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AFMF-SFBM-A08: Alaali Behavioral Sustainability Forecasting Model (A-BSF)

Hasan Mohamed Husain Alaali
AIA, CPA, IPA Fellow Member
DFAS Research Center, Kingdom of Bahrain
Email: founder@dfas.ai
Alternative email: hasan.mohd.alaali@gmail.com

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1. Abstract

Background: Sustainability assessment commonly remains retrospective, providing limited capacity to anticipate behavioral deterioration, resilience shifts, or the effects of ESG-related shocks. Building on the Alaali Behavioral Sustainability Index (A-BSI) and the Alaali Expected Behavioral Efficiency Index with Adaptive Intelligence, this study develops the Alaali Behavioral Sustainability Forecasting Model (A-BSF), the eighth analytical model in the Alaali Self-Funded Behavioral Model (AFMF-SFBM) series.

Methods: The study develops a conceptual simulation-based forecasting framework that integrates behavioral durability, financial resilience, governance alignment, environmental integration, behavioral volatility, and ESG shocks. The model introduces Behavioral Forecast Confidence (BFC), which combines relative forecast error and behavioral forecast entropy, and the Dynamic Resilience Function (DRF), which represents post-shock recovery capacity. Illustrative Monte Carlo simulations (10,000 iterations) were conducted using Bayesian-updated input assumptions across alternative behavioral and ESG conditions. The reported accuracy measure represents the relative agreement between the model forecast and the simulated benchmark outcome; it does not constitute validation against real-world historical observations.

Results: Under the simulated high-sustainability condition—behavioral durability coefficient (βd) above 0.80 and behavioral volatility below 0.20—the model produced simulation forecast accuracy between 93% and 97%. The results indicate, within the model's simulated conditions, that higher behavioral durability supports forecast stability, whereas greater behavioral volatility reduces forecast confidence and ESG shocks alter projected sustainability trajectories. These findings are illustrative and require subsequent empirical validation using longitudinal organizational data.

Discussion: A-BSF shifts behavioral sustainability analysis from descriptive measurement toward structured predictive assessment. Its contribution is a transparent simulation architecture for examining how behavioral resilience, uncertainty, and ESG disturbances may interact over time. The framework is proposed as a decision-support and research instrument rather than as an empirically validated forecasting system. Future research should calibrate its parameters and test its predictive performance across organizations and sectors.

Keywords: Behavioral sustainability; sustainability forecasting; Monte Carlo simulation; behavioral forecast confidence; dynamic resilience; ESG shocks; organizational resilience; behavioral managerial finance; AFMF-SFBM.

2. Novelty and Theoretical Contribution

Conceptual Novelty

The Alaali Behavioral Sustainability Forecasting Model (AFMF-SFBM-A08) extends behavioral-sustainability assessment from current-state measurement toward simulation-based forward-looking analysis. It integrates behavioral durability, financial resilience, governance alignment, environmental integration, behavioral volatility, and ESG shocks within a structured forecasting architecture. The model is proposed as a conceptual and methodological framework for examining projected behavioral-financial resilience under alternative conditions.

Theoretical Contributions

1. Extends the AFMF-SFBM series from behavioral-sustainability measurement toward simulation-based forecasting of sustainability conditions (Alaali, 2025a).
2. Specifies how behavioral durability, financial resilience, governance alignment, environmental integration, behavioral volatility, and ESG shocks may interact within a projected sustainability path.
3. Introduces three analytical constructs: Behavioral Forecast Confidence (BFC), Dynamic Resilience Function (DRF), and Predictive Value Index (PVI).
4. Positions sustainability as a dynamic and potentially adjustable relationship among behavioral conditions, financial resilience, governance alignment, and external ESG disturbances.

Methodological Innovation

1. Integrates Monte Carlo simulation, stochastic behavioral-volatility modelling, conceptual Bayesian recalibration, and multi-scenario forecasting.
2. Uses period-to-period changes in behavioral durability, financial resilience, governance alignment, and environmental integration as inputs to the projected sustainability outcome.
3. Applies illustrative sensitivity analysis to examine the potential effects of behavioral volatility and ESG shocks on projected sustainability and forecast confidence.
4. Defines the Predictive Value Index (PVI) as:

PVI = (Accuracy × Confidence × Timeliness) / Resource Cost

The index is proposed as an analytical measure of forecasting value rather than an empirically established return-on-investment measure.

Conceptual Progression

The model represents the forecasting extension of the AFMF-SFBM series, moving from behavioral-sustainability measurement toward simulation-based sustainability analysis (Alaali, 2025a). Its design and interpretation apply DFAS-FEP principles of documentation, traceability, auditability, declaration, and classification (Alaali, 2025c).

3. Introduction

The Self-Funded Behavioral Model series (AFMF-SFBM) develops a behavioral-financial approach to incentive efficiency, resilience, self-regulation, adaptive learning, and sustainability assessment within the Alaali Financial Models Meta-Framework (AFMF). The foundational model establishes the self-funding behavioral logic, while subsequent models address behavioral efficiency, expected performance, cost recovery, self-regulation, adaptive learning, and sustainability assessment (Alaali, 2025a).

Within this progression, the Alaali Behavioral Sustainability Index (AFMF-SFBM-A07) provides a structured measure of behavioral-financial sustainability and current resilience (Alaali, 2025a). However, a contemporaneous index does not itself provide a mechanism for examining how sustainability may evolve under changing behavioral conditions, volatility, governance conditions, or ESG-related shocks. This limitation motivates the development of a forecasting extension.

The present manuscript introduces the Alaali Behavioral Sustainability Forecasting Model (AFMF-SFBM-A08) as a conceptual, simulation-based framework for projecting behavioral sustainability across future periods. The model incorporates behavioral durability, financial resilience, governance alignment, environmental integration, behavioral volatility, and ESG shocks. It also proposes Behavioral Forecast Confidence (BFC), Dynamic Resilience Function (DRF), and Predictive Value Index (PVI) as analytical constructs for examining forecast reliability, post-shock recovery, and the proposed value of forecasting (Alaali, 2025a).

The framework uses illustrative Monte Carlo simulation and conceptual Bayesian recalibration to examine alternative sustainability conditions. It does not claim empirical parameter estimation, implementation of a trained reinforcement-learning algorithm, or validation against observed historical organizational data. Its purpose is to define a transparent forecasting architecture that can be operationalized and empirically tested in future research.

Accordingly, A-BSF extends the AFMF-SFBM series from behavioral-sustainability measurement toward structured forward-looking analysis. The model is proposed as a decision-support and research framework for examining possible sustainability trajectories under alternative behavioral and ESG conditions.

Methodological Integration Statement

This manuscript is positioned within the integrated architecture of the Alaali Financial Models Meta-Framework (AFMF), the Dynamic Financial Applied Meta-Science (DFAS) doctrine, and the Applied Self-Evolving Science (ASES) doctrine. It represents a proposed transition from sustainability measurement through A-BSI toward simulation-based behavioral forecasting.

1. DFAS Layer – Ethical Meta-Governance

The DFAS-FEP provides the ethical and procedural reference for transparent forecasting design. It emphasizes documentation, traceability, auditability, declaration, and classification in the development and interpretation of predictive models (Alaali, 2025c). Within A-BSF, this layer requires that model assumptions, scenario settings, calibration ranges, and limits of interpretation are explicitly documented.

2. AFMF Layer – Structural and Analytical Framework

The AFMF supplies the analytical architecture linking A-BSF to its preceding behavioral-efficiency, adaptive-learning, and sustainability-measurement models. It integrates Behavioral Forecast Confidence, Dynamic Resilience Function, and Predictive Value Index within a proposed behavioral-financial forecasting structure (Alaali, 2025a).

3. ASES Layer – Evolutionary and Cognitive Doctrine

The ASES doctrine provides the conceptual basis for iterative recalibration. In the present study, this is represented through conceptual Bayesian updating and feedback-oriented simulation cycles rather than a trained reinforcement-learning algorithm. Forecast inputs may be adjusted across simulation cycles when behavioral, volatility, or ESG assumptions change.

Together, these layers connect ethical governance, behavioral-financial analysis, and iterative learning within the proposed A-BSF architecture. The model remains a simulation-based research framework whose parameters, measurement properties, and predictive performance require future empirical testing.

4. Conceptual Framework and Research Questions

Behavioral–Sustainability Pathway

The Alaali Behavioral Sustainability Forecasting Model (AFMF-SFBM-A08) extends the behavioral-financial continuum of the Alaali Financial Models Meta-Framework (AFMF) within the Self-Funded Behavioral Model series. The pathway is sequential and cumulative:

Incentive Formation – AFMF-SFBM-A02: The Alaali Behavioral Efficiency and Self-Funded ROI (A-SIRR / A-ROI-B)
→ Predictive Expectation – AFMF-SFBM-A03: The Alaali Expected Behavioral Efficiency Index (A-EBEI)
→ Recovery and Resilience – AFMF-SFBM-A04: The Alaali Behavioral Cost Recovery Ratio (A-BCRR)
→ Behavioral Regulation – AFMF-SFBM-A05: The Alaali Self-Regulation Multiplier (A-SRM)
→ Adaptive Intelligence – AFMF-SFBM-A06: The Alaali Expected Behavioral Efficiency Index with Adaptive Intelligence (A-EBEI-AI)
→ Sustainability Measurement – AFMF-SFBM-A07: The Alaali Behavioral Sustainability Index (A-BSI)
→ Forecasting and Strategic Foresight – AFMF-SFBM-A08: The Alaali Behavioral Sustainability Forecasting Model (A-BSF) (Alaali, 2025a).

This sequence describes the progression from behavioral-efficiency measurement toward simulation-based forecasting of sustainability conditions. Within the DFAS doctrine, the forecasting stage applies DFAS-FEP principles of documentation, traceability, auditability, declaration, and classification (Alaali, 2025c).

Research Questions

1. How can long-term behavioral sustainability be forecast within the AFMF using behavioral-sustainability trajectories and ESG-integrated data streams?
2. What are the simulated interactive effects of behavioral volatility, behavioral durability, and ESG shocks on projected sustainability?
3. How can the A-BSF framework be operationalized and empirically tested as a decision-support tool for sustainability-oriented decision-making?

These questions provide the theoretical and empirical basis for integrating behavioral forecasting into sustainability analysis. A-BSF extends the AFMF-SFBM series toward structured behavioral-sustainability foresight while remaining subject to future empirical validation.

5. Theoretical Foundations

The Alaali Behavioral Sustainability Forecasting Model (AFMF-SFBM-A08) draws on sustainability forecasting, behavioral learning, system dynamics, organizational resilience, managerial control, and AI-supported forecasting. Together, these perspectives support the proposed simulation architecture and clarify its conceptual boundaries.

5.1 Sustainability Forecasting Theory

Drawing from the triple-bottom-line foundations proposed by Elkington (1997) and sustainability-accounting frameworks advanced by Gray and Bebbington (2001), sustainability is treated as a dynamic process rather than a static accounting outcome. Recent evidence also indicates that ESG conditions may affect firm performance and risk, although their effects depend on institutional context, governance, strategy, and measurement choices (Gillan et al., 2021; Jain et al., 2025).

Within the AFMF-SFBM series, the Alaali Behavioral Sustainability Index (A-BSI) provides a structured representation of behavioral-financial sustainability, while A-BSF extends this basis toward simulated forward-looking analysis (Alaali, 2025a).

5.2 Behavioral Learning and Adaptation

Rooted in reinforcement-learning theory (Sutton & Barto, 2018), behavioral learning can be understood as a feedback process in which performance information and changing conditions inform subsequent decisions. In the AFMF-SFBM series, A06 introduces an adaptive-learning orientation that is extended by A-BSF toward simulation-based forecasting (Alaali, 2025a).

In this study, adaptive learning is conceptual rather than an implemented reinforcement-learning algorithm. This distinction is important because empirical AI forecasting requires observed data, explicit training procedures, and independent performance validation (Makridakis et al., 2022).

5.3 System Dynamics and Cybernetic Feedback

The cybernetic principles of Forrester (1961), Beer (1972), and Sterman (2000) inform the structural logic of feedback, adjustment, and stability across time. The A-BSF framework applies this logic by representing behavioral durability, resilience, volatility, and ESG shocks as interacting inputs to a projected sustainability path.

The model's treatment of post-shock recovery is also informed by organizational-resilience research, which characterizes resilience as the capacity to anticipate, cope with, and adapt to disruption (Duchek, 2020). Within the AFMF-SFBM series, the recovery and self-regulation logic developed in A04 and A05 informs the conceptual basis for financial resilience and governance alignment in A-BSF (Alaali, 2025a).

5.4 Managerial Control and Behavioral Governance

Managerial control systems provide an institutional basis for monitoring performance, managing incentives, and governing the use of forecasting information (Simons, 1995; Merchant & Van der Stede, 2017). Under the DFAS doctrine, these functions are connected to documentation, transparency, accountability, and auditability through the DFAS-FEP protocol (Alaali, 2025c).

5.5 Integration within the AFMF Behavioral Doctrine

The earlier AFMF-SFBM models address behavioral efficiency, expected performance, recovery, self-regulation, adaptive learning, and sustainability measurement. A-BSF integrates these elements into a proposed simulation-based forecasting architecture for examining projected behavioral sustainability under alternative conditions (Alaali, 2025a).

The framework combines behavioral and financial conditions with governance, volatility, and ESG-shock assumptions. It is proposed as a conceptual extension subject to future operationalization, parameter estimation, and empirical validation.

6. Model Development

The Alaali Behavioral Sustainability Forecasting Model (AFMF-SFBM-A08) extends the behavioral-financial sustainability logic established in the Alaali Behavioral Sustainability Index (AFMF-SFBM-A07). It also draws on the adaptive-learning orientation introduced in the Alaali Expected Behavioral Efficiency Index with Adaptive Intelligence (AFMF-SFBM-A06) (Alaali, 2025a). The model is a conceptual, simulation-based forecasting framework designed to examine how behavioral, financial, governance, environmental, and ESG-related conditions may affect projected sustainability outcomes. It is not presented as an empirically calibrated forecasting system.

6.1 Core Forecast Equation

Alaali Behavioral Sustainability Forecast (t + 1) = Alaali Behavioral Sustainability Index (t) + α ($\Delta\beta d$ + ΔFr + ΔGa + ΔEI) − $\lambda\sigma\_behavioral$ + γ(ESG Shock_t)

Where:

- A-BSF(t + 1): projected behavioral sustainability outcome for the next period.
- A-BSI(t): Alaali Behavioral Sustainability Index observed at the current period.
- $\Delta\beta d$: change in behavioral durability from period t − 1 to period t.
- ΔFr: change in financial resilience from period t − 1 to period t.
- ΔGa: change in governance alignment from period t − 1 to period t.
- ΔEI: change in environmental integration from period t − 1 to period t.
- σ_behavioral: behavioral volatility index.
- ESG Shock_t: direction and magnitude of an ESG-related external or institutional disturbance during period t.
- α: forecast sensitivity coefficient.
- λ: volatility-penalty coefficient.
- γ: ESG-shock sensitivity coefficient.

The change terms represent period-to-period movements rather than absolute values. A positive $\Delta\beta d$, for example, indicates improved behavioral durability between the preceding and current periods.

For the illustrative simulations in this study, α, λ, and γ are calibrated scenario assumptions. They are not estimated from historical organizational data, regression analysis, machine-learning tuning, or empirically fitted Bayesian models. Their purpose is to enable transparent testing of how behavioral-volatility and ESG-shock conditions influence projected sustainability outcomes.

6.2 Parameter Specification

Parameter	Illustrative value/range	Function in the model	Selection method for the simulation
α	0.30–0.70	Sensitivity to changes in durability, resilience, governance, and environmental integration	Scenario-calibrated assumption
λ	0.10–0.40	Reduction in forecast output associated with behavioral volatility	Scenario-calibrated assumption
γ	0.05–0.20	Magnitude of forecast response to an ESG shock	Scenario-calibrated assumption
βd	0.70–0.95	Behavioral durability or persistence	Scenario input
Fr	0.60–1.00	Financial resilience	Scenario input derived conceptually from A-BCRR logic (Alaali, 2025a)
Ga	0.60–1.00	Governance alignment	Scenario input derived conceptually from A-SRM logic (Alaali, 2025a)
EI	0.60–1.00	Environmental integration	Scenario input based on ESG conditions
σ_behavioral	0.10–0.30	Instability and uncertainty in behavioral conditions	Scenario input
ESG Shock_t	−0.30 to +0.20	Adverse or favourable ESG-related disturbance	Scenario input

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The reported values are illustrative calibration ranges used to generate and compare simulated conditions. They should be re-estimated using longitudinal organizational data before the model is applied operationally.

6.3 Behavioral Forecast Confidence (BFC)

Behavioral Forecast Confidence (BFC) measures the internal reliability of a forecast by combining relative forecast accuracy with Behavioral Forecast Entropy (BFE):

$$BFC = (1 - |A\text{-}BSF(t + 1) - \text{Simulated Benchmark}| / |\text{Simulated Benchmark}|) \times (1 - BFE)$$

Where BFE represents uncertainty in the simulated forecast distribution.

BFC is expected to range from 0 to 1. A value closer to 1 indicates low forecast deviation and low uncertainty under the simulated conditions. A value closer to 0 indicates greater forecast deviation, greater uncertainty, or lower internal reliability. Both a larger deviation from the simulated benchmark and higher BFE reduce the BFC score. For interpretation, values below 0 or above 1 should be bounded to the 0–1 range.

For this simulation study, forecast accuracy is defined as:

$$\text{Accuracy} = 1 - |\text{Forecast} - \text{Simulated Benchmark}| / |\text{Simulated Benchmark}|$$

The reported accuracy does not measure agreement with observed historical outcomes. It measures relative agreement between the model's forecast and the benchmark outcome generated within the same simulation design.

6.4 Dynamic Resilience Function (DRF)

The Dynamic Resilience Function (DRF) represents post-shock behavioral recovery:

$$DRF = 1 - e^{(-k \times \text{Recovery Speed})}$$

Where k is a resilience constant and Recovery Speed represents the simulated rate at which behavioral conditions return toward their pre-shock level. Higher DRF values indicate faster simulated recovery capacity after ESG-related or systemic disruption. This recovery logic is conceptually consistent with the resilience dimension developed in the AFMF-SFBM series (Alaali, 2025a).

6.5 Predictive Value Index (PVI)

The Predictive Value Index (PVI) assesses the proposed efficiency of a forecasting exercise:

$$PVI = (\text{Accuracy} \times \text{Confidence} \times \text{Timeliness}) / \text{Resource Cost}$$

For operational interpretation:

- **Accuracy:** simulated forecast-accuracy value defined above.
- **Confidence:** BFC score.
- **Timeliness:** whether the forecast is produced sufficiently before a decision point to enable managerial action; it can be normalized on a 0–1 scale.
- **Resource Cost:** normalized cost of generating and maintaining the forecast, including data preparation, computational resources, analyst time, and governance review; it can be normalized on a 0–1 scale.

Within this proposed framework, PVI > 1 is interpreted as favourable predictive value. This is a proposed analytical interpretation, not a universal threshold or empirically established return-on-investment rule. The index extends the behavioral-efficiency and self-funded return logic of the AFMF-SFBM series (Alaali, 2025a).

6.6 Bayesian Updating

Bayesian updating is included as a conceptual recalibration sequence within the simulation architecture, not as a fully estimated statistical model.

Prior Parameters → New ESG and Behavioral Evidence → Posterior Update → Next Simulation Cycle

Each cycle begins with prior assumptions for behavioral durability, volatility, financial resilience, governance alignment, environmental integration, and ESG-shock exposure. Newly specified behavioral and ESG evidence adjusts these assumptions for the subsequent cycle. The resulting posterior values then become inputs for the next simulation iteration.

This process demonstrates the logic of adaptive recalibration. It does not claim estimation of posterior distributions from observed organizational data.

6.7 Reinforcement Learning and Adaptive Learning

Reinforcement learning is not implemented in this manuscript as a trained algorithm, agent, or empirical machine-learning model. Instead, adaptive learning is used as a conceptual simulation-design principle: forecasts may be recalibrated in subsequent cycles when deviations, volatility, or ESG conditions change.

The model therefore applies a feedback-oriented learning logic rather than a completed reinforcement-learning implementation. Future empirical research may operationalize this component using observed reward functions, decision feedback, and longitudinal training data.

6.8 Forecast Indicators

To support interpretation across simulation cycles, the model incorporates five supplementary indicators:

- **Forecast Stability Score (FSS):** consistency of simulated forecasts across repeated iterations.
- **Prediction Resilience Index (PRI):** forecast stability under simulated behavioral and ESG stress.
- **Temporal Accuracy Decay (TAD):** simulated reduction in forecast accuracy as the forecasting horizon increases.
- **Behavioral Uncertainty Coefficient (BUC):** degree of uncertainty associated with behavioral conditions.
- **External Shock Absorption (ESA):** simulated capacity to limit the effect of ESG-shock amplitude on projected sustainability.

These indicators are proposed analytical tools. Their measurement properties, thresholds, and practical utility require future empirical validation.

7. Simulation Framework

The Alaali Behavioral Sustainability Forecasting Model (AFMF-SFBM-A08) is examined through an illustrative, simulation-based forecasting architecture. The simulation explores how alternative behavioral, financial, governance, and ESG conditions may affect projected sustainability outcomes. It does not constitute empirical validation against historical organizational observations.

7.1 Input Data

The simulation uses illustrative parameter inputs informed conceptually by:

- Behavioral-sustainability constructs represented in the Alaali Behavioral Sustainability Index (AFMF-SFBM-A07) (Alaali, 2025a).
- Governance-alignment logic represented in the Alaali Self-Regulation Multiplier (AFMF-SFBM-A05) (Alaali, 2025a).

Journal of Research and Innovation in Technology, Commerce and Management
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- Financial-resilience logic represented in the Alaali Behavioral Cost Recovery Ratio (AFMF-SFBM-A04) (Alaali, 2025a).
- Illustrative ESG conditions, macro-environmental conditions, and behavioral-volatility assumptions.

No proprietary or organization-level historical dataset was used to estimate or validate the model parameters. The inputs are simulation assumptions intended to demonstrate the model's analytical behavior under varying conditions.

7.2 Simulation Design

- **Methodology:** 10,000 Monte Carlo iterations using the illustrative parameter ranges specified in Section 6.2.
- **Adaptive recalibration:** Conceptual Bayesian updating logic, in which prior parameter assumptions are adjusted after specified behavioral or ESG evidence is introduced into the next simulation cycle.
- **Adaptive-learning logic:** Feedback-oriented simulation design; reinforcement learning is not implemented as a trained algorithm or empirical machine-learning procedure.
- **Time horizon:** Ten-year illustrative forecasting horizon.
- **Governance and traceability:** Simulation assumptions, scenario settings, and output definitions are documented in accordance with DFAS-FEP principles of documentation, traceability, auditability, declaration, and classification (Alaali, 2025c).

7.3 Scenario Architecture

Scenario	**Probability**	**Impact on A-BSF**	**Horizon**
Mandatory ESG Adoption	40%	+0.12	2–3 years
Institutional Behavioral Crisis	20%	−0.25	6–12 months
Accelerated Technological Transformation	30%	+0.15	3–5 years
Baseline / No Material Change	10%	0.00	1–3 years

The scenario probabilities total 100%. The baseline scenario represents conditions in which no material ESG, institutional, or technological shock is introduced beyond normal simulated variation.

These scenarios are illustrative analytical cases, not probability forecasts of real-world events. They are used to test the model's projected sensitivity to alternative conditions and to examine simulated behavioral resilience and sustainability equilibrium.

7.4 Output Metrics

The simulation records the following outputs:

- **Mean A-BSF:** average projected behavioral-sustainability forecast across iterations.
- **Behavioral Forecast Entropy (BFE):** uncertainty within the simulated forecast distribution.
- **Behavioral Forecast Confidence (BFC):** internal forecast-reliability measure based on relative forecast accuracy and entropy.
- **Simulation Forecast Accuracy:** relative agreement between the simulated forecast and its simulated benchmark outcome.
- **Sustainability Duration (SD):** simulated period during which the forecast remains within the defined equilibrium range.
- **Volatility Persistence (VP):** extent to which behavioral variance persists across simulated periods.

These outputs are retained for transparent comparison of scenarios and sensitivity conditions. They should not be interpreted as evidence of real-world predictive performance until the model is tested using longitudinal organizational data.

8. Results and Interpretation

Scenario	βd	σ_behavioral	A-BSI (t_0)	A-BSI (t_5)	BFE	BFC	Simulation Forecast Accuracy (%)
Low Resilience	0.70	0.25	0.68	0.61	0.42	0.493	85
Moderate Stability	0.85	0.20	0.84	0.86	0.31	0.642	93
High Sustainability	0.92	0.15	0.90	0.94	0.25	0.728	97

Note: These results are generated from illustrative simulation scenarios. Simulation Forecast Accuracy reflects agreement between the model forecast and the simulated benchmark outcome; it is not validated predictive accuracy based on field, organizational, or historical data. BFC is calculated as Simulation Forecast Accuracy × (1 − BFE).

8.1 Interpretive Findings

Within the specified simulation conditions, higher behavioral durability and lower behavioral volatility are associated with greater forecast stability. The moderate-stability and high-sustainability scenarios, where βd is at least 0.80 and σ_behavioral is at or below 0.20, produce higher Simulation Forecast Accuracy values of 93% and 97%, respectively. After accounting for forecast entropy, they also produce higher BFC values of 0.642 and 0.728.

The results show that lower behavioral volatility is associated with lower Behavioral Forecast Entropy (BFE). In the low-resilience scenario, higher volatility (σ_behavioral = 0.25) coincides with greater uncertainty (BFE = 0.42), lower BFC (0.493), and lower Simulation Forecast Accuracy (85%). Within the model structure, volatility therefore reduces both the projected stability of the sustainability path and confidence in the forecast.

These findings demonstrate the internal behavior of the proposed simulation framework. They do not establish empirical causal effects or real-world forecasting performance. Such claims require future testing using longitudinal organizational and ESG data.

8.2 Illustrative Sensitivity Analysis

The following sensitivity analysis holds the other input conditions constant and illustrates the effect of increasing behavioral volatility on projected sustainability and forecast confidence.

Volatility condition	σ_behavioral	Illustrative projected A-BSF	Illustrative BFC	Interpretation
Low volatility	0.15	0.94	0.728	Lower volatility supports a more stable projected sustainability outcome, lower entropy, and higher forecast confidence.
Medium volatility	0.20	0.86	0.642	Moderate volatility reduces the projected outcome and confidence, while the model remains within a comparatively stable range.
High volatility	0.25	0.61	0.493	Higher volatility produces a lower projected sustainability outcome, greater uncertainty, and lower forecast confidence.

The sensitivity analysis shows a negative relationship, within the simulation design, between σ_behavioral and both projected A-BSF and BFC. As behavioral volatility increases, the volatility penalty in the core equation becomes larger, reducing the projected sustainability outcome. Greater volatility also raises uncertainty in the forecast distribution, which reduces BFC through the entropy component of the measure.

The analysis is illustrative and depends on the parameter assumptions specified in Section 6.2. It should not be interpreted as empirical evidence of the size or universality of these relationships.

8.3 Results Discussion

Within the simulation framework, higher behavioral durability (βd) is associated with greater forecast stability. Behavioral durability represents the persistence of constructive behavioral conditions across consecutive periods. When βd is higher, the positive behavioral contribution to the forecast is less sensitive to short-term variation, allowing the projected A-BSF path to remain comparatively stable. This interpretation is consistent with organizational-resilience research, which views resilience as a capability involving anticipation, coping, and adaptation over time rather than as a static organizational attribute (Duchek, 2020).

Behavioral volatility (σ_behavioral) reduces forecast confidence because it increases uncertainty about whether current behavioral conditions can persist. Within the model, higher volatility increases the volatility penalty and broadens the simulated forecast distribution. This is reflected in higher Behavioral Forecast Entropy (BFE) and lower Behavioral Forecast Confidence (BFC). The simulated relationship also aligns with forecasting research, which emphasizes that forecast performance depends on the stability, quality, and predictability of the underlying data-generating conditions (Makridakis et al., 2022).

ESG shocks alter the projected sustainability path through the γ(ESG Shock) component of the model. Positive shocks, such as credible ESG adoption or improved environmental integration, increase the projected A-BSF outcome; adverse shocks, such as institutional disruption or material ESG events, reduce it. This design reflects the wider ESG literature, which finds that the relationship between ESG conditions and firm performance is context-dependent and moderated by governance, strategy, institutional conditions, and measurement choices (Gillan et al., 2021; Jain et al., 2025).

These interpretations describe relationships generated within the proposed model and its illustrative simulation assumptions. They are not empirically verified causal findings and do not demonstrate real-world predictive performance. Future research should test the model using longitudinal organizational data and compare its forecasts with observed sustainability outcomes.

9. Discussion

The Alaali Behavioral Sustainability Forecasting Model (A-BSF) proposes a simulation-based extension of the AFMF-SFBM series for examining long-term behavioral sustainability under changing resilience, governance, environmental, and ESG conditions (Alaali, 2025a). By integrating Behavioral Forecast Confidence (BFC), Dynamic Resilience Function (DRF), and Predictive Value Index (PVI), the model provides a structured approach for examining projected behavioral-sustainability paths and their sensitivity to volatility and ESG shocks.

Within the illustrative simulation, higher behavioral durability is associated with greater forecast stability because it represents the persistence of constructive behavioral conditions across consecutive periods. When durability remains comparatively strong, the projected sustainability path is less sensitive to short-term variation. This is a model-based interpretation rather than an empirically verified causal finding.

Behavioral volatility reduces projected sustainability outcomes and forecast confidence within the simulation design. Higher volatility increases the volatility penalty in the core equation and is associated with greater uncertainty in the forecast distribution. Consequently, higher Behavioral Forecast Entropy is associated with lower Behavioral Forecast

Confidence. This relationship reflects the assumptions and structure of the proposed model and requires empirical testing.

ESG shocks alter the projected sustainability path according to their assumed direction and magnitude. Positive shocks, such as stronger ESG adoption or improved environmental integration, increase the projected outcome, whereas adverse shocks reduce it. The effect is moderated within the model by the assumed behavioral, resilience, governance, and volatility conditions.

The framework applies DFAS-FEP principles of documentation, traceability, auditability, declaration, and classification to the specification and interpretation of assumptions, scenarios, and simulated outputs (Alaali, 2025c). This governance layer supports transparent use of the framework but does not substitute for empirical validation.

The model's principal contribution is conceptual and methodological. It provides an explicit forecasting architecture that can be calibrated, operationalized, and tested in future research. Its practical usefulness depends on future work that defines measurable proxies for its variables, estimates its parameters from longitudinal organizational data, and compares its forecasts with observed sustainability outcomes.

The model should consequently be interpreted as a proposed decision-support framework rather than a validated predictive system.

10. Integration within the Alaali Financial Models Meta-Framework (AFMF)

The Alaali Behavioral Sustainability Forecasting Model (AFMF-SFBM-A08) extends the first analytical sequence of the Self-Funded Behavioral Model series within the Alaali Financial Models Meta-Framework (AFMF) (Alaali, 2025a).

The preceding models progressively address self-funding behavioral logic, incentive efficiency, expected behavioral performance, cost recovery, self-regulation, adaptive learning, and behavioral-sustainability measurement. A-BSF builds on these elements by proposing a simulation-based approach for examining projected sustainability conditions under alternative behavioral, volatility, governance, environmental, and ESG-shock assumptions.

Accordingly, A-BSF should be interpreted as a conceptual extension of the AFMF-SFBM series rather than as a real-time or empirically validated sustainability forecasting engine. The model applies DFAS-FEP principles of documentation, traceability, auditability, declaration, and classification to the transparent specification and interpretation of its assumptions and simulated outputs (Alaali, 2025c).

11. Practical Implications

Stakeholder	Application within the Alaali Financial Models Meta-Framework (AFMF)
Corporate Boards	Integrate the **Alaali Behavioral Sustainability Forecasting Model (AFMF-SFBM-A08)** into three-to-five-year strategic dashboards to anticipate behavioral-resilience trends and sustainability risks.
Investors	Evaluate predictive ESG integrity through **Behavioral Forecast Confidence (BFC)** and **Prediction Resilience Index (PRI)** to guide portfolio-level sustainability decisions.
Policymakers	Employ the **Alaali Behavioral Sustainability Forecasting Model (AFMF-SFBM-A08)** as a national early-warning and ESG-monitoring instrument for predictive sustainability governance.

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Researchers	Extend the model across sectors, calibrating its parameters for cross-industry AI-driven policy simulations and behavioral sustainability experiments.

These applications operationalize the **Alaali Financial Models Meta-Framework (AFMF)** as a multi-stakeholder decision-intelligence system, bridging behavioral finance, ethical AI, and sustainability governance.

12. Ethical and Transparency Framework

The Alaali Behavioral Sustainability Forecasting Model (AFMF-SFBM-A08) applies the ethical and transparency principles of the Dynamic Financial Applied Meta-Science (DFAS) doctrine and the DFAS-FEP protocol (Alaali, 2025b, 2025c). Because the present model is simulation-based and not empirically validated, these principles guide the documentation and interpretation of model assumptions, parameter ranges, scenarios, and outputs.

DFAS-Aligned Ethical Pillars

- **Transparency and explainability:** Forecast outputs should be accompanied by the underlying behavioral-financial assumptions, parameter values, scenario conditions, and interpretation limits.
- **Data governance:** Any future empirical implementation should use lawfully obtained, reliable, and appropriately anonymized behavioral, ESG, and organizational data.
- **Bias and fairness review:** Future applications should assess whether variable definitions, data sources, calibration choices, or scenario assumptions systematically disadvantage specific groups, organizations, or contexts.
- **Human oversight and forecast-risk governance:** Model outputs should support—not replace—managerial, investment, or policy judgment. Material decisions should be subject to human review, contextual assessment, and documented accountability.

These principles support traceability, auditability, and responsible interpretation of the proposed forecasting framework. They do not establish that the model itself has achieved ethical validity or real-world predictive reliability; those claims require empirical testing and practical governance assessment.

13. Limitations and Future Research

The Alaali Behavioral Sustainability Forecasting Model (AFMF-SFBM-A08) is a conceptual extension within the Alaali Financial Models Meta-Framework (AFMF). Its current simulation-based form has limitations that define the agenda for future empirical research.

13.1 Limitations

1. Absence of Empirical Validation

The current A-BSF model is based on illustrative simulation scenarios. Its parameters, scenario ranges, and forecast relationships have not been estimated or tested against longitudinal organizational, behavioral, or ESG data. Accordingly, the reported Simulation Forecast Accuracy reflects agreement with simulated benchmark outcomes rather than observed real-world forecasting accuracy.

2. Scenario-Based Parameter Assumptions

The values assigned to behavioral durability, financial resilience, governance alignment, environmental integration, behavioral volatility, and ESG shocks are scenario-calibrated assumptions. Their ranges may not represent all industries, organizational structures, geographic contexts, or sustainability-reporting environments. Future research should empirically estimate these parameters and assess their stability across settings.

3. Limited Operationalization of Variables

Several model constructs, including behavioral durability, governance alignment, Behavioral Forecast Entropy, and Dynamic Resilience Function, require clearer observable proxies and measurement protocols. The model therefore requires operational definitions, data-collection procedures, and reliability testing before practical implementation.

4. Conceptual Adaptive-Learning Component

Bayesian updating and adaptive learning are presented as conceptual simulation mechanisms rather than empirically implemented statistical or machine-learning systems. The model does not currently include a trained reinforcement-learning algorithm, real-time ESG data ingestion, or continuous automated recalibration.

13.2 Future Research Directions

Future research should test A-BSF with longitudinal organizational data, develop validated measures for its behavioral and governance constructs, estimate model parameters empirically, and evaluate forecasting performance against observed sustainability outcomes across different sectors and institutional contexts.

A potential future extension is AFMF-SFBM-A09: The Alaali Behavioral Sustainability Forecasting Artificial Intelligence Model (A-BSF-AI). This future conceptual extension may explore data-driven adaptive forecasting, provided that its learning process, governance controls, performance criteria, and ethical safeguards are specified and empirically tested (Alaali, 2025a).

Any future AI-enabled extension should apply DFAS-FEP principles of documentation, traceability, auditability, declaration, and classification, and should remain subject to independent validation before operational deployment (Alaali, 2025c).

14. Conclusion

The Alaali Behavioral Sustainability Forecasting Model (AFMF-SFBM-A08) proposes a conceptual, simulation-based framework for examining how behavioral durability, financial resilience, governance alignment, environmental integration, behavioral volatility, and ESG shocks may affect projected sustainability outcomes.

The model introduces three core constructs: Behavioral Forecast Confidence (BFC), Dynamic Resilience Function (DRF), and Predictive Value Index (PVI). Together, they provide a structured approach for examining forecast reliability, post-shock recovery, and the proposed value of forecasting relative to timing and resource requirements.

A-BSF extends the preceding AFMF-SFBM models by moving from behavioral-sustainability measurement toward simulated forward-looking assessment (Alaali, 2025a). It should therefore be understood as a proposed analytical extension within the AFMF-SFBM series rather than as a fully empirically validated forecasting system.

The framework applies DFAS-FEP principles of documentation, traceability, auditability, declaration, and classification to support transparent specification and interpretation of the simulation framework (Alaali, 2025c).

The simulation results indicate that higher behavioral durability and lower behavioral volatility are associated with more stable projected sustainability paths and stronger forecast confidence. ESG shocks change the projected trajectory according to their assumed direction and magnitude. These findings reflect the structure and assumptions of the simulation model; they do not establish empirically verified causal effects or real-world forecasting accuracy.

Future research should operationalize the model's variables using longitudinal organizational data, estimate its parameters empirically, test its forecasts against observed sustainability outcomes, and assess its applicability across industries and institutional settings.

15. Applied Behavioral Exercises (AFMF-SFBM-A08)

These illustrative exercises demonstrate the simulation logic of A-BSF. They are not empirical tests or evidence of real-world predictive performance. The model assumptions and calculations should be interpreted within the proposed simulation framework and DFAS-FEP documentation principles (Alaali, 2025c).

Exercise 1 – Computing the Alaali Behavioral Sustainability Forecast (A-BSF)

Scenario

At time t_0, an organization reports:

A-BSI(t) = 3.20; $\Delta\beta d = -0.15$; $\Delta Fr = -0.10$; $\Delta Ga = 0.00$; $\Delta EI = -0.05$; $\sigma\_behavioral = 0.18$; $\alpha = 0.50$; $\lambda = 0.20$; $\gamma = 0.10$; ESG Shock = −0.15.

Task

Estimate A-BSF(t + 1).

Answer

$$\text{A-BSF}(t + 1) = \text{A-BSI}(t) + \alpha(\Delta\beta d + \Delta Fr + \Delta Ga + \Delta EI) - \lambda\sigma\_behavioral + \gamma(\text{ESG Shock})$$

$$= 3.20 + 0.50(-0.15 - 0.10 + 0.00 - 0.05) - (0.20 \times 0.18) + (0.10 \times -0.15)$$

$$= 3.20 + 0.50(-0.30) - 0.036 - 0.015$$

$$= 3.20 - 0.15 - 0.036 - 0.015$$

$$= 2.999 \approx 3.00$$

Interpretation

Within this illustrative scenario, the projected sustainability outcome remains close to 3.00 despite a mild adverse ESG shock and negative changes in selected inputs.

Exercise 2 – Calculating Behavioral Forecast Confidence (BFC)

Scenario

Predicted A-BSF = 3.00; simulated benchmark A-BSI(t_1) = 2.95; Behavioral Forecast Entropy (BFE) = 0.25.

Task

Compute BFC.

Answer

$$\text{BFC} = (1 - |\text{Forecast} - \text{Simulated Benchmark}| / |\text{Simulated Benchmark}|) \times (1 - \text{BFE})$$

$$= (1 - |3.00 - 2.95| / 2.95) \times (1 - 0.25)$$

$$= (1 - 0.05 / 2.95) \times 0.75$$

$$= (1 - 0.0169) \times 0.75$$

$$= 0.9831 \times 0.75$$

$$= 0.737$$

Interpretation

Within the simulation, BFC = 0.737 reflects low relative forecast deviation moderated by the stated uncertainty level. It does not represent empirically validated forecast reliability.

Exercise 3 – Measuring Dynamic Resilience Function (DRF)

Scenario

Resilience constant (k) = 0.40; Recovery Speed = 2.00.

Task

Compute DRF.

Answer

DRF = 1 − e^(−k × Recovery Speed)

= 1 − e^(−0.40 × 2.00)

= 1 − e^(−0.80)

= 1 − 0.449

= 0.551

Interpretation

Within the proposed model, DRF = 0.551 represents moderate simulated post-shock recovery capacity.

Exercise 4 – Evaluating Predictive Value Index (PVI)

Scenario

Accuracy = 0.95; Confidence = 0.737; Timeliness = 0.90; Resource Cost = 0.45.

Task

Compute PVI.

Answer

PVI = (Accuracy × Confidence × Timeliness) / Resource Cost

= (0.95 × 0.737 × 0.90) / 0.45

= 0.6301 / 0.45

= 1.40

Interpretation

Within this proposed framework, PVI = 1.40 is interpreted as favourable predictive value. It is not an empirically established return-on-investment measure.

Exercise 5 – Forecasting Behavioral Entropy Impact

Scenario

Behavioral Forecast Entropy decreases from 0.40 to 0.25 while σ_behavioral = 0.15.

Task

Compute Behavioral Clarity Gain (BCG):

BCG = ΔEntropy / σ_behavioral

Answer

BCG = (0.40 − 0.25) / 0.15

= 0.15 / 0.15

= 1.00

Interpretation

Within this illustrative scenario, BCG = 1.00 indicates that the reduction in simulated uncertainty equals the assumed behavioral-volatility level.

Author's Insight – Behavioral Reflection

Forecasting supports preparation by making model assumptions, uncertainties, and possible sustainability paths explicit. In A-BSF, BFC, DRF, and PVI are proposed analytical constructs for examining forecast reliability, simulated recovery, and predictive value. Their practical application requires empirical calibration, validation, and accountable human oversight.

Author Declaration

The author retains full responsibility for the research purpose, conceptual framework, model specification, analytical decisions, parameter assumptions, scenario design, interpretation of results, and final manuscript approval.

Ethical Statement

This manuscript applies the principles of the Dynamic Financial Applied Meta-Science (DFAS) doctrine and the DFAS-FEP protocol, including documentation, traceability, auditability, declaration, and classification (Alaali, 2025b, 2025c). The author is responsible for the accuracy, integrity, and transparent presentation of the manuscript.

AI and Computational Assistance

AI-assisted tools were used to support drafting, language refinement, structural editing, formatting, and citation alignment. The author reviewed, revised where necessary, and approved all final content. AI assistance did not replace the author's responsibility for the manuscript's scholarly claims, methodological decisions, interpretations, or final submission.

Conflict of Interest

The author declares no financial, academic, or institutional conflict of interest related to the development or publication of this manuscript.

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This research received no external funding. It was developed as part of the author's independent research program under the Alaali Financial Models Meta-Framework and Dynamic Financial Applied Meta-Science doctrines.

Data Availability

No external or proprietary dataset was used to estimate or validate the model. The reported results are derived from illustrative simulation assumptions and theoretical constructs described in the manuscript.

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Appendix A – DFAS-FEP Authorship Classification and Compliance:

This manuscript complies with the **DFAS-FEP Protocol,** a structured authorship governance framework introduced by **Author.**

DFAS-FEP (Dynamic Financial Applied Meta-Science – Future Engine Prototype) provides an ethical protocol to ensure transparent and accountable authorship in AI-assisted financial research. It defines and enforces the distinction between fully human-generated content and AI-supported elements to uphold integrity, intellectual responsibility, and traceability across all components of this manuscript.

This classification directly supports the ethical architecture of the **DFAS-IFRS Code of Ethics**, which applies DFAS-FEP standards to financial disclosures influenced by artificial intelligence.

For reference, see the published DFAS-FEP Protocol:

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5260517

Appendix A.1 – DFAS-FEP Authorship and AI-Assistance Disclosure for AFMF-SFBM-A08

This appendix records the author's responsibility for the manuscript and discloses the use of AI-assisted tools in its preparation. The classifications distinguish between author-directed substantive scholarship and AI-assisted drafting, editing, formatting, or reference-support activities (Alaali, 2025c).

Manuscript component	DFAS-FEP classification	Disclosure and author responsibility
Research purpose, conceptual direction, and model scope	Class 1 – Author-directed substantive content	The author defined the research purpose, the intended contribution of A-BSF within the AFMF-SFBM series, and the conceptual scope of the manuscript.
Model constructs and analytical architecture	Class 1 – Author-directed substantive content	The author is responsible for the specification and final approval of the A-BSF equation, BFC, DRF, PVI, variable definitions, parameter roles, scenario architecture, and interpretation boundaries.
Simulation assumptions and methodological decisions	Class 1 – Author-directed substantive content	The author determined the simulation purpose, parameter ranges, scenario probabilities, sensitivity structure, and the distinction between simulated outputs and empirical validation.
Results interpretation and conclusions	Class 1 – Author-directed substantive content	The author reviewed, revised, and approved the interpretation of the simulation outputs, limitations, practical implications, and future research directions.
Narrative drafting and language refinement	Class 2 – AI-assisted, author-validated content	AI-assisted tools were used to support drafting, editing, clarity, structure, and language refinement. The author reviewed and approved the final wording.
Tables, formatting, and presentation	Class 2 – AI-assisted, author-validated content	AI-assisted tools may have supported table organization, formatting consistency, and presentation. The author reviewed the content and retained responsibility for all values, labels, and interpretations.
Literature review and citation alignment	Class 2 – AI-assisted, author-validated content	AI-assisted tools supported reference formatting and citation alignment. The author is responsible for selecting sources, verifying their relevance, and confirming citation accuracy.
Compliance statements and appendices	Class 2 – AI-assisted, author-validated content	AI-assisted tools supported organization and wording. The author reviewed the disclosure and accepts responsibility for its accuracy.

Overall Manuscript Classification

Class 2 – AI-Assisted, Author-Validated Manuscript

The manuscript contains AI-assisted drafting, editing, formatting, and citation-support activities. The author retains full responsibility for all substantive scholarly content, including the research purpose, conceptual claims, model structure, simulation assumptions, results interpretation, and final approval.

Additional Clarifications

Author Responsibility

The author retains full intellectual and ethical responsibility for AFMF-SFBM-A08. This includes responsibility for the model's conceptual purpose, analytical decisions, formulas, parameter assumptions, scenarios, claims, limitations, interpretation of results, and final manuscript submission.

AI-Assisted Content

AI-assisted tools were used to support drafting, language refinement, structural editing, formatting, and citation alignment. Such assistance did not replace the author's scholarly judgment or responsibility. All AI-assisted material was reviewed, revised where necessary, and approved by the author before inclusion in the manuscript.

Simulation and Evidence Disclosure

The manuscript presents a conceptual, simulation-based framework. Its parameter ranges, scenarios, and reported outputs are illustrative unless explicitly identified as empirically tested. Simulation Forecast Accuracy refers to agreement with a simulated benchmark outcome and does not constitute validation against real-world historical or organizational data.

Integrity Safeguards

The manuscript documents its conceptual boundaries, parameter assumptions, scenario conditions, output definitions, and limitations. The author has reviewed the final manuscript for accuracy, proper attribution, consistency of claims, and compliance with the journal's authorship, AI-use, and research-integrity requirements.

Compliance Statement – AFMF-SFBM-A08

AFMF-SFBM-A08 applies the DFAS-FEP principles of documentation, traceability, auditability, declaration, and classification to the development and presentation of the manuscript (Alaali, 2025c). The author declares responsibility for all substantive content and for the final version submitted for publication.

Certification

This appendix is a good-faith disclosure of authorship responsibility and AI-assisted work in AFMF-SFBM-A08. The author confirms that the manuscript has been reviewed and approved in its final form and accepts responsibility for its scholarly claims, methodological presentation, citations, interpretation, and ethical compliance.

Appendix B – Version History Log (VHL): AFMF-SFBM-A08

Version 1.0 – First published on SSRN, 30 September 2025.
Version 1.1 – Revised version, 19 December 2025.

Version 2.0 – Revised for submission to JRITM, 13 August 2026.

- **Record:** https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5611650
- **Substantive authorship:** The author retains responsibility for the research purpose, conceptual framework, model specification, analytical decisions, parameter assumptions, scenario design, interpretation of results, and final manuscript approval.
- **AI assistance:** AI-assisted tools were used for drafting, language refinement, structural editing, formatting, and citation alignment. All material was reviewed, revised where necessary, and approved by the author. AI assistance did not replace author responsibility for the manuscript's scholarly claims, methodological decisions, interpretations, or final submission.
- **Classification:** Class II – AI-Assisted, Author-Validated.