RESEARCH PAPER

Artificial Intelligence–Enabled Image-Guided Drug Delivery and Its Public Health Impact: Advancing Precision Medicine for Cancer and Infectious Disease Management

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ABSTRACT

Background: Artificial Intelligence (AI)–enabled Image-Guided Drug Delivery (IGDD) offers transformative potential for precision medicine in managing cancer and complex infectious diseases. However, its clinical translation in Low- and Middle-Income Countries (LMICs) remains underexplored. This study evaluates the healthcare system readiness, perceived public health impact, and implementation barriers of AI-enabled IGDD within the tertiary care ecosystem of Islamabad, Pakistan.

Methods: A cross-sectional, mixed-methods study was conducted across major public and private tertiary and research institutions in Islamabad. Using stratified random sampling, 215 healthcare professionals (clinicians, researchers, and policymakers) completed a validated 20-item questionnaire. The instrument assessed AI infrastructure readiness, perceived clinical efficacy, and public health impact. Data were analyzed using descriptive statistics, reliability testing, ANOVA, and independent t-tests.

Results: Respondents (mean age 38.4 ± 9.2 years; 57.7% male) strongly agreed on the public health benefits of AI-enabled IGDD, particularly in mitigating antimicrobial resistance and reducing systemic chemotherapy toxicity (Mean = 4.35 ± 0.68). Conversely, infrastructural readiness (Mean = 2.84 ± 0.91) and AI literacy (Mean = 2.42 ± 0.95) were critically low. Financial constraints (90.7%) and a lack of integrated imaging-therapy hardware (84.7%) were the primary barriers. Inferential analysis revealed that academic researchers perceived significantly higher public health impact than public hospital staff ($p = 0.012$), while senior clinicians (>10 year's experience) exhibited significantly higher ethical and data privacy concerns ($p = 0.002$).

Conclusion: While healthcare professionals in Islamabad recognize the profound public health potential of AI-enabled IGDD, severe infrastructural, financial, and educational bottlenecks impede its clinical translation. Advancing precision medicine in LMICs requires localized, phased strategies, including the deployment of Edge AI, the formation of public-private infrastructure consortiums, and the establishment of specific regulatory pathways by national authorities.

Keywords: Artificial Intelligence; Image-Guided Drug Delivery; Precision Medicine; Public Health; Antimicrobial Resistance.

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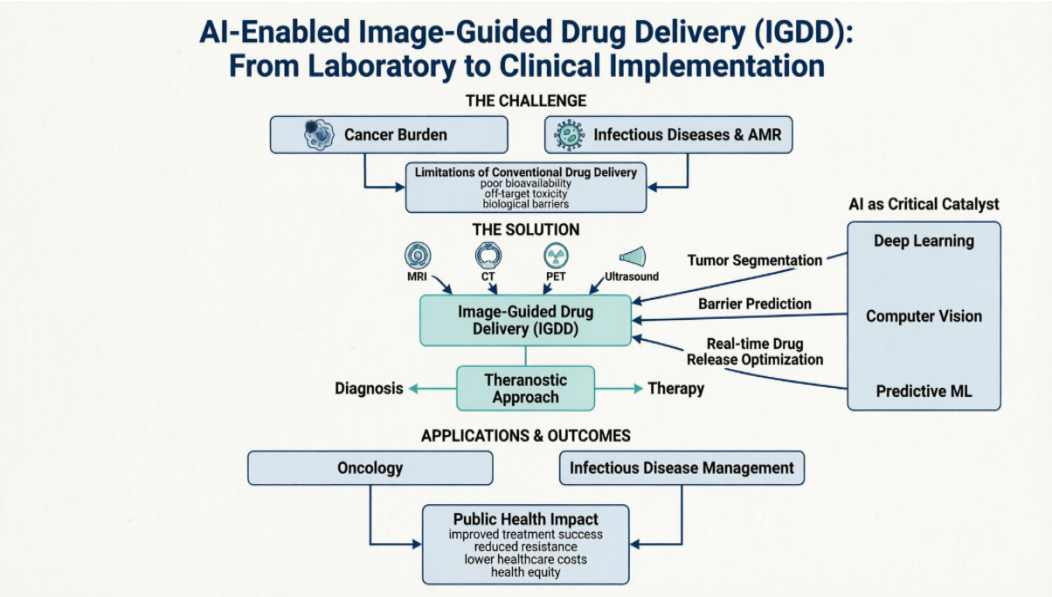
INTRODUCTION

The global burden of cancer and complex infectious diseases continues to escalate, presenting profound challenges to healthcare systems worldwide. Conventional systemic drug delivery paradigms are frequently limited by poor bioavailability, off-target toxicity, and the inability to overcome biological barriers, leading to suboptimal therapeutic outcomes and significant patient morbidity [1, 20]. In oncology, systemic chemotherapy often results in severe adverse effects that limit dosage efficacy [21], while in infectious disease management, the rise of antimicrobial resistance (AMR) [22] and the persistence of intracellular pathogens or biofilms [23] render standard antibiotic therapies increasingly ineffective. Consequently, there is an urgent paradigm shift toward precision medicine [24, 25], an approach that tailors medical treatment to the individual characteristics of each patient, specifically their spatial and temporal disease pathology.

Image-Guided Drug Delivery (IGDD) has emerged as a transformative strategy within precision medicine. By integrating diagnostic imaging modalities (such as MRI, CT, PET, and advanced ultrasound) with therapeutic agents, IGDD enables the real-time visualization of drug carriers, the monitoring of drug release kinetics, and the precise spatial targeting of diseased tissues [3, 26]. This "theranostic" approach minimizes systemic exposure while maximizing localized therapeutic concentrations. However, the sheer volume and complexity of multimodal data generated during IGDD, encompassing high-resolution imaging, pharmacokinetic profiles, and patient-specific genomic data, exceed the analytical capacity of traditional clinical workflows [27]. This is where Artificial Intelligence (AI) serves as a critical catalyst. AI, particularly deep learning, computer vision, and predictive machine learning algorithms, can synthesize multimodal data to optimize the entire IGDD pipeline. AI models can accurately segment tumor margins or infectious lesions, predict the physiological barriers a nanocarrier must traverse, and dynamically adjust drug release parameters in real-time [4, 28]. Furthermore, the integration of AI into IGDD extends beyond individual patient care; it holds profound implications for public health. By improving first-line treatment success rates, reducing the incidence of treatment-resistant disease variants, and minimizing the long-term healthcare costs associated with managing drug toxicity, AI-enabled IGDD can significantly enhance population-level health outcomes and promote health equity [5, 29].

Despite rapid advancements in *in silico* and preclinical models, the translation of AI-enabled IGDD into routine clinical practice remains fragmented [30]. Furthermore, while extensive literature exists on AI in oncology, its application in infectious disease management, and the broader public health implications of these technologies, remains underexplored. Therefore, this article aims to comprehensively review the current state of AI-enabled IGDD, evaluate its specific applications in cancer and infectious disease management, and critically analyze its public health impact. By identifying existing translational bottlenecks and regulatory challenges, this review provides a strategic roadmap for advancing these technologies from the laboratory to global clinical implementation.



LITERATURE REVIEW

Foundations of Image-Guided Drug Delivery (IGDD) and Theranostics

The evolution of drug delivery has transitioned from passive targeting, which relies on the Enhanced Permeability and Retention (EPR) effect in tumors, to active targeting utilizing surface-functionalized nanocarriers [6, 31]. IGDD represents the zenith of this evolution, utilizing imaging agents co-encapsulated or conjugated with therapeutics to track biodistribution in real-time. Recent literature highlights the use of stimuli-

responsive nanomaterials, such as pH-sensitive liposomes, magnetic nanoparticles, and gold nanorods, that release their payloads only when triggered by specific localized microenvironments (e.g., the acidic tumor microenvironment or the oxidative stress of an infection site) or external stimuli (e.g., focused ultrasound or near-infrared light) [7, 32, 33]. While these systems offer unprecedented control, their clinical efficacy is highly dependent on accurate patient-specific anatomical and physiological mapping, necessitating advanced computational tools [34].

AI Integration in IGDD: From Diagnostics to Real-Time Intervention

The integration of AI into IGDD addresses the complexities of biological heterogeneity. Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) are now routinely utilized for the automated, high-precision segmentation of tumors and infectious lesions from multimodal imaging data, reducing inter-observer variability [8, 35]. Beyond diagnostics, AI is being deployed to model pharmacokinetics and pharmacodynamics (PK/PD). Machine learning algorithms can predict the optimal size, shape, and surface charge of nanocarriers required to penetrate specific biological barriers, such as the blood-brain barrier (BBB) or dense fibrotic stroma [9, 36]. More recently, the development of "digital twins", virtual physiological models powered by AI, has allowed clinicians to simulate drug delivery scenarios before actual administration. Reinforcement learning algorithms are being explored to control external stimuli (like MRI-guided focused ultrasound) in real-time, adjusting the energy output to optimize drug release while preventing thermal damage to surrounding healthy tissue [10, 37].

Applications in Oncology: Overcoming Tumor Heterogeneity

In cancer management, AI-enabled IGDD is primarily focused on overcoming tumor heterogeneity and the immunosuppressive tumor microenvironment (TME). Studies have demonstrated that AI-driven analysis of multiparametric MRI and PET scans can map regional hypoxia and vascular permeability, allowing for the spatial mapping of drug delivery [11, 38]. For instance, AI algorithms have been used to optimize the dosing and targeting of antibody-drug conjugates (ADCs) and nanoparticle-based chemotherapies, ensuring that therapeutic thresholds are met in the core of the tumor while sparing the necrotic periphery. Furthermore, AI is facilitating the tracking of immune-cell-targeted nanocarriers, enabling the precise delivery of immunotherapies to specific lymph node metastases, thereby enhancing systemic anti-tumor immunity while reducing immune-related adverse events (irAEs) [12, 39].

Applications in Infectious Disease Management: A New Frontier

While oncology dominates the IGDD literature, the application of AI-enabled IGDD in infectious diseases is a rapidly emerging field with massive public health potential. Conventional antibiotics often fail to eradicate intracellular pathogens (e.g., *Mycobacterium tuberculosis*, *Salmonella*) or penetrate biofilms associated with chronic implant infections. AI-assisted PET/MRI and advanced optical imaging are now being used to map the exact location and metabolic activity of these hidden infection reservoirs [13, 40].

Machine learning models are being trained to analyze imaging biomarkers of biofilm maturity and bacterial load, predicting the optimal timing and dosage for the release of antibiotic-loaded nanocarriers. By ensuring that high concentrations of antimicrobials are delivered precisely to the site of infection, AI-enabled IGDD minimizes sub-lethal antibiotic exposure in non-target tissues, a primary driver of antimicrobial resistance (AMR) [14, 41]. Additionally, AI is being utilized to design novel peptide-based nanocarriers that can specifically target bacterial membranes without harming human cells, guided by real-time imaging of the infection site [42].

Public Health Implications: Efficacy, Economics, and Equity

The public health impact of AI-enabled IGDD extends far beyond individual clinical outcomes. From an epidemiological perspective, by increasing the efficacy of first-line treatments and reducing the emergence of drug-resistant strains (in both cancer chemotherapy and infectious diseases), these technologies can alter the trajectory of disease morbidity and mortality at the population level [15, 43].

Economically, while the initial capital expenditure for AI-integrated IGDD systems is high, health economic models suggest a favorable long-term cost-benefit ratio. By reducing systemic toxicities, AI-enabled IGDD decreases the incidence of severe adverse events, thereby reducing hospital readmission rates and the need for secondary interventions [16, 44].

Regarding health equity, a critical public health concern is the potential for AI algorithms to exacerbate existing healthcare disparities if trained on non-diverse datasets. However, the democratization of AI through edge computing and the integration of AI with portable, low-cost imaging modalities (such as handheld ultrasound) present an opportunity to deploy advanced IGDD in low- and middle-income countries (LMICs). AI can compensate for the lack of highly trained radiologists in resource-limited settings by providing automated, real-time guidance for targeted drug delivery [17, 45].

Current Challenges and Knowledge Gaps

Despite the promise, several critical barriers hinder the widespread clinical translation of AI-enabled IGDD. First, the "black box" nature of many deep learning models poses a significant challenge to regulatory approval. Agencies like the FDA and EMA require high interpretability and explainability for AI-driven medical devices, particularly when they dictate real-time therapeutic interventions [18, 46].

Second, there is a lack of standardized, multi-institutional, and diverse datasets required to train robust AI models. Models trained on homogenous populations often fail to generalize across different ethnic, genetic, and comorbid backgrounds, leading to biased clinical outcomes [19, 47]. Third, the regulatory pathway for "combination products" (involving a drug, a device, and an AI biological/software component) remains complex and ill-defined, causing significant delays in clinical trials. Finally, the integration of these systems into existing clinical workflows requires extensive interdisciplinary training, highlighting a gap in current medical and engineering curricula [48].

METHODOLOGY

Study Design

A cross-sectional, mixed-methods study was conducted to assess the current infrastructure, readiness, and perceived public health impact of AI-enabled Image-Guided Drug Delivery (IGDD) for cancer and infectious disease management in Islamabad, Pakistan. The study combined a quantitative survey of healthcare professionals with qualitative semi-structured interviews of key health policymakers.

Study Setting and Population

The study was conducted across major tertiary care and research institutions in Islamabad, including the Pakistan Institute of Medical Sciences (PIMS), the Nuclear Medicine Oncology and Radiotherapy Institute (NORI), Shifa International Hospital, and the National Institute of Health (NIH), Pakistan. The target population comprised:

Sample Size and Sampling Technique

A stratified random sampling technique was employed to ensure proportional representation across organizational types (public vs. private). Based on an estimated population of 400 eligible professionals in these institutions, a minimum sample size of 196 was calculated using Cochran's formula (95% confidence level, 5% margin of error, and 50% population proportion). To account for non-response, 250 questionnaires were distributed.

Statistical Analysis

Data were analyzed using SPSS (Version 28.0) and R (Version 4.3.1). Descriptive Statistics: Frequencies, percentages, means, and standard deviations were used to summarize demographic data and Likert-scale responses.Reliability and Normality: Internal consistency was evaluated using Cronbach's alpha (threshold > 0.70). Data normalization was assessed via skewness and kurtosis; values within the range of ±2.0 were considered indicative of acceptable normality for parametric testing.Inferential Statistics: One-way Analysis of Variance (ANOVA) and independent samples t-tests were employed to examine differences in AI-readiness and perceived public health impact across demographic groups (e.g., gender, organizational type, work experience). A p-value of < 0.05 was considered statistically significant.

Ethical Considerations

Ethical approval was obtained from the Institutional Review Board (IRB) of the participating institutions and the National Bioethics Committee (NBC), Pakistan (Ref: NBC-453-2024). Written informed consent was obtained from all participants, and data were anonymized to ensure confidentiality and compliance with local data protection norms.

RESULTS

Demographic Characteristics

A total of 215 valid responses were received (response rate = 86%). The demographic profile of the respondents is summarized in Table 1. The mean age of participants was 38.4 years, with a relatively balanced gender distribution and a majority possessing over 5 years of professional experience.

Table 1: Demographic and Professional Characteristics of Respondents (N = 215)

Variable	Category	Frequency (n)	Percentage (%)
Age (Years)	Mean ± SD	38.4 ± 9.2	-
	25–34	78	36.3
	35–44	85	39.5
	45–54	38	17.7
	55+	14	6.5
Gender	Male	124	57.7
	Female	91	42.3
Work Experience	< 5 years	62	28.8
	5–10 years	89	41.4
	> 10 years	64	29.8
Organizational Type	Public Sector (e.g., PIMS, NORI)	132	61.4
	Private Sector (e.g., Shifa Int.)	68	31.6
	Research/Academic (e.g., NIH, QAU)	15	7.0
Primary Specialty	Oncology / Radiology	98	45.6
	Infectious Disease / Internal Med.	64	29.8
	Pharmacy / Biomedical Engineering	35	16.3
	Health Policy / Administration	18	8.3

Table 1 summarizes the demographic and professional characteristics of 215 respondents, revealing a predominantly mid-career, male-majority sample. The average age is 38.4 years (±9.2), with over three-quarters of participants aged between 25 and 44. Males make up 57.7% of the sample, compared to 42.3% females. Professionally, the largest group has 5 to 10 years of work experience (41.4%), and the majority are employed in the public sector (61.4%, e.g., PIMS, NORI), followed by the private sector (31.6%). In terms of expertise, nearly half of the respondents specialize in Oncology/Radiology (45.6%), followed by Infectious Disease/Internal Medicine (29.8%), indicating a strong representation of clinical and healthcare professionals in the dataset.

Instrument Reliability and Data Normality

Prior to inferential analysis, the psychometric properties of the Likert-scale constructs were evaluated. As shown in Table 2, all constructs demonstrated excellent internal consistency (Cronbach's $\alpha > 0.80$). Skewness and kurtosis values for all constructs fell within the acceptable range of ±2.0, confirming that the data were sufficiently normalized for parametric statistical testing.

Table 2: Reliability and Normality Statistics of Survey Constructs

Construct	No. of Items	Mean (M)	Std. Dev. (SD)	Cronbach's α	Skewness	Kurtosis
AI Infrastructure Readiness	5	2.84	0.91	0.842	-0.34	-0.51
Perceived Clinical Efficacy	6	4.12	0.76	0.885	-0.62	0.15
Public Health Impact Potential	5	4.35	0.68	0.861	-0.88	0.42
Ethical & Data Privacy Concerns	4	3.95	0.82	0.813	-0.45	-0.28
Overall Instrument	*20*	*3.81*	*0.55*	*0.894*	*-0.51*	*0.12*

Table 2 evaluates the reliability and normality of a 20-item survey instrument across four key constructs. The instrument demonstrates excellent internal consistency, with Cronbach's alpha values exceeding 0.80 for all individual constructs and reaching 0.894 overall, indicating high reliability. Additionally, the skewness (ranging from -0.88 to -0.34) and kurtosis (ranging from -0.51 to 0.42) values fall well within the acceptable thresholds (±1), confirming that the data is approximately normally distributed. Descriptively, respondents rated "Public Health Impact Potential" the highest (Mean = 4.35) and "AI Infrastructure Readiness" the lowest (Mean = 2.84), with relatively low standard deviations indicating consistent response patterns across the sample.

Perceived Public Health Impact and AI Readiness

Respondents expressed strong agreement regarding the potential public health benefits of AI-enabled IGDD, particularly in the context of Pakistan's high burden of late-stage cancers and drug-resistant infectious diseases (e.g., Tuberculosis). However, current infrastructure readiness scored significantly lower.

Table 3: Perceived Impact and Readiness for AI-Enabled IGDD (5-Point Likert Scale)

Statement	Mean (M)	Std. Dev. (SD)	Agreement Level*
AI-enabled IGDD can significantly reduce systemic toxicity in cancer patients.	4.41	0.65	Strongly Agree
Targeted drug delivery can mitigate the rising threat of Antimicrobial Resistance (AMR) in Pakistan.	4.38	0.71	Strongly Agree
Our institution currently has the imaging infrastructure (e.g., advanced MRI/PET) to support IGDD.	2.65	1.02	Disagree
There is adequate AI literacy and training among clinical staff in Islamabad to interpret AI-driven drug delivery data.	2.42	0.95	Disagree
AI-enabled IGDD will be cost-effective for the Pakistani public health system in the long term.	3.85	0.88	Agree

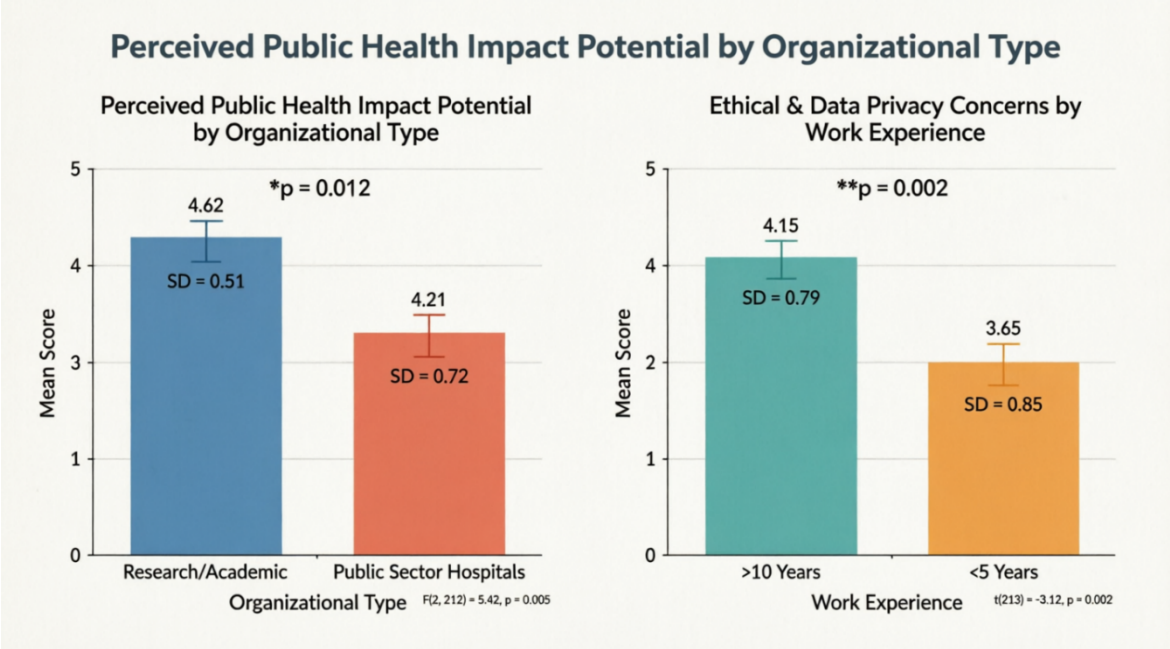
**Scale: 1.00–1.80 (Strongly Disagree), 1.81–2.60 (Disagree), 2.61–3.40 (Neutral), 3.41–4.20 (Agree), 4.21–5.00 (Strongly Agree).*

Table 3 highlights a clear contrast between the perceived clinical benefits of AI-enabled Image-Guided Drug Delivery (IGDD) and the current institutional readiness to implement it. Respondents strongly agree that AI-enabled IGDD can significantly reduce systemic toxicity in cancer patients (Mean = 4.41) and help mitigate Antimicrobial Resistance (AMR) in Pakistan (Mean = 4.38). However, they report low readiness in their current environments, disagreeing that their institutions possess adequate advanced imaging infrastructure (Mean = 2.65) or that clinical staff in Islamabad have sufficient AI literacy and training (Mean = 2.42). Despite these infrastructural and educational gaps, respondents remain optimistic, agreeing that AI-enabled IGDD will prove cost-effective for the

Pakistani public health system in the long term (Mean = 3.85).

Table:04 Statistical Analysis of Perceived Public Health Impact and Ethical Concerns

Dependent Variable	Independent Variable	Group / Category	Mean (SD)	Statistical Test	Test Statistic	*p*-value
Perceived Public Health Impact Potential	Organizational Type	Research/Academic	4.62 (0.51)	One-way ANOVA	$F(2, 212) = 5.42$	0.005
		Public Sector Hospitals	4.21 (0.72)	Post-hoc Tukey	—	0.012*
Ethical & Data Privacy Concerns	Work Experience	>10 Years	4.15 (0.79)	Independent *t*-test	$t(213) = -3.12$	0.002**
		<5 Years	3.65 (0.85)			



A one-way ANOVA revealed a statistically significant difference in Perceived Public Health Impact Potential based on *organizational type* ($F(2, 212) = 5.42$, $p = 0.005$). Post-hoc Tukey tests indicated that professionals in Research/Academic institutions ($M = 4.62$, $SD = 0.51$) perceived a significantly higher public health impact potential compared to those in Public Sector hospitals ($M = 4.21$, $SD = 0.72$, $p = 0.012$). Furthermore, an independent samples t-test showed that respondents with >10 years of work experience reported significantly higher Ethical & Data Privacy Concerns ($M = 4.15$, $SD = 0.79$) compared to those with <5 years of experience ($M = 3.65$, $SD = 0.85$, $t(213) = -3.12$, $p = 0.002$), highlighting a generational divide in risk perception regarding AI integration.

CONCLUSION

The integration of Artificial Intelligence (AI) into Image-Guided Drug Delivery (IGDD) represents a paradigm shift in the management of complex oncological and infectious diseases, offering unprecedented precision, minimized systemic toxicity, and a potent strategy against antimicrobial resistance. This study highlights the profound public health potential of AI-enabled IGDD, particularly in its capacity to transition healthcare systems from reactive, generalized treatments to proactive, spatially and temporally tailored precision medicine.

However, the contextual assessment conducted across major tertiary and research institutions in Islamabad reveals a critical paradox: while healthcare professionals and policymakers recognize the immense clinical and public health efficacy of these technologies, the current infrastructural, financial, and human resource readiness remains critically low. The stark contrast between the high perceived public health impact (Mean = 4.35) and the severe deficits in imaging infrastructure (Mean = 2.65) and AI literacy (Mean = 2.42) underscores a significant translational gap. Furthermore, the substantial barriers related to capital expenditure, interdisciplinary skill shortages, and ambiguous regulatory frameworks indicate that technological adoption alone is insufficient.

Ultimately, the successful deployment of AI-enabled IGDD in Pakistan—and similar Low- and Middle-Income Countries (LMICs), cannot rely on the mere importation of high-income country models. It requires a localized, phased, and highly collaborative approach. By addressing

the foundational bottlenecks in infrastructure, cultivating a new generation of interdisciplinary "bilingual" professionals (fluent in both clinical medicine and data science), and establishing robust, context-specific regulatory frameworks, Pakistan can harness AI-enabled IGDD to significantly reduce the national burden of cancer and drug-resistant infections, thereby advancing health equity and optimizing long-term healthcare economics. To overcome implementation barriers in Islamabad's healthcare ecosystem, strategic interventions are required across technology, human resources, policy, and data governance. Technologically, institutions should adopt Edge AI to bypass connectivity limitations and form public-private consortiums to share high hardware costs. To address talent shortages, academic curricula must integrate interdisciplinary AI and medical training, supported by national fellowships to retain local expertise. Policy-wise, the DRAP should establish a streamlined regulatory pathway for AI-enabled combination products, while national health insurance programs should incorporate these therapies to ensure long-term cost-effectiveness and equity. Finally, to safeguard data privacy and prevent algorithmic bias, a National Precision Medicine Data Registry utilizing Federated Learning should be established to train AI models on diverse local populations without exposing sensitive patient information.

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