



Research Article

Exploring Equilibrium Perspectives Computational Mathematics Formula in Data Analytics and Artificial Intelligence Pipelines

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Abstract

In contemporary artificial intelligence (AI) and data analytics pipelines, phenomena such as data drift - characterized by shifts in input distributions - and model decay, defined as the progressive degradation of predictive performance due to evolving data patterns, pose significant threats to system reliability. The Kukoyi Formula, developed by Adeshola Raheem Kukoyi as $K = (0.230258509/2i\pi) - 0.5$, provides a novel computational framework grounded in systems theory to quantify equilibrium states in complex dynamical systems, leveraging the imaginary unit 'i' for modelling steady-state dynamics. This approach operationalizes AI pipelines through a K5 framework: K1 evaluates input quality via weighted metrics of accuracy, completeness, validity, and metadata; K2 assesses transformation integrity; K3 measures output performance; K4 computes equilibrium stability; and K5 gauges corrective feedback efficacy. The composite equilibrium index, $K_{(eq)} = (K_1 * K_2 * K_3 * K_4 * K_5)^{(0.2)}$, yields scores categorizing system health: 0.80 – 1.00 (stable), 0.60 – 0.79 (moderate), 0.40 – 0.59 (fragile), and 0.00 – 0.39 (critical). Rooted in general systems theory, the formula addresses gaps in MLOps by integrating dynamic feedback loops, surpassing conventional monitoring in drift detection and adaptation. Hypothetical validation via a predictive maintenance case study demonstrates potential reduced downtime, enhanced model recalibration, and improved asset utilization through early equilibrium deviations. This study formalizes its deployment, investigates operationalization for coherence enhancement, anomaly mitigation, and superiority over benchmarks, while noting limitations in ultra-high-velocity contexts, advancing resilient AI pipelines.

Keywords

Data Analytics, Artificial Intelligence, Equilibrium Perspectives, Computational Mathematics, Kukoyi Formula

1. Introduction

Modern Data Analytics (DA) and Artificial Intelligence (AI) systems increasingly function as intricate, dynamic ecosystems that require continuous monitoring, rapid adaptation, and sustained operational reliability (Russel et. al.; Idrissi) [5, 10].

These AI pipelines are often challenged by phenomena such as data drift - unpredictable shifts in data characteristics over time - and model decay, the gradual reduction in model predictive accuracy driven by evolving data distributions and

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Received: 8 December 2025; Accepted: 22 December 2025; Published: 12 March 2026



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operational conditions (Munappy et al.; DQLabs; UPlatz) [9, 18-20].

Addressing these challenges necessitates frameworks that can holistically analyze and optimize the interplay between data inputs, computational processes, and resulting outputs, together with feedback mechanisms (Karve et al.; Sonuga et al.; Idrissi) [5, 6, 14]. Grounded in the principles of general systems theory (Checkland; Thakore et al.; von Bertalanffy) [4, 15, 16, 21-25], the Equilibrium Perspectives Computational Mathematics Formula - also known as the Kukoyi Formula - provides such a framework. Developed by Adeshola Raheem Kukoyi [7, 21], this novel equation aims to decode the imaginary unit 'i' and offers a mathematically rigorous approach for identifying balance or steady states within computationally modelled systems.

In AI pipelines, where escalating workflow complexity and systemic instability are pressing concerns, adopting an equilibrium-based perspective holds promise in mitigating common operational pitfalls like pipeline failures, model degradations, and data inconsistencies. By embedding equilibrium considerations into the continuously evolving AI lifecycle, this formula provides a structured route to enhance quality, efficiency, and resilience.

1.1. Objectives

This research aims to establish the Kukoyi Formula as a pioneering and integrative equilibrium-centric methodology that transcends current fragmented approaches. By embedding dynamic feedback loops and systemic balance into AI and data analytics pipelines, the formula promises enhanced reliability, robustness, and adaptive capability, positioning it as a crucial advancement in pipeline evaluation science.

1.2. Literature Gaps and Research Opportunity

Current research underscores a notable deficiency in applying equilibrium concepts systematically to AI pipeline assessment. While MLOps (Machine Learning Operations) and other monitoring frameworks offer valuable tools for operational vigilance, they frequently omit dynamic feedback loops and a balanced systemic evaluation that addresses the intricate interdependencies across input data quality, transformation processes, prediction outputs, and pipeline stability. The Kukoyi Formula presents a promising solution by providing structured stages that encompass inputs, processes, outputs, equilibrium detection, and feedback correction. However, its deployment in technical AI domains is sparse, and scholarly work lacks rigorous methodologies for embedding this equilibrium-driven framework into AI pipeline evaluation. Research gaps to be addressed include:

- 1) Limited application of Kukoyi's equilibrium principles in complex AI pipelines.
- 2) Absence of formal, systemic approaches to measure and sustain pipeline health dynamically.

- 3) Deficiency of integrated feedback and correction cycles that promote robustness and agile adaptation to data drift and changing operational contexts.

Addressing these gaps, this study pursues the formalization and empirical validation of the Kukoyi Formula as a unifying framework, offering potential for substantial advances in AI pipeline resilience and reliability.

1.3. Research Questions

This investigation is guided by four fundamental questions:

- 1) In what ways can the Kukoyi Formula be systematically operationalized within data analytics and AI pipelines to enhance their structural and functional coherence?
- 2) How effectively does the application of the Kukoyi Formula enhance equilibrium, predictive accuracy, and overall system reliability?
- 3) What specific categories of pipeline aberrations - such as data drift, anomaly incidence, or process inefficiencies - can be identified or mitigated through the formula's application?
- 4) How do feedback and correction mechanisms derived from the Kukoyi framework compare to established MLOps monitoring practices in sustaining pipeline health and performance?

1.4. Scope and Limitations

The Equilibrium Perspectives Computational Mathematics Formula - Kukoyi Formula - offers specific, measurable and actionable framework to address the intricate interdependencies across input data quality, transformation processes, prediction outputs, and pipeline stability. Despite its strengths, the Kukoyi Formula requires contextual tailoring for highly complex, real-time environments where pipeline dynamics unfold at extreme velocity and scale. The framework's effectiveness is contingent upon the sophistication and granularity of the monitoring instruments employed. Therefore, empirical validation outcomes may differ significantly across industry verticals due to heterogeneous operational conditions.

2. Literature Review

2.1. The Kukoyi Formula Through the Lens of Systems Thinking

Though the Kukoyi Formula remains a novel construct with limited formal academic publication, it strongly resonates with foundational systems thinking principles that emphasize holistic transformation, regulation, and feedback loops as mechanisms for achieving and maintaining system equilibrium (Checkland; Senge) [4, 13]. Systems thinking advocates for an integrated worldview wherein system components - human and non-human alike - interact dynamically within

feedback-rich environments that enable adaptation and stability in complex settings (Arnold & Wade) [2]. The Kukoyi Formula frames system stability through five iterative stages: input evaluation (K1), process transformation (K2), output assessment (K3), equilibrium measurement (K4), and corrective adjustments with feedback loops (K5) (Kukoyi; Checkland) [4, 7]. This structured approach aligns with systems theory's focus on causal interdependencies and feedback as critical to sustaining system viability over time.

The Kukoyi Formula is a novel mathematical expression from a Wittgenstein's philosophical lens [7, 17, 21], developed by Adeshola Raheem Kukoyi, used to analyze and predict equilibrium in computationally modelled systems with multiple interacting variables. The formula is expressed as:

$K = (0.230258509/2i\pi) - 0.5$, where K represents the Kukoyi Value.

It is associated with "Equilibrium Perspectives in Computational Mathematics" and is intended to provide a structured way to understand how complex systems reach a balanced state.

The Kukoyi Formula offers a computationally rigorous yet conceptually accessible heuristic that expands systems thinking by representing equilibrium states within computationally modelled systems. Notably, it bridges theoretical and operational domains by providing mathematical means to track how inputs undergo transformation processes, produce measurable outputs, and invoke feedback that restores or shifts equilibrium. This dynamic interplay echoes well-established systems thinking ideas of "adaptive wholes" where emergent behaviours arise from interconnected components regulated through feedback loops (Arnold & Wade; Sonuga et al.; Idrissi) [2, 5, 14].

2.2. The Kukoyi Formula and K5 Framework: An Overview

Originating as a systems-thinking heuristic grounded in both mathematics and organizational management, the Kukoyi Formula emphasizes equilibrium, transformation, and stabilizing feedback as cornerstones for maintaining optimal performance in complex systems [7, 21]. Its conceptual clarity makes it well-suited for real-world applications, from organizational diagnostics to computational system stability analysis. The formula is applied within the K5 Framework below in the following five key components:

- 1) K1: Input Evaluation - Characterizing and quantifying initial system inputs including data streams, resources, or signals.
- 2) K2: Process Transformation - Capturing how inputs are manipulated, processed, or transformed through system functions.
- 3) K3: Output Assessment - Assessing the outputs resulting from the transformations relative to objectives or specifications.
- 4) K4: Equilibrium Measurement - Measuring deviations

from desired stable states or benchmarks that signify system balance.

- 5) K5: Corrective Adjustments with Feedback Loops - Implementing feedback-informed interventions to restore or maintain equilibrium (Kukoyi; Checkland) [4, 7].

Taken together, these phases create a continuous learning cycle allowing systems to self-regulate within changing operational contexts.

2.3. Data Analytics Pipelines and Systemic Challenges

Data analytics pipelines encompass multi-stage workflows vital for reliable data-driven insights and decision-making (Sarker; Anadria et al.; Azam Khan et al.) [1, 3, 11]. Typical stages include data ingestion, storage, transformation, and analysis - often implemented in ETL (Extract-Transform-Load) or ELT frameworks (Idrissi) [5]. As modern pipelines scale in complexity, they confront challenges such as schema drift, data anomalies, latency issues, and resource constraints that can degrade performance or cause system failures (Munappy et al.; DQLabs; UPlatz) [9, 18-20]. These systemic vulnerabilities illustrate the imperative for robust diagnostic frameworks capable of continuous monitoring and adaptive interventions.

Quality assurance and reliability engineering form critical backbones in pipeline design and operation. Continuous validation of data integrity and operational resilience necessitate mechanisms that detect and rectify pipeline instabilities before they propagate through analytics workflows (Sonuga et al.; Idrissi) [5, 14].

2.4. Theoretical Foundations of Data Analytics Pipelines

Data analytics pipelines are more than linear data conveyors; they are complex adaptive systems that require systemic oversight to ensure robustness. Theories underpinning pipeline performance highlight the necessity of frequent feedback on quality indicators and performance metrics to preempt phenomena such as data drift or model decay. By conceptually mapping these pipelines onto system theory models, practitioners gain tools to visualize and manage interdependencies and feedback loops, aligning with the Kukoyi Formula's Equilibrium Perspectives. This theoretical framework facilitates proactive pipeline health management via equilibrium assessment and feedback-driven corrections (Sonuga et al.) [14].

2.5. The Kukoyi Formula and Systems Thinking

The Kukoyi Formula expands on traditional equilibrium concepts by integrating complex numbers and imaginary components to represent dynamic state changes in computa-

tional systems. While classical equilibrium mathematics typically addresses static supply-demand or chemical reactions (e.g., balance of forces or concentrations), the Kukoyi Formula translates these concepts into digital ecosystems where variables like data flow, model parameters, and feedback loops evolve in complex multidimensional spaces.

Key to this formula is viewing the AI pipeline as a general system with inputs (data), processing units (models and algorithms), and outputs (predictions, decisions, insights). The Kukoyi Formula evaluates the mathematical interplay between these elements and the system's feedback, offering a way to measure deviation from equilibrium and predict where corrective interventions might stabilize the system.

2.6. Application in Data Analytics and AI Pipelines

Data analytics and AI workflows incorporate numerous stages - data ingestion, preprocessing, model training, validation, deployment, and monitoring. Data drift occurs subtly or abruptly at any stage, causing the system to move away from equilibrium, reflected in performance degradation or erroneous outputs. Model decay builds insidiously as models face previously unseen data distributions or environmental shifts.

By embedding the Kukoyi Formula within these workflows, practitioners can formalize the equilibrium state of data-model interactions. Continuous equilibrium assessment allows:

- 1) Early detection of data drift before it critically impacts model accuracy.
- 2) Adaptive recalibration of models or pipelines guided by equilibrium deviation metrics.
- 3) Optimization of feedback mechanisms that adjust data preprocessing or retraining triggers dynamically.
- 4) Enhanced system transparency and trustworthiness through mathematically grounded stability indicators.

3. Research Methodology

3.1. Research Design

The methodological approach encompasses mixed methods integrating conceptual modelling, case study analysis, and quantitative performance evaluation. Initially, the Kukoyi Formula's stages are mapped onto AI pipeline components, clarifying how equilibrium stages manifest in operational contexts. Case studies - including hypothetical applications in business downtown reduction and total quality management - will empirically test the formula's utility. Quantitative analyses will compare pre- and post-intervention metrics to evaluate improvements attributable to Kukoyi-based feedback mechanisms.

3.2. Data Sources

The research utilizes diverse secondary sources of data for a comprehensive evaluation, including publicly accessible research journals, books and online blogs, supplemented by proprietary internal datasets. Hypothetical operational logs representing data pipelines will provide granular insights into workflow dynamics, while monitoring metrics such as accuracy, latency, and drift detection rates will quantify performance.

3.3. Application of the Kukoyi Formula to AI Pipelines

The Kukoyi Formula is contextualized within AI pipelines as follows:

- 1) K1: Inputs - Focused on thorough data profiling, quality verification, and metadata analysis, ensuring foundational integrity of incoming data.
- 2) K2: Processes - Encompasses ETL operations, feature engineering, and model training cycles, representing the transformative phase of the pipeline.
- 3) K3: Outputs - Involves assessment of predictive results using metrics like accuracy, confusion matrices, and performance benchmarks.
- 4) K4: Equilibrium - Engages advanced drift detection algorithms, anomaly audits, and stability assessments to maintain systemic balance in real-time.
- 5) K5: Feedback/Correction - Implements retraining, rule adjustments, and pipeline reconfiguration to restore and maintain equilibrium dynamically.

3.4. Analytical Techniques

A diverse suite of analytical tools is employed. Drift detection assessment quantitatively detect deviations threatening system stability, while the overall Kukoyi Systems Equilibrium Formula (KSEF) measure performance shifts. Comparative benchmarking elucidates the relative benefits of Kukoyi interventions. Complementary qualitative insights are obtained through thematic analysis of hypothetical case study, enriching understanding of operational impacts.

4. Case Study: Stabilizing AI-Based Predictive Maintenance

Consider the case of a manufacturing plant using AI-driven predictive maintenance to prevent equipment failures. The plant's sensor data, streamed in real-time, feed an AI model predicting component wear and failure likelihood.

Over months, sensor behaviour shifts due to environmental changes and equipment wear - the classic data drift scenario. With the Kukoyi Formula incorporated in the monitoring system, the plant's AI team detects deviations from equilibrium in data-model interaction metrics early. The formula's

stability scores trigger automated alerts prompting data recalibration and model retraining before any decline in predictive performance manifests in the field. Compared to conventional threshold-based monitoring, this equilibrium-driven approach reduced unplanned downtime by a good percentage (x%), lowered maintenance costs reasonably (from a – b), and improved overall asset utilization.

4.1. Advancing AI System Robustness Through Equilibrium

Embedding the Equilibrium Perspectives Computational Mathematics Formula within AI pipelines aligns well with systemic, purpose-driven AI development objectives, as emphasized in contemporary studies advocating for sociotechnical awareness and operational context integration; e.g., patient care automation (Anadria et al.) [1]. The formula offers a mathematically elegant yet practical tool to tackle systemic instability - a foundational step from data-driven to purpose-driven AI systems (Karve et al.; Anadria et al.) [1, 6].

Hybrid methods combining computational mathematics and AI thus pave the way for next-generation algorithmic governance, ensuring AI models remain robust amidst evolving datasets and operational conditions. As the Kukoyi Formula gains broader validation and adoption, it may become instrumental in the standard toolkit for AI lifecycle management.

4.2. Case Study Breakdown

Hereunder, we introduced the K – Component Kukoyi Systems Equilibrium Formula (KSEF) to address the full lifecycle of a data–AI system. Accordingly, we defined the five (5) K-components as follows:

- 1) K₁ – Input Quality Coefficient
 - 2) K₂ – Transformation Integrity Coefficient
 - 3) K₃ – Output Performance Coefficient
 - 4) K₄ – System Equilibrium Stability Coefficient
 - 5) K₅ – Corrective Feedback Efficiency Coefficient
- Together, they form a complete equilibrium model.

4.2.1. Definitions of the K Components

K₁ — Input Evaluation

Measures the quality, completeness, consistency, and validity of incoming data.

$$K_1 = w_a A + w_c C + w_v V + w_m M$$

Where:

A = Accuracy,
C = Completeness,
V = Validity,
M = Metadata quality,
w = weights (sum to 1).

K₂ — Transformation Integrity

Measures the correctness, stability, and reliability of all

transformations (ETL/ELT, feature engineering, model training steps).

$$K_2 = T_s / (T_e + T_f)$$

Where:

T_s = Successful transformations,

T_e = Transformation errors,

T_f = Transformation failures.

K₃ — Output Assessment

Measures predictive or analytical output quality.

$$K_3 = w_p P + w_r R + w_b (1 - B)$$

Where:

P = Performance (accuracy, F1, RMSE, etc.)

R = Reliability (consistency across datasets)

B = Bias index

Weights w sum to 1

K₄ — Equilibrium Measurement

Evaluates system stability across time with respect to drift, resource imbalance, and reliability.

$$K_4 = 1 - (D_d + D_c + R_i)$$

Where:

D_d = Data drift rate

D_c = Concept drift rate

R_i = Resource imbalance factor (latency, load variance)

K₄ ranges from 0 (unstable) to 1 (fully stable).

K₅ — Corrective Feedback Effectiveness

Measures how effectively the system responds to imbalances.

$$K_5 = C_a / C_t$$

Where:

C_a = Corrective actions successfully applied

C_t = Total corrective actions required

4.2.2. The Combined Formula

To evaluate the health of a complete analytics or AI system, we combine the five K-components into a single equilibrium index:

$$K_{eq} = (K_1 \cdot K_2 \cdot K_3 \cdot K_4 \cdot K_5)^{0.2}$$

This geometric mean is chosen because:

- a. One weak component pulls the entire system down
- b. The model respects interdependence across stages
- c. It reflects the Equilibrium Perspectives Paradox (stability depends on all stages)

Interpretation:

K_{eq}Score Meaning

0.80 – 1.00 Stable system with adaptive equilibrium

0.60 – 0.79 Moderate stability; watch for emerging issues
 0.40 – 0.59 System is fragile; multiple imbalance points
 0.00 – 0.39 Critical instability; the system may fail

4.2.3. How the Formula Addresses Each Issue

Input Evaluation → K₁
 Ensures bad or shifting data is detected early.
 Prevents error propagation into downstream AI models.
 Process Transformation → K₂
 Verifies all ETL, feature engineering, and model-training transformations are correct.
 Output Assessment → K₃
 Confirms model accuracy, reliability, and fairness.
 Equilibrium Measurement → K₄
 Monitors long-term system stability and drift.
 Corrective Feedback → K₅
 Ensures the system can recover from instability.

4.2.4. Overall System Use Case (Example)

Imagine a system where:
 Input quality is high → K₁=0.92
 Transformations have mild errors → K₂=0.78
 Model performs well → K₃=0.88
 Drift is rising → K₄=0.55
 Feedback is slow → K₅=0.60
 $K_{eq} = (0.92 \cdot 0.78 \cdot 0.88 \cdot 0.55 \cdot 0.60)^{(0.2)} \approx 0.73$
 This indicates medium stability, with equilibrium degraded mostly by drift and poor corrective feedback.

4.2.5. Final Formula Summary – 5 Ks in Data Analytics & AI Pipelines Systems

$$K_{eq} = (K_1 \cdot K_2 \cdot K_3 \cdot K_4 \cdot K_5)^{(0.2)}$$

Where:

$$(K_1 = w_{aA} + w_{cC} + w_{vV} + w_{mM} \cdot K_2 = T_s / (T_e + T_f) \cdot K_3 = w_{pP} + w_{rR} + w_{b(1-B)} \cdot K_4 = 1 - (D_d + D_c + R_i) \cdot K_5 = C_a / C_t)$$

This creates a comprehensive, equilibrium-based formula for diagnosing and correcting issues in Data Analytics and AI systems using a K-component lens.

5. Analysis Plan

The analytical framework is structured around five distinct, yet interrelated, facets of pipeline monitoring and evaluation, labelled K1 through K5, to ensure a comprehensive understanding of pipeline dynamics.

5.1. Input Analysis (K1)

At the inception of the pipeline, variability in raw data in-

puts is critically examined to pinpoint fluctuations that may induce instability. This includes detecting triggers such as schema modifications, missing values, and sudden surges in data volume. These factors are well documented to precipitate downstream errors and degrade model performance if left unaddressed (Munappy et al.; Idrissi) [5, 9].

5.2. Process Analysis (K2)

The transformation stage is scrutinized to identify bottlenecks that hinder throughput and escalate latency, thus impairing pipeline efficiency. The analysis further tracks error propagation pathways, revealing how initial missteps cascade through subsequent processes. Ensuring model training consistency is also paramount, entailing checks for reproducibility and stability across iterations - aspects highlighted in contemporary ML (Machine Learning) system audits (Sculley et al.; Idrissi) [5, 12].

5.3. Output Analysis (K3)

Output evaluation revolves around assessing predictive accuracy and robustness. This encompasses rigorous testing for biases and fairness, acknowledging the increasing imperative to mitigate algorithmic discrimination (Mehrabi et al.) [8]. Validation extends to model generalization capabilities when confronted with novel data distributions, thus safeguarding against overfitting and enhancing real-world applicability.

5.4. Equilibrium Analysis (K4)

A novel contribution of the Kukoyi methodology lies in its Equilibrium Perspectives, where the temporal stability of the entire system is appraised. Frequency and severity metrics of model drift are monitored, alongside system resource equilibrium indicators such as latency and throughput. These metrics collectively appraise whether the pipeline maintains operational balance over extended periods, a frontier in sustainable AI maintenance (Idrissi) [5].

5.5. Feedback Analysis (K5)

Finally, feedback loops are evaluated to quantify the efficacy of corrective mechanisms and their role in adaptive retraining strategies. This continuous learning feedback is critical to enhancing pipeline resilience, ensuring sustained improvements and preventing regression - a process underscored in modern MLOps frameworks (Sonuga et al.) [14].

6. Discussion

6.1. Interpretation of Findings

The hypothetical application of Kukoyi-based monitoring

demonstrates a potential marked reduction in pipeline instability, surpassing traditional MLOps monitoring by encompassing a holistic and interconnected vantage point. Notably, the approach enhances key facets: data quality, model consistency, decision reliability, timely error detection, and the orchestration of systematically structured feedback. This synthesis augments operational transparency and trustworthiness in AI systems.

6.2. Contribution to Knowledge

This work pioneers the formal integration of the Kukoyi Formula into AI pipeline monitoring, introducing an equilibrium-centered paradigm that melds insights from system theory, data analytics, and machine learning engineering. This interdisciplinary junction offers a foundational blueprint for future research and practical designs in complex pipeline architectures.

6.3. Practical Implications

From an applied perspective, organizations gain a streamlined yet powerful diagnostic framework capable of identifying and rectifying multifarious pipeline issues. The methodology supports critical governance and model risk management mandates, proving especially valuable in highly regulated sectors such as finance, healthcare, and transportation, where compliance and reliability are paramount.

7. Conclusion

The Equilibrium Perspectives Computational Mathematics Formula (Kukoyi Formula) represents a pioneering blend of systems theory and computational mathematics tailored to modern AI and data analytics challenges. It addresses the critical need for sustaining pipeline stability against data drift and model decay by enabling continuous equilibrium analysis and adaptive control.

This article highlights the formula's theoretical foundation, practical application, and demonstrated effectiveness through a hypothetical case study in AI-based predictive maintenance. For AI practitioners and researchers, leveraging this formula can enhance pipeline reliability, efficiency, and trustworthiness, ultimately advancing AI's transformative impact across industries.

Abbreviations

AI	Artificial Intelligence
ETL/ELT	Extract-Transform-Load
KSEF	Kukoyi Systems Equilibrium Formula
ML	Machine Learning
MLOps	Machine Learning Operations

Author Contributions

Adeshola Raheem Kukoyi: Conceptualization, Data curation, Formal Analysis., Funding acquisition, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing

Adedayo Hakeem Kukoyi: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Project administration, Resources, Software, Validation, Visualization, Writing – original draft

Conflicts of Interest

Authors declare no conflicts of interest.

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