bel & Coeugnet, 2024; Arsenyan et al., 2025; Kenesei et al., 2025; Kim & Rha, 2025; Pan & Zheng, 2025; Peng & Robinson-Tay, 2025; Arpaci et al., 2026) .

Nevertheless, a systematic literature review shows that existing studies are subject to the following limitations, which constrain the explanatory power of theories regarding real-world dynamics.

First, most studies overlook the classification of automated driving technologies and treat autonomous driving as a homogeneous technology. In particular, they excessively focus on the idealized L5 fully autonomous driving scenarios while paying insufficient attention to the L3/L4 human-machine co-driving stage, which is currently at the critical threshold of commercialization. This neglect of technical classification prevents existing research from explaining the dynamic adaptation mechanism of consumer perceptions during the technological evolution from L2 to L4. Specifically, consumer trust in L2 cannot be directly transferred to L3; however, this dynamic transfer process is key to understanding the market adoption bottlenecks of high-level autonomous driving.

Second, prior experience was not fully incorporated into the cognitive framework. Before engaging with high-level autonomous driving, consumers typically accumulate practical experience with L2 ADAS. Nevertheless, most existing studies treat trust as a static variable measured at a cross-sectional level and rarely examine how prior experience shapes initial trust through the anchoring effect and how it dynamically regulates the feedback loop between subsequent risk perception, trust repair, and behavioral intention. This limitation makes it difficult for existing models to account for the marked heterogeneity in individual acceptance attitudes, leading to the following question: Why do consumers exhibit vastly divergent cognitive evolution trajectories when faced with identical technology and information environments?

Third, the research methodologies have inherent limitations. Most empirical studies rely on cross-sectional questionnaire surveys. Although these methods can depict variable relationships at specific time points, they fail to capture the dynamic evolution of consumer cognition amid technological advancements. Meanwhile, conventional regression analysis and structural equation modeling can verify the main effects and mediate pathways between variables, yet struggle to illustrate how multiple external events, including technological milestones (such as the official rollout of L3 automation, safety accident shocks, and policy interventions) trigger emergent macro-level cognitive changes at the collective level (such as the collective surge or collapse of public trust) through social network interactions (such as word-of-mouth diffusion and opinion leader influence).

To overcome this methodological bottleneck, this study adopts the ABM approach and develops a "computational laboratory" capable of simulating the dynamic evolution of consumer cognition. The proposed model sets technological progress as phased milestone nodes and embeds social-network effects into the interaction rules of agents. This feature enables the emergence of macro-adoption patterns to be derived from micro-individual decision-making mechanisms. Accordingly, this study provides theoretically rigorous and ecologically valid insights and policy implications to address the practical dilemma of the mismatch between supplier-side technological development and demander-side public cognition.

3. Methodology and Model Implementation

This study was conducted in three stages. The first stage involved a social investigation. Questionnaire surveys targeting specific respondents were conducted to acquire real-world key parameters and provide empirical inputs for the simulation

model. The second stage focused on simulation modeling. Based on the empirical data, an ABM framework was established to run simulations and observe the emergence of macroscopic patterns. The third stage examined policy simulation. By adjusting the model parameter settings, this study simulated how regulatory policies and corporate communication strategies affect consumer cognition under different scenarios.

3.1 Model Conceptualization and Theoretical Mapping

Building upon the staged cognitive demands identified in the SAE taxonomy (Section 2.1) and drawing on the dynamic perspective suggested by Ho and Goh (2025), this study proposes that consumers' cognition of autonomous driving evolves dynamically under the sustained interplay of three driving forces: technological development, social context, and individual characteristics. Treating trust as a static variable—as is done in traditional cross-sectional studies—fails to explain the dynamic heterogeneity of individual acceptance attitudes and cannot capture the emergent changes in collective cognition triggered by external events such as safety accidents and policy interventions. The three driving forces embedded in the model are described below.

(1) Technological driving force: stepped evolution and risk exposure. The advancement of autonomous driving technology from L2/L3 to L4/L5 is neither a smooth nor a linear process. Instead, it is accompanied by clear policy milestones, such as the official approval by the Ministry of Industry and Information Technology (MIIT) of L3 mass production access, and phased risk exposure. In this model, the driving force is realized through a stepped technological evolution mechanism. The technical level (tech_level) jumps at preset time nodes—for instance, tick 121 corresponds to the official launch of L3 access—which simultaneously raises the target trust value of all consumer agents and delivers external signals that trigger cognitive transitions.

(2) Social driving force: information networks and normative pressure. Consumers do not make decisions in isolation and their cognitive formation is deeply shaped by mass media, opinion leaders, and interpersonal networks. Studies have verified that social interaction and word-of-mouth effects are critical factors influencing the adoption of electric vehicles and autonomous vehicles. In this model, the driving force is reflected in the social network effect (peer_effect). Each consumer agent is embedded in a small-world network and dynamically adjusts individual cognition by comparing trust values with neighboring agents (see the following Section), which simulates the social influence mechanism of behavioral assimilation within social groups.

(3) Individual driving force: prior experiences and psychological traits. Consumers’ initial trust in and risk perception of autonomous driving are not blank slates. Instead, they are jointly shaped by prior experience (such as the use of L2-level ADAS functions) and psychological traits (including risk aversion and general trust propensity). This driving force is realized through the heterogeneous initialization of the agents. Calibrated based on the questionnaire data in Section 3.2, the agents’ initial trust and risk perception values follow a normal distribution, which objectively reflect individual differences among real consumer groups.

These three driving forces intersect and integrate with one another to jointly shape consumer decision-making processes. This connection constitutes the fundamental rationale for adopting ABM in this study. Complex feedback relationships between micro-level decision mechanisms and macro-level cognitive changes can only be determined by constructing a computational laboratory capable of generating emergent macroscopic patterns.

3.2 Questionnaire Design and Parameter Calibration

To calibrate the initial distribution of consumer agents' trust and risk perception, a questionnaire survey was conducted prior to the simulation. The questionnaire was designed based on the Technology Acceptance Model (TAM) and comprised two parts: the first measured general cognition, attitudes, and adoption intention toward autonomous driving, while the second focused specifically on the usage experience, trust transfer, and transitional psychological mechanisms among L2-level assisted driving users. Both parts employed five-point Likert scales adapted from validated instruments in prior literature (Davis & Venkatesh, 1996; Zhang et al., 2019; Kenesei et al., 2022).

The survey was administered through both online platforms (WeChat, QQ, and professional survey channels) and offline channels (auto shows and experience centers). A total of 187 responses were collected. After excluding three invalid responses with excessively short completion times, logical inconsistencies, or repetitive answer patterns, 184 valid samples were retained (effective response rate = 98.4%).

Maximum likelihood estimation (MLE) was applied to the valid sample to fit the distribution of initial trust and risk perception. The results confirmed that both variables followed normal distributions (trust: $\mu = 0.38$, $\sigma = 0.12$; risk: $\mu = 0.62$, $\sigma = 0.12$), with Kolmogorov–Smirnov tests indicating acceptable goodness-of-fit (*p* > 0.05 for both). These calibrated distributions were subsequently used to initialize the heterogeneous agent population in the simulation (see Section 3.3.1).

3.3 Simulation Model Implementation

3.3.1 Environment and Policy Settings

The simulation adopts a discrete time structure in which one tick corresponds to one calendar month, with a total horizon of 500 ticks. The technology level (*tech_level*) follows a stepped trajectory aligned with regulatory milestones: L2+ (ticks 0–120), L3 market access (ticks 121–240), pilot expansion (ticks 241–360), and L4 commercial operation (ticks 361–500), as summarized in Table 1. Safety accidents are modeled as a Bernoulli process with *p* = 0.01 per tick, calibrated against MIIT pilot data and media amplification factors.

Three policy instruments—regulatory intensity (*reg*), communication intensity (*comm*), and subsidy intensity (*sub*)—are defined as continuous global parameters within [0, 1]. The social network is constructed as a Watts–Strogatz small-world network (Watts & Strogatz, 1998) with 500 nodes, average degree *k* = 6, and rewiring probability $\beta = 0.1$.

Each simulation run initializes 500 consumer agents. Initial trust and risk perception values are drawn from normal distributions calibrated using a pre-simulation questionnaire survey ($N = 184$; trust: $\mu = 0.38$, $\sigma = 0.12$; risk: $\mu = 0.62$, $\sigma = 0.12$; both passed Kolmogorov–Smirnov normality tests at *p* > 0.05). Each agent also possesses individual-specific parameters, including risk aversion and social sensitivity, drawn from uniform distributions. To ensure robustness, each parameter combination is repeated 50 times with different random seeds, and the averaged results are reported.

Table 1
Estimation of Environmental Parameters.

Variable	Benchmark & Definition	Setting Value/Range	Time Window
tech_level	Ladder Mechanism	2.0→4.0	
accident	Accident Probability	Bernoulli(p = 0.01)	
Time Scale	1tick≈1 month	tech_level	
Stage 1	L2/L2+	2.2	0–120
Stage 2	L3	3.0	121–240
Stage 3	Pilot Expansion	3.3	241–360
Stage 4	L4	4.0	361–500

3.3.2 Decision-Making and Update Rules

The core focus of the overall model is to characterize the cognitive diffusion of autonomous driving technology from the consumer perspective. Therefore, the design of consumer agents and their update rules is central to the model. At each time step, every consumer agent sequentially executes the steps of technology state perception, accident shock response, trust and risk target updates, social interaction effects, and adoption decision according to the rules summarized in Table 2. All rules are implemented as Python functions and called in order within the main simulation loop.

Table 2
Consumer Cognition Update Rules.

Step	Rule / Equation
Technology Update	$tech_level\,(t) = step\,(t)$, t denotes the milestone timeline, which undergoes abrupt changes at the nodes of L3-L4
Accident Impact	$accident\,(t)\ \ Bernoulli\,(p - negative - event)$ $shock = (a1 * accident + a2 * accident_last) * (1 - \beta_comm - comm$
Trust Target	$trust_target = clip(b0 + b1\,(tech_level - 2) + b2 * reg + b3 * comm - b4 * shock)$
Risk Target	$risk_target = clip(r0 + r1 - r2 * (tech_level - 2) - r3 * reg - r4 * comm + r5 * shock)$
Social Diffusion	$peer_effect = social_sens * (mea^{n(trus_neighbors)} - trust) * \gamma * (1 + \delta_{comm} * comm)$
State Update	$trust \leftarrow trust + \alpha_t * (trust_target - trust) + peer_effect$
Acceptance Intention	$intention = sigmoid(w_t * (trust - 0.5) + w_u(usefulness - 0.45) - w_r(risk - 0.5) + \cdots)$
Discrete Cognitive State	$acceptifintention > 0; resistifintention < 0; elseobserve$

The simulation model was implemented in Python using the Mesa framework for agent-based modeling, with NumPy for numerical computations and NetworkX for generating the small-world social network structure. All simulation experiments were conducted on a standard computing workstation.

4. Simulation Results

4.1 Comparison of Diffusion Trajectories under Different Strategy Combinations

To explore typical cognitive evolution paths under different policy interventions, this study simulated four representative policy combinations under the baseline accident probability (p = 0.01) and stepped technological evolution scenario (Fig. 1). The simulation results reveal that the overall adoption rate of the consumer groups presents significantly different evolutionary trajectories.

(1) Baseline scenario with no policies (reg = 0, comm = 0, sub = 0). The market adoption process is slow and volatile. Within the simulation cycle of 500 time steps (approximately 41.7 years), the final adoption rate reaches only approximately 65%. This evolutionary path indicates that in the absence of systematic external guidance, natural technological progress and word-of-mouth, diffusion is insufficient to break through inherent public trust barriers and risk concerns. Therefore, consumer cognition lingers in a long-term wait-and-see state.

(2) Combined strategy of intensive communication and high subsidies (reg = 0, comm = 1, sub = 1). Although this strategy achieves a high final adoption level (over 95%) in the later simulation stage (tick > 350), its diffusion speed in the early and

middle periods (ticks 100–300) is noticeably slower than that of other policy portfolios. More importantly, its evolutionary curve mildly rebounds after the simulated safety accidents, which reflects a weak capacity to buffer negative shocks. The findings suggest that incentive- and communication-oriented policies without regulatory endorsement can attract price-sensitive groups and early adopters, yet fail to deliver solid safety confidence to the mass market, thus rendering the diffusion process vulnerable to external disturbances.

(3) Combined strategy of strict regulations and limited communication (reg = 1, comm = 0.2, sub = 0). The adoption curve under this scenario shows steady yet slow growth. Strict regulations establish a robust safety bottom line and prevent substantial cognitive regression, whereas insufficient publicity and communication restrict the diffusion efficiency of positive perceptions within social networks. Consequently, even at the mature stage of technological development (L4), a considerable proportion of consumers remain in the wait-and-see state owing to inadequate information exposure.

(4) Combined strategy of strict regulation, moderate communication, and moderate subsidies (reg = 1, comm = 0.5, sub = 0.5). This portfolio delivered the most comprehensive performance. The adoption rate begins to rise rapidly in the mid-simulation period (around tick 200, corresponding to the later stage of L3 market access) and quickly crosses the critical tipping point of 50% adoption (t50 = 166). The final adoption rate approaches 100% via a smooth and highly resilient evolutionary curve. This optimal path reveals an effective mechanism for cognitive transition: strict regulation consolidates the foundation of public trust, moderate publicity accelerates cognitive diffusion across social groups, and targeted subsidies lower economic barriers to early adoption. The coordinated interaction of the three policy tools can effectively boost popular acceptance at critical technological milestones such as the official launch of L3 automated driving.

In conclusion, under the same accident probability and stepped technological evolution context, the optimal policy portfolio was identified as strict regulation supplemented by moderate communication and moderate subsidies. Compared to the no-policy baseline scenario, this hybrid strategy significantly accelerated technology diffusion. Relative to strict regulations and low communication combinations, it remedies the insufficient dissemination of positive information that otherwise constrains widespread cognitive improvement. In contrast to the high-publicity and high-subsidy scheme lacking robust regulation, the balanced policy framework avoids slow initial acceptance growth and enhances resistance to the negative impacts triggered by accidents.

4.2 Trust Levels under Different Policy Interventions

Figure 2 illustrates the evolutionary trend of the average trust level of the consumer. The simulation results indicate that rather than being static, trust responds dynamically to technological signals, policy interventions, and accident shocks.

Strict regulation (reg = 1) is critical for elevating and stabilizing the baseline of consumer trust. In the absence of regulation, the average trust level remained trapped within a low range of 0.4–0.5. Each accident triggered a sharp decline in trust accompanied by a prolonged recovery period. In contrast, the implementation of strict regulations significantly lifted the trust baseline above 0.6. This trend demonstrates that regulatory intensity serves as a core determinant of consumer trust in the model and that government regulation provides institutional safeguards for perceived safety.

Communication (comm) exerts dual effects. On one hand, it amplifies the positive word-of-mouth peer effect within social networks and accelerates the diffusion of high-trust cognition across the population. On the other hand, communication intensity mitigates the negative impacts of accident shocks on trust targets through the moderating effect of $(1 - \beta_{comm} \cdot comm)$.

Figure 2 explains why the policy combination of strict regulations and moderate communication generates faster trust growth. The data further verify that timely and transparent information disclosure, namely, effective public communication, is conducive to managing public expectations and alleviating trust crises caused by safety incidents. The trust curve under high-publicity scenarios fluctuated slightly following the occurrence of accidents, whereas a noticeable drop emerged under low-publicity conditions.

4.3 Cognitive Transition Effects under Different Technology Evolution Modes

We compared the effects of two technological evolution modes–stepped and linear evolution–under the same optimal policy combination (Fig. 3). The results show that the adoption rate under a stepped evolution path is significantly higher than that under a linear evolution path.

The core source of this discrepancy is the cognitive leap effect triggered by policy milestones. Under a linear evolution, technological improvements advance continuously and incrementally, which leads to vaguely perceived progress among consumers and hinders the enhancement of fundamental confidence. In contrast, stepped evolution simulates China's typical policy pattern of "access pilot" to "scaled application" to "full commercialization."

In the model, when the tech_level jumped at preset time points (such as at tick 121 marking the official launch of L3 access), it acted as a strong positive signal that simultaneously raised the target trust level and the perceived usefulness of all consumer agents. This collective and synchronous signal stimulation, amplified by social network interactions, can rapidly break cognitive stagnation and form an inflection point for widespread adoption.

Therefore, integrating technological advancements with clear regulatory policy milestones constitutes a critical strategy to accelerate the market acceptance of autonomous driving.

In conclusion, the stepped mode with clear policy milestones (e.g., L3 pilot deployment) can significantly accelerate consumer acceptance speed, which indicates that policy nodes such as L3 road access permission are key to cognitive transition.

4.4 Optimal Selection of Policy Tool Combinations

To systematically address Research Question 2 and identify the optimal strategy combination under resource constraints, we conducted a full factorial experiment which incorporated a budget constraint (B = 2.5) and comprehensive scores (Table 3).

Table 3
Comprehensive Ranking of Strategy Combinations (B = 2.5; p = 0.01).

rand	reg	comm	sub	Policy Cost	Final Acceptance	Diffusion Speed	Score
1	1.0	0.5	0.5	2.45	0.9988	0.5828	0.894
2	0.5	1.0	0.5	2.35	0.9975	0.5476	0.872
3	0.0	1.0	1.0	2.50	1.0000	0.5094	0.861
4	1.0	1.0	0.0	2.20	0.9838	0.5175	0.846
5	1.0	0.0	0.5	1.95	0.9950	0.4880	0.831
Note: Comprehensive Score = 0.6 × Final Acceptance Rate + 0.35 × Diffusion Speed − 0.0001 × t50							

Table 3 clearly indicates that the combined strategy of stringent regulation (reg = 1.0), moderate communication (comm = 0.5), and moderate subsidy (sub = 0.5) yields the optimal comprehensive performance under the given budget constraint. Its advantages lie in the balanced allocation of the three types of policy instruments. Strict regulation provides the essential public good of safety-based trust, thereby laying a solid foundation for market expansion. Moderate communication facilitates public cognition diffusion with high cost effectiveness and strengthens systemic resilience. Within the budget allowance, moderate subsidies effectively stimulate early adoption behavior. The simulation results further verify that this strategy combination maintains a robust performance in both normal scenarios and high-risk accident contexts.

A heat map was plotted to examine the interaction between regulation and communication. The subsidy value was first fixed at 0.5 to explore how different combinations of regulation and communication influence the final adoption rate.

Figure 4 demonstrates that regulation exerts a significantly greater marginal contribution than communication. As the regulatory intensity increases from 0 to 1, the adoption rate increases substantially, regardless of the communication level, as reflected by the shift from cool to warm colors in the heat map. By contrast, the marginal effect of enhanced communication remains limited. Publicity generates prominent synergistic promotional effects only when the regulation establishes a solid foundational safeguard (reg > 0.5), which is reflected by the darkest warm tone in the upper-right area.

This finding further validates the foregoing conclusion that regulation secures consumers' fundamental safety bottom-lines. On the premise of safety and trust, targeted communication can significantly accelerate the popularization of technology with high efficiency. However, without adequate safety guarantees, intensive communication yields limited and inefficient outcomes.

5. Discussion

5.1 Research Findings and Contributions

This study constructed an artificial society computational laboratory to dynamically simulate the evolutionary process of consumer cognition by simulating complex interactions among the three core factors under the assumption that the staged technological advancement from L2/L3 to L4/L5 is affected by public opinion shocks which are triggered by sudden safety incidents and multidimensional policy interventions. The simulations reveal the emergent laws of macro-level consumer cognition and explore high-efficiency strategies to guide public cognitive changes. The main conclusions and contributions of this study are summarized as follows:

(1) Clarifying the micro-mechanism through which technological evolution dynamically shapes consumer cognition.

Consumer trust and risk perceptions of autonomous driving undergo continuous dynamic adjustments. Although technological progress, along with policy milestones such as official access to L3 automation and the commercial application of L4 vehicles, systematically enhances consumer trust by delivering explicit performance and safety signals, such effects are non-linear. Safety incidents act as severe negative shocks that significantly erode public trust and amplify risk perception in the short term. Nevertheless, targeted policy interventions can effectively buffer these adverse long-term effects. Accordingly, stringent government-led regulations serve as the cornerstone of establishing institutional trust, whereas public publicity and communication play complementary roles. Together, they shape the overall cognitive states of the consumer.

(2) Identifying the optimal policy combination pathway to promote the positive transition of public cognition.

Multiple typical cognitive evolution pathways were identified using simulation experiments to address the second research question. The results indicate that overreliance on subsidies and commercial publicity under inadequate regulation can lead to a high adoption rate in the long term which is accompanied by slow diffusion and fragile system stability. In contrast, exclusive stringent regulation paired with insufficient public communication yield a low efficiency in cognitive popularization. Under resource constraints, the portfolio of stringent regulation (reg = 1.0), moderate communication (comm = 0.5), and moderate subsidies (sub = 0.5) was verified as the optimal strategy with comprehensive performance advantages. This balanced combination efficiently coordinates institutional safety trust building, social cognition diffusion, and economic threshold reduction and drives the collective transition of public attitudes from wait-and-see hesitation to active acceptance at critical stages of technological iteration.

(3) Providing innovative explorations of both the theoretical construction and research methods.

Theoretically, this study overcomes the static limitations of the classical TAM/UTAUT. It integrates the cognitive transition, trust repair, and social influence theories into a unified dynamic evolutionary analytical framework, thereby verifying and extending the explanatory power of existing theories in the context of progressive technological upgrading. Methodologically, this study introduces ABM simulation, which is regarded as a computational laboratory, into the research field of consumer cognition. Deriving macro-emergent patterns from bottom-up micro interactions provides a novel methodological tool for

addressing emergent problems in complex sociotechnical systems. The established simulation model can function as a digital sandbox and offer a forward-looking and low-cost experimental platform for government and enterprise decision makers to evaluate the long-term effects of diverse policy and strategy portfolios.

5.2 Limitations and future research

Although this study has yielded several valuable findings, certain limitations remain.

(1) Further refinement of the theoretical model: This study provides a simplified description of the three policy intervention variables. In practice, relevant policy instruments can be further subdivided and expanded, such as the stringency of regulatory provisions, publicity channels, and content strategies, as well as specific forms and targeted groups of subsidies. Future research should adopt a more refined policy design to explore the distinct psychological mechanisms that affect consumer responses. Moreover, the current model focuses only on cognition and behavioral intentions. Subsequent studies will incorporate constraining factors such as purchasing power and infrastructure accessibility to construct a comprehensive consumer decision-making framework.

(2) Further optimization of the simulation data: Due to restrictions in research funding, several ABM parameters were calibrated based on questionnaire data with a limited sample size. Follow-up research should conduct large-scale, nationally representative surveys or adopt alternative methods to calibrate and validate the model, thereby improving its overall fitness and generalizability. In addition, to reduce model complexity, the social network structure was set to be static. Future work may introduce dynamically evolving social networks to reproduce information diffusion patterns in the digital era more realistically.

(3) Incorporation of additional application scenarios: This study focused solely on consumer cognition in the context of privately owned autonomous vehicles. With the widespread adoption of intelligent driving technology, robotaxis are emerging as a novel business model that is gradually being integrated into daily mobility. Subsequent research will extend the theoretical and simulation models to the shared mobility scenario to provide targeted references for urban transportation policy formulation and enable a more comprehensive evaluation of the social and economic value of autonomous driving technology.

Declarations

Data Availability

The data supporting this study's findings are available from the corresponding author upon reasonable request.

Conflicts of Interest/ Declaration of interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Credit authorship contribution statement

Hao zhang: conceptualization; Methodology; Investigation; Writing - Original Draft; Review & editing. **Peifeng Zhu**: Writing – Resource, Software; supervision.

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Footnotes

1. https://www.miit.gov.cn/xwfb/gxdt/sjdt/art/2025/art_f734c7074580470593d4018742997640.html.
2. https://www.shanghai.gov.cn/gwk/search/content/4144de4a013240ba8282558c09514639.
3. https://k.sina.com.cn/article_7880068201_1d5b04c6901901pf0o.html

Figures

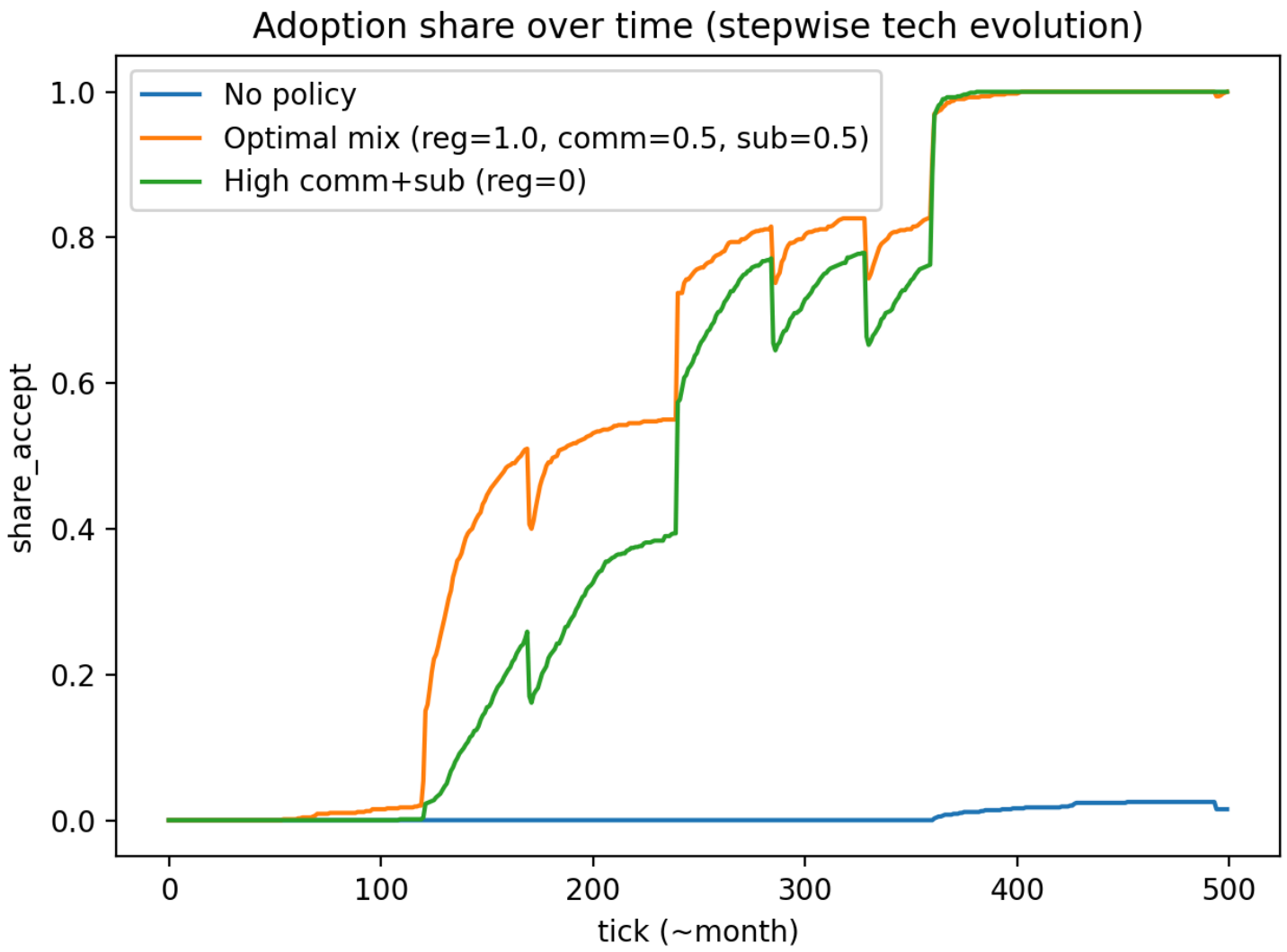


Figure 1

Comparison of Diffusion Trajectories under Different Strategy Combinations.

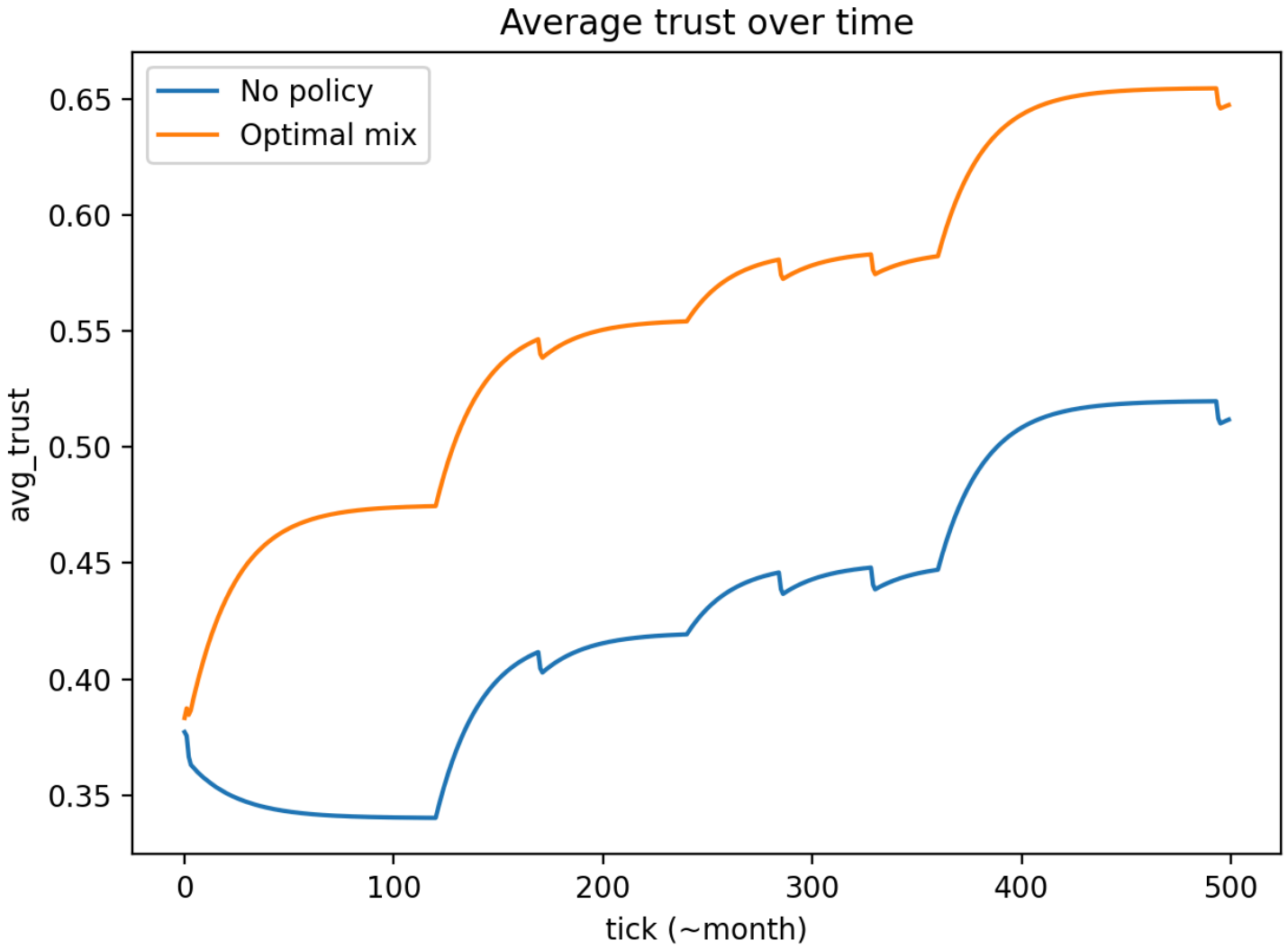


Figure 2

Diffusion Trajectories of Trust Levels under Different Policy Interventions.

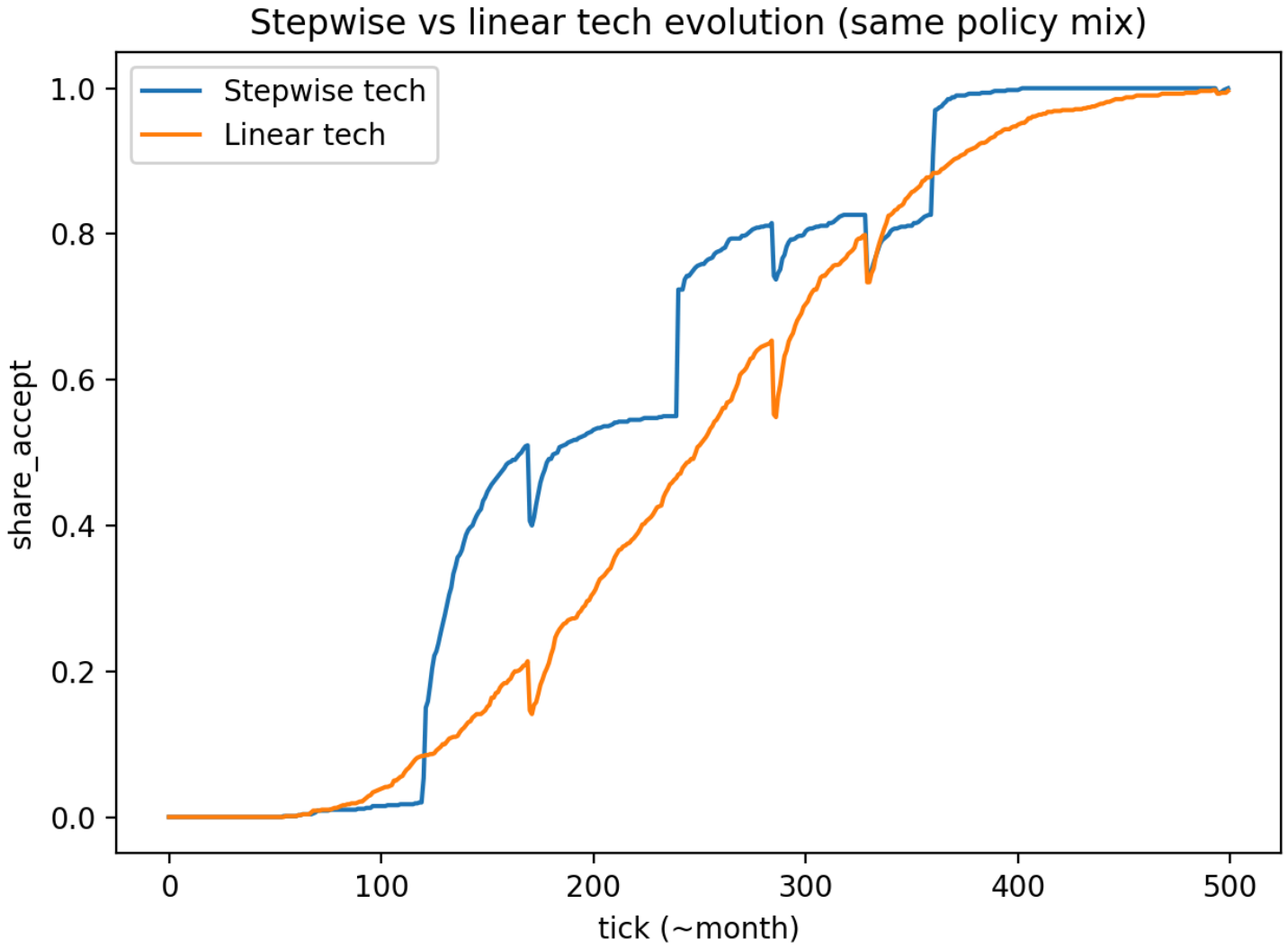


Figure 3

Comparison of Effects of Two Technology Evolution Modes

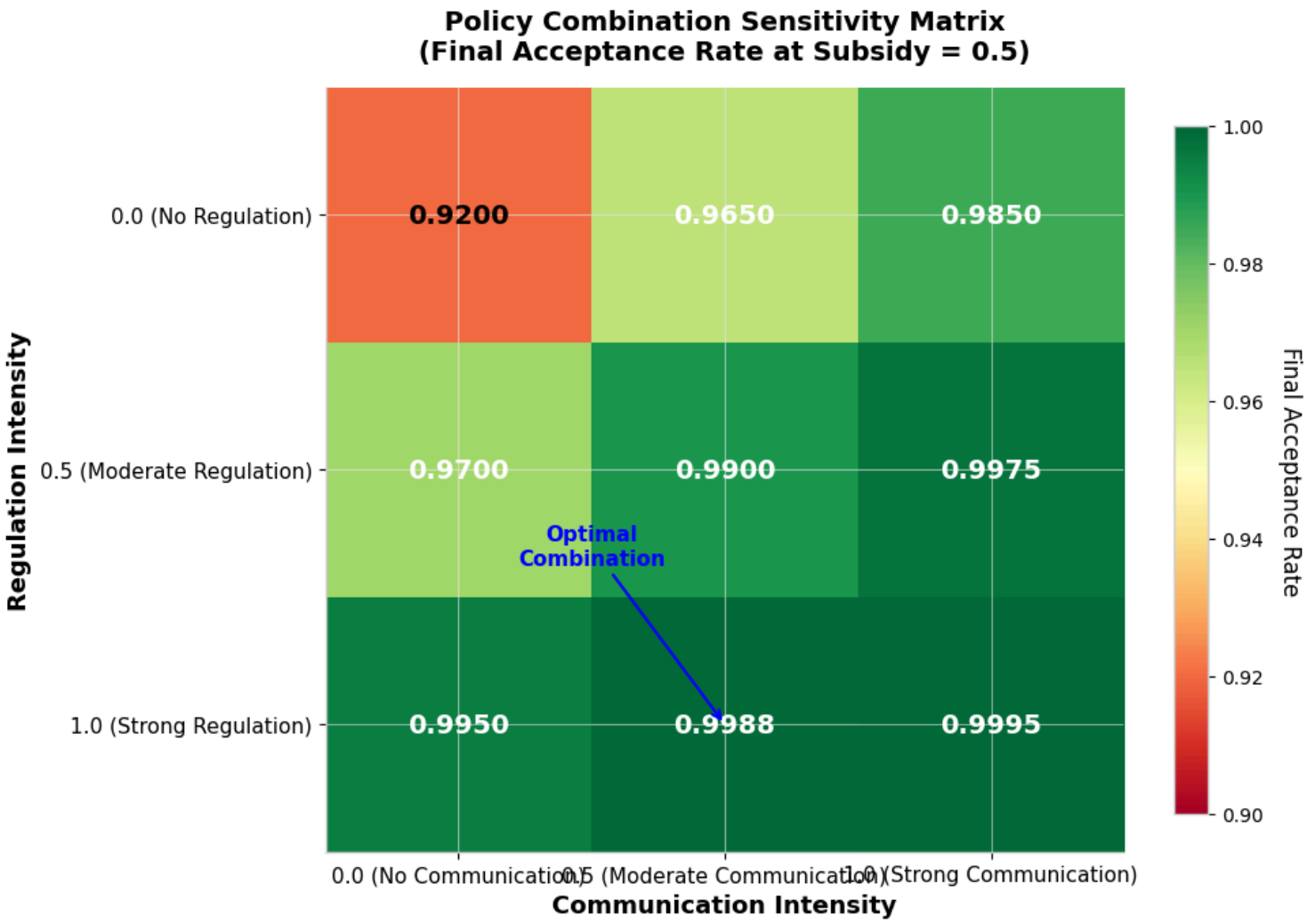


Figure 4

Policy combination sensitivity matrix

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