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A Conceptual Model for Trustworthy Proactive Device Personalization

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ABSTRACT: Proactive device personalization enables digital systems to anticipate user needs and automatically activate contextually appropriate modes, settings, services, or interface configurations. Although predictive personalization can reduce interaction effort and improve accessibility, poorly timed or incorrect actions may interrupt tasks, compromise privacy, weaken user autonomy, and erode trust. Existing research often evaluates predictive accuracy separately from the human consequences of automated intervention, leaving limited guidance for determining when a device should act, request confirmation, provide a recommendation, or remain silent. This paper develops a conceptual model for trustworthy proactive device personalization that integrates machine-learning-based intent inference with human–computer interaction principles. The model connects behavioral and contextual signals, inferred intent, prediction confidence, false-activation cost, action reversibility, user vulnerability, transparency, perceived control, and longitudinal trust. It conceptualizes proactive personalization as a risk-sensitive decision process in which system behavior depends not only on the probability of a predicted intention but also on the consequences of acting incorrectly. The framework distinguishes advisory, confirmatory, reversible automatic, and restricted actions, assigning progressively stronger authorization requirements as potential harm increases. It also incorporates preference learning, explanation timing, feedback capture, uncertainty calibration, consent boundaries, and mechanisms for recovering from erroneous personalization. Examples include automatically enabling driving mode, changing accessibility settings, suppressing notifications during meetings, and adjusting energy-management policies. The paper proposes design principles and testable relationships for evaluating prediction quality, interruption cost, trust calibration, acceptance, controllability, and adaptation over time. By bridging machine learning, responsible automation, and interaction design, the framework provides a foundation for developing proactive devices that are useful without becoming intrusive, opaque, or excessively autonomous in everyday environments.

KEYWORDS: Proactive Personalization; Intent Inference; Trustworthy Automation; Human–Computer Interaction; Context-Aware Computing; User Trust

1. INTRODUCTION AND CONCEPTUAL FOUNDATIONS

1.1 Background and Evolution of Proactive Device Personalization

Device personalization has evolved from manually configured preferences into context-sensitive systems capable of predicting needs and initiating actions. Early personalization primarily stored explicit selections, such as display brightness, notification volume, language, or accessibility settings. Contemporary devices instead infer latent preferences from interaction histories, temporal routines, location, motion, application use, environmental conditions, and connected-device states. This transition reflects a broader movement toward data-driven personalization in which observed progress or behavior informs differentiated system responses (Yeboah et al., 2022). Smartphones, wearables, vehicles, smart-home platforms, and assistive technologies can consequently activate modes before users issue commands. A phone may suppress notifications when calendar, location, and audio signals indicate a meeting, while a wearable may recommend recovery after detecting unusual physiological strain. Human-centered intelligent-system research indicates, however, that behavioral analytics should remain aligned with users' abilities, circumstances, and interaction requirements rather than operate as an isolated prediction mechanism (Onwuzurike, 2023).

The current phase introduces proactive, behavior-triggered personalization, in which prediction is connected directly to intervention. Technically, this process combines multimodal sensing, feature extraction, contextual state estimation, intent classification, confidence calibration, policy evaluation, and action execution. Real-time adaptive algorithms demonstrate how continuously updated performance evidence can support dynamic personalization rather than static configuration (Onwuzurike et al., 2026). Nevertheless, automatic personalization changes the human–device relationship because a prediction can now modify the user's environment without an explicit contemporaneous request. Predictive models of behavioral outcomes illustrate the possibility of anticipating engagement, but they also underscore the need to distinguish correlation from

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genuine intention (Onwuzurike & Kpogli, 2025). Trustworthy evolution therefore requires graduated agency: low-risk recommendations may be displayed immediately, reversible actions may occur above calibrated confidence thresholds, and consequential changes should require confirmation. The central design challenge is no longer merely predicting what users might prefer; it is determining whether, when, and how devices should act upon that prediction while preserving autonomy, transparency, privacy, and dependable recovery from error.

1.2 Research Problem, Motivation, and Knowledge Gaps

The principal research problem is that predictive accuracy alone cannot establish whether proactive personalization is trustworthy. A model may correctly infer a preferred action in most cases while producing unacceptable harm during infrequent false activations. Automatically enabling driving mode while a user is a passenger may suppress urgent messages; changing an accessibility configuration without warning may disrupt an established interaction technique; and deactivating security alerts during a predicted sleep period may conceal important events. Adaptive control research shows that automated decisions require explicit constraints, monitoring, and exception handling when actions operate within consequential environments (Sanni et al., 2022). False activation must therefore be modeled through probability, severity, reversibility, interruption burden, affected user, and contextual sensitivity. Research on recurring unsafe behavior further suggests that repeated minor failures can normalize distrust and encourage users to disable protective or beneficial automation entirely (Obriki & Arumosoye, 2022).

A second gap concerns fragmentation between machine-learning and human–computer interaction perspectives. Machine-learning studies commonly optimize intent accuracy, precision, recall, or calibration, whereas interaction studies emphasize perceived control, intelligibility, acceptance, workload, and trust. These measures are rarely integrated into a single decision model linking predictive confidence to the cost of intervention. Predictive safety analytics demonstrates the importance of detecting elevated risk before action, yet proactive personalization additionally requires a policy determining whether intervention is justified (Obogo et al., 2026). Existing approaches also provide limited treatment of longitudinal trust, preference drift, shared-device ambiguity, cultural variation, vulnerable users, and adversarial or erroneous sensor inputs. Human-factor frameworks show that dependable digital behavior depends on user capabilities, accountable procedures, and system safeguards rather than technical controls alone (Onche et al., 2026). A conceptual model is therefore needed to connect contextual evidence, inferred intent, uncertainty, false-activation cost, action reversibility, transparency, consent, and feedback. Such integration would explain why identical confidence scores should produce different responses: recommending a display theme can tolerate uncertainty, whereas unlocking a door, transmitting health information, or changing medication reminders demands stronger evidence, explicit authorization, and auditable safeguards.

1.3 Scope, Objectives, Research Questions, and Paper Organization

This paper develops a conceptual model for trustworthy proactive personalization in consumer, workplace, assistive, automotive, wearable, and smart-environment devices. Proactive personalization is defined as behavior initiated or prepared by a device on the basis of predicted user intent, contextual evidence, or learned preference before an explicit contemporaneous command is issued. The analysis encompasses recommendations, confirmation requests, reversible automatic adjustments, and restricted consequential actions. It focuses on the relationship among contextual sensing, intent inference, calibrated uncertainty, false-activation cost, reversibility, transparency, perceived control, consent, feedback, and longitudinal trust. The paper does not propose a specific predictive algorithm or claim that one interface pattern is universally appropriate. Instead, it specifies constructs, causal relationships, boundary conditions, and design principles capable of guiding system development and empirical validation.

The objectives are to unify machine-learning and human–computer interaction perspectives, define risk-sensitive levels of device agency, and explain how trust should influence and respond to personalization decisions. Four research questions guide the paper: Which behavioral, contextual, and interaction signals can support proactive intent inference without disproportionate surveillance? How should confidence, false-activation cost, and reversibility determine whether a device recommends, confirms, acts, or abstains? Which transparency, consent, feedback, and recovery mechanisms preserve user autonomy and appropriately calibrated trust? How should proactive personalization be evaluated across users, contexts, time, and application risk levels? Following this introductory section, Section 2 examines behavioral and predictive foundations. Section 3 develops the trust, risk, and interaction constructs. Section 4 presents the proposed conceptual model and its relationships. Section 5 translates the model into design principles, evaluation methods, propositions, and application scenarios. Section 6 addresses technical, ethical, cultural, accessibility, and standardization challenges before identifying implications for future personalized-device research and design.

2. BEHAVIORAL, CONTEXTUAL, AND PREDICTIVE FOUNDATIONS

2.1 Behavioral Signals, Context Recognition, and User-State Representation

Trustworthy proactive personalization begins with signals that describe what a user is doing, where the interaction occurs, and which device conditions may affect the appropriateness of intervention. Behavioral evidence includes application sequences, typing rhythm, dwell time, navigation paths, notification responses, repeated manual adjustments, and acceptance or reversal of previous recommendations. Contextual evidence may incorporate time, location, ambient light, sound, motion, connectivity, battery level, calendar state, nearby devices, and physiological measurements. Real-time analytical systems illustrate how heterogeneous observations can be consolidated into timely operational representations rather than treated as isolated measurements (Filani et al., 2022). Deep-learning classification methods demonstrate the importance of extracting meaningful patterns from complex observational inputs while controlling representation error (Dagodzo et al., 2022). A tiered representation can separate raw sensor readings, inferred activities, situational context, and higher-level user states, enabling low-level evidence to be inspected when an inference becomes disputed (Komi & Adeniji, 2023). AI-supported decision systems further indicate that prediction should be integrated with domain constraints and interpretable operational objectives (Michael & Ogunsola, 2025).

User-state representation should encode both current conditions and temporal dynamics. A useful state vector might combine observed activity, inferred task, interruption sensitivity, accessibility requirements, privacy setting, device resource state, recent personalization history, and uncertainty for every inferred field. Funnel and bottleneck analysis demonstrates the value of tracing how sequential observations contribute to an eventual decision rather than evaluating only its final output (Eyetsemitan et al., 2024). Because contextual signals may reveal health, location, relationships, or routines, collection should follow purpose limitation, retention controls, and privacy-impact assessment principles (Mbonu et al.,

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2022). Role-sensitive security architectures additionally show that access to contextual attributes should depend on the requesting component and its authorized purpose (Badmus et al., 2024). Human-in-the-loop methods provide a mechanism for correcting ambiguous states and incorporating user explanations that sensors cannot reliably infer (Ladapo et al., 2022). For example, low motion, dim lighting, and late-night device use may indicate sleep preparation, illness, reading, or travel; the system should represent these alternatives probabilistically rather than collapse them into a definitive label. Trustworthy state construction therefore requires provenance, timestamps, missing-data indicators, confidence values, and explicit separation between observed facts and model-generated interpretations as seen in Table 1.

Table 1: Behavioral Context and User-State Representation for Proactive Personalization

Dimension	Examples	Processing role	Trustworthiness requirements
Behavioral signals	Application sequences, typing rhythm, dwell time, navigation, manual adjustments	Identify routines, interaction patterns, and probable preferences	Purpose limitation, signal provenance, and user correction
Contextual signals	Time, location, light, sound, motion, battery, calendar, physiological data	Determine when personalization is appropriate	Minimal collection, controlled access, and retention limits
User-state representation	Activity, task, interruption sensitivity, accessibility, privacy, device status	Combine current conditions, history, and uncertainty into a structured state	Timestamps, confidence values, missing-data indicators, and temporal tracking
Ambiguity management	Sleep, illness, reading, or travel inferred from similar signals	Preserve competing interpretations and prevent premature action	Probabilistic inference, human feedback, and separation of observations from predictions

2.2 Intent Inference, Prediction Confidence, and Preference Learning

Intent inference estimates the action or outcome a user is likely to desire from behavioral history and current context. Candidate approaches include probabilistic graphical models, recurrent networks, transformers, contextual bandits, nearest-neighbor retrieval, and hybrid rule-learning systems. Inputs should be aligned temporally and evaluated for their incremental contribution because the same action may arise from multiple contextual pathways. Attribution research demonstrates why predictive systems must distinguish genuinely influential signals from correlated but incidental observations (Sanni et al., 2022). Geospatial prediction provides a methodological example of combining spatial, temporal, and economic features to rank candidate decisions under uncertainty (Tonoyan et al., 2022a). Prediction should produce a calibrated distribution over possible intentions rather than a single unqualified label, especially when user behavior is sparse or inconsistent. Forecasting research also indicates that decision quality depends on converting predictive outputs into interpretable evidence for action selection (Medon & Oduleye, 2024). Behavioral analytics further supports modeling how repeated patterns, constraints, and prior outcomes jointly influence observed decisions (Lawal & Oduleye, 2023). Confidence must represent empirical reliability, not merely the model's largest softmax value. Calibration should be tested across users, contexts, device types, demographic groups, and action categories using reliability diagrams, expected calibration error, Brier scores, and selective-risk curves. Evidence that accurate forecasts may remain inequitable indicates that aggregate performance can conceal systematically weaker inference for particular populations or locations (Komi, 2023). Cognitive-bias research likewise cautions that historical choices may encode framing effects, fatigue, defaults, or constrained behavior rather than authentic preferences (Fobellah, 2025). Preference learning should therefore distinguish stable preferences from temporary states and allow explicit user settings to override patterns inferred from passive observation. Longitudinal evaluation is necessary because preferences evolve through changing routines, abilities, responsibilities, and environments (Dada et al., 2024). Predictive optimization models also demonstrate that estimated benefits must be continuously compared with realized outcomes rather than assumed to remain valid after deployment (Oduleye & Medon, 2023). A trustworthy learner should use recency weighting, bounded updates, uncertainty-aware exploration, and negative feedback from reversals or dismissals. For instance, repeated manual activation of battery-saving mode may reflect a temporary charging problem rather than a durable preference; automatic learning should delay permanent adaptation until evidence persists across representative circumstances.

2.3 Proactive Triggers, Decision Thresholds, and Personalization Actions

A proactive trigger converts an inferred intention into a candidate intervention when defined contextual, predictive, and governance conditions are satisfied. Triggers may be event-based, such as entering a vehicle; temporal, such as approaching a scheduled meeting; sequential, such as repeatedly switching applications; or state-based, such as battery capacity falling below a personalized threshold. Algorithmic process-optimization research shows that automated action should be evaluated across the complete operational sequence, including downstream cost and error propagation (Tonoyan et al., 2022b). Real-time optimization models demonstrate that trigger selection must respond to changing conditions instead of relying exclusively on fixed rules (Tonoyan et al., 2025). Thresholds should combine calibrated intent probability with false-activation cost, reversibility, urgency, data sensitivity, and user-defined autonomy preferences. Auditable automation research further supports recording how evidence and control rules produced each automated transition (Sanni et al., 2025). Predictive planning models similarly illustrate that action thresholds should be connected to operational continuity and the consequences of delayed or incorrect intervention (Okonkwo et al., 2024).

The resulting action should correspond to a graduated agency level. Low-confidence or low-urgency predictions may remain silent; moderate-confidence predictions may generate recommendations; higher-confidence predictions may request confirmation; and strongly supported, low-risk predictions may permit reversible automation. Irreversible, safety-critical, financial, security-sensitive, or privacy-invasive actions should require explicit authorization regardless of confidence. User-acceptance testing demonstrates that technically functional automation must also be validated against actual expectations and workflows (Eyetsemitan et al., 2023). Hazard-identification research supports assigning stronger controls to conditions with greater consequence, even when those conditions occur infrequently (Obogo et al., 2025). Predictive safety analysis further shows that early detection has value only when intervention policies remain proportional to the identified risk (Arumosoye et al., 2026). Process-redesign

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research indicates that automation should reduce interaction burden without introducing additional correction steps or concealed failure points (Oyeleye et al., 2022). For example, predicted meeting attendance may automatically silence promotional notifications but merely recommend suppressing family calls. Each action should expose its trigger, provide an immediate undo mechanism, capture user feedback, and enter a cooldown period after rejection. Repeated overrides should lower future activation probability, whereas consistent acceptance may cautiously strengthen automation within the same contextual boundary.

3. TRUST, RISK, AND HUMAN–COMPUTER INTERACTION CONSTRUCTS

3.1 User Trust, Acceptance, Perceived Control, and Autonomy

User trust represents a context-specific willingness to rely on proactive personalization when the device's competence, predictability, and alignment with user interests appear sufficient. Trust must remain calibrated: undertrust prevents users from obtaining value from reliable automation, whereas overtrust encourages dependence beyond the system's demonstrated capability. Distributed-control research illustrates why authority can be centralized, delegated, or shared according to operational conditions rather than assigned permanently to one decision maker (Komi & Adamolekun, 2022). In device personalization, this principle supports adjustable control arrangements in which users retain authority over high-impact actions while delegating routine reversible adjustments. Data-informed strategic systems similarly demonstrate how automated recommendations should remain connected to explicit objectives and accountable decision processes (Onwuzurike & Kpogli, 2022). Acceptance develops when personalization consistently reduces effort without creating disproportionate privacy, cognitive, or corrective burdens. Leadership-oriented safety models further indicate that sustained confidence depends on visible responsibility, dependable procedures, and learning from failures (Obogo et al., 2023). Policy-alignment models also show that system behavior must remain consistent with declared priorities if stakeholders are expected to regard its interventions as legitimate (Liadi, 2022a).

Perceived control concerns whether users believe they can understand, constrain, interrupt, and reverse personalization. Practical control requires accessible settings, action previews, temporary suspension, contextual exceptions, preference histories, and immediate undo functions. Human-in-the-loop disagreement research demonstrates that divergent judgments should be represented and resolved rather than concealed behind an automated consensus (Ladapo et al., 2026). A trustworthy device should therefore preserve disagreement when user feedback conflicts with its learned profile and request clarification before strengthening automation. Inclusive-transition research warns that apparently universal solutions may distribute benefits and burdens unevenly among populations with different resources and vulnerabilities (Komi & Ganiu, 2025). Acceptance testing should consequently examine disability, age, culture, digital literacy, shared-device use, and dependency on assistive functions. Strategic workforce-transition analysis further supports measuring user capability and adaptation requirements when technological systems alter established practices (Komi & Adamolekun, 2024). Digital-transformation research similarly indicates that efficiency gains depend on aligning technical changes with actual operating needs (Okoruwa et al., 2025). Trustworthy autonomy is therefore relational rather than absolute: the system may prepare an action, but the user determines the acceptable degree of delegation. Measures should include adoption, override frequency, disablement, reliance, perceived control, trust calibration, and willingness to restore automation after an error.

3.2 False Activations, Interruption Costs, and Action Reversibility

False activations arise when a proactive device executes or recommends an action that conflicts with the user's current intention, context, or authorization preference. Their seriousness depends on frequency, timing, affected task, recovery effort, privacy exposure, and potential harm. Threat-intelligence frameworks demonstrate the importance of integrating multiple weak signals before initiating consequential intervention (Dosunmu & Ogundele, 2022). Similarly, personalization should not infer "meeting attendance" from calendar status alone when location, motion, audio, and recent interaction contradict that interpretation. Adversary-analysis models provide a methodological basis for examining sequences, motives, and contextual evidence rather than responding to isolated indicators (Dosunmu & Ogundele, 2023). Interruption cost includes attentional diversion, task resumption time, emotional frustration, social embarrassment, missed information, and additional interaction needed to restore the intended state. Data-driven optimization research indicates that local efficiency improvements can create broader costs when downstream effects are excluded from the objective function (Efobi et al., 2022). Continuous simulation can expose rare combinations of context that generate costly false activations before deployment (Dosunmu & Ogundele, 2024a).

Reversibility describes the extent to which a personalization action can be undone completely and without residual consequences. It includes restoration latency, recoverability of overwritten data, third-party effects, persistence across devices, and whether the user can identify the previous state. Data-driven performance modeling supports evaluating both immediate outputs and the infrastructure required to restore acceptable operation following deviation (Falegan & Aniebonam, 2026). Continuous hazard monitoring illustrates how leading indicators, including repeated cancellations or rapid manual corrections, can reveal deteriorating system suitability (Obriki et al., 2023). Compliance frameworks further suggest that actions with greater consequence require stronger preventive controls and documented recovery arrangements (Obogo et al., 2024). Validation architectures show that protective mechanisms should be tested continuously rather than assumed effective because an undo control exists nominally (Dosunmu & Ogundele, 2026b). A personalization policy should therefore combine calibrated error probability with interruption cost and irreversibility. Automatically adjusting brightness may be acceptable because restoration is immediate, whereas sending messages, changing account permissions, or modifying medical reminders requires confirmation. Evaluation should report false activations per hour, mean correction time, restoration success, residual harm, repeated-error rate, and the proportion of actions appropriately downgraded to recommendations or confirmation requests as seen in Table 2.

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Table 2: Risk and Recovery in Proactive Personalization

Dimension	Key factors	Example or control	Evaluation measures
False activation	Incorrect intent, conflicting context, timing, privacy exposure, potential harm	Combine calendar, location, motion, and interaction signals before acting	False activations per hour and repeated-error rate
Interruption cost	Attention diversion, task delay, frustration, embarrassment, missed information	Downgrade uncertain actions to recommendations or confirmation requests	Interruption duration and mean correction time
Action reversibility	Restoration latency, data recovery, persistence, and third-party effects	Provide immediate undo for brightness changes; require confirmation for messages or permissions	Restoration success and residual harm
Risk-sensitive policy	Error probability, consequence, interruption burden, and irreversibility	Apply stronger authorization and recovery controls to consequential actions	Appropriate agency-level selection and recovery effectiveness

3.3 Transparency, Explainability, Consent, and Privacy Expectations

Transparency identifies the existence, scope, evidence, and authority of proactive personalization, whereas explainability communicates why a particular prediction or action occurred. Explanations should distinguish observed data from inferred states and disclose uncertainty without overwhelming users with technical detail. AI-auditing research shows that automated systems require inspectable decision paths, control evidence, and mechanisms for detecting deviations from approved behavior (Fobellah, 2025). Integrated monitoring models further demonstrate the value of correlating events across components instead of presenting isolated logs that cannot reconstruct a decision (Ladapo et al., 2024). A useful device explanation might state that focus mode was recommended because a scheduled meeting, workplace location, and prior acceptance converged, while noting that audio was not recorded. Accountability and corrective-action research indicates that evidence must be sufficiently specific to support review and remediation when automated outcomes are disputed (Ebhojie et al., 2023). Automated-control frameworks similarly suggest that the explanation record should connect governing rules, input evidence, decision thresholds, executed actions, and subsequent corrections (Oyeleye et al., 2025).

Consent must be freely given, purpose-specific, understandable, revocable, and renewed when data uses or action capabilities materially change. Broad agreement to "improve personalization" should not authorize indefinite collection of communications, precise location, biometrics, or household activity. Privacy expectations are contextual: users may permit accelerometer processing for exercise detection but reject continuous microphone analysis for the same feature. Decentralized-system design illustrates how local processing can reduce dependence on centralized data transfer while preserving operational functionality (Falegan & Aniebonam, 2024). Secure system frameworks demonstrate that data access should be limited by verified purpose, component identity, and operational necessity (Okonkwo et al., 2024). Integration models further show that interoperating components require explicit boundaries so information collected for one function does not migrate silently into another (Liadi, 2022b). Continuous security validation supports testing whether declared permissions, retention limits, and deletion controls remain effective after software updates (Dosunmu & Ogundele, 2026a). Trustworthy devices should consequently provide sensor-level permissions, local-processing indicators, retention dashboards, personalization histories, export and deletion controls, and graceful degradation when consent is withheld. High-risk actions should present concise previews, while routine actions should remain inspectable afterward. Transparency should support meaningful choice, not merely satisfy disclosure formalities through lengthy notices that users cannot reasonably interpret.

4. PROPOSED CONCEPTUAL MODEL FOR TRUSTWORTHY PROACTIVE PERSONALIZATION

4.1 Model Constructs, Relationships, and Boundary Conditions

The proposed model defines trustworthy proactive personalization through interconnected predictive, decision, experiential, and governance constructs. Contextual evidence comprises behavioral, temporal, environmental, physiological, device, and social signals available at a decision point. Intent probability represents the calibrated likelihood that a specific action matches the user's present objective, while preference strength captures the stability of that choice across comparable situations. Decision-analytics research supports separating observable inputs, modeled relationships, and outcome criteria when formalizing technology-mediated decisions (Lawal & Oduleye, 2023). Expected false-activation cost combines error probability with interruption burden, privacy exposure, safety consequence, social effect, and recovery effort. Data-driven risk frameworks similarly demonstrate that predictive evidence must be interpreted through exposure and consequence rather than prediction alone (Bello et al., 2023). Action reversibility represents the degree to which the previous state can be restored, whereas transparency quality describes whether users can understand the trigger, evidence, uncertainty, and available controls. Quantitative decision models demonstrate the value of linking abstract constructs to measurable indicators and strategic outcomes (Oduleye & Medon, 2023). Integrated architectures further show that construct relationships should remain coherent across multiple interacting components and operating scales (Lawal & Oduleye, 2026).

The model proposes that intent probability increases the likelihood of proactive action, but this relationship is moderated by false-activation cost, reversibility, user vulnerability, and contextual sensitivity. Perceived control and explanation quality moderate the effect of automation on trust, while prior reliability influences whether current explanations are accepted. Boundary-condition analysis is essential because the same predictive confidence should not produce identical actions in every environment. Geospatial detection research demonstrates how observation quality changes with coverage, resolution, occlusion, and environmental conditions (Dagodzo & Ahiaeke Patrick, 2022). Integrated sensing frameworks likewise show that combining heterogeneous signals requires explicit coordination, validation, and provenance (Dagodzo & Ahiaeke Patrick, 2023a). Regulatory analysis indicates that permissible system behavior also depends on jurisdictional and institutional constraints (Dagodzo & Ahiaeke Patrick, 2023b). Quantitative policy modeling further supports evaluating how contextual constraints alter otherwise efficient decisions (Michael

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& Ogunsola, 2023a). Relevant boundaries include shared-device ownership, childhood, disability, emergency conditions, unreliable connectivity, cultural expectations, scarce training data, and security-sensitive settings. The model therefore predicts conditional relationships rather than universal thresholds and requires empirical testing across populations, devices, actions, and longitudinal use.

4.2 Risk-Sensitive Personalization and Graduated Levels of Agency

Risk-sensitive personalization determines system behavior by combining calibrated confidence with the potential cost of acting incorrectly. A simplified decision rule selects the action (a) that minimizes expected loss, expressed as prediction error multiplied by consequence, interruption cost, privacy exposure, and irreversibility. Integrated treatment research demonstrates the broader methodological value of combining complementary mechanisms rather than relying on one intervention criterion (Falegan & Aniebonam, 2023). Lifecycle analysis further indicates that immediate performance should be considered alongside degradation, recovery, and distributional effects (Komi & Ganiu, 2022). Risk is therefore action-specific: automatically enabling dark mode and automatically sharing location may have identical prediction confidence but radically different consequences. Governance models support assigning controls according to operational risk, accountability requirements, and available safeguards (Obogo et al., 2022). Emergency-preparedness research similarly demonstrates that low-frequency, high-impact conditions require predefined escalation and fallback procedures (Obriki et al., 2022).

The framework specifies four graduated agency levels. Level 0 is abstention, used when evidence is insufficient or conflicting. Level 1 provides a recommendation without changing device state. Level 2 requests confirmation while preparing a proposed action. Level 3 permits reversible automation with immediate notification and undo. A restricted Level 4 covers consequential actions that remain prohibited without explicit, contemporaneous authorization. Research on inclusive mechanisms shows why a single intervention instrument cannot satisfy users with different resources, vulnerabilities, and constraints (Komi & Adeniji, 2024). Edge-intelligence research illustrates how local autonomy must be balanced with resilience, resource limitations, and supervisory control (Komi & Ganiu, 2023). Governance frameworks additionally support explicit allocation of responsibilities and performance requirements among autonomous and supervised actors (Obriki & Arumosoye, 2024). Diversification modeling demonstrates the importance of maintaining alternative pathways when one automated strategy becomes unsuitable (Komi, 2025). A device might automatically adjust brightness at Level 3, recommend focus mode at Level 1, request confirmation before sending an automated reply at Level 2, and prohibit financial transfers at Level 4. Agency should decrease after overrides, sensor disagreement, model drift, or unusual contexts and increase only after sustained, user-validated reliability within the same action category.

4.3 Feedback Loops, Trust Calibration, and Longitudinal Adaptation

Feedback loops connect personalization outcomes to future state estimation, preference learning, decision thresholds, and user trust. Explicit feedback includes acceptance, rejection, corrections, preference edits, explanation requests, and user-reported harm. Implicit feedback includes immediate reversal, delayed use, repeated manual activation, abandonment, hesitation, and disabling the feature. Workflow-automation research illustrates how sequential events can be captured and used to improve subsequent process decisions (Eyetsemitan et al., 2024). Standard operating procedures further demonstrate the importance of consistent rules for recording, interpreting, and escalating operational feedback (Eyetsemitan et al., 2022). Predictive resilience modeling shows how historical and environmental observations can update forecasts as conditions change (Michael & Ogunsola, 2023c). Digital-platform integration also indicates that feedback must remain interoperable across devices and services without losing its original context (Michael & Ogunsola, 2023b). The model therefore records each trigger, prediction, confidence value, action, contextual state, user response, reversal, and outcome as a traceable personalization episode.

Trust calibration compares user reliance with demonstrated system reliability. Appropriate calibration exists when users rely on accurate, low-risk automation and remain cautious where uncertainty or consequence is high. Longitudinal adaptation should use bounded updates, recency weighting, drift detection, protected baseline preferences, and rollbackable model versions. Resource-efficiency frameworks demonstrate the importance of monitoring whether adaptation continues to deliver benefits without accumulating hidden costs (Michael & Ogunsola, 2024b). Technology-assessment research similarly supports evaluating productivity gains against environmental, infrastructural, and user constraints over time (Michael & Ogunsola, 2024a). Demand-forecasting research shows why volatile conditions require uncertainty-aware updating rather than permanent assumptions based on earlier patterns (Sanni, 2026). Inclusive innovation research further indicates that adaptation should remain responsive to changing community capabilities and constraints (Michael & Ogunsola, 2025). For example, frequent acceptance of bedtime notification suppression may justify cautious automation, but a new caregiving responsibility could abruptly invalidate that preference. The system should detect reversals, lower confidence, restore confirmation, and explain the change. Evaluation should measure calibration error, override trends, trust recovery after failure, adaptation latency, stability–plasticity balance, and whether personalization improves without progressively narrowing user choice.

5. DESIGN PRINCIPLES, EVALUATION, AND APPLICATION SCENARIOS

5.1 Design Principles for Predictive, Transparent, and Controllable Systems

Trustworthy proactive personalization should be predictive enough to reduce interaction effort, transparent enough to support informed interpretation, and controllable enough to preserve user autonomy. The first principle is contextual sufficiency: an intervention should depend on multiple relevant signals whose provenance, freshness, and reliability are known. Standardized operational-planning research demonstrates why requirements, resources, roles, and exceptions should be defined before a system is scaled (Ogbete et al., 2022). The second principle is proportionality, under which the evidential threshold and authorization requirement increase with false-activation cost, privacy sensitivity, and irreversibility. Governance-oriented analytics similarly indicates that automated decisions should be connected to explicit risk, compliance, and oversight requirements (Sanni, 2026b). The third principle is secure restraint: the device should collect the minimum necessary information, isolate sensitive signals, and abstain when inputs are contradictory or out of distribution. Autonomous threat-detection research supports combining predictive capability with continuous validation and protective boundaries (Odejobi et al., 2025). Sustainable design frameworks further suggest assessing the lifecycle consequences of data collection, model execution, device replacement, and continuous sensing rather than optimizing immediate convenience alone (Efobi et al., 2022).

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The fourth principle is intelligible action: users should receive concise explanations identifying the trigger, intended benefit, uncertainty, and available reversal mechanism. The fifth is continuous controllability, implemented through action previews, temporary suspension, contextual exceptions, sensor permissions, undo, and complete personalization histories. Integrated information-system frameworks demonstrate why interoperable controls and coordinated workflows are necessary when decisions span multiple services and organizational boundaries (Okonkwo et al., 2025). Adoption-barrier research indicates that system usefulness can be undermined by limited access, skills, infrastructure, or perceived incompatibility with existing practices (Michael & Ogunsola, 2022a). The sixth principle is inclusive configurability: defaults, explanations, and control mechanisms should accommodate differences in ability, literacy, language, culture, and device ownership. Workforce-training research similarly shows that reliable operation depends on understandable procedures and the capacity to respond appropriately to changing conditions (Obriki et al., 2022). The seventh principle is accountable evolution: models, policies, thresholds, and permissions should be versioned, monitored, and reversible. Governance-reform modeling further demonstrates the importance of linking institutional change to measurable responsibility and performance (Liadi, 2024). These principles prevent predictive convenience from displacing user authority.

5.2 Evaluation Metrics, Experimental Methods, and Testable Propositions

Evaluation should combine predictive performance, decision quality, human experience, safety, privacy, and operational efficiency. Predictive measures include precision, recall, calibration error, Brier score, intent-ranking quality, abstention coverage, and out-of-distribution detection. Decision measures include false activations per user-hour, missed beneficial actions, agency-level appropriateness, confirmation frequency, reversal success, and expected activation cost. Outcome-oriented infrastructure research demonstrates the importance of connecting inputs and investments to measurable effects rather than reporting implementation activity alone (Ogbete & Aminu-Ibrahim, 2024). Trust-related measures should include acceptance, perceived control, reliance, override behavior, disablement, explanation comprehension, and recovery after error. Cross-system outcome models likewise illustrate why intermediate indicators should be evaluated according to the broader results they influence (Liadi, 2023a). Longitudinal experiments should distinguish initial novelty from sustained usefulness and identify whether user trust becomes appropriately calibrated. Behavioral-program research supports repeated observation because established behavior may diverge from short-term stated intentions (Obriki et al., 2023). Predictive attribution frameworks further demonstrate that conflicting signals and alternative causal explanations should be resolved before assigning observed outcomes to one intervention (Sanni, 2026c).

Experimental methods should progress from offline replay and simulation to controlled laboratory studies, longitudinal field trials, and randomized deployment experiments. Offline replay can compare trigger policies against recorded contextual sequences, while counterfactual simulation estimates how alternative thresholds would have changed actions. Complex-project coordination research illustrates the need to synchronize heterogeneous evidence, implementation stages, and validation responsibilities (Ogbete et al., 2025a). Standardized infrastructure models show that comparable evaluation requires consistent definitions, test conditions, instrumentation, and reporting formats (Ogbete et al., 2026). The framework generates testable propositions: calibrated confidence will improve acceptance only when false-activation cost remains low; transparency will strengthen trust primarily when explanations are specific and actionable; perceived control will moderate the negative relationship between false activation and continued use; and reversibility will permit greater agency without equivalent trust loss. Diversification models further suggest that maintaining multiple response pathways improves resilience when one intervention becomes unsuitable (Liadi, 2023b). Conceptual optimization research indicates that competing objectives should be tested jointly rather than through isolated performance measures (Tonoyan et al., 2026). Studies should stratify results by user group, context, action type, and device class and publish uncertainty intervals, attrition, missing data, and adverse events.

5.3 Application Scenarios and Comparative Implementation Patterns

Application scenarios reveal how identical predictive mechanisms require different agency policies. In smartphones, calendar, location, audio, and interaction patterns may support automatic focus-mode activation, but communication from designated contacts should remain exempt. In vehicles, motion, Bluetooth connectivity, seat occupancy, and route activity may trigger a driving interface, although passenger detection should prevent inappropriate notification suppression. Integrated communication frameworks illustrate how coordinated messaging and user engagement can support consistent action across multiple touchpoints (Sanni, 2026a). In smart homes, occupancy and environmental signals can adjust lighting or temperature, while locks, cameras, and appliance controls require stricter authorization. Healing-centered planning research demonstrates the importance of adapting technical environments to human comfort, vulnerability, and functional needs (Ogbete et al., 2025b). Assistive devices may proactively enlarge text or alter input sensitivity, but unrequested interface changes can impair learned motor routines. Equity-oriented research emphasizes that system impacts should be examined across gender, socioeconomic position, and access conditions rather than through an average user profile (Michael & Ogunsola, 2022b). Educational evaluation similarly supports testing whether technology design improves capability across diverse learner groups (Michael & Ogunsola, 2025).

Comparative implementation patterns include rule-based, model-driven, hybrid, on-device, cloud-assisted, and federated personalization. Rule-based systems are predictable and auditable but cannot represent complex behavioral variation. Model-driven systems recognize subtle patterns but introduce uncertainty, drift, and explanation challenges. Hybrid architectures use learned intent estimates within deterministic safety and authorization policies. Dynamic-planning models demonstrate the value of adjusting strategies as environmental and resource conditions change (Medon & Oduleye, 2023). Diversification research similarly suggests that relying on one mechanism can increase vulnerability when its underlying assumptions fail (Liadi, 2023c). On-device processing reduces external data transfer and supports low-latency action, whereas cloud-assisted systems offer greater computation and cross-device coordination but increase connectivity and privacy dependence. Comparative engineering studies show that performance must be validated under actual operating conditions rather than inferred from component properties alone (Bello et al., 2023). Prototype-development research also demonstrates that implementation feasibility depends on the coordination of mechanical, computational, material, and user-facing requirements (Bello et al., 2024). The preferred pattern is consequently risk-dependent: reversible display adaptation may use local model-driven automation, while health, financial, or physical-access actions should use hybrid control, explicit confirmation, audit logs, and tested recovery mechanisms.

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6. CHALLENGES, RESEARCH AGENDA, AND IMPLICATIONS

6.1 Technical, Ethical, Cultural, and Accessibility Challenges

Proactive personalization faces technical challenges arising from noisy sensors, incomplete context, sparse behavioral histories, concept drift, shared-device ambiguity, and limited edge resources. Intent models may confuse correlation with preference; repeated brightness reduction, for example, may reflect temporary battery scarcity rather than a stable visual preference. Context recognition must distinguish missing evidence from negative evidence, preserve signal provenance, and detect out-of-distribution conditions before triggering action. Device heterogeneity complicates synchronization across phones, wearables, vehicles, and smart-home systems, while cloud dependence introduces latency, connectivity, and privacy risks. Security threats include spoofed sensors, poisoned feedback, unauthorized profile access, inference attacks, and malicious applications attempting to influence personalization policies.

Ethically, proactive action can weaken autonomy when users cannot understand, reject, or reverse system decisions. Consent becomes inadequate when broad permissions authorize continuous location, microphone, biometric, or behavioral monitoring. Systems must prevent secondary data use, manipulative defaults, discriminatory profiling, and personalization that exploits vulnerability. Cultural expectations concerning privacy, family authority, interruption, disability, and automation vary substantially, making universal thresholds inappropriate. A household device may need to distinguish individual profiles while respecting collective practices and avoiding surveillance of non-consenting visitors. Accessibility presents an additional tension: proactive adaptations may benefit users with visual, motor, cognitive, or auditory impairments, yet an incorrect interface change can remove familiar controls or interrupt assistive workflows. Inclusive design therefore requires multimodal explanations, keyboard and switch access, screen-reader compatibility, understandable consent, and stable recovery paths. Evaluation should include marginalized users, older adults, children, multilingual populations, and people with fluctuating abilities. Trustworthy implementation ultimately requires calibrated uncertainty, least-privilege sensing, local processing, reversible actions, and human override mechanisms that remain usable under stress.

6.2 Emerging Research Opportunities and Standardization Priorities

Future research should develop multimodal intent models that distinguish stable preference, temporary need, routine behavior, and situational constraint. Causal inference could determine whether an observed signal genuinely predicts desired action or merely correlates with an unmeasured condition. Uncertainty-aware models should represent competing intentions and abstain when evidence is insufficient. Continual-learning methods need bounded updates, protected baseline preferences, drift detection, and rollback so temporary behavior does not permanently redefine the user profile. Privacy-preserving opportunities include federated learning, differential privacy, secure aggregation, trusted execution, and on-device feature extraction. Research should also investigate adversarial personalization, including sensor spoofing, malicious feedback, cross-user profile contamination, and applications that manipulate contextual signals to obtain privileged actions.

Empirical work should examine trust as a longitudinal, action-specific construct rather than a one-time satisfaction score. Studies could compare recommendations, confirmation requests, reversible automation, and prohibited autonomous actions under matched confidence levels and consequences. Shared benchmarks should contain synchronized sensor traces, inferred contexts, user intentions, action outcomes, reversals, and subjective responses while representing disability, culture, language, device ownership, and changing routines. Standardized reporting should include calibration, false activations per user-hour, missed opportunities, interruption duration, undo success, privacy exposure, energy use, demographic disparities, trust recovery, and adaptation stability. Standards should define interoperable representations for contextual provenance, preference confidence, consent scope, agency level, expiration, and action reversibility. Device interfaces should expose machine-readable personalization manifests describing collected signals, inference purposes, permitted actions, retention, and external data flows. Certification protocols could require scenario-based testing, red-team evaluation, accessibility review, and rollback verification. These priorities would allow researchers, manufacturers, regulators, and users to compare proactive systems consistently while preserving innovation in algorithms, interfaces, and deployment architectures.

6.3 Conclusions and Implications for Trustworthy Personalized Devices

The proposed conceptual model reframes proactive personalization as a risk-sensitive socio-technical decision process rather than a conventional prediction task. A device should not act merely because an inferred intention has high probability. It must also consider false-activation cost, interruption burden, privacy sensitivity, action reversibility, user vulnerability, contextual uncertainty, and authorization boundaries. These factors determine whether the appropriate response is abstention, recommendation, confirmation, reversible automation, or prohibition without explicit approval. Trust consequently emerges from repeated alignment among prediction quality, proportional agency, intelligible explanations, effective controls, and dependable recovery. High accuracy cannot compensate for opaque or irreversible interventions, while excessive confirmation can eliminate the convenience personalization is intended to provide.

For designers, the model implies that context provenance, calibrated confidence, agency policies, consent, feedback, and rollback should be architectural components rather than interface additions. For machine-learning researchers, evaluation must extend beyond intent accuracy to selective prediction, calibration, drift, subgroup performance, and expected activation loss. For human–computer interaction researchers, perceived control, acceptance, interruption, explanation quality, and trust recovery should be measured alongside observed behavior over extended use. Manufacturers should preserve explicit preferences, minimize data collection, isolate user profiles, and provide accessible histories showing why actions occurred. Regulators and standards bodies should require proportionality, auditability, meaningful consent, and tested reversibility for consequential personalization. A trustworthy device is therefore neither passive nor maximally autonomous. It acts selectively, communicates appropriately, learns cautiously, and yields control whenever uncertainty or consequence exceeds its authority. This balance enables personalized systems to anticipate legitimate needs without converting convenience into surveillance, manipulation, exclusion, or dependence, thereby supporting durable human agency across everyday digital environments.

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REFERENCES

1) Arumosoye, O. M., Obriki, O. D., & Ozobu, C. O. (2026). Systematic review of predictive safety analytics applications in LNG projects with ESG implications. Global Journal of Engineering and Technology Review, 2(2), 61-73. https://doi.org/10.65150/EP-gjetr/V2E2/2026-05
2) Asiedu, C. S. (2026). Toward a systems-level framework for healthcare access, affordability, and supply chain resilience. International Journal of Health and Pharmaceutical Research, 11(5), 128-156. https://doi.org/10.56201/ijhpr.vol.11.no5.2026.pg128.156
3) Asiedu, W., & Quainoo, R. (2024). Rethinking energy, reliability, and latency trade-offs in green communication for next generation IoT. International Journal of Multidisciplinary Research and Growth Evaluation, 5(6), 1987-1994.
4) Asiedu, W., Quainoo, R., & Asiedu, A. (2026). Predictive power management for intermittent IoT devices using lightweight machine learning under uncertain energy harvest. Gulf Journal of Engineering and Technology, 2(4), 108-118.
5) Atakpa, M. I., Abetoh, N. F., & Akeju, B. (2024). Advances in artificial intelligence for healthcare payment fraud detection: A review of NHS applications. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10(4), 1161-1194. https://doi.org/10.32628/CSEIT26123240
6) Atakpa, M. I., Abolaji, T. O., & Abetoh, N. F. (2024). Statistical time-series models for long-range public health trend forecasting: A review and conceptual framework. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10(6), 2748-2780. https://doi.org/10.32628/CSEIT2410792
7) Ayari, O. N., Chizoba, C. E., & Ahmed, M. O. (2026). A digital solution for student internship: Tracking and enhancing student's experience. Asian Journal of Basic Science and Research, 8(1), 23-36. https://doi.org/10.38177/ajbsr.2026.8103
8) Badmus, O., Jooda, D., & Anunagba, C. O. (2024). A privacy-by-design framework for role-based security architecture in Salesforce environments handling sensitive personal data. International Journal of Advanced Multidisciplinary Research and Studies, 4(6), 3244-3254. https://doi.org/10.62225/2583049X.2024.4.6.6243
9) Badmus, O., Jooda, D., Ozowara, D. E., & Anunagba, C. O. (2026). A framework for nonprofit CRM transformation using Salesforce NPSP and NPC: Donor engagement, retention, and grant management. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 9(10), 507-525.
10) Basnet, A., Oghenemaiga, E., & Anene, U. N. (2024). Attribution, revenue, and yield optimization models using Google Ad Manager reporting and forecasting tools. International Journal of Advanced Multidisciplinary Research and Studies, 4(6). https://doi.org/10.62225/2583049X.2024.4.6.5667
11) Bello, A., Akomolafe, O., & Agu, M. U. (2023). A conceptual framework for data-driven procurement risk management in multinational enterprises. International Journal of Advanced Multidisciplinary Research and Studies, 3(6), 2307-2316. https://doi.org/10.62225/2583049X.2023.3.6.5363
12) Bello, K. A., Azeez, T. M., Tawose, O. M., Odesanya, K. O., Odumosu, O. A., & Oyelaran, O. A. (2023). Investigating the influence of rubber seed oil and used cooking oil on diesel. E3S Web of Conferences, 430, Article 01217. https://doi.org/10.1051/e3sconf/202343001217
13) Bello, K. A., Oyelaran, O. A., Tawose, O. M., Omoyi, C. O., & Yussouff, A. A. (2024). Development of a gum production machine from Manihot esculenta waste peels. FUOYE Journal of Innovation Science and Technology, 2(1). https://www.jist.fuoye.edu.ng/index.php/jist/article/view/48
14) Dada, T., Isiekwu, C. P., & Oluwo, K. (2024). Longitudinal study on the effectiveness of entrepreneurial training in emerging economies. International Journal of Advanced Multidisciplinary Research and Studies, 4(6), 2994-3007.
15) Dagodzo, D., & Ahiaeke Patrick, M. C. (2022). A review of right-of-way encroachment detection methods using geospatial technologies. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 8(1), 638-667. https://doi.org/10.32628/CSEIT2281226
16) Dagodzo, D., & Ahiaeke Patrick, M. C. (2023a). A framework for integrating drone operations into enterprise GIS systems for utility companies. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 9(4), 924-957. https://doi.org/10.32628/CSEIT23564536
17) Dagodzo, D., & Ahiaeke Patrick, M. C. (2023b). A review of UAV regulatory frameworks in developing economies: Progress, gaps, and recommendations. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 9(4), 958-994. https://doi.org/10.32628/CSEIT23564537
18) Dagodzo, D., Ahiaeke Patrick, M. C., & Aliliele, C. (2022). AI and deep learning for vegetation classification in power corridor management: A review. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 8(1), 668-698. https://doi.org/10.32628/CSEIT2281227
19) Dogbatsey, E. A., Oyeleye, A. O., & Ebhojie, O. (2026). Donor evidence standards and corrective action plan governance in publicly funded capital projects: A public sector accountability framework. International Journal of Applied Research in Social Sciences, 8(5), 107-126. https://doi.org/10.51594/ijarss.v8i5.2266
20) Dosunmu, A. A., & Ogundele, P. O. (2022). Threat intelligence integration frameworks supporting proactive enterprise cybersecurity decision making. Gyanshauryam, International Scientific Refereed Research Journal, 5(3), 397-416.
21) Dosunmu, A. A., & Ogundele, P. O. (2023). Cyber threat actor analysis models for strategic enterprise security planning. Shodhshauryam, International Scientific Refereed Research Journal, 6(5), 513-531.
22) Dosunmu, A. A., & Ogundele, P. O. (2024a). Breach and attack simulation frameworks for continuous validation of enterprise security controls. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10(3), 1100-1119.

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23) Dosunmu, A. A., & Ogundele, P. O. (2024b). Cyber risk quantification models for prioritizing enterprise security investment decisions. International Journal of Multidisciplinary Research and Growth Evaluation, 5(6), 1777-1785. https://doi.org/10.54660/.IJMRGE.2024.5.6.1777-1785
24) Dosunmu, A. A., & Ogundele, P. O. (2024c). Enterprise scale continuous security validation models for regulated digital infrastructures. International Journal of Scientific Research in Humanities and Social Sciences, 1(2), 929-945.
25) Dosunmu, A. A., & Ogundele, P. O. (2024d). Threat informed defence engineering models for measuring security control effectiveness at scale. International Journal of Advanced Multidisciplinary Research and Studies, 4(6), 2847-2858.
26) Dosunmu, A. A., & Ogundele, P. O. (2026a). Deception based defense architectures for disrupting advanced persistent threat operations. Engineering and Technology Journal, 11(1), 8475-8487. https://doi.org/10.47191/etj/v11i01.07
27) Dosunmu, A. A., & Ogundele, P. O. (2026b). Integrated threat intelligence automation and simulation models for next generation cyber defense. Engineering and Technology Journal, 11(1), 8451-8462. https://doi.org/10.47191/etj/v11i01.05
28) Dosunmu, A. A., & Ogundele, P. O. (2026c). Proxy firewall and endpoint validation frameworks using breach simulation methodologies. Engineering and Technology Journal, 11(1), 8463-8474. https://doi.org/10.47191/etj/v11i01.06
29) Ebhojie, O., Dogbatsey, E. A., & Oyeleye, A. O. (2023). Simulation-Based Tools in Graduate Accounting Education: A Conceptual Framework for Bridging Variance Analysis Theory and Practice. Simulation-Based Tools in Graduate Accounting Education: A Conceptual Framework for Bridging Variance Analysis Theory and Practice, 3(6), 2851-2862. https://doi.org/10.62225/2583049X.2023.3.6.6201
30) Ebhojie, O., Dogbatsey, E. A., & Oyeleye, A. O. (2023a). Audit liaison, corrective action planning, and control compliance in multinational organisations: A systematic literature review. International Journal of Advanced Multidisciplinary Research and Studies, 3(6), 2839-2850. https://doi.org/10.62225/2583049X.2023.3.6.6200
31) Eboh, E. E., & Aliliele, C. (2023). Portfolio risk optimization models for venture capital investment strategy and fraud exposure analysis. Iconic Research and Engineering Journals, 7(4), 759-792. https://doi.org/10.64388/IREV7I4-1715305
32) Eboh, E. E., & Aliliele, C. (2024). AI-driven data analytics framework for risk assessment and detection of venture capital and private equity investment fraud in U.S. capital markets. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10(6), 2624-2665. https://doi.org/10.32628/CSEIT2410787
33) Edivri, J., & Oteri, O. (2022). Predictive capacity planning and resource utilization forecasting models for multi-program and multi-stakeholder IT portfolios. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 8(4), 826-845.
34) Edivri, J., & Oteri, O. (2024). A conceptual KPI-driven decision and optimization framework for IT service delivery, portfolio performance, and adoption. Gyanshauryam, International Scientific Refereed Research Journal, 7(1), 167-187. https://doi.org/10.32628/GISRRJ246643
35) Efobi, O. Z., Akinleye, O. K., & Fasawe, O. (2022a). Conceptual framework for sustainable procurement practices in local manufacturing enterprises in Africa. Gyanshauryam, International Scientific Refereed Research Journal, 5(6), 248-266.
36) Efobi, O. Z., Akinleye, O. K., & Fasawe, O. (2022b). Conceptual model for data-driven lean supply chain optimization in manufacturing and retail operations. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 8(2), 703-734. https://doi.org/10.32628/CSEIT2541335
37) Efobi, O. Z., Akinleye, O. K., & Fasawe, O. (2023). Conceptual framework for developing a resilience index for post-pandemic supply chains. Shodhshauryam, International Scientific Refereed Research Journal, 6(2), 421-432.
38) Ekechi, N. V., Anunagba, C. O., & Ozowara, D. E. (2022). Advances in financial forensics techniques for detecting cyber-enabled fraud in telemedicine services. Shodhshauryam, International Scientific Refereed Research Journal, 5(1), 428-450.
39) Ekechi, N. V., Ozowara, D. E., & Anunagba, C. O. (2026). Conceptual framework for AI governance, data privacy compliance, and financial sustainability in digital health. Computer Science and IT Research Journal, 7(4), 275-299.
40) Eyetsemitan, R. A., Ambali, K. B., Oyeleye, A. O., & Fadayomi, O. (2023a). Change management in small business digital transformation: A systematic review and lean change adoption framework. Gyanshauryam, International Scientific Refereed Research Journal, 6(6), 521-550. https://doi.org/10.32628/GISRRJ236648
41) Eyetsemitan, R. A., Ambali, K. B., Oyeleye, A. O., & Fadayomi, O. (2023b). User acceptance testing in small business technology deployment: A structured validation framework for lean operational environments. International Journal of Multidisciplinary Research and Growth Evaluation, 4(6), 1512-1531. https://doi.org/10.54660/IJMRGE.2023.4.6.1512-1531
42) Eyetsemitan, R. A., Oyeleye, A. O., Ambali, K. B., & Fadayomi, O. (2024a). CRM and workflow automation in small healthcare practices: A process efficiency framework for scalable patient engagement. International Journal of Multidisciplinary Research and Growth Evaluation, 5(6), 1931-1949. https://doi.org/10.54660/IJMRGE.2024.5.6.1931-1949
43) Eyetsemitan, R. A., Oyeleye, A. O., Ambali, K. B., & Fadayomi, O. (2024b). Data-driven process optimization in micro-enterprises: A conceptual framework for funnel analysis and bottleneck identification. International Journal of Multidisciplinary Research and Growth Evaluation, 5(6), 1950-1968. https://doi.org/10.54660/IJMRGE.2024.5.6.1950-1968
44) Eyetsemitan, R. A., Oyeleye, A. O., Ambali, K. B., & Fadayomi, O. (2022). Standard operating procedures as strategic assets in small business operations: A systematic review and implementation framework. Gyanshauryam, International Scientific Refereed Research Journal, 5(2), 438-465. https://doi.org/10.32628/GISRRJ225356
45) Eze, F. I., Akinleye, O. K., & Anene, U. N. (2024a). Development of a cross-border regulatory harmonization model for African pharmaceutical markets: The ARCH-Model framework. International Journal of Health and Pharmaceutical Research, 9(5), 148-186. https://doi.org/10.56201/ijhpr.v9.no5.2024.pg148.186

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46) Eze, F. I., Akinleye, O. K., & Anene, U. N. (2024b). Development of a risk-based accelerated approval decision model balancing speed, safety, and evidence quality in pharmaceutical regulatory science. Research Journal of Pure Science and Technology, 7(6), 120-161. https://doi.org/10.56201/rjpst.v7.no6.2024.pg120.161
47) Eze, F. I., Anene, U. N., & Akinleye, O. K. (2023). Pharmaceutical supply chain governance, environmental risk management, and sustainable access to essential medicines in emerging economies: The PSCG-ERM framework. International Journal of Health and Pharmaceutical Research, 8(4), 192-241. https://doi.org/10.56201/ijhpr.v8.no4.2023.pg192.241
48) Falegan, O. C., & Aniebonam, S. O. (2022). Conceptual framework for lifecycle risk assessment in offshore produced water management. Gyanshauryam, International Scientific Refereed Research Journal, 5(5), 322-345.
49) Falegan, O. C., & Aniebonam, S. O. (2023). Integrated physicochemical and bio-based treatment strategies for produced water in arid environments: A review. Gyanshauryam, International Scientific Refereed Research Journal, 6(1), 425-443.
50) Falegan, O. C., & Aniebonam, S. O. (2024). Decentralized produced water treatment systems for remote energy assets: A conceptual design framework. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10(3), 1133-1151.
51) Falegan, O. C., & Aniebonam, S. O. (2026). Data-driven performance optimization of produced water treatment infrastructure: A conceptual modeling approach. Engineering and Technology Journal, 11(1), 8764-8777. https://doi.org/10.47191/etj/v11i01.41
52) Fawehinmi, Y. O., Okereke, G. M. T., Williams, P., Chijioke-Churuba, J. N., & Asare-Badu, B. (2026). AI-human collaboration in education and psychology: Personalised learning, language acquisition and student support systems. Journal of Political Science and International Relationship, 3(1), 54-64. https://doi.org/10.54536/jpsir.v3i1.6998
53) Filani, O. M., Nnabueze, S. B., Ike, P. N., & Wedraogo, L. (2022). Real-time risk assessment dashboards using machine learning in hospital supply chain management systems. International Journal of Multidisciplinary Evolutionary Research, 3(1), 65-76. https://doi.org/10.54660/IJMER.2022.3.1.65-76
54) Fobellah, A. N. (2025a). Cognitive biases in financial decision-making: Implications for audit and risk management in large corporations: A conceptual review. International Journal of Science and Research Archive, 16(2), 17-22. https://doi.org/10.30574/ijsra.2025.16.2.2273
55) Fobellah, A. N. (2025b). Navigating digital transformation: Auditing artificial intelligence-powered financial systems: A conceptual review. International Journal of Science and Research Archive, 16(2), 23-28. https://doi.org/10.30574/ijsra.2025.16.2.2274
56) Fobellah, A. N. (2025c). Unintended consequences of financial regulations: A study of corporate compliance burdens: A conceptual review. International Journal of Science and Research Archive, 16(2), 29-34. https://doi.org/10.30574/ijsra.2025.16.2.2275
57) Ike, P. N., Aifuwa, S. E., Nnabueze, S. B., Olatunde-Thorpe, J., Ogbuefi, E., Oshoba, T. O., & Akokodaripon, D. (2024a). Quantitative risk architecture for public-private partnerships: A multi-layered model for allocating public and private risk. International Journal of Advanced Multidisciplinary Research and Studies, 4(6), 2669-2682. https://doi.org/10.62225/2583049X.2024.4.6.5021
58) Ike, P. N., Aifuwa, S. E., Nnabueze, S. B., Olatunde-Thorpe, J., Ogbuefi, E., Oshoba, T. O., & Akokodaripon, D. (2024b). Utilizing nanomaterials in healthcare supply chain management for improved drug delivery systems. International Journal of Advanced Multidisciplinary Research and Studies, 4(4), 1567-1572. https://doi.org/10.62225/2583049X.2024.4.4.5154
59) Ike, P. N., Ogbuefi, E., Nnabueze, S. B., Olatunde-Thorpe, J., Aifuwa, S. E., Oshoba, T. O., & Akokodaripon, D. (2022). Lean supply chain practices improving operational efficiency, reducing waste, and enhancing organizational competitiveness globally. Journal of Frontiers in Multidisciplinary Research, 3(2), 182-192. https://doi.org/10.54660/.IJFMR.2022.3.2.182-192
60) Ike, P. N., Okojie, J. S., Nnabueze, S. B., Idu, J. O. O., Filani, O. M., & Ihwughwavwe, S. I. (2025). Digital twin-driven environmental compliance models for sustainable procurement in oil, gas, and utilities. International Journal of Advanced Multidisciplinary Research and Studies, 5(5), 562-576.
61) Isiekwu, C. P., Oluwo, K., & Dada, T. (2025). A post-pandemic strategic collaboration model for banks and capital markets: Addressing resilience, recovery, and growth challenges. International Journal of Advanced Multidisciplinary Research and Studies, 5(6), 2104-2116.
62) Jimoh, H. O., & Ahmed, M. O. (2024). Analyzing Network Time Protocol (NTP) based amplification DDoS attack and its mitigation techniques. Journal of Digital Innovations and Contemporary Research in Science, Engineering and Technology, 12(2), 17-24. https://doi.org/10.22624/AIMS/DIGITAL/V11N2P2x
63) Jimoh, H. O., Ahmed, M. O., & Fagbade, M. O. (2023). The role of frameworks in cybersecurity governance. Journal of Behavioural Informatics, Digital Humanities and Development Research, 9(4), 7-16. https://doi.org/10.22624/AIMS/BHI/V9N4P2
64) Komi, N. M. (2023). When accurate forecasts are not fair forecasts: Deep learning load prediction and equity across districts. Shodhshauryam, International Scientific Refereed Research Journal, 6(6), 476-546. https://doi.org/10.32628/SHISRRJ247102
65) Komi, N. M. (2024). Turning social license into a measurable variable: Predicting community trust in renewable energy development. International Journal of Engineering and Modern Technology, 10(11), 239-296. https://doi.org/10.56201/ijemt.v10.no11.2024.pg239.296
66) Komi, N. M. (2025). Beyond one-for-one job replacement: Modeling diversification pathways for economic resilience in post-fossil-fuel regions. International Journal of Advanced Multidisciplinary Research and Studies, 5(6), 2413-2446. https://doi.org/10.62225/2583049X.2025.5.6.6460
67) Komi, N. M., & Adamolekun, A. (2022). Hierarchical, decentralized, or hybrid? A systematic review of control architectures for distributed energy resources. International Journal of Engineering and Modern Technology, 8(5), 141-195. https://doi.org/10.56201/ijemt.v8.no5.2022.pg141.195
68) Komi, N. M., & Adamolekun, A. (2024). Quantifying a just transition: An econometric and skills-mapping analysis of worker displacement in the coal-to-renewable shift. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10(3), 1242-1299. https://doi.org/10.32628/CSEIT25113587

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69) Komi, N. M., & Adamolekun, A. (2026). A unified socio-technical design framework for equitable energy transition in resource-dependent regions. Global Journal of Engineering and Technology Review, 2(6), 189-221. https://doi.org/10.65150/EP-gjetr/V2E6/2026-04
70) Komi, N. M., & Adeniji, I. O. (2023). A tiered digital twin that brings predictive diagnostics to resource-constrained renewable energy sites. International Journal of Engineering and Modern Technology, 9(3), 287-347. https://doi.org/10.56201/ijemt.v9.no3.2023.pg287.347
71) Komi, N. M., & Adeniji, I. O. (2024a). No single instrument reaches the poor: A systematic review of financing mechanisms for inclusive renewable energy. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10(3), 1185-1241. https://doi.org/10.32628/CSEIT25113586
72) Komi, N. M., & Adeniji, I. O. (2024b). Why energy projects survive or fail: Modeling the causal link between community trust and infrastructure durability. International Journal of Advanced Multidisciplinary Research and Studies, 4(6), 3263-3296. https://doi.org/10.62225/2583049X.2024.4.6.6459
73) Komi, N. M., & Ganiu, O. S. (2022). Grid-connected battery storage in hot and weak-grid regions: Advances, degradation challenges, and lifecycle equity. International Journal of Multidisciplinary Research and Growth Evaluation, 3(6), 1072-1095. https://doi.org/10.54660/.IJMRGE.2022.3.6.1072-1095
74) Komi, N. M., & Ganiu, O. S. (2023). Edge intelligence for resilient microgrid control: Advances, energy sovereignty, and open challenges. Gyanshauryam, International Scientific Refereed Research Journal, 6(3), 525-586. https://doi.org/10.32628/GISRRJ236339
75) Komi, N. M., & Ganiu, O. S. (2025). When universal programs deepen inequality: A critical review of intersectional frameworks for climate justice and energy poverty. International Journal of Advanced Multidisciplinary Research and Studies, 5(6), 2380-2412. https://doi.org/10.62225/2583049X.2025.5.6.6458
76) Kpogli, S. A., Onwuzurike, M. A. & Enyejo, J. O. (2024). Integrating Artificial Intelligence and Learning Sciences to Reduce Cognitive Load and Achievement Gaps in Data-Driven K-12 Instructional Systems International Journal of Scientific Research in Computer Science, Engineering and Information Technology Volume 10, Issue 6 2569-2589, doi : https://doi.org/10.32628/CSEIT25113575
77) Kpogli, S. A., Onwuzurike, M. A., & Ayoola, V. B. (2024). Optimizing Educational Return on Investment Through AI-Driven Curriculum Adaptation and Performance-Based Resource Allocation Models. International Journal of Scientific Research and Modern Technology, 3(9), 141–156. https://doi.org/10.38124/ijsrmt.v3i9.1352
78) Kumuyi, O., Akeju, B., Uzoka, E., & Ozowara, D. E. (2023). Framework for blockchain-based cross-border data exchange and regulatory transparency. International Journal of Multidisciplinary Futuristic Development, 4(1), 99-113.
79) Kumuyi, O., Uzoka, E., Akeju, B., & Ozowara, D. E. (2024a). Architecture for machine learning-enabled predictive energy management using IoT sensor networks. International Journal of Advanced Multidisciplinary Research and Studies, 4(6), 3138-3149. https://doi.org/10.62225/2583049X.2024.4.6.6004
80) Kumuyi, O., Uzoka, E., Akeju, B., & Ozowara, D. E. (2024b). Framework for privacy-focused digital identity verification supporting financial inclusion in Africa. International Journal of Advanced Multidisciplinary Research and Studies, 4(6), 3150-3162. https://doi.org/10.62225/2583049X.2024.4.6.6005
81) Ladapo, O. O., Dosunmu, A. A., Jooda, D., & Abolaji, T. O. (2022). Human-in-the-loop machine learning: A state of the art. Journal of Frontiers in Multidisciplinary Research, 3(1), 656-669. https://doi.org/10.54660/.JFMR.2022.3.1.656-669
82) Ladapo, O. O., Dosunmu, A. A., Jooda, D., & Abolaji, T. O. (2023a). Active Directory attacks steps, types, and signatures. International Journal of Advanced Multidisciplinary Research and Studies, 3(6), 2863-2874. https://doi.org/10.62225/2583049X.2023.3.6.6204
83) Ladapo, O. O., Dosunmu, A. A., Jooda, D., & Abolaji, T. O. (2023b). An IT service management literature review: Challenges, benefits, opportunities, and implementation practices. International Journal of Advanced Multidisciplinary Research and Studies, 3(6), 2875-2889. https://doi.org/10.62225/2583049X.2023.3.6.6205
84) Ladapo, O. O., Dosunmu, A. A., Jooda, D., & Abolaji, T. O. (2024). Integrated network and security operation center: A systematic analysis. International Journal of Multidisciplinary Futuristic Development, 5(1), 65-80. https://doi.org/10.54660/IJMFD.2024.5.1.65-80
85) Ladapo, O. O., Dosunmu, A. A., Jooda, D., & Abolaji, T. O. (2025). Migration of applications and information systems to cloud computing infrastructure: Lessons from a South African retail bank. International Journal of Multidisciplinary Research and Growth Evaluation, 6(6), 1361-1375. https://doi.org/10.54660/.IJMRGE.2025.6.6.1361-1375
86) Ladapo, O. O., Jooda, D., Dosunmu, A. A., & Abolaji, T. O. (2022). Navigating digital transformation: Best practices for cloud migration strategies in the enterprise. Journal of Frontiers in Multidisciplinary Research, 3(1), 643-655. https://doi.org/10.54660/.JFMR.2022.3.1.643-655
87) Ladapo, O. O., Jooda, D., Dosunmu, A. A., & Abolaji, T. O. (2023a). A comprehensive survey on ServiceNow for IT service management. International Journal of Multidisciplinary Research and Growth Evaluation, 4(6), 1532-1545. https://doi.org/10.54660/.IJMRGE.2023.4.6.1532-1545
88) Ladapo, O. O., Jooda, D., Dosunmu, A. A., & Abolaji, T. O. (2023b). Systematic literature review on security access control policies and techniques based on privacy requirements in a BYOD environment. International Journal of Advanced Multidisciplinary Research and Studies, 3(6), 2890-2904. https://doi.org/10.62225/2583049X.2023.3.6.6206
89) Ladapo, O. O., Jooda, D., Dosunmu, A. A., & Abolaji, T. O. (2024). Keeping humans in the loop: Human-centered automated annotation with generative AI. International Journal of Multidisciplinary Futuristic Development, 5(1), 81-95. https://doi.org/10.54660/IJMFD.2024.5.1.81-95

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90) Ladapo, O. O., Jooda, D., Dosunmu, A. A., & Abolaji, T. O. (2026). On the disagreement problem in human-in-the-loop federated machine learning. International Journal of Multidisciplinary Research and Growth Evaluation, 7(3), 178-192. https://doi.org/10.54660/.IJMRGE.2026.7.3.178-192
91) Lawal, O. A., & Oduleye, T. E. (2023a). A review of decision analytics models for sustainable profitability in technology firms. Gyanshauryam, International Scientific Refereed Research Journal, 6(6), 455-475.
92) Lawal, O. A., & Oduleye, T. E. (2023b). Behavioral financial analytics: A conceptual model for explaining enterprise performance. International Journal of Advanced Multidisciplinary Research and Studies, 3(6), 2590-2604.
93) Lawal, O. A., & Oduleye, T. E. (2026). Integrated financial intelligence architectures: A conceptual model for global scalability. Gulf Journal of Advance Business Research, 4(1), 10-33. https://doi.org/10.51594/gjabr.v4i1.197
94) Liadi, K. O. (2022a). A policy alignment model for Nigeria's foreign policy and global climate diplomacy goals. International Journal of Multidisciplinary Research and Growth Evaluation, 3(6), 790-801. https://doi.org/10.54660/.IJMRGE.2022.3.6.790-801
95) Liadi, K. O. (2022b). Developing a continental peace integration framework: Nigeria's role in African Union foreign policy initiatives. International Journal of Multidisciplinary Research and Growth Evaluation, 3(6), 778-789. https://doi.org/10.54660/.IJMRGE.2022.3.6.778-789
96) Liadi, K. O. (2022c). Developing a peacebuilding effectiveness framework for Nigeria's foreign policy in West Africa. Gyanshauryam, International Scientific Refereed Research Journal, 5(1), 388-412. https://doi.org/10.32628/GISRRJ203359
97) Liadi, K. O. (2023a). A model for linking Nigeria's diplomatic engagement to sustainable development outcomes in ECOWAS states. Gyanshauryam, International Scientific Refereed Research Journal, 6(3), 392-420.
98) Liadi, K. O. (2023b). An economic interdependence model of Nigeria-China relations and its effects on industrial growth and infrastructure. Shodhshauryam, International Scientific Refereed Research Journal, 6(4), 570-599. https://doi.org/10.32628/SHISRRJ236175
99) Liadi, K. O. (2023c). Designing an oil diplomacy diversification model: Assessing the shift from petroleum influence to broader economic engagement. Shodhshauryam, International Scientific Refereed Research Journal, 6(3), 418-447. https://doi.org/10.32628/SHISRRJ236925
100) Liadi, K. O. (2024a). A soft power projection framework: Education, cultural diplomacy, and regional development in Nigeria's foreign policy. Gyanshauryam, International Scientific Refereed Research Journal, 7(2), 241-268.
101) Liadi, K. O. (2024b). Conceptualizing a governance reform impact model for Nigeria's peacekeeping missions in post-conflict states. International Journal of Advanced Multidisciplinary Research and Studies, 4(1), 1622-1636.
102) Lilian, I. N., Liadi, K. O., & Yeboah, T. J. (2024). Multilingual ecofeminism and environmental justice: Rethinking gender, language, and ecology in global contexts. Journal of Humanities and Social Policy, 10(6), 195-222. https://doi.org/10.56201/jhsp.v10.no6.2024.pg195.222
103) Lilian, I. N., Liadi, K. O., & Yeboah, T. J. (2025a). Intersectionality, language, and identity: Multilingual perspectives on inclusion and social justice. Iconic Research and Engineering Journals, 8(9), 1761-1788. https://doi.org/10.64388/IREV8I9-1713695
104) Lilian, I. N., Liadi, K. O., & Yeboah, T. J. (2025b). Language and collaboration across the humanities and social sciences: Addressing global challenges through multidisciplinary dialogue. Iconic Research and Engineering Journals, 9(1), 2024-2050. https://doi.org/10.64388/IREV9I1-1713696
105) Mbonu, I. S., Aliliele, C., Iwuanyanwu, U., & Uzoka, E. (2022). A conceptual framework for AI enabled IT general controls and SOX audit automation processes. Gyanshauryam, International Scientific Refereed Research Journal, 5(5), 384-414. https://doi.org/10.32628/GISRRJ2256239
106) Mbonu, I. S., Iwuanyanwu, U., Aliliele, C., & Uzoka, E. (2022a). A review of data protection impact assessment models in multi cloud financial infrastructure systems. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 8(1), 589-623. https://doi.org/10.32628/CSEIT25442
107) Mbonu, I. S., Iwuanyanwu, U., Aliliele, C., & Uzoka, E. (2022b). Advances in cloud identity and access governance optimization in large scale AWS enterprise environments. Shodhshauryam, International Scientific Refereed Research Journal, 5(3), 403-438. https://doi.org/10.32628/SHISRRJ225490
108) Medon, J. J., & Oduleye, T. E. (2022). A comprehensive financial reporting model for strengthening compliance and organizational accountability systems. International Journal of Multidisciplinary Research and Growth Evaluation, 3(6), 768-777.
109) Medon, J. J., & Oduleye, T. E. (2023). Developing a financial planning model for sustainable profitability in dynamic business environments. Shodhshauryam, International Scientific Refereed Research Journal, 6(3), 418-447. https://doi.org/10.32628/SHISRRJ236926
110) Medon, J. J., & Oduleye, T. E. (2024). An integrated predictive analytics model for enhancing strategic financial forecasting and decision accuracy. Gyanshauryam, International Scientific Refereed Research Journal, 7(3), 258-279. https://doi.org/10.32628/GISRRJ247322
111) Michael, O. N., & Ogunsola, O. E. (2022a). Examining the socioeconomic barriers to technological adoption among smallholder farmers in remote rural areas. Shodhshauryam, International Scientific Refereed Research Journal, 5(6), 484-519.
112) Michael, O. N., & Ogunsola, O. E. (2022b). Exploring gender inclusion and equity across agricultural value chains in Sub-Saharan Africa's emerging markets. Gyanshauryam, International Scientific Refereed Research Journal, 5(5), 258-289.
113) Michael, O. N., & Ogunsola, O. E. (2023a). Applying quantitative agricultural economics models to improve food system efficiency and policy decision-making. Shodhshauryam, International Scientific Refereed Research Journal, 6(1), 228-255.
114) Michael, O. N., & Ogunsola, O. E. (2023b). Comparative study of digital platform integration for improving agricultural market access and value chain efficiency. International Journal of Advanced Multidisciplinary Research and Studies, 3(1), 1528-1543.

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https://doi.org/10.62225/2583049X.2023.3.1.5144
115) Michael, O. N., & Ogunsola, O. E. (2023c). Development of predictive data models for enhancing crop resilience and climate adaptation in agrarian economies. International Journal of Advanced Multidisciplinary Research and Studies, 3(1), 1510-1527. https://doi.org/10.62225/2583049X.2023.3.1.5143
116) Michael, O. N., & Ogunsola, O. E. (2024a). Assessing the potential of renewable energy technologies for sustainable irrigation and smallholder farm productivity. International Journal of Scientific Research in Humanities and Social Sciences, 1(1), 380-411.
117) Michael, O. N., & Ogunsola, O. E. (2024b). Developing circular economy frameworks for waste reduction and resource efficiency in agricultural systems. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10(8), 271-300.
118) Michael, O. N., & Ogunsola, O. E. (2025a). Advancing rural agribusiness innovation strategies for building climate-resilient and economically inclusive communities. Journal of Social Science and Human Research Studies, 1(5), 161-177. https://doi.org/10.65150/EP-jsshrs/V1E5/2025-02
119) Michael, O. N., & Ogunsola, O. E. (2025b). Agribusiness diversification strategies for managing economic volatility in resource-constrained agricultural economies. Iconic Research and Engineering Journals. [Incomplete record; volume, issue, and pages not given in source, verify on profile.]
120) Michael, O. N., & Ogunsola, O. E. (2025c). Assessing the role of artificial intelligence in transforming decision-making across modern agricultural systems. Engineering and Technology Journal, 10(12), 8027-8048. https://doi.org/10.47191/etj/v10i12.06
121) Michael, O. N., & Ogunsola, O. E. (2025d). Evaluating the impact of sustainable agriculture curriculum integration on STEM education and career outcomes. Journal of Social Science and Human Research Studies, 1(5), 178-194. https://doi.org/10.65150/EP-jsshrs/V1E5/2025-03
122) Monye, S. I., Bello, K. A., Omotehinse, S. A., Ikumapayi, O. M., Tawose, O. M., Adeleke, T. B., Awogbemi, O., Monye, N. S., & Boboye, O. (2025). Achieving energy sustainability in Nigeria's telecommunications industry through renewable propane. NIPES Journal of Science and Technology Research, 7(2), 3320-3325. https://doi.org/10.37933/nipes/7.4.2025.SI398
123) Monye, S. I., Daniyan, I. A., Monye, N. S., Ikumapayi, O. M., Bello, K. A., Boboye, O., Awogbemi, O., Tawose, O. M., & Adesoji, A. A. (2025). Hydrogen infrastructure for a sustainable future: Challenges, innovations, and global opportunities. NIPES Journal of Science and Technology Research, 7(2), 3302-3308. https://doi.org/10.37933/nipes/7.4.2025.SI395
124) Obi, L. I., Dogbanya, G., Awah, L. C., Tawose, O. M., Ubani, C., Ayo-ige, A. B., Odedele, M., & Edafeadhe, O. (2025). A systematic analysis of effectiveness of nurse-led dementia care interventions on health outcomes among community-dwelling older adults. Journal of Pharma Insights and Research, 3(5), 24-33. https://doi.org/10.69613/3f5cq717
125) Obogo, S. F., Arumosoye, O. M., & Obriki, O. D. (2024). Review of sustainable environmental practices in occupational safety management systems. International Journal of Scientific Research in Civil Engineering, 8(3), 164-196. https://doi.org/10.32628/IJSRCE248420
126) Obogo, S. F., Nwafor, M. I., & Ozobu, C. O. (2023). Conceptual leadership model for safety culture development in construction and engineering projects. International Journal of Scientific Research in Civil Engineering, 7(6), 121-153. https://doi.org/10.32628/IJSRCE237554
127) Obogo, S. F., Obriki, O. D., & Arumosoye, O. M. (2022). Conceptual safety governance model for large commercial facility operations. Gyanshauryam, International Scientific Refereed Research Journal, 5(6), 383-410. https://doi.org/10.32628/GISRRJ225639
128) Obogo, S. F., Ozobu, C. O., & Nwafor, M. I. (2024). Conceptual environmental safety compliance framework for construction and infrastructure projects. International Journal of Scientific Research in Civil Engineering, 8(3), 132-163. https://doi.org/10.32628/IJSRCE248419
129) Obogo, S. F., Ozobu, C. O., Garba, B. M. P., & Adio, S. A. (2026). Predictive safety analytics model for early detection of high-risk construction activities. Global Journal of Engineering and Technology Review, 2(3), 92-109. https://doi.org/10.65150/EP-gjetr/V2E3/2026-03
130) Obogo, S. F., Ozobu, C. O., Nwafor, M. I., & Adio, S. A. (2025). Advances in hazard identification systems for large scale construction operations. International Journal of Scientific Research in Civil Engineering, 9(6), 37-70. https://doi.org/10.32628/IJSRCE2154969
131) Obogo, S. F., Ozobu, C. O., Sanusi, A. N., & Ajirotutu, R. O. (2025). Conceptual integrated safety management model for multi zone urban infrastructure projects. International Journal of Scientific Research in Civil Engineering, 9(5), 22-55. https://doi.org/10.32628/IJSRCE2593012
132) Obriki, O. D., & Arumosoye, O. M. (2022). Conceptual framework explaining recurrence mechanisms of unsafe behaviors in high-hazard worksites. Shodhshauryam, International Scientific Refereed Research Journal, 5(3), 380-402. https://doi.org/10.32628/SHISRRJ225489
133) Obriki, O. D., & Arumosoye, O. M. (2024a). Conceptual governance framework for subcontractor safety performance management. International Journal of Advanced Multidisciplinary Research and Studies, 4(6), 3020-3033. https://doi.org/10.62225/2583049X.2024.4.6.5894
134) Obriki, O. D., & Arumosoye, O. M. (2024b). Systematic review of incident investigation approaches and prevention-oriented learning in industrial operations. Shodhshauryam, International Scientific Refereed Research Journal, 7(4), 239-263. https://doi.org/10.32628/SHISRRJ247163
135) Obriki, O. D., Arumosoye, O. M., & Obogo, S. F. (2023). Advances in continuous hazard monitoring systems for workplace safety. International Journal of Advanced Multidisciplinary Research and Studies, 3(6), 2742-2759. https://doi.org/10.62225/2583049X.2023.3.6.6075

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136) Obriki, O. D., Arumosoye, O. M., & Ozobu, C. O. (2025). Conceptual model linking leading safety signals to sustained injury-free project performance. International Journal of Scientific Research in Humanities and Social Sciences, 2(3), 233-254. https://doi.org/10.32628/IJSRHSS252342
137) Obriki, O. D., Obogo, S. F., & Arumosoye, O. M. (2022a). Advances in workforce safety training models for operational risk reduction. Gyanshauryam, International Scientific Refereed Research Journal, 5(6), 349-382. https://doi.org/10.32628/GISRRJ225638
138) Obriki, O. D., Obogo, S. F., & Arumosoye, O. M. (2022b). Review of emergency preparedness and evacuation systems in high density commercial buildings. Gyanshauryam, International Scientific Refereed Research Journal, 5(6), 411-438. https://doi.org/10.32628/GISRRJ225640
139) Obriki, O. D., Obogo, S. F., & Arumosoye, O. M. (2023). Review of behavioral safety programs for risk reduction in large workforces. International Journal of Advanced Multidisciplinary Research and Studies, 3(6), 2760-2775. https://doi.org/10.62225/2583049X.2023.3.6.6076
140) Odejobi, O. D., Okonkwo, C. S., Ahiaeke Patrick, M. C., Okeke, O. T., & Mayo, W. (2025). AI-augmented secure software engineering: Leveraging deep learning for autonomous threat detection and mitigation. International Journal of Engineering and Modern Technology, 11(12), 101-121. https://doi.org/10.56201/ijemt.vol.11.no12.2025.pg101.121
141) Oduleye, T. E., & Medon, J. J. (2023a). A predictive model for optimizing cash flow and working capital management in corporations. Gyanshauryam, International Scientific Refereed Research Journal, 6(5), 739-754. https://doi.org/10.32628/GISRRJ236537
142) Oduleye, T. E., & Medon, J. J. (2023b). A quantitative model for measuring the strategic impact of financial analysis on enterprise growth. International Journal of Advanced Multidisciplinary Research and Studies, 3(1), 1663-1672. https://doi.org/10.62225/2583049X.2023.3.1.5334
143) Ogbete, J. C., & Aminu-Ibrahim, A. Y. (2024). Translating healthcare infrastructure investment into measurable population health and diagnostic outcomes. International Journal of Scientific Research in Humanities and Social Sciences, 1(2), 955-985. https://doi.org/10.32628/IJSRSSH242775
144) Ogbete, J. C., Aminu-Ibrahim, A. Y., & Ambali, K. B. (2022). Design standards and operational planning frameworks for scalable blood collection networks. Gyanshauryam, International Scientific Refereed Research Journal, 5(6), 267-300. https://doi.org/10.32628/GISRRJ225635
145) Ogbete, J. C., Aminu-Ibrahim, A. Y., & Ambali, K. B. (2023). Lifecycle performance evaluation of purpose built diagnostic laboratories supporting long term healthcare delivery. International Journal of Advanced Multidisciplinary Research and Studies, 3(6), 2605-2621. https://doi.org/10.62225/2583049X.2023.3.6.5698
146) Ogbete, J. C., Aminu-Ibrahim, A. Y., & Iwuanyanwu, O. C. (2025a). Digital and BIM enabled coordination methods for delivering complex medical facility projects. International Journal of Advanced Multidisciplinary Research and Studies, 5(6), 1991-2010. https://doi.org/10.62225/2583049X.2025.5.6.5701
147) Ogbete, J. C., Aminu-Ibrahim, A. Y., & Iwuanyanwu, O. C. (2025b). Integrating healing-centered design principles into diagnostic and laboratory facility planning. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 11(6), 516-553. https://doi.org/10.32628/CSEIT251117149
148) Ogbete, J. C., Aminu-Ibrahim, A. Y., & Iwuanyanwu, O. C. (2026). Scaling molecular diagnostic facilities through standardized infrastructure and operational design models. World Scientific News, 212, 220-258. https://doi.org/10.65770/ZUIY6924
149) Ogbole, J. I., Okoruwa, P. O., Fadayomi, O., Akeju, B., Edivri, J., & Abolaji, T. O. (2025). Security analytics and digital forensics for enterprise risk management, advances and practical implications. International Journal of Advanced Multidisciplinary Research and Studies, 5(6), 2017-2028.
150) Ogbona, C. S., Bobga, M. A., Boakye, K., & Yeboah, T. J. (2024). Leadership practices supporting Black student-athletes' mental health in collegiate sport: A qualitative inquiry. International Journal of Multidisciplinary Research and Growth Evaluation, 5(5), 1192-1208. https://doi.org/10.54660/.IJMRGE.2024.5.5.1192-1208
151) Okonkwo, C. S., Agbabiaka, J., Mayo, W., & Okeke, O. T. (2024a). Conceptual framework for digital supply chain governance in energy and infrastructure sectors. Gyanshauryam, International Scientific Refereed Research Journal, 7(4), 335-356. https://doi.org/10.32628/GISRRJ247423
152) Okonkwo, C. S., Agbabiaka, J., Mayo, W., & Okeke, O. T. (2024b). Framework for secure and scalable supply chain systems supporting national energy reliability. International Journal of Advanced Multidisciplinary Research and Studies, 4(6), 2816-2826. https://doi.org/10.62225/2583049X.2024.4.6.5494
153) Okonkwo, C. S., Agbabiaka, J., Mayo, W., & Okeke, O. T. (2024c). Model for predictive procurement planning to sustain operational uptime. International Journal of Scientific Research in Humanities and Social Sciences, 1(2), 909-928. https://doi.org/10.32628/IJSRSSH242772
154) Okonkwo, C. S., Agbabiaka, J., Okeke, O. T., & Mayo, W. (2025). Framework for national-scale supply chain optimization through integrated IT and procurement systems. Gulf Journal of Advance Business Research, 3(12), 1610-1625. https://doi.org/10.51594/gjabr.v3i12.189
155) Okoruwa, P. O., Babatope, O. M., Akokodaripon, D. A., & Akinleye, O. K. (2025). Digital procurement transformation approaches for strengthening efficiency in global supply chain management. International Journal of Multidisciplinary Research and Growth Evaluation, 6(5), 975-985.
156) Okwah, M. N. (2022). Integrating triglyceride-glucose index and echocardiographic parameters for improved cardiovascular risk stratification in Sub-Saharan Africa. International Journal of Cardiology, 1(2), 1-16. https://doi.org/10.34218/IJC_01_02_001

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157) Okwah, M. N., Abah, M. A., Oladosu, M. A., Blessing, T. B., Anku, A. I., & Agida, O. D. (2026). Anti-inflammatory effects of omega-3 fatty acids: Evidence from circulating biomarkers and inflammatory gene-expression studies. African Research Reports, 2(4), 365-382. https://doi.org/10.65221/0167
158) Olaogun, B. O., Adesuyi, M. O., Akomolafe, O., Ndukwe, V. U., & Sakyi, J. K. (2025). Macroeconomic impact model for blockchain-enabled payment adoption in emerging economies. International Journal of Multidisciplinary Research and Growth Evaluation, 6(6), 835-853. https://doi.org/10.54660/.IJMRGE.2025.6.6.835-853
159) Oluwadele, J. F., Aganga, A. A., Ekeocha, A. H., Tawose, O. M., Adetumbi, T., Akinlabi, E. Y., & Gode, D. (2025). Effect of feeding selected farm residues on growth performance, digestibility and nitrogen balance of West African dwarf bucks. Journal of Applied Life Sciences and Environment, 58(1), 33-41. https://doi.org/10.46909/alse-581163
160) Oluwadele, J. F., Samuel, O., Tawose, O. M., Ekeocha, A. H., & Adika, A. O. (2025). Evaluation of alternative energy sources to replace maize in Marshall broiler diets: Effects on growth performance, meat quality, and serum biochemistry. EUREKA: Life Sciences. https://doi.org/10.21303/2504-5695.2025 [Author list truncated in source; verify full authorship.]
161) Oluwadele, J. F., Tawose, O. M., Akinlabi, E. Y., Ekeocha, A. H., Odumboni, A. A., Akinboye, J., Gabriel, G. O., Dandara, G. B., & Gode, D. (2025). Optimizing broiler diets with dietary fiber: Impact on growth performance, carcass characteristics, and sensory evaluation. Journal of the Selva Andina Animal Science. https://doi.org/10.36610/j.jsaas.20252324
162) Oluwadele, J. F., Tawose, O. M., Ekeocha, A. H., Adika, O. A., Arowosegbe, P. D., & Akinlabi, E. Y. (2025). Alternative feeds for West African dwarf rams: A cost-benefit relationship and their long-term effect. Journal of the Selva Andina Animal Science, 12(1), 45-57. https://doi.org/10.36610/j.jsaas.2025.120100045
163) Omo Enabulele, A. B., Oyebamiji, I., Ikubanni, O., Okwah, M. N., Babalola, W. S., Azeez, O. M., & Olaniyi, A. O. (2025). A coordinated project-management approach to multisite implementation of motor-rehabilitation programs for children with autism spectrum disorder in United States healthcare systems: A narrative review. Cureus, 17(12), e100513. https://doi.org/10.7759/cureus.100513
164) Onche, V. O., Adegbite, M. P., & Ogbonna, C. S. (2026). Human factors in information security: A capability framework for administrative professionals in the digital workplace. World Journal of Innovation and Modern Technology, 10(5), 154-179. https://doi.org/10.56201/wjimt.v10.no5.2026.pg154.179
165) Onwubuya, L. I., Fawehinmi, Y. O., Sunday, D., Igwenagu, M. O., Adeniran, A. O., & Agyapong, E. A. (2026). Adaptive learning systems powered by artificial intelligence for STEM education improvement. Asian Journal of Education and Social Studies, 52(6), 553-566. https://doi.org/10.9734/ajess/2026/v52i63115
166) Onwuzurike, M. A. & Enyejo, J. O. (2026). A Business Intelligence Framework for AI Powered Educational Platforms Linking Learning Analytics to Strategic Decision Making in K-12 Schools International Journal of Recent Research in Commerce Economics and Management (IJRRCEM) Vol. 13, Issue 2, pp: (21-42), DOI: https://doi.org/ 10.5281/zenodo.19510038
167) Onwuzurike, M. A. & Kpogli, S. A. (2025). Predictive Modeling of Student Engagement and Behavioral Outcomes Using Machine Learning Techniques in Technology-Enhanced Classrooms International Journal of Scientific Research in Humanities and Social Sciences Volume 2, Issue 6, 58-79 doi : https://doi.org/10.32628/IJSRHSS2525135
168) Onwuzurike, M. A. (2023). Human-Centered Design of Intelligent Tutoring Systems Integrating Behavioral Analytics and Inclusive Pedagogical Principles for Early Learners International Journal of Scientific Research in Science, Engineering and Technology Volume 10, Issue 3, Page Number 720-738, doi : https://doi.org/10.32628/IJSRSET2310330
169) Onwuzurike, M. A., & Kpogli, S. A. (2022). Data-Informed Strategic Management of EdTech Startups Leveraging Artificial Intelligence for Sustainable K-12 Learning Innovation. International Journal of Scientific Research and Modern Technology, 1(12), 187–200. https://doi.org/10.38124/ijsrmt.v1i12.1117
170) Onwuzurike, M. A., & Raphael, F. O. (2025). Ethical Governance Models for Artificial Intelligence Deployment in K–12 Education: Balancing Algorithmic Personalization, Accountability and Child Protection Policy. International Journal of Scientific Research and Modern Technology, 4(8), 193–208. https://doi.org/10.38124/ijsrmt.v4i8.1271
171) Onwuzurike, M. A., Enyejo, J. O. & Peter-Anyebe, A. C. (2026). Design And Evaluation Of Real Time Adaptive Learning Algorithms For Personalized K-12 Curriculum Optimization Using Student Performance Analytics. World Journal of Advance Multidisciplinary Research, 3(3), Pg. 21-36 https://doi.org/10.5281/zenodo.19131296
172) Onwuzurike, M. A., Igba, E. (2023). Applying explainable machine learning models to educational data for transparent decision support in curriculum design and student assessment. Journal of Frontiers in Multidisciplinary Research. 2023;4(1):585–599. doi:10.54660/.JFMR.2023.4.1.585-599
173) Oteri, O., & Edivri, J. (2026). An operational reliability and service assurance framework for enterprise IT systems supporting large user populations. Gulf Journal of Engineering and Technology, 2(1), 1-19. https://doi.org/10.51594/gjet.v2i1.205
174) Oyeleye, A. O., Dogbatsey, E. A., & Ebhojie, O. (2025). Embedding automated close controls in public sector ERP systems: A conceptual model for audit readiness and financial reporting quality. Zenodo. https://doi.org/10.5281/zenodo.20097950 [Originally numbered 2(1), 110-130; journal name not captured in source.]
175) Oyeleye, A. O., Eyetsemitan, R. A., Ambali, K. B., & Fadayomi, O. (2022). Reducing client onboarding cycle time in small professional services firms: A Lean Six Sigma process redesign framework. Gyanshauryam, International Scientific Refereed Research Journal, 5(2), 467-498. https://doi.org/10.32628/GISRRJ225357
176) Ozowara, D. E., Adebayo, A., & Anunagba, C. O. (2022). A systematic review of cybersecurity investments and their impact on healthcare financial performance. Shodhshauryam, International Scientific Refereed Research Journal, 5(1), 404-427.
177) Ozowara, D. E., Adebayo, A., & Anunagba, C. O. (2025). Advanced conceptual model for strengthening audit quality using data analytics across financial institutions. International Journal of Advanced Multidisciplinary Research and Studies, 5(6), 2246-2268. https://doi.org/10.62225/2583049X.2025.5.6.6050

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178) Ozowara, D. E., Anunagba, C. O., & Adepoju, P. A. (2025). A review of ransomware economics and financial resilience strategies in hospital networks. International Journal of Advanced Multidisciplinary Research and Studies, 5(6), 2284-2298. https://doi.org/10.62225/2583049X.2025.5.6.6052
179) Quainoo, R., & Ogundapo, O. (2026a). A system-level power behavior model for Bluetooth and Wi-Fi coexistence in dual-mode wireless devices. International Journal of Computer Science and Mathematical Theory, 12(2), 298-358. https://doi.org/10.56201/ijcsmt.vol.12.no2.2026.pg298.358
180) Quainoo, R., & Ogundapo, O. (2026b). Wireless system-on-chip performance in next-generation Internet of Things devices: A systematic review of integrated transceiver testing methodologies. World Journal of Innovation and Modern Technology, 10(5), 76-126. https://doi.org/10.56201/wjimt.v10.no5.2026.pg76.126
181) Quainoo, R., Ogundapo, O., & Asiedu, W. A. (2025a). Predicting throughput degradation in Wi-Fi 6 networks under varying channel conditions: A physical layer performance model. International Journal of Engineering and Modern Technology, 11(12), 205-264. https://doi.org/10.56201/ijemt.vol.11.no12.2025.pg205.264
182) Quainoo, R., Ogundapo, O., & Asiedu, W. A. (2025b). Test automation in wireless hardware engineering: A comprehensive review of scripting frameworks and instrument control strategies. International Journal of Engineering and Modern Technology, 11(10), 405-464. https://doi.org/10.56201/ijemt.vol.11.no10.2025.pg405.464
183) Sanni, J. O. (2026a). Artificial intelligence driven demand forecasting models addressing volatility in complex service organizations. Computer Science & IT Research Journal, 7(1), 1-26. https://doi.org/10.51594/csitrj.v7i1.2170
184) Sanni, J. O. (2026b). Integrated advertising and marketing framework for U.S. retail growth. International Journal of Marketing and Communication Studies, 10(1), 12-36. https://doi.org/10.56201/ijmcs.v10.no1.2026.pg12.36
185) Sanni, J. O. (2026c). Marketing analytics frameworks addressing governance risk compliance decision making gaps for executives. International Journal of Marketing and Communication Studies, 10(1), 37-64. https://doi.org/10.56201/ijmcs.v10.no1.2026.pg37.64
186) Sanni, J. O. (2026d). Predictive marketing frameworks resolving revenue attribution conflicts in regulated professional services environments. World Scientific News, 212, 52-81. https://doi.org/10.65770/QPHC9342
187) Sanni, J. O., Atima, M. E., & Attah, A. (2022). Systematic review of attribution modeling methods resolving bias in multi-touch journeys. Shodhshauryam, International Scientific Refereed Research Journal, 5(1), 304-334. https://doi.org/10.32628/SHISRRJ247135
188) Sanni, J. O., Iwuanyanwu, U. A., & Essien, M. A. (2025). Problem-oriented process mining for auditable marketing automation lifecycle control. International Journal of Advanced Multidisciplinary Research and Studies, 5(6), 1933-1947. https://doi.org/10.62225/2583049X.2025.5.6.5650
189) Sanni, J. O., Iwuanyanwu, U. A., & Essien, M. A. (2026). Designing explainable AI based marketing automation architectures for healthcare and financial applications. World Scientific News, 213, 119-148. https://doi.org/10.65770/MJFK8593
190) Sanni, J. O., Iwuanyanwu, U. A., Essien, M. A., Atima, M. E., & Attah, A. (2022). Adaptive control models for AI-driven marketing automation in financial compliance environments. Shodhshauryam, International Scientific Refereed Research Journal, 5(1), 243-270. https://doi.org/10.32628/SHISRRJ247133
191) Sunday, E. A., & Omoegun, G. O. (2022). Smart fault detection in HVAC systems using sensor-based monitoring. International Journal of Scientific Research in Science, Engineering and Technology, 7(4), 380-403.
192) Tawose, O. M., & Oluwadele, J. F. (2025). Comparative analysis of the nutritional potentials of selected tuber peel meals as feed supplements for ruminant animals. Nigerian Journal of Agriculture and Agricultural Technology, 5(3A). https://njaat.com.ng/index.php/njaat/article/view/1169
193) Tonoyan, A., Dada, O., & Ayivi-Donkor, S. S. (2022a). Advances in geospatial analysis: Predictive analytics methods for store location selection and market entry return on investment. International Journal of Marketing and Communication Studies, 6(2), 78-105. https://doi.org/10.56201/ijmcs.v6.no2.2022.pg78.105
194) Tonoyan, A., Dada, O., & Ayivi-Donkor, S. S. (2022b). Algorithmic process optimization and cost reduction: A review of simulation modeling and financial impact assessment. Journal of Accounting and Financial Management, 8(8), 139-169. https://doi.org/10.56201/jafm.vol.8.no8.2022.p139.169
195) Tonoyan, A., Dada, O., & Ayivi-Donkor, S. S. (2022c). Conceptual model for predictive cost optimization: Machine learning applications in business transformation analysis. International Journal of Economics and Business Management, 8(6), 68-102. https://doi.org/10.56201/ijebm.v8.no6.2022.pg68.102
196) Tonoyan, A., Dada, O., & Ayivi-Donkor, S. S. (2025). A conceptual model for real-time route optimization: Algorithmic pathways to delivery profitability and logistics cost reduction. World Journal of Innovation and Modern Technology, 9(12), 308-364. https://doi.org/10.56201/wjimt.v9.no12.2025.pg308.364
197) Tonoyan, A., Dada, O., & Ayivi-Donkor, S. S. (2026). Conceptual framework for financial brand architecture optimization: Portfolio analysis and economic value maximization. Gulf Journal of Advance Business Research, 4(3), 145-164.
198) Walawalkar, G., Oduleye, T. E., Adesuyi, M. O., & Kalu, A. (2026). Next-generation financial analytics frameworks for AI-enabled enterprises. International Journal of Advanced Multidisciplinary Research and Studies, 6(1), 1779-1791.
199) Yeboah, T. J., Bobga, M. A., Boakye, K., & Ogbona, C. S. (2022). Data-driven teaching: Using student progress data to personalize learning in special education classrooms. Journal of Frontiers in Multidisciplinary Research, 3(2), 225-240. https://doi.org/10.54660/.JFMR.2022.3.2.225-240
200) Yusuf, I. A., Badero, O. J., Ihesiulo, A., Okwah, M. N., Oshodin, A., & Asikong, E. (2026). Aldosterone synthase inhibitors in uncontrolled and resistant hypertension: A phenotype-stratified systematic review and network meta-analysis of randomized trials. PLOS ONE, 21(6), e0349932. https://doi.org/10.1371/journal.pone.0349932

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