

Performance Metrics Design and Implementation for the Cultural Genealogy Protocol (CGP)

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Abstract- The Cultural Genealogy Protocol (CGP), conceived and designed by Dr. Bayomock Linwa Andre Claude and published in IJSET (2026, Vol. 14, Issue 1), defines a comprehensive framework for African-centered genealogy management. A first implementation of the CGP platform was produced by Mr. Coulibaly Monpi Kapo Darrell at IUGB, establishing the foundational data management infrastructure. However, the performance metrics module explicitly specified in the CGP protocol as a core objective had not yet been implemented. This article presents the design, mathematical formalization, and prototype implementation of this metrics framework as a contribution intended for integration into the existing CGP platform. Eight statistically grounded metric groups are introduced, covering demographic analysis, matrimonial statistics, longevity indexes, name frequency analysis with phonetic similarity detection, and paternal branch elder identification. A dual-perspective analytics dashboard is described, and validation results obtained on a 22-member, four-generation dataset are reported. All metrics were computed in under 300 milliseconds, confirming the feasibility and correctness of the proposed approach.

Keywords: Cultural Genealogy Protocol, CGP, performance metrics, African genealogy, statistical dashboard, tree analytics.

I. INTRODUCTION

Genealogy, defined as the study and tracing of lines of descent, represents a fundamental dimension of cultural identity across human societies. In many African communities, family lineage knowledge is preserved through oral tradition, carried by designated elders and griots who serve as living repositories of ancestral memory. This mode of transmission, while culturally rich, is inherently fragile: when an elder passes away without a designated successor, entire branches of family history may be permanently lost. The UNESCO Charter on the Preservation of Digital Heritage (2003) [9] emphasizes the urgency of digitizing such intangible cultural assets before they disappear. The digital revolution offers an unprecedented opportunity to complement this tradition by providing structured, searchable, and durable storage for genealogical data.

Existing commercial genealogy platforms, including Ancestry.com, MyHeritage, and FamilySearch, have been predominantly designed around Western nuclear family models. As documented by Bayomock and Coulibaly (2026), these platforms fail to

accommodate polygamous union structures, ethnic group affiliations, family group traceability, and the cultural complexities that define African genealogical identity. To address this gap, Dr. Bayomock Linwa Andre Claude conceived and formally published the Cultural Genealogy Protocol (CGP), a comprehensive data model and architecture for African-centered genealogy management, in the International Journal of Science, Engineering and Technology (IJSET, 2026, Vol. 14, Issue 1).

A first implementation of the CGP platform was produced by Mr. Coulibaly Monpi Kapo Darrell as his capstone project at IUGB. That work established the foundational infrastructure: account management, family tree creation following the CGP main flow, person registration with cultural metadata, partner and child management, and the database schema. The platform as it stood after that initial implementation constitutes the reference system upon which the present contribution builds.

The CGP protocol paper (Bayomock and Coulibaly, 2026) explicitly lists a set of performance statistics as a core platform objective, including persons per family group and ethnic group, name frequency variance, average lifespan, children per couple,

doyen identification, and percentage distributions of cultural affiliations. None of these had been implemented in the existing platform at the time of this work. The present article addresses this gap: it describes the design, mathematical formalization, and prototype implementation of a performance metrics framework developed for integration into the CGP platform. This work is conducted under the supervision and intellectual ownership of Dr. Bayomock Linwa Andre Claude, to whom the CGP platform and all associated intellectual contributions belong.

This article is organized as follows. Section II presents the motivations. Section III reviews related literature. Section IV defines the problem and objectives. Section V describes the CGP as the foundation of this implementation. Section VI presents the performance metrics framework with mathematical formulations. Section VII describes the global architecture. Section VIII presents the metric visualizations and dashboard. Section IX details the implementation. Section X reports results. Section XI presents the integration roadmap and future directions. Section XII concludes.

II. MOTIVATIONS

The motivations for this contribution arise from three converging factors: a documented gap in the existing CGP platform, the explicit statistical objectives of the CGP protocol specification, and the cultural importance of quantitative insights for African family heritage management.

The CGP protocol paper (Bayomock and Coulibaly, 2026, Section IV) lists seventeen statistics as part of the platform objectives. These include finding persons per family group or ethnic group with filters on gender and name, counting distinct persons per group, computing name variance, finding the average death age per family tree, counting children per couple, identifying the number of fathers or mothers with or without children, and computing family group and ethnic percentage distributions per person. The existing CGP platform, as delivered by Mr. Coulibaly, covers the core data management flows but does not yet include any of these statistics.

From a technical standpoint, formalizing these statistics as mathematical expressions and implementing them as a computation engine provides a testable, reproducible realization of the statistical objectives defined in the original publication. The metrics presented in this work extend and deepen those listed in the CGP paper, introducing additional indicators such as a longevity index by gender, an average age at first marriage by gender, phonetic name similarity grouping, and a paternal branch elder identification algorithm.

From a cultural standpoint, African families and researchers benefit from quantitative insights that no existing platform provides in a culturally adapted context. Knowing the generational depth of a tree, the gender distribution across generations, the marriage patterns within a family, or the identity of the eldest living ancestor in the paternal branch are all meaningful pieces of information for African families seeking to understand and document their heritage. The doyen concept, in particular, reflects a core African social institution: the recognized elder whose wisdom and memory anchor the family identity. Research by Huston et al. (2025) [29] shows that public engagement through social media significantly improves the quality of genealogical data, supporting the CGP's social group-based information quality improvement objective. Vansina (1985) [10] established that oral tradition constitutes a primary historical source in African societies, underscoring the value of digital systems that preserve and extend such knowledge.

III. LITERATURE REVIEW

The literature on genealogy systems and cultural heritage management can be organized into four categories, following the classification established in the CGP protocol paper (Bayomock and Coulibaly, 2026).

A. The Cultural Genealogy Protocol

The foundational reference for this work is the CGP publication by Bayomock Linwa and Coulibaly (2026) in IJSET (Vol. 14, Issue 1, ISSN 2348-4098). The paper defines a genealogy protocol covering seven key challenges: multi-partner relationships, family and

ethnic group traceability, tree-level navigation, root node reassignment, multimedia integration, social group-based information quality improvement, and relevant statistics. The data model comprises 25 interconnected tables organized across seven domains: Account, Person, Known Unions, Cultural aspects, End of Life, Enrollment, and Transaction. The protocol explicitly identifies a set of statistics as a core objective, and the present article constitutes the implementation of that objective.

The importance of memory and naming practices in shaping genealogical identity is further illustrated by Brzegowy (2025) [30], who traces how heraldic naming traditions evolved across generations of Polish nobility, demonstrating the cross-cultural relevance of name-based genealogical analysis. In the African context specifically, Akumjika Chikamma Michael et al. (2026) [31] examine naming practices among diasporic Igbo communities, showing that first names carry deep socio-pragmatic functions that genealogical systems must preserve, a consideration directly reflected in the phonetic name frequency metric (M7) introduced in this article.

B. Existing Genealogy Platforms

Ancestry.com [17], founded in 1983, is the world's largest for-profit genealogy platform, providing access to billions of historical records. Its collections are heavily biased toward North American and European sources and its data model assumes Western naming conventions and nuclear family structures (Hoitink, 2015) [32]. MyHeritage [18], founded in 2003, offers broader internationalization across 42 languages and integrates machine learning for facial recognition in historical photographs. FamilySearch [19], operated by The Church of Jesus Christ of Latter-day Saints, is the world's largest free genealogy platform. While it has made notable internationalization efforts, none of these platforms support the specific African cultural metadata defined in the CGP: ethnic group hierarchy, family group traceability, or polygamous union modeling.

C. Family History Research and Technology

Shan and Luther (2024) conducted a qualitative human-computer interaction study analyzing how

technology supports genealogy research practices, collaboration, and learning. Their work emphasizes the growing role of digital systems in the professionalization of genealogy, a perspective directly relevant to the analytics contribution of this article. Reher (2024) examines the current state of family history research in historical and social sciences, noting a need for methodological innovation. Shaw et al. (2024) show how DNA testing reshapes genealogical identities through biological evidence, opening perspectives for future CGP integration.

D. Computational and Genetic Genealogy

Wang et al. (2024) detail how next-generation sequencing expands pedigree tracing and kinship inference in forensic contexts. Liu et al. (2024) provide a bibliometric analysis of kinship analysis literature from 1960 to 2023, mapping methodological shifts in analytical genealogy. Schulz and Evans (2025) [25] introduce signature-based approaches to genealogy modeling in computational graphs. Wakano et al. (2025) [26] use population models to study how cultural traits propagate through genealogical structures, linking genealogical dynamics to intergenerational trait transmission, a perspective directly relevant to the ethnic and family group traceability objectives of the CGP. Hage and Harary (1996) [11] provided foundational work on kinship network analysis using graph theory, demonstrating that family structures can be represented as mathematical graphs with measurable properties. These works collectively illustrate the growing convergence of computational methods and genealogical research, a direction that the CGP platform is positioned to support through its structured data model and the analytics capabilities introduced in this contribution.

IV. PROBLEM AND OBJECTIVES

A. Problem Statement

The Cultural Genealogy Protocol defines a comprehensive set of statistics as a platform objective (Bayomock and Coulibaly, 2026, Section IV). The existing CGP implementation, as delivered by Mr. Coulibaly Monpi Kapo Darrell, provides the core genealogical data management infrastructure

but does not include a metrics computation engine, a statistical dashboard, phonetic name analysis, geographic origin visualization, or any of the seventeen statistics listed in the protocol paper. This absence represents a documented gap between the CGP specification and its current implementation.

Beyond the missing metrics, the implementation of the CGP data model in a maintainable, well-documented technology stack was identified as a prerequisite for any future analytics development. The original codebase was developed in a technology stack that was not aligned with the skills available for this contribution. With the endorsement of Dr. Bayomock Andre, a prototype implementation was therefore developed in Python and Django 5.2, which facilitated the clean integration of the metrics module and provides a documented reference for future development cycles.

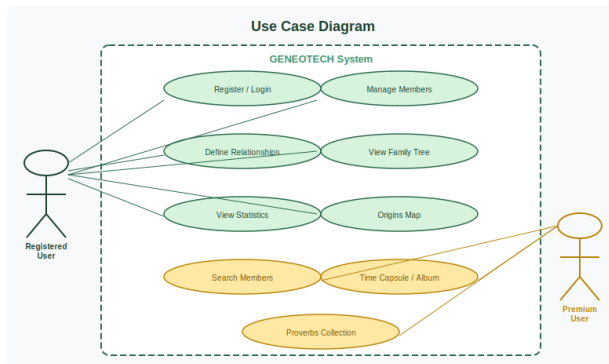


Figure 1. Use Case Diagram — CGP platform actors and functionalities

B. Objectives

The objectives of this contribution are the following. The first objective is to design and formally specify the CGP performance metrics as mathematical expressions, extending the statistics listed in the protocol paper. The second objective is to implement a computation engine, the TreeStatistics class, that calculates all metrics efficiently from the CGP data model. The third objective is to develop interactive visualizations using Chart.js, D3.js, and Leaflet that present the metrics through a dual-perspective dashboard for both family members and administrators. The fourth objective is to validate the metrics on a real dataset and report quantitative results. The fifth objective is to document the metrics

module in a form that facilitates its integration into the existing CGP platform under the direction of Dr. Bayomock Linwa Andre Claude.

It is important to emphasize the scope of this work. The CGP platform itself, its ownership, its long-term roadmap, and its intellectual foundations belong to Dr. Bayomock Linwa Andre Claude. This contribution is a metrics module designed for integration into that existing system, not an independent platform.

V. THE CULTURAL GENEALOGY PROTOCOL: FOUNDATION OF THIS IMPLEMENTATION

All data modeling decisions in this prototype implementation derive directly from the CGP specification published by Bayomock and Coulibaly (2026). The CGP defines 25 interconnected database tables organized across seven domains. Table 1 summarizes the key CGP entities as implemented in the Django prototype.

Table 1. CGP entities as implemented in the Django prototype

CGP Entity	Django Model	Key Attributes
Account / Client	Profile (extends User)	Role (user/premium/admin), share token, premium permissions
Person	FamilyMember	Name, gender, birth/death dates, generation (integer), is_root, ethnic group, birth city/country
Known Unions	Union	Six union types (marriage, civil, traditional, religious, partnership, other); children via ManyToMany; anti-cycle validation

CGP Entity	Django Model	Key Attributes
Cultural aspects	EthnicGroup, Ethnicity, Country, Region	Two-level ethnic hierarchy; hierarchical geographic location

Family Tree	FamilyTree	Visibility (private/family/public); merged-tree support
End of Life	FamilyMember.date_of_death	Living status inferred from absence of death date
Multimedia Heritage	FamilyAlbum, FamilyPhoto, TimeCapsule, FamilyProverb, MemberDocument	Nine document types; time capsule with open date enforcement

The tree creation process follows the CGP Main Flow as defined in the protocol paper (Bayomock and Coulibaly, 2026, Section VI). The hierarchical structure of family trees in relational databases, including anti-cycle constraints and recursive traversal, is discussed in depth by Celko (2012) [7]. Upon account creation, Django signal handlers automatically create a Profile, FamilyTree, and root FamilyMember, implementing steps 1 and 2 of the CGP main flow. The subsequent addition of fathers, mothers, partners, and children follows the CGP protocol exactly, with each action refreshing the tree dashboard. Table 2 summarizes the implementation status of each CGP protocol feature.

Table 2. CGP protocol feature implementation status

CGP Protocol Feature	Status	Implementation Detail
Multi-partner relationships	Implemented	Union model supports 6 union types; multiple simultaneous unions per member; polygamy natively supported
Family and ethnic group traceability	Implemented	EthnicGroup and Ethnicity hierarchy; each FamilyMember linked to ethnic group and ethnicity
Tree-level navigation	Implemented	Generation integer field on FamilyMember; D3.js hierarchical rendering by generation level
Root node reassignment	Implemented	FamilyMember.is_root flag; context processor injects active root into all templates
Multimedia integration	Implemented	MemberDocument (9 types), FamilyPhoto, TimeCapsule with open date gating
Social group / information quality	Implemented	Cross-tree member search with phonetic similarity scoring; FamilyAlbum collaboration
Relevant statistics (CGP-defined)	Implemented (core contribution)	TreeStatistics class with 7 computation methods covering 8 metric groups

Duplicate node detection	Implemented	Duplicate detection view with phonetic skeleton comparison across trees
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VI. PERFORMANCE METRICS DESIGN AND IMPLEMENTATION

This section constitutes the primary academic contribution of this article: the design, mathematical formalization, and prototype implementation of the performance metrics framework for the CGP platform. The metrics extend and formalize the seventeen statistics listed in the CGP protocol paper (Bayomock and Coulibaly, 2026, Section IV).

A. Selection Criteria

The performance metrics were selected and designed according to four criteria. First, alignment with the CGP specification: each metric corresponds to a statistic explicitly listed or implied in the protocol paper. Second, cultural relevance: each metric reflects a concept meaningful in African family culture, such as elder recognition (doyen), ethnic distribution, generational depth, and marriage pattern analysis. Third, computability from the CGP data model: all metrics are derivable from FamilyMember, Union, and related entities without additional data collection. Fourth, interpretability: results must be understandable by non-technical family members as well as by researchers studying African demographic patterns.

B. TreeStatistics Class Architecture

The metrics are implemented in a class named TreeStatistics, located in the models module of the Django application. The class is instantiated per request with a reference to the target FamilyTree object and pre-loads all required data into memory structures to avoid repeated database queries. It exposes a single public method, compute_all(), which returns a structured dictionary containing the results of seven specialized computation methods. The class follows the Facade design pattern as described by Gamma et al. (1994) [13], providing a simplified interface to the underlying metric computation subsystem.: basic demographics, name statistics, demographic analysis, marriage statistics, children

statistics, longevity statistics, and champion identification (doyen).

C. Mathematical Formulations

The following expressions govern each metric group, formally extending the statistics defined in the CGP protocol paper.

M1. Basic Demographics

$$N = |M|$$
$$\text{male\%} = (|M_male| / N) \times 100$$
$$\text{female\%} = (|M_female| / N) \times 100$$

M is the set of all FamilyMember instances in the tree. This metric implements the CGP statistics: count distinct persons per family group and per ethnic group.

M2. Living and Deceased Members

$$\text{alive} = |\{m \text{ in } M : \text{date_of_death} = \text{NULL}\}|$$
$$\text{deceased} = N - \text{alive}$$

Living status is inferred from the absence of a recorded date_of_death, consistent with the CGP EndofLife entity semantics.

M3. Marriage Rate

$$\text{married} = |\{m \text{ in } M : \text{exists } u \text{ in } U_tree :$$
$$(m = u.partner1 \text{ or } m = u.partner2) \text{ and}$$
$$u.partner2 \neq \text{NULL}\}|$$

Computed within the tree scope only. married_pct = married / N x 100. Validation result on test tree: 54.5 percent (12 married out of 22 members).

M4. Average Age at First Marriage

$$a_male = (1 / |A_M|) \times \text{sum}(\text{marriage_year}(m) -$$
$$\text{birth_year}(m)) \text{ for } m \text{ in } A_M$$

Computed separately for males (A_M) and females (A_F). This metric extends the CGP statistic: death average age per family tree. Test results: males 24.7 years, females 21.2 years.

M5. Children per Union

$$C = (1 / |U'|) \times \text{sum}(|\text{children}(u)| \text{ for } u \text{ in } U'$$
$$\text{ where } U' = \{u \text{ in } U_tree : |\text{children}(u)| > 0\}$$

This metric directly implements the CGP statistic: number of children per couple. Also computed separately for male and female children. Test result: 2.5 children per union on average, maximum 4.

M6. Longevity Index

$$C = (1 / |U'|) \times \text{sum}(|\text{children}(u)| \text{ for } u \text{ in } U'$$
$$\text{ where } U' = \{u \text{ in } U_tree : |\text{children}(u)| > 0\}$$

This metric directly implements the CGP statistic: death average age per family tree. Computed by gender. Test results: average 43.6 years (males 40.3, females 48.4). Maximum recorded: 86 years.

M7. Name Frequency and Phonetic Similarity

$$\text{freq}(n) = |\{m \text{ in } M : \text{first_name} = n\}| \text{ sim}(n1, n2)$$
$$= (\text{consonant_skeleton}(n1) =$$
$$\text{consonant_skeleton}(n2))$$

This metric implements the CGP statistic: find names variance. The consonant skeleton is computed by removing all vowels from the name except the first letter. Names sharing the same skeleton are grouped. Test result: Akissi (frequency 2), Koffi (frequency 2), all others unique.

M8. Doyen: Eldest Member of the Paternal Branch

P is the paternal branch collected by recursive depth-

$$\text{doyen_M} = \text{argmax}\{\text{age}(m) : m \text{ in } P, m.\text{gender} = 'M'\}$$
$$\text{doyen_F} = \text{argmax}\{\text{age}(m) : m \text{ in } P, m.\text{gender} = 'F'\}$$

first traversal from the root node through fathers, spouses, and children. Test results: Koffi Yao (75 years, generation -2) and Akissi Kouadio (86 years, generation -2).

VII. GLOBAL ARCHITECTURE INCLUDING PERFORMANCE METRICS

The prototype implementation follows a layered Model-View-Template (MTV) architecture as enforced by the Django 5.2 framework. The performance metrics module is fully integrated at the application and domain layers, as illustrated in Figure 2.

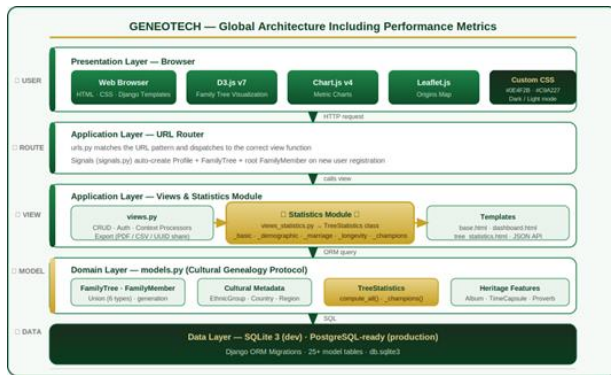


Figure 2. Global Architecture of the CGP Platform Prototype Including the Performance Metrics Module

The architecture is organized into five layers. The presentation layer consists of Django templates extended from a common base template. D3.js (Bostock, 2023) [4] handles family tree rendering in the browser; Chart.js (Chart.js Contributors, 2024) [6] renders the metric charts including donut, bar, and line charts; Leaflet

(Agafonkin, 2023) [5] renders the ancestral origins map. The styling uses a custom CSS design system without any external UI framework.

The application layer is divided into two components. The URL router (urls.py) dispatches HTTP requests to view functions, and Django signal handlers automatically create the initial user profile, family tree, and root member upon account registration, implementing the CGP account creation step. The views and statistics module handles CRUD operations, authentication, and data export through views.py, while the metrics dashboard is managed by a dedicated module (views_statistics.py) that instantiates TreeStatistics, calls compute_all(), and renders the results template. A JSON API endpoint serves metric data for client-side Chart.js rendering, following REST architectural principles supported by the Django REST Framework (2024) [8].

The domain layer contains models.py, which implements the 25-table CGP data model as Django model classes. The TreeStatistics class at the end of this file serves as the computation engine for all metrics. The data layer uses SQLite 3 (SQLite

Consortium, 2024) [15] for the prototype and is designed to be migrated to PostgreSQL for production deployment. The schema is managed through Django ORM migrations.

VIII. METRIC VISUALIZATIONS AND DASHBOARD DESIGN

The metrics computed by TreeStatistics are rendered in a dedicated statistics dashboard. Table 3 maps each metric group to its visualization type.

Table 3. Metric groups and their visualization types

Metric Group	Visualization	Library
Total members, alive, deceased	Summary KPI cards	HTML and CSS
Gender distribution	Donut chart	Chart.js v4
Members per generation	Vertical bar chart	Chart.js v4
Marriage rate and age	Grouped bar chart by gender	Chart.js v4
Children per union	Horizontal bar and summary cards	Chart.js v4
Births and deaths timeline	Grouped bar by decade or year	Chart.js v4
Longevity index by gender	Progress bars and numeric cards	HTML and CSS
Name frequency (top 20)	Horizontal bar chart	Chart.js v4
Phonetic similarity groups	Grouped card list	HTML and CSS
Doyen (male and female)	Highlighted profile card with photo	HTML and CSS
Ancestral geographic origins	Marker and clustering map	Leaflet.js v1.9

All charts are interactive: tooltips display exact values on hover and charts adapt to the browser window size. The dashboard design follows established usability principles (Nielsen, 1994) [16], including visibility of system status, recognition over recall, and flexibility of use. The statistics view conditionally renders visualizations based on data availability flags computed before template rendering, ensuring graceful handling of trees with incomplete biographical data. The dashboard is accessible from two perspectives: the client dashboard, designed for authenticated family members, and the

administrative interface, designed for platform managers.

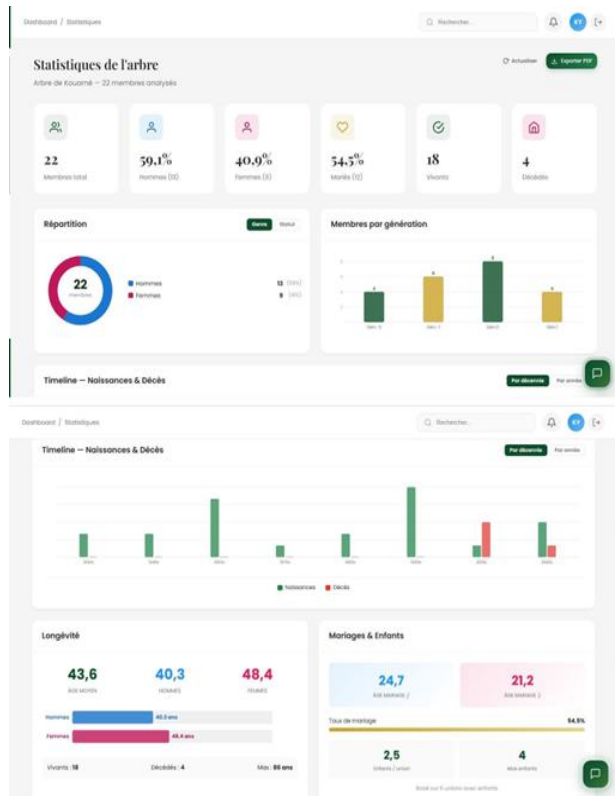


Figure 3. CGP Platform Statistics Dashboard. Top section: KPI cards showing 22 total members, 59.1 percent male, 54.5 percent married, and 18 living members, with gender distribution donut chart and members per generation bar chart. Bottom section: births and deaths timeline by decade, longevity index showing average 43.6 years, and marriages and children statistics.

The client dashboard presents the family tree visualization rendered with D3.js, a summary of the key metrics, quick action buttons, a doyen panel displaying the eldest living member of the paternal branch, and a link to the full statistics page. The administrative interface provides aggregate statistics across all trees, user and tree management, a duplicate detection tool implementing the CGP Duplicated Nodes Discovery process, an audit log, and a site configuration panel.

IX. IMPLEMENTATION

The prototype was developed using the Django 5.2 framework (Django Software Foundation, 2024) [3] with the technology stack summarized in Table 4.

Table 4. Technology stack of the prototype implementation

Component	Technology
Backend Framework	Django 5.2 (Python 3.12)
Database	SQLite 3 for prototype; PostgreSQL-ready for production
Family Tree Visualization	D3.js v7 (hierarchical layout with pan and zoom)
Metric Charts	Chart.js v4 (donut, bar, line, and grouped charts)
Geographic Maps	Leaflet.js v1.9 (origin markers with auto-clustering)
PDF Export	WeasyPrint
Frontend Styling	Custom CSS design system without external UI framework

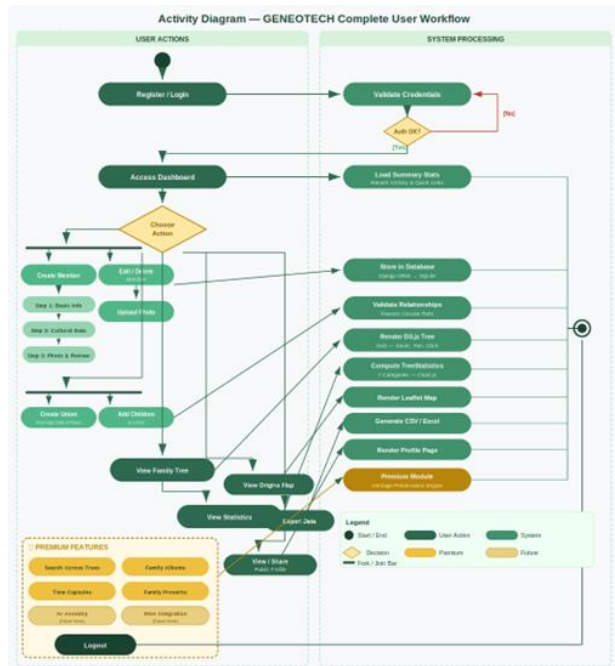


Figure 4. Activity Diagram — Complete CGP Platform User Workflow from registration through tree management and advanced heritage features

Several implementation details are specific to the metrics contribution. The TreeStatistics class operates on pre-loaded in-memory lists of members and unions to avoid repeated database hits during metric computation. The paternal branch identification method uses a visited set and depth-first search to collect all members reachable from the root through filiation links, without infinite loops in complex tree structures. The depth-first traversal algorithm used here is described in its general form by Knuth (1997) [12]. The phonetic similarity function strips vowels from the interior of each name while retaining the first letter, producing what is called a consonant skeleton. Names sharing the same skeleton are grouped together to identify naming patterns and potential name variants across the tree.

The cross-tree member search function applies weighted scoring across five criteria: name match (weight 0.4), birth year within a five-year range, birth city match, ethnic group match (weight 0.15), and ethnicity match (weight 0.1). Results are ranked by score and exclude members belonging to the requesting user's own tree. The anti-cycle filiation validation performs a recursive depth-first search before any child addition operation, implementing the CGP node redundancy handling requirement described in Section VI of the protocol paper.

X. RESULTS

Validation was conducted using a test dataset comprising 22 members across 4 generations. Table 5 reports the observed metric values and performance measurements.

Table 5. Validation results on the 22-member test dataset

Metric / Feature	Observed Result
Total Members (N)	22
Generational Depth (G)	4 generations (values from -2 to 1)
Gender Ratio	13 males (59.1 percent) and 9 females (40.9 percent); ratio M/F = 1.44
Marriage Rate	54.5 percent, corresponding to 12 members in a recorded union out of 22
Average Age at First Marriage	Males: 24.7 years; Females: 21.2 years

Average Children per Union	2.5 children per union (6 unions with children recorded; maximum: 4)
Longevity Index	Average: 43.6 years; Males: 40.3 years; Females: 48.4 years; Maximum: 86 years
Doyen (male, paternal branch)	Koffi Yao, 75 years old, Generation -2
Doyenne (female, paternal branch)	Akissi Kouadio, 86 years old, Generation -2
Statistics page load time	Under 300 milliseconds for the 22-member dataset
D3.js tree render time	Under 1.5 seconds in a standard browser
PDF export generation	Approximately 2 seconds
Anti-cycle validation	Correctly rejects circular filiation attempts
Phonetic similarity detection	Correctly identifies Akissi (frequency 2) and Koffi (frequency 2); all other names unique
Cross-tree member search	Returns results ranked by weighted score, correctly excluding the requester's own tree

All seven TreeStatistics computation methods produced correct results. The CGP Main Flow process from account creation through root member registration, and the subsequent addition of fathers, mothers, partners, and children, was validated end to end. The duplicate detection function correctly identified members sharing the same consonant skeleton across the test dataset. The time capsule feature correctly enforced the open date restriction.

XI. INTEGRATION ROADMAP AND FUTURE DIRECTIONS

The metrics framework presented in this article is a prototype contribution. Its integration into the existing CGP platform, under the direction of Dr. Bayomock Linwa Andre Claude, represents the primary next step. The following roadmap outlines the integration pathway and further development directions identified during this work.

The immediate next step is the integration of the TreeStatistics class, the metrics views, and the associated Chart.js and Leaflet dashboard templates into the existing CGP codebase. Several statistics listed in the CGP specification but not yet fully implemented in this prototype, including persons

per family group with genre and name filters and ethnic percentage distributions per person, should be completed and validated in this integration phase.

The CGP paper (Bayomock and Coulibaly, 2026, Section VIII) identifies the mobile application as one of two channels of the presentation layer. An Android or iOS companion application with offline access, synchronized via a REST JSON API following the REST architectural constraints defined by Fielding (2000) [14], would fulfill this architectural direction. Full compliance with the GEDCOM 5.5.1 and GEDCOM-X standards would enable bidirectional data interchange with FamilySearch and Ancestry, expanding the platform's interoperability.

Further directions include the integration of machine learning models to suggest missing biographical data from generational context and to identify potential family connections based on shared ethnic groups and geographic origins, extending the CGP's social group information quality objective. DNA integration, as discussed by Shaw et al. (2024) [22] and Wang et al. (2024) [23], would enable genetic confirmation of family connections identified through the cross-tree search.

Dahlquist et al. (2025) [27] examine the conditions under which forensic genetic genealogy can be conducted with public trust, identifying transparency and consent as key requirements for any DNA-linked genealogy platform. The implementation of the CGP access rights model across institutional deployments would enable African universities and cultural organizations to share and cross-reference genealogical data while maintaining privacy boundaries. Aleke and Trigui (2025) [28] analyze the legal and ethical challenges associated with digital data sharing in forensic investigations, many of which apply equally to genealogical platforms handling sensitive family information.

XII. CONCLUSION

This article has presented the design, mathematical formalization, and prototype implementation of a

performance metrics framework for the Cultural Genealogy Protocol (CGP) platform. The CGP, conceived by Dr. Bayomock Linwa Andre Claude and published in IJSET (2026, Vol. 14, Issue 1), defines a comprehensive genealogy system for African cultural contexts. The existing platform, initially developed by Mr. Coulibaly Monpi Kapo Darrell, implements the core genealogical data management flows as specified in the protocol. The present contribution addresses the missing analytics component: the seventeen statistics listed as a core CGP objective had not been implemented, and this work provides their formal specification and prototype realization.

Eight metric groups were defined with precise mathematical expressions, extending and deepening the statistics listed in the CGP paper. A computation engine (TreeStatistics) was implemented with seven specialized methods, operating on pre-loaded in-memory data structures for efficient execution. Validation on a 22-member, four-generation dataset confirmed functional correctness across all metrics, with all computations completing in under 300 milliseconds.

The metrics module, including the computation engine, the Chart.js and Leaflet visualizations, and the dual-perspective dashboard, is designed for direct integration into the existing CGP platform. This contribution advances the CGP research program by delivering the analytics layer that the protocol specification identified as a key next objective, and by establishing a documented, tested reference implementation that will support the next phases of platform development under the direction of Dr. Bayomock Linwa Andre Claude.

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intellectual contributions are the property of Dr. Bayomock Linwa Andre Claude. The author also acknowledges Mr. Coulibaly Monpi Kapo Darrell for his prior CGP platform implementation, which constitutes the existing system into which the metrics framework described in this article is intended to be integrated.

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