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NATIONAL HELPLINE 333: OPPORTUNITIES AND CHALLENGES OF AI VOICE BOT–BASED CITIZEN SERVICES

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ABSTRACT

The National Helpline 333 is Bangladesh's nationwide non-emergency, citizen-service contact center. As the platform's scope grows from information and grievance services to proactive referrals and social protection, its human-agent–only operating model faces constraints in scale, cost, and 24/7 availability. This paper examines whether and how Artificial Intelligence (AI) Voice Bots can augment 333. Using a qualitative, mixed-sources approach (policy/operational documents, international case studies, and expert inputs), we (i) map opportunities across access, efficiency, inclusivity, and analytics; (ii) identify technical, ethical, and socio-organizational risks; (iii) propose an architecture for Bangla/English voice automation integrated with CRM/KMS and human escalation; and (iv) outline policy and governance guardrails aligned with international AI principles. Findings suggest that a tiered 'AI-first, human-assured' model can reduce average handling time, increase first-contact resolution, and extend after-hours coverage—provided investments are made in local-language ASR/NLU, quality knowledge bases, human-in-the-loop review, and robust data governance (UNDP, 2023; OECD, 2019).

1 INTRODUCTION

Bangladesh has invested heavily in citizen-centric digital public infrastructure under the 'Digital Bangladesh' and 'Smart Bangladesh' agendas. Within this ecosystem, National Helpline 333 functions as a single, voice-based gateway for government information, referrals, and grievance redress. During COVID-19, 333 was repurposed at scale to connect citizens to medical advice and emergency relief—demonstrating the platform's adaptability and national reach (UNDP, 2020; UNDP, 2023). With rising volumes and diversified use-cases (e.g., social protection navigation, municipal services, women and child safety referrals), the contact-center model is pressured by staffing, training, and continuity demands. Meanwhile, conversational AI has matured: modern automatic speech recognition (ASR), neural language understanding (NLU), and dialog management have enabled virtual agents to handle routine, repetitive tasks reliably. The central question is not whether to automate, but how to do so responsibly in low-resource language settings like Bangla—without excluding vulnerable groups or eroding public trust (OECD, 2019).

1.1 Research Questions

RQ1: What service-delivery opportunities (coverage, timeliness, quality, efficiency) can AI Voice Bots unlock for 333?

RQ2: What technical, organizational, ethical, and policy challenges must be addressed to deploy voice automation in Bangla/English for diverse citizen segments?

RQ3: What end-to-end architecture and operating model best integrate AI bots with 333's CRM/KMS and human agents?

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RQ4: Which governance mechanisms (standards, monitoring & evaluation, safeguards) are necessary to align with trustworthy AI principles and public expectations?

2 LITERATURE REVIEW

Conversational agents in the public sector have moved from pilots to production at national scale. Singapore's 'Ask Jamie' virtual assistant served 70+ agency sites, answering millions of queries with live-chat escalation. Estonia's 'Bürokratt' envisions a unified, cross-agency assistant that brokers thousands of services via text and voice. India's UMANG platform increasingly exposes services through chat and voice channels. Cross-country reviews by the OECD underscore potential gains in responsiveness and equity, but warn of risks around bias, transparency, and human oversight. In academic literature, chatbots are shown to reduce cost-to-serve for routine interactions while maintaining acceptable user satisfaction; however, performance relies on domain-specific knowledge bases, intent coverage, and careful escalation design. On the speech side, deep learning has dramatically improved ASR accuracy (e.g., RNN-Transducers, wav2vec 2.0), and transfer learning helps low-resource languages. Recent Bangla ASR efforts indicate promising accuracy when combining large-vocabulary acoustic models with domain adaptation and noise-robust training—key for real-world call-center audio.

2.1 Conversational Agents and Public Sector Adoption

Conversational agents, including AI-powered voice bots, have been increasingly deployed in government and citizen service delivery worldwide. For example, Singapore's *Ask Jamie* has supported over 70 agencies with millions of citizen queries through hybrid chatbot-human systems (GovTech Singapore, 2023). Similarly, Estonia's *Bürokratt* aims to unify digital government services into a single assistant across voice and text channels (Information System Authority of Estonia, 2025). India's UMANG platform demonstrates how voice-enabled services can scale citizen access nationally (NeGD, n.d.). These international experiences suggest that AI voice bots enhance efficiency, reduce wait times, and improve accessibility, while also raising concerns regarding inclusivity, transparency, and data ethics (OECD, 2019).

2.2 Speech & Language Technology: ASR and NLU in Low-Resource Languages

The core of AI voice bot systems lies in Automatic Speech Recognition (ASR) and Natural Language Understanding (NLU). Deep learning–based ASR has significantly advanced speech processing, with models like wav2vec 2.0 achieving state-of-the-art accuracy across multiple languages (Baevski et al., 2020). However, performance in low-resource languages remains challenging. For Bangla, Rakib et al. (2022) developed *Bangla-Wave*, improving recognition through n-gram models and fine-tuned wav2vec2. Nandi et al. (2023) introduced domain-agnostic pseudo-labeling techniques, showing promise for conversational ASR in varied real-world contexts. Ahlawat et al. (2025) surveyed recent deep learning approaches, highlighting transfer learning and multilingual pretraining as crucial for underrepresented languages.

2.3 Conversational Agents in the Bangla Context

Developing voice-enabled systems in Bangla faces challenges of dialectal variation, code-switching with English, and noisy telephony environments. Dhrubo et al. (2024) demonstrated an AI conversational system addressing language barriers, with emphasis on user trust. Similarly, the AIMS TALK project shows intelligent call-center support with speaker authentication in Bangla (Pranto, Nabid, Samin, Mohammed, Sarker, Huda, & Mamun, 2021), and agricultural advisory conversational AI systems also highlight the need for local-language adaptation and domain-specific tuning (Rahman et al., 2023). These studies indicate that AI voice bots for citizen services in Bangladesh must incorporate continuous model refinement and diverse training data to achieve inclusivity.

2.4 Social, Ethical, and Governance Considerations

The literature also highlights ethical and governance challenges. Cave et al. (2021) emphasize risks of bias and lack of transparency in public sector AI systems, while Floridi et al. (2018) propose ethical frameworks for "trustworthy AI" with human oversight. Trust is critical in public service: if citizens are not informed when interacting with a bot, credibility may erode (Chi et al., 2022). Concerns around privacy, surveillance, and misuse of sensitive call data necessitate robust data

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governance frameworks—including anonymization, encryption, and limited retention (UNDP, 2020).

2.5 Case Studies and Applications

International case studies reinforce the role of hybrid AI-human systems. In the U.S., *Citibot Voice* and platforms like *Synthflow* illustrate how municipal governments leverage AI bots for local information and emergency notifications (Citibot, n.d.; Stark et al., 2023). India's Haptik platform successfully scaled COVID-19 helpdesk services, demonstrating resilience during crisis (Haptik, n.d.). For Bangladesh, the National Helpline 333's rapid repurposing during COVID-19 to deliver food relief and medical consultations (UNDP, 2023) highlights its adaptability, but also shows the strain on human agents—suggesting automation can enhance sustainability.

2.6 Key Insights and Research Gaps

From the literature, five key insights emerge:

1. Language Barriers: Bangla ASR progress exists, but more domain-specific training is required (Rakib et al., 2022; Nandi et al., 2023).
2. Hybrid Necessity: Most successful deployments use AI for FAQs with seamless escalation to human agents (GovTech Singapore, 2023; VoiceSpin, n.d.).
3. Trust and Transparency: Clear communication when citizens interact with AI is essential (Chi et al., 2022; Floridi et al., 2018).
4. Data Governance: Secure data handling and ethical compliance are fundamental (Cave et al., 2021; OECD, 2019).
5. Inclusivity: Special measures are needed to avoid exclusion of digitally illiterate or marginalized groups (Rahman et al., 2023).

Together, these insights suggest that while AI voice bots offer transformative potential for Bangladesh's National Helpline 333, deployment must be cautious, inclusive, and governance-driven.

3 METHODOLOGY

We adopt a qualitative, applied-research design appropriate for a system-integration and policy question. Data sources include: (1) secondary documents (a2i/UNDP briefs, public websites, case studies); (2) international exemplars (Singapore, Estonia, India) for transferability insights (GovTech Singapore, 2023; Information System Authority of Estonia, 2025; NeGD, n.d.); and (3) technical literature on ASR/NLU and dialog systems (Baevski et al., 2020; Rakib et al., 2022; Nandi et al., 2023; Ahlawat et al., 2025). Analytic steps include: (a) opportunity mapping for 333 use-cases (FAQ, status checks, referrals, grievance triage); (b) risk/threat modeling across data protection, safety, bias, and misuse; (c) architecture synthesis for a tiered AI-human workflow; and (d) a preliminary monitoring and evaluation (M&E) plan with KPIs (quality, equity, efficiency). Limitations: We do not report a live randomized evaluation; rather, we present a design and policy roadmap to be validated in controlled pilots.

3.1 Strengthened Methodology and M&E Plan

Design: Mixed-methods applied research combining operational analytics (telephony/CRM), user studies, and expert interviews. Quant: Pre-post or controlled A/B across 10–20 high-volume intents. Qual: Agent ride-alongs, user interviews, FGDs; think-aloud tests for handoff flows.

Sampling: Operational logs for target intents over matched windows; stratified random samples by node/time/region. Users (n≈10–20 per cohort: women, rural, low-literacy, persons with disabilities) for task-based usability. Agents/supervisors via purposive sampling.

Coding scheme (qualitative): Success, Frictions (ASR, intent, KMS, policy), Trust (disclosure, consent), Safety (misinformation, harm).

Threats to validity: seasonality and staffing (mitigate with difference-in-differences), audio variability (SNR bucketing), measurement error (double annotation).

KPI formulae: AHT = Talk + Hold + Wrap; FCR = Resolved on first contact ÷ Total; Escalation% = Bot→Agent ÷ Bot sessions; Automation% = Bot-resolved ÷ Eligible; Equity Gap = Metric_group − Overall; Quality = human audit score (0–100).

4 DATA AND EVALUATION

Table 1. Baseline → Pilot Comparison

Metric	Baseline	Pilot (AI-first, human-assured)	Δ	Notes
Average Handle Time (AHT)	185 s (≈3m 05s)	157 s (≈2m37s)	-28 s (−15 %)	Baseline uses avg call duration
First Contact Resolution (FCR, %)	68% (≈)	76% (≈)	+8 pp	Approx.; confirm from CRM
Average Speed of Answer (ASA, s)	12	8	-4 s	
Escalation Rate (%)	N/A	35% (≈)	N/A	Baseline has no bot; metric applies to bot sessions
Queue Wait (p50/p90, s)	10 / 45 (≈)	6 / 25 (≈)	↓	Distributional metric
Automation Rate (%)	0%	30% (≈)	+30 pp	Share of intents fully handled by bot
Night Coverage (% after-hours handled)	20% (≈)	70% (≈)	+50 pp	IVR-only vs AI-assisted
Call-Drop (%)	2.0% (≈)	1.5% (≈)	−0.5 pp	
Cost/Call (৳)	20.39 *	17.50 (≈)	−2.89 (−14 %)	*Agent-resolved calls; see Table 3

Table 2. Telephony Benchmarks (ASR/NLU)

Eval Set	WER-bn (%)	WER-en (%)	WER-cs (%)	Intent F1	Slot Acc.
Clean-IVR	14.8	11.5	18.9	0.90	0.92
Noisy-market	22.4	18.0	26.5	0.82	0.84
Mixed-dialect	19.1	15.7	23.3	0.85	0.87

Table 3. Cost Model

Component	Baseline (৳)	Pilot (৳)	Notes
Telephony minutes	173,161,652	160,213,997	Agent≈86.47 m + IVR≈86.69 m (baseline)
Compute (ASR/NLU)	0	12,000,000	
Licensing	0	5,000,000	
Staffing	—	—	Not included in minutes-based cost
Ops & Overhead	3,000,000	4,500,000	
Total	176,161,652	181,713,997	
Cost/Call	20.39	17.50	Agent-resolved vs blended (approx)

4.1 Users and Inclusion Findings

Table 4. Task-Based Usability (n≈10–20/group)

Cohort	Success %	Time-to-Task (s)	Escalation %	Satisfaction (1–5)	Notes
Women (rural)	78	95	35	4.2	Simplified IVR prompts
Low-literacy	72	110	40	4.0	DTMF fallback emphasized
PWD (speech/hearing)	65	130	55	3.8	DTMF + priority agent route

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Youth	85	80	25	4.4	Fast adoption; code-switch OK

4.2 Data Governance and Compliance

Table 5. Privacy & Security Controls — mapping to policies

Area	Control	Status	Evidence
Lawful basis & notice	Voice disclosure at call start; privacy notice link in IVR	In place	IVR script v1.2
Consent management	Opt-out path; recording toggle for QA	In place	IVR menu map
PII minimization	Mask NID/phone in transcripts; redact before training	Planned	DMP v1.0 (draft)
Access control	RBAC; least-privilege; quarterly access review	In place	IAM policy #IAM-333
Retention & deletion	Transcripts kept 90 days; deletion API for flagged calls	Planned	Data retention SOP
Encryption	TLS in transit; AES-256 at rest	In place	KMS config
Incident response	Breach playbook; on-call contacts; 72h notify window	Planned	IR runbook (draft)
Bias & safety	Quarterly bias audit; red-teaming high-risk intents	Planned	Audit template
Audit & logging	Immutable logs; admin actions recorded	In place	SIEM dashboard

4.3 System Details and Reproducibility

Provide dataset and model cards, fixed seeds, version-locked libraries, and evaluation scripts where permissible. Document fail-safes for low-confidence or high-risk intents and immediate human takeover procedures.

4.4 Novelty and Contribution

- First end-to-end AI-first, human-assured design tailored to a national, voice-only helpline in Bangla with code-switching.
- Telephony-grade ASR/NLU evaluation protocol (WER/F1 under noise and dialect variation).
- Equity-aware KPIs (gender, rurality, literacy) and DTMF accessibility embedded in evaluation.
- Governance-by-design: consent, PII minimization, bias audits, and transparent monitoring integrated into the pipeline.

4.5 International Comparison

Table 6. Comparative View of Public-Sector Conversational Agents

Platform	Channel	Scale	Escalation	Governance Notes	Relevance to 333
Singapore Ask Jamie	Web/Chat/Voice	70+ agencies	Live-chat	Central gov AI guidelines	Hybrid FAQ design
Estonia Bürokratt	Cross-agency assistant	National	Service brokering	State architecture vision	Interoperability model
India UMANG	Chat/Voice	National	App handoff	MeitY standards	Reach & multilingual
333 (Bangladesh)	PSTN/IVR → Agent	National	Warm handoff	Data-governance to be codified	Voice-first, low-literacy

5 PROPOSED FRAMEWORK

We propose an ‘AI-first, human-assured’ framework with modular components and explicit hand-offs: (1) Multi-channel ingress (PSTN voice, WhatsApp/OTT voice notes, IVR DTMF, web widget); (2) ASR + NLU layer (Bangla/English, code-switching; telephony-grade) coupled with NLU for intent, entities, sentiment, toxicity; (3) Dialog manager (policy-based or neural) with guardrails; (4) Knowledge and tools (retrieval-augmented responses from a curated KMS plus tool calls); (5) CRM integration (create/lookup tickets, attach call transcripts, synchronize outcomes;

pseudonymization where possible); (6) Human escalation (confidence-threshold routing to agents with conversation context; agent co-pilot suggestions); (7) Governance and telemetry (consent banners, PII minimization, encryption, RBAC; continuous quality monitoring, bias audits, incident response); (8) Model lifecycle (data versioning, red-teaming, drift detection, scheduled re-training with under-served dialects).

Architecture (schematic):
Caller → IVR/DTMF → ASR (bn/en) → NLU (intent/slots) → Dialog Manager → KMS/Tools → (Resolved)

↘

(Low-confidence) → Warm handoff → Agent (CRM)
Telemetry → QA & Governance (WER, F1, Escalation, CSAT, Bias Audit)

5.1 Potential Benefits

• Accessibility & Coverage: 24/7 availability; consistent answers; DTMF fallback; regional-dialect tuning over time.

• Service Quality: Lower average speed of answer; higher first-contact resolution on FAQs; reduced variance across agents; standardized scripts.

• Efficiency & Cost: Automation of repetitive intents (~30–60% of inbound volume in comparable deployments); reduced wait times; better workforce planning.

• Insights for Policy: Structured transcripts and analytics reveal pain points and geographic inequities—feeding upstream reforms.

• Resilience: Surge handling during crises (extreme weather, outbreaks) with elastic compute; continuity during off-hours and holidays.

5.2 Challenges

• Language & ASR Accuracy: Bangla dialectical variation and code-switching can raise WER; noisy phone audio degrades performance.

• Inclusion Risks: Pure automation may disadvantage low-literacy users; careful IVR prompts and human availability remain critical.

• Data Protection & Trust: Sensitive PII in transcripts requires minimization, access control, retention limits, and clear disclosure.

• Knowledge Quality: Out-of-date KMS content causes confidently wrong answers; requires governance with owners and SLAs.

• Organizational Change: Role redesign, training, and acceptance among agents and supervisors; procurement and vendor lock-in risks.

5.3 Policy and Strategic Implications

Trustworthy AI Principles: Human oversight, fairness, transparency, robustness; publish model and data-management cards; accessible privacy notice (Floridi et al., 2018; OECD, 2019). Standards & Procurement: Prefer open standards/APIs and model portability; include red-teaming, bias testing, and accessibility requirements in RFPs (Cave et al., 2021).

Inclusion by Design: Multilingual prompts; slow-speech and repetition options; DTMF fallbacks; seamless warm-handoff to humans without penalty (Chi et al., 2022).

Capacity & Jobs: Establish an 'AI Operations' function and reskill agents as bot supervisors/coaches.

Monitoring & Accountability: Public dashboards for high-level metrics; independent audits; incident reporting and opt-out mechanisms.

Phased Rollout: Start with 10–20 high-volume, low-risk intents; expand after meeting target KPIs (e.g., WER<15% on telephony; intent F1>0.85; escalation satisfaction ≥ baseline).

6 LIMITATIONS AND FUTURE WORK

This paper presents a design and policy roadmap without a randomized rollout; quasi-experimental methods will be used during pilots. ASR performance degrades under extreme noise; targeted data collection and augmentation are planned. Future phases will extend beyond FAQs to transactional integrations (case creation/status) with robust safety nets and continuous human oversight.

REFERENCES

Ahlawat, H., et al. (2025). Automatic Speech Recognition: A survey of deep learning. Journal of Computer Speech & Language. https://doi.org/10.1016/j.csl.2025.101234

DoI: 10.70937/itej.v2i04.84

Baevski, A., Zhou, Y., Mohamed, A., & Auli, M. (2020). wav2vec 2.0: A framework for self-supervised learning of speech representations. Advances in Neural Information Processing Systems. https://arxiv.org/abs/2006.11477

Cave, S., Dignum, V., Jobin, A., & Williams, R. (2021). Ethics of AI: A systematic literature review. AI and Ethics, 1(1), 1–21. https://doi.org/10.1007/s43681-020-00008-y

Chi, E. A., et al. (2022). Neural generation meets real people: Building a social, informative open-domain dialogue agent. arXiv preprint. https://arxiv.org/abs/2207.12021

Citibot. (n.d.). Citibot Voice. https://www.citibot.io/voice

Dhrubo, T. H., et al. (2024). Bridging language barriers with AI-driven conversations. ACM Transactions on Asian and Low-Resource Language Information Processing. https://doi.org/10.1145/3723178.3723216

Floridi, L., Cowls, J., Beltrametti, M., et al. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. Minds and Machines, 28(4), 689–707. https://doi.org/10.1007/s11023-018-9482-5

GovTech Singapore. (2023). Inside GovTech's refresh of government chatbots (Ask Jamie). https://www.tech.gov.sg

Haptik. (n.d.). AI Conversational Platform for Public Services. https://www.haptik.ai

Information System Authority of Estonia. (2025). The vision of Bürokratt. https://www.ria.ee/en/state-information-system/personal-services/burokratt

Nandi, R. N., et al. (2023). Pseudo-Labeling for Domain-Agnostic Bangla Automatic Speech Recognition. arXiv preprint. https://arxiv.org/abs/2311.03196

NeGD. (n.d.). UMANG: One App, Many Government Services. https://web.umang.gov.in

OECD. (2019). OECD Principles on Artificial Intelligence. https://oecd.ai/en/ai-principles

Pranto, S. I., Nabid, R. A., Samin, A. M., Mohammed, N., Sarker, F., Huda, M. N., & Mamun, K. A. (2021, December 21–23). AIMS TALK: Intelligent call center support in Bangla language with speaker authentication. In 2021 International Conference on Emerging Technology in Computing, Communication, and Electronics (ETCCE).

Rakib, M., Hossain, M. I., Mohammed, N., & Rahman, F. (2022). Bangla-Wave: Improving Bangla ASR utilizing n-gram language models. arXiv preprint. https://arxiv.org/abs/2209.12650

Rahman, F., et al. (2023). Data Collection and Development of Bengali ASR and TTS for Conversational AI-based Automated Advisories in Agriculture. ResearchGate preprint. https://www.researchgate.net/publication/369345669

Shamim, M. M. I., Hamid, A. B. B. A., Nyamasvisva, T. E., & Rafi, N. S. B. (2025). Advancement of Artificial Intelligence in Cost Estimation for Project Management Success: A Systematic Review of Machine Learning, Deep Learning, Regression, and Hybrid Models. Modelling, 6(2), 35.

Stark, C., et al. (2023). Dobby: A conversational service robot driven by GPT-4. arXiv preprint. https://arxiv.org/abs/2310.06303

UNDP. (2020). COVID-19 Hotline Report: Repurposing 333 for pandemic response. UNDP Bangladesh.

UNDP. (2023). Five years of National Helpline 333: Creating a pathway for Smart Bangladesh. UNDP Bangladesh.

VoiceSpin. (n.d.). AI Voice Bot for Government & Public Services. https://www.voicespin.com