BIAS-BLIND BEHAVIORAL PATTERN RECOGNITION FRAMEWORK (BB-BPRF)

CLAIMS

1. A computer-implemented method for bias-free behavioral pattern recognition through individual calibration, comprising: (a) collecting behavioral measurement data during subject interactions operating independently of demographic classifications; (b) establishing statistical baselines by computing mean and variance exclusively from the subject's own observations, and computing within-individual variance $\sigma^2_{individual}$ while not defining or computing any between-group variance; (c) generating calibration coefficients based solely on intra-individual statistics; and (d) applying real-time adjustments to recognition algorithms using the calibration coefficients, wherein recognition is performed only relative to the subject's baseline and behavioral history.

2. The method of claim 1, wherein variance-reduction coefficients are computed solely from the subject's time series by comparing pre-calibration and post-calibration within-individual dispersion, yielding an individual variance-reduction factor $(\sigma^2_{pre} - \sigma^2_{post})/\sigma^2_{post}$.

3. The method of claim 1, wherein between-group variance $\sigma^2_{between}$ is not computed, stored, or represented, such that its value is undefined rather than zero, thereby precluding statistical inference across demographic categories.

4. The method of claim 1, wherein optimization proceeds over an individual's parameter space using a Lipschitz-continuous objective with bounded coefficients, and convergence is declared under a monotone decrease condition on a norm of successive adjustment vectors.

5. The method of claim 1, wherein alerts are generated in a configurable manner, including: (a) routine notifications delivered after completion of a session; (b) urgent notifications delivered in real time during subject interaction; (c) delivery in operational contexts including, but not limited to, those illustrated in the specification; and (d) generation prior to detection of an overt behavioral event.

6. The method of claim 1, wherein applying real-time adjustments comprises comparing current-session measurements to prior-session baselines and to aggregated subject history, thereby enabling detection of deviations relative to both short-term and long-term behavior.

7. The method of claim 1, further comprising compile-time and runtime enforcement that structurally prohibits cross-user operations and ingestion of demographic or group-correlated variables, returning explicit error codes indicative of prohibited operations.

8. The method of claim 1, wherein demographic blindness is achieved by design through structural exclusion of demographic attributes, compile-time enforcement that rejects prohibited feature namespaces, and runtime guards that prohibit ingestion or inference of demographic proxies.

9. The method of claim 1, further comprising generating Ephemeral Initialization Vectors (EIVs) as temporary calibration placeholders during an observation window and discarding the EIVs upon convergence of intra-individual calibration, wherein the EIVs are non-persistent and not reused.

10. The method of claim 9, wherein EIV weighting decays such that $Weight\_EIV \rightarrow 0$ as calibration converges.

11. The method of claim 9, wherein the EIV classification progressively improves confidence at a rate of at least 0.015 per behavioral observation.

12. The method of claim 9, wherein the EIV classification achieves at least 75% confidence within 90 seconds under standard interaction conditions comprising at least two behavioral modalities and natural user engagement.

13. The method of claim 1, wherein baseline calibration further comprises ephemeral initialization vectors evidencing cryptographic initialization without demographic reliance.

14. The method of claim 1, further comprising generating configurable reports including one or more of: baseline calibration statistics, variance stability measures, EIV decay confirmation, and session metadata, wherein report fields and formats are selectable

according to operational requirements and reports exclude protected-class attributes, redact direct identifiers, and reference unlinkable receipt identifiers.

15. The method of claim 1, further comprising collecting system-status data during subject interactions to verify that input devices, sampling rates, and calibration routines operate within defined specifications.

16. The method of claim 1, further comprising performing quality-assurance checks that reject or flag behavioral input streams when sensor integrity, timing accuracy, or feature-extraction performance fall outside defined tolerances.

17. The method of claim 1, wherein establishing the baseline comprises computing context-conditioned statistics using only the subject's own observations and non-demographic session metadata selected from sensor conditions, acquisition quality, task state, and time-of-day, and deriving all thresholds from the subject's within-individual distribution without using external datasets or cross-subject comparisons.

18. The method of claim 1, wherein establishing the baseline comprises initializing with EIVs and updating per-individual parameters by online Bayesian updates over the subject's observed data stream, all comparisons being performed exclusively against the subject's own prior and posterior distributions.

19. The method of claim 1, further comprising computing a drift score as a normalized deviation of current behavior from the established baseline, declaring drift when the drift score exceeds a configured threshold, and initiating recalibration limited to the subject's own observations.

20. The method of claim 1, wherein convergence of intra-individual calibration is determined by a configurable threshold on the change between successive adjustment vectors.

21. The method of claim 1, wherein the real-time adjustments are implemented as low-complexity linear-algebra operations suitable for sub-millisecond per-inference latency on commodity hardware.

22. The method of claim 1, wherein configuring data-collection apparatus to establish individual behavioral baselines applies identically across any behavioral parameter

type, including but not limited to speech, visual, response timing, gesture, keystroke, textual, pointer movement, handwriting, and decision-making inputs.

23. The method of claim 1, wherein a cultural-context module generates $C = [c_1,c_2,c_3,c_4] \in [0,1]^4$ from observable behavior and normalizes each component by either (i) per-individual robust scaling using rolling median and median absolute deviation, or (ii) a demographic-blind reference corpus aggregated from studies that exclude protected-class attributes.

24. The method of claim 1, further comprising integrating human feedback with a bounded weight not exceeding 0.2 of total update influence, combining algorithmic and feedback signals via Bayesian updating, and rejecting any feedback update when a measured correlation between the candidate update and protected-class proxies exceeds a configured threshold.

25. The method of claim 1, wherein multi-modal fusion weights are derived solely from the subject's per-modality within-individual variances and exclude any population priors.

26. The method of claim 1, wherein for text evaluation the system selects prompts from a validated prompt bank, maintains independent per-prompt baselines for the subject, and performs comparisons only within the same prompt, prohibiting cross-prompt normalization.

27. The method of claim 1, wherein establishing the baseline provides an information utilization advantage of at least 6× compared to demographic-based categorization, thereby maintaining permanent O(n) computational complexity with respect to subject population size.

28. The method of claim 27, wherein the information utilization advantage is between 6× and 12× compared to demographic-based categorization.

29. The method of claim 27, wherein the information utilization advantage is at least 10× when utilizing temporal dynamics in behavioral parameters.

30. The method of claim 1, wherein calibration incorporates convergence acceleration such that classification into behavioral ephemeral vectors occurs within approximately

90 seconds and average calibration sessions decrease as the user base increases through network-driven effects.

31. The method of claim 1, wherein meta-learning operates exclusively on calibration process metadata comprising convergence time, iteration count, and success flags, without accessing or aggregating any user behavioral measurements, thereby optimizing algorithmic parameters while maintaining complete user data isolation.

32. The method of claim 1, wherein the exponential reduction in calibration time results from learning optimal algorithmic parameters including EIV decay rates, convergence thresholds, and feature extraction sequences, accomplished without any cross-user behavioral data comparison or aggregation.

33. The method of claim 1, further comprising detecting adversarial behavior by monitoring cross-modal coherence, temporal stability, and physiological plausibility bounds, and flagging sessions where variance exceeds 4× the established individual baseline.

34. The method of claim 33, wherein upon detecting potential adversarial behavior, the method weights historical baseline at least 70% and current session data at most 30% to prevent baseline poisoning.

35. The method of claim 1, further comprising validating behavioral parameters remain within human performance envelopes, excluding invalid parameters from calibration, and terminating sessions where more than 30% of parameters fall outside valid ranges.

36. The method of claim 1, wherein the real-time adjustments require fewer than 100 floating-point operations per inference.

37. A system for bias-free behavioral pattern recognition, comprising: (a) a multi-modal data collection apparatus to capture behavioral inputs from an individual subject; (b) a baseline establishment engine configured to calibrate recognition parameters exclusively to the subject’s within-individual statistics without defining or computing any between-group variance; (c) a cultural-context module generating demographic-blind feature vectors from observable behavior; and (d) a real-time calibration

processor applying adjustment operations to recognition algorithms based solely on the subject's baseline and behavioral history.

38. The system of claim 37, wherein the real-time calibration processor is configured to prohibit cross-user operations such that recognition is performed exclusively within a single-subject context.

39. The system of claim 37, wherein the system is architected without any module, memory structure, or computational path capable of computing between-group variance, such that σ^2_between is undefined and unavailable for inference.

40. The system of claim 37, further comprising a system-integrity module configured to collect status data verifying that input devices, sampling rates, and calibration routines operate within defined specifications.

41. The system of claim 37, further comprising a quality-assurance module configured to monitor sensor integrity, timing accuracy, and feature-extraction performance, and to reject or flag input streams when said parameters deviate from defined tolerances.

42. The system of claim 37, further comprising a reporting module configured to generate configurable reports including one or more of: baseline calibration statistics, variance stability measures, EIV decay confirmation, and session metadata, wherein report fields and formats are selectable according to operational requirements.

43. The system of claim 37, further comprising an EIV generator configured to instantiate temporary calibration placeholders and decay them to zero as σ^2_individual stabilizes.

44. The system of claim 37, wherein baseline calibration further comprises ephemeral initialization vectors evidencing cryptographic initialization without demographic reliance.

45. The system of claim 37, further comprising compile-time and runtime guards that block cross-user operations and return explicit error codes selected from the group consisting of E-NO-COMPARE and E-PROXY-RISK, and a proxy-detector engine that rejects input features correlated with protected-class proxies beyond a configured threshold.

46. The system of claim 37, wherein demographic blindness is achieved by design through architectural exclusion of demographic attributes, compile-time enforcement that blocks prohibited feature paths, and runtime guards that reject demographic or proxy inputs beyond a configured threshold.

47. The system of claim 37, further comprising a manifest and attestation module configured to verify at load-time and runtime that deployed libraries, feature schemas, and configuration files contain no fields designated as protected-class attributes, aborting initialization upon violation.

48. The system of claim 37, wherein the baseline establishment engine and inference pipeline execute within a hardware-backed secure enclave in an offline-first mode that stores only per-subject statistical summaries and discards raw samples after featurization.

49. The system of claim 37, further comprising a notification module configurable to emit (i) routine post-session reports and (ii) urgent real-time alerts during subject interaction, with delivery policies selectable per operational context.

50. The system of claim 37, further comprising a research-ingestion gate that admits external reference parameters only if associated studies satisfy pre-defined quality criteria including minimum sample size, peer-review status, and reliability thresholds, and that excludes any inputs containing protected-class stratification.

51. The system of claim 37, further comprising a cryptographic receipt generator configured to issue blind-signed, unlinkable receipts per inference, said receipts being verifiable independently while remaining unlinkable across sessions.

52. The system of claim 37, wherein an adjustment calculation engine applies mathematically orthogonal vectors comprising: (a) an amplification vector A implemented as a diagonal matrix; (b) a dampening vector D with per-dimension coefficients; (c) a threshold vector T implementing adaptive shifts of $\pm k \cdot \sigma\_individual$ with k determined by demographic-blind contextual features; and (d) a relationship matrix R with bounded off-diagonal correlations; wherein orthogonality is verified by

bounded dot-products among A, D, and T, enabling independent optimization in behavioral subspaces.

53. The system of claim 52, wherein linear-algebra operations comprise a transformation $X\_adjusted = A \bullet (D \circ X) + T + R \bullet X$ and are implemented with low-complexity kernels optimized via vectorized instructions and cache-aligned memory to provide low-latency inference.

54. The system of claim 37, wherein the baseline establishment engine achieves at least a 6× information utilization advantage relative to demographic-based categorization, maintaining permanent O(n) computational complexity with respect to subject population size.

55. The system of claim 54, wherein the information utilization advantage is between 6× and 12×.

56. The system of claim 54, wherein the information utilization advantage is at least 10× when utilizing temporal dynamics in behavioral parameters.

57. The system of claim 37, wherein the real-time calibration processor executes adjustment operations as low-complexity linear-algebra kernels with sub-millisecond per-inference latency on commodity hardware.

58. The system of claim 37, wherein the baseline establishment engine and calibration processor implement convergence acceleration, enabling exponential reduction in calibration sessions by combining rapid ephemeral initiation vector recognition with network-driven scaling effects.

59. The system of claim 37, wherein network effects arise from aggregating only calibration process performance metrics to optimize algorithm parameters, specifically excluding any aggregation of user behavioral data, such that no user's behavioral patterns influence another user's calibration.

60. The system of claim 37, further comprising an adversarial detection module configured to identify intentional falsification through statistical anomaly detection, cross-modal inconsistency analysis, and physiological plausibility validation.

61. The system of claim 60, wherein the adversarial detection module implements Sequential Probability Ratio Testing (SPRT) for real-time change detection and Mahalanobis distance calculation for multivariate anomaly detection.

62. A non-transitory computer-readable medium storing instructions that, when executed by a processor, cause the processor to perform a method comprising: (a) collecting behavioral measurement data during subject interactions without requesting or inferring protected-class attributes; (b) establishing statistical baselines by computing mean and variance exclusively from the subject's own observations, and computing within-individual variance $\sigma^2\_individual$ while not defining or computing any between-group variance; (c) generating calibration coefficients based solely on intra-individual statistics; and (d) applying real-time adjustments to recognition algorithms using the calibration coefficients, wherein recognition is performed only relative to the subject's baseline and behavioral history.

63. The non-transitory computer-readable medium of claim 62 wherein the instructions further cause a processor to collect system-status data and to perform quality-assurance checks rejecting or flagging behavioral input streams when sensor integrity, timing accuracy, or feature-extraction performance fall outside defined tolerances.

64. The non-transitory computer-readable medium of claim 62, wherein the instructions further cause a processor to prohibit cross-user operations such that recognition is performed exclusively within a single-subject context.

65. The non-transitory computer-readable medium of claim 62, wherein the instructions further cause a processor to generate configurable reports including one or more of: baseline calibration statistics, variance stability measures, EIV decay confirmation, and session metadata, with report fields and formats selectable according to operational requirements and with redaction of direct identifiers and use of unlinkable receipt identifiers.

66. The non-transitory computer-readable medium of claim 62, wherein the instructions further cause a processor to bound human-feedback influence to a maximum weight,

to combine feedback with algorithmic assessments via Bayesian updating, and to reject updates correlated with protected-class proxies above a configured threshold.

67. The non-transitory computer-readable medium of claim 62, wherein the instructions further cause a processor to select prompts from a prompt bank, maintain per-prompt baselines per subject, and restrict comparisons to within-prompt responses.

68. The non-transitory computer-readable medium of claim 62, wherein the instructions further cause a processor to compute a drift score relative to the subject's baseline, trigger recalibration when the score exceeds a threshold, and log an unlinkable audit receipt for each recalibration event.

69. The non-transitory computer-readable medium of claim 62, wherein the instructions further cause a processor to perform startup attestation of libraries and configuration against a policy that forbids protected-class fields and to halt execution upon violation.

70. The non-transitory computer-readable medium of claim 62, wherein the instructions further cause a processor to generate ephemeral initialization vectors evidencing cryptographic initialization without demographic reliance.

71. The non-transitory computer-readable medium of claim 62, wherein the instructions further cause a processor to achieve demographic blindness by design through structural exclusion of demographic attributes, compile-time rejection of prohibited features, and runtime guards preventing ingestion or inference of demographic proxies.

72. The non-transitory computer-readable medium of claim 62, wherein the instructions further cause a processor to achieve an information utilization advantage of at least 6× relative to demographic-based categorization, maintaining permanent O(n) computational complexity with respect to subject population size.

73. The medium of claim 72, wherein the information utilization advantage is between 6× and 12×.

74. The medium of claim 72, wherein the information utilization advantage is at least 10× when utilizing temporal dynamics in behavioral parameters.

75. The non-transitory computer-readable medium of claim 62, wherein the instructions further cause a processor to implement low-complexity linear-algebra operations with sub-millisecond inference latency on commodity hardware.

76. The non-transitory computer-readable medium of claim 62, wherein the instructions further cause a processor to perform convergence acceleration such that calibration sessions required for stability decrease with system growth through behavioral ephemeral initiation vector recognition and network-driven scaling.