Reinterpreting the Saemaul Spirit for Education in the AI Era: A Design and Implementation Case Study of a Reward-Based Learning Ecosystem Platform for Mitigating Educational and Economic Polarization

— Focusing on the Implementation Report and Policy Implications of the Web3-based NodajiFi Platform —

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Abstract

This study aims to reconstruct the social and economic operating mechanisms of Korea's Saemaul Undong (New Village Movement) of the 1970s-1980s within the context of 21st-century artificial intelligence (AI) and blockchain technology, and to report the design principles and an implementation case of a reward-based learning ecosystem aimed at mitigating global educational and economic polarization. Previous discussions on the digitalization of the Saemaul spirit have largely remained at the level of metaphorical or declarative borrowing of the three values of "diligence, self-help, and cooperation," making it difficult to translate the spirit into concrete prescriptions for contemporary digital-era problems. To overcome this limitation, this study extracts four essential operating mechanisms from the original Saemaul Undong: (1) village-level self-organization, (2) matching of external seed funding with internal labor (matching grant), (3) performance-based differentiated support, and (4) immediate visibility of outcomes. These mechanisms are reinterpreted as design principles for token economies and decentralized autonomous organizations (DAOs) in the Web3 era.

The case under analysis—the NodajiFi and GlobalPiggy platform—instantiates these mechanisms as a concrete system. As implemented, its core architecture is a dual-unit structure in which learners earn an immediate reward unit (NGEM) through interaction with AI tutors, complemented by a supply-side settlement and governance unit (NDJI). The study also presents, as a reference model of the full design space, a tri-token structure that adds a USD-pegged stable unit of value (NUSD), while explicitly noting that NUSD is a conditional design element whose implementation is deferred in light of the evolving regulatory environment for stablecoins. The study additionally proposes a virtual experiment and laboratory module that combines on-device AI and augmented reality (AR) as a means to alleviate STEM education disparities arising from the absence of physical laboratory infrastructure. Furthermore, the study formalizes the institutional design that secures the integrity of human attestation — scoped attestation contracts, a two-stage disciplinary process in which statistics indict and humans judge, precedent-bound adjudication, and regional compartmentalization — and maps each element onto the village-grading, mutual-monitoring, and village-level accountability structures of the original Saemaul Undong.

Methodologically, this study adopts design research and case study approaches. Full-scale empirical validation remains a task for future research; this paper instead reports preliminary qualitative and quantitative observations from a pre-launch internal alpha test (N=42), interpreted alongside expected effects suggested by prior empirical literature. The observed direction of effects regarding learning persistence and engagement is consistent with prior large-scale empirical findings (e.g., Kestin et al., 2025).

The study further articulates the deeper design principles that a reward-based learning ecosystem must satisfy to remain sustainable. Taking the risks of the overjustification effect and Goodhart's law as premises, it argues for repositioning rewards from payment for learning to a lubricant of a trust circuit, and for shifting the highest-order reward from monetary gain to the acquisition of status (as a guarantor) and opportunity (access to the demand side). This reconstruction structurally corresponds to the Saemaul Undong's village-grade system and the Saemaul leader institution.

The academic contributions of this study are threefold. First, it offers a theoretical mapping that reconstructs the operating mechanisms of the Saemaul Undong as token-economy design principles. Second, it derives policy implications of the Digital Saemaul model for the new forms of polarization specific to the AI era—namely, the overlapping structure of the "AI divide" and capital-labor income inequality. Third, it analyzes the potential of on-device AI and AR to reduce STEM education gaps, with concrete attention to subject-specific scope of substitutability.

Keywords: Digital Saemaul Undong, Hongik Ingan, reward-based learning, Learn-to-Earn, AI tutoring, blockchain governance, educational inequality, economic polarization, on-device AI, augmented reality (AR), self-determination theory, overjustification, Goodhart's law, guarantor economy, intrinsic motivation

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1. Introduction

1.1. Background and Problem Statement

A generation into the 21st century, humanity is simultaneously experiencing the deepening of two great asymmetries. One is the explosive rise in productivity driven by the technological innovations of artificial intelligence and digital assets; the other is the deepening polarization in which the gap widens between those who can access these benefits and those who cannot. These two currents do not exist in isolation but reinforce one another, and as a result, structural inequality is becoming entrenched across both the educational and economic domains.

According to global poverty statistics released by the World Bank, as of 2024 approximately 839 million people worldwide still live in extreme poverty, and about 10.3 percent of the global population lives below the newly adjusted poverty line of three dollars per day (World Bank, 2025). Even more serious is the learning-poverty indicator observed in the educational domain. According to joint measurements by the World Bank and UNESCO, a substantial proportion of children in low-income and lower-middle-income countries cannot read and understand even a basic short passage by the end of primary education; this is diagnosed not merely as a problem of insufficient school attendance but as a more fundamental crisis—the failure of learning itself (World Bank & UNESCO, 2022).

While many structural factors lie behind this learning crisis, this study pays particular attention to the problem of the opportunity cost of education that learners face. For children and adolescents in absolute-poverty households, devoting time to learning is not merely the sacrifice of leisure but the direct loss of labor time that could contribute to the household's livelihood. From the perspective of human capital theory as established by Becker (1964), education is an investment in future income; but the asymmetry in which this investment has a gestation period of years to decades while the reward of labor is immediate becomes a powerful incentive that tilts the rational decision-making of poor households toward avoiding learning.

Onto this is superimposed a new divide of a 21st-century dimension. The "AI divide" between those who can use generative AI as a tool and those who cannot goes beyond the earlier simple digital divide and directly translates into a divide in cognitive and productive capacity (Acemoglu & Restrepo, 2022). At the same time, as the phenomenon in which the growth rate of capital income structurally exceeds that of labor income (Piketty, 2014) deepens, the many learners and workers who hold no assets face an asymmetry in which they can hardly reach asset formation through their labor alone. In other words, 21st-century polarization is not merely an income gap but a multilayered structure that is a polarization of the very "eligibility to access learning resources" and the "eligibility to form assets."

In this situation, traditional official development assistance (ODA) models or supplier-centered EdTech infrastructure support alone can hardly solve the problem. Aid that builds school buildings and sends textbooks does not resolve learners' opportunity-cost problem, and EdTech centered on one-directional video lectures cannot exert sufficient effect for learners who need one-on-one personalized guidance. This is a moment that calls for a new incentive structure in which the act of learning is itself recognized as a value-creating activity of the learner in the present, and in which that learning is simultaneously connected to an immediate and trustworthy reward.

1.2. The Need to Reinterpret the Saemaul Undong for the 21st Century

At this juncture, this study seeks to shed new light on the contemporary implications of the Saemaul Undong that Korea has promoted since the 1970s. The Saemaul Undong is generally known for its three-fold spirit of "diligence, self-help, and cooperation" and for its rural environmental-improvement projects, and attempts to apply it to the digital age have been made on several occasions. The limitation of existing Digital Saemaul discussions, however, is that they have reduced the Saemaul Undong to a spirit and remained at the level of its metaphorical application. Discussions of the form "diligence is applied in the digital age as diligent learning" or "self-help is interpreted as self-directed learning" are rhetorically smooth but cannot be reduced to concrete system-design principles.

The core claim of this study is that the true success factor of the Saemaul Undong lay not in its spirit but in its operating mechanisms. The reason Korea's rural areas changed in a short period in the 1970s was not that farmers suddenly became more diligent, but that four mechanisms were combined: (1) a self-organizing structure in which projects were decided upon and taken responsibility for autonomously at the village level; (2) a matching-grant method in which, when the government provided seed materials such as cement, the village combined its labor; (3) an incentive system that classified villages into superior, self-help, and basic villages and provided differentiated support according to performance; and (4) a feedback structure that made immediate and visible outcomes—such as roof improvement and the paving of village roads—apparent (So, 2017; Choi, 2020).

These four mechanisms correspond, remarkably, almost one-to-one with the core design principles of the 21st-century Web3 token economy and decentralized autonomous organizations (DAOs). Village self-organization corresponds to the governance-voting structure of token holders; the matching grant to the structure combining external funds (advertising revenue and sponsorship) with internal effort (learning activity); performance-based differentiated support to a token-distribution algorithm keyed to learning achievement; and immediate visible feedback to blockchain-based real-time reward settlement. This structural mapping suggests that a digital reinterpretation of the Saemaul Undong is possible not as a mere borrowing of spirit but as a transplantation at the level of system design.

This carries practical significance beyond mere academic interest. Although 21st-century polarization takes a different form from the rural-urban gap Korea faced in the 1970s, the fundamental problem structure—how a resource-poor majority can pool its own resources, combine them with external resources, and advance toward self-reliance through staged outcomes—is identical. The mechanisms of the Saemaul Undong were Korean society's response to this problem structure, and if those mechanisms can be reproduced in a digital environment, there is potential to contribute to mitigating polarization at the global level.

1.3. Research Objectives and Research Questions

On the basis of the above problem awareness, this study sets the following objectives.

First, it reconstructs the essential operating mechanisms of the Saemaul Undong as system-design principles that operate in the 21st-century Web3·AI environment. This is the work of clarifying the Saemaul Undong—beyond existing spirit-centered discussion—as mechanisms that are academically analyzable and systemically transplantable.

Second, on the basis of the above design principles, it reports the system architecture and implementation status of the NodajiFi and GlobalPiggy platform, an actually-implemented case. This study is not a full-scale, large-sample empirical study but a design study and implementation report, and it honestly presents the results of an internal alpha test at the pre-launch stage.

Third, it derives the policy implications this model may have for 21st-century polarization—particularly the overlapping structure of the AI divide and learning poverty—and presents concrete recommendations for the Korea Saemaul Undong Center and Korean ODA agencies.

The research questions that give concrete form to the above objectives are as follows.

> Research Question 1. How can the social operating mechanisms of the 1970s-1980s Saemaul Undong be decomposed, and what structural correspondence do those mechanisms have with 21st-century token-economy and DAO design principles?
>
> Research Question 2. For each of the core components of AI-era polarization (the AI divide, capital-labor asymmetry, and the persistence of learning poverty), through what operating pathways can the Digital Saemaul model theoretically have a mitigating effect?
>
> Research Question 3. To what extent does the NodajiFi/GlobalPiggy platform implement the above design principles at the system level, and how do the qualitative and preliminary quantitative indicators observed in pre-launch user behavior compare with the expectations of prior literature?
>
> Research Question 4. To what range can a virtual experiment/practice module combining on-device AI and AR contribute to closing STEM education gaps, and in which subjects and practice domains are its limits clear?

1.4. Research Methods and Structure of the Paper

Methodologically, this study adopts a combined approach of design research and case study. This study is not a hypothesis-testing empirical study but has the character of clarifying the design principles of a socio-technical system and reporting its implementation case. Accordingly, the form of its conclusions is not statistical generalization but an argument for the coherence of the design principles and the validity of the implementation.

The sources of data are composed of three layers. First, it reviews existing academic literature and policy reports on the operating mechanisms of the Saemaul Undong to establish the academic basis for the extraction of mechanisms. Second, it uses the NodajiFi whitepaper (NodajiFi Labs, 2025) and system-design documents that are the case of this study, as well as user logs and interview data from the pre-launch internal alpha test (N=42, December 2025 to April 2026). Third, it uses recent empirical studies on the effects of AI tutoring and reward-based learning (Kestin et al., 2025; Lah et al., 2024) as comparative reference points.

The limitations of this study must be clearly acknowledged. Because the platform analyzed in this study is at the development-completed and pilot-preparation stage immediately before full-scale commercial launch, this paper does not present a quantitative effect analysis based on large-scale user data. Accordingly, the conclusions of this study have the character not of statistical generalization but of an argument for the coherence of the design principles and the validity of the system implementation. Full-scale empirical validation is left as a task for future research, and its validation design is presented concretely in Chapter 7. The academic coherence of the design principles, the concreteness of the system implementation, and the clarification of the future validation design can be understood as the core contribution of this study at the stage before empirical data have been secured.

The paper is structured as follows. Chapter 2 decomposes the operating mechanisms of the Saemaul Undong into four and reconstructs each as a digital design principle. Chapter 3 analyzes the structure of 21st-century polarization and sets the policy coordinates of the Digital Saemaul model. Chapter 4 explains the system architecture of the NodajiFi platform, and Chapter 5 reconstructs the deep principles of reward design from payment to a trust circuit. Chapter 6 discusses the design and limitations of the module supporting experiment, practice, and skill acquisition by combining on-device AI and AR. Chapter 7 presents the pilot operation plan and future validation design, and Chapter 8 discusses the study's limitations and implications. Finally, Chapter 9 presents policy recommendations and future tasks.

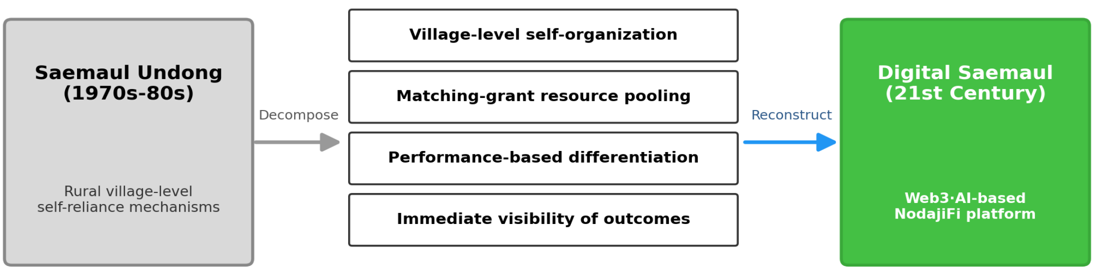


Figure 1-1. Analytical framework: extraction and digital reconstruction of Saemaul mechanisms

2. Theoretical Background: The Operating Mechanisms of the Saemaul Undong and Their Digital Reconstruction

2.1. The Essence of the Saemaul Undong: From Spirit to Mechanism

The most common difficulty encountered in analyzing the Saemaul Undong academically is that the moment the movement is reduced to the slogan "diligence, self-help, and cooperation," it loses its analytical depth. These three words are effective in summarizing the movement's ethical appeal, but they are insufficient for explaining how the movement operated. Rural areas did not change through ethical appeal alone. Farmers did not suddenly become more diligent; rather, a structure was newly created in which diligence was rewarded.

Accordingly, this study holds that in analyzing the Saemaul Undong a shift in the unit of analysis from spirit to mechanism is needed. The spirit is a cultural shell formed after the fact on top of the movement's effects; what actually made the movement work was the social and economic incentive structure that existed beneath it. Such mechanism-centered analysis opens the possibility of the academic universalization of the Saemaul Undong. Spirit is easily reduced to Korea's unique culture, whereas a mechanism can be abstracted into a design principle transplantable to other times and places (So, 2017).

A comprehensive review of existing Saemaul Undong research (So, 2017; Park, 2009; Choi, 2020) compresses the core mechanisms that explain the movement's operation into the following four. First, village-level self-organization. Rather than an external administrative office unilaterally deciding the priorities and methods of projects, a governance structure operated that had decisions made within the village through the village assembly and the Saemaul leader. Second, matching-grant-style resource combination. When the government provided seed materials such as cement and steel, the village combined corvée-style labor and land to complete the project. A project that would have been impossible with external resources alone, or with internal resources alone, became possible through the combination of the two. Third, performance-based differentiated support. Rather than distributing resources equally to all villages, villages were classified into basic, self-help, and self-reliant villages according to project performance, and higher-grade villages received more differentiated support. This functioned as an incentive mechanism that induced constructive competition among villages. Fourth, immediate feedback of visible outcomes. Roof improvement, village-road paving, communal-well installation, and the like were projects whose effects became visible within a few days, and this visibility reinforced additional motivation for participation.

Each of these four mechanisms has an associated academic concept. Self-organization connects to Ostrom's (1990) theory of common-pool resource governance; the matching grant to the discussion of complementary inputs in development economics; performance-based differentiation to incentive-design theory. The last, immediate visibility, connects to behavioral economics' discussion of overcoming delay discounting and to Skinner's (1953) theory of positive reinforcement. These academic connections suggest that the mechanisms of the Saemaul Undong were not an ad hoc expedient that happened to work but a design consistent with universal principles of social science.

The core claim of this study is that these four mechanisms can be transplanted, almost one-to-one, into digital design principles that operate in the 21st-century Web3 technological environment. The following sections discuss in turn how each mechanism can be reconstructed in a digital environment.

[Table 2-1] The Four Saemaul Mechanisms and Associated Academic Concepts

Mechanism	Operation in the 1970s-80s	Associated Academic Theory	Key References
Village-level self-organization	Village-assembly decision-making · intermediary leadership of the Saemaul leader · autonomous determination of project priorities	Common-pool resource governance	Ostrom (1990); So (2017)
Matching-grant-style resource combination	Government seed materials of cement·steel + combination of village labor·land	Complementary-inputs theory · combination of human and physical capital	Becker (1964); Park (2009)
Performance-based differentiated support	Classification into basic·self-help·self-reliant villages and staged differentiated resource allocation	Incentive-design theory	Choi (2020); So (2017)
Immediate feedback of visible outcomes	Priority promotion of short-term visible projects such as roof improvement·village-road paving	Positive reinforcement · overcoming delay discounting	Skinner (1953); Mullainathan & Shafir (2013)

2.2. Mechanism 1 — Village-Level Self-Organization and DAO Governance

The most essential yet most frequently overlooked element of the Saemaul Undong is the self-organizing governance centered on the village assembly. What the Korean government attempted through the Saemaul Undong was not the direct control of rural development but the creation of a structure in which the village itself became the subject of decision-making. The Saemaul-leader institution, the decision-making method of the village assembly, and the autonomous determination of project priorities are all constituent elements of this self-organizing structure. The principle that, even when resources were injected from outside, the village decided where and how to use them secured the movement's sustainability.

This self-organizing structure is structurally identical to the core design principle of the 21st-century decentralized autonomous organization (DAO). A DAO is a structure in which token holders participate directly in the organization's decision-making through governance voting; in that the members themselves—rather than an external institution—become the subjects of decision-making, it can be called a digital equivalent of the Saemaul village assembly (Buterin, 2014; Hassan & De Filippi, 2021). One difference is that a village is a geographical unit, whereas a DAO is a virtual unit—a global community of learners.

The digital reconstruction of this self-organization requires careful design. The self-organization of the 1970s Saemaul Undong operated on the strong social bonds of the village community, whereas a global learner DAO has no such prior bonds. Therefore, in the Digital Saemaul model, a mechanism is needed that secures the authenticity of governance participants through a dual eligibility of token holding and learning activity. This is why NodajiFi's governance token (NDJI) is designed so that it is combined not with mere holding but with acquisition through learning activity.

It is also worth remembering that what complemented village-level self-organization in the Saemaul Undong was the intermediary leadership of the Saemaul leader. Even in a digital environment, rather than a completely flat governance, a hierarchical governance in which users who have accumulated learning achievement and community contribution perform a natural intermediary role may be realistic. This is reflected in the design of NodajiFi's governance structure discussed later.

2.3. Mechanism 2 — Matching Grant and the Combination of Advertising, Sponsorship, and Study Effort

The second mechanism of the Saemaul Undong is matching-grant-style resource combination. The simple structure in which, when the government provided cement and steel, the village combined labor and land was in fact a very sophisticated design in development-economics terms. Welfare aid, in which the government bears all costs, tends to induce the moral hazard of the recipient; conversely, a self-reliance model in which the recipient must bear all costs cannot be applied to capital-poor households. The matching grant is a middle path that simultaneously avoids the limits of both extremes while utilizing the complementarity of external resources and internal effort.

Another strength of the matching-grant method is that it forces the village to have "skin in the game" with respect to external resources. Because the village put in its own labor, a sense of responsibility for the project's outcome arises, and an autonomous monitoring mechanism operates that prevents external resources from being wasted or made merely formal. This was a structural solution to the resource-leakage problem commonly observed in welfare aid.

How can this mechanism be reconstructed in the Digital Saemaul model? This study maps external resources onto advertising revenue and sponsorship funds, and internal effort onto the learner's learning activity. In NodajiFi's operating model, the advertising fees paid by advertisers and the donations of external sponsors perform the same external-resource role as the cement of the 1970s, while the study time the learner invests in problem-solving and interaction with the AI tutor performs the same internal-resource role as the village's corvée labor. When these two resources are combined through the token-issuance algorithm, the learner experiences their study time being converted into monetary value.

What must be emphasized here is that the Digital Saemaul matching grant is fundamentally different from a simple advertising-viewing reward (points granted immediately upon viewing). A simple advertising reward is a structure that sells the learner's time to advertisers and does not contribute to the learner's development. By contrast, in a matching-grant-style learning reward the learning activity itself is the core of value creation, and advertising is merely a flow of external resources that makes that activity possible. This distinction is important both ethically and in terms of the learner's long-term human-capital formation.

Furthermore, in the digital reconstruction of the matching grant, the transparency of resources is decisive. In the 1970s Saemaul Undong, how many bags of cement the government sent to which village was verifiable through administrative records, but in a digital environment there is a great risk that how advertising revenue and donations are distributed to learners will be opaque. At exactly this point, the on-chain transparency of the blockchain functions as the digital equivalent that replaces the administrative records of the Saemaul Undong (Tapscott & Tapscott, 2016).

2.4. Mechanism 3 — Performance-Based Differentiation and the Token-Distribution Algorithm

The most contested yet most powerful mechanism of the Saemaul Undong is the village-grading system. The government did not distribute resources equally to all villages but classified villages into basic, self-help, and self-reliant villages on the basis of project performance and provided differentiated support. Villages that rose to a higher grade received more resources, and villages that remained at a lower grade received relatively fewer. This structure is open to criticism from an egalitarian standpoint, but it was the core incentive that generated the movement's momentum.

The operating principle of this mechanism can be analyzed in two respects. First, differentiated support created comparability among villages and thereby provided the driving force of constructive competition. Second, because the possibility of grade advancement was made visible in stages, it was easy for a village to set attainable short-term goals. Rather than the burden of having to become a self-reliant village all at once, a visible path of staged entry from basic village to self-help village was presented.

The digital reconstruction of differentiated support is a problem of designing the token-distribution algorithm. Instead of a flat structure that grants the same reward to all learning activities, a design is required in which rewards are differentiated according to learning achievement, consistency, and difficulty. This differs from a simple scoring system. The learner must be able to clearly recognize their current grade and the criteria for the next grade, and to visually confirm the degree of progress between them. The learner-level system and the staged reward-multiplier structure implemented in NodajiFi's alpha version can be called the digital equivalent of this mechanism.

However, the digital reconstruction of differentiated support requires new ethical considerations that did not exist in the 1970s. Because the village-grading system operated at the village level, the differentiation of individual farming households was not directly made visible, whereas in a digital environment the grade of an individual learner is directly made visible. This can heighten learning motivation but at the same time risks bringing a stigma effect to lower-grade learners. Therefore, the Digital Saemaul model requires a balanced design that preserves the incentive effect of differentiated support while providing lower-grade learners with feedback centered on individual progress rather than explicit grades.

It is also worth emphasizing that the core of differentiated support is the clarity of the upgrade path. In the 1970s Saemaul Undong the criteria for village-grade advancement were clear, and meeting those criteria guaranteed grade advancement. In a digital learning environment as well, the operating principle of the reward algorithm must be transparently disclosed to learners, and learners must be able to trust that algorithm. Black-boxing the algorithm undermines the operation of this mechanism.

2.5. Mechanism 4 — The Behavioral Economics of Visibility and Immediate Feedback

The fourth mechanism is the element that seems the most trivial yet is the most powerful. What the early projects of the Saemaul Undong—roof improvement, village-road paving, communal-laundry installation—had in common was that their results became visible within a few days. This visibility functioned as a core mechanism securing the movement's sustainability, beyond mere aesthetic satisfaction.

In behavioral-economics terms, this connects to the universal principle of overcoming delay discounting. Humans tend to value a reward received in the future lower than a reward of the same value received in the present, and this tendency becomes even stronger under conditions of poverty (Mullainathan & Shafir, 2013). For a decision-maker in absolute poverty, "a large reward five years from now" can hardly beat "a small reward today." That the early projects of the Saemaul Undong had immediate visibility means that the movement was designed not to run counter to the delay-discounting tendency of farmers but to align with it.

In Skinner's (1953) theory of operant conditioning as well, it is consistently reported that the effect of positive reinforcement is proportional to the immediacy of the moment of reinforcement. Learning is reinforced when the reward follows immediately after the learning behavior occurs, and the effect of reinforcement diminishes sharply as the time interval lengthens. This is a universal principle observed consistently not only in humans but also in animal learning.

The essential reason traditional education systems struggle with learning motivation lies at exactly this point. The rewards of learning—degrees, certificates, employment—entail a delay of years to decades, which conflicts with the natural decision-making structure of humans. Some learners with strong self-control and future orientation can endure such delay, but the many learners—particularly those in poverty—cannot. Only when learning can be experienced not as an "abstract future value" but as a "concrete present value" is learning behavior stably maintained.

A blockchain-based immediate-reward system is a digital design that aligns with this behavioral-economics principle. When a learner solves a problem, the reward is credited to the wallet within seconds, and the fact that the reward is convertible into real value is made visible. This must be distinguished from mere gamification. Whereas the points of gamification are a virtual unit that remains within the game, a blockchain-based reward is a genuine asset convertible into real value beyond the platform, and in that respect the cognitive weight it gives the learner is different (Voshmgir, 2020).

One point to be careful of in the digital reconstruction of this mechanism, however, is the risk that immediate reward confines the learner to short-term extrinsic motivation and thereby damages long-term intrinsic motivation. According to Self-Determination Theory (Deci & Ryan, 2000), if extrinsic reward is not appropriately designed, it can crowd out intrinsic motivation. Therefore, the Digital Saemaul model recommends a staged design in which immediate reward is positioned as a "barrier-lowering device" until the learner discovers the value of learning itself, and in which, as learning progresses, the form of reward gradually diversifies into meaningful achievement certification, communal recognition, and the like.

2.6. A Global Digital-Commons Interpretation of the Hongik Ingan Ideal

The four mechanisms discussed so far explain the operating principles of the Saemaul Undong, but by themselves they do not explain the movement's directionality. Even if some society adopts these mechanisms, the results may differ according to the goal toward which the mechanisms are oriented. The mechanisms of self-organization, matching grant, differentiated support, and immediate feedback can be applied to a military organization or a corporate organization. That the Saemaul Undong could have the direction of the self-reliance of Korea's rural areas was because its mechanisms were located within the larger value orientation that Korean society shared.

This study finds that value orientation in the Hongik Ingan (弘益人間) ideal. Hongik Ingan, an idea originating in Korea's founding myth, contains the universal orientation toward the welfare of humanity—"to broadly benefit humankind." In that it is a thought oriented toward the welfare of all humanity, not reducible to national chauvinism or ethnocentrism, it is an intellectual resource that can connect with the 21st-century discourse of the global digital commons.

In particular, in that the Digital Saemaul model targets not the rural development of a single nation but a global learning community, the universalist orientation of Hongik Ingan becomes not mere rhetoric but a core element constituting the model's legitimacy. When Korean academia and the Korean government promote this model at the global-ODA level, the answer to the question "why is Korea promoting such a model" secures stronger legitimacy when it is found not in Korea's economic interest or diplomatic influence but in the ideal of universal human welfare that Korea's intellectual tradition has oriented itself toward.

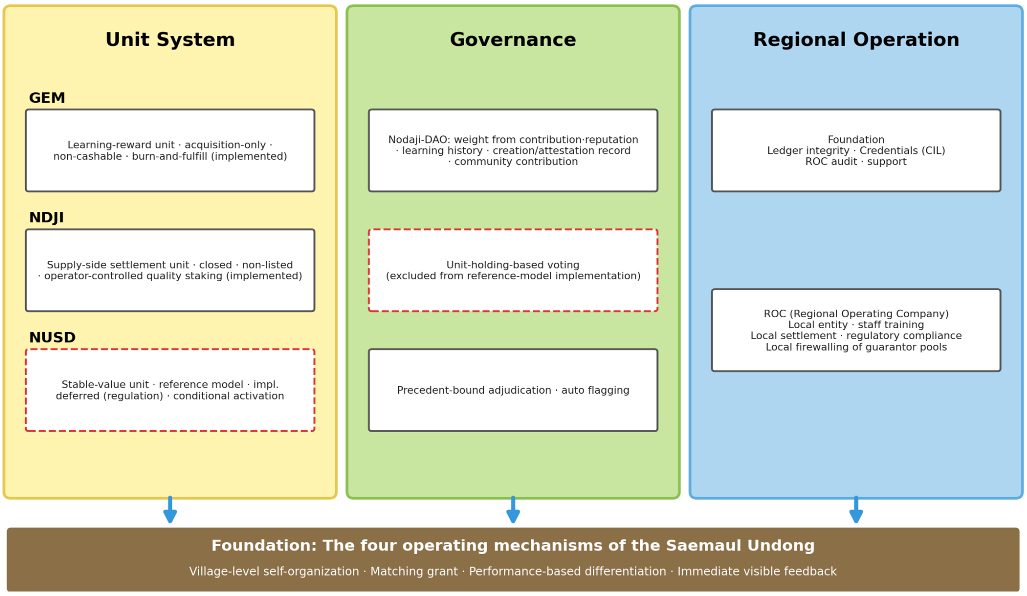
The universalism of the Hongik Ingan ideal also has particularly important implications in the digital age. Whereas past ODA was a structure in which a resource-rich nation transmitted resources one-directionally to a resource-poor nation, cooperation in the digital age allows for two-directional contribution and learning. A structure in which global learners share their knowledge and experience on the NodajiFi platform and it is transmitted to other learners opens the possibility of cooperation beyond the distinction between benefactor and beneficiary. The expression "to broadly benefit" in Hongik Ingan does not imply the one-directionality of benefaction but can be interpreted as implying mutual benefit among humans.

This intellectual position makes clear that this study's model is not a mere technical system but a value-oriented social design. Technology cannot be value-neutral, and the value toward which it is designed determines its social meaning. The Digital Saemaul model is positioned not as a technical system whose primary goal is efficiency or profitability, but as a socio-technical system whose primary goal is the value orientation of mitigating global learning poverty and polarization.

[Table 2-2] Mapping of the Four Saemaul Mechanisms and the Digital Saemaul Model

Mechanism	Operation in the 1970s-80s	Digital Equivalent (Design Principle)	NodajiFi System Implementation Element
(1) Self-organization	Village-assembly decision-making / Saemaul-leader mediation	Token-based distributed governance (DAO)	Nodaji-DAO voting system / NDJI holders' decision rights / Foundation mediation
(2) Matching grant	Government cement (external) + village labor (internal)	Algorithmic combination of external resources and internal effort	Advertising·sponsorship (external) + study time (internal) → automatic NGEM issuance
(3) Performance-based differentiation	Grade-differentiated support: basic → self-help → self-reliant village	Performance-based differentiated-reward algorithm	Learner-level system / reward multiplier / visualization of the staged attainment path
(4) Immediate visibility	Short-term visible projects such as roof improvement	Blockchain-based immediate settlement	Algorand 3.3-second transaction finality / NGEM credited to wallet right after learning / visualization of cumulative rewards

Figure 2-1. Three-layer structure of the Digital Saemaul model: unit system, governance, regional operation



3. 21st-Century Polarization and the Policy Coordinates of the Digital Saemaul Model

3.1. The New Divide of the AI Era: The AI Divide and the Weakening of Labor Income

At the start of the 21st century, the rapid development of artificial intelligence—particularly generative AI—is directly affecting the domain of human cognitive labor. In just a few years since the public release of ChatGPT at the end of 2022, a substantial portion of tasks that once required high human capital—text generation, coding, image generation, translation, summarization—has been automated to a quality above a certain level through AI tools. This change dramatically raises humanity's productivity while at the same time creating a new form of divide.

This study names this new divide the "AI divide." The AI divide is not merely a difference in accessibility to AI tools but includes a difference in the ability to use AI tools effectively. AI tools are formally accessible to anyone (especially in the case of free or low-cost services), but to derive meaningful results through those tools in practice requires the ability to formulate appropriate questions, to evaluate results critically, and to integrate them into one's own workflow. Such abilities are formed by prior education and experience and are themselves polarized (Acemoglu & Restrepo, 2022).

The essence of the problem is that the AI divide combines with other existing divides to accelerate them. Well-educated learners use AI tools effectively to further raise their productivity, whereas learners short of educational resources cannot access the potential benefit AI tools provide. This has a structure similar to the digital divide observed at the time of internet diffusion in the late 1990s, but its intensity and speed are greater. If the internet divide was a divide in information access, the AI divide directly translates into a divide in cognitive capacity itself.

At the same time, AI's impact on the labor market is asymmetric. Repetitive and routinized cognitive labor is rapidly replaced by AI, whereas in the domains that use AI to create higher value-added, rewards are increasing. As a result, the distribution of labor income becomes polarized, and a weakening of middle-tier cognitive labor is observed (Acemoglu & Restrepo, 2022). This is highly likely to proceed not as a mere temporary shock but as a long-term restructuring of the labor market's structure.

The challenge learners face in this environment is clear. Education in the traditional sense—school education that completes a set curriculum within a set period—alone can hardly adapt to the labor-market changes of the AI era. Lifelong learning and self-directed capacity development are required, but the social support system for this remains inadequate. In particular, for poor learners, lifelong learning tends to be perceived as a luxury that conflicts with the daily pressure of livelihood.

3.2. The Asymmetry Between the Return on Capital and the Return on Learning

The core observation Piketty (2014) presented in Capital in the Twenty-First Century is that the return on capital (r) tends to structurally exceed the rate of economic growth (g). This inequality suggests that the wealth of those who hold assets grows faster than the labor income of those who do not, which means that wealth polarization naturally deepens over time.

This study seeks to extend this discussion into a comparison of the return on learning and the return on capital. Learning requires the input of time and cognitive effort, and its output is recovered in the form of an improvement in future labor-market value. But this recovery entails a delay of years to decades, and the recovery process itself is subordinate to the operation of the labor market. Capital, by contrast, provides its holder with relatively immediate and automatic returns in the form of interest, dividends, and capital gains.

From the standpoint of poor learners, this asymmetry is decisive. A household holding capital can stably support its children's long-term educational investment, and the human capital that child forms through learning is again converted into capital returns (parental capital → child's education → child's human capital → child's capital formation). By contrast, a capital-poor household is pressured to convert its children's study time into labor time, which impedes the human-capital formation of the child generation and reinforces the intergenerational transmission of poverty.

The policy significance of the Digital Saemaul model lies precisely in the structural mitigation of this asymmetry. By directly connecting learning activity to immediate and certain digital-asset formation, it shortens the recovery delay of the return on learning and redefines the learning activity itself as an asset-formation activity. If a learner can form digital assets in the form of NUSD immediately through learning (as discussed in Section 4.4, NUSD is a design-stage unit whose implementation is deferred pending regulatory review), this becomes not a mere learning aid but a new pathway of capital formation. In that this pathway operates through the learner's own effort, independently of whether the parental generation holds capital, it can have the effect of partially mitigating the asymmetry of capital formation.

This possibility must, however, be evaluated with caution. The scale of assets the Digital Saemaul model can form is realistically not large. The value of the reward obtainable through daily learning may be meaningful compared with the daily labor income of a poor household, but it can hardly translate directly into asset formation on a scale meaningful in the capital market. Therefore, the policy significance of the Digital Saemaul model should be seen as lying not in the direct resolution of asset polarization but in the construction of a cognitive and practical connecting channel between the act of learning and asset formation. Once this connecting channel is created, learners can come to perceive themselves not as mere providers of labor but as subjects of asset formation, and this change in perception itself may have a larger effect in the long run.

3.3. The Persistence of Global Learning Poverty and the Limits of ODA

According to the learning-poverty measurements of the World Bank and UNESCO, a majority of children at the end of primary education in low-income and lower-middle-income countries cannot read and understand a basic short passage. This indicator worsened during the COVID-19 pandemic and, as of 2024, shows a pattern of becoming chronic without recovery (World Bank & UNESCO, 2022; World Bank, 2025). Learning poverty suggests not a mere problem of insufficient school attendance but a more fundamental crisis in which learning does not occur even where schools exist.

The traditional ODA response to this crisis was infrastructure-centered support such as school construction, textbook provision, and teacher training. Such support has made a certain contribution, but its limits were also clear. First, infrastructure-centered support does not create the economic conditions under which learners can invest time in learning. Even if a school is built, learning does not occur so long as learners are mobilized into household labor. Second, the effect of teacher training is limited, and providing quality teachers in sufficient numbers is difficult under resource constraints. Third, standardized curricular content is unsuited to learners of diverse levels, and one-on-one personalized guidance was nearly impossible in terms of labor cost.

The advent of generative AI presents a potential solution to this third limit. One-on-one personalized guidance, which was impossible in cost terms with human teachers, may become possible through AI tutors. A randomized controlled trial conducted at Harvard University (Kestin et al., 2025) showed that a well-designed AI tutor can achieve higher learning outcomes in less time than active-learning-based in-class instruction. This result carries great implications for the problem of global learning poverty. Providing quality teachers in sufficient numbers is difficult, but distributing quality AI tutors globally is technically possible.

However, the availability of AI tutors alone does not resolve learning poverty, because the first limit—the absence of economic conditions under which learners can invest time in learning—still remains. Resolving this first limit requires a reward mechanism that gives immediate economic value to learning activity, and this is the core contribution of the Digital Saemaul model proposed by this study. That is, by combining the availability of AI tutors with the immediacy of learning rewards, the Digital Saemaul model can function as a policy tool that simultaneously attacks the two structural limits of global learning poverty.

Another limit of the existing ODA model lies in the transparency and efficiency of resource delivery. Resource delivery that passes through intermediary institutions has high operating costs and the risk of resource leakage, and it is difficult for donors to confirm how their donations were used. A blockchain-based direct-delivery structure has drawn attention as a technical solution to this limit (Tapscott & Tapscott, 2016). The GlobalPiggy module of the NodajiFi platform is an attempt to apply the possibility of such direct delivery to the concrete use case of learning rewards.

3.4. The Policy Position of the Digital Saemaul Model

Synthesizing the above discussion, the Digital Saemaul model is located at the following policy coordinates.

First, this model can function as a tool for mitigating the AI divide. Learning through an AI tutor naturally forms the learner's ability to use AI tools effectively, and this forms, together with mere content learning, the "AI literacy" that is a core competency of the AI era. The experience of posing questions to AI, evaluating its answers critically, and integrating them into one's own learning flow naturally accumulates in an AI-tutoring environment.

Second, this model can function as a tool for the partial mitigation of capital-labor asymmetry. By connecting learning activity to digital-asset formation, it provides a channel through which even learners who hold no capital can become subjects of asset formation through their own learning effort. The scale of this channel is limited, but it can have a meaningful effect at the level of a change in perception.

Third, this model can function as a new ODA tool for global learning poverty. Beyond infrastructure-centered welfare-type ODA, it presents a new paradigm of active ODA that connects learners' self-directed learning to immediate economic value. In the context in which the Korean government and the Korea Saemaul Undong Center have promoted a global Saemaul movement, this model can be positioned as the 21st-century evolutionary form of that movement.

In evaluating the policy significance of this model, however, the following caution is required. First, this model is not a panacea and should be in a position that complements, not replaces, existing school education and infrastructure support. Second, the effect of this model must be verified through future full-scale empirical research, and the design principles this study presents are only the starting point of that verification. Third, the token-economy aspect of this model may conflict with the virtual-asset regulations of each country, and legal review must proceed in parallel (this point is discussed in detail in Chapter 8).

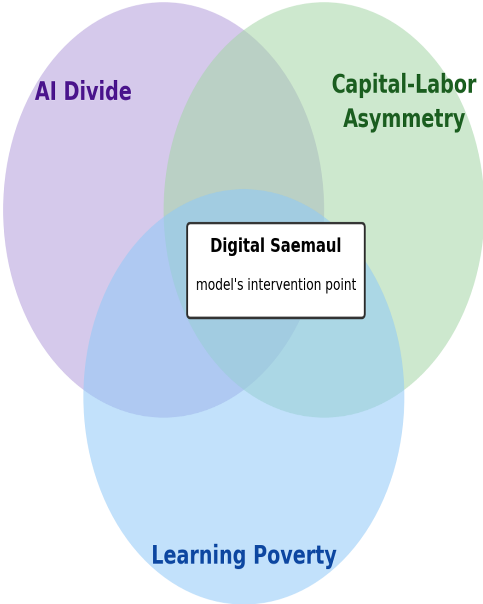


Figure 3-1. The overlapping structure of 21st-century polarization and the intervention point of the Digital Saemaul model

4. System Design and Implementation of the NodajiFi Platform

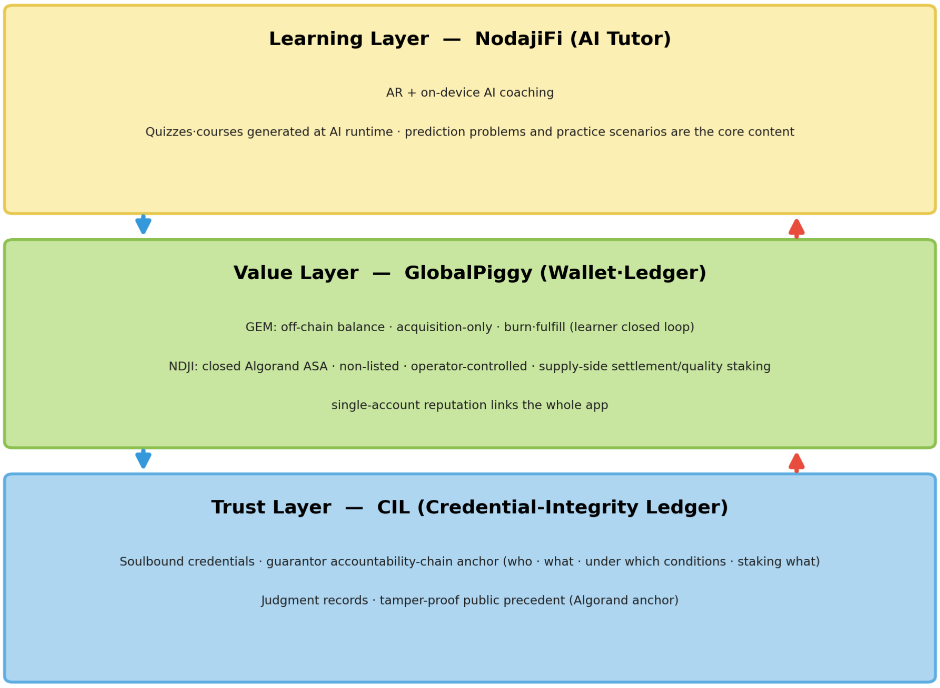
4.1. Integrated Ecosystem Architecture

The NodajiFi platform, which this study takes as the object of case analysis, is an integrated ecosystem that attempts to implement, in the 21st-century digital environment, the four mechanisms of the Saemaul Undong derived in Chapter 2. The system is composed of two main layers. The first is the learning layer, NodajiFi, where the production and consumption of learning content and interaction with the AI tutor take place; the second is the value layer, GlobalPiggy, which stores and circulates the value generated from learning activity. The two layers have independent user interfaces while synchronizing data in real time on the backend through the Algorand blockchain mainnet and an API gateway (NodajiFi Labs, 2025).

The design intent of this dual-layer structure is to clearly separate the act of learning from value formation while directly connecting the two. The separation is to secure the specialization and simplicity of each layer, and the connection is to realize the core proposition of this model—that learning is itself value formation. This corresponds to the structure of the Saemaul Undong in which a village's project activity (e.g., roof-improvement labor) and the recognition of that project's outcome (e.g., the granting of a self-help-village grade) were separated yet directly connected.

The overall flow of the platform is as follows. A learner accesses the NodajiFi learning layer and solves problems while interacting with the AI tutor. The result of the learning activity is immediately settled as the learning-reward unit NGEM (NodajiGem) and credited to the learner's GlobalPiggy wallet. The learner can use accumulated NGEM for learning and cultural goods and services within the platform. The initial design (NodajiFi Labs, 2025) presented a tri-token structure that converts NGEM into NUSD (Nodaji-USD) pegged to the USD value and connects it to the governance token NDJI (NODAJI); however, the revised whitepaper (NodajiFi Labs, 2026) deferred the implementation of NUSD for compliance with financial regulation and adjusted the implementation scope to a dual structure of the learning unit (NGEM) and the supply-side settlement and governance unit (NDJI). This paper describes the tri-token structure as the reference model of the design space and the dual structure as the implementation case.

Figure 4-1. NodajiFi integrated platform architecture



4.2. NodajiFi: The AI-Based Learning Layer

The core component of the NodajiFi learning layer is a large-language-model (LLM)-based AI tutor system. This tutor analyzes in real time the learner's response patterns, accuracy rate, study time, and repeated-learning behavior, and adjusts the difficulty and type of the next problem to present. This can be understood as an attempt to implement Vygotsky's concept of the zone of proximal development algorithmically (Vygotsky, 1978). If the learner only solves problems that are too easy, learning stagnates for lack of cognitive challenge; conversely, if the learner encounters only problems that are too difficult, they become frustrated and drop out. The AI tutor dynamically adjusts the optimal difficulty between the two.

The alpha version of the AI tutor is implemented by combining an external LLM service (e.g., OpenAI's GPT series, Google's Gemini) with an in-house prompt-engineering layer. The in-house layer uses the learner's accumulated data to provide appropriate context to the external LLM and to post-process responses to match the learner's level. This structure is a compromise design that uses the powerful general intelligence of the external LLM while securing response quality specialized for the learning domain.

The academically interesting aspect of this layer is that the AI tutor is designed to form not a mere content-deliverer but a dialogical relationship with the learner. When a learner presents an incorrect answer, the tutor does not simply give the correct answer but traces the thought process that led to the incorrect answer and provides a hint matched to it. This is an approach that imitates the Socratic method algorithmically and is a pedagogical design principle whose effect has been reported in recent AI-tutoring research (Kestin et al., 2025).

NodajiFi's learning content is differentiated into three sub-modules. First, Nodaji-Kids is a module for children that provides basic literacy and numeracy in a gamified manner. Second, Nodaji-Fly is a module for young learners that covers competencies needed to enter the global labor market, such as IT skills, coding, foreign languages, and global business etiquette. Third, Nodaji-Silver is a module that supports the digital literacy and cognitive-ability maintenance of elderly learners. This life-cycle-based differentiation reflects the design intent for the Digital Saemaul model to function not as something confined to a particular demographic but as a universal learning-support system.

4.3. GlobalPiggy: The Value Storage and Circulation Layer

GlobalPiggy is the fintech infrastructure that stores and circulates the value generated in the learning layer. The core functions of this layer are (1) providing the learner's digital-asset wallet, (2) recording learning rewards (NGEM) and settling their use within the platform, and (3) the transparent delivery of donations; in the tri-token reference model, (4) conversion among tokens (NGEM ↔ NUSD ↔ NDJI) and external payment/remittance functions are added. Each function operates through smart contracts implemented on the Algorand blockchain.

The technical rationale for selecting the Algorand blockchain is as follows. First, transaction finality is very short, at about 3.3 seconds, meeting the immediacy requirement of learning rewards. Second, transaction fees are very low (about 0.001 ALGO per transaction), making the cumulative operation of small rewards economically feasible. Third, it operates via Pure Proof of Stake, giving high energy efficiency and securing environmental sustainability. These characteristics suit this model's use case of accumulating small rewards for global low-income learners.

In the reference model, GlobalPiggy's most distinctive function is the conversion of NGEM generated from learning activity into NUSD. NGEM is a unit that immediately recognizes the act of learning and provides the learner with a behavior-reinforcement effect, but by itself it is not connected to external value. Conversion into NUSD was designed as the decisive step connecting learning activity to the external economy. NUSD is a stable unit of value designed to be pegged to the USD value, and the initial whitepaper presented a reserve structure for it (the "Global Piggybank")—collateral assets composed of 30% precious metals and 70% trusted external stablecoins (NodajiFi Labs, 2025). However, the revised whitepaper (NodajiFi Labs, 2026) deferred the implementation of NUSD in consideration of the stablecoin regulatory environment; in the current implementation, the learner's NGEM operates as a closed unit that is not cashed out, and when a learner uses NGEM, the platform settles it via a burn-and-fulfill method in which it burns the NGEM and fulfills goods and services with its own operating funds.

Whether the value-stability mechanism of NUSD actually operates properly in a real operating environment is a separate matter, however, and this depends on the transparency, external audit, and regulatory compliance of the operating stage. This study develops a separate, careful discussion of this point in Chapter 8. This chapter is limited to reporting the design intent and structural characteristics of the system.

4.4. Design Principles of the Token Structure: Tri-Token Reference Model and Dual-Unit Implementation

The most distinctive element of the NodajiFi platform's design space is the tri-token reference model. This structure is an attempt at structural separation to avoid the functional conflict a single-token system can have—namely, the incentive distortion that arises when reward incentive, value stability, and governance authority are combined in a single token (Voshmgir, 2020).

NGEM (NodajiGem) functions as the immediate-reward unit of learning activity. When a learner solves a problem or completes a learning session with the AI tutor, NGEM is issued immediately, and the learner can immediately confirm it in their GlobalPiggy wallet. As the digital equivalent of positive reinforcement in behavioral economics, NGEM supports the stable maintenance of learning behavior. NGEM itself is not traded on external exchanges and functions as a unit of recognition within the platform.

NUSD (Nodaji-USD) is the unit responsible for value stability. A learner can convert accumulated NGEM into NUSD at a set ratio, and NUSD is designed to be pegged to the USD value. NUSD can be used as a medium of value exchange both inside and outside the platform and, unlike ordinary cryptocurrencies with high volatility, is intended to provide the learner with predictable purchasing power. This unit corresponds, in the matching-grant structure of the 1970s Saemaul Undong, to the outcome of the external resource—that is, the economic asset the farmer ultimately obtained through participation in Saemaul projects.

NDJI (NODAJI), as a governance token, represents the authority to participate in the platform's decision-making. NDJI holders can participate in voting on the platform's policy changes, adjustment of the token-distribution algorithm, the introduction of new features, and the like. NDJI is positioned as the digital equivalent of the structure in the Saemaul Undong in which the decision-making authority of the village assembly was granted to village members.

The design strength of this tri-token structure is that, because the function of each token is clearly separated, incentive conflict does not arise. In a single-token system, fluctuations in the token price can distort the value of learning rewards, and governance decisions can be distorted by the short-term interests of token holders. The tri-token separation is an attempt to structurally block such distortion. However, the operational complexity of this structure is a drawback, and there is a user-experience challenge in that learners may find it hard to intuitively understand the difference among the three tokens.

Meanwhile, at the time of this paper's analysis, the revised whitepaper (NodajiFi Labs, 2026) deferred the implementation of NUSD among this reference model and finalized, as the implementation architecture, a dual-unit structure composed of the learning unit (NGEM) and the supply-side settlement and governance unit (NDJI). The direct background of this adjustment is the stablecoin regulatory environment—Korea's Virtual Asset User Protection Act, the U.S. GENIUS Act, and the EU's MiCA—discussed in detail in Section 8.2. Notably, this adjustment is not a mere retreat but structurally converges with the reward-design principles argued in Chapter 5. The direction of reducing the scope of rewards carrying monetary value and shifting the highest-order reward to status and opportunity is at once a defense against overjustification and Goodhart's law and a defense against regulatory risk. Therefore, this study preserves the tri-token reference model as the theoretical whole of the design space while positioning NUSD as a conditional design element that is activated only under conditions in which a regulatory pathway (e.g., a regulatory sandbox, or partnership with a licensed stablecoin issuer) is secured. In addition, the same revised whitepaper (v6.2) made explicit a second bifurcation between the reference model and the implementation architecture. The governance function that had been combined with NDJI in the reference model is separated in the implementation, so that NDJI is limited to a supply-side settlement, access, and quality-staking unit, and the governance weight is derived not from the amount of units held but from verified contribution and reputation. This separation can be interpreted as carrying through, at the implementation level, the demand for dual participation eligibility raised in Section 2.2—that authenticity of governance should be secured by activity, not holding.

[Table 4-1] Functional Separation of the Tri-Token Reference Model

Item	NGEM (NodajiGem)	NUSD (Nodaji-USD)	NDJI (NODAJI)
Core function	Immediate-reward unit of learning activity	Stable-value unit (1:1 USD peg target)	Governance token
Issuance condition	Automatically issued upon completion of learning activity	Issued upon NGEM-conversion request	Fixed supply (1 billion units recommended)
Value stability	In-platform unit · external trading not allowed	30% precious metals + 70% stablecoin collateral	Linked to ecosystem growth (variable)
Governance authority	None	None	Policy-decision voting rights
Technical implementation	Platform DB (off-chain)	Algorand ASA (on-chain)	Algorand ASA (on-chain)
Saemaul Undong equivalent	Immediate visible-feedback mechanism	Resultant value of the matching grant	Decision-making authority of the village assembly

Note: The NUSD column is a conditional design element whose implementation is deferred, and the governance authority of NDJI is likewise a description of the reference model; in the implementation architecture it is separated into contribution- and reputation-based weighting.

4.5. Governance Structure: The Dual Structure of DAO and ROC

The governance structure of the NodajiFi platform is designed not as a single DAO model but as a dual structure combining a digital-governance unit and a regional-operation unit (NodajiFi Labs, 2025). The design motivation of this dual structure is the recognition that, for a global digital platform to actually operate on the legal and institutional environments of each country, pure digital governance alone has limits.

The digital-governance unit, Nodaji-DAO, is responsible for the platform's overall policy decisions. Whereas the reference model described a structure in which token holders express their will through voting, in the implementation architecture (NodajiFi Labs, 2026) the eligibility and weight for governance participation are derived not from the amount of units held but from verified contribution—learning history, creation/attestation records, community contribution—and reputation, and decided matters are automatically executed through smart contracts. Nodaji-DAO is, in this study, the digital equivalent corresponding to the self-organization mechanism of the Saemaul Undong.

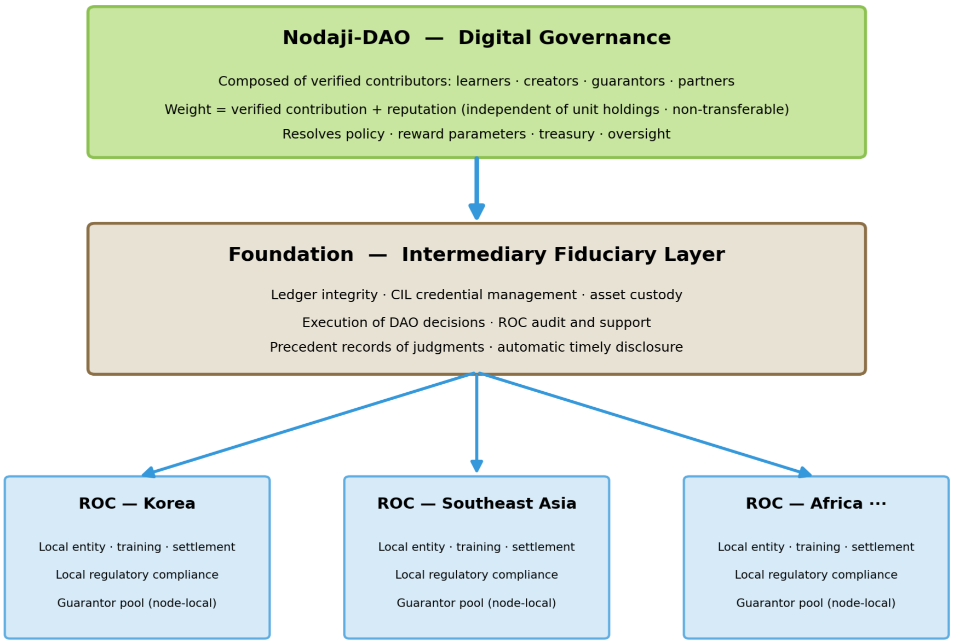
The regional-operation units, Regional Operating Companies (ROCs), are corporate entities registered in accordance with the legal environment of each country and are responsible for offline activities in the relevant region (local marketing, exchange with local currency, operation of vocational-training programs, and so on). ROCs are established in the form of cooperatives or ordinary corporations, and their operating performance is distributed to the ROC's legal equity holders in the form of regional-level dividends. ROCs perform the role of ensuring operation suited to the social and economic context of each region in the platform's global-expansion process.

What mediates between these two units is the Foundation. The Foundation, a legal entity registered in a crypto-friendly jurisdiction, is the operating body that executes the DAO's decisions and simultaneously is responsible for the audit and support of the ROCs. This Foundation is the core node that secures the platform's trust structure.

This dual structure is an academically interesting design. It is an attempt to combine the strength of the global anonymous governance that a pure DAO model has with the strength of local adaptability that a traditional corporate model has. This approach accords with the "hybrid governance" model discussed in recent Web3-governance research (Hassan & De Filippi, 2021). The actual operation of this model must, however, be evaluated according to how the distribution of authority between the DAO and the Foundation, and between the Foundation and the ROCs, is operated, and this can be verified only through post-launch operating data.

This dual structure also forms an interesting parallel with the governance structure of the Saemaul Undong. In the Saemaul Undong, the self-organization of the village assembly was not separated from the central government's administrative system, and the Saemaul leader performed the role of mediating between the village and the administration. In that NodajiFi's Foundation mediates between digital governance (DAO) and regional operation (ROC), it can be interpreted as the digital equivalent of this Saemaul leader.

Figure 4-2. NodajiFi dual governance structure (DAO + Foundation + ROC)



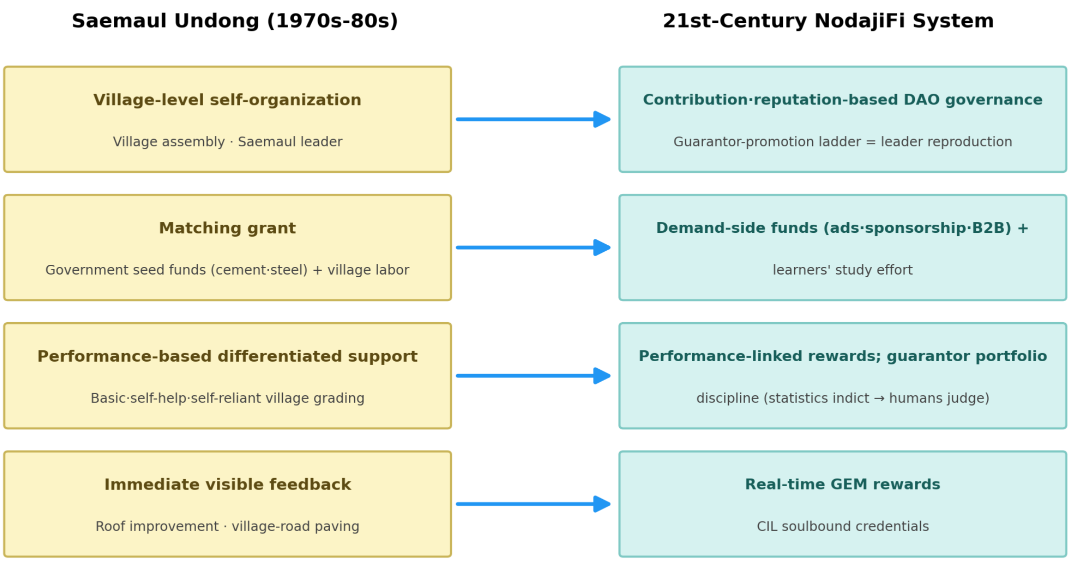


Figure 4-3. Structural correspondence between the four Saemaul mechanisms and NodajiFi system components

5. Reconstructing Reward Design: From Payment to Trust Circuit

5.1. Problem Statement: Re-examining the Premise of "Reward-Based"

The token structure of NodajiFi described in the previous chapter focuses on connecting immediate reward to learning activity. However, the most fundamental question to be examined when designing a reward-based learning ecosystem is not how to disburse rewards more finely but what position reward should occupy in the learning ecosystem. This chapter critically re-examines the very premise of "reward-based" and presents design principles that relocate the role of reward. This is not a negation of the system design of the previous chapter but the work of identifying the deep principles that design must possess in order to operate sustainably.

The risks a reward-based learning model faces are broadly of two layers. The first is the psychological layer—the risk of overjustification, in which extrinsic reward can erode the intrinsic motivation of learning (Lepper, Greene, & Nisbett, 1973). The second is the institutional layer—the risk of Goodhart's law, in which an indicator on which reward is placed becomes an object of manipulation (Strathern, 1997). These two risks have been empirically observed in recent blockchain-based learning/activity-reward models (so-called Learn-to-Earn, Move-to-Earn), and many projects experienced user attrition together with a decline in the value of the reward asset. The purpose of this chapter is to present principles of reward design that structurally circumvent these risks, connecting them to the mechanisms of the Saemaul Undong.

The conclusion this chapter reaches, presented in advance, is as follows. A sustainable design demotes reward from payment for learning to a lubricant of the trust circuit and shifts the platform's highest-order reward from the acquisition of money to the acquisition of status and opportunity. From the perspective of this reconstruction, the true foundation of this model is not reward but trust, and reward corresponds to the plumbing that circulates that trust circuit.

5.2. The Grammar of Reward: From Payment to Recognition

The precise mechanism of the overjustification effect indicates the direction of the prescription. According to Deci and Ryan's Self-Determination Theory, extrinsic reward damages intrinsic motivation when the reward is perceived as controlling (Deci & Ryan, 2000). The grammar of the conditional contract "if you do this, I will give you that" weakens the learner's perception of autonomy and reframes learning as wage labor. Conversely, when the same reward is perceived as informational—that is, as evidence of the learner's competence—the reward does not harm intrinsic motivation and can even reinforce it.

This distinction provides the core diagnostic criterion of reward design: does the learner read the reward as payment for labor, or as a measure of growth? The method of granting a fixed amount of tokens per problem solved belongs to the former grammar and embeds a structure in which the learner drops out the moment the reward dries up. The latter grammar aims at recognition of achievement at unpredictable moments, nonlinear reward for breaking through difficulty, and above all a structure in which qualification itself becomes the reward. Expressed in this model's language, the learning-reward unit must be a report card before it is money.

This reinterpretation accords with the mechanisms of the Saemaul Undong. The village-grading system discussed in Chapter 2 (basic, self-help, self-reliant villages) was not a mere monetary distribution but a system of public recognition of a village's achievement. The status of a self-reliant village was itself a reward, and although this status was combined with additional resource allocation, the symbolic value of the status preceded its material value. The reward design of the Digital Saemaul model must restore this order—recognition first, payment next.

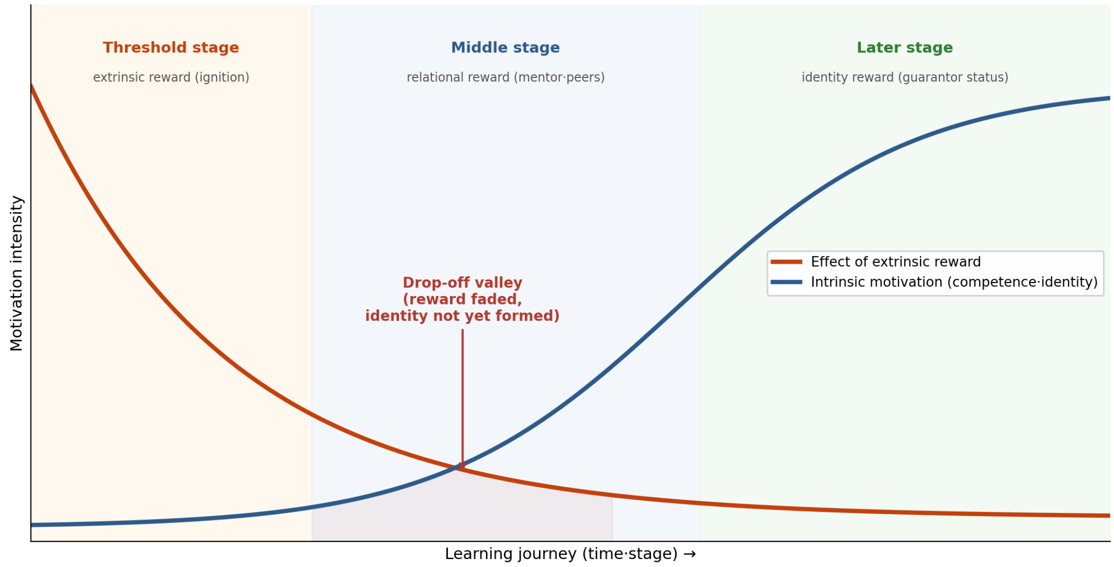
5.3. The Reward Gradient: From Threshold to Identity

There is one place where extrinsic reward is legitimate: the threshold. At the point where a learner has never experienced a particular skill and cannot know its intrinsic enjoyment, extrinsic incentive plays the role of a starter motor that gets learning started. The problem is what comes next. The marginal utility of extrinsic reward diminishes quickly, whereas intrinsic motivation—such as competence and identity—grows slowly. The interval before these two curves cross—the valley in which reward has faded but the identity of "I am a person who does this" has not yet formed—is the main site of learner attrition. The high dropout rate observed in massive open online courses (MOOCs) occurs in substantial part in this interval.

Therefore, placing the reward schedule uniformly across the entire learning journey is a design error. Reward must be designed as a gradient whose form shifts according to the stage of the journey. Early on, dense extrinsic reward lowers the barrier to entry; in the middle, it shifts to relational reward—the attention of a mentor, the recognition of a peer learning cohort; and in the later stage, it transitions to identity reward—guarantor status, the authority to guide junior learners. Parasocial interest in K-content or cultural affinity is, within this framework, likewise ignition fuel rather than cruising fuel, and the transfer point to cruising fuel must be explicitly provided in the product design.

This gradient design corresponds directly to the staged village-grade advancement path of the Saemaul Undong. The path from basic village to self-help village to self-reliant village differed in what was required and what was provided at each stage. Early on, the input of external resources was large, but as the stage rose, the voluntariness and communal identity of village members moved to the center of the driving force. The reward gradient of the Digital Saemaul model is the digital reproduction of this transition structure.

Figure 5-1. The reward gradient: transition from extrinsic reward to identity reward



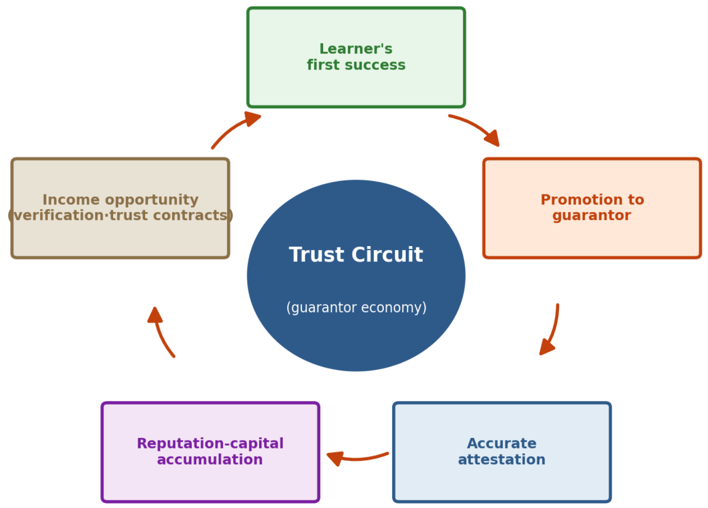
5.4. Rewarding the Trust Circuit: The Guarantor Economy

The practical conclusion at which the foregoing discussions converge is that the object of reward should not be limited to the individual learner but expanded to the entire trust circuit. What is truly scarce on this platform is not the will to learn but trustworthy verification. Proving in a trustworthy way that a learner actually possesses a particular competency—this is the gateway through which the learning ecosystem connects to the labor market and to society. Yet the conventional allocation of the reward budget concentrates on learners and allocates almost nothing to guarantors.

This study proposes to reconsider this allocation. The path in which mentors and guarantors accumulate reputational capital through accurate attestation, and that reputation is converted into substantive income opportunities—more verification requests, trust contracts with demand-side firms—must become the main body of reward design. This is of one piece with the cold-start problem—the problem of how to trigger the first circulation of the early ecosystem. If the promotion of a first-success learner to guarantor is itself designed as the highest-order reward, then the motivation infrastructure (role models) and the verification infrastructure (guarantors) grow simultaneously on the same budget. A message more powerful than "if you learn, you can earn" is "if you learn, you become like that person," and that "person" must wear the status of guarantor within the platform.

The guarantor economy corresponds structurally to the Saemaul-leader institution of the Saemaul Undong. As discussed in Chapter 2, the Saemaul leader was a leadership mediating between village and administration, and that status was based on communal trust and role identity rather than material reward. The design of promoting a successful learner to guarantor restores this Saemaul-leader reproduction mechanism in a digital environment. The design in NodajiFi's governance structure (Chapter 4) that has users who have accumulated learning achievement and community contribution perform an intermediary role can be understood as an early implementation of this principle.

Figure 5-2. The virtuous cycle of the guarantor economy



Promoting first-success learners to guarantors grows the role-model (motivation) and verifier (trust) infrastructures together

5.5. Reward as Opportunity Rather Than Consumption

Setting the terminal point of reward as a consumer good must be reconsidered. The cycle of converting a learning reward into a stable unit of value and consuming courses or goods places the final destination of reward in consumption. Yet what is truly scarce for learners in vulnerable regions is not goods but the opportunity to prove—winning real-world tasks, trial requests from demand-side firms, the chance to perform before a guarantor.

Converting a substantial part of the reward budget from "things one can buy" into "opportunities one can prove" mitigates three problems simultaneously. First, because the reward is directly connected to the next rung of the learning ladder, it circumvents overjustification—since opportunity is itself an informational signal of competence. Second, because demand-side firms enter the ecosystem as suppliers of opportunity, the essential task of connecting the learning ecosystem to the labor market is partially resolved. Third, because the record of having obtained and performed an opportunity itself accumulates as evidence of competence, the cost of subsequent verification is lowered. A platform whose highest reward is not a consumption basket but an opportunity for verification—this is the decisive line of differentiation from ordinary Learn-to-Earn and a shift that moves the object of "earn" from money to opportunity.

This principle gains concreteness when combined with the Regional Operating Company (ROC) structure discussed in Chapter 4. If ROCs are responsible for connecting local vocational/technical training and real-world tasks, the higher form of learning reward can be designed as real-world opportunity mediated by the ROC. This also connects to the support for experiment, practice, and skill acquisition discussed in Chapter 6. When the path in which competency formed through virtual practice leads to real-world opportunity is embedded within the reward structure, learning becomes not accumulation for consumption but accumulation for self-reliance.

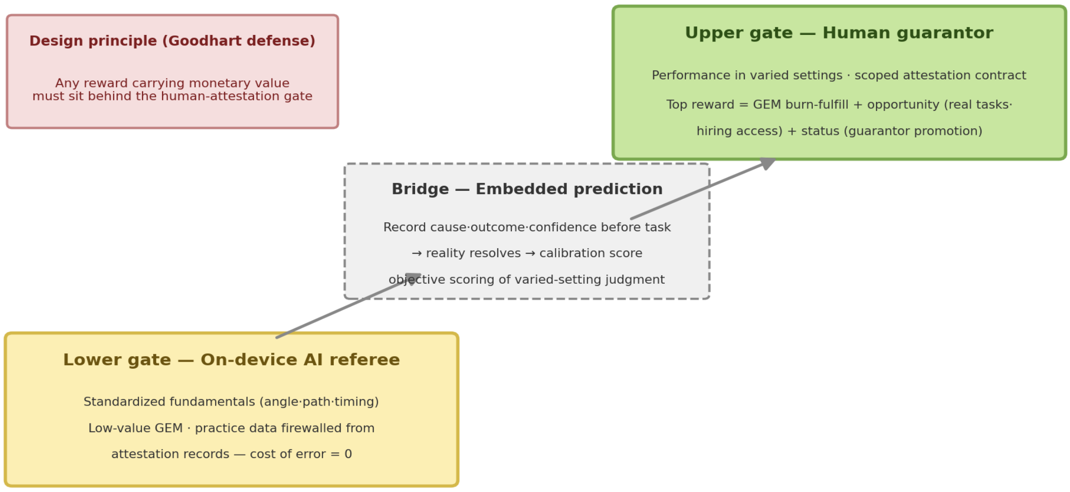
5.6. Designing Under the Premise of Goodhart's Law

The most frequent cause of failure of reward-based platforms is not the failure of motivation theory but abusing—that is, the exploitation of the reward system. Goodhart's law—that the moment reward is placed on a measure, that measure becomes an object of manipulation (Strathern, 1997)—must be the first premise of reward design. Cases in which location-information manipulation occurred in a model that placed reward on distance moved, and mass forgery through automated bots occurred in a model that placed reward on activity volume, are the material evidence of this law.

The principle of defense compresses into one: reward must be placed only on signals whose forgery cost is higher than the reward value. Automatically measured indicators such as click counts, viewing time, and number of problems solved can be forged almost infinitely by artificial intelligence and automation tools, so directly connecting monetary value to them is a design that invites bot farms. Conversely, signals with high forgery cost are those discussed above—the in-person confirmation of a human guarantor who has staked reputation, and hiring/contract records for which the demand side has actually paid.

From this a dual-gate structure is derived. The low-value reward at the bottom of the ladder is handled by the on-device AI referee (Chapter 6), while the higher reward carrying monetary value is placed behind a human-attestation gate. This design accords with the self-organization mechanism of the Saemaul Undong. Just as the performance judgment of village projects passed not through the unilateral measurement of external administration but through the mutual monitoring of the village community and the confirmation of the Saemaul leader, so too the higher-reward judgment of the Digital Saemaul model must pass not through the automatic measurement of an algorithm but through the human confirmation of a trust chain. That the conclusion of abuse defense and the reconstruction of reward grammar converge on the same point—the shift of the center of gravity from automatic measurement to the attestation chain—is no coincidence.

Figure 5-3. Dual-gate structure: AI referee at the bottom, human attestation at the top



5.7. Quantifying the Health of Motivation

The final principle is a problem of measurement. The standard indicators of a reward-based platform—daily active users, task-completion rate, reward-disbursement volume—all observe only behavior while the reward is operating. But because the damage of overjustification is revealed after the reward stops, these standard indicators alone cannot discern whether the platform is cultivating or exhausting intrinsic motivation.

Therefore, this study proposes to promote the health of motivation to a separate measurement indicator. Specifically, the following indicators are required: the voluntary return rate in intervals where no reward is placed; the voluntary selection rate of high-difficulty tasks to which no reward is linked; pure retention that returns without notification or inducement; and, if possible, a cohort experiment that applies a different reward schedule to some cohorts and compares the residual learning volume after reward removal. These indicators must be integrated into the pilot validation design presented in Chapter 7.

The reason such quantification is important is to catch warning signals early. If the motivation-health indicators worsen while the standard activity indicators improve, that may be not growth but the mining of motivation—the phenomenon of exchanging future intrinsic motivation for present activity indicators. This distinction is the self-diagnostic capacity a reward-based learning ecosystem must possess to secure sustainability.

5.8. Institutional Design of the Attestation Network: Contract, Discipline, Adjudication, Compartmentalization

The conclusion of Sections 5.4 and 5.6—that the center of gravity of the reward system must shift from automatic measurement to the human attestation chain—immediately gives rise to the following question. Human attestation is itself a corruptible signal; what secures the integrity of attestation? The revised whitepaper (NodajiFi Labs, 2026) made explicit a five-fold institutional apparatus in answer to this question, and this section formalizes it academically and maps it onto the institutional design of the Saemaul Undong. The gist is as follows. What the blockchain anchors un-forgeably is not the truth of technology but the guarantor's chain of accountability—who attested, to what, under what conditions, staking what—and therefore the platform's true identity is not an objective measuring machine but the orchestrator of a trust network.

The first apparatus is the scoped attestation contract. Every attestation is recorded not as an open-ended recommendation but as a machine-readable specification—that skill X was performed under condition Y (equipment, materials, environment), meeting evidence criterion Z. The structured definition of each individual skill (prerequisites, difficulty, durability, evidence requirements, verification method) becomes the vocabulary of this contract. The primary function of this specification is the ex ante extinction of disputes. Even if a certified competency later fails, if that failure occurred outside the scope of attestation, the question of responsibility is closed by a lookup rather than a trial. The best court is a court that never opens, and it is made not by a judge but by the contract designer.

The second apparatus is the two-tier ladder of verification and the bridge between them. The bottom of the ladder—standardized fundamentals—is handled by the on-device AI referee of Chapter 6, but the practice data is firewalled from the attestation record so that the cost of error is kept at zero (consistent with the informational-reward principle of Section 5.2). The top of the ladder—performance in varied environments—can be scored only by a human witness who has staked reputation. And between them lies the bridge of embedded prediction. If the learner is made to record a cause diagnosis and outcome prediction, together with a confidence level, before undertaking the actual task, then the physical work becomes a deadline-embedded prediction problem in which reality discloses the answer within hours, and the accumulated calibration score of predictions becomes an objective, hard-to-forge scoring of judgment in varied environments that cameras and rubrics cannot reach. This makes possible the compromise of deploying the guarantor only at the moment of confirming the resolution, so that the scarce labor of the human witness is concentrated at an irreplaceable single point.

The third apparatus is two-stage discipline against false attestation. The truth-finding of an individual dispute is costly and carries a high risk of misjudgment, but a portfolio is readable. The system continuously compares each guarantor's distribution of attestee performance against the peer distribution, but statistical deviation itself is never a sentence. Discipline is divided into two stages—statistics indict (an anomalous distribution automatically opens a hearing and the entire evidence chain is disclosed to the guarantor), and humans judge (a panel of senior peer guarantors outside the relevant node, together with the operator, deliberates before any sanction). No guarantor is stripped of status by an algorithm alone, and no objection is decided without figures. This structure is a design to satisfy simultaneously the efficiency of statistical justice and the procedural dignity that a guild living by honor demands. In that the village-grading system of the Saemaul Undong was a differentiation based not on the single judgment of an individual project but on the cumulative distribution of village-level performance, and in that its judgment passed not through the unilateral measurement of the administration but through the community's mutual monitoring and on-site confirmation, this two-stage discipline can be read as the digital formalization of the village-grading system.

The fourth apparatus is adjudication under precedent. A novel dispute outside the specification must be adjudicated by someone, and the revised whitepaper names the platform operator as that sovereign but binds it with three technical chains. All judgments and their grounds are recorded tamper-proof and disclosed; a differing judgment on a similar case is automatically flagged by the system as an inconsistency; and the statistical bias of judgments (e.g., a deviation in the direction of a particular stakeholder) is computed and posted without anyone's permission. That is, the third-party watchdog is implemented not as a hard-to-secure person but as a protocol, and because every judgment accumulates as a binding precedent from day one, sovereignty is transferred over time from the founder to case law. This is a gradual transition from rule by persons (人治) to rule by law (法治), and it is the substantive content of gradual decentralization in this model—the unit of decentralization is the accumulation of precedent, not token voting.

The fifth apparatus is the compartmentalization of trust. A system of human witnesses will someday, somewhere, be betrayed, and the design must presume that day. The guarantor pool is firewalled by region and occupation so that reputation, staking, and burning operate node-locally. If collusion among a group of guarantors in a particular region is detected, the status of that node is burned and its credentials are flagged, but the record of the accountability chain proves to the stakeholders of every other node why their credentials remain intact. The failure of one witness community must be a local fire and must not become a fire of the whole system—trust that cannot fail locally will in the end fail globally. This compartmentalization is another expression of the same principle as the ROC structure of Chapter 4 and the federated segmentation discussed in Section 5.9, and it is the digital reproduction of the Saemaul Undong's operating on the village as a natural unit of accountability.

In summary, the institutional design of the attestation network is completed in five layers: contract (ex ante extinction of disputes), bridge (objective scoring of judgment), discipline (two-stage: statistics indict and humans judge), adjudication (precedent-bound and automatically flagged), and compartmentalization (localization of failure). Thereby the reward-design principle of Chapter 5—shifting the highest-order reward to guarantor status—obtains the institutional foundation that secures the integrity of that status. The proposition that guarantor promotion is the highest reward (Section 5.4) and the proposition that the integrity of attestation is the platform's only moat hold simultaneously only on this five-layer institution.

5.9. A Remaining Tension: The Scarcity of Status and Opportunity versus the Ideal of Universal Education

The status (guarantor promotion) and opportunity (demand-side access) presented above as the highest forms of reward contain one essential tension. Status and opportunity, by their nature, have value only if they are scarce. If everyone becomes a guarantor, the value of attestation falls; if opportunity is given to everyone, opportunity is no longer a distinguishing signal. That is, this reward design stands structurally on a pyramidal scarcity—a structure in which only a few reach the summit—and this stands in direct tension with this model's founding ideal of "education for all" and with the universalism of Hongik Ingan discussed in Chapter 2. That monetary reward can in principle be issued infinitely but status reward cannot is the final contradiction that a reward-based egalitarian platform faces.

This study does not disguise this tension as resolved. It presents, however, two directions of mitigation. The first is federated segmentation. Rather than placing guarantor status in a single global hierarchy, this approach divides it into countless segments by region, occupation, and language, creating "many small summits." If multiple paths to becoming a guarantor in a particular occupation in a particular region coexist, the absolute scarcity of status is mitigated while the signal value within each domain is maintained. This combines naturally with the ROC structure of Chapter 4—a structure in which independent operating units coexist by region.

The second is the stratified separation of scarce reward and universal reward. Scarce rewards such as identity, status, and opportunity are placed at the top of the ladder, while at the bottom and middle of the ladder, rewards that do not depend on scarcity—the informational feedback of competence, the intrinsic satisfaction of learning itself, communal belonging—are designed to operate. Seen this way, the ideal of universal education is reinterpreted not as the promise that "everyone reaches the summit" but as the promise that "the first rung of the ladder and the path of ascent are fairly open to all." In the Saemaul Undong, too, not every village became a self-reliant village, but the path and criteria for grade advancement were fairly open to all villages. The universalism of the Digital Saemaul model, likewise, can be compatible with the tension of scarcity when it is understood as the fair opening of the path rather than the equality of outcomes.

This tension is not, however, completely resolved, and whether status scarcity has an essential character that does not disappear even through segmentation and stratified separation remains a problem to be continuously observed through future operation. This study explicitly states this problem as an unresolved open task, and as a fundamental challenge that the design of a reward-based learning ecosystem faces, it becomes an important subject of future research.

6. Supporting Experiment, Practice, and Skill Acquisition with On-Device AI and AR

6.1. Background: The Gap in Experimental Infrastructure

The learning layer of the NodajiFi platform discussed so far focuses mainly on text-based problem-solving and dialogue with the AI tutor. This structure is effective for text-mediated learning domains such as language, mathematics, the humanities, and social science, but by itself it is not sufficient for the domain of experiment, practice, and skill acquisition that accompanies physical performance and tool manipulation. The subject treated in this chapter is not limited to STEM experiments in the narrow sense. Not only science experiments such as chemistry and physics, but also vocational and technical training in general—electrical and electronic circuit assembly, machine maintenance, medical and nursing practice, cooking, welding—all require physical tools, a safe practice space, and the opportunity for repeated performance. This gap in practice resources is not only a gap in science education but also a structural barrier that blocks the vocational-competency formation and economic self-reliance of low-income learners. Recalling that the 1970s Saemaul Undong helped rural residents toward self-reliance by disseminating practical skills such as housing improvement and farming techniques, the support for experiment, practice, and skill acquisition in the Digital Saemaul model directly touches the movement's original orientation toward the formation of self-reliance capacity, beyond a mere supplement to subject-matter education.

This infrastructure gap is not a problem only of low-income countries. Domestically as well, there exist learners who cannot access sufficient experimental equipment and a safe experimental environment because of urban-rural and inter-school gaps. Reagents used in chemistry experiments are costly and difficult to manage safely, so many schools cannot provide sufficient experimental opportunities, and the specimens needed for anatomy practice are subject to ethical and practical constraints. This reality has been supplemented by text-based learning, but text has the limit that it cannot sufficiently substitute for the cognitive and embodied aspects of experiments.

In this chapter, as a technical combination with the potential to partially mitigate this gap, the combination of on-device AI and augmented reality (AR) is proposed as the STEM education module of the Digital Saemaul model, and its possibilities and limits are analyzed. This module, combined with the core reward mechanism of the NodajiFi platform, provides an integrated experience in which the learner performs a virtual experiment and obtains a reward for that learning activity.

6.2. Design of the On-Device AI and AR Combination

AR-based virtual experiment modules are not in themselves a new concept. Meta-analytic studies verifying the effect of AR/VR-based learning have accumulated across various fields such as chemistry, physics, and biology, and improvements in learning outcomes have been consistently reported (Lah et al., 2024; Cao & Hsu, 2023). The limits of existing AR learning systems, however, were twofold. First, the computing resources for high-quality AR content were provided on a cloud basis, so they do not operate in environments with unstable internet connectivity. Second, they lacked intelligent feedback that responds dynamically to the learner's behavior, so they easily remained mere visualization tools.

These two limits can be partially resolved by the combination of two technological currents that have advanced in recent years. First, the development of on-device AI technology. The performance of lightweight language and vision models mounted directly on mobile devices has improved dramatically, reaching a level at which basic analysis of learner responses and generation of feedback are possible even without an internet connection. This reduces cloud dependence and opens the possibility of a learning system that can operate even in environments with unstable internet infrastructure. Second, the popularization of mobile AR technology. As AR functions using the camera and sensors of an ordinary smartphone have become standardized, it has become possible to provide a virtual experiment environment without separate expensive equipment.

The design principle of this module is as follows. When the learner points their mobile device at a flat surface (e.g., a desk), the AR interface projects a virtual experiment environment—experiment table, reagents, equipment—onto it. The learner proceeds through the experiment procedure by screen or voice, and when they mix reagents or manipulate equipment, the result is immediately reflected visually and aurally. At the same time, the on-device AI module observes the learner's procedural performance and, when a mistake occurs, provides immediate feedback or additional explanation of the meaning of the procedure.

This design combines naturally with NodajiFi's reward structure. When the learner completes a virtual experiment, NGEM is issued immediately according to the degree and accuracy of completion. This is an extension into the STEM domain of "immediate feedback of visible outcomes" among the four mechanisms of the Saemaul Undong. In addition, virtual experiments have the additional strengths of securing safety and ethics in chemistry experiments handling dangerous reagents, anatomy practice with ethical burdens, and the like.

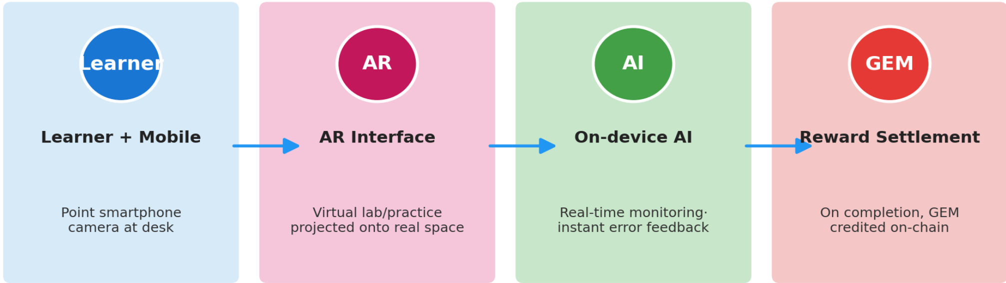


Figure 6-1. Workflow of the on-device AI + AR virtual experiment/practice module

6.3. Analysis of Subject-by-Subject Substitutable Range

A virtual experiment/practice module is not equally effective in all practice domains. Because the learning goal and the essence of practice in each field differ—whether cognitive understanding is central, or physical mastery is central—the range within which the AR+AI combined module can substitute for physical experiment/practice shows clear differences by field. This study, including not only science experiments but also vocational and technical training domains, presents the following estimated ranges synthesized from prior review and related meta-analyses (Lah et al., 2024; Cao & Hsu, 2023; Pottle, 2019). It is made clear that these ranges are presented not as absolute values but as hypotheses to be verified in future empirical research.

Chemistry experiments (substitutable range about 70-80%): The chemistry-experiment domain is one of the fields where the effect of virtual experiments is greatest. The visualization of chemical reactions such as reagent-mixing reactions, crystal formation, and gas generation can be accurately reproduced through computer simulation, and for highly hazardous experiments (highly toxic reagents, explosive reactions, etc.) virtual experiments are rather superior in terms of safety. However, the fine tool-manipulation sense of measuring the actual mass of reagents and of precise titration is hard to form sufficiently in a virtual environment.

Electrical and electronic circuits (substitutable range about 75-85%): Circuit assembly, understanding of circuit diagrams, and signal analysis via oscilloscope are domains where simulation is highly effective. Circuit simulators (of the SPICE family) are already used as an industry standard, and visual circuit assembly through AR provides learners with intuitive understanding of abstract concepts. However, the mechanical characteristics of actual components and manual-work domains such as soldering have limits in a virtual environment.

Anatomy and biology (substitutable range about 80-90%): The learning of the anatomical structure of the human body and animals is a domain where the effect of 3D visualization and decomposable virtual models is very large. Considering ethical burdens and the difficulty of securing specimens, the strengths of the virtual environment are even greater. Microscopic structures at the cellular level can also be effectively conveyed through magnified visualization. However, high-level manual-skill training such as surgical operation requires the combination of a separate haptic-feedback device to achieve sufficient effect.

Physics experiments (substitutable range about 60-70%): The simulation of physical phenomena such as mechanics, optics, and electromagnetism is effective, but the sense of handling precision measuring instruments and the experience of the statistical treatment of error are limited in a virtual environment. However, for dangerous experiments (high voltage, radiation, etc.) or experiments whose time scale is beyond human perception (high-speed collision, quantum phenomena), the virtual environment can rather heighten learning effect.

Cooking and culinary practice (substitutable range about 40-50%): Procedure learning and hygiene-management education are possible in a virtual environment, but because multisensory elements such as temperature, texture, and taste are essential, the substitutable range is limited.

Welding and machining (substitutable range about 30-40%): The virtual environment is useful for safety education and procedure confirmation, but practice in which the fine adjustment of the hand and the mechanical response of tools are central requires training in a physical environment.

This field-by-field differentiation carries important implications for the policy application of the Digital Saemaul model. First, it must be clearly recognized that virtual experiments are not a complete substitute for physical experiments but are in a position of partial, complementary substitution. Second, a policy priority can be derived as to which fields should receive priority placement of virtual experiments in resource-constrained environments. The chemistry, electrical-electronics, and anatomy domains are top-priority application targets because the effect of the virtual environment is large while at the same time the cost, risk, and ethical burden of the physical environment are large. By contrast, manual-skill-centered practice still requires the prior securing of a physical environment.

[Table 6-1] Estimated Subject-by-Subject Substitutable Range of AR+AI Virtual Experiments

Field	Substitutable Range	Strengths	Limitations	Priority Application
Chemistry experiments	70-80%	Reagent-mixing·reaction simulation · safe substitution for hazardous experiments	Hard to form the sense of precise titration·fine tool manipulation	Priority
Electrical·electronic circuits	75-85%	Circuit-assembly simulation · oscilloscope AR overlay · SPICE-verified accuracy	Limits in mechanical characteristics of components·manual work such as soldering	Priority
Anatomy·biology	80-90%	3D organ decomposition · magnification of cellular microstructure · avoidance of ethical burden	Surgical manual skill requires a haptic device	Priority

Field	Substitutable Range	Strengths	Limitations	Priority Application
Physics experiments	60-70%	Mechanics·optics·electromagnetism simulation · safe substitution for high-speed·high-voltage experiments	Limited sense of precision instruments·experience of error handling	Auxiliary
Cooking·culinary practice	40-50%	Procedure learning·hygiene-management education possible	Multisensory essentials such as temperature·texture·taste	Complementary
Welding·machining	30-40%	Limited to safety education·procedure confirmation	Fine adjustment of the hand·mechanical response of tools is central	Physical env. first

Note: These estimated ranges are hypothetical estimates synthesized from prior review and related meta-analyses (Lah et al., 2024; Cao & Hsu, 2023) and are subject to verification in future empirical research.

6.4. Limitations and Complementary Design

When such a module is integrated into the Digital Saemaul model, the limits that may arise and the complementary design for them need to be discussed.

First, the gap in hardware accessibility. The virtual experiment module requires a certain level of mobile-device performance. On low-spec devices, AR functions may not operate or may degrade, giving rise to the paradox that precisely the learners who most need help cannot use the module. As complements, the following can be considered: (1) providing a lightweight version of the module; (2) placing shared devices at service hubs; and (3) a design that links part of the learning reward to be usable for device upgrades.

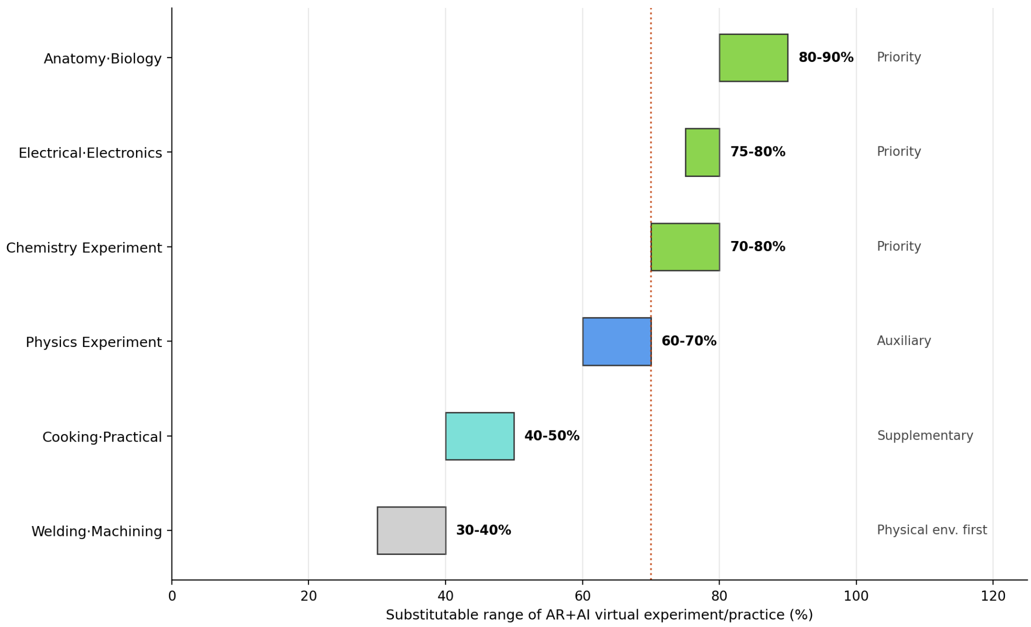
Second, the burden of verifying learning effect. The claim that virtual experiments have a learning effect equivalent to physical experiments must be verified through rigorous future empirical research. When this module is integrated into the Digital Saemaul model, its learning effect must be measured not simply by a satisfaction indicator that the user enjoyed using it, but by improvement in actual concept understanding and procedural-performance ability. To this end, this study proposes the development and validation of learning-outcome assessment tools as a core task for future research.

Third, the limit of embodied learning. Theoretically, learning is not a mere cognitive activity but an activity combined with physical and sensory experience (Wilson, 2002), and a virtual environment cannot fully reproduce this embodied aspect. Therefore, positioning virtual experiments as pre-lab or complementary learning for physical experiments is the academically justifiable range, and complete substitution must be approached cautiously.

Fourth, the capability limit of on-device AI. Current on-device AI is sufficient for general learning feedback but shows limits, compared with cloud-based large models, in sophisticated responses to complex learner questions. As complements, the following can be considered: (1) a hybrid mode that supplements with a cloud model when the internet is available; (2) pre-caching of responses to frequently occurring question patterns; and (3) a natural handoff mechanism to a peer learner or a human tutor.

Considering these limits, the on-device AI + AR module should be positioned not as a panacea but as a complementary approach to the STEM education gap of the Digital Saemaul model. Its value lies not in the complete substitution of physical experiments but in lowering the barrier to entry to STEM learning in resource-constrained environments, expanding learning opportunities in domains with large risk and ethical burdens, and—combined with the learning-reward mechanism—reinforcing the motivation for STEM learning.

Figure 6-2. Subject-by-subject AR+AI substitutable range and staged adoption priority



7. Pilot Operation Plan and Future Validation Design

7.1. The Position of the Research Stage and the Purpose of This Chapter

The NodajiFi platform analyzed in this study is, at the time of this paper's writing, at the development-completed and pilot-preparation stage immediately before full-scale commercial launch. Therefore, this chapter does not present an empirical analysis based on large-scale user data. This is because this study, as a design study and case study, places its primary purpose on arguing for the coherence of the system-design principles and the validity of the implementation.

The purpose of this chapter is twofold. First, it presents concretely a pilot operation plan for future full-scale empirical validation. Second, it presents a methodological blueprint for the study design and measurement tools through which that validation should be conducted. Such clarification of prior design is an academic contribution that the study can have even at the stage before empirical data have been secured. A well-designed validation plan is itself the foundation of subsequent research and prevents the errors that hasty data interpretation can bring.

7.2. Pilot Operation Plan

The pilot operation is designed as a stage that inspects the functional integrity of the system and the initial user experience. This study proposes the following staged operation plan.

The first stage is the closed pilot. With a limited number of voluntary participants, it inspects whether the core functions of the system—interaction with the AI tutor, immediate settlement of learning rewards, token conversion, governance voting—operate technically stably. The purpose of this stage is not the measurement of effect but functional verification and the discovery of critical defects.

The second stage is the open pilot. After supplementing the problems found in the closed pilot, it observes user behavior in a real operating environment targeting a particular region and learner group. At this stage, initial indicators such as learning persistence, reward-utilization patterns, and user satisfaction can be collected, but until a controlled experimental design is in place, these indicators are positioned merely as operational-monitoring data.

The third stage is the full-scale empirical study. After the system has stabilized through the open pilot, a controlled empirical study is conducted according to the validation design described below. Only at this stage can the hypotheses presented by this study be rigorously verified.

7.3. Future Validation Design: Measurement Variables and Study Design

The design elements that a full-scale empirical study must possess are proposed as follows. This is the work of clarifying how the theoretical claims of this study can be empirically verified.

In terms of study design, future empirical research should adopt a randomized controlled trial or a quasi-experimental design. To isolate the effect of reward-based learning, it is necessary to set up comparison groups that are provided the same AI-tutoring content but differ in the presence or absence of the reward mechanism or in the degree of reward immediacy. Only through such a design can the effect of reward be measured separately from the effect of the content itself.

In terms of sampling, the calculation of a sample size to secure sufficient statistical power must precede the study, and a recruitment strategy is required to control the selection bias arising from voluntary participation. In addition, as this model aims at global application, samples should be secured from multiple cultural spheres rather than a single region, so as to examine cross-cultural generalizability.

In terms of measurement variables, this study proposes the measurement of the following multilayered outcome variables. The first layer is learning-behavior indicators, such as learning-persistence rate, study time, and task-completion rate. The second layer is learning-outcome indicators, that is, improvement in actual concept understanding and competency through pre-post assessment. The key is to measure not mere activity volume but whether substantive learning occurred. The third layer is economic-utilization indicators, that is, how obtained rewards are utilized and what contribution they make to the learner's household economy. The fourth layer is psychological-change indicators, that is, the learner's self-efficacy, future orientation, and change in attitude toward learning.

In terms of observation period, a sufficient observation period is required to distinguish short-term activation effects from long-term settlement effects. In particular, to examine whether extrinsic reward damages intrinsic motivation (from the perspective of self-determination theory) and whether reward dependence forms, a design is needed that tracks learning behavior even after the provision of reward is stopped.

7.4. Methodological Issues to Consider in Interpretation

This section organizes the methodological issues that must be recognized in advance when interpreting data in future empirical research. The prior recognition of such issues secures caution in data interpretation.

The first is the Hawthorne effect. Because pilot participants recognize that they are trial users of a new system, they may show more active learning behavior than usual. Therefore, directly extrapolating the positive indicators of the pilot stage to the effect of the full-scale operation stage must be guarded against.

The second is selection bias. Users who voluntarily participate in an early pilot are likely to have higher new-technology affinity and learning motivation than the general population. Because the true policy value of this model depends on its effect on groups marginalized from learning rather than on such active users, the validation design must separately measure reach and effect for this group.

The third is the problem of attribution of effect. This model operates as an integration of several elements—AI tutoring, immediate reward, token structure, governance participation. To isolate which element an observed effect originates from requires a sophisticated experimental design that varies each element independently.

The clarification of the above validation design and methodological issues functions, even though this study is at a stage where it cannot present full-scale empirical data, as an academic contribution that guides future empirical research to be conducted in a trustworthy manner. The expected effects suggested by prior literature (Kestin et al., 2025; Lah et al., 2024) support the potential effectiveness of this model, but whether that potential is realized in this model's concrete implementation can be confirmed only through rigorous verification according to the design presented above.

8. Discussion: Limitations and Implications

8.1. Academic Contributions of This Study

The academic contributions of this study can be organized on three dimensions.

First, a contribution to Saemaul Undong research. Whereas existing Saemaul Undong research has concentrated on spirit- and value-centered analysis, this study decomposed the movement's operating mechanisms into four and reduced them to academically analyzable units. Such mechanism-centered analysis can contribute to expanding Saemaul Undong research from a culturally unique Korean case into one case of a universal social-design theory. The four mechanisms—self-organization, matching grant, performance-based differentiation, and immediate visibility—are analytical tools applicable to various social-design problems beyond the context of Korean rural development.

Second, a contribution to Web3 research and token-economy research. Web3 token-economy design has hitherto been discussed mainly on the basis of financial engineering and game theory, but its social-science foundation regarding social legitimacy and operating principles was relatively weak. By combining the mechanisms of the Saemaul Undong—a historical social movement—with token-economy design principles, this study provides a new analytical resource for the social-science legitimacy of Web3 systems. This suggests that a token economy may be not a mere product of financial engineering but one response to the universal problem of the design of cooperation and incentives in human society.

Third, a contribution to global education-gap and ODA research. This study proposed the Digital Saemaul model as a new policy tool for resolving learning poverty. This presents the possibility of active ODA that complements infrastructure-centered welfare-type ODA, and shows a pathway by which Korea can reinterpret its own development experience in a 21st-century manner and contribute to the formation of a global commons.

8.2. A Careful Review of the Regulatory and Legal Environment

The token-economy aspect of the NodajiFi platform analyzed in this study requires careful review in relation to the virtual-asset regulations of each country. In particular, the USD-value-pegged structure of NUSD may entail substantial legal obligations in the regulatory environment for stablecoin issuers, such as Korea's Virtual Asset User Protection Act and the U.S. GENIUS Act. The EU's MiCA regulation also imposes strict capital requirements and reserve-management standards on the issuance of asset-referenced tokens. In fact, this regulatory environment was directly reflected in the design evolution of this case. The revised whitepaper (NodajiFi Labs, 2026) deferred the implementation of NUSD and adjusted the implementation scope to a dual structure of the learning unit and the supply-side settlement unit, which is an example showing the process by which design research is iteratively revised within its interaction with the regulatory environment. Furthermore, the latest revision (v6.2) finalized, under the judgment that the enforcement of closedness and the burning of authority cannot coexist, a direction in which the operator intentionally retains the powers of management, freezing, and recall of NDJI and fully discloses the record of their exercise for audit. This is a choice that prioritizes the regulatory defensibility of the closed loop over the rhetoric of decentralization, and it is a compromise that can be justified in a system whose primary goal is minor protection. Meanwhile, the reward pathway for guarantors (cash compensation for verification labor and a non-transferable revenue-sharing right) is judged to be defensible against securities classification in that it is contribution-based reward; however, because an appearance of profit expectation can form when combined with a status-promotion narrative, a securities-law review specifically of the relevant provision is required.

While acknowledging that legal analysis is beyond the scope of this paper, this study emphasizes that, if the Digital Saemaul model is promoted at the policy level, the following legal reviews must proceed in parallel. First, if NUSD is activated in the future, a jurisdiction-by-jurisdiction analysis of how its legal character is classified (whether it is a security, whether it is a stablecoin) must precede. Second, a review is needed of the possibility that a structure of obtaining tokens through learning activity is classified as unlicensed financial activity in some countries. Third, a compliance design is required so that token transfer among global learners does not conflict with anti-money-laundering (AML) regulation.

These legal risks do not undermine the policy legitimacy of this model, but they affect the model's implementation pathway. Possible response directions are as follows. First, through jurisdiction-by-jurisdiction differentiated operation, design operating forms suited to the regulatory environment of each region (this is consistent with the ROC structure presented in the NodajiFi whitepaper). Second, if policy promotion is undertaken at the level of the Korean government and the Korea Saemaul Undong Center, the use of a regulatory sandbox within Korea can be considered. Third, in some jurisdictions, an alternative form in which the reward unit is operated not as a token but as a non-blockchain-based digital voucher can also be considered.

8.3. Research Limitations and Future Empirical Tasks

This study clearly acknowledges its limitations as follows.

First, the absence of empirical data. Because this study was written at the stage immediately before the platform's commercial launch, it cannot present effect verification based on full-scale user data. Therefore, the theoretical claims and design principles presented by this study must be empirically confirmed through future empirical research according to the validation design presented in Chapter 7.

Second, the task of full-scale empirical design. Future research needs an empirical design equipped with the following elements: (1) large-scale random-sample recruitment (target N≥1,000); (2) setting a comparable control group (e.g., users of a non-reward learning platform); (3) a sufficient observation period (at least 12 months); and (4) measurement of multilayered outcome variables (learning behavior, learning outcomes, economic utilization of rewards, change in learner self-efficacy). Only through such a design can the hypotheses presented by this study be rigorously verified.

Third, the tracking of long-term effects. The true value of the Digital Saemaul model lies in its impact on the learner's long-term life course, beyond short-term changes in learning behavior. A longitudinal study of how the human capital a learner forms through the platform is converted into value in the actual labor market, and of how it contributes to the household's economic self-reliance and to blocking the intergenerational transmission of poverty, is a core future task.

Fourth, the verification of cross-cultural generalization. Considering that the mechanisms of the Saemaul Undong operated in the social and cultural context of Korean rural areas, whether their digital reconstruction has the same effect in other cultural contexts requires separate verification. Future research needs to comparatively analyze operability in different cultural spheres such as Southeast Asia, Africa, and South America.

Fifth, the review of ethical and social side effects. A model that combines monetary reward with the act of learning requires continuous monitoring of potential side effects—that is, the possibility of damaging the intrinsic motivation of learning, the possibility of forming reward dependence, and the possibility of reproducing inequality among learners in a new form. Research on such side effects is essential for the responsible development of this model.

In addition, the reconstruction of reward design presented in Chapter 5 of this study contains the unresolved tension of the scarcity of status and opportunity. Because status- and opportunity-based reward has value only if it is scarce by nature, it stands in structural tension with the ideal of universal education. This study presented federated segmentation and the stratified separation of scarce and universal rewards as directions of mitigation, but this tension is not completely resolved, and as a fundamental challenge in the design of a reward-based learning ecosystem, it remains a task to be continuously explored in both the empirical and theoretical dimensions.

9. Conclusion and Policy Recommendations

9.1. Summary

This study reconstructed the social operating mechanisms that the Korean Saemaul Undong of the 1970s-1980s possessed within the context of 21st-century artificial-intelligence and blockchain technology, and reported the design principles and an implementation case of a reward-based learning ecosystem for mitigating global educational and economic polarization.

The core claims of this study are summarized as follows. First, the essence of the Saemaul Undong lay not in the spirit of "diligence, self-help, and cooperation" but in four operating mechanisms: (1) village-level self-organization, (2) matching-grant-style resource combination, (3) performance-based differentiated support, and (4) immediate feedback of visible outcomes. Second, these four mechanisms can be reconstructed in the 21st-century Web3 environment into digital equivalents—respectively, DAO governance, the combination of advertising/sponsorship/study effort, a token-distribution algorithm, and blockchain-based immediate settlement. Third, the NodajiFi platform, as a concrete attempt at such reconstruction, implements the above mechanisms at the system level through a NGEM-NDJI dual-unit structure (with NUSD of the tri-token reference model deferred pending regulatory review) and a dual governance structure. Fourth, a virtual experiment module combining on-device AI and AR provides the possibility of partially mitigating the STEM education gap, but the substitutable range differs by field and should be in a complementary position rather than a complete substitute for the physical environment.

In addition, this study analyzed the policy implications the Digital Saemaul model can have for the new forms of 21st-century polarization—the AI divide, capital-labor asymmetry, and the persistence of learning poverty. This model is not a panacea, but by constructing a cognitive and practical connecting channel between the act of learning and asset formation, it has the potential to contribute to mitigating polarization.

9.2. Recommendations for the Korea Saemaul Undong Center and ODA Agencies

On the basis of this study's analysis, the following policy recommendations are presented for the Korea Saemaul Undong Center and Korean ODA agencies (KOICA, etc.).

Recommendation 1. Building an academic discourse on the 21st-century redefinition of the Saemaul Undong: Rather than embalming the Saemaul Undong as a historical case of rural-development projects, the Korea Saemaul Undong Center needs to invest in building an academic discourse that re-establishes its mechanisms as universal social-design principles applicable to 21st-century social problems. The "mechanism-centered analysis" presented by this study can be one starting point of that re-establishment.

Recommendation 2. Promoting a pilot project of the Digital Saemaul movement: The Korean government and the Korea Saemaul Undong Center can promote a pilot project of the Digital Saemaul model in one or two jurisdictions. The design of the pilot project should focus on verifying, in the form of full-scale empirical research, how the four mechanisms presented by this study operate in a real operating environment.

Recommendation 3. Reviewing a shift to the active-ODA paradigm: Korean ODA agencies should review the possibility of active ODA that complements infrastructure-centered welfare-type ODA. Active ODA is a model that supports recipient-country learners in forming immediate value through learning activity, and it has the strengths of little resource leakage and the reinforcement of recipients' self-efficacy.

Recommendation 4. Making Korea's intellectual resources a global commons: The universal orientation toward human welfare that the Hongik Ingan ideal possesses is an intellectual resource that can contribute to the 21st-century discourse of the global digital commons. Korean academia and government can actively utilize this intellectual resource not as a mere means of promoting national culture but as a core asset with which Korea can contribute to the discussion of global digital governance.

Recommendation 5. Creating an experimental environment for the token economy through a regulatory sandbox: To safely experiment with the token-economy aspect of the Digital Saemaul model within Korea, the use of a regulatory sandbox can be considered. This can contribute to Korea positioning itself as a responsible leader in the discussion of global token-economy governance.

9.3. Academic and Practical Future Tasks

This study concludes by presenting the following future tasks.

First, the promotion of full-scale empirical research. According to the validation design presented in Chapter 7, full-scale empirical validation through a randomized controlled trial or a quasi-experimental design is required. This validation can be promoted through the cooperation of academic researchers, NodajiFi Labs, and, if possible, Korean government agencies.

Second, cross-cultural comparative research. In that this study's model was created in Korea but aims at global application, comparative research on its operability in different cultural spheres is essential. Comparative research analyzing differences in user response and learning effect in each region—Southeast Asia, Africa, South America, and so on—will provide core information for the practical development of this model.

Third, research isolating the effect of each mechanism. Although the four mechanisms presented by this study operate in an integrated manner, the individual contribution of each mechanism was not measured separately. Future research needs to form a precise understanding of which element of the model brings which effect by separately measuring the independent effect of each mechanism on learning behavior.

Fourth, research on the design of ethical safeguards. The design of safeguards to prevent the potential side effects of a model that combines reward with learning needs to become a separate research domain. Indicators that monitor the occurrence of reward dependence, reward designs that do not damage intrinsic motivation, and algorithm designs that prevent the occurrence of new inequality among learners will be its core subjects.

Fifth, research on the activation conditions of the conditional design element. The NUSD that this study preserved as a reference model is a conditional design element whose implementation is deferred (Sections 4.4 and 8.2), and at present this paper is the only official record of its activation pathway. Future research needs to systematize this condition—the legal-institutional conditions under which activation is justified when a certain regulatory pathway (regulatory-sandbox approval, partnership with a licensed stablecoin issuer, explicit permission of a particular jurisdiction, etc.) is met; the economic conditions under which a transition to the tri-token structure is required when the dual-unit structure runs into certain functional limits (e.g., cross-border value transfer, long-term preservation of learner purchasing power); and the design conditions for activation not to conflict with the reward-design principle of Chapter 5 of this study—the reduction of rewards carrying monetary value—and with the minor-protection structure of the closed loop. This research, by making explicit the transition rules between the ideal type and the implementation, can contribute by making the very process in which design research evolves through interaction with the regulatory environment an academic object.

This study is one response to the question of how Korea, in the era of new 21st-century polarization, can reinterpret its own historical experience to contribute to the formation of a global commons. If the 1970s Saemaul Undong was a social invention that created the self-reliance of Korean rural areas, the Digital Saemaul model has the potential to become a socio-technical invention that supports the self-reliance of 21st-century global learners. This study hopes to contribute to clarifying that potential academically and presenting a pathway for its practical development.

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Appendices

Appendix A. Collection of System Screen Captures

[Appendix A placeholder] This appendix contains screen captures of the NodajiFi platform at the pre-launch stage. Because UI/UX improvement work is in progress at the time of this paper's writing, the screens included are based on the pre-improvement version and may differ in design detail from the launch version. The screen captures are included not to show the completeness of the design but as evidence that the mechanisms described in Chapter 4 are implemented at the actual screen level.

Recommended screen composition:

- A-1. NodajiFi main learning screen (Nodaji-Fly module)
- A-2. Dialogue interface with the AI tutor
- A-3. Problem-solving and NGEM reward-settlement screen
- A-4. GlobalPiggy wallet main screen
- A-5. NGEM use (in-platform consumption/settlement) screen
- A-6. Governance-voting screen (using NDJI)
- A-7. Virtual chemistry-experiment module (AR interface)
- A-8. Example of differentiated UI for Nodaji-Kids / Silver
- A-9. Transparent donation-delivery screen
- A-10. Learner level and progress screen

Each screen capture is annotated with a caption noting (1) the Saemaul Undong mechanism the screen implements and (2) the section number in the main text to which the screen corresponds. Where a particular screen capture cannot be secured due to UI/UX improvement work, that item is omitted, but as a principle the minimum composition showing the core learning-reward-storage cycle (A-1, A-2, A-3, A-4) is maintained.

Appendix B. Key Token-Economy Parameters

This appendix summarizes the key token-economy parameters of the NodajiFi platform. This information is based on the initial edition (NodajiFi Labs, 2025) and the revised edition (NodajiFi Labs, 2026) of the NodajiFi whitepaper and organizes the design specifications at the time of this paper's analysis. NUSD is a unit of the reference model whose implementation is deferred in the revised edition (see Section 4.4). In the full operation stage, some parameters may be adjusted according to governance decisions.

B-1. NGEM (NodajiGem) Key Specifications

Item	Specification
Function	Immediate-reward unit of learning activity
Issuance condition	Automatically issued upon completion of learning activity
Value stability	In-platform unit, external trading not allowed
Technical implementation	Platform database (off-chain)
Issuing body	NodajiFi Labs (Foundation in the operation stage)
Saemaul Undong equivalent	Immediate-visibility mechanism

B-2. NUSD (Nodaji-USD) Key Specifications — Reference Model (Implementation Deferred)

Item	Specification
Function	USD-value-pegged stable unit of value
Issuance condition	Issued upon NGEM-conversion request
Value stability	1:1 USD peg target
Collateral structure (target)	30% precious metals + 70% external stablecoins
Technical implementation	Algorand Standard Asset (ASA)
Saemaul Undong equivalent	Resultant value of the matching grant

B-3. NDJI (NODAJI) Key Specifications

Item	Specification
Function	Supply-side settlement·access·quality-staking unit (implementation architecture); governance token (reference model)
Total issuance	Fixed supply (1 billion units recommended)
Distribution structure	No public sale — participation-based issuance and operator-treasury management (per revised whitepaper; the initial design's allocation table is discarded)
Technical implementation	Algorand Standard Asset (ASA)
Governance authority	Reference model: policy-decision voting rights / Implementation: governance weight derived from contribution·reputation, not holdings (Section 4.5)
Saemaul Undong equivalent	Decision-making authority of the village assembly

B-4. Key Variables of the Reward Algorithm (Summary)

The exact specifications of this algorithm are undisclosed for reasons of security and abuse prevention and may be adjusted according to governance decisions. The following is a general list of the main variables the algorithm considers.

- Difficulty grade of the learning activity - Learner's current level - Whether the answer is correct and the accuracy rate - Consistency of study time - Depth of interaction with the AI tutor - Daily/weekly activity limits

Appendix C. Mapping Table of Saemaul Mechanisms and System Components (Extended)

This appendix organizes, in summary form, the mapping relationships discussed in Chapters 2 and 4 of the main text.

Saemaul Mechanism (1970s-80s)	Digital Equivalent Principle	NodajiFi System Implementation Element	Related Academic Concept	Section in This Paper
Village-level self-organization	Token-based distributed governance	Nodaji-DAO voting system, decision rights of NDJI token holders	Common-pool resource governance (Ostrom, 1990); DAO theory (Hassan & De Filippi, 2021)	2.2, 4.5
Matching-grant-style resource combination (cement+labor)	Combination of external resources and internal effort	Advertising revenue·sponsorship (external) + study time (internal) → NGEM issuance	Complementary-inputs theory, combination of human and physical capital	2.3, 4.3
Village-grading system and differentiated support	Performance-based differentiated reward	Learner-level system, reward-multiplier adjustment	Incentive-design theory	2.4, 4.4
Immediate feedback of visible outcomes	Blockchain-based immediate settlement	Algorand 3.3-second finality, NGEM credited right after learning	Positive reinforcement (Skinner, 1953); overcoming delay discounting (Mullainathan & Shafir, 2013)	2.5, 4.2
Intermediary leadership of the Saemaul leader	Intermediate node of hybrid governance	Foundation's DAO-ROC mediation role	Hybrid governance (Hassan & De Filippi, 2021)	4.5
Complementing the absence of rural infrastructure	Complementing the learning gap in resource-poor environments	On-device AI + AR virtual experiment module	Meta-analysis of AR/VR learning effect (Lah et al., 2024)	5.2, 5.3
Universal-welfare orientation of Hongik Ingan	Orientation toward the global digital commons	Global learner community and transparent donation system	Global-commons theory	2.6, 8.2

This mapping table compresses the core academic contribution of this study onto a single page. Future research can conduct independent empirical verification of each row of this mapping and can extend the analytical framework by adding new mapping items.

[1] The NUSD column is a conditional design element whose implementation is deferred, and the governance authority of NDJI is likewise a description of the reference model; in the implementation architecture it is separated into contribution- and reputation-based weighting.