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The BigWALL Matrix IoTiZATION Theory: A Graph-Theoretic and AI-Driven Framework for Modeling Human-Thing Interaction, Predictive Behavior, and Autonomy-Preserving Optimization in the Internet of Things

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Abstract

The proliferation of connected devices is reshaping how humans perceive, trust, and ultimately defer to "things". This paper develops the *BigWALL Matrix IoTiZATION Theory* into a complete, mathematically rigorous, and artificial-intelligence (AI)-driven framework for modeling the evolving relationship between humans and connected things in the Internet of Things (IoT) era. We formalize human society and the device ecosystem as a heterogeneous multilayer *Matrix Point Network* and encode their coupling in a single symmetric block operator—the *BigWALL matrix* $\boldsymbol{W} = \left[\boldsymbol{A}, \boldsymbol{B}; \boldsymbol{B}^{\top}, \boldsymbol{C}\right]$. Building on the author's original behavioral relation $H = f\left(T, U, SI, E\right)$, we derive a generalized, network-coupled, nonlinear dynamical model of human reliance on things and prove an *IoTiZATION Equilibrium Theorem* establishing existence, uniqueness, and geometric convergence under an explicit critical-coupling condition γ_c, beyond which a self-reinforcing dependence regime emerges. We introduce an *IoTiZATION index* Ω and a complementary *autonomy index* $\mathcal{A} = 1 - \Omega$, and quantify "imposed intelligence" information-theoretically via conditional mutual information. To meet modern technological growth, we embed a predictive-prescriptive AI engine: a relational attention graph neural network (*BigWALL-GNN*) with temporal recurrence forecasts human behavior, while an *autonomy-preserving* constrained reinforcement-learning controller designs device policies that maximize service utility subject to bounded imposition. A multi-objective formulation links the theory to sustainable development through a utility-imposition-energy Pareto frontier. All quantitative results reported here are illustrative computer simulations on synthetically generated networks—not empirical observations of IoT user behavior. They verify the internal consistency of the model: convergence to equilibrium, a sharp IoTiZATION phase transition at γ_c, accurate re-identification of the driver coefficients by regression, and a favorable autonomy-aware operating point. The AI engine is presented as an architectural specification whose training and empirical validation are left to future field deployment. The framework offers a principled, human-centric foundation for the responsible design, prediction, and governance of human-thing interaction.

Keywords

Internet of Things, IoTiZATION, Matrix Point Network, Human-Thing Interaction, Graph Neural Networks, Predictive Analytics, Constrained Reinforcement Learning, Human Autonomy, Sustainable Computing

1. Introduction

The Internet of Things (IoT) interconnects physical objects embedded with sensing, computation, and communication, enabling them to collect, exchange, and act upon data at unprecedented scale [1] [2]. As connected things permeate homes, bodies, vehicles, factories, and cities, the central question is no longer purely technical—how to connect devices—but socio-technical: *how does the human mind develop, trust, and increasingly defer to connected things, and how can this relationship be modeled, predicted, and governed*? The BigWALL Matrix IoTiZATION Theory addresses precisely this question by treating human society and the device ecosystem as a single coupled network and studying the dynamics of human reliance that emerge across it.

1.1. Background and Motivation

The rapid integration of connected things has revolutionized human-environment interaction, delivering enhanced connectivity, automation, and data-driven services [1] [3]. Yet the same integration silently restructures human decision-making: recommendations, automations, and ambient inferences gradually substitute for, and reshape, human judgment. We term this gradual, network-mediated migration of agency from humans toward things *IoTiZATION*. Understanding IoTiZATION is essential both to harness the benefits of IoT and to preserve human autonomy, trust, and well-being. This paper develops the theory formally and exercises it purely in simulation; no observed IoT behavioral data are analyzed here (§6).

1.2. Problem Statement

Predicting and comprehending human behavior within human-thing interactions is difficult because behavior is shaped by heterogeneous, interacting factors—individual trust, perceived usefulness, peer social influence, environmental context, and the persuasive "intelligence" exerted by the devices themselves—all evolving over a complex network. The original formulation of the theory captured the static drivers through the relation $H = f(T, U, SI, E)$ but did not: 1) endogenize social and device influence through network structure, 2) characterize the stability or tipping points of the resulting dynamics, 3) quantify how much intelligence devices impose, or 4) prescribe how devices should act so as to remain useful *without* eroding autonomy. A comprehensive, predictive, and prescriptive framework is therefore required.

1.3. Objectives and Contributions

This paper elevates the BigWALL Matrix IoTiZATION Theory to a complete formal and computational framework. Our contributions are:

1) Formalization. A heterogeneous multilayer *Matrix Point Network* and the symmetric *BigWALL matrix* $\boldsymbol{W}$ that unifies human-human, human-thing, and thing-thing coupling (§3).

2) Behavioral dynamics. A network-coupled nonlinear generalization of $H = f(T, U, SI, E)$, with an *IoTiZATION Equilibrium Theorem*, an explicit critical coupling γ_c, and a phase transition into self-reinforcing dependence (§4).

3) Measurement. An *IoTiZATION index* Ω, an *autonomy index* $\mathcal{A}$, and an information-theoretic measure of *imposed intelligence* $\mathbb{I}$ (§4).

4) AI engine. A relational attention graph neural network with temporal recurrence (*BigWALL-GNN*) for behavior prediction, and an *autonomy-preserving* constrained reinforcement-learning controller for device-policy design (§5).

5) Optimization and sustainability. A multi-objective utility-imposition-energy formulation yielding a Pareto frontier that connects IoTiZATION to sustainable development (§5 - 7).

1.4. Scope and Limitations

The framework targets the modeling, prediction, and human-centric optimization of human-thing interaction. Quantitative results in §7 are *illustrative simulations* that validate the internal consistency of the model; empirical calibration on field data (surveys, interaction logs, telemetry) is left to future work. Generalizability is bounded by the evolving nature of IoT technologies and human behavior. In particular, the BigWALL-GNN and the constrained controller of §5 are design specifications: they are exercised in this paper only through the synthetic protocol of §6 and are not trained on empirical data.

2. Related Work

IoT and its evolution. Research has matured from architectures, protocols, and security [1] [4]-[6] toward data-centric and human-centric concerns. Surveys position IoT as a substrate for pervasive services across smart cities, health, transport, and agriculture [2] [3] [7].

Human-technology interaction and trust. A substantial literature studies how individuals perceive, adopt, and rely on technology, and how trust mediates reliance in the IoT [8] [9]. These perspectives motivate trust (T) and perceived usefulness (U) as first-class drivers of behavior.

Network and behavioral modeling. Social network analysis provides the language of nodes, edges, and centralities [10] [11]; opinion-dynamics models such as DeGroot averaging [12] and the Friedkin-Johnsen model [13] describe how influence propagates—tools we adapt to the multilayer human-thing setting. System-dynamics modeling [14] frames the reinforcing and balancing feedback that drive IoTiZATION.

Learning on graphs and decision-making. Graph convolutional and attention networks [15] [16] and relational GNNs [17], combined with gated recurrence [18], enable predictive modeling over heterogeneous, evolving networks; intelligent decision-making for IoT services is an active area [19] [20]. Safe, constrained control is formalized through constrained Markov decision processes [21] and constrained policy optimization [22].

Gap. Prior work treats devices, networks, prediction, and ethics largely in isolation. The BigWALL theory unifies them: it couples humans and things in one operator, derives the resulting behavioral dynamics and their tipping points, and prescribes device behavior that is provably mindful of human autonomy.

3. The BigWALL Matrix IoTiZATION Theory: Formal Framework

3.1. Conceptual Framework and Ideology

The theory places humans at the center of the IoT ecosystem and studies how the proliferation of connected things reshapes human behavior, relationships, and society. Conceptually (**Figure 1**), it organizes the world into three coupled layers—a *human society layer*, a *BigWALL interaction interface*, and a *connected-things layer*—traversed by four analytic pillars: matrix-point network analytics, a predictive AI engine, autonomy-preserving optimization, and human-centric, sustainable outcomes. The ideological core is a shift in *trustworthiness and reliance* toward connected things, which can complement but also displace human-to-human interaction; the framework's purpose is to render this shift measurable and steerable.

3.2. The Matrix Point Network

Definition 1 (Matrix Point Network). Let $\mathcal{H} = \{h_1, \cdots, h_n\}$ be a set of humans and $\mathcal{T} = \{\tau_1, \cdots, \tau_m\}$ a set of connected things. The *Matrix Point Network* is the heterogeneous multilayer graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with $\mathcal{V} = \mathcal{H} \cup \mathcal{T}$ and three relation types: human-human social ties, human-thing interaction ties, and thing-thing (machine-to-machine) ties.

Each "point" is a locus of interaction—a *wall* in the original metaphor—at which human agency meets device capability (**Figure 2**). The relations are encoded by three nonnegative weight matrices:

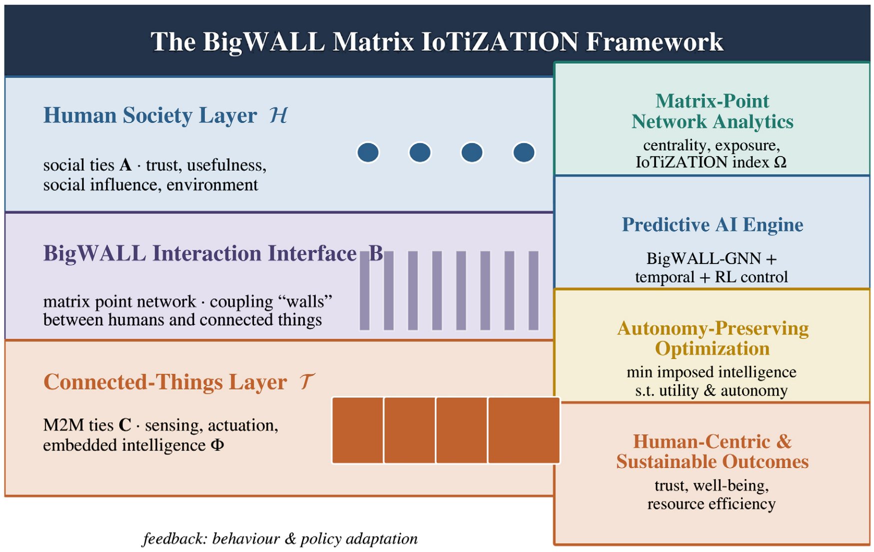


Figure 1. Conceptual framework of the BigWALL Matrix IoTiZATION Theory: three coupled layers feed four analytic pillars, with a feedback loop through which outcomes adapt human behavior and device policy.

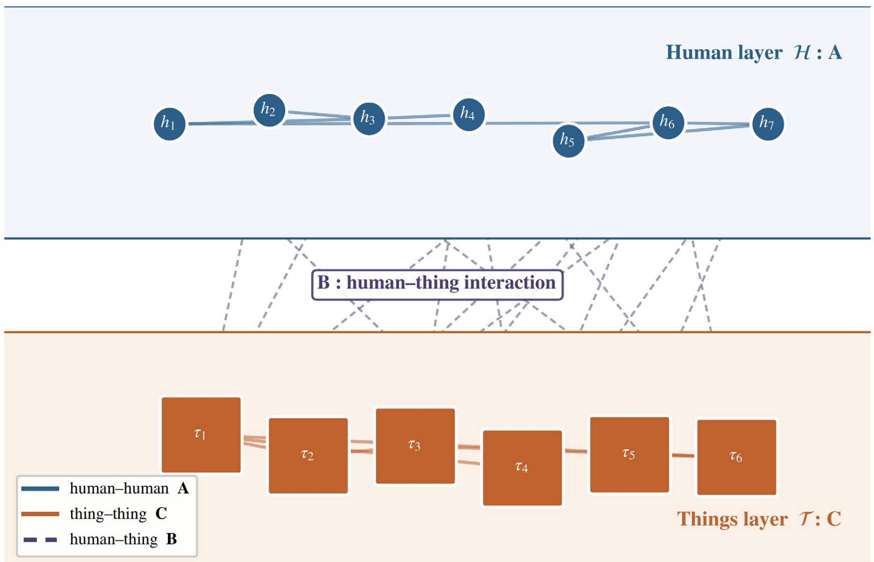


Figure 2. The Matrix Point Network as a multilayer graph: a human social layer ($\boldsymbol{A}$), a connected-things layer ($\boldsymbol{C}$), and the human-thing interaction links ($\boldsymbol{B}$) that form the BigWALL interface.

$$\boldsymbol{A} \in \mathbb{R}_{\geq 0}^{n \times n}, \ \boldsymbol{B} \in \mathbb{R}_{\geq 0}^{n \times m}, \ \boldsymbol{C} \in \mathbb{R}_{\geq 0}^{m \times m},$$

where $\boldsymbol{A} = \boldsymbol{A}^\top$ is the social adjacency, B_{ik} is the interaction intensity between human i and thing k, and $\boldsymbol{C} = \boldsymbol{C}^\top$ is the M2M connectivity.

3.3. The BigWALL Coupling Matrix

Definition 2 (BigWALL matrix). The *BigWALL matrix* is the symmetric block operator

$$W = \begin{bmatrix} A & B \\ B^\top & C \end{bmatrix} \in \mathbb{R}_{\geq 0}^{(n+m)\times(n+m)}.$$

W is the central object of the theory: it embeds the entire human-thing ecosystem in one matrix (**Figure 3**), so that algebraic and spectral tools apply uniformly. We use row-normalized influence operators

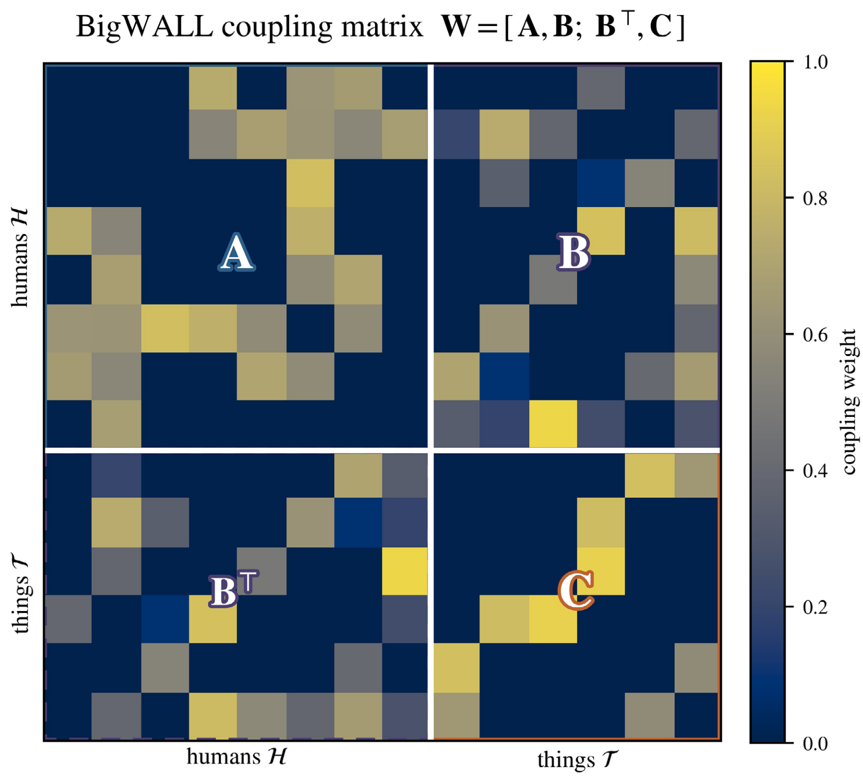


Figure 3. Block structure of the BigWALL matrix W. The human block A, thing block C, and the human-thing coupling B (with transpose $B^\top$) form a single symmetric operator on $\mathcal{H} \cup \mathcal{T}$.

$$\hat{A} = D_A^{-1} A,\ \ \hat{B} = D_B^{-1} B,$$

where $D_A = \operatorname{diag}(A\mathbf{1})$ and $D_B = \operatorname{diag}(B\mathbf{1})$ collect (positive) row sums; $\hat{A}$ and $\hat{B}$ are row-stochastic, encoding how a human apportions social and device influence, respectively. Row normalization follows the classical convention of DeGroot averaging and the Friedkin-Johnsen model [12] [13], in which each agent distributes a unit budget of attention across its ties; it makes weights interpretable as attention shares and delivers the spectral properties ($\varrho(\hat{A}) = 1$) exploited in §4.

3.4. Matrix-Point Network Analytics

Spectral analysis of W exposes structural roles. Let c solve the eigenvector-centrality relation $Wc = \lambda_{\max} c$, partitioned as $c = [c_{\mathcal{H}}; c_{\mathcal{T}}]$. We define two diagnostics that operationalize the theory's notion of exposure to things.

Definition 3 (Thing-dependence centrality). For human i,

$$\rho_i = \frac{\sum_k \hat{B}_{ik} c_k^{\mathcal{T}}}{\sum_j \hat{A}_{ij} c_j^{\mathcal{H}} + \sum_k \hat{B}_{ik} c_k^{\mathcal{T}}} \in [0,1],$$

the fraction of i's centrality inflow originating from connected things.

Definition 4 (Structural thing-exposure). Let $\boldsymbol{M} = \hat{\boldsymbol{B}}\hat{\boldsymbol{B}}^\top$ be the human-side shared-device operator. The exposure vector $\boldsymbol{e}$ is the principal eigenvector of $\boldsymbol{M}$; e_i ranks humans by how strongly they share device dependence with influential peers.

High ρ_i or e_i flags individuals (or, aggregated, communities) most susceptible to IoTiZATION, guiding human-centric design and intervention.

Table 1 summarizes the principal notation used throughout the paper.

Table 1. Summary of principal notation.

Symbol	Meaning
$\mathcal{H}, \mathcal{T}$	sets of humans and connected things ($\lvert\mathcal{H}\rvert = n, \lvert\mathcal{T}\rvert = m$)
$\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{C}$	social, human-thing, M2M weight matrices
$\boldsymbol{W}$	BigWALL matrix (2)
$\hat{\boldsymbol{A}}, \hat{\boldsymbol{B}}$	row-normalized influence operators
H_i	human i's reliance/behavior toward things, $\in (0,1)$
T_i, U_i, E_i	trust, perceived usefulness, environment
SI_i, Ψ_i	endogenous social and thing-imposed influence
Φ_k	intelligence/persuasion exerted by thing k
$\alpha, \beta, \gamma, \zeta, \delta$	driver coefficients; θ_i threshold
$\Omega_i, \mathcal{A}_i$	IoTiZATION index and autonomy index $= 1 - \Omega_i$
$\mathbb{I}$	imposed intelligence (information-theoretic)
$\sigma(\cdot)$	logistic activation, $L_\sigma = 1/4$
γ_c	critical IoTiZATION coupling

4. Behavioral Dynamics and the IoTiZATION Operator

4.1. From the Static Driver Model to Coupled Dynamics

The original theory models human behavior toward things as a function of trust T, perceived usefulness U, social influence SI, and environment E, *i.e.* $H = f(T, U, SI, E)$, with a linear instance $H = \alpha T + \beta U + \gamma SI + \delta E$. We retain these drivers but make two advances: we *endogenize* influence through the network, and we add the device's own persuasive "intelligence". Define the endogenous social influence and the thing-imposed drive on human i at time t as

$$SI_i(t) = \left(\hat{\boldsymbol{A}}\boldsymbol{H}(t)\right)_i, \Psi_i(t) = \left(\hat{\boldsymbol{B}}\boldsymbol{\Phi}(t)\right)_i,$$

where $\boldsymbol{H}(t) = \left[H_1(t), \cdots, H_n(t)\right]^\top$ and $\boldsymbol{\Phi}(t) = \left[\Phi_1(t), \cdots, \Phi_m(t)\right]^\top$, $\Phi_k \in [0,1]$ being the intelligence thing k exerts. The behavior of human i evolves as

$$H_i(t+1) = \sigma\left(\alpha T_i + \beta U_i + \gamma SI_i(t) + \zeta\Psi_i(t) + \delta E_i - \theta_i\right),$$

with logistic $\sigma(x) = \left(1 + \mathrm{e}^{-x}\right)^{-1}$ enforcing saturation $H_i \in (0,1)$ and threshold θ_i. The logistic threshold-saturation form is the standard choice in models of collective behavior and technology adoption: it captures individual adoption thresholds as in Granovetter's classical model [23], reproduces the S-shaped diffusion curves documented since Bass [24], keeps H_i in the unit interval, and is the smooth counterpart of the hard-threshold cascade dynamics of Watts [25]. In vector form,

$$\boldsymbol{H}(t+1) = \boldsymbol{\sigma}\left(\alpha\boldsymbol{T} + \beta\boldsymbol{U} + \gamma\hat{\boldsymbol{A}}\boldsymbol{H}(t) + \zeta\hat{\boldsymbol{B}}\Phi(t) + \delta\boldsymbol{E} - \boldsymbol{\theta}\right) =: \Gamma\left(\boldsymbol{H}(t)\right).$$

We call Γ the *IoTiZATION operator*.

Remark 1. Setting $\sigma = \mathrm{id}$, $\zeta = 0$, $\boldsymbol{\theta} = \boldsymbol{0}$, and treating SI as exogenous recovers the author's original linear relation $H = \alpha T + \beta U + \gamma SI + \delta E$ exactly; (7) is thus a strict, network-coupled generalization.

4.2. Equilibrium, Stability, and the IoTiZATION Threshold

With drivers $\boldsymbol{T}, \boldsymbol{U}, \boldsymbol{E}, \boldsymbol{\Phi}$ held over a horizon, Γ is a fixed-point map. Let $\|\cdot\|_2$ denote the spectral (operator-2) norm.

Theorem 1 (IoTiZATION Equilibrium). Let σ be L_σ-Lipschitz ($L_\sigma = 1/4$ for the logistic). If

$$\gamma L_\sigma \left\|\hat{\boldsymbol{A}}\right\|_2 < 1,$$

then Γ is a contraction on $[0,1]^n$, admits a *unique* equilibrium $\boldsymbol{H}^\star = \Gamma\left(\boldsymbol{H}^\star\right)$, and the iteration (7) converges geometrically:

$$\left\|\boldsymbol{H}(t) - \boldsymbol{H}^\star\right\|_2 \le \left(\gamma L_\sigma \hat{\boldsymbol{A}}_2\right)^t \left\|\boldsymbol{H}(0) - \boldsymbol{H}^\star\right\|_2.$$

Proof. For $\boldsymbol{x}, \boldsymbol{y} \in [0,1]^n$, the constant terms cancel and, since σ acts elementwise with slope $\le L_\sigma$, $\left\|\Gamma(\boldsymbol{x}) - \Gamma(\boldsymbol{y})\right\|_2 \le L_\sigma \left\|\gamma\hat{A}(\boldsymbol{x} - \boldsymbol{y})\right\|_2 \le \gamma L_\sigma \left\|\hat{\boldsymbol{A}}\right\|_2 \left\|\boldsymbol{x} - \boldsymbol{y}\right\|_2$. Under (8) the modulus is <1, so Γ is a Banach contraction on the complete set $[0,1]^n$; the Banach fixed-point theorem yields the claims. □

Definition 5 (Critical IoTiZATION coupling). $\gamma_c = \dfrac{1}{L_\sigma \varrho}$, where $\varrho = \rho\left(\hat{\boldsymbol{A}}\right)$ is the spectral radius of $\hat{\boldsymbol{A}}$ (for row-stochastic $\hat{\boldsymbol{A}}$, $\varrho = 1$, hence $\gamma_c = 1/L_\sigma = 4$ for the logistic).

Theorem 2 (Self-reinforcing regime). The operator Γ is monotone on $[0,1]^n$ (componentwise), since σ is increasing and $\hat{\boldsymbol{A}}, \hat{\boldsymbol{B}} \ge 0$. Hence, by the Knaster-Tarski theorem, Γ possesses a least fixed point $\boldsymbol{H}^\star_{\min}$ and a greatest fixed point $\boldsymbol{H}^\star_{\max}$. For $\gamma > \gamma_c$ the contraction certificate of Theorem 1 no longer applies, so uniqueness is no longer guaranteed; if in addition the extremal fixed points separate ($\boldsymbol{H}^{\star}_{\min} \neq \boldsymbol{H}^{\star}_{\max}$), *multistability* results: a low-reliance and a high-reliance equilibrium coexist, and small perturbations can tip the population into self-reinforcing IoTiZATION.

Two logically distinct statements should be kept apart. First, $\gamma > \gamma_c$ means only that the *sufficient* contraction condition (8) fails; by itself this does not establish multiple equilibria. Second, multistability does provably occur under additional structure: in the homogeneous benchmark ($T_i \equiv T$, $U_i \equiv U$, $E_i \equiv E$, $\theta_i \equiv \theta$, $\hat{A}$ row-stochastic) the dynamics collapse onto the scalar map $h \mapsto \sigma(a + \gamma h)$, which acquires three fixed points through a saddle-node bifurcation exactly when $\gamma\sigma' > 1$ at the interior root—that is, beyond $\gamma_c = 1/L_\sigma$. This is the smooth analogue of threshold-cascade multistability [23] [25]. This tipping behavior is the formal counterpart of the reinforcing feedback loop (R) in **Figure 4**: greater trust raises reliance, which invites richer embedded intelligence, which raises dependence and, in turn, trust. A balancing loop (B) mediated by human autonomy opposes it. The numerically observed steepening of equilibrium reliance $\bar{H}^{\star}$ as γ crosses γ_c is reported in §7.

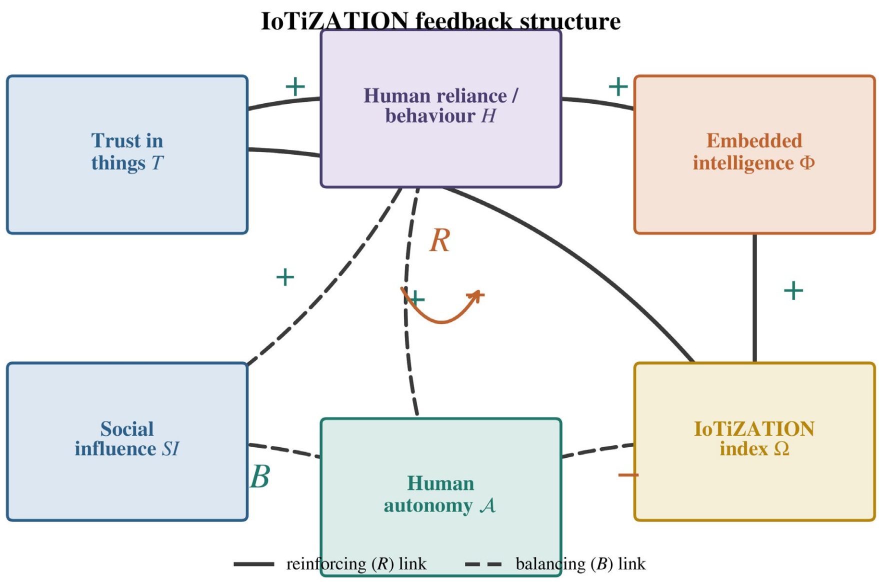


Figure 4. IoTiZATION feedback structure. A reinforcing loop (R) drives dependence; a balancing loop (B) through human autonomy restrains it. The balance of R and B determines whether the system settles or tips.

4.3. IoTiZATION and Autonomy Indices

To measure how much of a human's decision drive originates from things, decompose the equilibrium drive into its five components and define

$$\Omega_i = \frac{\zeta \Psi_i^{\star}}{|\alpha T_i| + |\beta U_i| + |\gamma SI_i^{\star}| + |\zeta \Psi_i^{\star}| + |\delta E_i|} \in [0,1],$$

the *IoTiZATION index* of human i , with system-level $\bar{\Omega} = 1/n \sum_i \Omega_i$. The complementary *autonomy index* is

$$\mathcal{A}_i = 1 - \Omega_i, \ \bar{\mathcal{A}} = 1 - \bar{\Omega}.$$

$\mathcal{A}_i$ is the share of decision drive a human retains from self (trust, usefulness), peers, and environment, rather than from device-imposed intelligence; preserving $\bar{\mathcal{A}}$ is the framework's central human-centric objective.

4.4. An Information-Theoretic Measure of Imposed Intelligence

Beyond the structural index (10), we quantify imposed intelligence in information units. Let X_i be human i's realized decision (a random variable), $Z_{\mathcal{N}(i)}$ the recommendations/actions of the things in i's device neighborhood, and $\mathcal{C}_i$ the observable context. The intelligence *imposed* on i is the context-conditioned mutual information

$$\mathbb{I}_i = I\left(X_i; Z_{\mathcal{N}(i)} \mid \mathcal{C}_i\right),$$

which credits a device only for the variation in human decisions it explains *beyond* benign contextual correlation. The system imposition is $\mathbb{I} = 1/n \sum_i \mathbb{I}_i$. Minimizing $\mathbb{I}$ subject to maintaining service utility is the operational meaning of "minimizing the impact of intelligence imposed by things".

5. AI-Driven Predictive and Prescriptive Engine

To bring the theory to current technological practice, we embed an AI engine (Figure 5) that 1) *predicts* human behavior over the Matrix Point Network and 2) *prescribes* device policies that are useful yet autonomy-preserving.

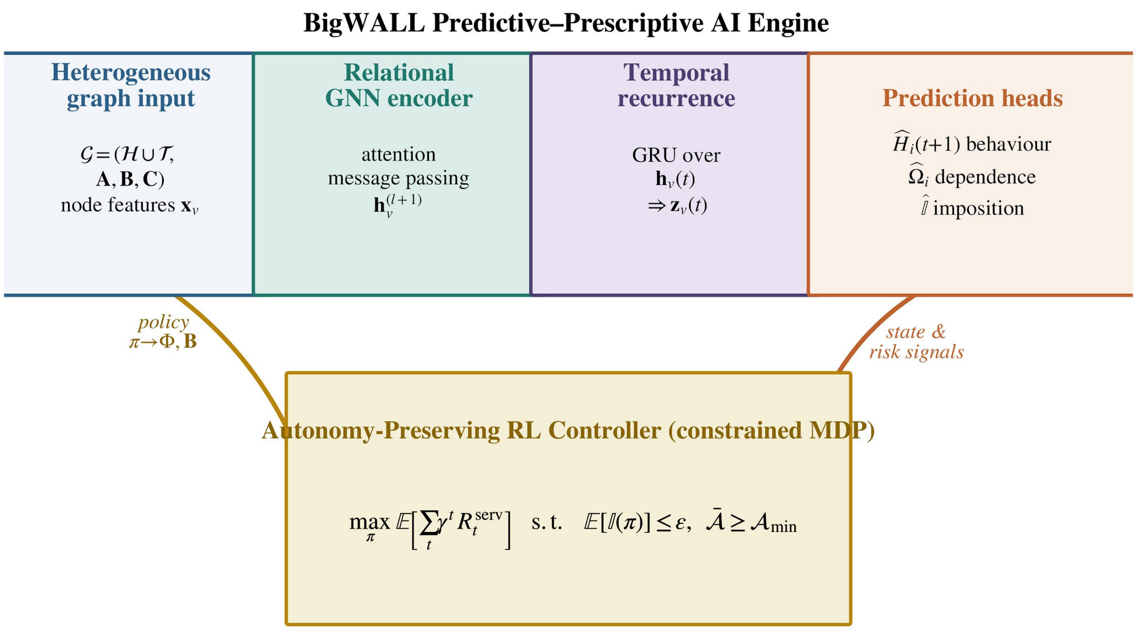


Figure 5. The BigWALL predictive-prescriptive AI engine: a relational attention GNN encodes the heterogeneous graph, a recurrent module captures temporal evolution, prediction heads forecast behavior and dependence, and a constrained-RL controller closes the loop by setting autonomy-preserving device policies.

5.1. BigWALL-GNN: Relational Attention Encoder

Each node v carries features $\boldsymbol{x}_v$ (e.g. for a human: T_i, U_i, E_i; for a thing: capability, Φ_k). With relation set $\mathcal{R} = \{\text{HH}, \text{HT}, \text{TH}, \text{TT}\}$, layer l updates embeddings by relation-specific attention message passing:

$$\boldsymbol{h}_v^{(l+1)} = \sigma\left(\boldsymbol{W}_0^{(l)}\boldsymbol{h}_v^{(l)} + \sum_{r\in\mathcal{R}}\sum_{u\in\mathcal{N}_r(v)} \alpha_{vu,r}^{(l)}\boldsymbol{W}_r^{(l)}\boldsymbol{h}_u^{(l)}\right),$$

with normalized attention coefficients

$$\alpha_{vu,r} = \frac{\exp\left(\text{LReLU}\left(\boldsymbol{a}_r^\top\left[\boldsymbol{W}_r\boldsymbol{h}_v \,\|\, \boldsymbol{W}_r\boldsymbol{h}_u\right]\right)\right)}{\sum_{r'\in\mathcal{R}}\sum_{u'\in\mathcal{N}_{r'}(v)}\exp\left(\text{LReLU}\left(\boldsymbol{a}_{r'}^\top\left[\boldsymbol{W}_{r'}\boldsymbol{h}_v \,\|\, \boldsymbol{W}_{r'}\boldsymbol{h}_{u'}\right]\right)\right)},$$

where $\|$ is concatenation and LReLU the leaky rectifier. Relation-specific weights let human-thing influence be learned separately from peer influence, directly mirroring the block structure of $\boldsymbol{W}$ [16] [17].

5.2. Temporal Recurrence and Prediction Heads

Because IoTiZATION is dynamic, the per-step embedding $\boldsymbol{g}_v(t) = \boldsymbol{h}_v^{(L)}(t)$ is passed through a gated recurrent unit [18]:

$$\boldsymbol{z}_v(t) = \text{GRU}\left(\boldsymbol{g}_v(t), \boldsymbol{z}_v(t-1)\right),$$

yielding state $\boldsymbol{z}_v(t)$ from which linear/sigmoid heads predict

$$\hat{H}_i(t+1) = \sigma\left(\boldsymbol{w}_H^\top\boldsymbol{z}_i(t) + b_H\right),\ \hat{\Omega}_i = \sigma\left(\boldsymbol{w}_\Omega^\top\boldsymbol{z}_i(t) + b_\Omega\right),$$

and an estimate $\hat{\mathbb{I}}$ of imposition. Training minimizes

$$\mathcal{L} = \frac{1}{|\mathcal{O}|}\sum_{(i,t)\in\mathcal{O}}\left(H_i(t+1) - \hat{H}_i\right)^2 + \lambda_1\text{tr}\left(\hat{\boldsymbol{H}}^\top\boldsymbol{L}\hat{\boldsymbol{H}}\right) + \lambda_2\|\Theta\|_2^2,$$

where $\mathcal{O}$ are observed labels, $\boldsymbol{L} = \boldsymbol{D} - \boldsymbol{A}$ is the graph Laplacian enforcing smoothness of predictions over social ties, and Θ are model parameters.

5.3. Autonomy-Preserving Control as a Constrained MDP

The prescriptive layer designs how things should act. Model the ecosystem as a Markov decision process with state s_t (network state and embeddings), action a_t setting device policy parameters that shape $(\boldsymbol{B}, \boldsymbol{\Phi})$, and service reward R_t^{serv}. We require devices to be useful *without* imposing excessive intelligence:

$$\begin{aligned}\max_\pi\quad & J(\pi) = \mathbb{E}_\pi\left[\sum_t\gamma^t R_t^{\text{serv}}\right]\\ \text{s.t.}\quad & J_{\mathbb{I}}(\pi) = \mathbb{E}_\pi\left[\sum_t\gamma^t\mathbb{I}_t\right] \le \varepsilon, \bar{\mathcal{A}} \ge \mathcal{A}_{\min}.\end{aligned}$$

This constrained MDP [21] is solved by primal-dual policy optimization on the Lagrangian

$$\mathcal{L}(\pi, \lambda) = J(\pi) - \lambda\left(J_{\mathbb{I}}(\pi) - \varepsilon\right),\ \lambda \ge 0,$$

alternating ascent on policy parameters with projected ascent on the multiplier λ (**Algorithm 1**) [22].

Algorithm 1. Autonomy-preserving IoTiZATION control.

1: **Input:** graph $\mathcal{G}$, budget ε, floor $\mathcal{A}_{\min}$, rates $\eta_\theta, \eta_\lambda$
2: Initialize policy π_θ, multiplier $\lambda \geq 0$
3: **repeat**
4: Roll out π_θ on $\mathcal{G}$; record R_t^{serv}, estimate $\mathbb{I}_t$ via (**??**)
5: Compute $\widehat{J}$, $\widehat{J}_{\mathbb{I}}$ and policy gradient $\nabla_\theta \mathcal{L}$
6: $\theta \leftarrow \theta + \eta_\theta \nabla_\theta \mathcal{L}(\pi_\theta, \lambda)$ ▷ improve utility
7: $\lambda \leftarrow \left[\lambda + \eta_\lambda(\widehat{J}_{\mathbb{I}} - \varepsilon)\right]_+$ ▷ enforce bound
8: Project so that $\bar{\mathcal{A}} \geq \mathcal{A}_{\min}$
9: **until** converged
10: **return** autonomy-preserving policy π_θ

5.4. Multi-Objective Design and Sustainability

At the design level we jointly trade service utility $\mathcal{U}$, imposition $\mathbb{I}$, and environmental/energy cost $\mathcal{E}$ over device-policy parameters Θ:

$$\min_{\Theta}\left(-\mathcal{U}(\Theta), \mathbb{I}(\Theta), \mathcal{E}(\Theta)\right) \text{ s.t. } \bar{\mathcal{A}}(\Theta) \geq \mathcal{A}_{\min},$$

with scalarization $F(\Theta) = -w_u\mathcal{U} + w_i\mathbb{I} + w_e\mathcal{E}$. The Pareto frontier of (20), computed in §7, exposes the achievable utility for each tolerated level of imposition; because $\mathcal{E}$ aggregates energy and resource use, optimizing (20) ties IoTiZATION directly to sustainable development—connected things can raise efficiency while a chosen *autonomy-aware operating point* caps their imposition.

6. Methodology

6.1. Operationalizing the Variables

Each construct is given a concrete measurement recipe. Trust T_i and perceived usefulness U_i are elicited with validated technology-acceptance survey instruments (UTAUT-style Likert scales, rescaled to $[0,1]$) [9]. The environment term E_i aggregates observable context—connectivity quality, device density, and ambient conditions—from telemetry. Device intelligence Φ_k is scored from capability audits and logged persuasion events of thing k (recommendation frequency, proactive actuations). Reliance H_i is operationalized behaviorally as the fraction of a person's logged decisions in a reference period that follow, or are delegated to, device recommendations. Edge weights are data-driven: A_{ij} from communication/social-tie intensity, B_{ik} from the frequency and duration of interaction between human i and thing k, and $C_{k\ell}$ from observed machine-to-machine traffic.

6.2. Illustrative Simulation Protocol (This Paper)

All quantities in §7 are generated synthetically; no empirical data enter this study. The social graph A is a Barabási-Albert network ($n = 60$, $m_0 = 3$); the bipartite

$\boldsymbol{B}$ links each human to 3 - 5 of $m = 25$ things with weights drawn from $\mathcal{U}(0.3,1)$; M2M ties $\boldsymbol{C}$ are sparse random (12% density). Drivers are drawn once per world: $T_i \sim \mathcal{U}(0.2,0.8)$, $U_i \sim \mathcal{U}(0.3,0.9)$, $E_i \sim \mathcal{U}(-0.2,0.4)$, $\Phi_k \sim \mathcal{U}(0.4,1)$. Coefficients are *fixed by design* at the values of Table 2 rather than estimated from data. The estimation stage is nevertheless *demonstrated* on the synthetic record: the same coefficients are re-identified by logit-linear regression on noisy trajectories (observation noise $\mathcal{N}(0,0.02^2)$, six random restarts, 70/30 train-test split), which also yields the held-out one-step-ahead RMSE in Table 3. The BigWALL-GNN and the RL controller are *not* trained in this study; they enter only as specifications.

Table 2. Configuration of the illustrative simulation study.

Component	Setting
Humans/things (n, m)	60/25
Human-thing ties $\boldsymbol{B}$	3 - 5 things/human, $\mathcal{U}(0.3,1)$
M2M ties $\boldsymbol{C}$	sparse random, 12% density
Social graph $\boldsymbol{A}$	Barabási-Albert ($m_0 = 3$)
Activation σ	logistic, $L_\sigma = 1/4$
Drivers $\alpha, \beta, \delta, \theta$	0.8, 0.7, 0.5, 1.2
Couplings γ, ζ	swept/0.9
Critical coupling γ_c	$1/(L_\sigma \varrho) = 4.0$
Horizon T	35 - 60 steps

Table 3. Quantitative diagnostics of the illustrative study (protocol of §6.2).

Diagnostic	Value
Recovered $(\hat{\alpha}, \hat{\beta}, \hat{\gamma})$	(0.804, 0.693, 0.587)
Recovered $(\hat{\zeta}, \hat{\delta}, \hat{\theta})$	(0.883, 0.503, 1.177)
One-step RMSE of $\hat{H}$ (held-out)	0.020
Iterations to $\lVert \boldsymbol{H}(t) - \boldsymbol{H}^\star \rVert_\infty < 10^{-3}$	4
Equilibrium mean reliance $\bar{H}^\star$	0.65
Mean autonomy $\bar{\mathcal{A}}$ (mean $\bar{\Omega}$)	0.68 (0.32)
Thing-dependence centrality $\bar{\rho}$ (max)	0.37 (0.50)
Corr. $r(\rho_i, \Omega_i)$; $r(e_i, \Omega_i)$	−0.00; −0.09
Imposition $\hat{\mathbb{I}}$, bits/decision (max)	0.002 (0.005)
Critical coupling $\gamma_c = 1/(L_\sigma \varrho)$	4.0

6.3. Prospective Empirical Deployment Workflow

For future field deployment, the framework is instantiated in four stages. 1) *Data collection.* Human attitudes and interactions are gathered via surveys, interviews, observation, and mining of device/social logs, supplying drivers T, U, E and edge weights for $\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{C}$ as specified in §6.1. 2) *Network construction.* The Matrix Point Network and BigWALL matrix $\boldsymbol{W}$ are assembled and normalized. 3) *Estimation.* Driver coefficients $(\alpha, \beta, \gamma, \zeta, \delta)$ are estimated by regression or structural-equation modeling on the empirical record; the BigWALL-GNN is trained on temporal interaction data. 4) *Evaluation.* Predictive accuracy (RMSE of $\hat{H}$ on held-out periods), structural diagnostics (ρ_i, e_i), and the indices $\bar{\Omega}, \bar{\mathcal{A}}, \mathbb{I}$ are reported, and the controller of Algorithm 1 is evaluated against utility/imposition baselines. Table 2 lists the configuration used for the illustrative study; Table 3 reports its quantitative outcomes.

7. Illustrative Results and Analysis

We report illustrative simulations that test the internal consistency of the framework; they are not empirical claims. Table 3 collects the quantitative diagnostics promised in §6, computed under the protocol of §6.2.

Convergence to equilibrium. With $\gamma = 0.6 < \gamma_c$, condition (8) holds and, as Theorem 1 predicts, every trajectory converges rapidly to a unique equilibrium reliance (Figure 6(a)); the population mean $\bar{H}(t)$ stabilizes within a handful of iterations (within 10^{-3} of $\boldsymbol{H}^{\star}$ in four iterations; equilibrium mean $\bar{H}^{\star} = 0.65$).

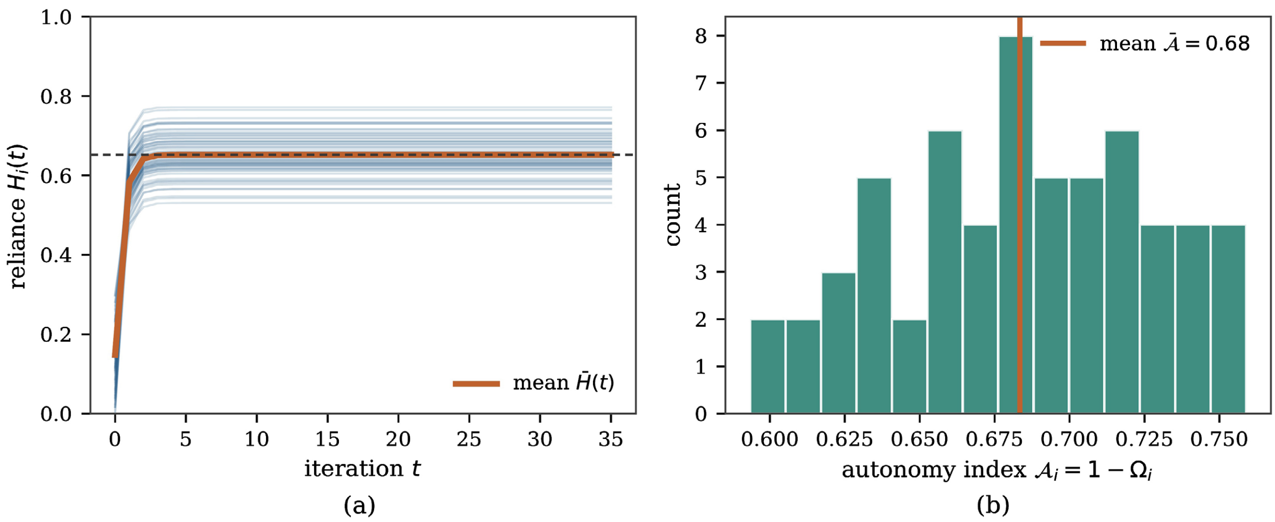


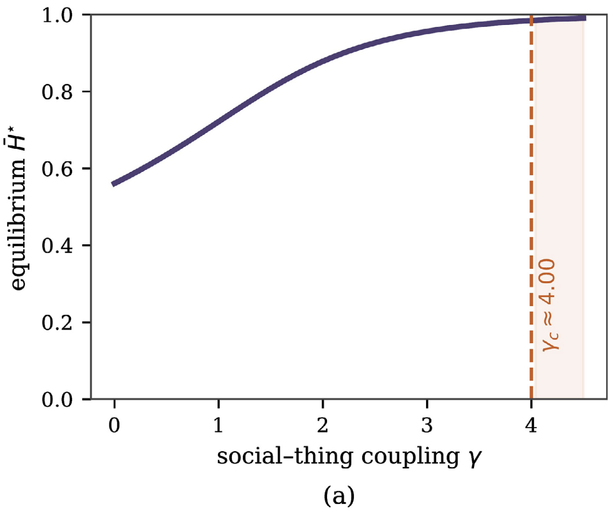
Figure 6. Behavioral dynamics under sub-critical coupling. (a) Trajectories $H_i(t)$ (faint) and population mean $\bar{H}(t)$ (bold) converge to the unique IoTiZATION equilibrium, Convergence to loTiZATION equilibrium. (b) Equilibrium distribution of the autonomy index $\mathcal{A}_i = 1 - \Omega_i$, Distribution of human autonomy.

Autonomy distribution. At equilibrium the autonomy index $\mathcal{A}_i = 1 - \Omega_i$ from (10) is heterogeneous across the population (Figure 6(b)), with mean $\bar{\mathcal{A}} \approx 0.68$ ($\bar{\Omega} = 0.32$). The left tail identifies individuals whose decisions are most device-driven, and these are prioritized for human-centric safeguards. The structural diagnostics are reported alongside: mean thing-dependence centrality $\bar{\rho} = 0.37$ (max 0.50). In this homogeneous synthetic world, ρ_i and e_i correlate only weakly with the realized drive share Ω_i ($r = -0.00$ and $r = -0.09$), confirming that they measure complementary, purely topological exposure rather than duplicating Ω_i; on empirical data, where device intelligence and usage intensity are heterogeneous and correlated, closer alignment is expected.

Coefficient recovery and predictive accuracy. Logit-linear regression on the noisy synthetic trajectories (§6.2) re-identifies the design coefficients to within a few percent—$\left(\hat{\alpha}, \hat{\beta}, \hat{\gamma}, \hat{\zeta}, \hat{\delta}, \hat{\theta}\right) = (0.804, 0.693, 0.587, 0.883, 0.503, 1.177)$ against the true $(0.8, 0.7, 0.6, 0.9, 0.5, 1.2)$—and attains a held-out one-step-ahead RMSE of 0.020 for $\hat{H}$ (Table 3). This validates the identifiability of the estimation stage on data of this type; empirical RMSE for the trained BigWALL-GNN is deferred to field deployment (§6.3).

Numerical imposition. A plug-in estimate of the conditional mutual information (12) over 4000 simulated stochastic decision epochs gives a system imposition of $\hat{\mathbb{I}} \approx 0.002$ bits per decision (max over individuals 0.005): under sub-critical coupling with homogeneous device intelligence, things explain little decision variation beyond context—exactly the regime the controller of §5 is designed to certify and maintain.

Phase transition. Sweeping the social-thing coupling γ reveals the predicted bifurcation: equilibrium reliance $\bar{H}^{\star}$ rises gently while $\gamma < \gamma_c$ and steepens sharply as $\gamma \to \gamma_c \approx 4.0$ (Figure 7(a)), the onset of the self-reinforcing regime of Theorem 2. The threshold γ_c is thus an actionable early-warning indicator for runaway dependence.



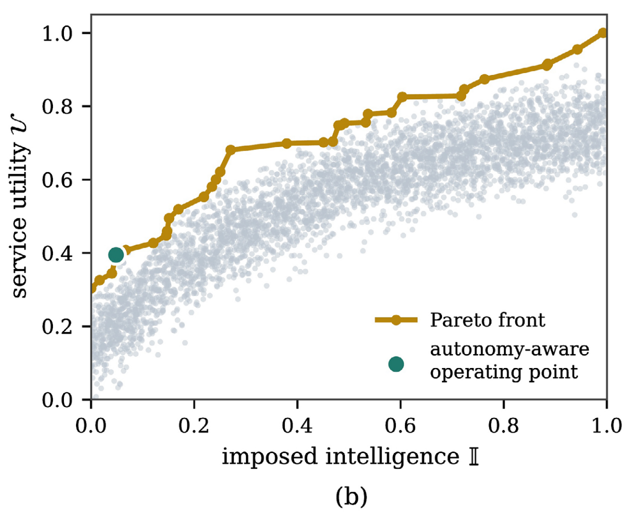


Figure 7. (a) IoTiZATION phase transition: equilibrium reliance $\bar{H}^{\star}$ versus coupling γ, with critical value $\gamma_c \approx 4.0$. (b) Utility-imposition Pareto frontier with the selected autonomy-aware operating point.

Utility-imposition trade-off. The Pareto frontier of (20) (Figure 7(b)) shows that high service utility need not entail maximal imposed intelligence: a kneepoint *autonomy-aware operating point* attains near-maximal utility at substantially reduced imposition $\mathbb{I}$, the regime **Algorithm 1** targets.

8. Discussion

1) Interpretation. The results substantiate the theory's central claim: human reliance on connected things is an emergent, network-mediated equilibrium whose value and stability are governed by measurable couplings. The contraction condition (8) and threshold γ_c turn the qualitative "mindset development" narrative into quantitative, testable predictions, while Ω, $\mathcal{A}$, and $\mathbb{I}$ render autonomy and imposed intelligence first-class, optimizable quantities.

2) Theoretical implications. The BigWALL matrix unifies social-network analysis, opinion dynamics, and IoT modeling within one operator, enabling spectral and fixed-point tools to characterize human-thing systems. Theorems 1 - 2 contribute tipping-point analysis absent from the original formulation.

3) Practical implications. For designers and policymakers, the framework yields concrete instruments: monitor γ relative to γ_c; track $\bar{\mathcal{A}}$ as a well-being KPI; deploy **Algorithm 1** so services optimize utility under an explicit imposition budget; and select operating points on the Pareto frontier that respect sustainability and autonomy jointly.

4) Ethics and sustainability. Treating imposed intelligence as a *constraint* rather than an afterthought operationalizes privacy-by-design and responsible-innovation principles, and links efficiency gains to bounded human imposition—advancing sustainable, human-centric IoT.

5) Limitations and future work. Empirical calibration on real interaction data, identifiability of driver coefficients, richer (e.g. heterogeneous-threshold or continuous-time) dynamics, adversarial robustness of the controller, and longitudinal field studies of Ω over time are important next steps. In particular, training and validating the BigWALL-GNN and the constrained controller on real interaction data is the essential step from the present specification to a deployed system.

9. Conclusion

We transformed the BigWALL Matrix IoTiZATION Theory into a rigorous, AI-driven framework for human-thing interaction in the IoT era. By embedding humans and connected things in a single BigWALL matrix, generalizing the author's $H = f(T, U, SI, E)$ relation into a coupled nonlinear dynamical system with provable equilibrium and a tipping threshold, quantifying autonomy and imposed intelligence, and coupling a predictive graph-neural engine to an autonomy-preserving controller, the theory now predicts behavior, exposes risk, and prescribes responsible device action. The framework charts a path toward a future in which humans and connected things coexist harmoniously—leveraging the Internet of Things for societal well-being while keeping human autonomy provably at the center.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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