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Economic evaluation of diabetes prevention interventions in Bangladesh: A modelling study

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ABSTRACT

Aim: To model the long-term cost-effectiveness of scaling up two prevention interventions against type 2 diabetes mellitus (T2DM), i.e. community mobilisation through participatory learning and action (PLA) and mHealth mobile phone messaging, implemented in rural Bangladesh as part of the “DMagic” trial.

Methods: A health-economic Markov model of the three-arm, cluster-randomised controlled DMagic trial was developed. A cohort of individuals aged 50 years entered the model with impaired glucose tolerance (IGT). Outcomes included the costs (provider perspective), quality-adjusted life-years gained (QALY), incremental cost-effectiveness ratios (ICERs) and incidence of T2DM in a lifetime period. Deterministic and probabilistic sensitivity analyses were performed to reflect uncertainty.

Results: PLA yielded substantial reductions in diabetes incidence with only 25 % of the IGT population developing T2DM (versus 46 % in the control arm). The intervention was cost-effective against control with an ICER of 167 INT$ per QALY gained. The mHealth intervention revealed limited effectiveness at low cost, leading to an ICER of 189 INT$ per QALY gained. At willingness-to-pay ranges between 3 % and 45 % of Bangladesh GDP per capita, PLA demonstrated up to 90 % probability of being cost-effective.

Conclusions: PLA is a low-cost, effective strategy to reduce the burden of T2DM, offering good value for money.

Trial registration: The DMagic trial was registered with the ISRCTN registry, number ISRCTN41083256.

Strengths and limitations of this study

- State-transition models such as Markov models are well-established in modelling chronic disease progression and informing medical decision-making.
- Cost data and transition probabilities of this study were derived from epidemiological studies, including the DMagic and others, preferably where available from Bangladesh.
- Cohort-based Markov models may not fully capture the heterogeneity in the intermediate hyperglycaemic population, as physiological changes may be continuous.

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- The study focused on diabetes-related costs and quality-adjusted life years, providing a comprehensive analysis in the context of diabetes prevention.
- Benefits of lifestyle programmes on other disease entities such as obesity or hypertension were not captured but would likely optimise cost-effectiveness.

1. Background

Diabetes mellitus is a common metabolic disorder imposing major human, health, and economic burden on individuals, families, health systems, and societies. More than 537 million adults in 2021 had diabetes, of which over 3 in 4 lived in low- and middle-income countries (LMICs) [1]. Worldwide the direct medical costs of diabetes alone reached 966 billion US dollars (USD) in 2021, representing a 316 % increase over the last 15 years and 11.5 % of total global health spending [1]. In Bangladesh, data from the most recent Demographic and Health Survey show that almost 13 % of people aged 18 years or older had diabetes [2]. A study estimated that the annual health expenditure for diabetes was around 218 million USD in Bangladesh in 2017, and most of these expenditures were out-of-pocket payments by patients and their families [3,4].

Lifestyle and other non-pharmacological interventions have been evaluated through efficacy trials and have been shown to prevent or delay the onset of T2DM [5,6]. However, many of these interventions focus on targeting high-risk groups while a need for population-level strategies which also incorporate comprehensive economic evaluations prevails. With the findings of the Bangladesh DMagic trial, Fottrell et al. contributed notably to the implementation research of diabetes prevention and control [7]. The cluster-randomised controlled trial provides the first large-scale, population-level evidence concerning the costs and effects of mHealth mobile phone messaging, and participatory community mobilisation interventions for preventing the onset of T2DM. A process evaluation and five-year post-randomisation follow-up study of DMagic were recently published [8,9].

Previous evidence suggests lifestyle interventions are cost-effective in preventing diabetes in high-risk individuals, with varying economic estimates due to differences in target populations, intervention types, and modelling assumptions [10,11]. In their systematic review, Roberts et al. found that of 16 (primarily clinically delivered) lifestyle studies, the median incremental cost-effectiveness ratio (ICER) from a health system perspective was around 10,700 INT$/QALY gained [12]. The existing literature of economic evaluations of diabetes prevention interventions i) are lacking in resource-poor settings including Bangladesh, with the most research being conducted in high-income countries; ii) pay more attention to diabetes management and treatment programmes than to prevention and control interventions; iii) are predominantly based on short-term, within-trial analyses, while modelling studies with extrapolation of trial-based evidence for scale-up assessment yet to emerge, and iv) give little attention to the role of different modes and settings for preventive intervention strategies such as electronic or community delivery systems. To fill this evidence gap, this study examines the long-term cost-effectiveness of T2DM prevention interventions in Bangladesh using a decision-analytical Markov model.

2. Methods

This cost-effectiveness analysis follows the methodological framework proposed by the Consolidated Health Economic Evaluation Reporting Standards (CHEERS) statement to ensure structure, quality, and transparency in reporting [13] (Appendix 1).

2.1. Setting

A LMIC where diabetes has evolved to a public health concern is Bangladesh, a predominantly rural country in South Asia with a total population of around 170 million people [14]. To reduce the health and economic burden linked to projected diabetes trends, the Government of Bangladesh has published NCD policy initiatives which emphasise the horizontal integration of NCD prevention and control with the primary healthcare infrastructure [15]. This aims to improve access to and utilisation of prevention services at the local level and strengthen the public health system.

2.2. Alternatives compared

Two different interventions were compared, relative to control. DMagic was a stratified, cluster-randomised controlled trial, conducted in four rural subdistricts (upazilas) in Faridpur district, Bangladesh. Ninety-six clusters (villages) were randomly assigned to (a) control, (b) mHealth or (c) community mobilization through PLA intervention.

(a) The control arm assumed that participants received usual care without additional treatment. In the context of Bangladesh this is care seeking in government or private facilities – often associated with out-of-pocket-payment for blood glucose testing, consultations and treatments – and little or no preventative public health campaigning [7].
(b) The mHealth intervention entailed "twice-weekly health behaviour and awareness-raising voice messages sent to participants' mobile phones. Message content included information on diabetes symptoms, prevention, and advice on care seeking for T2DM and its complications. Message content was informed by formative research and behaviour change theories and was reviewed by medical experts. Messages were about 1 min long with various formats, including mini-dramas, dialogues and songs [7,8,16].
(c) The PLA intervention consisted of monthly group meetings, with an average of 27 group members. They were led by trained local lay facilitators, who guided participants through a four-phase participatory learning and action cycle focused on type 2 diabetes prevention and control. Through the cycle community members first identified and prioritised behavioural, social, and environmental threats to their health and barriers to healthy lifestyles. Next, they planned strategies with the community to address these threats and then put them into practice. Finally, they evaluated and reflected on their progress [8].

The primary outcomes of DMagic's trial arms were evaluated through baseline and endline sample surveys of 143 randomly selected permanent residents aged 30 years or older in each of the study clusters, using multi-stage simple random sampling. Details of the interventions can be found in the protocol, main trial and follow-up papers [7,9,17].

2.3. Model structure

A de novo economic decision-analytical model was developed by applying a Markovian approach [18]. As depicted in Fig. 1, the Markov model comprised four mutually exclusive health states:

1. normoglycaemia/normal glucose tolerance (NGT),
2. impaired glucose tolerance (IGT),
3. type 2 diabetes mellitus (T2DM) and
4. death.

It was assumed that a cohort of individuals aged 50 years entered the model with IGT based on DMagic's baseline survey where the average age of individuals was 49.53 years. The cohort could stay in this state,

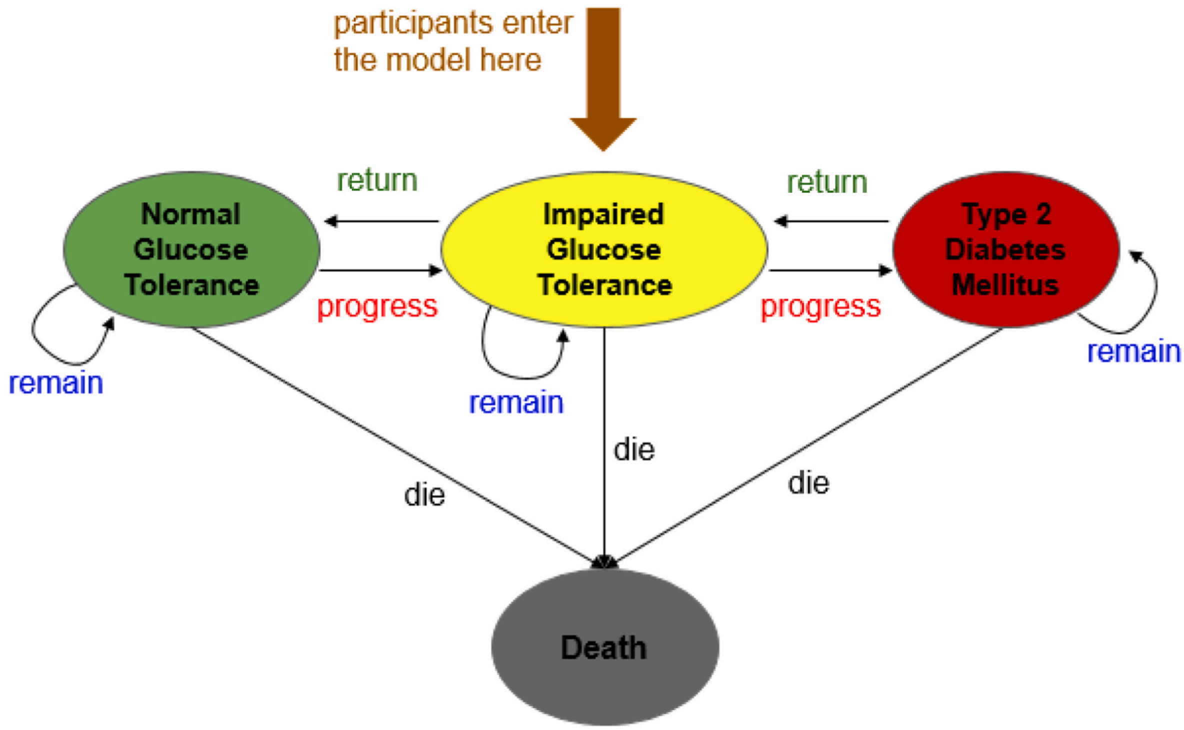

Fig. 1. The four-state structure of the Markov model.

advance to T2DM or return to normoglycaemia. Participants with NGT could either stay in their state or progress to IGT. Considering clinical reality, it was not possible to move directly to T2DM as a normoglycemic person. Equally, there was no possibility of moving directly to NGT as a person with diabetes. However, the reversal from T2DM to IGT was kept in the model because this transition is technically and physiologically possible [19]. At any time, participants with NGT, IGT or T2DM could die and, consequently, move to the absorbing state "death".

Participants move across the health states at the end of each discrete time interval, also known as a Markov cycle. Due to the low frequency of events in the slow disease progression of T2DM, a cycle length of one year was applied to reflect the nature of this chronic disease. As recommended by the WHO, the interventions were evaluated under the assumption that they were fully implemented over a ten-year implementation period [20]. While the intervention costs were applied for 10 years, the intervention effects were conservatively applied only to 2 years to reflect the original DMagic trial period. To account for all relevant differences in costs and effects between the alternative strategies being compared, a lifetime time horizon was modelled to capture all the relevant outcomes of interest, which is particularly important for prevention interventions or the treatment of chronic diseases such as T2DM. Further, a provider (health system) perspective was taken assuming that the Bangladesh Ministry of Health and Family Welfare or the Diabetic Association of Bangladesh would implement scale-up.

2.4. Model parameters

2.4.1. Clinical and epidemiological parameters

Glycaemic definitions and diagnostic criteria for normoglycaemia, impaired glucose tolerance and diabetes reflected WHO guidelines [21]. Fasting plasma glucose values below 6.1 mmol/l were considered normal. Impaired glucose tolerance was classified with values of 6.1–6.9 mmol/l as well as plasma glucose levels of 7.8–11.0 mmol/l 2 h after the 75-g oral glucose load as in a glucose tolerance test. T2DM was diagnosed either with fasting plasma glucose values $\geq$ 7.0 mmol/l, or 2-h glucose levels above 11.0 mmol/l on the 75-g oral glucose tolerance test [21].

Table 1 illustrates all transition probabilities from original states to subsequent states in matrix format. Transition probabilities were derived from epidemiological studies, including DMagic and others, preferably where available from Bangladesh [7,19,22]. Model parameters for the intervention arms reverted to control parameters after cycle 2 (i.e. year 2). The probability of dying for the general population was obtained from the national life table of Bangladesh. An increased

Table 1
Transition matrix and key parameter values.

Original state (From …)	Subsequent state (To …)			
	NGT	IGT	T2DM	Death
NGT	0.9029	0.0651	0.0000	0.0320
IGT	Control (Usual Care)			
	0.1772	0.6880	0.0900	0.0448
	mHealth Intervention[a]			
	0.1921	0.6764	0.0871	0.0444
	Community Intervention[a]			
	0.2964	0.6164	0.0489	0.0382
T2DM	0.0000	0.0050	0.9342	0.0608
Health state	**Diagnostic criteria**		**Annual cost of care (INT$)**	**Utility**
Normal Glucose Tolerance (NGT)	Fasting glucose <6.1 mmol/l		754.68	0.773
Impaired Glucose Tolerance (IGT)	Fasting glucose <7.0 mmol/l AND post-load glucose >7.8 mmol/l to <11.1 mmol/l		980.51	0.754
Type 2 Diabetes Mellitus (T2DM)	Fasting glucose >7.0 mmol/l OR post-load glucose >11.1 mmol/l		1148.00	0.687
Intervention	**Annual cost (INT $)**		**Relative risk of T2DM**	
mHealth Intervention	7.48		0.97 (95 % CI 0.72, 1.29)	
Community Intervention	14.16		0.49 (95 % CI 0.31, 0.80)	

[a] intervention transition probabilities reverted to the control transition probabilities after cycle 2 (year 2).

disease-specific probability of dying was added for participants with IGT and T2DM, in contrast to normoglycemic individuals [23,24]. Participants in the intervention arms were assumed to have a reduced disease-specific probability of dying. Relative risks of 0.97 (95 % CI 0.72, 1.29) and 0.49 (0.31, 0.80) for the mHealth and community mobilisation interventions, respectively, were applied to the disease-specific probability of dying during years 1–2 [7].

2.4.2. Costs

The cost of seeking care for T2DM averaged out at 1148 International Dollars (INT$) per patient per year. This amount was derived from five available studies (including DMagic's cost of seeking care survey conducted in 2018), which determined the direct medical costs of T2DM in Bangladesh [3,7,25–27]. The costs of all other studies were adjusted for inflation. Costs of NGT and IGT were calculated as proportions of T2DM costs [28,29]. Thus, NGT costs were assumed to be 66 % of T2DM costs, whereas IGT costs were assumed to be 85 % of T2DM costs.

The costs of the mHealth and PLA intervention were analysed based on DMagic trial data from a provider (health system) perspective. Programme costs incurred by the implementing organisation (e.g. materials, training costs of unformal health workers), the Diabetic Association of Bangladesh, and healthcare provider costs incurred by government health facilities were included in the calculations. The average cost of the mHealth and community intervention was 7.48 and 14.16 INT$, respectively, for each beneficiary (adults ≥30 years) per year.

2.4.3. Health effects

In the DMagic trial, the three-level EuroQol-5D (EQ-5D-3L) questionnaire was used to measure preference-based health-related quality of life (HRQoL) across diabetic health states. The dimensions of the EQ-5D-3L were converted into preference-based HRQoL using UK tariffs, resulting in utility scores of 0.773, 0.754 and 0.687 for NGT, IGT and T2DM, respectively. Incremental utilities gained from the interventions were not added.

To adjust both costs and effects for differential timing, an annual discount rate of 3 % was applied in accordance with international WHO recommendations [20]. This rate is varied in the sensitivity analysis. Table 1 summarises key parameter values.

2.5. Analyses

Outcomes over a lifetime-period were calculated for each intervention and included the (1) discounted cumulative healthcare costs and (2) the number of discounted QALYs gained associated with each intervention arm. (3) Incremental cost-effectiveness ratios (ICERs) were determined for the interventions, using the following formula:

ICER (INT$ per QALY) = (C1 - C0) ÷ (E1 - E0),

Where C1 is the cost of an intervention in INT$, E1 the corresponding effect of the intervention in QALYs gained, and C0 and E0 respectively the costs and effects of control. The comparison against control was chosen since the main trial also compared against usual care. A pairwise cross-comparison between the mHealth and community against each other can be found in Appendix 2 (Supplementary Table). (4) Incident cases of T2DM were modelled for the interventions and cost per case averted was calculated.

As input parameters can contribute to uncertainty, additional sensitivity and scenario analyses were conducted to explore the robustness of the base-case analysis. We applied both deterministic and probabilistic sensitivity analyses. Appendix 3 displays different scenarios and their parameters used in the deterministic sensitivity analysis (DSA) (Supplementary Table).

This model assumed a WTP threshold for Bangladesh in the range of 109–1636 INT$ per QALY (around 3 %–45 % of 2017 Gross Domestic Product (GDP) per capita) [30].

Probabilistic sensitivity analysis (PSA) was performed with simultaneous random variation of input parameters using a Monte Carlo simulation with 1000 iterations (Appendix 4, Supplementary Table). Parameter uncertainty was modelled using appropriate probability distributions to reflect the underlying statistical properties of each parameter, including beta distributions for utilities and transition probabilities and gamma distributions for cost inputs. To judge their stability, the results are presented as scatter plots on the cost-effectiveness plane, where each point represents one simulation. Moreover, cost-effectiveness acceptability curves (CEAC) were calculated to delineate the probability that each intervention was cost-effective compared to control.

Analyses of the trial data were conducted using STATA/SE 17 (StataCorp, College Station, USA). The Markov model and its analyses and simulations were conducted using Microsoft Excel 2021 (Microsoft Corporation, Redmond, USA).

Role of the funding source

The funder had no role in study design; data collection and analysis; writing of the manuscript; or the decision to submit the paper for publication.

2.6. Patient and public involvement statement

Community representatives were actively engaged in the DMagic trial from the outset, participating in a community orientation meeting and subsequently forming advisory groups. Community leaders further facilitated involvement, with the PLA intervention largely driven by the community's input. Trial findings were shared and interpreted collaboratively through participatory analysis.

2.7. Equity, diversity, and inclusion statement

Our mixed-gender author group includes junior, mid-career, and senior researchers from different disciplines and from low-, middle- and high-income countries. Several of us have immigrant backgrounds and belong to underrepresented communities.

3. Results

3.1. Base-case analysis

The results of the base-case analysis are presented in Table 2, illustrating the costs, QALYs gained, incidence and ICER (INT$/QALY and INT$/case averted) for each intervention arm. To begin with, in comparison to control (11,759 INT$), implementation of the mHealth and PLA interventions increased costs to 11,777 and 11,856 INT$, respectively. The incremental costs amount to 18 and 97 INT$, respectively. Furthermore, the mean QALYs gained by the mHealth and PLA interventions were respectively estimated as 9.43 and 9.85. Compared against control (9.39 QALYs), PLA showed to be an effective strategy with an incremental difference of 0.46 QALYs. Additionally, calculations of ICERs, relative to control, reveal that the PLA intervention is a cost-effective option, with an ICER of 210 INT$/QALY gained and 462 INT $ per case averted. The mHealth intervention was less cost-effective with 397 INT$/QALY gained and 900 INT$/case averted. Finally, with control, 46 % of the IGT population developed T2DM over 50 years. Diabetes incidence after 50 years was reduced to 44 % in the mHealth intervention arm and 25 % in the PLA arm.

3.2. Sensitivity analyses

The results of the DSA are depicted in the tornado diagrams in Appendix 5 (Supplementary Figure). It is apparent that ICERs in the

Table 2
Cost and consequences for participants in prevention interventions compared against control.

	Total cost (INT$)	Total effect (QALYs)	Incre-mental cost (INT$)	Incre-mental effect (QALYs)	ICER (INT $/QALY)	Incidence of T2DM after 50-year follow-up (%)	Cost (INT$)/case averted
Control (usual care)	11759	9.39	–	–	–	46 %	–
mHealth intervention	11777	9.43	18	0.04	397	44 %	900
PLA intervention	11856	9.85	97	0.46	210	25 %	462

intervention groups were especially sensitive to changes in the discount rate on costs. The intervention reduced their ICERs, when relative costs of the NGT and IGT states were reduced by 10 % in the mHealth and PLA intervention. In the scenario of a reduced intervention effect, the mHealth intervention was clinically inferior despite increasing cost relative to control (dominated). However, when the intervention effect was reduced for the PLA intervention, it still led to a positive ICER. When the intervention costs were tripled, it only increased to 343 INT $/QALY gained for PLA.

For the PSA, the results are shown in the ICER scatter plots on the cost-effectiveness planes in Figs. 2 and 3. For the mHealth intervention, second-order Monte Carlo simulations with 1000 iterations revealed that both mean incremental costs and QALYs were negative, i.e. the intervention was on average less costly but also less effective (southwest quadrant). In contrast, the mean incremental cost of PLA was dominant with 0.31 QALYs gained on average. The cost-effectiveness acceptability curve represents the probability that the interventions are cost-effective, relative to control, over a range of decision makers' willingness-to-pay (WTP) thresholds per additional QALY gained (Appendix 6, Supplementary Figure). This model assumed a WTP threshold for Bangladesh in the range of 109–1636 INT$ per QALY (around 3 %–45 % of 2017 Gross Domestic Product (GDP) per capita). Community mobilisation has the highest probability of being cost-effective within this range. At an average WTP threshold of 872 INT$, there is a 54 % and 73 % probability that the mHealth and PLA will be cost-effective, respectively. This probability reduces to 51 % and 52 %, if the WTP threshold is lower at 109 INT$, and increases to 57 % and 84 % with a higher WTP threshold of 1636 INT$. The probability of cost-effectiveness peaks at a WTP threshold of around 1300 INT$ for the PLA intervention and flattens out subsequently, whereas it remains relatively stable for the mHealth intervention throughout.

4. Discussion

In response to a lack of research regarding the economic evaluation of diabetes prevention strategies in LMICs, this paper is the first to model the long-term cost-effectiveness of two differently delivered interventions compared to control in Bangladesh. Economic and clinical consequences of mHealth and PLA interventions were extrapolated beyond the time horizon of the trial using a decision-analytical Markov approach and were modelled over a 10-year implementation period. Among the examined interventions, PLA is highly cost-effective and would provide the best value for money in the prevention of T2DM. By comparison, the mHealth intervention is associated with lower costs but limited effectiveness.

In the DMagic trial, Fottrell et al. also concluded that the mHealth intervention did not change disease outcomes significantly, notwithstanding its laudable foundation in behaviour change theory and in-depth formative research [8,16,31]. mHealth messaging is likely to be more successful if implemented as part of a multi-sectoral, multi-component approach to address T2DM and non-communicable disease risk factors. Problems in the intervention start and mobile message delivery might have contributed to the reduced effectiveness, which meant for the Markov model that transition probabilities for participants in the mHealth and control groups were almost comparable (Table 1).

The DSA suggests that the mHealth intervention could even be dominated, i.e. be cost-ineffective. This was the case when the transition probabilities from IGT to NGT/T2DM were varied within the limits of their 95 % confidence intervals to simulate a "reduced intervention effect" (Appendix 5, Supplementary Figure). Within the WTP range, the mHealth intervention is the least probable to be cost-effective and does not show any significant change with an elevation of the threshold (Appendix 6, Supplementary Figure). This may be explained by the fact

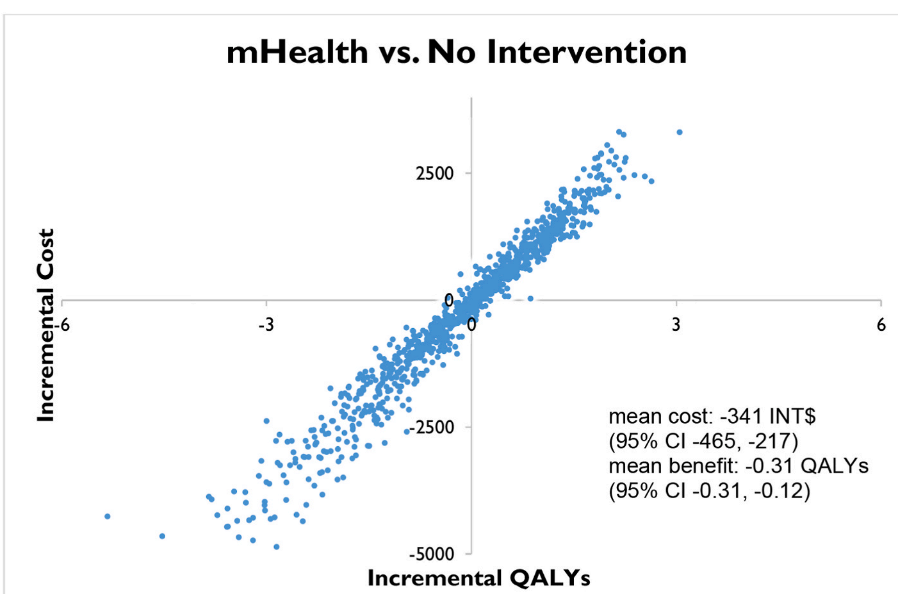

Fig. 2. Scatter plot of ICER values generated from probabilistic sensitivity analysis (PSA) for the mHealth intervention, relative to control.

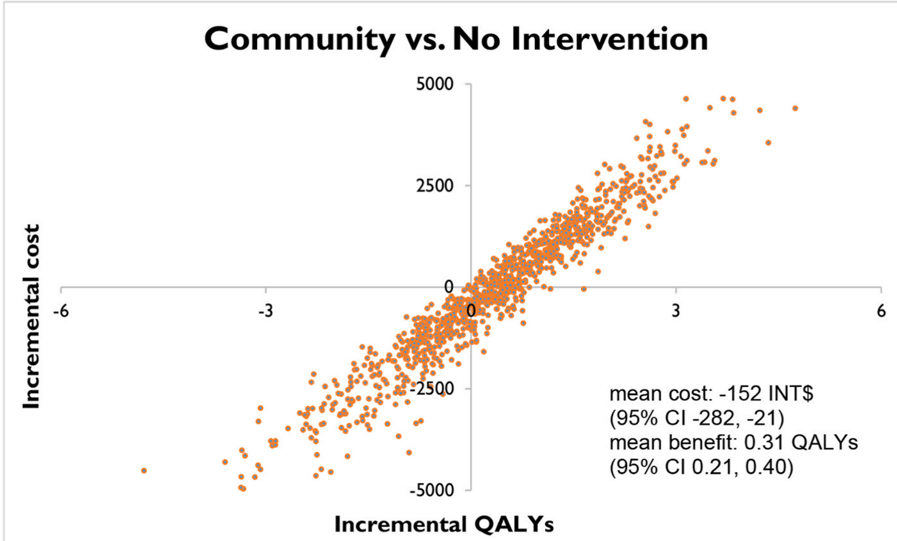

Fig. 3. Scatter plot of ICER values generated from probabilistic sensitivity analysis (PSA) for the community intervention, relative to control.

that many iterations lie in the southwest quadrant representing less costly, but also less effective outcomes. Given the assumptions in PSA, it is very unlikely that the probability of being cost-effective would change much, even if the WTP is increased to higher values. These findings differ from the diabetes-related mHealth interventions identified in two reviews [32,33]. Whilst these reviews have reported the cost-effectiveness or cost-saving benefits of mHealth interventions, most studies were conducted in high income countries and did not focus on prevention of diabetes which might have influenced cost-effectiveness estimates.

The PLA intervention delivers in comparison to the other intervention arms the greatest health benefits in terms of QALYs gained. With 0.46 additional QALYs per participant and an ICER of 210 INT$/QALY gained compared with the control arms, the intervention is cost-effective. It also yields a major percentage reduction in incident cases to only 25 % of the IGT population developing T2DM, avoiding 21 cases of T2DM per 100 participants (Table 2). The cost-effectiveness improves even more when a 10 % reduction in NGT/IGT state cost was assumed (Appendix 5, Supplementary Figure). The DSA also tested for differential discounting of costs, taking into consideration the likely elevation of the WTP threshold since future per capita GDP is anticipated to increase in Bangladesh. The rationale is that if the threshold is raised, future costs become less significant and can be discounted at a higher rate. Against this background, maintaining an effect discount rate of 3 % and increasing the cost discount rate to 6 % found that PLA was almost dominant/cost-saving, relative to control. This is reinforced by the results of the PSA, which found that the mean incremental cost is negative. The CEAC further illustrates that PLA appears to be the optimal decision at WTP thresholds between 109 and 1636 INT$, as it has the highest probability of cost-effectiveness of the interventions which reaches to 90 % (Appendix 6, Supplementary Figure). Incremental cross-comparison between interventions revealed that the PLA intervention was the most cost-effective option (Appendix 2, Supplementary Table).

These findings mirror those of previous economic evaluations examining the cost-effectiveness of community-based diabetes prevention interventions. For instance, community translations of the US DPP to interventions delivered by non-specialist staff such as lifestyle coaches or lay workers showed to be cost-effective (around 3400 INT $/QALY gained) or cost-saving [34,35]. Two Dutch studies have reported cost-effectiveness ratios ranging from around 3900–6300 INT $/QALY gained for prevention programmes focusing on nutrition and exercise [36,37]. One explanation for the higher ICER estimates could be that the intervention costs and health state costs are greater in these high-income countries compared to Bangladesh. The within-trial economic analysis of DMagic also suggested that PLA is cost-effective with cost-effectiveness ratios of $124 to $2551 per disability-adjusted life--year averted [7]. Clearly, further investigation to validate the cost-effectiveness of community-based interventions for diabetes prevention in low-resource settings is necessary. Importantly, the findings in this paper already corroborate that the PLA approach is highly cost-effective for a NCD, expanding its conceptual applicability beyond maternal and reproductive health [38].

Several limitations of this study should be acknowledged. In public health, state-transition models such as Markov models are well suited to model progression of chronic diseases and inform medical decision-making adequately. However, this model type does not capture the heterogeneity in the intermediate hyperglycaemic population. The physiological changes in people with intermediate hyperglycaemia are continuous variables and costs and benefits might vary accordingly. It could be argued that patient-based simulation modelling is more appropriate for economic evaluations of diabetes prevention programmes.

The model used in this study concentrated on IGT while the role of other types of intermediate hyperglycaemia were not explored. Additionally, while the model is structured around transition probabilities from the interventions' latest available data, the assumption of constant transitions across all cycles might be considered too strong. This could be addressed by adding additional states and incorporating time dependency into transitions, if more disaggregated data on intermediate hyperglycaemia in Bangladesh was available.

The interventions evaluated in the study were conducted in rural populations, which is advantageous since the majority of Bangladesh's inhabitants currently live in rural areas. However, the findings might not be transferable to other rural, urban or mixed populations, although homogeneity in rural Bangladeshi populations has been demonstrated [39]. Still, replication studies are needed to confirm intervention parameters. Furthermore, the model focused mainly on diabetes-related costs and QALYs. Benefits of lifestyle programmes on other disease entities such as obesity-related cancers or dementia were not captured but would likely optimise cost-effectiveness.

Our study had several strengths. To the best of our knowledge, this was the first health economic modelling study to estimate the long-term cost-effectiveness of scaling up diabetes prevention programs in Bangladesh. This paper uses a comprehensive four-state model of diabetes development that incorporates both disease reversal to NGT and disease progression to T2DM. Some studies have only focused on the transition from IGT to T2DM, thereby limiting the assessment of preventive impacts of interventions. This paper used population-based evidence from the Bangladesh DMagic trial to inform key parameters concerning HRQoL, mHealth and PLA interventions. Incremental utilities gained from the interventions were not possible to calculate because a random sample was taken at baseline and endline. Unlike other studies [29,40], intervention-specific increments were not added for the purposes of conservative modeling. Generally, this economic evaluation is not intended to be an exhaustive modelling of the interventions' cost-effectiveness, but rather a constantly evolving one reflective of the emerging evidence base. Rigorous follow-up evaluation of the interventions, examining e.g., how effect size changes at scale and attenuates over time, will be important for the adjustment and update of the model. The strength of the evaluation is in its framework as it has transferability since model structures/inputs can be adapted easily.

From a policy perspective, the findings provide evidence for community-based interventions as a means of reducing the burden of diabetes and fostering local engagement. Scale-up might protect households from financial catastrophe, by decreasing out-of-pocket spending attributed to T2DM due to lack of prepayment mechanisms. Uncontrolled diabetes can lead to morbidities, which can lead to lower quality of life and disability [41]. Considering that awareness of how to prevent and control T2DM is limited, access to diabetes prevention within the community environment is important at a populational level. Bangladesh's policymakers are encouraged to allocate urgently needed resources for prevention programmes, to raise the priority of diabetes and other NCDs [15]. They can use this cost-effectiveness evidence alongside other context-specific considerations around value for money, such as feasibility, equity or budget impact when making decisions.

A policy pathway could be to integrate the PLA approach into existing primary healthcare and NCD programmes by training community health workers and using community groups as platforms for screening, referral and behaviour-change support. Our model provides evidence supporting scale-up of PLA as a cost-effective diabetes prevention strategy, potentially over time easing pressure on overstretched health facilities by reducing future diabetes-related complications and service demand.

Continuing research in the following areas would be beneficial to further inform policy. First, gathering follow-up evidence to mitigate uncertainty regarding parameters and assumptions, including costs for normoglycaemia/intermediate hyperglycaemia, effect duration after cessation of programmes and incremental health utilities associated with interventions. Second, evaluating the impact of lifestyle programmes on different types or even combinations of intermediate hyperglycaemia (e.g. IFG-only, IGT and HbA1c). Third, exploring the role of T2DM screening and risk assessment methods (blood testing/risk scores) as well as intervention enrolment and compliance rates. These estimates should be accounted for in any future impact assessment of nation-wide implementation of prevention programmes. Fourth, implementing PLA interventions as part of multi-sectoral action to prevent diabetes through evidence-based approaches.

5. Conclusions

This paper is the first to model the long-term cost-effectiveness of scaling up two different interventions, relative to control, in Bangladesh. On balance, this analysis indicates that PLA is highly cost-effective at an ICER of 210 INT$/QALY gained and it substantially reduces diabetes incidence, providing good value for money. In comparison, evidence for the cost-effectiveness of mHealth in diabetes prevention remains limited, despite its potential for low-cost scalability. Policymakers can use this evidence in their decision-making while additional research is needed to reduce remaining uncertainty.

Contributors

EF,KA, HJ, JM, CK, and AK contributed to the design and impact evaluation of the D-Magic trial; DM and HHB contributed to the economic evaluation design; DM and HHB contributed to the analysis; SKS, MARC, NA, KA, and TN contributed to data acquisition; DM was responsible for the initial drafting of this manuscript; AK, RH, and TP provided critical comments on the analysis for interpretation of the findings; all authors contributed to the review of this manuscript and provided comments. All authors read and approved the final manuscript.

Data sharing statement

The data supporting this article can be found within the article itself and in its supplementary material, available online.

Ethics approval

The DMagic trial has been approved by the University College London Research Ethics Committee (4766/002) and by the Ethical Review Committee of the Diabetic Association of Bangladesh (BADAS-ERC/EC/t5100246).

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.dsx.2025.103370.

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