

Design and Prototype Development of a Patient Navigation Platform for Healthcare Services in Kigali, Rwanda

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Abstract

Background

Efficient healthcare navigation is essential for timely access to care, yet patients in Kigali, Rwanda, frequently struggle to identify appropriate facilities because of limited information on service availability, specialist schedules, waiting times, and insurance compatibility. This study assessed these navigation challenges among outpatients, used the findings to design and develop a decision-support platform prototype, and conducted a preliminary usability evaluation of the resulting system.

Methods

The study applied the Design Science Research Methodology (DSRM) across three phases. A structured questionnaire was administered over one month (15 April–14 May 2026) to adult outpatients across three district hospitals in Kigali City to characterise navigation practices, challenges, and feature priorities; 85 of 92 outpatients approached agreed to participate (92.4% response rate). Findings informed the requirements, architecture, and functional modules of a prototype, subsequently evaluated by 30 users using the System Usability Scale (SUS).

Results

Service or specialist unavailability on arrival was reported by 72.9% of participants, and 55.3% identified service availability as their single most important facility-selection criterion, yet only 3.5% reported verifying availability digitally beforehand. Chi-square/Fisher's exact testing found no significant association between this experience and gender, age, education, or insurance scheme (all $p > .05$), indicating a broadly distributed information gap across the surveyed participant groups. Friedman's test confirmed a significant hierarchy of feature priorities ($\chi^2(5) = 179.11$, $p < .001$, $n = 52$ complete-ranking cases), led by real-time specialist availability. The resulting prototype — a native Android (Java) application with a Spring Boot 3 backend and a facility-ranking algorithm weighting road distance, waiting time, service availability, and insurance compatibility — achieved a mean SUS score of 86.58 (SD = 12.15; 95% CI [82.04, 91.12]) across 30 evaluators, an "Excellent" usability grade, with 93.4% of scores at or above the acceptability threshold.

Conclusions

Patients in Kigali experience a substantial information gap in healthcare navigation across the surveyed population that a purpose-built digital platform can address with excellent usability among an initial, digitally literate evaluator group. The findings support the feasibility of progressing a patient-facing navigation solution toward field evaluation within Rwanda's digital health ecosystem.

1. Background

Effective navigation of healthcare systems is a recognized determinant of health outcomes worldwide. Patients everywhere face persistent difficulty identifying the healthcare facility best suited to their needs at a given time, which contributes to delayed care, overcrowding of tertiary institutions, and inefficient use of health-system resources. The World Health Organization's Global Strategy on Digital Health 2020–2025 names patient-centred digital tools and mobile health applications as essential instruments for addressing access and navigation challenges at scale [1], and digital technologies spanning mobile applications, artificial intelligence, and geographic information systems are increasingly deployed to help patients make informed care-seeking decisions and reduce time-to-treatment [2]. Globally, roughly three-quarters of patients report at least one barrier to accessing care, and about a third face multiple barriers simultaneously [3]. Evidence from AI-based waiting-time prediction models shows that timely information can materially reduce patient uncertainty and improve care-seeking efficiency [4, 5]. Despite this momentum, patient-facing navigation platforms remain underdeveloped in sub-Saharan African health systems, where the need may be greatest [6, 7]. The Smart Africa Digital Health Blueprint identifies mobile-enabled health navigation as a continental priority and explicitly calls for tools that account for the scheduling realities of African facilities, including specialist services offered only on designated days of the week [8].

These structural limitations are magnified in low- and middle-income settings. More than half of patients in sub-Saharan Africa report barriers related to distance, transport, and lack of information when seeking care [9], compounded by weak referral coordination between levels of care [10]. Mobile health deployment has nonetheless accelerated across the region, driven by smartphone penetration and growing recognition of ICT as a health-system enabler [7]. Rwanda, alongside Kenya and Uganda, leads East African ICT-for-health innovation [11]; nationwide programmes such as the RapidSMS maternal health monitoring system [12] and the e-ASCov community screening application [13] demonstrate the technical feasibility and community acceptance of mHealth tools locally. Structured, navigator-led interventions have also shown clinical benefit: a Rwandan military referral hospital reduced time-to-treatment for gastrointestinal cancer patients through in-person patient navigation [14]. However, navigator-led models are resource-intensive and cannot scale to the everyday navigation needs of the general outpatient population, underscoring the case for a technology-driven alternative.

Rwanda's health system has achieved substantial gains in outcomes, insurance coverage through the Mutuelle de Santé scheme, and digital health infrastructure, with the National Digital Health Strategic Plan 2020–2025 prioritising patient-facing digital tools [15], and 2025 media reports describe the national launch of AI-powered health applications [16]. Yet navigation challenges persist: patients attending primary healthcare facilities spend an average of 211 minutes per visit, of which roughly 81.5 minutes is waiting time alone [17], reflecting limited access to real-time information for decision-making. Kigali, the capital and most densely served urban centre, hosts the country's most complex healthcare infrastructure across the Gasabo, Kicukiro, and Nyarugenge districts [18, 19]. A specific and under-addressed challenge in this context is that many hospitals and health centres offer specialties such as

gynaecology, ophthalmology, physiotherapy, and dentistry only on designated days of the week; without this information, patients may travel to a facility only to find the required service unavailable. Differences between Mutuelle de Santé, the Rwanda Social Security Board (RSSB) medical scheme, and Military Medical Insurance (MMI) coverage further complicate facility selection [20]. To date, no integrated, patient-facing digital tool in Rwanda combines service scheduling, waiting-time information, geographic proximity, and insurance compatibility within a single platform.

Prior African patient-navigation research has documented these general barriers [14, 21] and regional digital health literature has repeatedly recommended integrated navigation platforms [7, 8], yet no published study has specifically investigated service-availability scheduling as a distinct navigation barrier in Kigali, nor developed and evaluated an integrated navigation platform that combines availability, waiting time, proximity, and insurance compatibility in the Rwandan context. AI-based waiting-time prediction has been demonstrated in high-income settings [4, 5] but remains largely unexplored in East Africa, and although mHealth usability evaluations exist for community-health-worker-facing Rwandan tools [22], none has reported a System Usability Scale evaluation of a patient-facing navigation platform locally.

In this paper, we report a three-phase Design Science Research study that (i) quantified the healthcare navigation challenges experienced by outpatients in Kigali, (ii) used these findings to design and develop a decision-support platform prototype, and (iii) evaluated the usability of the resulting prototype. The study addresses the gap between Rwanda's stated digital health ambitions and the absence of a validated patient-facing navigation tool, and provides evidence that can inform the design of similar solutions in comparable low-resource urban settings.

Beyond the specific case of Kigali, this work speaks to a broader methodological question in digital health research: whether patient-facing navigation tools for low-resource urban settings can be grounded in statistically confirmed user priorities rather than in assumptions carried over from high-income contexts. The clinical and public-health relevance of this work lies in its potential to reduce wasted journeys, shorten time-to-care, and support more equitable use of already-constrained health-system capacity. A platform that tells a patient, before they leave home, whether the specialist they need is on duty that day is a modest technical intervention with plausibly outsized effect on the daily friction of seeking care in an urban African health system.

2. Methods

2.1 Study design

The study applied the Design Science Research Methodology (DSRM) of Peffers et al. [23], which structures the creation and evaluation of information system artefacts intended to solve practical problems through six interrelated phases: problem identification and motivation, definition of solution objectives, design and development, demonstration, evaluation, and communication. These phases

guided the study from the identification of healthcare navigation challenges through prototype development to usability evaluation, informed by a pragmatist perspective that emphasises generating knowledge through the iterative design, implementation, and evaluation of solutions to real-world problems [24].

2.2 Needs assessment (Objective 1)

A cross-sectional questionnaire survey was conducted at three purposively selected district hospitals representing Kigali's three administrative districts: Kibagabaga District Hospital (Gasabo), Muhima District Hospital (Nyarugenge), and Masaka District Hospital (Kicukiro). Data collection was conducted over one month, from 15 April to 14 May 2026.

Eligible participants were adult outpatients (≥ 18 years) attending these facilities during the data collection period. Participants were recruited using systematic random sampling, with every third eligible outpatient in the waiting area invited to participate. Of 92 outpatients approached, 85 consented to participate and completed the questionnaire, while 7 declined, yielding a response rate of 92.4%. Within the DSRM framework, this sample was considered sufficient to identify priority user needs and inform prototype requirements, consistent with the formative rather than population-inferential purpose of this phase.

Data were collected using a structured digital questionnaire, available in English and Kinyarwanda and completed electronically in approximately 15–20 minutes with support from trained research assistants where needed. Data collection took place within outpatient waiting areas to minimise disruption to routine clinical activity while retaining access to patients actively seeking care. The instrument comprised five thematic sections: socio-demographic characteristics (8 items covering age, sex, district of residence, education level, insurance type, smartphone ownership, visit frequency, and language); current navigation practices (6 items on facility-selection methods, information sources, and waiting-time experience); service-availability awareness (5 items on prior experiences of unavailability, digital verification behaviour, and willingness to travel for available services); digital health readiness (5 Likert-scale items on smartphone use, prior mHealth experience, and willingness to adopt a navigation application); and feature preferences (6 items requiring an ordinal ranking of candidate platform functions). For the inferential analysis reported in Section 3.3, age was additionally dichotomised into two groups (18–34 years and 35–54 years); the four-category breakdown shown in Table 1 is retained for descriptive reporting. Content validity was established through expert review by health informatics and public health specialists, who assessed each item for relevance, clarity, and alignment with the study objectives, and the instrument was piloted with ten outpatients at a facility not included in the main study; feedback from both stages was incorporated into the final version. This needs-assessment questionnaire was developed specifically for this study; no existing validated instrument was identified that jointly captures healthcare-facility navigation behaviour, service-availability barriers, and mobile-health adoption readiness in the Rwandan context. Item construction was nonetheless informed by established conceptual frameworks: the socio-demographic and navigation-practice items drew on the predisposing and enabling constructs of Andersen's Behavioral Model of Health Services Use [31], the

service-availability, waiting-time, and transport-cost items were informed by the corresponding dimensions of Levesque et al.'s patient-centred access framework [32], and the digital-health-readiness items drew on constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT), including performance expectancy, effort expectancy, and facilitating conditions [33]. The English-language version of the questionnaire is provided as a supplementary file (Additional File 1).

Response consistency was supported by standardised administration and identical questionnaire versions across all three study sites; a formal internal-consistency (e.g., Cronbach's α) analysis was not performed on the multi-item sections.

Responses were captured in Google Forms, exported to Microsoft Excel for cleaning, and analysed in IBM SPSS Statistics Version 26. Descriptive statistics summarised participant characteristics and navigation experiences. Associations between socio-demographic characteristics and the experience of service unavailability were tested using Pearson's chi-square test, with Fisher's exact test applied where expected cell counts fell below 5; significance was set at $p < .05$. Feature-preference rankings were analysed using Friedman's non-parametric test.

2.3 Prototype design and development (Objective 2)

System requirements were derived directly from the needs-assessment findings and organised into functional and non-functional categories using MoSCoW prioritisation. Four navigation challenges shaped the design: (i) frequent service/specialist unavailability, addressed through a real-time facility-availability display; (ii) absent pre-visit queue information, addressed through live queue and waiting-time data; (iii) reliance on informal selection heuristics, addressed through a ranked, filterable facility-search function; and (iv) limited insurance-scheme transparency, addressed through facility-level insurance filtering. These requirements were operationalised into a use-case model defining four actor roles — Guest, Patient, Facility Staff, and Administrator — with progressively expanding capabilities.

The prototype was implemented as a native Android application structured in three layers. The presentation layer is a native Android application written in Java, using Material Design 3 components, the Google Maps SDK for in-app mapping, and Retrofit 2 for HTTP client communication with the backend. The application layer is a Spring Boot 3 service exposed via Spring MVC, implementing the core business-logic services — appointment management, facility-ranking, and real-time communication — and secured with Spring Security and JSON Web Token (JWT) authentication for role-based access control. The data and integration layer combines a local SQLite database for on-device persistence with two external integrations: the Open Source Routing Machine (OSRM) for road-network distance and routing calculations, and the Google Maps Platform for geocoding and map rendering; Socket.IO supports real-time messaging between patients and facility staff. A native Android implementation was selected over a web-based alternative to take advantage of the near-universal Android smartphone ownership documented in the needs assessment, to allow tighter integration with on-device mapping and location services for the distance-based ranking function, and to allow core navigation data to be

cached locally via SQLite for more resilient performance under the intermittent connectivity conditions common in outpatient waiting areas.

Facility recommendations are generated by a weighted, rule-based facility-ranking algorithm rather than a machine-learning or adaptive model. Each candidate facility is scored as a weighted sum of four inputs: road distance calculated via OSRM (40%), estimated waiting time derived from live queue data (30%), service or specialist availability (20%), and compatibility with the patient's insurance scheme (10%); facilities are then ranked in descending order of composite score, with ties broken by shorter distance. This weighting scheme reflects the priorities identified during the needs assessment (Section 3.4), with the greatest weight assigned to geographic accessibility and waiting time — the two factors participants could most directly act on once service availability itself was known. The relational schema included dedicated entities for services (with a dynamic availability flag), queue data (timestamped counts and wait estimates), and insurance schemes, enabling facility staff to update operational information without altering core facility records. Five functional modules were implemented: facility discovery and ranking, real-time service availability and queue status, appointment booking and tracking, patient-to-staff live chat, and administration/staff management.

2.4 Usability evaluation (Objective 3)

The completed prototype was evaluated by 30 participants using the System Usability Scale (SUS), a validated ten-item instrument originally developed by Brooke [35] and widely used to assess perceived usability [25, 26]. The SUS was not developed for this study; it is an existing, previously published instrument adopted here without modification. The usability evaluation was conducted over seven days, from 15 to 22 June 2026, after prototype development was complete. Usability evaluators were recruited independently of the needs-assessment sample: recruitment for this phase took place only after prototype development was complete, separately from and subsequent to the needs-assessment data collection, and no individual participated in both phases. Participants were recruited through purposive sampling and were eligible if they were adults with basic smartphone literacy, able to independently access and navigate a mobile application, and willing to provide informed consent.

Evaluation sessions followed a standardised procedure in which participants first completed seven representative navigation tasks using the prototype — (i) facility discovery and ranked recommendation, (ii) service-specific search, (iii) insurance-filtered search, (iv) real-time queue monitoring, (v) appointment booking and confirmation, (vi) in-app navigation to a selected facility, and (vii) patient–staff communication — before rating the ten SUS statements on a five-point scale. Raw scores were converted to the standard 0–100 SUS metric, and descriptive statistics (mean, standard deviation, 95% confidence interval) were calculated alongside item-level analysis of each statement's contribution to the aggregate score. Scores were classified against the SUS benchmarking framework of Bangor et al. [25], refined by Lewis and Sauro [27].

2.5 Ethical considerations

The study was conducted in accordance with the ethical principles of the Declaration of Helsinki [28]. Ethical approval was obtained from the University of Rwanda College of Medicine and Health Sciences Institutional Review Board (reference UR|CMHS|IRB|356|2026) prior to data collection, and all participants provided informed consent. Participant data were anonymised and stored securely, and participation in both the needs assessment and usability evaluation was voluntary.

3. Results

3.1 Participant characteristics

Eighty-five adult outpatients completed the needs-assessment questionnaire, all with sufficient data for analysis. Table 1 summarises participant characteristics. The sample was predominantly composed of young adults aged 25–34 years (65.9%), and 60.0% were female. Geographic coverage spanned all three districts (Gasabo 34.1%, Kicukiro 31.8%, Nyarugenge 15.3%). Most participants held university-level qualifications (70.6%), and the most prevalent insurance scheme was RSSB (41.2%), followed by Mutuelle de Santé (23.5%), MMI (18.8%), and private insurance (16.5%). Smartphone ownership was near-universal (97.6% personal device ownership).

Table 1
Socio-demographic characteristics of needs-assessment participants (N = 85)

Characteristic	Category	n (%)
Recruitment facility	Masaka District Hospital	40 (47.1)
	Muhima District Hospital	24 (28.2)
	Kibagabaga District Hospital	21 (24.7)
Age group	18–24 years	5 (5.9)
	25–34 years	56 (65.9)
	35–44 years	14 (16.5)
	45–54 years	10 (11.8)
Gender	Female	51 (60.0)
	Male	34 (40.0)
District of residence	Gasabo	29 (34.1)
	Kicukiro	27 (31.8)
	Nyarugenge	13 (15.3)
	Other / not specified	16 (18.8)
Education level	University or higher	60 (70.6)
	Secondary school	17 (20.0)
	Technical training	8 (9.4)
Health insurance scheme	RSSB	35 (41.2)
	Mutuelle de Santé	20 (23.5)
	MMI	16 (18.8)
	Private (UAP, Radiant, other)	14 (16.5)
Smartphone access	Personal device	83 (97.6)
	Shared device	2 (2.4)
<i>Note. Percentages are calculated within each characteristic category and may not sum to 100.0% due to rounding.</i>		

3.2 Navigation practices and challenges

Previous positive experience at a facility (41.2%) and simple proximity to home (36.5%) were the most common bases for facility selection; formal information-seeking behaviours such as online search or advice from a community health worker accounted for only 5.9% of responses combined. When asked to

name the single most important factor in facility choice, 55.3% cited service or specialist availability, followed by distance (16.5%), insurance acceptance (9.4%), and quality of care (9.4%).

Waiting times were commonly extended: 41.2% of participants typically waited one to two hours and a further 8.2% waited more than two hours, while only 12.9% waited less than 30 minutes. Transport cost represented at least a situational barrier for 71.7% of participants (58.8% “sometimes,” 12.9% “a major barrier”). Service or specialist unavailability on arrival had been experienced by 72.9% of participants at some point, with 58.8% reporting this within the preceding six months.

Despite service availability being the leading facility-selection priority, only 3.5% of participants reported having verified service or specialist availability digitally before travelling to a facility, underscoring the gap between stated priority and the means available to act on it.

3.3 Associations between characteristics and service unavailability

Chi-square and Fisher’s exact tests found no statistically significant association between the experience of service unavailability and gender ($\chi^2(1) = 0.72$, $p = .397$), age group (dichotomised as 18–34 vs. 35–54 years; $\chi^2(1) = 1.17$, $p = .279$), insurance scheme ($p = .655$), or education level ($p = .734$). The barrier therefore appeared distributed across the full outpatient population rather than concentrated within any socio-demographic subgroup.

3.4 Feature preferences

Friedman’s test on 52 complete-ranking cases revealed a statistically significant hierarchy of preference across the six candidate prototype features ($\chi^2(5) = 179.11$, $p < .001$). Real-time specialist service availability was the top priority (mean rank = 1.31; ranked first by 75.7% of respondents), followed by information on which specialist doctors were on duty (mean rank = 2.25), estimated waiting time (mean rank = 2.98), distance/directions (mean rank = 3.94), insurance compatibility (mean rank = 4.42), and Kinyarwanda-language content (mean rank = 5.48). Table 2 presents the full ranking results.

Table 2
Participant feature-preference rankings: mean rank scores and proportion assigning rank 1

Prototype feature	n*	Mean rank (SD)	Rank order	% assigned rank 1
Which specialist services are available today and on which days	70	1.31 (0.98)	1st	75.7
Which specialist doctors are on duty today (name, specialty, hours)	62	2.25 (0.99)	2nd	16.1
Estimated waiting time at each facility	56	2.98 (0.80)	3rd	7.1
Distance and directions to the nearest suitable facility	58	3.94 (0.80)	4th	6.9
Whether my insurance scheme is accepted at the facility	56	4.42 (1.42)	5th	12.5
Application content available in Kinyarwanda	54	5.48 (1.18)	6th	1.9

*n = number of respondents who ranked this specific item (partial-response count). The Friedman statistic, the overall hierarchy, and the reported mean ranks are all computed on the same n = 52 respondents who provided complete rankings across all six items. Note. Lower mean rank indicates higher perceived importance. Friedman's test (n = 52 complete cases): $\chi^2(5) = 179.11$, $p < .001$.

3.5 Prototype design outcomes

The needs-assessment findings were translated into a functioning prototype comprising a three-layer architecture (a native Android/Java presentation layer, a Spring Boot 3 application layer, and a SQLite/OSRM/Google Maps data and integration layer), a four-actor role-based access model (Guest, Patient, Facility Staff, Administrator), and five functional modules covering facility discovery and ranking, real-time availability and queue status, appointment booking and tracking, patient-to-staff messaging, and administration. Each major design decision was directly traceable to a specific, empirically confirmed user requirement: the service-availability display responded to the 72.9% unavailability finding, the live queue module responded to the demand for waiting-time information, the weighted facility-ranking algorithm (road distance 40%, waiting time 30%, service availability 20%, insurance compatibility 10%) responded to the reliance on informal selection heuristics, and the insurance-filtering function responded to the documented insurance-transparency gap.

3.6 Usability evaluation

The prototype achieved a mean SUS score of 86.58 (SD = 12.15; range 55.0–100.0; 95% CI [82.04, 91.12]) across 30 participants, corresponding to a grade of A and an adjectival rating of “Excellent.” Table 3 presents the distribution of scores by acceptability category: 56.7% of participants scored ≥ 90.0 (“Best Imaginable/Excellent”), 36.7% scored 70.0–89.9 (“Good”), and 6.7% scored 51.0–69.9 (“Marginal/Poor”); no participant scored below 51.0. Cumulatively, 93.4% of participants produced scores at or above the 70.0 acceptability threshold.

Table 3
Distribution of participant SUS scores by acceptability category (n = 30)

Category	SUS range	n	%	Grade
Best imaginable / Excellent	≥ 90.0	17	56.7	A+ / A
Good	70.0–89.9	11	36.7	B+ / B
Marginal / Poor	51.0–69.9	2	6.7	C / D
Not acceptable	< 51.0	0	0.0	F
Total	—	30	100.0	—
<i>Note. Mean SUS score = 86.58 (SD = 12.15; 95% CI [82.04, 91.12]), corresponding to grade A and an “Excellent” adjectival rating.</i>				

At item level, the strongest contributions came from the item addressing absence of cumbersome (M = 1.13, SD = 0.43; contribution 9.67/10), intended frequency of use (M = 4.63, SD = 0.67; 9.08/10), perceived learnability (M = 4.60, SD = 0.62; 9.00/10), and perceived complexity (M = 1.40, SD = 0.86; 9.00/10). The lowest — though still positive — contributions were recorded for perceived need for technical support (M = 2.00, SD = 1.17; 7.50/10) and perceived inconsistency (M = 2.03, SD = 1.19; 7.42/10), which also produced the highest inter-participant variability in the instrument.

4. Discussion

4.1 Summary of findings

This study found that healthcare navigation in Kigali is constrained by a substantial information gap that was broadly distributed across the surveyed participant groups: nearly three-quarters of outpatients had arrived at a facility only to find their required service or specialist unavailable, and this experience was unrelated to gender, age, education, or insurance scheme. Despite service availability being the single most important facility-selection criterion for most participants, fewer than one in twenty (3.5%) verified it digitally beforehand, relying instead on past experience or simple proximity. Guided by a statistically confirmed hierarchy of feature priorities, we designed and built a prototype integrating real-time availability, queue, proximity, insurance, and communication functionality, which 30 evaluators rated as excellently usable (mean SUS = 86.58), with over 93% of scores at or above the acceptability threshold.

4.2 Interpretation

What is most striking in these results is the gap between stated priority and actual behaviour: more than half of participants said service availability was their top selection criterion, yet almost none of them could act on that priority because no channel existed to verify it before travelling. This is not, in our reading, a demand-side failure of judgement so much as a supply-side failure of information infrastructure — patients were behaving rationally within an environment that gave them almost nothing to go on beyond memory and proximity. The uniformity of the unavailability experience across

demographic subgroups reinforces this interpretation: if the barrier were concentrated among, say, lower-income or less-educated participants, it would point toward cost or literacy as the underlying constraint. Instead, its universality points toward a structural absence of shared, accessible scheduling information — a problem that a digital platform is well positioned to solve.

4.3 Comparison with the literature

The magnitude of the unavailability finding (72.9%) is consistent with regional evidence identifying knowledge deficits about service availability and specialist schedules as a primary navigation barrier across African health systems [7, 21], and extends this evidence to the specific, previously undocumented case of day-of-week specialist scheduling in Kigali. The near-universal smartphone ownership and willingness to adopt a navigation application observed here are considerably more favourable than the readiness profiles reported for rural Rwandan populations, which have required additional training support for mHealth adoption [13, 22], suggesting that the binding constraint on adoption in this urban context may be the absence of a suitable platform rather than infrastructure or capability.

The prototype's usability outcome (SUS = 86.58) exceeds the meta-analytic benchmark for digital health applications generally (mean 68.0) [29] by roughly 1.5 standard deviations, and exceeds a comparable mobile clinical decision-support benchmark (79.2) [30]. Within Rwanda specifically, the most comparable published benchmark — the e-ASCov community screening application — reported favourable acceptability among community health workers, though on a different, largely qualitative/feasibility metric rather than SUS [13].

A comparison across these studies should be read with caution: sample composition differed substantially between them, and our own evaluators were young, university-educated, and highly digitally literate (Section 4.4), a profile generally associated with higher SUS scores independent of interface design. We therefore note the favourable comparison as suggestive rather than attributing it definitively to the evidence-to-design traceability enabled by DSRM; both explanations are plausible, and disentangling them would require testing the same prototype with a more heterogeneous, representative user sample.

Read through the lens of the Technology Acceptance Model, the high intended-frequency-of-use item (mean 4.63/5) and learnability item (mean 4.60/5) are consistent with favourable perceived ease of use, a TAM construct closely related to SUS. The high learnability score in particular carries practical implementation weight: platforms perceived as quickly learnable typically require less institutional training investment, a recognised determinant of mHealth scalability in resource-constrained settings. Considered together with Rwanda's National Digital Health Strategic Plan emphasis on patient-facing digital tools [15], these results position the prototype as a plausible candidate for progression to a field pilot, in which the staff-driven availability-update workflow and real-world response times could be evaluated under operational rather than laboratory conditions.

4.4 Strengths and limitations

This study's principal strength is its evidence-to-design traceability: each functional component of the prototype — the dynamic service-availability flag, the queue data model, the weighted ranking function, and the insurance filter — can be traced to a specific, statistically grounded finding from the needs assessment, addressing a recognised weakness in digital health tool development in sub-Saharan Africa, where artefacts are often built without formal needs-assessment grounding.

The study nonetheless has clear limits in scope. The needs assessment was conducted at three district hospitals within Kigali City; findings may not generalise to peri-urban or rural navigation experiences, where access patterns likely differ. The sample size ($n = 85$) was appropriate for the formative, design-oriented purpose of a DSRM needs assessment but was not intended to support population-level prevalence estimates, and the age distribution skewed toward younger adults (65.9% aged 25–34, with no participants aged 55 years or older), which may limit generalisability to older outpatients. Usability testing was conducted under controlled conditions rather than routine clinical use, so contextual factors such as network variability, device heterogeneity, and illness-related burden were not captured, and the evaluation sample's basic-to-high digital literacy may under-represent individuals with lower levels of digital literacy. The study also did not assess downstream clinical or utilisation outcomes, cost effects, or long-term adoption; these require field-level evaluation. Further research is necessary to test the prototype under real operational conditions — including staff-driven data-update workflows, appointment-confirmation latency, and chat response times — and across a more digitally heterogeneous user base. A further limitation concerns the usability instrument itself: although SUS is a well-validated general-purpose usability measure, it was not designed specifically for mobile health applications; purpose-built instruments such as the mHealth App Usability Questionnaire (MAUQ) [34] have since been developed to capture usability dimensions specific to mHealth tools, including information architecture and health-task usefulness, and could complement SUS in future evaluation phases of this prototype.

5. Conclusions

Patients in Kigali experience a substantial, demographically undifferentiated information gap when navigating healthcare services, most acutely around service and specialist availability. A prototype platform designed directly from this evidence — integrating real-time availability, queue, proximity, insurance, and communication features — achieved excellent usability among an initial, digitally literate group of evaluators, exceeding comparable digital health and regional mHealth benchmarks. These findings support the feasibility of a patient-centred digital navigation solution in Kigali and provide an evidence base for its progression to field piloting with a broader, more representative user base. Healthcare facilities should improve the availability and communication of up-to-date service, schedule, and waiting-time information; digital health stakeholders, including Rwanda's Ministry of Health, should consider integrating patient-facing navigation platforms of this kind into the national digital health ecosystem; and future development should prioritise real-time data integration from facilities, interoperability with existing health information systems, predictive waiting-time estimation, and

multilingual support, alongside evaluation under routine healthcare conditions to assess effectiveness, scalability, and long-term adoption.

Abbreviations

CI

Confidence interval

DSRM

Design Science Research Methodology

IRB

Institutional Review Board

JWT

JSON Web Token

MMI

Military Medical Insurance

MoSCoW

Must have, Should have, Could have, Won't have (requirements-prioritisation technique)

OSRM

Open Source Routing Machine

RSSB

Rwanda Social Security Board

SD

Standard deviation

SUS

System Usability Scale

TAM

Technology Acceptance Model

Declarations

Ethics approval and consent to participate

The study was approved by the University of Rwanda College of Medicine and Health Sciences Institutional Review Board (reference UR|CMHS|IRB|356|2026) and was conducted in accordance with the Declaration of Helsinki. All participants provided informed consent before enrolment.

Consent for publication

Not applicable. This manuscript does not contain identifiable individual participant data or images.

Availability of data and materials

The datasets generated and/or analysed during the current study are not publicly available, as this was not permitted under the terms of the ethical approval governing their collection, but de-identified data are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

DS conceived and designed the study, developed the survey instrument, collected and analysed the data, designed and developed the prototype, and drafted the manuscript. KN and AAM supervised the study, contributed to the conceptualisation and methodology, and critically reviewed and revised the manuscript. ME, CT, and DKT contributed to supervision, methodological guidance, interpretation, and critical revision of the manuscript. All authors read and approved the final manuscript.

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