Rapid Methods to Assess the Potential Impact of Digital Health Interventions, and their Application to Low Resource Settings

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ABSTRACT

Assessing the impact of digital health projects and applications is a key challenge, especially in low resource settings. Full evaluative field studies are resource-intensive and time-consuming. Less demanding approaches that could provide rapid insights would be helpful. This paper presents some "short-cut" approaches for rapid assessments that can provide useful early indications of strengths and weaknesses and can ensure that evaluative efforts are focused on key uncertainties, are not wasted on unpromising interventions, and make the most of what is already known.

Three rapid assessment approaches, all underpinned with logic modelling, are presented: identification of "upstream" obstacles; utilisation of knowledge about "downstream" effects; and Fermi estimation.

Their application is illustrated by examples, mainly considering assessment of mobile phone healthcare information applications for citizens and healthcare workers in medium and low-resource settings.

KEYWORDS

mhealth, evaluation; methodology; modelling; information; impact

1 INTRODUCTION

There are many challenges in assessing the impact of health care interventions, including:

- developing appropriate evaluative criteria and metrics
- selecting appropriate assessment methods
- identifying projects/applications that need to be evaluated
- persuading key stakeholders that evaluation is a priority
- acquiring resources - funding and people - for evaluation
- carrying out assessments including any necessary fieldwork
- disseminating the results
- using evaluation findings to influence practice

This - incomplete - list is already quite a formidable one, yet evaluation of the impact of ***digital*** health care interventions presents additional challenges. This is partly because of the *technology* element and also because digital interventions revolve around *information*, an intangible (and often a necessary but insufficient) component of a complex chain or network of interacting elements needed to impact on health.

Finding ways to overcome or at least mitigate these problems is important not least because evaluating digital health information applications is a global health issue, as indicated by the following statement from a WHO meeting: *"To improve health and reduce health inequalities, rigorous evaluation of eHealth is necessary to generate evidence and promote the appropriate integration and use of technologies."* . The associated WHO document [1] goes on to set out nine important principles - The Bellagio Principles - for eHealth evaluation. The WHO have recently pubished comprehensive guidance [2] on this topic. Some more general guidance on good evaluation practice in health informatics is given at ref [3].

eHealth of course includes mHealth, and a good deal of published work has stressed the need for more and better evaluations of mHealth interventions [4, 5, 6, 7, 8, 9] . The last two of these concluded respectively that: "The biggest gap in our knowledge about the use of mHealth strategies by frontline health workers at present is in the lack of evidence on how such strategies may improve health outcomes, health system efficiencies and cost-effectiveness of service delivery." and "mHealth evaluations must be improved to generate robust evidence for cost-effectiveness assessment and to allow for accurate identification of the contribution of mHealth initiatives to health systems strengthening and the impact on actual health

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outcomes". The approaches in this paper are illustrated through examples of assessing mHeath information applications but the basic principles should apply for assessing any digital health intervention.

Steps that could be taken to mitigate the assessment task should be useful anywhere but particularly for ***low resource settings***, where many of these challenges, e.g. funding and fieldwork, are especially demanding.

One key step would be to ensure evaluation is focused on the things that most need to be evaluated. For this it is useful to break down an intervention into components, drawing on logic model and causal chain concepts [10, 11]. For example, consider a very basic logic model or causal chain for the impact of healthcare information (Fig.1).

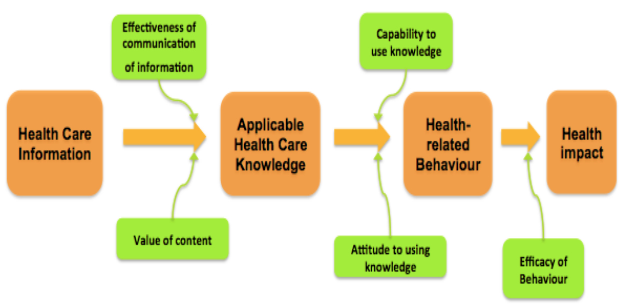


Figure 1: Basic logic chain for the impact of healthcare information

A full evaluation would run "end-to-end" and look at the health impact of the provision of health care information. This can take a lot of resource and a long time – sometimes so long that the results can be obsolete! But making a reasonable initial assessment of impact may not always require an "end-to-end" approach. The next section outlines some alternatives.

2. RAPID ASSESSMENT APPROACHES

2.1 Underlying principles

Digital health interventions can be divided into two segments, an "upstream" part and a "downstream' part. "upstream" concerns the information content, the technology, and the initial distribution mechanism. "downstream" particularly concerns the impact on users knowledge, behaviour and health.

This segmentation points to two types of possible "short cut" to assist with the estimation of impact, both drawing on the above basic logic model, or extensions of it:

- Identification of "upstream" obstacles
- Utilisation of "downstream" knowledge

A third possible rapid assessment approach is based on decomposition of the logic model, consideration of its individual components, and then reassembly. This method (named after its originator) is called:

- Fermi estimation

These approaches are outlined in turn below.

2.2 Identification Of "Upstream" Obstacles

Sometimes interventions can be shown on logical grounds as inherently ineffective, and in such cases further evaluation would be a waste of effort. There are various pre-requisites for a healthcare information intervention to have an impact on health – for example *information content* must be *assimilable* and *relevant*. Assessment of the extent to which an intervention could meet these "upstream" requirements can reveal obstacles that may limit its potential impact. Where no major obstacles are identified then fuller evaluation of "downstream" elements can be valuable. Where there are serious "upstream" obstacles then it is unlikely to be worthwhile to go on to test the intervention in the field - and indeed unlikely to be sensible to implement it at all.

This is the approach that has been used for an assessment, for the Healthcare Information for All (HIFA) network, of mobile health information "apps" for direct use by citizens, as outlined later in section 3.1.

2.3 Utilisation of Knowledge About "Downstream" Effects

Where evaluative fieldwork is required, it may still not be necessary for this to measure outcomes in terms of *health* impact. There will be links between, say, changes in *behaviour* and health impact. If the nature and magnitude of these connections are already known from other, quite separate, studies then, provided the context of the other studies is not too different from the situation in focus (for example in regard to cultural and motivational factors) an information evaluation may be able to utilise this knowledge about "downstream" impact of the relevant behaviour on health, and so be able to limit its efforts to identifying/quantifying the behavioural effects of providing healthcare information.

Similarly, if the *behavioural* effect of the relevant healthcare *knowledge* is already known from other research, it may be necessary only to evaluate the impact of the healthcare information project/application on that knowledge in order to make a reasonable assessment to the likely behavioural impact of the information provision.

In both cases this would not only save evaluative resources, it would also allow results to be obtained without having to wait for the ”downstream” effects to take place, thus not only reducing the risk of evaluation results being obsolescent but also helping useful interventions to be rolled out without delay. An illustration of this approach is outlined in section 3.2

2.4 Fermi Estimation

The Nobel laureate Enrico Fermi, as well as being famous for leading the team that developed the world’s first nuclear reactor, was also well known for using the simplest approach that would suffice for solving problems. He was renowned for his facility for using back-of-the-envelope calculations to get surprisingly good approximate estimates for complex quantities.

Fermi’s basic approach was to break down a complex question into simpler elements for which rough estimates could be made and to then combine these “guesstimates” to produce the overall answer. The method (popularised in recent years by the book “gue??timation” by Lawrence Weinstein and John Adam [12]) often works remarkably well, partly because errors in estimating the individual components tend often to cancel out.

Many impact evaluation problems, particularly those where some element of quantification is required, can usefully be broken down into a series of linked components (as for example in the basic logic model outlined above) which can be estimated *individually* and then *combined* to produce an overall estimate of impact.

Fermi estimation is, by definition, approximate, and will struggle to handle time-dependent, non-linear or feedback effects. For that more sophisticated simulation approaches, such as system dynamics modelling, will be required. But, provided the logic model is sound and the suporting data is plausible, it can often provide a helpful initial assessment. It is particularly useful in providing upper or lower bounds for the size of an effect. Even when producing a usable quantitative estimate is beyond its reach, it can still provide valuable insights about the likely value of an intervention and what is most needed for it to succeed. Section 3.3 provides an illustration of Fermi estimation for the impact of a digital health intervention.

3 ILLUSTRATIVE APPLICATIONS OF THESE APPROACHES

3.1 Identification of “upstream” obstacles: mHealth information applications for citizens in low resource settings

Various frameworks and criteria for assessing mHealth applications have been proposed see e.g. refs [13, 14, 15]. These are helpful but typically focus neither on low resource settings nor exclusively on mHealth information applications. Important exceptions are the useful evaluation guide [16] produced by the Mobile Alliance for Maternal Action (MAMA) and the short, incisive, paper [17] by Tomlinson on improving the evidence base for mHealth.

To remedy this gap, and drawing on the first stage in Figure 1, a set of “upstream” assessment criteria for mHealth information applications was identified, focusing on those of particular relevance to the aims and vision of the Healthcare Information for All (HIFA) network [18] that “*every person and every health worker will have access to the healthcare information they need to protect their own health and the health of those for whom they are responsible*”. The criteria are shown in Box 1 below:

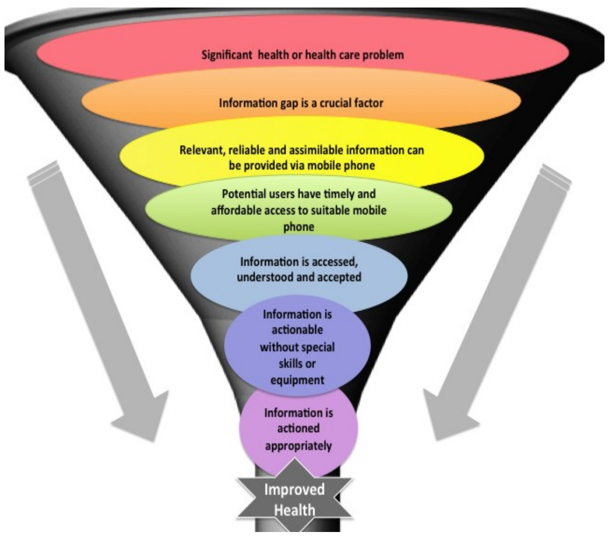
Box 1: Key criteria for a mHealth information application to meet Healthcare Information for All aims

- **Significance of the health problem(s)**: Is the application focused on a significant health or healthcare problem - a widespread serious condition, or an emergency or urgent need?
- **Appropriateness of the targeting**: is the application aimed at use in low resource settings or by low income or other priority groups e.g. mother and child, health educators?
- **Value of the information**: Is the information relevant to users’ needs for addressing the health problem; is it reliable; can it be easily related to practical action?
- **Ease of assimilation of the information**: is the information presented in an appealing and easy to understand way such as a video or voice clips; is it culturally appropriate and available in local language(s)?
- **Availability of the application**: is the application available across several regions or countries; is it available free to the user?
- **Technological accessibility of the application**: does it have a simple and intuitive user interface, is it accessible on a basic or feature phone; will it work “offline”; will it work on multiple operating systems; is it pre-loaded?

Clearly there is scope to add to or amend these criteria, for example some might prefer to take financial cost as a separate dimension. There are also of course wider criteria, such as data security and privacy, that also need to be considered when assessing mHealth applications, but we are focusing here on the more specific criteria for providing essential health care information in low resource settings.

These criteria can be visualised as successive filters in a funnel. See Fig 2. It cannot be assumed a priori that an application will be able to pass through these. As *all* of the filters have to be passed through for an application to have an impact it should be useful to consider if an application seems likely to fail at any of them, even – in fact especially - before any field investigation.

Figure 2: A funnel diagram showing filters through *all* of which a mHealth information application needs to pass to make an impact on health



The criteria were operationalised by disaggregating them into a total of sixteen separate components and then attributing simple "traffic light" indicators to each of these which would broadly indicate increasing "fit" of this aspect of an application to the achievement of HIFA aims - *red* indicating poor alignment to these aims, *green* a good fit and *amber* an intermediate match.

Using some earlier work [19] to help identify suitable candidate applications, eleven mHealth information applications were assessed, using the "traffic light " tool, for their potential to provide essential healthcare information to citizens and frontline healthcare workers in low resource settings. In the assessment [20] several apps performed quite well but others had "upstream" shortcomings that, from a HIFA perspective, significantly weakened their potential. For example some would work only when there was a network connection, others did not support local languages, and others did not provide actionable information about common health problems. *In none of these cases was any fieldwork required to demonstrate these shortcomings.*

3.2 Utilisation of "downstream" knowledge: potential impact of mobile health information about oral rehydration therapy

Globally, diarrhoea is a leading killer of children. UNICEF state [21] that it accounted for 9 per cent of all deaths among children under age 5 worldwide in 2015. This translates to about 526,000 children a year. The country with the highest child mortality from diarrhoeal disease is India, where, in 2005, it accounted for about one in seven of all 2.3 million annual deaths amongst 0-4 year olds– i.e. some 330 thousand deaths a year [22].

Treatment of diarrhoea in infants and young children has been revolutionised with the advent of an effective, simple, cheap and relatively easily administered treatment: oral rehydration therapy (ORT). Nevertheless 4 in 10 mothers in India were found to wrongly believe that they should *withhold* fluids if their baby develops diarrhoea [23] ; ORT has clearly not yet attained its full potential.

Suppose we want to assess the potential impact on child mortality of increasing mothers' knowledge about ORT for child diarrhoea through making information about ORT available to them through a mobile phone application. This is by no means a purely hypothetical question - such information (as well as much other health-related information for mothers and children) is for example currently being rolled out by HealthPhone in India [24].

The "ideal" way of doing such an assessment would be to mount a control trial in which one group of carers was provided with a mobile phone application giving them information about when and how to use ORT and another comparable group was not so provided, and the use of ORT and its impact on their children's' health was compared between the two groups over a suitable period of time.

Such trials are undoubtedly valuable, but are resource-intensive and take a long time. However, they could be simplified and speeded up if use was made existing information about the behavioural impact of knowledge of ORT and the health impact of such behaviour. Provided, as noted earlier, that such existing information related to situations that were not too different from the situation in focus, it might then be sufficient only to study the impact of mobile-phone mediated information about using ORT on knowledge about when and how to use ORT, and to supplement this with the "downstream" information, in order to get an estimate of the behavioural and health impacts of the mobile phone application.

Information of this type is available – for example, for a slum area in Delhi, a study [25] showed that about 65% of those that knew about ORT applied that knowledge to use ORT. Similarly a good deal is known about the efficacy of using ORT (as shown in the next section).

3.3 Fermi estimation of the potential impact of mobile health information

Staying with the ORT example, suppose for lack of resource or time we were not able to do *any* new study in the foreseeable future, could any progress be made with an assessment? In such a situation we could try Fermi estimation.

We first need a "baseline" estimate - the health impact (using lives saved as a our measure) of ORT in a given population. For a Fermi estimation this can be constructed as the product of factors as below:

Health impact (lives saved per year) =

Population size (children 0-4 years)

x

Incidence of child diarrhoea (annual episodes per child 0-4 years)

x

Mortality from diarrhoea without ORT (deaths per 1000 episodes)

x

Use of ORT (% of carers using it)

x

Efficacy of treatment (% reduction in episodic mortality achieved by use of ORT)

As one of the limited number of instances where information on all of the above is fairly readily available from the survey and research literature, we will use the case of India.

To ensure a reasonably coherent dataset we have drawn on papers mostly using data from 2005-2010 – so the example is purely illustrative. The figures are:

- Population size (children 0-4 years): 113m (ref [26])
- Incidence of child diarrhoea: Average of 2.4 episodes annually per child (ref [27])
- Mortality rate of diarrhoea without ORT: 1.34 deaths per 1000 episodes (ref [28])*

(note that the above figures give an estimate that there would be 363 thousand annual deaths in the absence of any ORT)

- Use of ORT: 45% of carers of those afflicted (refs [29, 30, 31]) **
- Efficacy of ORT in "real world" conditions (% episodic mortality reduction) : 50% (ref [32])***

Notes:

* trials witholding ORT would now be unethical given knowledge of its efficacy, this figure is obtained by extrapolation from diarrhoeal mortality rate when level of ORT take-up and efficacy is known

** There are various forms of ORT, which complicates assessment of impact, but we will here take a simple view that the crucial factor is that a child's fluid intake should be *increased* during an episode of diarrhoea. This figure is for any use of ORT, which will include some inappropriate use e.g. incorrect preparation or dosage

*** this reference, a systematic review, gives 93% for the mortality-reducing efficacy of ORS, but does not give figures for other ORT types, which are likely to be less effective, or for incorrect use of ORT; hence a conservative figure for mortality reduction in "real world" conditions of 50% is used here.

For the above level of use and "real world" efficacy ORT this gives a Fermi estimate of lives amongst children aged under 5 saved annually by ORT in India of :

113m x 2.4 x (1.34 /1000) x 0.45 x 0.5 = 82 thousand lives

i.e. ORT may have been reducing annual child deaths from diarrhoeal disease in India from a "pre-ORT" figure of about 360k to about 280k.

We now need to consider the potential impact of making information about using ORT readily available on mobile phones in a easily assimilable and actionable form, e.g. "how to" videos. (We assume for the purposes of this illustration that before 2010 there was little or no availability for low-income groups in India of information of this kind on mobile phones.)

The main factor in the above Fermi estimation that such provision could affect is the *proportion of carers using ORT.* (There is also the possibility that such provision could increase the *efficacy factor*, for instance by improving the way ORT is used; but for simplicity this will not be included here). The proportion of carers using ORT *can itself be decomposed to make a Fermi estimate,* as below.

Carers can be divided into three groups, those who have access to a mobile phone with actionable information on ORT, those who have access to mobile phone but without such information, and those who do not have access to a mobile phone.

The components of a Fermi decomposition for proportion of carers using ORT will therefore be:

- Proportion of carers with **access** to mobile phones (A)
- Proportion of mobile phones with ORT **information** (I)

- Proportion of carers who **know** about use of ORT (K) = Proportion of carers utilising phone information to learn how to use ORT (K_a) + Proportion of carers that already knew how to use ORT (K_b)

- Proportion of carers acting on this knowledge to **use** ORT (U)

(We will assume, for the purposes of this estimate, that K_b and U are the same for each of the three sub-groups, but that assumption could obviously be changed if there was good reason to do so.)

The Fermi decomposition will then be:

Proportion of carers using ORT =

$$[A \times I \times K \times U] + [A \times (1\text{-}I) \times K_b \times U] + [(1\text{-}A) \times K_b \times U]$$

Estimates of these components for India can be made as follows:

- Proportion (A) of carers with access to mobile phones (0.80 using lowest income quintile , ref [33])
- Proportion (I) of these mobile phones with ORT information (let us assume here that this is a major nation-wide programme, so say 0.95)
- Proportion (Ka) of carers utilising phone information to learn how to use ORT (assume 0.20)
- Proportion (Kb) of carers that already knew how to use ORT (0.70 , see earlier refs). (so $K = K_a + K_b$ = 0.90)
- Proportion (U) of carers acting on this knowledge to use ORT (0.65, see earlier refs)

This gives a Fermi estimate of the proportion of carers in India using ORT, when information on it is widely available on mobile phones, of:

(0.8 x 0.95 x 0.9 x 0.65) + (0.8 x 0.05 x 0.7 x 0.65) + (0.2 x 0.7 x 0.65) = 0.55

The corresponding Fermi estimate of annual child mortality reduction is therefore

113m x 2.4 x (1.34 /1000) x 0.55 x 0.5 = 100 thousand lives

so this illustrative national mobile health information initiative on ORT would be assessed, as a first rough estimate, of having the potential in India to save around an additional 100 - 82 = 18 thousand children's lives a year.

As mentioned earlier, the Fermi approach is also useful in estimating upper or lower bounds for an effect. We might take the case of almost complete (95%) penetration of mobile phones, with ORT information on 100% of them, and of say 95% penetration to relevant carers of this knowledge of how to use ORT, and usage of ORT by say 80% of those who have gained this knowledge though the mobile phone route (with no change in the knowledge and usage figures for others). That would give a Fermi estimate of the *upper bound* on the proportion of carers using ORT if such information was on all phones of:

(0.95 x 1.0 x 0.95 x 0.8) + (0.95 x 0.0 x 0.7 x 0.65) + (0.05 x 0.7 x0.65) = 0.74

We might also now factor in an information–driven increase in the quality of the ORT when given, raising its average efficacy from say 50% to 70%.

Hence the potential *maximum* possible information–driven reduction in child mortality would be:

113m x 2.4 x (1.34 /1000) x 0.74 x 0.70 = 188 thousand lives

i.e. of mobile phone information on ORT more than doubling (from 82k to 188k) the number of children's lives saved by ORT.

Of course these particular figures may not be entirely realistic. But the Fermi approach makes "what-if" scenario testing easy by substituting alternative figures, or even by adopting a different logic model and decomposition. It provides a starting point for more rigorous assessments, not least in indicating which components of impact most need estimates firming up through further study.

There are modelling methods that could help make better Fermi type estimates. For instance LIST (the **LI**ves **S**aved **T**ool) [34] developed by the Johns Hopkins School of Public Health, which interestingly has been used recently to assess the impact at a national level of mHealth (in general, not just for information applications) on neonatal mortality in low-resource settings [35].

Clearly the Fermi method could be extended to address other issues about digital health e.g. if unit costing figures were available it could be used to provide ball-park estimates of, say, cost per life saved for a digital health intervention.

4 CONCLUSIONS

This paper aims to support evaluation of eHealth through using initial approaches which are quick and simple. Rapid assessment approaches will not generally be a substitute for more thorough and rigorous evaluation, (nor in general will the underlying logic models substitute for more sophisticated modelling such as computer simulation), but they can provide useful early indications of strengths and weaknesses and ensure that further evaluative efforts in digital health are focused on key uncertainties, are not wasted on unpromising interventions, and make the most of what is already known. This should be valuable in any setting, and is crucial in settings where time and resources are tightly limited. The approaches can also assist at a crucial earlier stage - the *design* of digital health interventions - by assisting a sharper focus on areas needing design improvements and by highlighting designs, e.g. of mobile phone applications, that look to have the best chance of success.

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COMPETING INTERESTS

None

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