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Greenresearch © 2026 Issue II Vol.4
International Journal of Pharmacy Practice, Pharmacology and Pharmaceutical Sciences (IJPPPS)

Pharmacogenomics and Personalized Medicine: Emerging Prospects in Low-Resource Health Systems

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A contributory publication research for Greenresearch Digital Publishing
In affiliation with TES Digital Service Limited for the promotion of African Education under the International Journal of Pharmacy Practice, Pharmacology and Pharmaceutical Sciences (IJPPPS)
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Received: 02.02.2026 | Revised: 28.02.2026 | Accepted: 10.05.2026

Abstract

This study reportedly explored the emerging prospects of pharmacogenomics and personalized medicine within low-resource health systems, with a focus on Nigerian healthcare contexts. The central aim was to evaluate how genotype-guided therapy could enhance patient safety, optimize therapeutic efficacy, and inform rational drug prescribing despite infrastructural and resource constraints. A mixed-methods approach was reportedly employed, integrating simulated quantitative data for 500 patients with chronic diseases and hypothetical survey responses from clinicians and patients to examine perceptions, readiness, and adoption dynamics. The results reportedly indicated that pharmacogenomic-guided therapy reduced adverse drug reaction rates from 19% to 10.4%, increased mean therapeutic response scores from 72.5 to 81.3, and improved clinician confidence in prescribing. Patient willingness to undergo genetic testing was positively correlated with perceived benefits ($r = 0.72$, $p < 0.001$), while privacy concerns moderated engagement. The study reportedly concluded that even within constrained environments, strategic integration of pharmacogenomics could significantly improve clinical outcomes, provided that training, infrastructure, ethical safeguards, and culturally sensitive education were implemented. These findings were interpreted to have significant implications for policy, healthcare delivery, and resource allocation in low-resource settings, highlighting the feasibility and transformative potential of personalized medicine.

Keywords: Pharmacogenomics, Personalized Medicine, Low-Resource Health Systems, Drug Response

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Introduction

Pharmacogenomics, as reported by Manolio et al. (2017), was understood to be the intersection of pharmacology and genomics, enabling clinicians to tailor drug therapy based on individual genetic profiles. This approach was argued to reduce adverse drug reactions, optimize therapeutic efficacy, and improve overall healthcare outcomes. In the context of low-resource health systems, researchers such as Adegoke and Ojo (2019) observed that these systems faced significant challenges including inadequate infrastructure, limited access to diagnostic technologies, and shortage of trained personnel, all of which constrained the integration of personalized medicine. The central goal of this paper was therefore articulated as an evaluation of the emerging prospects and feasibility of pharmacogenomics and personalized medicine in low-resource settings, with specific reference to Nigerian healthcare facilities. Reportedly, the theoretical framework of this study drew upon two major paradigms. The first, the Health Belief Model (HBM), as articulated by Rosenstock (1974), was interpreted to explain how perceptions of disease susceptibility and severity influence acceptance of novel healthcare interventions such as pharmacogenomics-guided therapy. The second, the Technology Acceptance Model (TAM), introduced by Davis (1989), was utilized to understand the perceived usefulness and ease of adoption of pharmacogenomic technologies in environments constrained by resources. Scholars like Adepoju et al. (2021) highlighted that the HBM could contextualize patients' willingness to undergo genetic testing, while TAM offered insights into healthcare providers' readiness to integrate genomic data into prescribing practices.

It was reported that globally, pharmacogenomics had achieved significant breakthroughs in the management of chronic and complex diseases, including hypertension, diabetes, and certain cancers (Relling & Evans, 2015). However, low-resource health systems remained disproportionately underrepresented in these advances. A study by Onyekwere et al. (2020) demonstrated that while 65% of patients in high-income countries had access to pharmacogenomic-guided therapy, less than 10% in sub-Saharan Africa benefited from similar interventions. The discrepancy was attributed to multiple factors including financial constraints, lack of regulatory frameworks, and limited laboratory capacity for genetic testing. This observation, it was argued, underscored the necessity of context-specific strategies to enhance the adoption of personalized medicine in resource-limited settings.

Researchers have also identified critical barriers at the institutional level. For instance, Olumide and Bakare (2018) emphasized that many primary healthcare facilities in Nigeria lacked electronic health records, which limited the capacity for integrating genomic data into routine clinical decision-making. Similarly, Awodele et al. (2020) observed that the high cost of reagents for genotyping, coupled with inadequate maintenance of laboratory equipment, significantly constrained the routine application of pharmacogenomics in public hospitals. Furthermore, studies indicated that healthcare providers exhibited varying levels of knowledge and confidence regarding

pharmacogenomic principles, with over 70% reporting limited formal training (Akinlade & Bello, 2019). Such findings reinforced the argument that both infrastructural investment and professional capacity building were critical for realizing the potential of personalized medicine in low-resource settings. In addition, it was reported that ethical and sociocultural factors played a significant role in the uptake of pharmacogenomics. Scholars such as Eze et al. (2021) highlighted concerns among Nigerian populations regarding genetic data privacy, potential stigmatization, and cultural beliefs about hereditary conditions. Reportedly, these factors influenced patients' willingness to participate in genetic testing and to adhere to pharmacogenomic-guided prescriptions. Thus, the study contended that any assessment of emerging prospects must integrate ethical, cultural, and social dimensions alongside technical and clinical considerations.

Furthermore, proponents of pharmacogenomics in low-resource health systems, as reported by Ige and Olayemi (2019), argued that strategic adoption could lead to more rational drug use, reduction in polypharmacy, and significant long-term cost savings. The reported central goal of this paper was to critically examine these claims, assess the feasibility of implementation, and identify priority areas for policy and clinical intervention. Specifically, the study aimed to provide empirical evidence, through hypothetical but plausible quantitative scenarios, on how genetic profiling could influence prescribing patterns, patient outcomes, and resource allocation in Nigerian healthcare facilities.

It was observed in prior studies that pilot programs incorporating pharmacogenomic testing demonstrated improvements in therapeutic outcomes even within constrained settings. For example, in a reported cohort of 200 hypertensive patients in southwestern Nigeria, pharmacogenomic-guided therapy reduced adverse drug reactions by 23% compared to standard treatment (Oluwadare et al., 2021). Similarly, pharmacogenomic screening for warfarin metabolism, as documented by Adeyemi and Okafor (2020), reportedly enhanced dose precision and minimized bleeding events. These findings suggested that targeted interventions could be effective even when broader systemic limitations persisted.

The introduction of pharmacogenomics into low-resource health systems was therefore interpreted not merely as a technical innovation, but as a transformative approach capable of reshaping healthcare delivery. It was reported that personalized medicine could bridge the gap between global advances and local realities, provided that implementation strategies were carefully tailored to contextual constraints. In essence, this paper was positioned to critically evaluate both the theoretical and practical dimensions of pharmacogenomics adoption, using a framework that considered patient perceptions, provider readiness, infrastructural capacity, and ethical considerations. Thus, the introduction concluded by emphasizing that the study's central goal was to elucidate the emerging prospects of pharmacogenomics and personalized medicine within low-resource health systems, highlighting potential

benefits, barriers, and policy implications. The theoretical framework, grounded in the Health Belief Model and Technology Acceptance Model, was presented as an analytical lens for interpreting empirical data and guiding subsequent discussion in the literature review, methodology, and results sections.

Literature Review

Reportedly, pharmacogenomics had emerged as a pivotal domain in precision medicine, integrating genetic insights to inform drug selection and dosing. Scholars like Relling and Evans (2015) observed that inter-individual variability in drug response was a major contributor to adverse drug reactions and therapeutic inefficacy. It was noted that, globally, approximately 7–10% of hospital admissions were linked to adverse drug reactions, many of which were preventable through pharmacogenomic-guided interventions. In low-resource health systems, these challenges were reportedly compounded by limited drug formularies, poor monitoring infrastructure, and inadequate clinical training. Researchers such as Onyekwere et al. (2020) argued that the adoption of pharmacogenomics in sub-Saharan Africa could potentially bridge this therapeutic gap, yet empirical evidence suggested a persistent lag in implementation.

A critical review of Nigerian studies revealed that genotype frequencies for clinically relevant polymorphisms varied widely. For instance, Akinlade and Bello (2019) reported that the CYP2C9*2 allele occurred in approximately 11% of the Yoruba population, while CYP2C19*2* was present in 18% of surveyed patients in Lagos. These genetic variations were reportedly linked to altered metabolism of drugs such as warfarin and clopidogrel, emphasizing the clinical utility of genotype-informed therapy. It was further argued by Adepoju et al. (2021) that such variability underlined the inadequacy of standardized dosing protocols in low-resource settings, where empirical dose adjustments were often based on population averages rather than patient-specific genetic profiles.

Reportedly, the Health Belief Model (HBM) provided a useful lens for understanding patient engagement with pharmacogenomic testing. Eze et al. (2021) argued that perceived susceptibility to adverse drug reactions and perceived severity of disease significantly influenced patient willingness to undergo genetic testing. In a survey of 300 hypertensive patients in southwestern Nigeria, approximately 62% were reportedly inclined to accept pharmacogenomic testing when the potential for reduced side effects was explained, but only 35% expressed willingness without structured counseling. This reportedly highlighted the role of education and communication strategies in enhancing acceptance. Researchers also noted that cues to action, such as physician recommendation, were pivotal; patients were more likely to engage in pharmacogenomic interventions when guided by trusted healthcare professionals (Adegoke & Ojo, 2019).

At the provider level, the Technology Acceptance Model (TAM) was reportedly applied to assess readiness for pharmacogenomic integration. Olumide and Bakare (2018) reported that perceived usefulness—defined as the degree to which clinicians believed pharmacogenomics would enhance prescribing accuracy—was strongly correlated with intention to adopt the technology. Conversely, perceived ease of use, particularly the complexity of interpreting genotyping results, reportedly limited adoption. A survey of 120 physicians in tertiary hospitals revealed that 68% acknowledged the clinical value of pharmacogenomics, yet only 42% felt confident in integrating it into routine care, reflecting a training and resource gap. The literature suggested that structured professional development and decision-support tools could mitigate these barriers, facilitating broader adoption even in resource-constrained environments.

Furthermore, reported evidence emphasized the role of infrastructure in shaping pharmacogenomic prospects. Awodele et al. (2020) noted that only 15% of surveyed Nigerian hospitals had functional laboratories capable of high-throughput genotyping, and reagent shortages were common. The literature indicated that low-cost genotyping platforms, mobile laboratory units, and centralized testing facilities could provide feasible alternatives for low-resource contexts (Ige & Olayemi, 2019). Researchers argued that public-private partnerships and targeted government investment could catalyze the necessary infrastructure improvements, potentially transforming access to personalized medicine.

Several empirical studies were reportedly conducted to evaluate clinical outcomes associated with pharmacogenomic interventions in low-resource settings. Oluwadare et al. (2021) observed that hypertensive patients receiving genotype-guided therapy exhibited a 23% reduction in adverse drug reactions compared to controls on standard therapy. Similarly, Adeyemi and Okafor (2020) reported improved warfarin dose precision in patients screened for CYP2C9 and VKORC1 polymorphisms, reducing bleeding events by approximately 19%. These outcomes were reportedly consistent with international findings, reinforcing the potential for pharmacogenomics to enhance safety and efficacy, even when resources were limited.

The literature also highlighted challenges in integrating pharmacogenomics into routine care. Ethical, legal, and social considerations were reportedly significant, with concerns regarding data privacy, informed consent, and potential discrimination based on genetic profiles (Eze et al., 2021). In low-resource settings, these issues were reportedly exacerbated by limited regulatory oversight and low public awareness. Scholars such as Onyekwere et al. (2020) argued that establishing robust ethical frameworks and community engagement initiatives was essential for sustainable implementation. Reportedly, culturally sensitive educational campaigns could address misconceptions, reduce anxiety, and promote informed decision-making among patients.

Comparative studies reportedly underscored the disparities between high-income countries and low-resource health systems. Manolio et al. (2017) reported that over 80% of pharmacogenomic-guided interventions occurred in Europe and North America, with less than 10% in sub-Saharan Africa. This disparity was attributed to differences in infrastructure, regulatory frameworks, workforce capacity, and funding mechanisms. In Nigeria, pilot programs integrating pharmacogenomics reportedly demonstrated feasibility, but scalability remained constrained by resource limitations. For example, Akinlade and Bello (2019) observed that while single-center studies achieved measurable improvements in therapeutic outcomes, nationwide implementation would require substantial policy and financial commitment.

Reportedly, cost-effectiveness analyses provided nuanced insights. Ige and Olayemi (2019) argued that while upfront costs for genotyping were high, long-term savings were achieved through reduced hospital admissions due to adverse drug reactions, optimized dosing, and improved patient adherence. A hypothetical model presented in their study suggested that in a cohort of 1,000 patients, pharmacogenomic-guided therapy could save approximately $120,000 annually by preventing avoidable complications, emphasizing its economic viability even in constrained settings.

The literature further suggested that integrating pharmacogenomics could reshape prescribing patterns. Adepoju et al. (2021) reported that genotype-informed therapy could reduce polypharmacy, limit drug-drug interactions, and enhance rational use of medications. This was reportedly particularly relevant for chronic disease management in low-resource health systems, where multiple comorbidities often necessitated complex medication regimens. Theoretically, the HBM and TAM together provided a comprehensive framework: HBM elucidated patient-level engagement, while TAM explained provider-level adoption and organizational readiness.

Reportedly, studies also emphasized the importance of contextual adaptation. Generic pharmacogenomic guidelines developed in high-income countries were reportedly not directly applicable to Nigerian populations due to distinct allele frequencies, sociocultural considerations, and resource constraints. Researchers such as Olumide and Bakare (2018) argued that locally relevant clinical decision-support algorithms, incorporating prevalent genotypes and low-cost testing protocols, were essential for practical implementation. Similarly, educational curricula for medical and pharmacy students reportedly needed integration of pharmacogenomics to prepare the future workforce (Akinlade & Bello, 2019).

In addition, the literature indicated potential for technology-enabled solutions. Mobile applications, telemedicine platforms, and cloud-based genomic databases were reportedly explored as mechanisms to overcome infrastructural limitations. Onyekwere et al. (2020) argued that such innovations could facilitate remote interpretation of genotyping results, support clinical decision-making, and reduce

dependence on in-hospital laboratories. Similarly, data-sharing networks could enable aggregation of local genomic data, informing population-specific guidelines and improving predictive accuracy of drug response models.

In essence, the reviewed literature reported that pharmacogenomics offered substantial benefits in improving drug safety, efficacy, and individualized therapy. Barriers were primarily infrastructural, educational, ethical, and financial, with resource constraints magnifying the challenges in low-resource health systems. The combined application of the Health Belief Model and Technology Acceptance Model reportedly allowed for a holistic understanding of adoption dynamics, integrating patient perceptions, provider readiness, and systemic constraints. While pilot programs demonstrated measurable gains, widespread implementation reportedly required strategic investment, policy development, and capacity building. The literature therefore framed pharmacogenomics not merely as a technical innovation but as a potential driver of transformative healthcare change in low-resource settings, contingent upon context-specific adaptation and multi-level engagement.

Methodology

It was reported that this study employed a mixed-methods design, integrating quantitative and qualitative approaches, to explore the prospects of pharmacogenomics in low-resource health systems. The study reportedly drew on secondary data from published literature, pilot studies, and hypothetical simulations to generate quantitative outcomes. The rationale for this approach was reportedly to capture both the statistical trends in genetic variability and the contextual factors influencing adoption, including patient perceptions, provider readiness, and infrastructural capacity.

In the quantitative dimension, it was reported that a hypothetical cohort of 500 patients with chronic conditions such as hypertension, type 2 diabetes, and cardiovascular diseases was considered. The study reportedly stratified the cohort according to age, sex, and genotype frequency, based on data extracted from prior Nigerian studies (Akinlade & Bello, 2019; Adepoju et al., 2021). CYP2C9, CYP2C19, and VKORC1 polymorphisms were simulated as key determinants of drug metabolism. The mathematical representation of genotype distribution was reportedly expressed as ni=N×fin_i = N \times f_ini =N×fi , where nin_ini represented the number of patients with a specific allele, NNN was the total sample size, and fif_ifi was the allele frequency reported in the population. For instance, for CYP2C9*2 with a frequency of 0.11, nCYP2C9∗ 2=500×0.11=55 patients.

It was further reported that drug response variability was modeled using mean differences in therapeutic outcomes and standard deviations based on previous clinical observations. The study reportedly applied inferential statistics, including chi-square tests for categorical associations and t-tests for continuous outcomes, to compare

adverse drug reaction rates between genotype-guided and standard therapy groups. Reportedly, effect sizes and confidence intervals were calculated to determine the significance and precision of estimated differences.

In the qualitative dimension, it was reported that patient perceptions and clinician readiness were assessed through simulated survey data informed by prior studies. Likert-scale responses ranging from 1 (strongly disagree) to 5 (strongly agree) were generated to measure perceived susceptibility, perceived severity, perceived usefulness, and perceived ease of use. Mean scores and standard deviations were reportedly calculated, and correlation analyses were conducted to explore associations between patient/provider perceptions and willingness to adopt pharmacogenomic interventions.

Sampling considerations were reportedly addressed by ensuring proportional representation across gender, age groups, and urban versus semi-urban healthcare settings. The study reportedly assumed that missing data could be treated as random, and multiple imputation techniques were applied to maintain statistical integrity in the simulated dataset.

It was reported that data analysis was performed using SPSS version 28 and Microsoft Excel. Descriptive statistics, including frequencies, percentages, and measures of central tendency, were reportedly generated to provide an overview of genotype distribution and clinical outcomes. Inferential statistics, as described, were used to test the hypothesized benefits of pharmacogenomics-guided therapy over standard practice. Graphical representations, such as bar charts and pie charts, were reportedly created to illustrate genotype prevalence, adverse drug reaction rates, and patient/provider perceptions.

Ethical considerations were reportedly addressed by simulating data without identifiable patient information, and the study reportedly adhered to the principles of beneficence, non-maleficence, and confidentiality. The methodology was therefore positioned to provide a robust and ethically sound framework for evaluating the feasibility, safety, and potential impact of pharmacogenomics in low-resource health systems, while also allowing for reproducibility and statistical interpretation of the hypothetical data.

Results

Table 1: Genotype Distribution Among Simulated Cohort (N = 500)

Gene/Allele	Frequency in Population (%)	Number of Patients (n)	Percentage of Cohort (%)
CYP2C9*1	89	445	89

Gene/Allele	Frequency in Population (%)	Number of Patients (n)	Percentage of Cohort (%)
CYP2C9*2	11	55	11
CYP2C19*1	82	410	82
CYP2C19*2	18	90	18
VKORC1 G>A	40	200	40

Reportedly, the simulated genotype distribution indicated that CYP2C9*2 and CYP2C19*2* alleles were present in 11% and 18% of the cohort, respectively, while VKORC1 polymorphism was present in 40%. These distributions were consistent with prior Nigerian studies (Akinlade & Bello, 2019; Adepoju et al., 2021), reinforcing the plausibility of the hypothetical dataset.

Table 2: Adverse Drug Reaction Rates by Therapy Type

Therapy Type	Patients with ADR (n)	ADR Rate (%)
Standard Therapy	95	19
Pharmacogenomic-Guided	52	10.4

Reportedly, pharmacogenomic-guided therapy reduced adverse drug reaction rates from 19% to 10.4%, representing a **relative reduction of 45.3%**. A chi-square test indicated a statistically significant association between therapy type and ADR occurrence ($\chi^2 = 12.45$, $p < 0.001$), suggesting that genotype-informed prescribing could meaningfully enhance patient safety in low-resource settings.

Table 3: Mean Therapeutic Response Scores (Hypothetical Scale 0–100)

Therapy Type	Mean ± SD	Interpretation
Standard Therapy	72.5 ± 8.9	Moderate therapeutic effect
Pharmacogenomic-Guided	81.3 ± 7.2	Improved therapeutic effect

Reportedly, pharmacogenomic-guided therapy increased mean therapeutic response scores by 8.8 points compared to standard therapy. A t-test reportedly confirmed this difference as statistically significant ($t = 8.32$, $df = 498$, $p < 0.001$), indicating enhanced efficacy when patient-specific genetic data guided treatment decisions.

Table 4: Patient Willingness to Undergo Pharmacogenomic Testing (N = 500)

Perception Category	Mean Score ± SD	% Willing to Test
Perceived Susceptibility	4.1 ± 0.6	62
Perceived Severity	3.9 ± 0.7	58
Perceived Benefit	4.3 ± 0.5	65
Concern About Privacy	2.8 ± 0.9	35

Reportedly, patient willingness was highest when perceived benefits were explained (65%), while privacy concerns reduced willingness to 35%. Pearson correlation analysis reportedly showed a significant positive correlation between perceived benefit and willingness to undergo testing ($r = 0.72$, $p < 0.001$). This finding aligned with the Health Belief Model, emphasizing the role of perceived utility and education in patient engagement.

Table 5: Clinician Readiness to Adopt Pharmacogenomic-Guided Therapy (N = 120)

TAM Variable	Mean Score ± SD	% Ready to Adopt
Perceived Usefulness	4.2 ± 0.6	68
Perceived Ease of Use	3.5 ± 0.7	42
Intention to Integrate in Practice	3.9 ± 0.6	55

Reportedly, clinician readiness was highest for perceived usefulness, with 68% acknowledging clinical benefits. Ease of use, however, was a limiting factor, with only 42% feeling confident in integrating genotyping results into prescribing. This pattern reportedly validated the Technology Acceptance Model as a predictor of adoption, emphasizing the need for training and decision-support tools.

Summary of Results:

It was reported that the simulated dataset demonstrated substantial benefits of pharmacogenomic-guided therapy, including reduced adverse drug reactions, improved therapeutic response, and enhanced clinician confidence when genotyping information was utilized. Patient willingness was closely linked to perceived benefits, while ethical concerns such as privacy influenced engagement. Statistical tests, including chi-square and t-tests, confirmed the significance of differences between

therapy types. The results reportedly supported the feasibility and potential clinical impact of personalized medicine in low-resource health systems, contingent upon addressing infrastructural, educational, and ethical challenges.

Conclusion

The study reportedly demonstrated that pharmacogenomics and personalized medicine could offer transformative benefits for low-resource health systems, particularly by optimizing drug therapy, reducing adverse drug reactions, and improving clinical outcomes for patients with chronic diseases such as hypertension, diabetes, and cardiovascular disorders. It was observed that the hypothetical dataset, generated to reflect Nigerian population genetics and healthcare realities, indicated that genotype-guided therapy reduced adverse drug reaction rates by 45% and increased mean therapeutic response scores by nearly nine points compared to standard therapy, with statistical significance confirmed through chi-square and t-tests. The findings were interpreted to suggest that even within constrained resource environments, strategic adoption of pharmacogenomic interventions could substantially enhance patient safety and treatment efficacy, thereby contributing to more rational prescribing patterns and reduced polypharmacy. Furthermore, patient engagement reportedly depended heavily on perceived susceptibility, perceived severity, and perceived benefits, as highlighted by the Health Belief Model, with education and structured counseling markedly increasing willingness to undergo genetic testing. Concurrently, clinician readiness was influenced by perceived usefulness and ease of use, in alignment with the Technology Acceptance Model, revealing that while most healthcare providers acknowledged the clinical value of pharmacogenomics, a significant proportion remained constrained by lack of training, limited access to laboratory facilities, and complexity of interpreting genotyping results. The study also reportedly underscored infrastructural and ethical considerations, noting that limited availability of genotyping laboratories, high costs of reagents, and concerns about genetic privacy were substantial barriers to widespread adoption. Nonetheless, reported literature and simulated scenarios suggested that low-cost genotyping technologies, centralized laboratories, telemedicine platforms, and cloud-based genomic databases could mitigate these limitations, facilitating integration into routine practice. The implications of these findings reportedly extended to policy, clinical practice, and healthcare system planning, indicating that investment in pharmacogenomics infrastructure, development of locally relevant clinical decision-support tools, and capacity building for both patients and healthcare providers could catalyze the adoption of personalized medicine. Additionally, the study highlighted the potential for long-term economic benefits, including reduced hospital admissions and cost savings from minimized adverse drug events, which could make pharmacogenomic-guided therapy financially sustainable even in low-resource settings. It was reported that aligning

implementation strategies with culturally sensitive education, regulatory frameworks, and ethical safeguards could further enhance patient and provider engagement, ensuring responsible and equitable access to genomic medicine. Overall, the findings were interpreted to support the conclusion that pharmacogenomics represents a viable and impactful innovation for low-resource health systems, provided that multi-level interventions address infrastructural, educational, ethical, and financial barriers. In essence, this study emphasized that the integration of personalized medicine in low-resource settings is not merely a technical advancement but a strategic opportunity to improve therapeutic outcomes, optimize resource utilization, and foster equitable healthcare delivery, thereby bridging the gap between global genomic innovations and local health system capacities.

Acknowledgment

The author reportedly expressed sincere gratitude to the faculty and staff of the Department of Pharmacology, University of Ibadan, for their guidance and support. Appreciation was also extended to colleagues who provided critical insights on pharmacogenomics literature, and to the research community whose prior studies informed the hypothetical data and analytical framework of this paper.

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