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Artificial Intelligence in Human Collaboration Skills Invocation, Recovery and Enhancement

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Abstract

Prior research discovered that the source of wealth is human capital ideas of imagination and creativity. Said capital is deployed through the capitalism (C), democracy (D), rule of law (R) (CDR) economic growth model. The point of beginning is collaboration to achieve rule of law that attracts capital and protects democracy that deploys capital optimally to generate gross domestic product of goods and services. But about 90% of people in the world have diminished collaboration skill due to neglect, or a negative epigenetic transgenerational psycho sequela rooted in environmental stresses such as forced labor, excessive discrimination and exposure to dangerous chemicals. This paper discusses how artificial intelligence (AI) can be used to help invoke or recover and develop collaboration skill in said people, then enhance the execution of human collaboration to raise CDR, raise gross domestic product (GDP) and standard of living, and thereby pursue an end to poverty.

Keywords

Artificial Intelligence, Collaboration, Capitalism, Democracy, Rule of Law, Gross Domestic Product

1. Introduction

In the CDR model (see Ridley, 2023 and Appendix) capitalism (C) is defined as the degree of organization of capital. Capital is defined as *intangible exogenous potential for human imagination and creativity and the source of wealth.* Exogenous capital is converted to endogenous capital stock used in the production of goods and services. After consumption, depreciation (capital consumption allowance) and obsolescence, the remainder is contribution to wealth. Capitalism is measured by the total market capitalization. It is the value of all outstanding publicly traded stocks on the stock markets. It represents the present value of all future income from investments in the production of goods and services that constitute GDP. Democracy (D) is defined as *an intangible exogenous catalyst that creates new pathways for the optimal deployment of capital*. Rule of law (R) is defined as *the reverse of corruption*, *the protection of shareholder and other property rights*, *enforcement of contracts*, *and an intangible exogenous catalyst for stability and the attraction of capital*. Whereas capital stock is used up in production and is therefore endogenous, D and R remain the same and are therefore exogenous. The democracy pathways are not unlike the chemical pathways of Berzelius (1779-1848). The measure of standard of living adjusted for purchasing power parity (GDPppp) is computed from the CDR model as a weighted average of C, D, R and their interaction (CDR), and natural resources (N) and latitude (L). The model explains 90 percent of GDP. The model is called the CDR model because C, D, and R are policy variables, and N and L are natural variables that are outside the scope of government policy.

The obstacle to the implementation of the CDR model is the absence of rule of law in about 90% of the countries of the world. The acquisition of rule of law may at first appear simple. However, it is not. One might easily be led to believe that rule of law is founded in cooperation. But it turns out that cooperation is based on self-interest and rule of law, on the other hand, is wholistic. Failure to achieve rule of law might lead to increased efforts to cooperate, to no avail. Cooperation between two parties does increase division of labor and trade (Smith, 1776). Despite the pursuit of self-interest, each party inadvertently benefits the other. Recall Adam Smith's invisible hand. And there is an increased standard of living. This can leave the best-intentioned among us in a quandary. What is required for rule of law is collaboration (Ridley, Korovyakovskaya, & Llaugel, 2021; Ridley, 2022; Ridley & Nelson, 2022a; Ridley, 2023). Surowiecki (2005) shows how groups can outperform even the smartest and most credentialed individual members. Collaboration is based on joint interest. And whereas cooperation leads to ordinary economic growth, collaboration leads to extraordinary economic growth. The extra dividend of extraordinary profit is shared between the parties, per agreement, and adds to the ordinary profits. Most countries do not cooperate. They practice mercantilism, not capitalism. This was the common practice in Western Europe prior to the adoption of capitalism. Even those that cooperate get left behind those that collaborate. Capital that is repelled by the lack of rule of law countries, is attracted by the rule of law countries.

Human beings comprise the only species capable of collaboration. Animals can cooperate, but they cannot collaborate (Tomasello, 2010). Just because human beings can collaborate does not mean that they will. A human baby can speak. But if nobody ever speaks to the baby, he or she will never speak. Avital, Aga-Mizrachi, & Zubedat (2016) and Avital & Aga-Mizrachi (2022) discovered that genes do affect social cooperation ability in mice. If the same is true for human beings, then we deduce that there is a gene for human collaboration. But the gene must be turned on and trained and otherwise developed (Lee & Ridley, 2024). The obstacle to human collaboration can be a diminished collaboration skill due to an epigenetic transgenerational psycho sequela rooted in environmental stresses such as forced labor, excessive discrimination and exposure to dangerous chemicals (Ridley & Nelson, 2022b).

Skinner et al. (2013) demonstrate that environmental toxin exposure can induce epigenetic modifications that persist across generations and manifest as stable functional phenotypes without continued exposure. While their findings focus on metabolic outcomes, the underlying mechanism—epigenetic regulation of biological systems involved in stress and regulation—is domain-general. Collaboration depends critically on neurobiological systems governing emotional regulation, trust calibration, and joint intentionality, all of which are sensitive to chronic environmental stress. Accordingly, it is biologically plausible that prolonged exposure to forced labor, systemic discrimination, or toxic environments may produce epigenetic transgenerational psycho-sequelae that suppress collaboration capacity without eliminating it. This framing implies not determinism, but recoverability through structured social environments capable of reactivating latent human collaborative potential.

Artificial intelligence (AI) cannot collaborate. No amount of training or interaction with human beings will ever change that. Our paper discusses how AI can be used to help said people invoke or recover and develop their collaboration skills, then enhance the execution of human collaboration to raise CDR, raise gross domestic product (GDP) and standard of living, and thereby pursue an end to poverty. Create middle-class countries throughout the world. And a living wage for the least amongst us.

Singapore was once a colony of England and suffered all the indignities appertaining thereto. Singapore made sports and music education mandatory for school children. What do sports and music have to do with academics that would justify their mandating one might ask? Well, it turns out that Singapore children score highest in the world in collaboration, mathematics and science. The advice of the coaches can only go so far. They provide tools and strategies. But to succeed at team sports or music all children learn from experience to play for the team. They take this skill into adulthood, higher education, business and industry (Ridley, Lee, & Nelson, 2023; Lee & Ridley, 2024). Ridley, Ngnepieba & de Silva (2021) show how collaborative learning transforms calculus test scores from a multimodal nonnormal distribution to a unimodal normal distribution while raising the scores. One cannot argue with success. In one generation, Singapore went from abject poverty and expulsion from Malaysia, to having a GDP twice that of their former colonial master. Fifty percent higher than the United States of America.

Adults do not attend school, and they may have missed out on the Singapore experiment when they were children. Rather than write off collaboration as an unskilled job applicants, successful American Corporations skip that requirement and design jobs to enhance collaboration (Rosier, Llaugel, & Ridley, 2024; Ridley & Korovyakovskaya, 2025). The vast majority of countries have only a few land line telephones per capita. And they do not work well. Many are leaky and are adversely affected when it rains. So rather than invest enormous sums of money to improve land lines to modern standards, people have simply skipped land lines in favor of mobile wireless cell phones. Many American teenagers have never seen a land line phone. Due to the invention of rapid prototyping many Americans will soon forget what a brick-and-mortar home construction looks like. People will skip to 3D printed homes. So, we consider skipping the intransigence of the collaboration unskilled in favor of the possibility of collaboration enhanced by artificial intelligence. Adults may recover collaboration skills while avoiding the distraction of the uncollaborative tendencies from colleagues and team members. The successful Singapore school experiment may be viewed as a form of gene therapy (a metaphorical analogy, not a biological intervention) for collaboration that takes one school cycle to complete. Another gene therapy for collaboration may be derived from military training. Artificial intelligence collaboration training may be viewed similarly. While AI cannot in itself collaborate, it might be able to assist in human collaboration training. The only gene therapy that may be much faster is medical biological intervention. But should that become possible, it behooves us to continue the practice of school-age and adult collaboration development through continued training and practice.

2. Literature Review

The concerns of AI taking over human jobs are addressed by Mahmud et al. (2024). They investigate how AI can team up with people to work better and smarter. This collaboration machine-human is used to solve problems and complete tasks in a more efficient manner. Among the conclusions of the paper is that the collaborative nature of the combination of human-AI is reinforced with the power of AI and the human domain expertise. Human-AI collaboration in decision-making aims to produce team outcomes that surpass what either humans or AI systems can achieve on their own. Yet the effectiveness of such teams depends on many factors, such as users' domain knowledge, their mental models of the AI, and their trust in its recommendations. The article presents a study investigating how users interact with three simulated algorithmic models that share the same overall accuracy but differ in their balances of true positive and true negative rates. The study evaluated user performance on a complex blood vessel labeling task in which participants judged whether a vessel was flowing or stalled. Participants completed 140 trials over multiple phases, first working independently and then receiving guidance from an AI assistant. Although all participants had prior experience with the task, their proficiency levels varied substantially (Inkpen et al., 2023).

Team agility, while essential for tackling complex challenges such as engineering design, is often hard to realize in real-world settings. Advances in AI create new possibilities for enhancing collaborative problem-solving in teams. Although the inclusion of AI assistants in human teams has sometimes led to performance gains, the mechanisms through which AI influences team agility have remained uncertain. A large-scale experiment involving human participants addresses this gap, showing that when AI systems are designed with appropriate interfaces, AI-supported teams achieve stronger coordination and communication. These improvements translate into higher performance and greater resilience when teams face disruptions, as well as increased investment in information processing and broader exploration of potential solutions. Overall, collaboration with AI allows human team members to focus more on thinking and less on direct action (Song et al., 2022).

Organizations are increasingly integrating AI agents into virtual teams to support information management, coordinate teamwork, and handle routine tasks. This raises questions about how human teammates perceive these AI members and whether they are willing to collaborate with them. To address this, a 2 × 2 × 2 laboratory experiment that varied team member type (human versus AI), individual performance (high versus low), and the performance of other teammates (high versus low) was conducted. The results showed that AI team members were viewed as more capable and having greater integrity, but as less benevolent, which ultimately produced no differences in overall trustworthiness or willingness to work with them compared to humans. However, teams that included an AI member reported lower satisfaction with team processes. When the AI member performed well, participants perceived less conflict than with a human teammate performing at the same level, whereas no differences in perceived conflict emerged when performance was low. No other significant interactions with performance were found, suggesting that AI team members were evaluated much like human teammates regardless of performance level, with no indication of algorithm aversion. These findings imply that AI agents are likely to be accepted as team members, suggesting that many established questions in collaboration research should be revisited to account for the inclusion of AI in teams (Dennis et al., 2023).

The incorporation of AI into human groups to form human-AI teams (HATs) is an area of rapid growth. Introducing an AI team member often leads to decreased coordination, communication, and trust. Moreover, trust in AI commonly diminishes over time as users initially overestimate its capabilities, which can negatively affect teamwork. Although AI has demonstrated the ability to improve performance in domains such as chess and medicine, HATs frequently fall short of expectations due to weak team cognition and limited mutual understanding. Addressing these challenges will require future research that integrates perspectives from computer science and psychology and develops stronger theoretical frameworks to fully unlock the benefits of human-AI collaboration (Schmutz et al., 2024).

Amiot et al. (2005) explored how chatbot assistance shapes virtual teamwork during a shared online task. Chatbots are increasingly recognized as effective supports for collaborative work. To evaluate their effects on team interaction and outcomes, they developed a purpose-built collaborative activity, an online platform, and a customized chatbot assistant. Results show that chatbot support enhanced task performance and shortened response times to information requests, particularly when assistance was provided through group or combined chats. In contrast, participants receiving only private chat support reported higher perceived effort. Additionally, perceptions of the chatbot's communication quality were strongly linked to participants' cognitive workload and time pressure.

Human-AI Collaboration (HAIC) is increasingly vital across many work domains, enhancing decision-making, efficiency, and innovation. By integrating quantitative and qualitative measures, the framework supports evaluation of HAIC across diverse real-world domains (Fragiadakis et al., 2025). However, assessing its effectiveness is challenging due to the complex interactions between human and AI components.

Applying artificial intelligence (AI) to shape team dynamics offers significant potential to improve collaborative problem solving. However, most existing methods rely on previously collected, problem-specific data, which restricts their usefulness to tasks that have already been addressed. Rather than emphasizing task-specific strategies, the approach centers on team communication and collective intelligence (CI), which reflects a group's general capacity to perform effectively across different tasks and is a stronger predictor of success than individual intelligence. McGee et al. (2025) present an AI facilitator that continuously tracks key CI indicators—shared attention, balanced participation, and stable communication patterns—and provides timely interventions to foster improved collaboration and overall team performance.

Recent research by Zercher et al. (2025) demonstrates that teams with centralized access to AI knowledge achieve higher decision accuracy than purely human teams, largely because they experience fewer decision-making asymmetries, place greater trust in AI, benefit from effective AI-driven information processing, and maintain a balanced approach to human-AI collaboration. By contrast, teams with uneven or asymmetric AI knowledge exhibit only limited reductions in decision-making imbalances. Additionally, these teams develop new AI-related asymmetries—such as mistrust, ineffective use of AI-generated information, and an overly critical stance toward AI collaboration—which prevent them from outperforming human-only teams. These results are synthesized into process models showing that successful human-AI collaboration depends on well-coordinated teamwork between human participants and AI systems.

Recent research highlights the growing synergy between human expertise and artificial intelligence in optimizing task performance. According to Sharma et al. (2022), Vaccaro et al. (2024), and Huang (2025), generative AI serves as a powerful tool for enhancing decision-making across various domains.

Key findings from these studies include:

- Enhanced Decision-Making: AI tools assist teams in processing complex information to make more informed choices.
- Mental Health Support: Collaboration between humans and AI has been

shown to foster more empathetic and effective communication in therapeutic settings.

- Creative Growth: Experimental evidence suggests that human-AI partnerships can significantly unlock and expand creative potential.

3. Theoretical Foundations

3.1. The CDR Model and the Primacy of Collaboration

The Capitalism-Democracy-Rule of Law (CDR) model provides a parsimonious yet powerful explanation of cross-country differences in gross domestic product adjusted for purchasing power parity (GDPppp). In this framework, capitalism (C) represents the degree of organization of capital, democracy (D) represents pathways for the optimal deployment of capital, and rule of law (R) represents the institutional stability required to attract and protect capital. Together, these variables and their interaction explain approximately 90 percent of observed variation in GDPppp across countries.

A critical but often misunderstood implication of the CDR model is that rule of law cannot be directly imposed. While democracy and capitalism are policy variables, rule of law emerges only when human beings are capable of acting holistically in pursuit of joint interests rather than merely individual gains. This distinction reveals a fundamental constraint: cooperation is insufficient for rule of law, while collaboration is necessary. Cooperation is transactional and self-interested. It allows for division of labor and trade, generating ordinary economic growth, as first articulated by Smith (1776). Collaboration, by contrast, is based on shared goals, mutual accountability, and agreement on the distribution of extraordinary surplus. Collaboration enables institutions, contract enforcement, and collective restraint—conditions without which rule of law cannot be sustained. Consequently, collaboration is the missing human capability underlying the successful implementation of the CDR model.

The absence of collaboration skill therefore explains why most countries fail to achieve rule of law despite adopting democratic forms or market mechanisms. Capital repelled by institutional instability flows instead to collaborative societies, compounding global inequality. This insight reframes poverty not as a shortage of capital, intelligence, or effort, but as a deficit in collaboration capacity.

3.2. Cooperation versus Collaboration: A Structural Distinction

Although cooperation and collaboration are frequently used interchangeably in economic and organizational discourse, they represent fundamentally different behavioral regimes with distinct economic consequences.

Cooperation arises from aligned self-interest. Parties coordinate actions because each expects a net individual benefit, even in the absence of trust or shared purpose. Markets function on cooperation, and cooperation can scale through prices, contracts, and incentives. However, cooperation breaks down in environments characterized by uncertainty, power asymmetries, or weak enforcement mechanisms.

Collaboration, in contrast, requires participants to internalize the welfare of the group. It involves joint intention, shared mental models, and agreement on both objectives and surplus distribution. As Tomasello (2010) demonstrates, collaboration is unique to humans and depends on cognitive and social capacities that go beyond intelligence or technical skill.

The economic implication is profound. Cooperation generates ordinary returns, while collaboration generates extraordinary returns. The surplus generated through collaboration—what may be termed the "collaboration dividend"—is the foundation of advanced institutions, high-trust societies, and sustained economic growth. Without collaboration, attempts to impose rule of law remain fragile and reversible.

3.3. Biological and Epigenetic Constraints on Collaboration

The existence of collaboration as a uniquely human capability does not imply that it is universally expressed. As with language, collaboration capacity must be activated, trained, and reinforced through social interaction. Evidence from animal models suggests that genetic factors influence social cooperation (Avital et al., 2016; Avital & Aga-Mizrachi, 2022). If similar mechanisms apply to humans, collaboration may depend on genetic potential that is either activated or suppressed by environmental conditions.

Environmental stressors—such as forced labor, systemic discrimination, and exposure to toxic chemicals—can produce epigenetic transgenerational psychosequelae that impair social functioning (Skinner et al., 2013; Ridley & Nelson, 2022b). These effects persist across generations, not through changes in DNA sequence, but through altered gene expression.

Importantly, epigenetic impairment does not imply immutability. Just as physical skills can be rehabilitated, collaboration skills can be recovered through structured social experiences. However, the speed and effectiveness of recovery vary dramatically depending on the intervention. Traditional education-based approaches, such as those implemented in Singapore through mandatory team sports and music education, demonstrate that collaboration can be cultivated at scale—but typically over an entire generation.

The challenge, therefore, is to identify mechanisms capable of accelerating collaboration skill recovery among adults who did not benefit from such early interventions. This challenge motivates the exploration of artificial intelligence as a potential catalyst.

4. Background and CDR Enhancements

4.1. Institutions, Growth, and Rule of Law

Institutional economics has long emphasized the role of property rights, contract enforcement, and governance in economic growth. However, much of the extant literature treats institutions as exogenous or policy-imposed structures, rather than emergent outcomes of human interaction. The CDR model advances the literature by identifying collaboration as the behavioral prerequisite for institutional stability. Studies linking rule of law to GDP often fail to explain how rule of law itself emerges. This omission obscures the role of human behavioral capacity and leads to policy prescriptions that emphasize legal reform without addressing the underlying social skills required to sustain it.

4.2. Collaboration and Collective Intelligence

Research on collective intelligence demonstrates that groups can outperform even highly intelligent individuals when collaboration is effective (Surowiecki, 2005). Importantly, group performance is weakly correlated with average intelligence and strongly correlated with social sensitivity, turn-taking, and shared goals. Ridley, Korovyakovskaya, & Llaugel (2021), Ridley, Ngnepieba, & de Silva (2021), Ridley et al. (2023), Ridley & Nelson (2022a, 2022b), and Ridley (2023) extend this literature by empirically demonstrating that collaboration predicts standard of living more effectively than intelligence. These findings challenge prevailing assumptions in education, labor markets, and economic development policy.

4.3. Epigenetics, Trauma, and Social Skill Transmission

Emerging research in epigenetics highlights the long-term behavioral effects of environmental stress. Transgenerational transmission of trauma-related traits has been documented in both animal and human populations, with implications for social trust, cooperation, and emotional regulation. This literature provides a biological foundation for understanding why collaboration deficits persist even when economic conditions improve. It also underscores the ethical imperative to develop interventions that restore social capacity rather than exclude affected individuals.

4.4. Artificial Intelligence in Education and Workforce Development

AI has been widely studied as a tool for individualized learning, skill assessment, and performance optimization. However, most applications focus on cognitive or technical skills rather than social capabilities. Existing research treats AI as either a replacement for human labor or as an efficiency-enhancing tool, rarely as a social skill scaffold. This gap presents an opportunity to reconceptualize AI's role—not as an autonomous collaborator, but as an instrument for facilitating human collaboration.

5. Conceptual Framework: Artificial Intelligence as a Collaboration Catalyst

5.1. Why Artificial Intelligence Cannot Collaborate

Collaboration requires shared intentionality, moral agency, and intrinsic motivation—capacities that artificial intelligence does not possess. No amount of training enables AI to internalize joint interests or experience commitment. Therefore, AI cannot be a collaborator in the human sense. Recognizing this limitation is essential. Attempts to anthropomorphize AI obscure its true value and risk undermining human responsibility.

5.2. AI as a Collaboration Scaffold

While AI cannot collaborate, it can support the development and execution of human collaboration by providing structure, feedback, and mediation. AI systems can monitor interaction patterns, identify breakdowns in communication, and suggest corrective strategies in real time. In this role, AI functions analogously to a coach, conductor, or training simulator. Such scaffolding reduces cognitive and emotional load, allowing individuals with diminished collaboration skills to participate productively without triggering defensive or uncollaborative behaviors.

5.3. Skill Invocation, Recovery, and Enhancement

This framework distinguishes three stages of collaboration development (see **Figure 1** and **Figure 2**):

1) Invocation: Activating latent collaboration capacity that has never been exercised.

2) Recovery: Rehabilitating skills suppressed by trauma or environmental stress.

3) Enhancement: Refining collaboration among already skilled individuals.

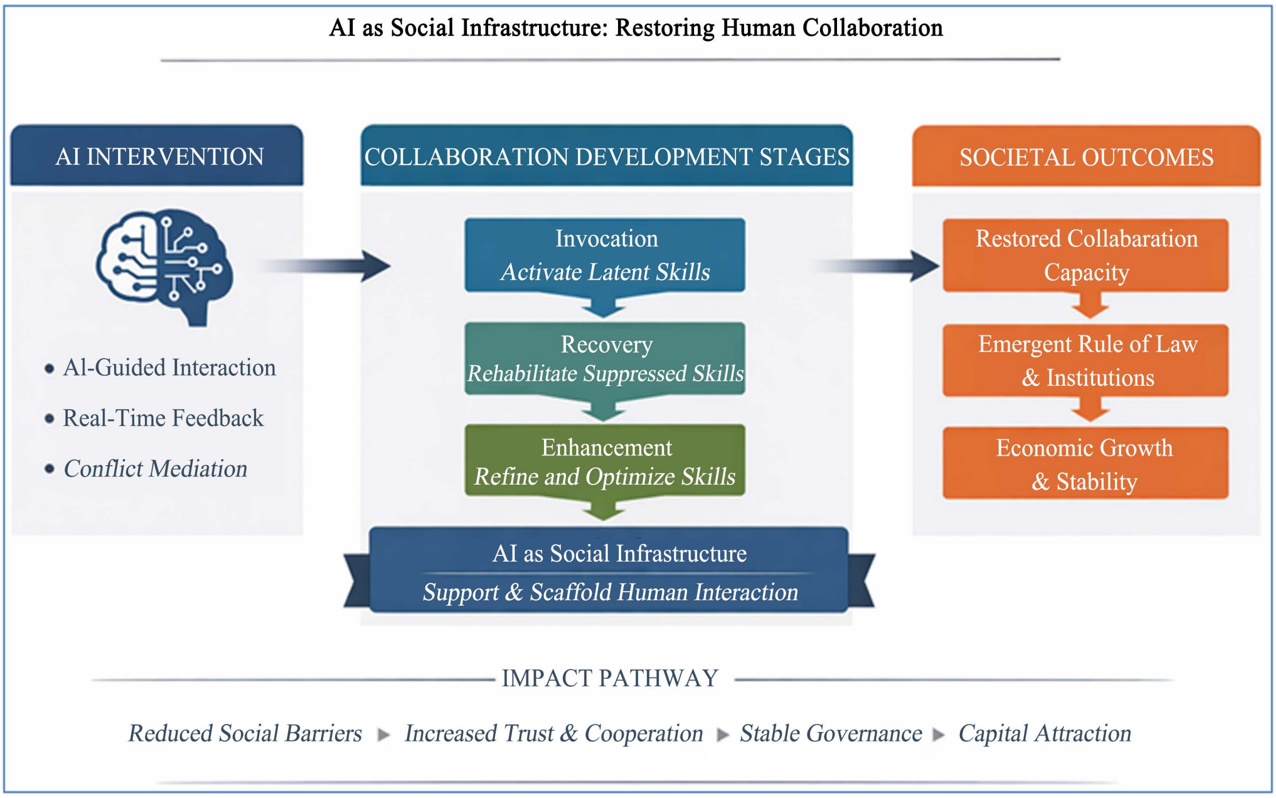

Figure 1. Artificial intelligence infrastructure for the recovery of human collaboration skills.

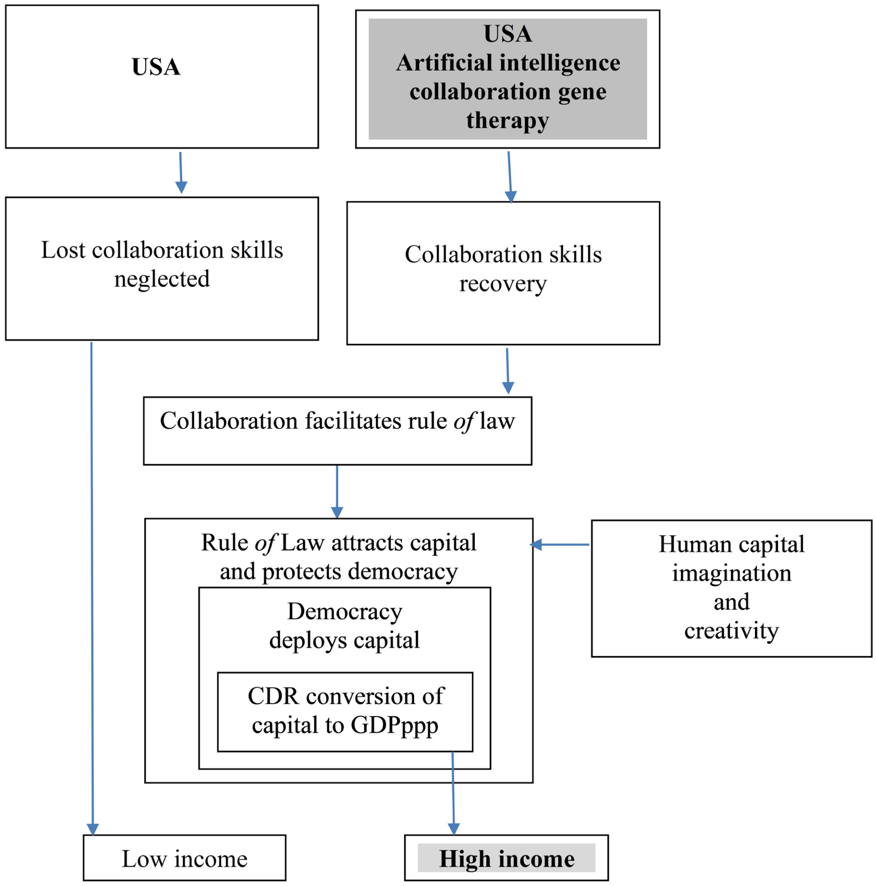

Figure 2. Artificial intelligence facilitates collaboration skills recovery and rule of law which attracts capital, and protects democracy for the optimal deployment of capital in the production of GDP and raised income.

AI-assisted environments can support all three stages by providing consistent reinforcement, reducing social risk, and accelerating experiential learning.

5.4. Analogies to Gene Therapy and Military Training

Singapore's education system and military training programs demonstrate that collaboration can be rapidly developed under structured, immersive conditions. AI-assisted collaboration training represents a civilian analogue—capable of operating at scale, across cultures, and without generational delay. While future biological interventions may further accelerate recovery, social training remains indispensable. AI thus serves not as a substitute for human interaction, but as an amplifier of it.

5.5. Technical Mechanisms for AI-Assisted Collaboration Scaffolding

While we are not proposing a specific implementation of AI to help foment collaboration, it is important to perhaps show a possible scaffolding that can be utilized. We propose a three-layer approach:

1) Observation Layer
2) State Estimation Layer
3) Intervention Layer

Our objective is not to implement or optimize collaboration, but to provide structural support that stabilizes interaction environments. Specifically, environments in which collaboration skills may be invoked, recovered, or enhanced. The proposed mechanisms avoid anthropomorphizing AI and preserve human moral agency.

A model (or agents) can be implemented in each layer to monitor communications. We also suggest utilizing statistical methods that can be fed into the agents for analysis. These AI agents can be directed to interact directly with the participants and/or through a facilitator. Direct interaction versus a facilitator may be decided depending on the level of dysfunctional behavior perceived.

The proposed scaffolding is intentionally communication-channel agnostic. In organizational contexts, this may include systems like Slack or Teams. In less formal or community-based settings, scaffolding may be integrated into commonly used social or messaging systems like WhatsApp, Discord and Telegram. This can also be as simple as email.

Because observational metrics are independent of platform-specific semantics, the same architectural approach applies across synchronous and asynchronous communication without requiring participants to adopt new tools or alter established interaction practices.

Observation Layer

At the observational level, AI systems need not interpret the semantic content of communication. NLP agents can monitor a host of activities such as: Turn-taking imbalance; Pronoun usage ("I" vs "we") and conflict escalation patterns. For these purposes we can utilize Tokenizers and shallow encoders, pronoun frequency analyzer and sentence length, pacing analyzers.

Collaboration-relevant signals can be extracted from paralinguistic and interaction metrics that capture how communication unfolds rather than what is communicated. These include turn-taking frequency and balance, response latency, participation persistence, and message pacing. Such metrics are well established in research on collective intelligence and group performance and can be computed in real time using rule-based counters and sliding-window statistics.

In text-based systems, shallow linguistic features—such as message length or question-to-assertion ratios—may be included strictly as structural indicators. By relying on non-semantic features, the system minimizes ethical risk and avoids attributing intent, emotion, or motivation to participants.

State Estimation Layer

While individual interaction metrics provide local signals, effective scaffolding requires a coherent estimate of the group's overall collaborative condition. This can be achieved using a hidden Markov model (HMM). These treat collaboration as a latent, evolving state inferred probabilistically from observed interaction patterns. The states might include stable collaboration, emerging imbalance, fragmentation, and withdrawal risk. Transitions between states capture the dynamic nature of group interaction, allowing gradual degradation or recovery to be modeled without imposing binary judgments. The HMM does not diagnose individuals; it estimates the condition of the interaction environment itself. This approach aligns with the view that collaboration is an emergent group property rather than an individual trait.

Intervention Layer

Intervention is implemented through a rule-based policy that responds to estimated collaboration states by adjusting interaction structure. When the system detects sustained imbalance or disengagement, it may:

- Prompt turn redistribution,
- Introduce temporary interaction pacing,
- Summarize prior discussion to re-anchor shared context,
- Or suggest structured role rotation.

These interventions are intentionally conservative and reversible. They do not influence task outcomes, beliefs, or preferences. They modify the interaction environment to reduce cognitive and social load. In this role, AI functions analogously to a facilitator or coach, providing external structure until intrinsic collaboration capacity is restored.

Scope and Limitations

This minimal architecture demonstrates how AI scaffolding for collaboration can be operationalized using existing, interpretable models without invoking deep semantic understanding, emotional inference, or autonomous decision-making. By restricting AI's role to observation, state estimation, and structural intervention, the framework remains consistent with our central claim: artificial intelligence cannot collaborate, but it can support the recovery and execution of uniquely human collaboration skills.

6. Applications and Implications of AI-Assisted Collaboration

6.1. Education and Adult Skill Recovery

Traditional education systems are effective at transmitting cognitive knowledge but are poorly suited to recovering collaboration skills in adults. Adults who experienced early-life deprivation, systemic discrimination, or environmental trauma often possess latent collaboration capacity that remains inactivated or suppressed. Conventional classroom instruction does little to address this deficit. AI-assisted collaboration environments offer a mechanism for accelerated adult skill recovery. By simulating structured social interaction, providing immediate feedback, and reducing interpersonal risk, AI systems can create conditions under which collaboration skills may be invoked and strengthened. Unlike traditional schooling, such systems can be deployed flexibly—within workplaces, vocational training programs, and community development initiatives. Importantly, AI does not replace human interaction in these settings. Rather, it stabilizes the interaction space, preventing early failure that would otherwise reinforce withdrawal or antagonism. In this sense, AI functions as a temporary prosthetic that supports collaboration until intrinsic capacity is restored.

6.2. Corporate and Organizational Design

Firms operating in competitive labor markets increasingly recognize that excluding collaboration-unskilled individuals is neither economically efficient nor socially sustainable. Recent research demonstrates that organizations can design roles and workflows that enhance collaboration rather than presuppose it (Rosier et al., 2024; Ridley & Korovyakovskaya, 2025). AI-assisted collaboration tools extend this approach by enabling organizations to engineer collaboration into job design. Examples include AI-mediated team formation, real-time feedback on communication balance, and adaptive conflict de-escalation protocols. Such systems allow individuals with diverse collaboration capacities to contribute productively while gradually developing their skills. The economic implication is significant. By expanding the effective labor pool and increasing team productivity, firms capture both ordinary and extraordinary returns. At scale, this mechanism contributes directly to national productivity and capital attraction.

6.3. National Development and Policy Implications

From a policy perspective, AI-assisted collaboration represents a potential institutional leapfrogging strategy. Just as mobile telecommunications allowed countries to bypass landline infrastructure, collaboration-supportive AI may allow societies to bypass generational delays associated with traditional education reform. Rather than attempting to impose rule of law through legal transplantation, policymakers can focus on cultivating the human capacity required to sustain institutions. AI-supported collaboration training programs—implemented through education, workforce development, and public service—can accelerate the emergence of stable governance, attract capital, and increase GDP. This approach reframes development aid from capital transfer to capacity restoration, aligning economic growth with human dignity and long-term institutional resilience.

7. Limitations, Risks, and Ethical Considerations

Despite its promise, AI-assisted collaboration is not without limitations. First, collaboration is culturally mediated, and AI systems must be carefully adapted to local norms to avoid reinforcing dominant cultural models at the expense of diversity. Second, there is a risk of over-reliance on AI mediation, which could inhibit the full internalization of collaboration skills if scaffolding is not gradually withdrawn. Effective implementation therefore requires deliberate phase-out strategies. Third, ethical concerns arise regarding surveillance, manipulation, and autonomy. Systems designed to monitor interaction must be transparent, consensual, and accountable. AI must support human agency, not supplant it. Finally, AI-assisted collaboration cannot substitute for structural justice. While skill recovery is essential, it must be accompanied by efforts to address ongoing sources of environmental stress that continue to impair collaboration capacity.

8. Conclusion and Future Research Agenda

This paper advances a conceptual framework linking collaboration capacity, artificial intelligence, and economic development. By situating collaboration as the human prerequisite for the rule of law within the CDR model, it reframes poverty as a solvable capacity deficit rather than an immutable condition. Artificial intelligence, while incapable of collaboration itself, can function as a catalyst for invoking, recovering, and enhancing human collaboration skills. Through structured interaction, feedback, and mediation, AI-assisted environments may compress what historically required generations into years or even months. Future research should empirically test this framework through controlled studies of AI-supported collaboration training in educational, corporate, and national development contexts. Longitudinal studies are needed to assess durability, transferability, and institutional impact. If validated, this approach offers a path toward sustainable economic growth, institutional stability, and a living wage for all—grounded not in technology alone, but in the restoration of humanity's most powerful collective capability.

Author Contributions

DR: Econometrics. FL: Literature review. CG: AI methodology.

Data Availability Statement

All data are generated in the paper.

Conflicts of Interest

The authors declare no conflict of interest.

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Appendix

Standard endogenous growth models

Traditional growth theories (Solow, endogenous growth, etc.) emphasize Physical capital accumulation, Labor growth, and Technological progress.

Cross-country CDR economic growth model

The Ridley (2020) CDR framework challenges and extends the traditional growth theories by treating capital not just as physical goods or machinery, but as *intangible capital* rooted in exogenous human ideas, imagination, and innovation. He argues that capital alone cannot generate growth unless deployed in a system with democratic freedoms and a strong legal framework—i.e., capitalism without democracy or rule of law is insufficient. Highlighting the institutional catalysts that attract and protect capital (especially intangible capital) and make entrepreneurial deployment effective.

1. *Collaboration as the Engine of Capital* (C) *Creation*

In the CDR framework, capital is not primarily machines or money; it is ideas made economically usable. No idea becomes productive capital in isolation. Collaboration matters because most economically valuable ideas are combinatorial: they emerge from the interaction of different skills, disciplines, and experiences. Entrepreneurs rarely innovate alone but are comprised of engineers, financiers, suppliers, marketers, and legal experts. Collaboration converts individual imagination into scalable capital. In CDR terms, capitalism thrives not on isolated genius, but on networks of collaboration under market incentives. Markets reward successful collaboration by allocating capital toward teams that coordinate efficiently.

2. *Democracy* (D) *as a Collaboration Multiplier*

Democracy matters in the CDR model because it broadens participation in economic collaboration. Democratic institutions enable: a) freedom of expression → ideas can be shared, challenged, and improved; b) open entry → more people can collaborate economically, not just elites; and political accountability → reduces fear that collaboration will be expropriated or punished. From a growth standpoint: a) more participants → more idea combinations; b) more feedback → faster learning; c) more trust → lower coordination costs. Democracy lowers the cost of collaboration across society, increasing the rate at which ideas become capital. This explains why highly centralized or authoritarian systems often struggle to convert talent into sustained growth despite high investment rates.

3. *Rule of Law* (R) *as the Trust Infrastructure*

Collaboration collapses without trust. The Rule of Law provides institutional trust. Economic functions of rule of law: a) enforce contracts; b) protect intellectual property; c) and guarantee predictable dispute resolution. In CDR logic: a) people collaborate only if expected gains exceed risks, and legal certainty reduces a) fear of theft; b) opportunism; and c) hold-up problems. Rule of law allows strangers to collaborate productively, which is essential in modern, complex economies. Without it, collaboration becomes: a) informal; b) limited to family or ethnic networks; and c) economically inefficient.

4. *Collaboration and Intangible Capital Accumulation*

A distinctive feature of the CDR model is its emphasis on endogenous intangible capital: knowledge, organizational know-how, business models and institutional memory. These assets a) cannot be built by individuals alone b) grow through repeated collaboration and c) compound over time. These imply that the CDR mathematical model should include an interactive CDR component, where collaboration increases the productivity of each component, not just their sum.

5. *Why Collaboration Explains Persistent Income Differences*

From a CDR standpoint, poor countries and regions are not poor because they lack ideas, they are poor because institutions prevent large-scale collaboration. For example, weak rule of law → firms stay small, limited democracy → ideas suppressed, crony capitalism → collaboration replaced by rent-seeking. The result is that ideas fail to become capital, capital fails to scale and growth stalls.

6. *Policy Implications* (*CDR Logic*)

If collaboration drives growth, then effective policy should strengthen legal institutions (R), expand economic and democratic political inclusion (D), and protect competitive capital markets (C). Notably, subsidies or investment alone are insufficient if collaboration is institutionally blocked.

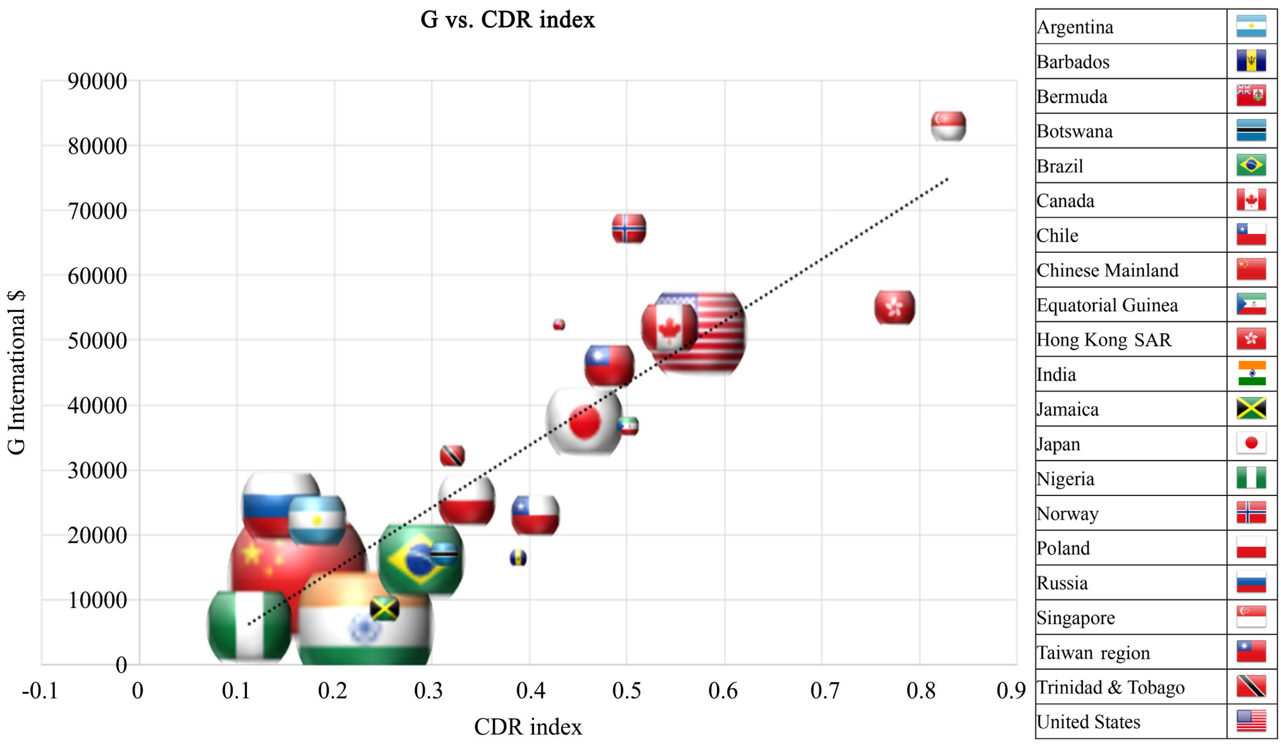

Figure A1. Year 2014 G vs CDR Index for 79 countries and regions (line). Bubble size (21 countries and regions) is the square root of population. This model was re-estimated for years 1995 to 2016 with similar results. For model estimation and additional comments on the countries and regions listed see Ridley (2020). $\hat{g} = 1.53C + 0.14D + 0.23R - 1.21CDR + 0.38N$. $R^2 = 0.9$. $G = \hat{g}$ (GDPppp highest-GDPppp lowest) + GDPppp lowest).

7. *Bottom Line* (*CDR View*)

From the CDR point of view economic growth is the outcome of collaborative idea formation operating within capitalism, enabled by democracy, and secured by the rule of law. Collaboration is the mechanism, institutions are the enablers, and growth is the result. The CDR economic growth model is shown is shown in **Figure A1**. The C, D and R variables all contribute positively to gross domestic product adjusted for purchasing power parity. The negative CDR coefficient represents friction between C, D and R due to differences in ideas that are almost certain to occur in a democracy. If there were perfect agreement and the agreement was the best possible decision, the decision could not be bettered, and the interaction coefficient would be zero. The model is called the CDR model because while C, D and R can be determined by government policy, natural resources (N) are determined by geography. For model specification, estimation, interpretation, and additional comments on the countries and regions included, see Ridley (2020).