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An application of Bayesian Network modelling to the HIV/AIDS epidemic in the Philippines

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A thesis in fulfilment of the requirements for the degree of

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Dedication

To my Mum and Dad.

Without the opportunities you provided, none of this would have been possible.

Acknowledgments

This thesis, as is the case with works such as this, could not have been completed without the help, support, and encouragement of a network of people. It has been a long road and the following people have played an integral role in ensuring that I have stayed on said road and completed the journey.

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1 Introduction

1.1 Introduction

An estimated 12.3% of the 33.3 million people living with HIV worldwide live in South and South East Asia [16]. The region, which is home to 60% of the world's population is vast, diverse, and has no single 'Asian HIV Epidemic' [11]. Despite the lack of a defined epidemic, HIV epidemics in Asia tend to follow patterns which are different from epidemics in other regions of the world. The main drivers of the epidemics in these countries stem from risk behaviours concentrated among certain population sub-groups: commercial interactions between female sex workers and male clients, anal sex between men/transgendered men, and sharing injecting equipment by injecting drug users [11, 13]. Also, Asian HIV epidemics are classified as concentrated epidemics. Most infections remain in the subpopulations that participate in these high-risk activities or though sexual contact with people who participate in high-risk activities. Examples of the latter include partners/spouses of men who are clients of female sex workers [18].

This thesis will examine the HIV epidemic in the Philippines, the epidemiology just prior to a recent epidemiological outbreak to identify factors which

could have accounted for the 'low and slow' historical development of the HIV epidemic until recently. It will also review the behavioural and epidemiological conditions that have been of concern for facilitating the emerging epidemic.

Additionally, this thesis will apply Bayesian Networks (BNs) to the HIV epidemic in the Philippines, as a suggested first step at a new approach to modelling evaluation of public health programming around epidemics. The BN model is used to address the research question: "What impact do changes in funding have on HIV incidence in a) men who have sex with men, b) female sex worker, c) intravenous drug user and d) non most-at-risk-population groups in the Philippines?". This model, which is a first of its kind in this field, will focus on the probabilistic relationships and the factors that contribute to new infections in these population, and hence the incidence of HIV.

The dynamics of national HIV epidemics are complex and almost all HIV epidemics consist of multiple sub-epidemics, with these sub-epidemics affecting different sub-populations, occurring with different timing and severity in different geographical areas, and evolve at different rates [9]. As a first step in trying to understand such an epidemic, a BN model is ideal as it allows for the modelling of the uncertainty involved in such an epidemic. Modelling the dynamics of many complex national epidemics realistically requires the ability to model the individual sub-epidemics of which they are composed, and the Bayesian Network framework allows this. In this thesis, a BN is proposed as a way in which to investigate the impact of funding changes on HIV incidence in the four populations of interest in the Philippines.

This thesis is organised in the following manner:

- Chapter 1: Introduction - a review of commonly used HIV/AIDS models
- Chapter 2: Bayesian Networks - a summary of Bayesian Networks, and their applicability in modelling HIV epidemics
- Chapter 3: The HIV/AIDS epidemic in the Philippines - a review of the epidemic in the Philippines and the an investigation into the causes of the epidemic's 'low and slow' status
- Chapter 4: A HIV/AIDS Bayesian Network Model applied to the

Philippines and results - development, quantification, validation and results of the HIV/AIDS Bayesian Network model for HIV incidence in the Philippines

- Chapter 5: Conclusion and further work - suggestions of the application of extended Bayesian Network models for HIV/AIDS.

1.2 Types and examples of HIV/AIDS Models

Responses to HIV/AIDS epidemics have often been informed by epidemiological modelling to project and estimate the impact, cost-effectiveness, and affordability of policy and programmatic strategies. These models differ in the information required and used, the modelling methodology, and projection capabilities. There are generally 3 kinds of HIV/AIDS models used for programmatic decision making:

1. Epidemic projection models based on curve fits and extrapolation, for example EPP/Spectrum.
2. 'Static' models based on risk behaviours and prevalence among key populations to determine the distribution of new infections.
3. 'Dynamic' models based on risk behaviours, epidemiology, and programmatic data, including spending (for example, the GOALS model), and tailored ODE or difference equation or individual based models.

1.2.1 Epi Model

The Epi Model is a World Health Organisation (WHO) model developed for the estimation, and short-term projection, of adult AIDS cases [7]. The Epi Model uses an HIV point prevalence estimate in conjunction with the estimated year when the HIV transmission became widespread and the HIV infection curve during the epidemic period. The data are used to calculate the annual cohorts of HIV-infected adults. The AIDS cases are then calculated by multiplying each annual cohort of HIV infected persons by the progression rates from infection to clinical AIDS.

The Epi Model is a simple tool which can provide reasonable insight into likely trends and numbers of AIDS cases over the succeeding 3-4 years. It

cannot provide reliable future estimates of HIV infections but either stopping or continuing HIV transmission after a specific year does not greatly affect short-term projections of AIDS cases. Sources of error in the model include estimating an HIV point prevalence and the annual progression rates from HIV infection to AIDS. The Epi model should not be used to project AIDS cases for periods longer than 4 years. The model itself does not provide additional insights about the epidemiological features of the pandemic and cannot be used to predict future HIV infections or the consequences of behavioural and social changes in populations [7].

1.2.2 UNAIDS Estimation and Projections Package (EPP)

The Estimation and Projections Package (EPP) is used to estimate and project adult HIV prevalence in countries with heterosexual epidemics [26]. It has been designed as a tool for epidemiologists and analysts to construct national and sub-national epidemic curves, which is an essential step in the estimation of levels and trends in the epidemic and its impact [9]. The EPP allows a user to define a national epidemic in terms of a locally relevant set of geographic and population group sub-epidemics, allowing the user to address epidemic complexity more realistically than has been possible in the past.

The model uses surveillance data from various sites and years showing HIV prevalence among pregnant women. The EPP is used to fit a simple epidemic model to data from urban and rural sites. The prevalence projection produced by EPP can be transferred to the Spectrum model (see Section 1.2.3) to calculate quantities such as the number of people infected, AIDS cases, and AIDS deaths. The EPP is currently the recommended tool for estimating and projecting HIV prevalence levels in countries with not just generalised epidemics, but almost universally [9].

A strength of the EPP is that it gives countries the capability to make full use of all available surveillance data in developing epidemic curves. By allowing countries to include separate sub-epidemics and combining them easily to obtain national prevalence, it simplifies the modelling process. As countries with complex concentrated epidemics obtain sufficient years of surveillance data in the sub populations that are influencing their epidemics, the EPP will provide an organising framework for collating and combining the results

of the various sub-epidemics into a national prevalence curve.

A major limitation of the EPP is the quality and non-representative nature of the data used, and that it is just at curve-fitting tool. For example, rural data that can be used in EPP may not actually be representative of rural populations as data may have only been collected at small regions. EPP has no way to resolve the problem and this issue must be fixed by improving the data systems being used. Similarly, surveillance data of HIV prevalence among IDUs may only occur in clinics at major cities or a handful of detention centres. The data obtained is therefore not representative of the sub-population [3].

The EPP is an improvement over previously used tools for estimating and projecting HIV prevalence. It is used by all countries for creating official estimates for UNAIDS. It should be noted that EPP and Spectrum are now combined into a single package.

1.2.3 Spectrum

Spectrum is a suite of tools and including all of the following policy models in a single, user-friendly program. It consists of nine components [8]:

- DemProj (Demography): projects the population for an entire country or region by age and sex, based on assumptions about fertility, mortality, and migration. A full set of demographic indicators can be displayed for up to 50 years into the future. Urban and rural projections can also be prepared. A companion model, EasyProj, supplies the data needed to make a population projection from the estimates produced by the Population Division of the United Nations.

- FamPlan (Family Planning): projects family planning requirements needed to reach national goals for addressing unmet need or achieving desired fertility. It can be used to set realistic goals, to plan for the service expansion required to meet program objectives, and to evaluate alternative methods of achieving goals. The program uses assumptions about the proximate determinants of fertility and the characteristics of the family planning program (method mix, source mix, discontinuation rates) to calculate the cost and the number of users and acceptors of different methods by source.

- AIM (AIDS Impact Model): projects the consequences of the HIV epidemic, including the number of people living with HIV, new infections, and AIDS deaths by age and sex; as well as the new cases of tuberculosis and AIDS orphans. AIM is used by UNAIDS to make the national and regional estimates it releases every two years.

- RAPID (Resources for the Awareness of Population Impacts on Development): projects the social and economic consequences of high fertility and rapid population growth for such sectors as labor, education, health, urbanisation, and agriculture. This program is used to raise policymakers' awareness of the importance of fertility and population growth as factors in social and economic development.

- Goals Model: helps efforts to respond to the HIV epidemic by showing how the amount and allocation of funding is related to the achievement of national goals, such as the reduction of HIV prevalence and expansion of care and support.

- PMTCT (Prevention of Mother-to-Child Transmission): evaluates the costs and benefits of intervention programs to reduce transmission of HIV from mother to child. Three sets of interventions are included in the model: drug treatment (seven possible options); type of delivery (vaginal or Cesarean section); and type of infant feeding (formula, breastfeeding, or mixed). Outputs include a benefit-cost ratio as well as cost-effectiveness measures such as cost per HIV infection averted.

- Lives Saved Tool (LiST- Child Survival): is a program to project the changes in child survival in accordance with changes in coverage of different child health interventions. more information on LiST can be found here.

- Safe Motherhood Model: estimates the impact of various scores from the Maternal-Neonatal Program Index (MNPI) on a country s maternal mortality ratio. The MNPI is an index of 81 indicators for national efforts to improve maternal and neonatal health services. The model helps managers to gain a better understanding of the impacts of policies, budgets, and service delivery improvements on maternal health outcomes.

- Allocate: examines the linkages and interactions among three main areas of a representative reproductive health action plan (RHAP): family planning, safe motherhood, and post-abortion care. Allocate also shows the interactive impacts of changing decisions about levels of funding.

- HIV Vaccine: is a model that explores the impact of potential HIV vaccines on the epidemic.

Spectrum uses default values from the UNAIDS Reference Group on Estimates, Modeling, and Projections and utilises the Estimation and Projection Package (EPP) model for its HIV incidence input assumptions [2]. It is able to provide output such as the number of people who need ART, annual costs for ARVs, cost for TB, labs, treatment of opportunistic infections (OI) and prophylaxis, nutrition, and service delivery costs. The model is also able to provide benefit-cost ratios (total costs savings divided by total costs of the intervention) as well as cost-effectiveness measures such as cost per HIV infection averted, cost of death averted, child and total infections averted, treatment cost savings, net and total intervention costs, and net cost per infection or death averted.

A limitation of the model is that it can be somewhat of a 'black box', with users unable to see the underlying governing equations or change them easily.

1.2.4 The Goals Model

The Goals Model is intended to support strategic planning at the national level by providing a tool to link program goals and funding. It can provide output such as how the amount and allocation of funding is related to the achievement of national goals such as reduction of HIV prevalence and expansion of care and support [15].

Since most countries have developed HIV/AIDS strategic plans with well developed goals for prevention, care and support and include specific activities to achieve these goals, costing of strategic plans is usually done as the last step. Often it is much more available top-down. It is difficult and resource intensive to get bottom-up unit costs. Budgets are usually prepared by estimating the costs of training a certain number of counsellors, purchasing so many condoms, operating a number of VCT centres and providing

antiretroviral therapy to a certain number of patients. This approach does not allow for any strategic planning of financial resource allocation since the budgets are not linked to the goals. As such, there is no way for the planners to know what would happen if more or less resources were available or if resources were allocated differently. This is where the Goals Model is useful.

The Goals Model is part of the Spectrum (see Section 1.2.3) and is designed to enhance strategic planning by showing how the amount and allocation of funding are related to the achievement of national goals such as the reduction of HIV prevalence and the expansion of treatment, care and support. The Goals Model estimates the resources required to implement specific interventions to achieve national goals. This model brings together information on costs and evidence of program impacts. It relates these data to trends in the country's HIV situation. It is generally implemented by a multi-disciplinary team composed of participants with various areas of expertise in areas such as demography, epidemiology, health finance, and planning, representing different aspects of society such as government, civil society, private sector, and donors. The model has a user friendly design and allows for the exploration of different scenarios to allow for widespread use by program planners [23].

The Goals Model links budget line items to coverage of services, behaviour change and prevention of new infections. The model maps the budget line-items to the major categories of prevention (such as VCT, school-based programs, condom promotion), care and treatment (for example palliative care, treatment of opportunistic infections), and program operations (such as policy, advocacy, and management). It displays a chart of coverage for key care and support services so that the effect of budget allocations on coverage goals can be seen easily. The model uses inputs from Spectrum for basic epidemiology and demand data. Data are gathered from health ministry offices, health care facilities, donors, implementing organisations, and published reports, and epidemiological data are collected from local studies, and regional defaults [1].

The model can help answer several key questions [15] such as how much funding is required to achieve the goals of the strategic plan; what goals can be achieved with the available resources; and what is the effect of alternate patterns of resource allocation on the achievement of program goals. It provides output such as prevalence, incidence, infections averted, coverage

of ART, OI treatment, palliative care, OI prophylaxis, and OVC [1].

There are a number of limitations of the model. Firstly, it requires a lot of data and does not incorporate macroeconomic conditions of the country. Additionally, the tool assumes that the cost of inputs does not change over the years covered [1]. Finally, it does not calculate the 'optimum' allocation pattern or recommend a specific allocation of resources between prevention, care and mitigation [15].

1.2.5 HIV Modes of Transmission Model (MoT)

The UNAIDS Modes of Transmission Model uses national prevalence and behaviour data to model the incidence distribution in key populations at risk of HIV infection [20] and helps to calculate the expected number of new infections per year on the basis of a description of the current distribution of infections and patterns of risk within a population [17]. Developed by the UNAIDS Reference Group on Estimates, Modelling and Projections, the model helps countries estimate the proportion of new HIV infections that occur through key transmission modes using basic epidemiological and behavioural data as input.

The initial use of the model illustrated the variation in patterns of new infections between countries and argued that this type of in-country application could be used to inform the planning of appropriately targeted responses. Since then, the model has since been recommended as part of the 'Know your Epidemic / Know your Response' (KYE/KYR) initiative by UNAIDS. This initiative aims to help countries become more systematic in their approach to prevention by using strategic information to make evidence-informed decisions related to planning appropriate responses to the HIV epidemic [17, 20].

The objective of the MoT spreadsheet model is to help countries calculate the expected number of new HIV infections over the coming year on the basis of a description of the current distribution of prevalent infections and patterns of risk within different populations. The model uses the current prevalence of HIV infection, the numbers of individuals with particular exposures, and the rates of these exposures to calculate the expected incidence of HIV infection over the coming year. The user of the spreadsheet has to provide biological and behavioural surveillance data to inform the

values in the cells for the spreadsheet. Some of these may be reasonably well estimated, whereas others may be poorly specified. Default estimates of transmission probability per contact are based on reviews of published literature, but can also be specified by the user. The adult population can be divided into groups with different risks of acquiring HIV. By estimating the size of these risk groups and their exposure to HIV infection, the groups where new HIV infections are most likely to occur can be identified [20].

The advantage of the MoT model is that it allows the testing of the extent to which the contribution of a risk group has to the total HIV incidence changes. This is useful when there is very little or no data available about a specific risk group. Additionally, the model is easy to implement and is not computationally expensive.

It does, however have some limitations. Because the model uses crude groupings of the population according to the means of exposure to HIV infection, the results obtained are only as good as the data entered in the spreadsheet on the estimated sizes of the risk groups, the current prevalence of HIV and other sexually transmitted infections, and the average risk behaviours within these groups. Also, the model only takes into account uncertainty related to the input parameters and does not incorporate the uncertainty inherent to the model assumptions, meaning that it is likely to underestimate total uncertainty. In some instances the uncertainty on the input parameters might appear as a subjective choice. When this information is lacking or when parameters have to be extrapolated from sub-national or foreign studies, it is necessary to make assumptions. If these are based on sound criteria they should provide a reasonable reflection of the actual uncertainty of these values [17, 20].

It should be noted that the methodology has been through a number of rounds of iteration for improvements. Recently, Case et al [6] reassessed the model's paradigm, structure, and data requirements and put forward a set of recommendations for improving the use of the modes of transmission model for estimating the source of new HIV infections.

1.2.6 UNAIDS Workbook

The Workbook Method is a spreadsheet-based method used to estimate and project adult HIV prevalence from surveillance data in countries that lack

HIV prevalence data from consistent sites over time. These estimates are based on HIV prevalence in populations with high risk behaviours and populations at low risk such as partners of IDUs and the general population, as well as estimates of the size of populations with high risk behaviours. The workbook is able to develop estimates for populations who are most exposed to HIV/AIDS and then combined to produce an overall estimate of adult prevalence [25]. It can develop epidemic curves, and the national prevalence projection produced by Workbook can then be used in EPP to develop a national incidence curve. The incidence curve is imported into Spectrum to calculate the number of people living with HIV, new HIV infections, AIDS cases, AIDS deaths, treatment needs, AIDS orphans, and other variables [19, 21, 25].

The required elements of the Workbook include: a definition of geographic regions and risk groups; data on high risk and low risk groups; the size of the high and low risk groups; the HIV prevalence within the risk groups; and the prevalence by year [19].

The Workbook has a number of strengths [25]. Firstly, there is a transparency in the estimation of prevalence estimates and projections/scenarios. The Workbook displays any assumptions used to make the estimate or scenarios; and the methodology allows for the planning or redesign of surveillance systems as missing or lacking data can be seen explicitly. Also, having an automatic audit checking system helps eliminate many errors and forces users to reconsider values or outputs that are out of the usual range. Additionally, by using state or regional spreadsheets and estimates for each of the regions, estimates based on median values for the country can mask large differences among regions. This is beneficial for populous and diverse countries. The approach emphasises ranges for the estimates instead of a point estimate. This can be important as the certainty range around estimates for countries with low level and concentrated epidemics can be quite large. Finally, by using Excel, the Workbook has advantages over stand alone packages. The workbooks build on a widely used application and most users in most countries are already familiar with the functioning of spreadsheets and can therefore easily alter the workbooks to fit their specific needs.

The primary weakness of the Workbook Method comes from the quality of data available when making the estimate [19, 25]. Few countries have good estimates of the size of many populations most exposed to HIV/AIDS

and often prevalence data for these groups are obtained among convenience samples. An especially problematic groups is clients of sex workers.

Another limitation of the method is that the static representations of various time points in the epidemic don't capture entrances into and exits from various groups at higher risk. People in some of the populations at higher risk may only stay in the risk groups for a few years. These people may become infected and then no longer are represented in identified risk groups. Also, the curve fitting approach for the epidemics in each of the groups at higher risk cannot capture real epidemic curves that over time may have multiple inflection points. Finally, it must be noted that, to date, there has been no prospective test of the validity of using this type of scenario building approach [25].

There have not been many dynamic epidemic models applied to the Asian context, with the most common are GOALS and the Asian Epidemic Model (which as recently changed name to the AIDS Epidemic Model). Since the latter is the most commonly used, it will be described below.

1.2.7 The Asian Epidemic Model (AEM)

The reviews above are of models that are used as tools for planning and estimation. Additionally, many models have been design for specific, mainly research, projects. Not many models have been applied in the Asian setting, however the most commonly used model in the region is the Asian Epidemic Model (AEM), which should be noted is the only model used to date in the Philippines.

In 2004, Brown and Peerapatanapokin [5] presented the Asian Epidemic Model (AEM). The model divides the population into nine compartments: males who are clients of sex workers (SW), males who are not clients of SWs, lower risk general population females, direct SWs, indirect SWs, high risk injecting drug users (IDU), low risk IDUs, male sex workers, and men who have sex with men (MSM) who are not SWs. The model is based on the assumption that epidemics in Asia follow the following pattern: it starts in the MSM population, spreads to IDU population, moves to the SW population, and from there it spreads to the general population.

The AEM is a semi-empirical process model that replicates the transmission dynamics of HIV in Asian settings [24]. It was developed to explore

the growth of epidemics in the region and to assist in quantifying the major factors affecting Asian epidemics and their influence on the rates of epidemic growth. The model has two major components, a heterosexual transmission component and an injecting drug transmission component, that model the key processes influencing HIV transmission in Asia [14].

The strength of the AEM is that because it is semi-empirical and must use specific data associated with HIV prevalence in each of the identified groups [5, 24]. It is patterned after the dominant modes of HIV transmission in Asian settings and uses semi-empirical fits to actual country data, the resulting projections are likely to reflect the actual HIV transmission patterns in the country. The large variety of outputs available allow numerous opportunities for external validation of the projections produced against other sources of data. If the projections stand up to validation, they give confidence that the model itself reflects local reality. Programme and policy analyses done with a well-validated model are more likely to be both accurate and relevant to the local conditions. Other strengths of the AEM are the ability to extract a more complete picture of what is driving the epidemic, and the model's ability to explore alternative scenarios, based upon achievable levels of behaviour change, are two other major strengths of the AEM [5].

With the ability to change behaviours on a yearly basis, the user of the model is able to explore "what might have been" by allowing retrospective evaluation of earlier programme impacts, and "what might be" by allowing the relative efficacy of different programme alternatives to be explored [5]. Additionally, by using both behavioural and epidemiological inputs, an integrated analysis of epidemiological and behavioural data can be undertaken. This means that all the data available on the epidemic is able to be used for modelling and forecasting [22]. Also, because almost all data inputs for the AEM have other uses in programme planning and evaluation, the AEM also helps to identify gaps in the national and local data collection systems. This is because it will be difficult for AEM to evaluate coverage, effectiveness, or impact of programmes if certain data inputs are missing [5]. This, of course is also a disadvantage of the AEM.

The AEM requires a lot of data and at present, most countries lack sufficient data to apply the model, but most countries in the region can still eventually run the AEM. Also, because it relies on such specific data, a full

uncertainty and sensitivity analysis cannot be performed. This means that users must understand what is driving their local epidemic and make certain that the key local modes of transmission are already included in the AEM. If not, modifications to the AEM may be required before use [4, 5]. Additionally, users must take care in evaluating the quality and validity of the behavioural and epidemiological inputs that are used in the AEM. If not then a situation may arise where 'garbage in - garbage out' may occur [5].

1.3 Conclusions

This chapter has reviewed some of the common HIV models being used to estimate HIV prevalence and predict trends in prevalence in the short term. Of the models reviewed, MoT and GOALS attempt to model HIV incidence. The HIV Bayesian Network Model proposed in this thesis (Chapter 4) as an alternative approach will attempt to model changes in HIV incidence that result from the impact of funding changes on new infections in the four population groups of interest in the Philippines.

The model proposed in this thesis uses Bayesian Networks (BNs), which are graphical models that compactly specify joint probability distributions and can be used for reasoning under uncertainty [10, 12]. This modelling method is suitable for modelling HIV incidence due to the following reasons:

- It can be used for small and incomplete data sets. This gives it an advantage over the common HIV models reviewed in this Chapter that require large data sets for the model to work.
- Different sources of knowledge, such as expert opinions as well as data sources from reports and studies, can be used in the model ensuring that what ever data is available can be used, if required.
- The kinds of reasoning possible with BNs, such as predictive, diagnostic and intercausal, can allow for more insightful conclusions from the model. Scenario-based testing is also quick and easy to do with BNs and it can provide more insightful resource allocation information than GOALs.
- The explicit treatment of uncertainty by BNs means that uncertainty can be incorporated in the input parameters of the model as well as the model assumptions, which is a limitation of the MoT model.

- BNs can encode managerial decisions (though not done in the model proposed in Chapter 4) which means that relationships between actions, knowledge and uncertainly can be encoded in the model.

The following chapter provides an overview of the Bayesian Network methodology.

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2

Overview of Bayesian Networks: preparing the way for a new HIV epidemiology approach

2.1 Preamble

As far as I am aware, the Bayesian Network methodologies have not previously been used in modelling the incidence of HIV/AIDS, or in assessing the expected impact of different programmative funding allocations. This chapter will provide an overview of the Bayesian Network methodology, highlighting the advantages of this methodology and its applicability to modelling the incidence of HIV/AIDS.

2.2 Introduction

A Bayesian Network (BN) is a graphical model [8, 13] that is used for reasoning under uncertainty [10], and as a tool for compactly specifying joint probability distributions [3]. BNs use nodes to represent a set of random variables, say $\mathbf{X} = X_1, X_2, ..., X_i, ..., X_n$, and a set of directed arcs that

connect nodes, $X_i \rightarrow X_j$, to represent direct dependencies between variables [9, 10, 13]. BNs provide a probabilistic framework that describes the strength of the relationships between the variables [3, 5, 8–10]. The directed acyclic graph (DAG) that results after the construction of a BN is quantified through a series of conditional probabilities based on data or information available about the system or problem [8, 10].

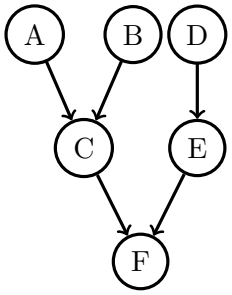

Figure 2.2.1: An sample Bayesian Network. Variables A, B, C, D, E and F are represented by nodes. The directed arcs show direct dependencies and influence between two variables. Here, A and B have a direct influence on C, which in turn has a direct influence on F. F is also dependent on E, which in turn is dependent on variable D.

2.3 Nodes and Values

The nodes of a BN are the variables of interest in the problem. The values that the nodes take must be mutually exclusive and exhaustive. For ease of construction, nodes are often discrete variables however continuous nodes can also be used [10]. Examples of common discrete nodes are boolean nodes (e.g. true or false), ordered values (e.g. low, medium, high) and integer values (e.g. 1-50).

2.4 Structure

The structure of a Bayesian Network should be such that it captures the qualitative relationships between the variables in the system being investigated. Nodes should be connected directly only if one affects or causes the other [8, 10].

The terminology of a BN is such that [10]:

- A node is a **parent** of a **child** if there is an arc from the former to the

latter. In Figure 2.2.1, A and B are parents of C, and variable F is a child of C.

- If there is a directed chain of nodes, one node is an **ancestor** of another it if appears earlier in the chain. It is a **descendant** of another if it comes later in the chain. In Figure 2.2.1, variable F is a descendant of variable A; variable D is an ancestor of F.
- Any node without parents is a **root** node. From Figure 2.2.1, variables A, B and D are root nodes.
- Any node without children is a **leaf** node. In Figure 2.2.1, variable F is an example of a leaf node.

2.5 Representation of Joint Probabilities

Bayesian Networks are directed acyclic graphs (DAG) which defines a factorisation of a joint probability distribution over the variables represented in the DAG. The factorisation is represented by the directed links in the DAG [8–10]. For a DAG, $\mathcal{G} = (\mathsf{V}, \mathsf{E})$, where V is the set of nodes and E is the set of directed links between nodes, a joint probability distribution, $\mathsf{P}(\mathbf{X}_\mathsf{V})$, over the set of variables $\mathbf{X}_\mathsf{V}$ can be factorised as

$$\mathsf{P}(\mathbf{X}_\mathsf{V}) = \prod_{v \in \mathsf{V}} \mathsf{P}\left(\mathbf{X}_\mathsf{V} | \mathbf{X}_{\mathrm{pa}(v)}\right), \tag{2.1}$$

where $\mathbf{X}_{\mathrm{pa}(v)}$ is the set of parent variables of variable $\mathbf{X}_\mathsf{V}$ for each node $v \in \mathsf{V}$. The factorisation of Equation 2.1 is a set of independence assumptions which are represented by the DAG interns of pairs of nodes that are not directly connected to each other by a directed link. The existence of such independence assumptions and the set of parents (usually a small set) for each node allows for the ability to specify the conditional probabilities and to perform inferences efficiently in a Bayesian network [3, 8–10].

Each conditional probability distribution given by $\mathsf{P}\left(\mathbf{X}_\mathsf{V} | \mathbf{X}_{\mathrm{pa}(v)}\right)$ represents a set of 'rules', where each 'rule', or conditional probability, takes the form

$$\text{If } \mathbf{X}_{\mathrm{pa}(v)} = x_{\mathrm{pa}(v)} \text{ then } \mathbf{X}_v = x_v \text{ with probability } z, \tag{2.2}$$

where x_v and $x_{\mathrm{pa}(v)}$ are the value assigned to $\mathbf{X}_v$ and a vector of values assigned to the parent variables of $\mathbf{X}_v$ respectively.

In actuality, the notion of 'rules' is only implicitly apparent in BNs. The explicit notion is that of the conditional probability distribution, $\mathsf{P}\left(\mathbf{X}_{\mathsf{V}}|\mathbf{X}_{\mathrm{pa}(v)}\right)$, each term is formulated by the conditional probability (parameter) of the form

$$\mathsf{P}\left(\mathbf{X}_v = x_v|\mathbf{X}_{\mathrm{pa}(v)} = x_{\mathrm{pa}(v)}\right) = z,$$

or, more simply,

$$\mathsf{P}\left(x_v|x_{\mathrm{pa}(v)}\right) = z.$$

2.6 Markov Property

Equation 2.1 shows that the probability distributions of are a BN is product of the conditional probabilities of all the variables in the BN, conditioned only on its parents [3, 8–10]. This means that BNs satisfy the Markov Property, which refers to the memoryless property of stochastic processes [3, 9]. In other words, the future states of a process, given the present and past states, depend only on the present state, i.e. the past is irrelevant because it does not matter how the current state was obtained. In terms of a BN, there are no other dependencies in the network apart from those that are represented by the directed links in the network [8, 10].

2.7 Dependence-separation (d-separation)

The Markov blanket of a node contains all the variables that shield the node from the rest of the network. This means that the Markov blanket of a node is the only knowledge needed to predict the behavior of that node. In a Bayesian network, the values of the parents and children of a node evidently give information about that node; however, its children's parents also have to be included, because they can be used to explain away the node in question. The term d-separation was coined by Pearl in 1988 [13] and is concerned with the blocking of information between nodes [3, 8–10].

The formal definition of d-separation is as follows: A path $\pi = \langle u, ...v\rangle$ in a DAG, $\mathcal{G} = (\mathsf{V}, \mathsf{E})$ is said to be blocked by $\mathsf{S} \subseteq \mathsf{V}$ if π contains a vertex w

such that either

- $w \in \mathsf{S}$ and the edges of π do not need head-to-head at w, or
- $w \notin \mathsf{S}$, $\mathrm{de}(w) \cap = \emptyset$, and the edges of π meet head-to-head at w.

For three subsets $\mathsf{A}, \mathsf{B}, \mathsf{S}$ of V, A and B are said to be d-separated if all paths between A and B are blocked by S.

In Figure 2.2.1, A and E are d-separated as no information can flow between these two nodes. If information can flow between nodes, they are d-connected. Again, from Figure 2.2.1, A and F are examples of d-connected nodes.

There are three possible types of connections in Bayesian networks [9]. Using Figure 2.2.1, as an example, these connections are:

- Serial Connections: information can be transmitted though a serial connection $\mathsf{A} \rightarrow \mathsf{C} \rightarrow \mathsf{F}$ unless the state of C is known.
- Diverging Connections: information may be transmitted through a diverging connection. In Figure 2.2.1, this could occur if a connection between B and E excited, so that $\mathsf{C} \leftarrow \mathsf{B} \rightarrow \mathsf{E}$ unless the state of B is known.
- Converging Connections: information may only be transmitted through a converging connection $\mathsf{A} \rightarrow \mathsf{C} \leftarrow \mathsf{B}$ if evidence on B or one of its decedents is available.

2.8 Reasoning

Bayesian networks provide a full representation of probability distributions over their variables. This means that they are able to condition upon any subset of their variables and support any direction of reasoning [8–10]. The types of reasoning that can be undertaken using a Bayesian network, shown graphically in Figure 2.8.1, are [10]:

- Diagnostic reasoning is reasoning from symptom to cause. This kind of reasoning occurs in the opposite direction to network arcs or links.
- Predictive reasoning is reasoning from new information about causes to new beliefs about effects. This kind of reasoning follows the direction of networks arcs.

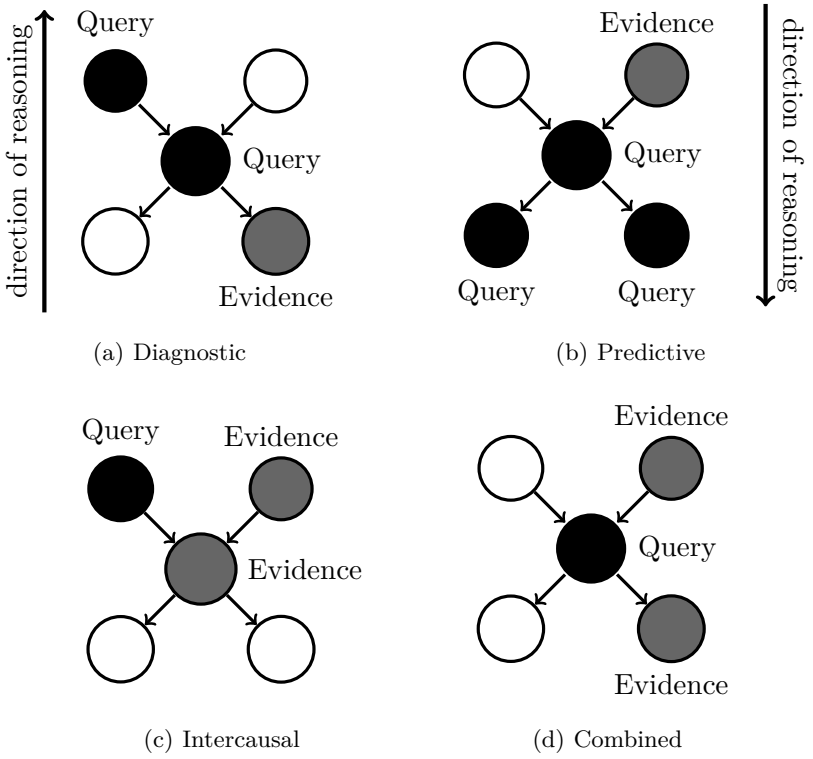

Figure 2.8.1: Schematics showing four types of reasoning that can be achieved using a Bayesian Network. Diagnostic reasoning is from symptom to cause, Predictive is from new causal information to new effect information, Intercausal reasoning is about mutual causes of a common effect and Combined reasoning is involves the use of both diagnostic and predictive reasoning.

- Inter-causal reasoning is reasoning about the mutual causes of a common effect. A specific kind of inter causal reasoning is called 'explaining away'. This kind of reasoning is generally represented by a v-structure in the network.
- Combined reasoning involves simultaneously employing diagnostic and predictive reasoning in a BN.

2.9 Quantification of Bayesian Networks

Building a Bayesian Network to represent a domain of interest is a three step process. Firstly, the variables of interest and importance must be identified. Secondly, the relationships between the variables must be found and

expressed in a graphical structure. The final step is to obtain the probabilities that constitute the network's quantitative part, that is, to obtain the probability distributions for each variable in the network [6, 16]. These probabilities can either be learnt from data, obtained from literature or elicited from domain experts.

Quantification of BNs in data-rich applications can easily be done by automatically learning the graphical structure of a probabilistic network [6, 11, 16, 19]. Buntine [2] provides a guide to the current literature on learning probabilistic networks from data and reviews different methods of learning Bayesian Networks from data. A list of statistical methodologies used for data structure learning is [2]:

- Maximum Likelihood and Minimum Cross Entropy Methods: these two approaches are equivalent, but suffer from over-fitting. The maximum likelihood approach is an important starting point as it is a simplification of other approaches. Thiesson [19] coupled a Maximum Likelihood Estimate with an Expectation-Maximisation (EM) algorithm in situations where there are incomplete observations to construct a hybrid method that preserves the global convergence of the EM algorithm, but with a higher rate of convergence.

- Hypothesis Testing Approaches: these approaches, while common and standard, are viable only if a small number of hypotheses are being tested.

- Extended Likelihood Approaches: these kinds of approaches, such as the penalised likelihood, Akaike information criteria and the Bayesian information criteria have been developed in order to overcome the problems of over-fitting and problems involved with hypothesis testing approaches.

- Minimum Information Complexity Approaches: these approaches are popular among engineers and computer scientists. It is claimed that one advantage of these approaches is that they require no prior and hence are objective, however the 'implicit prior' can be constructed in the code if necessary.

- Resampling Approaches: the strength of these methods is that they are a reliable black box method that can be used without the need

for complex mathematical treatments found in Bayesian or minimum complexity methods. These methods essentially create pseudo-samples from the original sample.

- Bayesian Approaches: the Markov Chain Monte Carlo (MCMC) family of algorithms and can be used for parameter fitting (sampling from different network parameters) and for structure learning (to sample from different possible probabilistic network structures).

These methods are some of the ways in which a BN can be quantified. Another method is by turning to literature from the relevant field of study being modelled. Literature often provides probabilistic information that can be used for the quantification of BNs [6]. Care should be taken, however, with using this information since this kind of information is often derived from a population with specific characteristics. In the case of data for health related problems for example, care should be taken not to use available information for populations with other characteristics [16]. Another problem with information from the literature is that it may not be relevant or appropriate to the probabilistic network being investigated as the conditional probabilities may be given in the opposite direction required for the network, or the information may be incomplete [6, 16]. When there is little or no reliable data available, and no information from the literature can be used, the knowledge and experience of experts in the domain can be used to quantify BNs.

Using an expert's knowledge can help to quantify a BN by providing the probabilities required but can also assist in fine tuning the probabilities obtained from other sources and in verifying the numbers within the context of a network [6, 16]. While expert knowledge is useful in this way, this method of quantifying a BN is not without its drawbacks. Firstly, the acquisition of knowledge from experts is costly and time-consuming [12]. Since networks can contain tens or hundreds of variables, the time and expense it would take to elicit the probabilities for large BNs may be outside the scope of some projects [6]. Secondly, some experts are uncomfortable with having to provide probabilities [16, 17]. Another drawback is that assessments by experts may be biased and may not be properly calibrated. These biases can be the result of the heuristics, or efficient shortcuts, that experts use for the assessment task and can result in overestimation [16, 23]. Of the three

methods for quantifying BNs, the use of expert judgement is considered the least objective and least accurate, however often it has to be utilised when other sources of probabilistic information are insufficient. Probability elicitation methods have been developed in an effort to remove bias and make this method of quantification more objective and accurate [11, 12, 16, 21].

Since BNs rely heavily on probabilistic information, it is important that the numbers employed are accurate. Inaccuracies will influence the network's output. There are a limited number of statistically rigrous quantification methods to date. Renooij [16] developed a scale of verbal-numerical probability expressions; Monti and Carenini [12] have modified the Analytic Hierarchy Process, and Laskey and Mahoney [11] used a systems engineering approach to probability elicitation.

2.10 Validation of Bayesian Networks

Once a BN has been quantified, it must be validated. Currently, the methods for the validation of a model, as suggested by Riesen [18], are: performing an elicitation review of the graph structure of the model and reviewing probabilities, performing sensitivity analysis to measure the effect of one variable on another and comparing the model with expert judgement. More recently, Pitchforth and Mengersen [14] have proposed a validation framework specifically for expert elicited Bayesian Networks.

2.10.1 Evidence Sensitivity

Evidence sensitivity measures the degree of variation in the BN's posterior distribution that results from changes in the evidence entered in the network. By using these values, the evidence nodes can be ranked in order to assist experts in targeting future data collection and to identify any errors in the BN structure or the conditional probability tables [15]. Two popular ways in which to measure evidence sensitivity are entropy and mutual information [15].

Entropy, $H(x)$, measures the randomness of a variable and is calculated as

$$H(X) = -\sum P(x) \log P(x),$$

where $P(x)$ is the probability distribution of X [10, 13]. The resulting value

can be interpreted as the average additional information necessary to specify an alternative [4].

The other measure of evidence sensitivity, mutual information $I(X, Y)$, gives an indication of the effect of one random variable X has on another, Y. This measure is calculated as

$$I(X, Y) = H(X) - H(X, Y).$$

This represents the extent to which the joint probability of X and Y differ from what it would have been if X and Y had been independent [10]. A result of $I(X, Y) = 0$ means that the variables are mutually independent [13].

2.10.2 Parameter Sensitivity

Identifying the sensitivity of the target node to changes in the probabilities of a BN is carried out using a mathematical sensitivity function which varies one of the parameters while keeping the others fixed, and then measures the variation in the output parameter [1]. To achieve this, a sensitivity function is required for the output probability $f(x)$ in terms of the parameter, x, being varied. The sensitivity function, given by

$$f(x) = \frac{\alpha x + \beta}{\gamma x + \delta},$$

is the quotient of two linear functions in the parameter being varied [22], where α, β, γ, and δ are constants built from the parameters which are fixed. The sensitivity value of parameter x and the target probability can be obtained by taking the first derivative of the sensitivity function,

$$f'(x) = \frac{\alpha\delta - \beta\gamma}{(\gamma x + \delta)^2}.$$

By using parameter sensitivity, it is possible to identify the parameters which cause the biggest changes in the posterior probabilities of the nodes of interest. Efforts to improve the level of accuracy for those parameters [15] can then be made.

2.10.3 Validation Framework for Expert Elicited Bayesian Networks

Pitchforth and Mengersen [14] have proposed a validation framework for expert elicited Bayesian Networks. To date, this is the most rigorous validation framework for these kinds networks to date. The validation framework [14] poses a seven types of validity, taken from psychometrics, to test the validity of the model structure, node discretisation, parameterisation, and overall model behaviour. These validity types and the respective questions that should be asked for each are as follows:

- Nomological validity
  - Does the BN model fit within an appropriate context in the literature?
  - Which theme and ideas are nomologically adjacent to the BN model, and which are nomologically different?
- Face validity
  - Does the model structure look the same as as the experts and/or literature predict?
  - Is each node of the network discretised into sets that reflect expert knowledge?
  - Are the parameters of each node similar to what the expert would expect?
- Content validity
  - Does the model structure contain all and only the factors and relationships relevant to the model output?
  - Does each node of the network contain all and only the relevant states the node can possibly adopt?
  - Are the discrete states of the nodes dimensionally consistent?
  - Do the parameters of the input nodes and CPT reflect all the know possibilities from expert knowledge and domain literature?
- Concurrent validity

  - Does the model structure or sub-networks act identically to a network or sub-network modelling a theoretically related construct?
  - In identical sub-networks, are the included factors discretised in the same way as the comparison model?
  - Do the parameters of the input nodes and CPTs in networks of interest match the parameters of the sub-network in the comparison model?

- Convergent validity
  - How similar is the model structure to other models that are nomologically proximal?
  - How similar is the discretisation of each node to the discretisation of nodes that are nomologically proximal independent of their network domain?
  - Are the parameters of nodes that have analogues in comparison models assigned similar conditional probabilities?

- Discriminant validity
  - How different is the model structure to other models that are nomologically distal?
  - How different is the discretisation of each node to the discretisation of nodes that are nomologically distal independent of their network domain?
  - Are the parameters of nodes in the comparison models that have oppositional definitions to the nodes in question parameterised differently?
  - When presented with a range of plausible models, can experts choose the 'correct' model or set of models?

- Predictive validity
  - Is the model behaviour predictive of the behaviour of the system being modelled?
  - Once simulations have been run, are the output states of the individual nodes predictive of aspects in the comparison models?

- Is the model sensitive to any particular findings or parameters to which the system would also be sensitive?
- Are there qualitative features of the model behaviour that can be observed in the system being modelled?
- Does the model including its component relationships predict extreme model behaviour under extreme conditions?

2.11 Advantages and Disadvantages of Bayesian Networks

The use of Bayesian Networks for modelling under uncertainty has a number of advantages, succinctly stated by Uusitalo [20] as:

1. Suitability for small and incomplete data sets, and also for large data: there is no such thing as too little data or minimum sample sizes for BNs as the analysis that takes place uses all the data available. The use of an Expectation-Maximisation (EM) algorithm to estimate the conditional probabilities of a model can be done [19] and requires only the model structure to be known beforehand [20].

2. Structural learning is possible: The two main approaches to learning the structure of a BN from data are the Bayesian approach and the constraint-based approach. In the Bayesian approach, the user constructs the BN with their knowledge and confidence and this is then combined with data to find the most likely model structure [7]. Constraint-based algorithms on the other hand, search for conditional probabilities between each pair of variables and build a model structure based on these probabilities.

3. The combination of different sources of knowledge: BNs can incorporate knowledge with different accuracies and data sources. Sources can include literature and experts [16], as well as results from other mathematical and statistical models. For example, BNs can be used with other Bayesian analysis methods such as Markov chain Monte Carlo (MCMC).

4. Explicit treatment of uncertainty and support for decision analysis: BNs can be constructed with variables that encode managerial decisions, meaning that these kinds of models can focus on the relation-

ships between actions, knowledge and uncertainty. They can be used to study the consequences of various management decisions.

5. Fast responses: Since BNs are solved analytically, a fast, real-time response to queries is possible.

Uusitalo [20] also mentions some of the challenges to using Bayesian Networks, including the discretisation of continuous variables, the collection and structuring of expert knowledge and the lack of support for feedback loops (particularly important in environmental modelling).

2.12 Conclusions

While BNs have are a relatively new modelling method, using this methodology in a context where probabilistic and causal relationships occur can provide additional information to a problem where these kinds of relationships occur, but have not yet been modelled. In the case of HIV incidence, the use of BNs to measure the impact of funding changes on new infections, and hence incidence, is a first step in modelling these relationships and will help to understand the effect of these changes.

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3

The HIV/AIDS Epidemic in the Philippines

3.1 Preamble

In this chapter, information regarding the HIV/AIDS epidemic in the Philippines is provided. This chapter was published in 2009 in the *Journal of the International AIDS Society* [Farr, A.C. and Wilson, D.P. (2009), An HIV epidemic is ready to emerge in the Philippines, Journal of the International AIDS Society, 13:16].

3.2 Introduction

Southeast Asia is experiencing numerous and diverse HIV epidemics that are evolving at varying rates, in different population groups, and in different geographical areas. Approximately 5 to 10 million people are living with HIV in Asia, with prevalence estimates of well over 1% among adults in numerous countries [52]. Yet there are some settings in which HIV prevalence has remained relatively very low.

The Philippines is one of the exceptional countries that has not faced

a large HIV epidemic. It is important to understand the reasons for the disparate nature of HIV in this country in order to ascertain whether lessons can be learnt for effective control in other settings and to ensure that a large HIV epidemic does not emerge in the Philippines. The first recorded case of HIV infection in the Philippines was in 1984 [2, 3, 7, 11, 15, 19, 30, 52, 54, 55]. Since then, the country has maintained an HIV prevalence of less than 0.1%, even among populations at high risk [3, 11, 15, 54], with a cumulative total number of HIV diagnoses of just over 3300 [34]. In this chapter, the current epidemiology and public health response to identify factors which could account for the low and slow development of the HIV epidemic in the Philippines, as well as to review behavioural and epidemiological conditions that may be of concern for facilitating an emerging epidemic.

The geography of the Philippines may be one of the first reasons for the slow spread of HIV. The Philippines is an archipelago of more than 7000 islands and islets; its complicated geography and separateness from mainland Asia could aid in shielding it from the larger regional epidemic [11, 19, 22, 47].

Additionally, the initial core group of people usually affected with HIV in Asian epidemics is not present to a large extent in the Philippines. Most HIV epidemics in southeast Asian settings initially establish among injecting drug users (IDUs) [61]. However, there are very low numbers of IDUs in the Philippines compared with most other southeast Asian countries [11, 47, 49, 54]. At present, there are only an estimated 10,000 IDUs in the Philippines [47] (out of its population of 90 million people; that is, 0.01%). In comparison, neighbouring Thailand, China and Indonesia have estimated IDU populations sizes (and population proportions) of 160,000 (0.38%), 1,800,000 (0.25%) and 219,000 (0.14%), respectively [31].

There also exists a culture of relative sexual conservatism in the Philippines [9, 54]. There are limited data available on sexual partner acquisition in the Philippines, and detailed behavioural sentinel surveillance data are not widely released [17]. The only reference to sexual partner rates of which we are aware is from a previous Philippines National AIDS Council Report, which indicates that the majority of the male population has only one sexual partner at any time and relatively low partnership breakup rates [45]. Although the validity of this statement should be questioned until solid data have been evaluated, this suggests that sexual conservatism exists in the Philippines relative to neighbouring countries.

The limited reporting available from behavioural surveillance conducted a number of years ago suggests that Filipinos tend to have fewer sexual partners than their counterparts in countries with higher HIV/AIDS rates [62] For example, sex workers in the Philippines tend to have fewer clients, an average of between two and four per week compared with 15 in many other settings [11, 44, 46, 47, 49]. Although this does not indicate levels of sexual activity in the general population, it is indicative of less sexual mixing outside regular partnerships.

However, fewer sexual partners is not necessarily a clear indicator of a smaller epidemic as reflected in China s expanding HIV epidemic despite reported sexual partner acquisition rates being similarly low [33]. One could expect different sexual behaviour across different social strata and thus an HIV epidemic sustained at low levels may not necessarily be a reflection of low average rates of partner change across a population.

There has also been the establishment of social hygiene clinics to allow for regular examination and sexually transmitted infection (STI) treatment for establishment-based female sex workers [11, 44, 49]. The prevalence of ulcerating STIs, which are believed to facilitate HIV transmission [18, 20], is relatively low [33] There is also a low occurrence of penile-anal sex in the Philippines [47] and a high rate of circumcision, 93% [12, 54], which is known to reduce the risk of males acquiring HIV in heterosexual intercourse [4, 6, 60].

Some countries, such as Vietnam, Indonesia and Papua New Guinea, have shown that a delayed HIV epidemic is possible [30, 39]. While HIV prevalence has remained 'low and slow' [11, 28, 30], the presence of many conditions for a large, increasing and generalized HIV epidemic are in place in the Philippines. These include: a low rate of condom use; unsafe injecting practices among IDUs; large migration rates; increasing trends in extramarital and premarital sex; a lack of education and common misconceptions about HIV/AIDS; and cultural factors that inhibit public discussion of issues of a sexual nature [55]. We will now expound these factors.

3.3 Condom use

The Philippines has the lowest documented rates of condom use in Asia [2, 8], at 20-30% among groups at highest risk of HIV (including sex workers)

[7, 9, 11, 19, 32, 46, 67]. This is concerning since the vast majority of HIV transmission in the Philippines is through sexual contact [8, 9, 47, 55]. A survey published in 2003 found that 63% of male respondents said that they had never used a condom [2]. Condom use among any extramarital partners is also rare [19].

There are various factors that may contribute to low condom use in the Philippines. A common perception is that condoms are only for birth control and not for protection against HIV and other STIs [19]. This perception is reinforced by the view that condoms are discouraged by the Roman Catholic Church. Government family planning programmes have policies against supplying condoms to unmarried people [7, 59].

The cost of condoms is also relatively high [17]. The majority of the supply of condoms is from international aid agencies (e.g., USAID) [19, 59]. Many female sex workers assert that knowing their client was reason enough to not use a condom [19]. Filipino women also tend to believe that the decision to use a condom is up to the man [19]. Men tend to feel the need to maintain their machismo image to the extent that they refuse to practice safe sex [29]. Culturally-sensitive but influential promotion of condoms appears to be an obvious gap in the Philippines HIV/AIDS response.

3.4 Casual sex

There is anecdotal evidence among numerous media sources and organizational reports that casual sexual activity, particularly among the male population aged 15-25, has been increasing. A study from over a decade ago estimated that 55% of young men have engaged in premarital sex compared with 23% of young women [7]. While most premarital sex in the Philippines is with the person who becomes a future spouse, men are more likely to have at least one additional partner compared with women [2, 7, 19]. Most casual sexual encounters are unprotected [10, 40, 46].

However, all of this evidence is based on relatively old data. There is a great need for behavioural surveillance data to be collected and reported systematically and regularly in order to monitor risk activities, particularly around casual sex, associated with transmission.

3.5 Injecting drug users

The most recent estimates of the size of the IDU population in the Philippines suggests that the number is relatively low [51]. However, serosurveillance of IDUs has only been available at one site, in Cebu City, and no data exist for other cities. It is possible that the actual number of IDUs is considerably greater than previously thought.

A 2004 report by the Philippines National AIDS Council estimated that only 48% of IDUs reported using sterile injecting equipment the last time they injected, and most IDUs reported that they regularly share injecting equipment [30]. A 2008 report published by the Joint United Nations Programme on HIV/AIDS (UNAIDS) indicated that the prevalence of sharing injecting equipment is still very high, with 29% of IDUs self-reporting use of an unsterile needle/syringe the last time they injected [51]. Sharing HIV-contaminated injecting equipment is an efficient mode of HIV transmission [5, 24]. Given the experience of neighbouring countries, IDUs could be an important population group for the spread of HIV in the Philippines if the size of the IDU population increases.

3.6 Overseas Filipino workers

There are approximately 7.5 million Filipinos working in 170 countries around the world, with more than 2000 workers departing from the country daily [8, 56]. By participating in casual unprotected sex or other risky behaviour while overseas in higher prevalence settings, overseas Filipino workers (OFWs) become a substantial source of new HIV cases in the Philippines upon their return home.

Of all the HIV/AIDS cases reported in the Philippines, OFWs account for 30-35% of all cases (this level has remained relatively steady over the past decade) [8, 11, 47]. Heterosexual sex is the dominant mode of transmission for OFWs, and the main occupations of OFWs who are infected with HIV are seafarers and domestic helpers. OFWs may be a bridge population for the spread of HIV and other STIs [8, 27, 43]. This population will undoubtedly be important in any HIV epidemic in the Philippines.

3.7 HIV/AIDS education and social factors

Even though awareness of the disease is high [11], misconceptions of HIV/AIDS are widespread among health workers, as well as in the general population [2]. For example, a survey of 1200 males found that many respondents believed that antibiotics, prayer and keeping fit would protect against HIV/AIDS [8]. Many young people also believe that HIV/AIDS can be prevented or treated by a concoction of drinks, douching with detergents, interrupting coitus and washing the penis [11]. The Young Adult Fertility Survey found that a large proportion (60%) of young people believed that there was now a cure for HIV/AIDS and, as such, they could become more complacent [23].

Women in the Philippines are not largely empowered to protect themselves and negotiate for safe sex due to cultural, physiological and socio-economic factors. An estimated 43% of women have admitted to being forced into sex, and 15% believed that they were obligated to have sex with their partners [11].

Condom use is also low among the population of men who have sex with men (MSM) [11, 30]. Unprotected penile-anal sex is a highly efficient mode of HIV transmission [13, 14, 26, 41, 57, 58]. Discrimination, harassment and intolerance of homosexuality, particularly male homosexuality, have resulted in MSM becoming a hidden population group, even though 20% of reported HIV cases involve male-to-male transmission [11]. With intolerance still high, it is difficult to provide MSM with HIV/AIDS information, education and treatment.

3.8 The current epidemiological state of HIV in the Philippines

In this section, we present HIV/AIDS surveillance data in the Philippines and analytical findings based on monthly diagnoses reported from March 2003 to June 2008 [11]. There is a steady increase in the cumulative number of HIV notifications in the Philippines (Figure 3.8.1).

However, the trends in HIV notifications differ between the genders. The cumulative number of HIV notifications among females has been increasing at a steady rate ($p < 0.0001$), suggesting that incidence is approximately constant and at an endemic equilibrium. In contrast, the trend among males

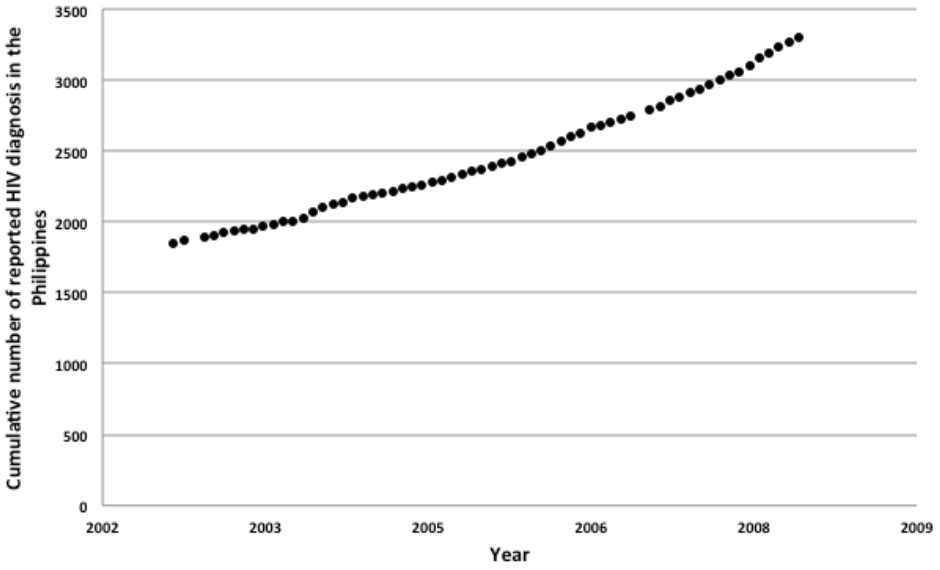

Figure 3.8.1: Cumulative number of HIV diagnoses in the Philippines by month from March 2003 to June 2008.

is not constant, incidence levels are substantially greater than in females, and the rate of new notifications is increasing (evidenced by the curvature away from linear). This suggests that there may be an emerging HIV epidemic among Filipino MSM.

The emergence of an increasing HIV epidemic in the Philippines is evident from trends in monthly reported HIV diagnoses (Figure 3.8.2). In mid-2003, there were 10 to 15 monthly HIV notifications and there are currently 30 to 50 notifications per month; that is, a three-fold increase over five years. The trend has increased even further from 528 notifications in 2008 to 835 in 2009 (a 58.1% increase in one year) [35]. This suggests that the epidemic could be approaching a large expansion phase.

However, the divergence in HIV diagnosis rates between men and women could also reflect possible differences in testing rates. There are no data to suggest differences in testing rates, and the Philippine AIDS Prevention and Control Act of 1998 encourages HIV testing of all individuals at high risk of contracting HIV, with informed content [1]. But this alternate explanation for the epidemic trends cannot be ruled out until reliable testing data are available.

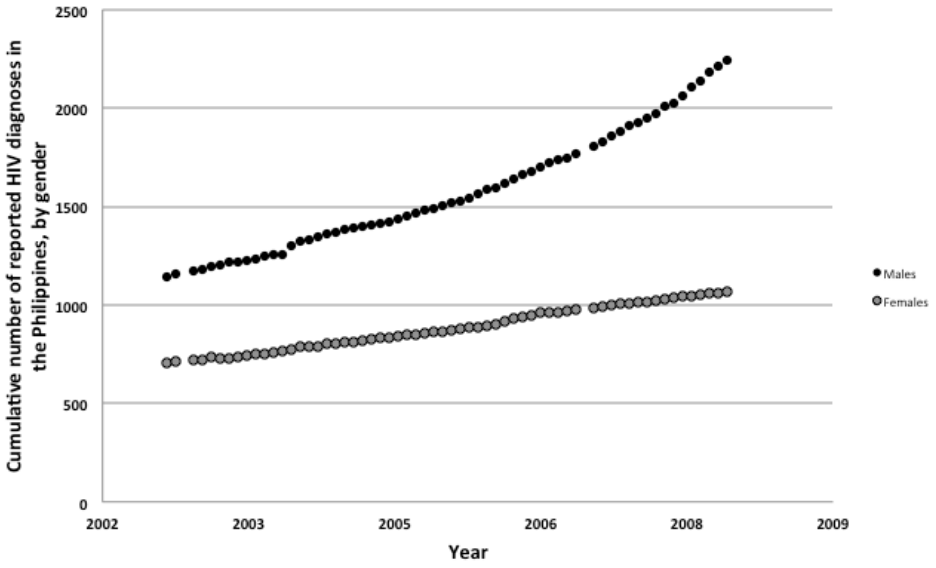

Figure 3.8.2: Cumulative number of HIV diagnoses in the Philippines by month from March 2003 to June 2008, by gender.

Diagnoses of HIV in the Philippines are notified according to various categories of likely route of exposure. These include: heterosexual contact; male homosexual contact; bisexual contact; blood transfusion; injecting drug use; needle prick injury; or perinatal exposure. Bisexual contact refers to men who have had sex with both men and women. It cannot be determined whether the initial actual transmission event was male-to-male sexual contact or transmission from an infected woman. It is more likely that the transmission was via male-to-male sexual contact due to biologically higher transmission rates, but the bisexual category accurately reflects a degree of uncertainty in the route of exposure.

The dominant mode of HIV transmission in the Philippines is sexual (92%). But the largest increases in the rate of new HIV notifications are due to homosexual and bisexual contact, and not heterosexual contact (Figure 3.8.3). Over the period, 2003-2008, there was an increase in the monthly number of diagnoses, from 328 for homosexual contact and 92 for bisexual contact to 704 and 289, respectively; that is, respective increases of 114% and 214%. Therefore, there appears to be an increasing epidemic of HIV among men who have sex with men. The increase among bisexual men also has important consequences for the spread of HIV to the general heterosex-

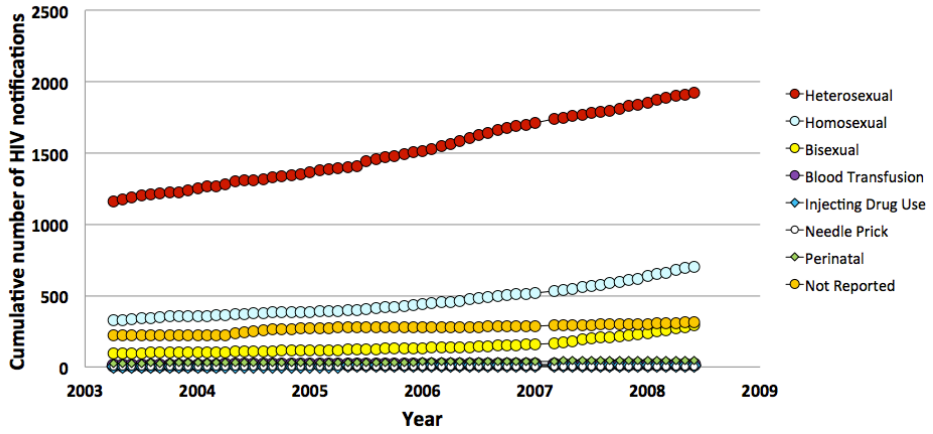

Figure 3.8.3: Cumulative number of HIV diagnoses in the Philippines by month from March 2003 to June 2008, by route of exposure.

ual population. However, data on testing rates would help to elucidate the extent to which these diagnoses rates are reflective of underlying incidence.

It should be noted that some of the rise in HIV diagnoses could be attributable to an increase in testing rates. This is evident by the decreasing proportion of all HIV cases that are detected with AIDS disease: 33% of diagnoses in 2003 were in AIDS stage disease and this has decreased to 24%. However, the disproportionate trend in diagnoses between genders and between different routes of exposure strongly suggests that the trends in diagnoses reflect actual trends in population incidence. But since a substantial proportion of infections is detected in late-stage disease, it is likely that the majority of all HIV cases are currently undiagnosed in the Philippines [5].

The cumulative number of AIDS deaths is increasing approximately constantly ($p < 0.0001$), suggesting that AIDS death rates are relatively constant. It could be expected that there will be a delay of a number of years before the rise in HIV diagnoses translates to a rise in AIDS-related deaths.

AIDS is now a reversible HIV-related condition due to combination antiretroviral therapy (ART). The number of people receiving ART in the Philippines has been increasing since 2004, with a rate of approximately 10% of diagnosed cases receiving treatment in 2006, and ART coverage has now increased to approximately 30% [55, 66]. But this is still considerably less than desirable levels. Universal treatment access for HIV-infected

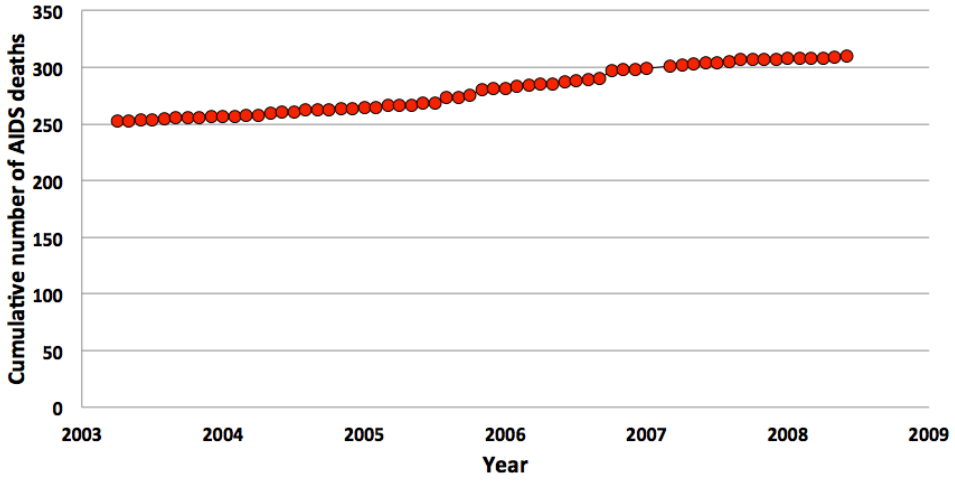

Figure 3.8.4: Cumulative number of AIDS deaths by month from March 2003 to June 2008.

people is becoming a reality in some of the poorest countries of the world. Since HIV is relatively contained in the Philippines, there is the opportunity to substantially scale up treatment access before the number of HIV cases increases out of control. Treatment should be universal for HIV-positive pregnant women for preventing mother to child transmission (PMTCT) [50]. However, PMTCT is relatively uncommon in the Philippines.

One of the reasons for such low rates of ART is that funding for such care and treatment of HIV-infected persons makes up a mere 1.6% of the Philippines HIV/AIDS budget [50]. While expenditure on treatment and care is currently low, the Philippine National AIDS Council s 4th AIDS Medium Term Plan and its country report for the period, January 2006 to December 2007, to the United Nations General Assembly Special Sessions (UNGASS) states that it will endeavour to improve access to treatment, care and support to HIV-infected persons [46, 47] Treatment not only sustains life among HIV-infected people, but by reducing their viral loads, it reduces infectiousness. At the population level, this would likely prevent considerable numbers of secondary transmissions of HIV [21, 64, 65].

The average age at HIV diagnosis in the Philippines was 35-36 years prior to 2005, but recently, the average age at diagnosis has been decreasing ($p=0.0067$) (Figure 3.8.5). It is now 29 years of age. Although it is possible that increased testing rates mean infections are detected earlier, the extent of decrease in ages cannot be attributable to changes in testing rates.

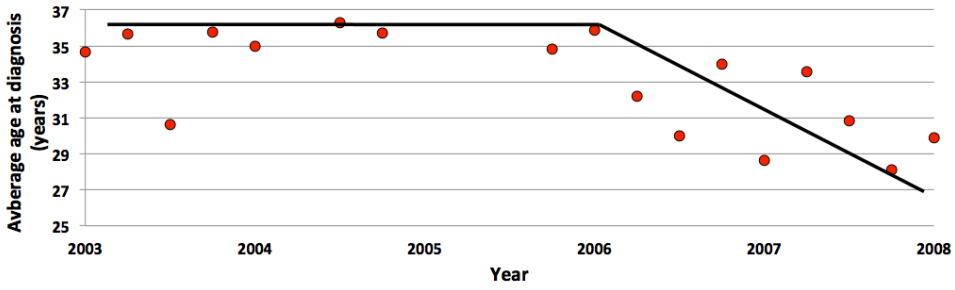

Figure 3.8.5: Trend in the average age of HIV diagnosis for three-monthly notifications in the Philippines.

The trend in decreased age at diagnosis is likely to reflect a decrease in age at infection. Younger age groups tend to have greater sexual activity. The fact that the average age is decreasing is a strong indicator that HIV incidence could increase substantially in the future in the Philippines. This trend is also in contrast to most other settings where epidemics are being controlled [63]. However, younger age is not necessarily indicative of greater sexual activity among all population groups, particularly among men who have sex with men, as suggested from other settings [25]. As men who have sex with men are the population group greatest affected with HIV in the Philippines, the decreasing age at diagnoses may not necessarily suggest a future increase in HIV.

3.9 Conclusion

The Filipino government and other stakeholders have responded to the HIV/AIDS threat in the Philippines in a number of ways in order to circumvent a large HIV epidemic from arising. The Philippine National AIDS Council (PNAC) was created in 1992 to act as an advisory body to the President for the development of policy for the control of AIDS. The PNAC consists of members from the government, public, civil society, private sector and non-governmental organisations (NGOs), and is the central advisory, planning and policy-making body for the comprehensive and integrated HIV/AIDS prevention and control programme [11]. But its small budget has limited its ability to instigate implementation of large intervention and education campaigns.

The official response of the Philippines Government to the HIV threat was to enact the Philippine AIDS Prevention and Control Act of 1998 (Republic Act No. 8504) [1]. This Act was enacted by Congress after a long process of deliberation and advocacy by the PNAC and other stakeholders [45]. The Act called for: a comprehensive nationwide HIV/AIDS educational and information campaign; full protection of the human rights of known and suspected HIV-infected persons; promotion of safe and universal precautions in practices and procedures that carry risks of HIV transmission; the eradication of conditions that aggravate spread of HIV infection; and recognition of the important role that affected individuals could have in promoting information and messages about HIV/AIDS. The Act also states that local governments are to provide community-based HIV/AIDS prevention, control and care services.

While the Act is a step in the right direction, it is far from effective due to a lack of monetary commitment from the government, relying heavily on NGOs for funding for HIV/AIDS education and prevention programmes, and the current government s seemingly unwilling attitude to promote wide condom use for fear of angering the Roman Catholic Church [59]. Its statements are also broad and do not outline targeted strategies with specific goals.

Other programmes have also been established for monitoring the spread, understanding key epidemic drivers and planning the control of HIV in the Philippines. There are currently four types of surveillance systems in place in the Philippines:

1. The HIV/AIDS Registry was established in 1987 and is a passive surveillance system. It continuously records Western Blot-confirmed HIV cases reported by hospitals, laboratories, blood banks and clinics that are accredited by the Department of Health.

2. The HIV Sentinel Surveillance System (HSSS) was established in 1993 with a grant from the US Agency for International Development (USAID). It monitors 10 key cities: Baguio City, Angeles City, Iloilo City, Zamboanga City, Pasay City, Quezon City, Cebu City, Cagayan de Oro City, Davao City and General Santos City. It pays particular attention to establishment-based female sex workers, freelance female sex workers, MSM and IDUs [3, 8, 30].

3. Behavioural Sentinel Surveillance was added at the 10 HSSS sites in

1997 and is a systematic and repeated cross-sectional survey of behaviour related to the transmission of HIV and other STIs [3, 8, 53]. Its major purpose is to detect trends among vulnerable populations and groups at high risk whose behavioural change would have the greatest impact on the HIV epidemic.

4. The Sentinel STI Etiologic Surveillance System was set up in December 2001, but made operational in 2003. It monitors STI trends that could guide programme interventions to prevent the transmission of HIV.

These surveillance systems have been monitoring the progress of HIV in the Philippines and have provided valuable data to inform appropriate response measures.

The PNAC's 4th AIDS Medium Term Plan for 2005 to 2010 is one of the plans that utilised data from the surveillance systems [11, 44]. This plan aligns with the Philippines AIDS Prevention and Control Act, with the aims of scaling up and improving the quality of preventive interventions and the quality of treatment, care and support services for people infected with and affected by HIV/AIDS. It also aims to integrate stigma reduction measures in the preventive treatment, care and support services and in the design of management systems.

The current state of HIV in the Philippines is not attributable to any one factor. While the Philippines response is associated with effectively controlled levels of HIV, there is no guarantee that a large HIV epidemic will be avoided in the near future. Indeed, an expanding HIV epidemic is likely to be only a matter of time as the components for such an epidemic are already present in the Philippines.

Mathematical modelling studies have shown that even in countries where overall HIV prevalence has remained relatively low (e.g., Bangladesh), moderate changes in behaviour or HIV infections could initiate a large epidemic that may otherwise have taken numerous decades to develop [16, 42]. Current data from the PNAC show that young adults, men who have sex with men, male and female sex workers, injecting drug users, overseas Filipino workers, and the sexual partners of people in these groups are particularly vulnerable to HIV infection [47].

The current behavioural, social and epidemiological conditions suggest that an HIV epidemic in the Philippines may be unavoidable in the near

future. The number of diagnoses is increasing, particularly due to homosexual and bisexual contact; there are low condom-use rates; and the age at diagnosis is decreasing. The underlying cause of these symptoms needs to be addressed in order to prevent an emergent epidemic. The promotion of HIV prevention and education messages is underfunded and has been relatively ineffective. It is recommended that more investment be made into these programmes in order to maintain the 'low and slow' development of HIV in the Philippines.

3.10 Short update to the HIV epidemic since publication

Whie the Philippines still has a low HIV prevalence, which is estimated at 0.036% in 2011, or 36 cases per 100,000 adult Filipinos, the HIV epidemic in the Philippines has unfortunately taken off since the publication of this work in 2009 [38]. It is one of only nine countries in which there have been increasing HIV cases with a 25% in HIV cases between 2001 and 2009. The primary drivers of the epidemic are unprotected sexual intercourse in the MSM population, needle sharing among IDUs and unprotected sex with FSWs [38]. The most alarming of these trends has been the increase in HIV infections among IDUs (see Table 3.10.1).

Population	**2009**	**2011**
Registered Female Sex Workers (RFSW)	0.23%	0.13%
Freelance Female Sex Workers (FFSW)	0.54%	0.68%
Men who have sex with Men (MSM)	1.05%	2.12%
Injecting Drug Users (IDUs)	0.21%	13.00%

Table 3.10.1: HIV prevalence among FSW, MSM and IDUs [37].

Between 1984 and 2006, there were only seven reported cases of HIV where the mode of transmission was through IDU, however 2010 alone the reported number of cases was 147 [38]. This alarming trend is most noticeable in Cebu City, where the HIV prevalence among IDUs increased from 0.59% to 53% between 2009 and 2011 (Figure 3.10.1).

The MSM population in the Philippines is also of interest. While the HIV prevalence in this sub-group did not increase as dramatically compared to

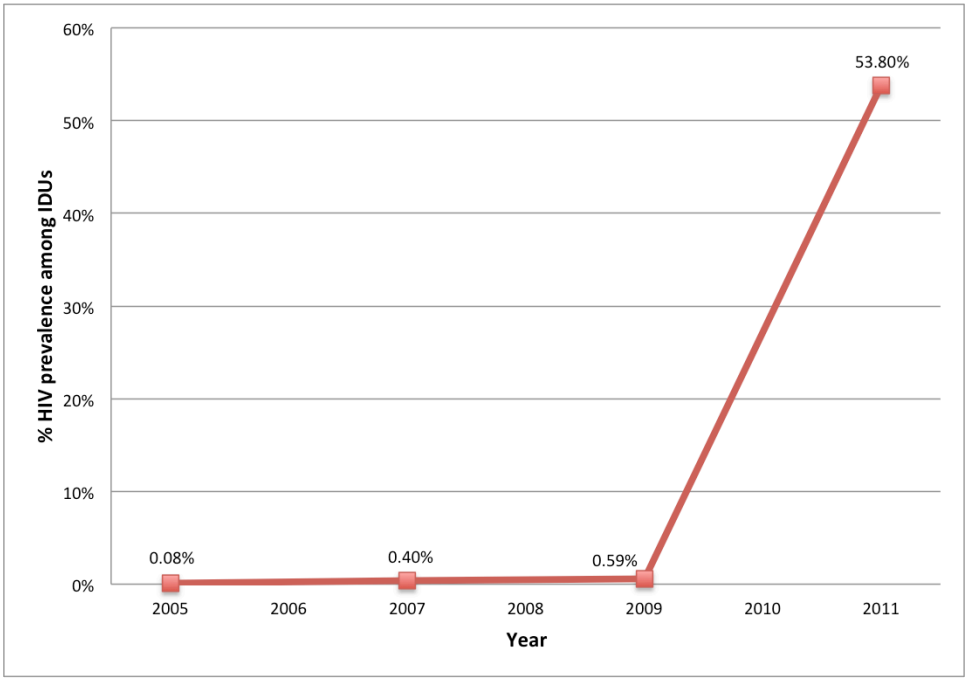

Figure 3.10.1: HIV prevalence in Cebu City from 2005 - 2011 [36, 37, 48].

the IDU population, it did increase from 1.05% to 2.12% between 2009 and 2011 (Table 3.10.1).

With increases in HIV prevalence occurring in the Philippines, with some alarming increases particularly in IDUs, it is important to have a way in which to investigate what impact changes in funding will have on HIV incidence and prevalence. This is especially significant when funding is decreasing worldwide [68].

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4

Applying Bayesian Network modelling to the HIV/AIDS epidemic in the Philippines

4.1 Introduction

Historically, the Philippines was one of the few countries which had not faced a large HIV epidemic. The reasons for this have been discussed in Chapter 3, and while it was found that the state of the current HIV epidemic was not attributable to one factor, I argued that an expanding HIV epidemic in the Philippines was only a matter to time. Unfortunately, the epidemic has recently emerged with a 100-fold increase in prevalence among intravenous drug users (IDUs) in Cebu and an increase in annual HIV notifications between 2009 and 2012 from 11,980 to 22,840 [34].

These developments, and with indications of a decrease in HIV funding to the Asia region including the Philippines [47], it is important to assess the potential impact of changes in funding, and therefore programs, will have on HIV incidence. To investigate these impacts in the present research, a Bayesian Network (BN) methodology was chosen. The theory involved in BNs has been previously covered in Chapter 2 of this thesis.

Bayesian Networks (BNs) have been successfully used to model complex and multi-faceted issues in a wide range of disciplines including health, ecology, natural resource management, and forensic science [17, 21, 28, 30, 32]. BNs are probabilistic graphical models used for reasoning under uncertainty [24]. They use nodes to represent a set of variables of interest and arcs to represent their conditional inter-dependencies [24, 25] and have a qualitative and quantitative component. The nodes and arcs form the qualitative component of a BN - the directed acyclic graph (DAG). The quantitative part of a Bayesian Network is the conditional probability distributions that underlie the relationships between the variables. They give the probabilities for each node given the value of its parent node(s) [24]. The conditional probabilities are quantified using data or information available about the system or problem [16, 20] and defines a factorisation of a joint probability over the variables represented in the DAG, which are represented by the arcs in the DAG [16, 19].

This chapter describes the development of a HIV Bayesian Network model for the investigation of the impact of funding changes on new infections, and subsequently incidence, in the Philippines. Like many low and middle income countries, the Philippines has a paucity of data relating to new infections and incidence. While this may be an issue for other modelling methodologies, Bayesian Networks are particularly suited to modelling scarce data from various sources. If data are scarce, BNs are still able to encode any correlations between input variables to allow dependencies between variables to be seen [14].

The model developed here can be used as a management and decision support tool for changes in funding, as well as for looking at the expected impact on incidence of changes in the funding of different programs in the country. The results of a BN are presented in the form of a probability distribution rather than single values, which is an integral feature of BNs [7]. This explicit representation of the uncertainty attached to the prediction makes it an ideal tool for investigating the expected impacts of changes in funding on incidence. This model is designed to be a complementary tool to current HIV models for investigating the impact of changes in funding on incidence.

4.2 Methods

The HIV Bayesian Network (HIV-BN) was developed using a modified version of the Iterative Bayesian Network Development Cycle (IBNDC) proposed by Johnson et at [18]. The IBNDC, shown in Figure 4.2.1, consists of two primary processes: a *Core Process* and a *Recursive Process*. The *Core Process*, which is performed once modelling commences, provides the foundation for the *Recursive Process*. The *Core Process* is manual and in the development of this network, was supported by constant interaction with subject area experts at the Kirby Institute for Infection and Immunity in Society at the University of New South Wales (Kirby) in order to define the target nodes, identity key factors. The *Recursive Process*, which consists of four iterative phases, utilises many of the automated features of the BN modelling software, in conjunction with input from subject area experts. The four iterative phases were continually revisited as the network structure and the network quantification was developed.

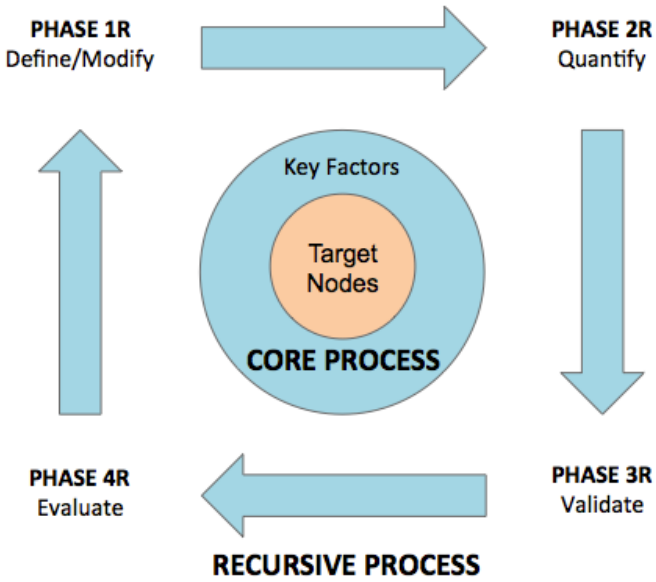

Figure 4.2.1: A modified version of the Iterative BN Development Cycle (IBNDC) by Johnson et al [18].

4.2.1 The Core Process

The *Core Process* of the modified IBNDC [18] comprises of defining the target nodes and defining the key factors involved in the problem.

Target Nodes

This is the most important step in the process as it provides the answer to the question 'What issue do we want to address?' [43]. Careful definition of the target node is crucial to the structure, assumptions and key factor identification of the model. Discussions with subject area experts found that the question of interest was to investigate the impact of funding changes on the number of infections in the sub-groups of interest in the Philippines, namely Men who have sex with Men (MSM), Intravenous Drug Users (IDUs), Female Sex Workers (FSW), and the Non-Most At Risk Population (Non-MARPS). The target nodes, therefore are *MSM Infections*, *IDU Infections*, *FSW Infections*, and *Non-MARP Infections*.

Key Factors

A list of relevant factors that contribute to, or have impact on, the target nodes is required. The list of these factors was obtained during workshops with staff at Kirby, along with the definitions for each factor. These can be seen in Table 4.2.1. The information was transcribed into Hugin Expert A/S software [15], and the *Recursive Process* of the IBNDC started.

4.2.2 The Recursive Process

The four phases in the Recursive Process of the IBNDC are Define/Modify, Quantify, Validate, and Evaluate.

Define/Modify

The first iteration of this phase required a review of the nodes that were defined in the *Core Process*, and using these nodes to create a conceptual model of the network. This involved the placement of nodes and connection of nodes through directed links. In this phase, node definitions were documented in the BN software and were consistently referred to, in order to ensure that the relationships between the nodes are correct. The subsequent

iterations of this phase which include the addition, deletion and modification of nodes and directed links result from outcomes of Phases 3R and 4R. The nodes chosen for this network were *MSM Infections*, *IDU Infections*, *FSW Infections*, *Non-MARP Infections*, *Detectable Viral Load*, *Behavioural Changes*, *ART*, *Treatment Programs*, *Testing Programs*, *Primary Prevention Programs*, and *Funding*.

Quantify

The quantification phase consists of defining the states for each node and populating the underlying conditional probability tables (CPTs) in the network. Experts from Kirby were interviewed to provide the required probabilities needed to quantify the network. These experts had experience in the HIV epidemic in the Philippines as well as the funding and programs that were in the country. The experts were used to provide feedback on the model structure, the node states, and provided the conditional probability values used in the network. This information exchanged was undertaken via electronic means such as email and Skype, as well as face-to-face meetings.

The states for each node in the network are shown in Table 4.2.1. Where possible, the number of states for the nodes were minimised in order to prevent unwieldy probability tables.

The process for populating the CPTs involved a workshop with the staff at Kirby where staff provided justification for the numbers provided for the CPTs. The justifications for each of the CPT entries underlying each node are shown below.

Funding

- P(*increase* in funding) = P (*decrease* in funding) = 50%
  - This node was given a very flat prior as this is currently the situation relating to funding in the Philippines. With the current funding arrangements due to change at the end of 2014, there is uncertainty regarding the direction funding will take in the years post-2014.

Treatment Programs

Node	Description	States
ART	Is a person living with HIV (PLHIV) on Antiretroviral Treatment (ART)?	Yes, No
Behavioural Changes	The changes in behaviour that is of interest. In this case, testing, condom use, and safe syringe use are behaviours of interest.	Increase in Testing Decrease in Testing Increase in Condom Use in MSM No change in Condom Use in MSM Decrease in Condom Use in MSM Increase in Condom Use in FSW No change in Condom Use in FSW Decrease in Condom Use in FSW Increase in Condom Use in Non-MARPs No change in Condom Use in Non-MARPs Decrease in Condom Use in Non-MARPs Increase in use of Contaminated Syringe No change use of Contaminated Syringe Decrease use of Contaminated Syringe
Funding	The level of funding available	Increase, Decrease
FSW Infections	The change in infections in FSWs	Increase, No change, Decrease
IDU Infections	The change in infections in IDUs	Increase, No change, Decrease
MSM Infections	The change in infections in MSMs	Increase, No change, Decrease
Non-MARP Infections	The change in infections in Non-MARPs	Increase, No change, Decrease
Primary Prevention Programs	Funding available for primary prevention programs	Increase Decrease
Testing Programs	Funding available for testing programs	Increase, Decrease
Treatment Programs	Funding available for treatment programs	Increase, Decrease
Detectable Viral Load	The level of a person's Detectable Viral Load	Increase, Remains the Same, Decrease

Table 4.2.1: Description and states of the nodes of the HIV-BN.

- P(Treatment Program Funding *increase* | Funding *increase*) = 95%
  - If there is an increase in HIV/AIDS funding, then an increase in Treatment Program funding is very likely. There is a very big push for ART, not only because treatment is needed clinically for treatment sake, but also treatment as prevention. The World Health Organisation are working with the Philippines Department of Health (DoH) to push for an increase in treatment. The DoH has identified this as a priority. The only possible limitation is the presence of infrastructure such as Social Hygiene Clinics, however the infrastructure is currently adequate for an increase in coverage.
- P(Treatment Program Funding *decrease* | Funding *decrease*) = 5%
  - ART will not decrease even if there is a decrease in HIV/AIDS funding since there is a commitment to treat those already on ART. There will be an increased wave or burden of people requiring ART due to the current trend of the HIV epidemic in the Philippines. Funding for ART programs can only increase.
- P(Treatment Program Funding *increase* | Funding *decrease*) = 70%
  - The decrease would be from a decrease in President's Emergency Plan For AIDS Relief (PEPFAR) and The Global Fund to Fight AIDS, Tuberculosis and Malaria (GFATM) funding, but the DoH would not decrease funding to these programs. The DoH is committed to sustaining treatment programs, with an acceptance that they may have to forego prevention programs to do so. Given the increased need due to the HIV epidemic in the Philippines, funding for treatment programs will likely continue to increase irrespective of overall funding levels.

Testing Programs

- P(Testing Program Funding *increase* | Funding *increase*) = 95%
  - The Philippines has a strong culture in the HIV sector for testing underpinning prevention education and its linkage to care.

- P(Testing Program Funding *decrease* | Funding *decrease*) = 30%
  - If international funding sources decrease, domestic funding will remain stable due to pressure to fill in some of the gap. Testing in the Philippines is scaling up, at least until the end of 2014 due to Asia Development Bank (ADB) and World Bank (WB) funding. In 2015, even with resource constraints, the DoH will prioritise testing however they may not be able to sustain donor levels as implemented through Population Services International (PSI) and the Philippine NGO Council on Population, Health and Welfare (PNGOC).

Primary Prevention Programs

- P(Primary Prevention Program Funding *increase* | Funding *decrease*) = 70%
  - The ADB/WB covers these kinds of programs until the end of 2014. If these programs work, the DoH will continue to fund these programs. If not, there will still be pressure for the DoH to continue to fund these programs to an extend. 70% in 2015 is considered to be reasonable.
- P(Primary Prevention Program Funding *increase* | Funding *decrease*) = very, very small probability (0.01%)
  - A decrease in HIV funding would make an increase in these kinds of programs almost impossible since the other programs (treatment and testing) are considered more important. There is an obligation to continue treatment programs and funding will be directed towards these programs.

ART

- P(PLHIV on ART | Funding *increase* for Testing and Treatment Programs) = 30%
  - Currently, there are approximately 15% of PLHIV on ART. Treatment will increase, and by 2015 this could be at 30%.

- P(PLHIV on ART | Funding *decrease* for Testing Programs and Funding *increase* for Treatment Programs) = 25%
  - There is currently a relatively large demand for ART among PLHIV, who are treatment-eligible. Those who are already diagnosed will continue to be treated. However, testing will still continue.

Detectable Viral Load (DVL)

- P(*increase* in DVL | PLHIV on ART) = 0%
  P(*no change* in DVL | PLHIV on ART) = 25%
  P(*decrease* in DVL | PLHIV on ART) = 75%
  - This result is taken from Bonner et al [6].
- P(*increase* in DVL | PLHIV not on ART) = 0%
  P(*no change* in DVL | PLHIV not on ART) = 100%
  P(*decrease* in DVL | PLHIV not on ART) = 0%
  - Only rare elite controllers have undetectable viral load when not on ART.

Behavioural Changes

- Given an *increase* in Testing Program Funding and an *increase* in Treatment Program Funding, then:
  - P(*increase* in Testing) = 75%
    P(*no change* in Testing) = 20%
    P(*decrease* in Testing) = 5%
    * The changes in testing levels is highly likely as this is the targeted outcome. Among MSM, the 'Love Yourself' community group has been highly successful in increasing testing levels. IDUs and FSWs are not as forthcoming, but there is an increase.
  - P(*increase* in Condom Use among MSM) = 70%
    P(*no change* in Condom Use among MSM) = 20%
    P(*decrease* in Condom Use among MSM) = 10%

    * The ADB is funding prevention among MSM in Manila until the end of 2014. There is a focus to increase condom use by flooding the city MSM hotspots with condoms.
  - P(*increase* in Condom Use among FSW) = 45%
    P(*no change* in Condom Use among FSW) = 45%
    P(*decrease* in Condom Use among FSW) = 10%
    * Condom use will slowly increase, however there is not as much emphasis on condom use among FSWs.
  - P(*increase* in Condom Use among Non-MARPs) = 10%
    P(*no change* in Condom Use among Non-MARPs) = 80%
    P(*decrease* in Condom Use among Non-MARPs) = 10%
    * There is unlikely to have much/any effect on causal and definitely not on regular partners. Programs until the end of 2014 are not targeting Non-MARPs except small amounts to partners of MARPs.
  - P(*increase* in use of contaminated syringes) = 10%
    P(*no change* in use of contaminated syringes) = 40%
    P(*decrease* in use of contaminated syringes) = 50%
    * There is now a needle syringe pilot program endorsed by the Dangerous Drug Board after considerable obstacles. WHO have set up a small clinic in Cebu. The pilot program is for 'experimental' purposes. This program is not widespread and will only run in Cebu until the end of 2014.

- Given an *increase* in Testing Program Funding and a *decrease* in Primary Prevention Program Funding, then:
  - P(*increase* in Testing) = 25%
    P(*no change* in Testing) = 50%
    P(*decrease* in Testing) = 25%
    * The increase in testing program funding would likely be used for infrastructure (sites, laboratories) and for on-off testing days and campaigns. The decrease in primary prevention program funding would mean less access, coverage, and reach to target groups to bring them in for testing and counselling, which is a critical enabler for testing coverage.

- P(*increase* in Condom Use among MSM) = 25%
  P(*no change* in Condom Use among MSM) = 60%
  P(*decrease* in Condom Use among MSM) = 15%
- P(*increase* in Condom Use among FSW) = 25%
  P(*no change* in Condom Use among FSW) = 60%
  P(*decrease* in Condom Use among FSW) = 15%
- P(*increase* in Condom Use among Non-MARPs) = 5%
  P(*no change* in Condom Use among Non-MARPs) = 90%
  P(*decrease* in Condom Use among Non-MARPs) = 5%
- P(*increase* in use of contaminated syringes) = 5%
  P(*no change* in use of contaminated syringes) = 85%
  P(*decrease* in use of contaminated syringes) = 10%
  * Testing is not reaching large numbers of IDUs. There is very little prevention, so having a decrease in primary prevention programs will have no real effect.

- Given a *decrease* in Testing Program Funding and an *increase* in Primary Prevention Program Funding, then:
  - P(*increase* in Testing) = 60%
    P(*no change* in Testing) = 30%
    P(*decrease* in Testing) = 10%
    * Donors are largely influencing prevention and targeting. Donors commission technical support from international experts to inform priorities of prevention. Testing is a current nominal priority but is considered insufficient coverage. In linking to care, treatment is considered part of the 'package' even without testing dollars. Post-2014, the DoH may sustain primary prevention programs to some degree but will still prioritise testing. This could be through community models.
  - P(*increase* in Condom Use among MSM) = 50%
    P(*no change* in Condom Use among MSM) = 40%
    P(*decrease* in Condom Use among MSM) = 10%
    * Prevention programs are targeting MSM (in Manila) thorugh ADB-funded PSI implemented programs to 2014. This may

be sustained, therefore there will be a larger influence on MSMs.

  - P(*increase* in Condom Use among FSW) = 35%
    P(*no change* in Condom Use among FSW) = 55%
    P(*decrease* in Condom Use among FSW) = 10%
  - P(*increase* in Condom Use among Non-MARPs) = 5%
    P(*no change* in Condom Use among Non-MARPs) = 90%
    P(*decrease* in Condom Use among Non-MARPs) = 5%
  - P(*increase* in use of contaminated syringes) = 15%
    P(*no change* in use of contaminated syringes) = 45%
    P(*decrease* in use of contaminated syringes) = 40%
    * Evidence of this situation is currently being implemented in Cebu.

- Given a *decrease* in Testing Program Funding and a *decrease* in Primary Prevention Program Funding, then:
  - P(*increase* in Testing) = 5%
    P(*no change* in Testing) = 35%
    P(*decrease* in Testing) = 60%
  - P(*increase* in Condom Use among MSM) = 10%
    P(*no change* in Condom Use among MSM) = 70%
    P(*decrease* in Condom Use among MSM) = 20%
  - P(*increase* in Condom Use among FSW) = 20%
    P(*no change*in Condom Use among FSW) = 45%
    P(*decrease* in Condom Use among FSW) = 35%
  - P(*increase* in Condom Use among Non-MARPs) = 2%
    P(*no change* in Condom Use among Non-MARPs) = 92%
    P(*decrease* in Condom Use among Non-MARPs) = 6%
  - P(*increase* in use of contaminated syringes) = 20%
    P(*no change* in use of contaminated syringes) = 70%
    P(*decrease* in use of contaminated syringes) = 10%
    * These probabilities are based on expert opinion.

New Infections

- Given a behaviour change where there is an *increase* in testing and there is *no change* in DVL, then:
  - P(*increase* in New Infections) = 0%
  - P(*no change* in New Infections) = 95%
  - P(*decrease* in New Infections) = 5%
    * The increase in testing does no change other behaviours such as condom use, and the no change in DVL means that transmission is not inhibited. So there is irrelevant influence on new infections apart from very small counselling-induced behaviour change on being abstinent or reducing the number of partners, however this is not very realistic.
- Given a behaviour change where there is an *increase* in testing and there is a *decrease* in DVL, then:
  - P(*increase* in New Infections) = 55%
  - P(*no change* in New Infections) = 35%
  - P(*decrease* in New Infections) = 10%
    * The change is DVL is associated with the treatment coverage attained, which is at a change of 15% - 25% based on the HPTN052 trial results [10], which showed a 96% reduction for undetectable viral load. The increase in testing is not enough prevention to counter the decrease in DVL (or increase in undetectable viral load) due to effective ART. The epidemic in the Philippines is increasing, and while a decrease in DVL may assist in the stabilisation of the epidemic, it is unlikely that it can be stemmed without large primary prevention and treatment programs.
- Given *no change* in testing and there is a *decrease* in DVL, then:
  - P(*increase* in New Infections) = 60%
  - P(*no change* in New Infections) = 25%
  - P(*decrease* in New Infections) = 15%
    * This result is a slight shift from the situation above to worse.

- Given a behaviour change where there is an *decrease* in testing and there is *no change* in DVL, then:
  - P(*increase* in New Infections) = 10%
  - P(*no change* in New Infections) = 90%
  - P(*decrease* in New Infections) = 0%
    * Considering where the epidemic is going naturally, there will be small increase in new infections. Counselling around testing may lead to very small behavioural changes such as abstinence and reduced number of partners.
- Given a behaviour change where there is an *decrease* in testing and there is a*decrease* in DVL, then:
  - P(*increase* in New Infections) = 65%
  - P(*no change* in New Infections) = 25%
  - P(*decrease* in New Infections) = 10%
    * Relative to testing, there will be small shift to an increase in the number of new infections.
- Given an *increase* in condom use among MSM and there is *no change* in DVL, then:
  - P(*increase* in New Infections) = 5%
  - P(*no change* in New Infections) = 35%
  - P(*decrease* in New Infections) = 60%
    * The level of condom use is aimed to be sufficiency (at least in Manila) to reduce incidence during the ADB/WB implementation of 2014.
- Given an *increase* in condom use among MSM and there is a *decrease* in DVL, then:
  - P(*increase* in New Infections) = 5%
  - P(*no change* in New Infections) = 25%
  - P(*decrease* in New Infections) = 70%

        * Effective prevention from primary prevention and treatment as prevention.

- Given a *decrease* in condom use among MSM and there is *no change* in DVL, then:
    - P(*increase* in New Infections) = 85%
    - P(*no change* in New Infections) = 10%
    - P(*decrease* in New Infections) = 5%
        * The worsening in behaviour together with the increase in the epidemic means that there will be a very high likelihood of an increase in new infections.

- Given a *decrease* in condom use among MSM and there is a *decrease* in DVL, then:
    - P(*increase* in New Infections) = 75%
    - P(*no change* in New Infections) = 15%
    - P(*decrease* in New Infections) = 10%
        * The decrease in DVL offsets the risk compensation a little.

- Given an *increase* in condom use among FSW and there is *no change* in DVL, then:
    - P(*increase* in New Infections) = 5%
    - P(*no change* in New Infections) = 60%
    - P(*decrease* in New Infections) = 35%
        * This is due to different expected relative levels of condom use in population groups and given there is an increase in the condom use among FSW.

- Given an *increase* in condom use among FSW and there is a *decrease* in DVL, then:
    - P(*increase* in New Infections) = 5%
    - P(*no change* in New Infections) = 50%
    - P(*decrease* in New Infections) = 45%

    * Different from MSM due to expected change to occur in condom use in this population group. Even though there is an increase in condom use among FSW, it has relatively little influence on the epidemic.

- Given a *decrease* in condom use among FSW and there is *no change* in DVL, then:
  - P(*increase* in New Infections) = 45%
  - P(*no change* in New Infections) = 50%
  - P(*decrease* in New Infections) = 5%
- Given a *decrease* in condom use among FSW and there is a *decrease* in DVL, then:
  - P(*increase* in New Infections) = 35%
  - P(*no change* in New Infections) = 55%
  - P(*decrease* in New Infections) = 10%
    * The decrease in DVL offsets the risk a little.
- Given an *increase* in condom use among Non-MARPs and there is *no change* in DVL, then:
  - P(*increase* in New Infections) = 0%
  - P(*no change* in New Infections) = 95%
  - P(*decrease* in New Infections) = 5%
- Given an *increase* in condom use among Non-MARPs and there is a *decrease* in DVL, then:
  - P(*increase* in New Infections) = 8%
  - P(*no change* in New Infections) = 45%
  - P(*decrease* in New Infections) = 47%
    * Condom use will be largely irrelevant. The influence on new infections will be the decrease in DVL.
- Given a *decrease* in condom use among Non-MARPs and there is *no change* in DVL, then:

  - P(*increase* in New Infections) = 5%
  - P(*no change* in New Infections) = 95%
  - P(*decrease* in New Infections) = 0%

- Given a *decrease* in condom use among Non-MARPs and there is a *decrease* in DVL, then:
  - P(*increase* in New Infections) = 8%
  - P(*no change* in New Infections) = 47%
  - P(*decrease* in New Infections) = 45%

- Given a *decrease* in condom use among Non-MARPs and there is a *decrease* in DVL, then:
  - P(*increase* in New Infections) = 8%
  - P(*no change* in New Infections) = 47%
  - P(*decrease* in New Infections) = 45%

- Given *no change* in the condom use of MSM, or FSW, or non-MARPs and there is a *decrease* in DVL, then:
  - P(*increase* in New Infections) = 10%
  - P(*no change* in New Infections) = 45%
  - P(*decrease* in New Infections) = 45%
    * There will be a very minor change in the number of new infections.

- Given an *increase* in the use of contaminated syringes and there is *no change* in DVL, then:
  - P(*increase* in New Infections) = 95%
  - P(*no change* in New Infections) = 5%
  - P(*decrease* in New Infections) = 0%
    * The HIV epidemic has taken off among IDU in the Philippines. This is a primary driver in the epidemic and so a large increase in new infections is highly likely.

- Given an *increase* in the use of contaminated syringes and there is a *decrease* in DVL, then:
  - P(*increase* in New Infections) = 55%
  - P(*no change* in New Infections) = 35%
  - P(*decrease* in New Infections) = 10%
    * Syringe sharing is the primary driver and cannot be curtailed with treatment coverage.
- Given *no change* in the use of contaminated syringes and there is a *decrease* in DVL, then:
  - P(*increase* in New Infections) = 10%
  - P(*no change* in New Infections) = 45%
  - P(*decrease* in New Infections) = 45%
    * The change in DVL makes the difference in the number of new infections.
- Given a *decrease* in the use of contaminated syringes and there is *no change* in DVL, then:
  - P(*increase* in New Infections) = 10%
  - P(*no change* in New Infections) = 30%
  - P(*decrease* in New Infections) = 60%
    * Since syringe sharing is a primary driver of the epidemic, a decrease in the use of contaminated syringes will have a reasonably high change of making an impact.
- Given a *decrease* in the use of contaminated syringes and there is *no change* in DVL, then:
  - P(*increase* in New Infections) = 5%
  - P(*no change* in New Infections) = 30%
  - P(*decrease* in New Infections) = 65%

Validate

The quantified network was tested in order to examine whether predictions were consistent with known behaviour. The software, Hugin Expert A/S, was used to perform data conflict analysis in order to ensure that evidence entered into the model was in line with the model structure. Any inconsistent behaviour discovered required a reassessment of nodes, links and probabilities and were addressed in further iterations of Phase 1R and 2R. Validation tests using Hugin Expert A/S [15] was also performed in this phase.

The network, its structure, and the discretisation were also validated using Pitchforth and Mengersen's [27] validation framework for Bayesian Networks. This framework proposes a broad range of validity tests that can be used to establish confidence in the validity of a Bayesian Network where the model has been entirely expert-elicited. The framework is presented in Table 4.2.2.

Evaluate

Evaluation of a Bayesian Network is through sensitivity analysis [29], evaluation through inference [11], and scenario testing. Sensitivity refers to how sensitive a model's performance is to minor changes in the model. In BNs, the conclusion is drawn based on the posterior probabilities of queries. Sensitivity analysis investigates the changes in probability parameters on the posterior probabilities corresponding to the queries made on the network [45]. Two kinds of sensitivity analyses was undertaken: parameter sensitivity and evidence sensitivity. Parameter sensitivity analysis identifies the model parameters for which the CPT values produce the greatest changes in the network, while evidence sensitivity, analyses the sensitivity of the target nodes to evidence entered into the network.

Inference evaluation of the network was done in three modes: predictive, prescriptive, and diagnostic [11]. Predictive inference looks at the effect on the target nodes if the states of particular factors are specified; prescriptive inference investigates the best level of a factor if states of other factors are specified; and diagnostic inference looks at the circumstances that correspond to the best or worst scenarios for the target nodes.

	Nomological Validity
NV1	Does the BN model fit within an appropriate context in the literature?
NV2	Which theme and ideas are nomologically adjacent to the BN model, and which are nomologically different?
	Face Validity
FV1	Does the model structure look the same as as the experts and/or literature predict?
FV2	Is each node of the network discretised into sets that reflect expert knowledge?
FV3	Are the parameters of each node similar to what the expert would expect?
	Content Validity
C_1V1	Does the model structure contain all and only the factors and relationships relevant to the model output?
C_1V2	Does each node of the network contain all and only the relevant states the node can possibly adopt?
C_1V3	Are the discrete states of the nodes dimensionally consistent?
C_1V4	Do the parameters of the input nodes and CPT reflect all the know possibilities from expert knowledge and domain literature?
	Concurrent Validity
C_2V1	Does the model structure or sub-networks act identically to a network or sub-network modelling a theoretically related construct
C_2V2	In identical sub-networks, are the included factors discretised in the same way as the comparison model?
C_2V3	Do the parameters of the input nodes and CPTs in networks of interest match the parameters of the sub-network in the comparison model?
	Convergent Validity
C_3V1	How similar is the model structure to other models that are nomologically proximal?
C_3V2	How similar is the discretisation of each node to the discretisation of nodes that are nomologically proximal independent of their network domain?
C_3V3	Are the parameters of nodes that have analogues in comparison models assigned similar conditional probabilities?
	Discriminant Validity
DV1	How different is the model structure to other models that are nomologically distal?
DV2	How different is the discretisation of each node to the discretisation of nodes that are nomologically distal independent of their network domain?
DV3	Are the parameters of nodes in the comparison models that have oppositional definitions to the nodes in question parameterised differently?
DV4	When presented with a range of plausible models, can experts choose the 'correct' model or set of models?
	Predictive Validity
PV1	Is the model behaviour predictive of the behaviour of the system being modelled?
PV2	Once simulations have been run, are the output states of the individual nodes predictive of aspects in the comparison models?
PV3	Is the model sensitive to any particular findings or parameters to which the system would also be sensitive?
PV4	Are there qualitative features of the model behaviour that can be observed in the system being modelled?
PV5	Does the model including its component relationships predict extreme model behaviour under extreme conditions?

Table 4.2.2 Risk factor and Management validation framework [27]

Sensitivity Analysis: Parameter Sensitivity

Parameter sensitivity analysis measures the variation in the target node while one of the parameters in the network is varied, and the other parameters fixed [5]. This analysis requires a sensitivity function for the output probability $f(x)$ in terms of the parameter, x, being varied. The function expresses the sensitive change in posterior probability of the target query due to the variation of a Bayesian network s probability parameters [45]. If B is a Bayesian network, x be the probability parameter, y be a query, and e be evidence entered into B. This function is given by

$$f(x) = \frac{\alpha x + \beta}{\gamma x + \delta}.$$

The sensitivity of the parameter x and the target probability is the first derivative of the sensitivity function [22, 42]:

$$f'(x) = \frac{\alpha\delta - \beta\gamma}{(\gamma x + \delta)^2}.$$

This finds the sensitivity value of query x at x given e. To determine the value of α, β, γ, and δ, there are only three message propagations necessary for each given evidence. If, for example, the inference for x's values were set as 0, 0.5, 1, and by letting $\delta = 1$, the values of the coefficients are determined by

$$\begin{aligned} \beta &= p^0 \\ \gamma &= \frac{\beta - p^{0.5}}{p^{0.1} - p^1} - 1 \\ \alpha &= p^1(\gamma + 1) - \beta, \end{aligned}$$

where p^0, $p^{0.5}$, and p^1 denote the corresponding probabilities of $p(y|e)$ respectively [42, 45].

The results of as sensitivity analysis are unit-less and range between zero and one. The higher the result is for a node, the more sensitive the target node (or node being investigated) is to changes in that node. Hugin Expert A/S [15] was used to run this analysis on the target nodes.

Sensitivity Analysis: Evidence Sensitivity

Evidence sensitivity is the analysis of how sensitive the results of a belief update is to variations in the set of evidence. It measures the degree of variation in a BN's posterior distribution that results from changes in the evidence entered in the network [18]. Entropy, $H(X)$, is one of the ways in which evidence sensitivity is measured. Entropy measures the randomness of a variable and the higher the value the more random the variable. So entropy essentially calculates the randomness of a variable [20, 26] and is given by:

$$H(X) = \sum P(x) \log P(x),$$

where $P(x)$ is the probability distribution of X.

Another measure of evidence sensitivity, is mutual information. This measure gives an indication of the extent to which the joint probability of two variables differs from what it would have been if they were independent [20]. A value of zero for mutual information between two factors means that they are independent [19, 26]. So entropy, $I(X, Y)$, gives an indication of the effect of one random variable, X, on another random variable, Y is calculated as

$$I(X, Y) = H(X) - H(X/Y).$$

Inference Evaluation: Predictive Inference

The results of the parameter sensitivity analysis and the mutual information scores provide a starting point for predictive inference. Combining the results from these previous tests, predictive inference was used to test the impact of the other nodes in the network on the target nodes.

Inference Evaluation: Prescriptive Inference

Prescriptive inference and scenario testing are quite similar evaluation techniques in that states of factors are specified and the resulting impact on nodes of interest are evaluated.

Inference Evaluation: Diagnostic Inference

Diagnostic inference looks at the circumstances that account for the best and worst scenarios for the target nodes. Applying this inference technique to the target nodes in the network can give insight into what changes in the other nodes can account for best and worst case scenarios.

4.3 Results

4.3.1 Network Structure

The final network structure is shown in Figure 4.3.1, with the results of the posterior probabilities for the complied network displayed in Figure 4.3.2. Each node in the network has a corresponding probability table, which was quantified using expert knowledge. The final CPTs can be found in the Appendix (4.4).

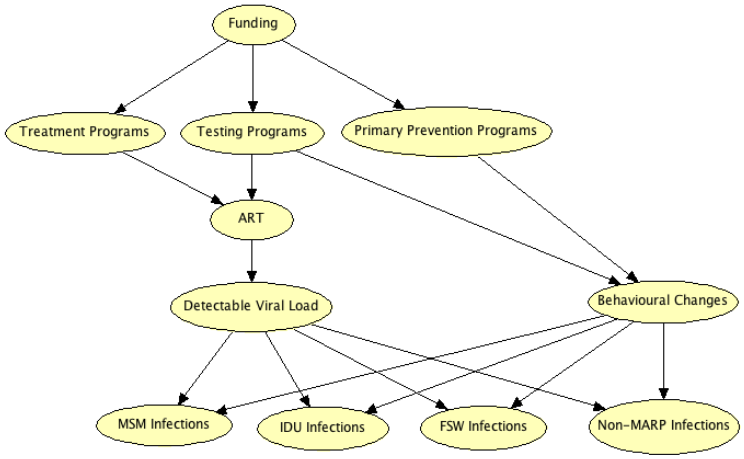

Figure 4.3.1: The final HIV/AIDS Bayesian Network (HIV-BN) model.

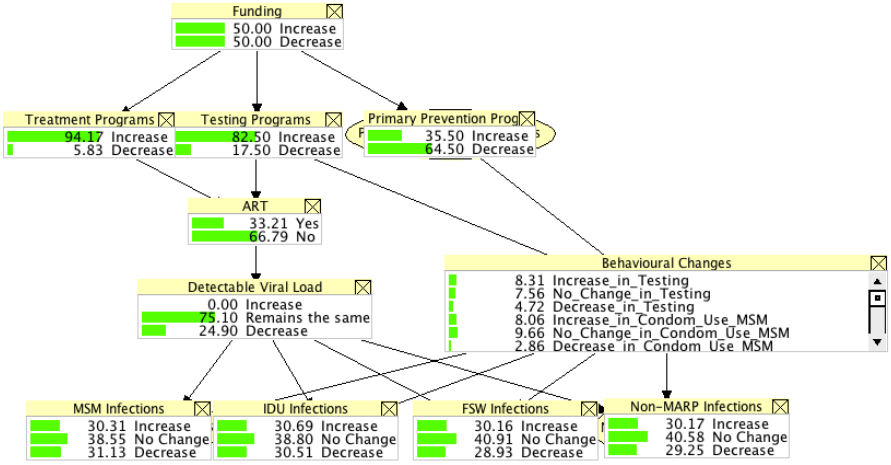

Figure 4.3.2: The posterior probabilities of the compiled HIV-BN.

4.3.2 Validation

The validity of a Bayesian Network relies on the confidence in the network's structure, discretisation, parameterisation/quantification and model behaviour [27]. The *Core Process*, the iterative nature of Phase 1R and 2R of the IBNDC [18], and feedback from experts at Kirby provided the validation mechanisms required for the final model. The final model was placed through the validation framework by Pitchforth and Mengersen [27] to provide more rigourous validation. The model's performance against the relevant forms of validity presented by the framework can be seen in Table 4.3.1. The model failed to satisfy the Concurrent and Convergent validity tests, however this is because there have been no other BN models in this field previously. It performed well under all the other validity tests provided by this framework.

To further validate the model structure and quantification, the known relationship of an increase in funding leading to a decrease in incidence was tested. The network validated this result: changing the *Funding* state to '100% increase' caused a decrease in the infections across all four populations of interest (see Figure 4.3.3).

The iterative nature of the IBNDC is able to provide a good level of validation for a BN's structure, discretisation and quantification. The model developed undertook several iterations of the IBNDC in order to construct the correct structure for the model, to have the correct discretisation chosen and to have a final quantified model. An application of Pitchforth and Mengersen's validation framework [27] and the model's performance against that framework shows that the model presented here has been adequately validated.

4.3.3 Evaluation

Sensitivity Analysis: Parameter Sensitivity

The results of a sensitivity analysis test are unitless and lie between zero and one. The higher the result is for a node, the more sensitive the node being investigated is to changes in that node. A parameter sensitivity analysis test was undertaken on the four target nodes of *MSM Infections*, *FSW Infections*, *IDU Infections*, and *Non-MARP Infections*. Both *MSM Infections* and *IDU*

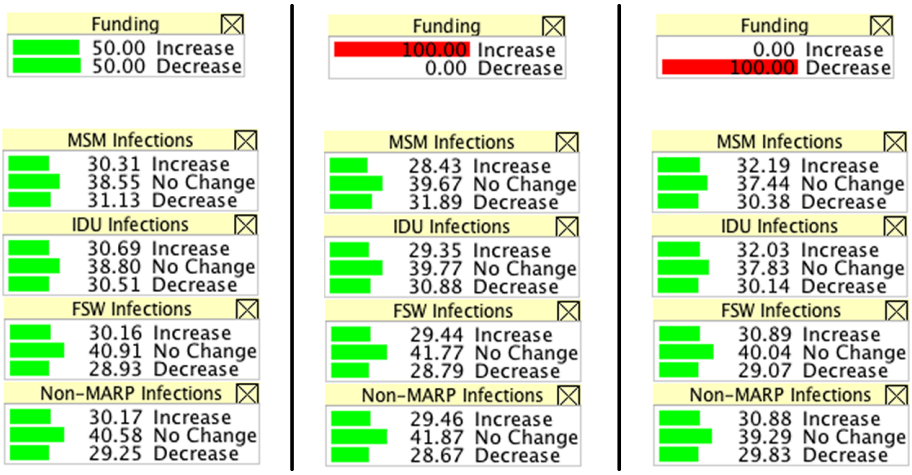

Figure 4.3.3: Predictive validation: relationship between funding and infections in the four populations of interest.

infections are most sensitive to changes in *Funding*, followed by *Behavioural Changes*, while *FSW Infections* and *Non-MARP Infections* most sensitive to changes in *Behavioural Changes* (see Table 4.3.2).

Sensitivity analysis for *Behavioural Changes* was also performed since the target nodes are sensitive to changes in this node. The analysis found that *Funding* (0.09), *Primary Prevention Programs* (0.06), and *Testing Programs* (0.02) were the nodes to which *Behavioural Changes* was sensitive.

Sensitivity Analysis: Evidence Sensitivity

Entropy is one of the ways in which evidence sensitivity is measured. The higher the value of entropy for a variable, the more random the variable is. The entropy results for the HIV-BN found that *Behavioural Changes* is the variable that is most random, with *Treatment Programs* being the least random (see Table 4.3.3).

Another measure of evidence sensitivity, Mutual Information(MI), gives an indication of the effect of one random variable on another. MI results lie between zero and one, with a result of zero meaning independence between the two variables, and a result of one showing dependence between the two variables. An MI test for all the nodes was performed to see the strength of

	Nomological Validity
NV1	The model, which looks at the impact of funding changes on HIV incidence, sits within and is complementary to the suite of models that exist such as the Epi Model [9], EPP [4, 13, 46], Spectrum [2, 12], Goals [1, 33, 39], the Modes of Transmission Model [35, 37], the UNAIDS workbook [36, 38, 44], and the Asian Epidemic Model [8, 31, 40].
	Face Validity
FV1	The model structure itself was validated with experts via the Recursive Process of the IBNDC. The model was changed to reflect the relationships that existed within the modelling question posed.
FV2	The nodes in the network were discretised to either reflect the research question and the situations that were of interest in the context of HIV in the Philippines, or to minimise the resulting CPTs. For example, there are a myriad of behavioural changes that a person can make, however in the context of HIV in the Philippines, testing, condom use, and use of contaminated syringes were of interest so these were the discretisations chosen for the node *Behavioural Changes*.
FV3	Where data were available, it was used to quantify the nodes in the model, and the quantification of the other nodes came from the experts at Kirby.
	Content Validity
C_1V1	The purpose of the model was to investigate the impact of funding changes on the HIV incidence for sub-groups of interest. The factors that were chosen and model was structured in such a way as to answer this.
C_1V2	The nodes were well defined and reflected the research question and so the states were chosen in such a way as so as they contributed the most to the research question.
C_1V4	Where data were available, they were used to quantify the nodes.
	Concurrent Validity
	This test refers to the possibility that a network or section of a network can behave identically to a section of another network. In the case of the model developed in this research, there have been no previous networks developed, and as such this validity test cannot be applied to this model.
	Convergent Validity
	This test investigates the model's validity compared to other networks in the same context. A Bayesian Network has not previously been constructed in this context and as such it was not possible to make a comparison for structure, discretisation, or parameterisation. It should be noted however that the factors considered in the BN are similar to the factors and variables used in the models discussed in Chapter 1.
	Discriminant Validity
	This test examines the degree to which a model's structure, discretisation, and parameterisation is different to models that describe a different system. Using an example from ecology, Johnson's cheetah relocation BN [18] identifies the factors that are critical to ensure the successful relocation of cheetahs in South Africa. A comparison of these two models finds that they are quite dissimilar to each other in 'structure, discretisation and parameterisation.
	Predictive Validity
	The validity assessed by this test encompasses both model behaviour and model output. Sensitivity analysis and model evaluation through inference was undertaken. The details and results of this can be seen in the next section, Phase 4R: Evaluation.

Table 4.3.1: Evidence sensitivity analysis for the posterior network, showing the calculated entropy.

Parameter Sensitivity Analysis: *MSM Infections*	
Node	**Sensitivity Value**
Funding	0.04
Behavioural Changes	0.02
Primary Prevention Programs	0.02
Treatment Programs	0.02
ART	0.00735
Testing Programs	0.00624

Parameter Sensitivity Analysis: *FSW Infections*	
Node	**Sensitivity Value**
Behavioural Changes	0.02
Treatment Programs	0.02
Funding	0.01
ART	0.01
Primary Prevention Programs	0.00978
Detectable Viral Load	0.00633
Testing Programs	0.00158

Parameter Sensitivity Analysis: *IDU Infections*	
Node	**Sensitivity Value**
Funding	0.03
Behavioural Changes	0.02
Primary Prevention Programs	0.02
Treatment Programs	0.01
ART	0.00936
Testing Programs	0.0799
Detectable Viral Load	0.0553

Parameter Sensitivity Analysis: *Non-MARP Infections*	
Node	**Sensitivity Value**
Behavioural Changes	0.02
Treatment Programs	0.01
Funding	0.01
ART	0.01
Primary Prevention Programs	0.00974
Detectable Viral Load	0.00634
Testing Programs	0.0018

Table 4.3.2: Results for the sensitivity analysis performed on the four target nodes of *MSM Infections*, *FSW Infections*, *IDU Infections*, and *Non-MARP Infections*.

Node	Entropy
Behavioural Changes	2.48
MSM Infections	1.09
FSW Infections	1.09
IDU Infections	1.09
Non-MARP Infections	1.09
Funding	0.69
Primary Prevention Programs	0.65
ART	0.64
Detectable Viral Load	0.56
Testing Programs	0.46
Treatment Programs	0.22

Table 4.3.3: Evidence sensitivity analysis for the posterior network, showing the calculated entropy.

dependence between the variables (see Table 4.3.4). It can be seen that the four target nodes are more dependent on *Behavioural Changes* than other nodes. Relative to the other nodes, there is a higher dependence relationship between *Behavioural Changes* and *Primary Prevention Programs* and *MSM Infections*. *Primary Prevention Programs* has a high dependence on *Funding*, which is consistent with the opinions of experts from Kirby who stated that these programs will be funded if funds are available since these kinds of programs have a lower priority than Treatment or Testing Programs. The independence result and low dependence result between *Funding* and *Treatment Programs* and *Testing Programs* respectively also show this.

Inference Evaluation: Predictive Inference

Predictive inference was been performed on the impact of changes in *Funding* on the target nodes as part of the validation process. Further predictive inferencing was undertaken by investigating the impact of changes in certain states of *Behavioural Changes* on the probability of an increase in MSM and IDU infections since these are two populations are of interest in the Philippines (Table 4.3.5). The largest change in the probability of an increase in MSM infections resulted from an decrease in condom (+52.21%), followed by an increase in condom use (-25.31%). These results show that condom

Node	ART	Behavioural Changes	Detectable Viral Load	FSW Infections
ART	-	0.0000182	**0.37**	0.00157
Behavioural Changes	0.0000182	-	0.0000122	**0.07**
Detectable Viral Load	**0.37**	0.0000122	-	0.00235
FSW Infections	0.00157	0.07	0.00235	-
Funding	0	0.05	0	0.000182
IDU Infections	0.00123	0.08	0.00186	0.00864
MSM Infections	0.00205	**0.09**	0.00308	0.00876
Non-MARP Infections	0.00181	0.06	0.00272	0.00782
Primary Prevention Programs	0	**0.09**	0	0.000383
Testing Programs	0.000577	0.03	0.000387	0.0000824
Treatment Programs	0.06	0.0000643	0.03	0.000199

Node	Funding	IDU Infections	MSM Infections	Non-MARP Infections
ART	0	0.00123	0.00205	0.00181
Behavioural Changes	0.05	**0.08**	**0.09**	**0.06**
Detectable Viral Load	0	0.00186	0.00308	0.00272
FSW Infections	0.000182	0.00864	0.00876	0.00782
Funding	-	0.000435	0.00835	0.000345
IDU Infections	0.000435	-	0.00951	0.00786
MSM Infections	0.000835	0.00951	-	0.00887
Non-MARP Infections	0.000345	0.00876	0.00887	-
Primary Prevention Programs	**0.32**	0.000746	0.00152	0.000709
Testing Programs	0.06	0.000242	0.000285	0.0000123
Treatment Programs	0.000634	0.000158	0.000261	0.0000226

Node	Primary Prevention Programs	Testing Programs	Treatment Programs
ART	0	0.000577	**0.37**
Behavioural Changes	0.09	0.03	0.0000122
Detectable Viral Load	0	0.000387	-
FSW Infections	0.000383	0.0000824	0.00235
Funding	**0.32**	**0.06**	0
IDU Infections	0.000746	0.000242	0.00186
MSM Infections	0.00152	0.000285	0.00308
Non-MARP Infections	0.000709	0.0000123	0.00272
Primary Prevention Programs	-	0.03	0
Testing Programs	0.03	-	0.000387
Treatment Programs	0.000336	0.0000668	0.03

Table 4.3.4: Mutual Information results for each node.

use has a greater impact on the probability of an increase in MSM infections than an increase in testing. The greatest change in the probability of an increase in IDU infections comes from an increase in contaminated syringe use (+54.6%), followed by a decrease in contaminated syringe use (-21.94%).

State of *Behaviour Change*	**Change in the probability of an Increase in** *MSM Infections*	**Change in the probability of an increase in** *IDU Infections*
Increase in testing	-16.49%	-16.87%
No change in testing	+ 9.7%	+ 9.32%
Decrease in testing	-7%	-7.38%
Increase in Condom Use (MSM)	-25.31%	+ 2.64%
No change in Condom Use (MSM)	-2.67%	+ 2.64%
Decrease in Condom Use (MSM)	+ 52.21%	+ 2.64%
Increase in Contaminated Syringe Use	+ 3.02%	+ 54.6%
No change in Contaminated Syringe Use	+ 3.02%	-3.19%
Decrease in Contaminated Syringe Use	+ 3.02%	-21.94%

Table 4.3.5: Predictive testing: what impact do changes in behaviour have on the probability of an increase in MSM and IDU infections.

Inference Evaluation: Prescriptive Inference

Prescriptive inference and scenario testing was performed to see the impact of the various levels of *Funding*, *Treatment Programs*, *Testing Programs*, and *Primary Prevention Programs* on the two target populations of interest, *MSM Infections* and *IDU Infections* (Table 4.3.6). The circumstances that result in the largest increase in the probability of an increase in *MSM Infections* and *IDU Infections* is a decrease in *Funding*, *Treatment Programs*, and *Testing Programs*, and no change in *Primary Prevention Programs*. A scenario where there are decreases in *Treatment Programs*, *Testing Programs*, and *Primary Prevention Programs* and no change in *Funding* has the same result, is not a logical situation and is discarded. Conversely, the largest decrease in the probability of an increase in *MSM Infections* and *IDU Infections* is a increase in *Funding*, *Treatment Programs*, and *Testing Programs*, and no change in *Primary Prevention Programs*.

Funding	Treatment Programs	Testing Programs	Primary Prevention Programs	Changes in the probability of an increase in MSM Infections	Changes in the probability of an increase in IDU Infections
↑	↔	↔	↔	-1.88%	-1.34%
↑	↑	↔	↔	-2.09%	-1.5%
↑	↑	↑	↔	-2.16%	-1.58%
↑	↑	↑	↑	-3.63%	-2.51%
↑	↑	↔	↑	-3.38%	-2.32%
↑	↔	↑	↑	-3.47%	-2.41%
↔	↑	↑	↑	-3.72%	-2.6%
↔	↔	↑	↑	-3.47%	-2.41%
↔	↔	↔	↑	-3.38%	-2.32%
↓	↔	↔	↔	1.88%	1.34%
↓	↓	↔	↔	4.44%	3.23%
↓	↓	↓	↔	5.33%	4.5%
↓	↓	↓	↓	4.47%	3.25%
↓	↓	↔	↓	1.92%	1.37%
↓	↔	↓	↓	2.59%	2.42%
↔	↓	↓	↓	5.36%	4.52%
↔	↔	↓	↓	2.59%	2.42%
↔	↔	↔	↓	1.86%	1.28%

Table 4.3.6: Prescriptive inference and scenario testing looking at the impact changes in funding and programs on the probability of an increase in the two target populations of interest, $MSM\ Infections$ and $IDU\ Infections$. Here, an ↑ indicates an increase, ↓ indicates a decrease, and ↔ indicates no change in the state of the node.

	Impact on other nodes of interest
100% increase	-4.52% change in the probability of an increase in testing
in *MSM Infections*	-6.73% change in the probability of an increase in condom use by MSM
	-3.09% change in the probability of an increase in funding
100% decrease	-6.64 % change in the probability of an increase in testing
in *MSM Infections*	8.12% change in the probability of an increase in condom use by MSM
	1.22% change in the probability of an increase in funding
100% increase	-4.75% change in the probability of an increase in testing
in *IDU Infections*	3.38% change in the probability of an increase in contaminated syringe use
	2.18% change in the probability of an increase in funding
100% decrease	-6.61% change in the probability of an increase in testing
in *IDU Infections*	-1.75% change in the probability of an increase in contaminated syringe use
	0.61% change in the probability of an increase in funding

Table 4.3.7: Diagnostic inference investigating the best and worst case scenario for *MSM Infections* and *IDU Infections*.

Inference Evaluation: Diagnostic Inference

Diagnostic inference finds the circumstances that contribute to the best and worst scenarios of the target nodes (Table 4.3.7). In both cases the impact of condom use among MSM contribute more to the best and worst case scenarios of *MSM Infections*. For *IDU Infections*, the best case scenario (100% decrease in infections), is a combination of a decrease in the use of contaminated syringes and a small increase in funding. For the worst case scenario (100% increase in infections) is a result of a decrease in testing, a small increase in funding, and an increase in the probability of contaminated syringe use. This last factor overrides the increase in funding.

4.4 Discussion

This study developed a Bayesian Network model to investigate the impacts of funding changes on infections on four populations of interest, *MSM, IDU, FSW, Non-MARPs*, in the Philippines. The model found that changes in funding had the most impact on the infection in these populations through primary prevention programs and behavioural changes. By using this methodology in this context, the probabilistic relationships between the variables

could be investigated. The network synthesised in this study is aimed to be a complementary technique to the existing HIV/AIDS models. In its current form, the network should not be used as a stand-alone model but instead should be used as a management and decision support tool alongside existing models.

The HIV-BN was formulated using the IBNDC [18] since this is currently the best way in which to build an expert elicited BN due to the iterative nature of BN modelling. While validation of the structure, discretisation and quantification of the network is an inherent part of the IBNDC, the network that was developed was also further validated using Pitchforth and Mengersen's validation framework [27]. The network fulfilled five of the seven tests of this validation framework. The two tests that tested concurrent and convergent validity were only not applicable due to the fact that this network is the first of its kind to model HIV incidence. Further validation of the model has been shown using predictive inference which showed that an increase in funding resulted in a decrease in infections across the four populations of interest.

The results from the parameter and evidence sensitivity tests show that behavioural changes have the contribute the most to changes in infection across the four populations of interest. In particular, condom use by MSM and contaminated syringe use have the greatest impact on infections in MSM and IDUs respectively.

A strength of BN modelling is its ability to highlight relationships between factors and target nodes that may have not been viewed as important. One such relationship that emerged is the importance of *Behavioural Changes* on *New Infections* and in particular *Incidence*. Predictive inference showed that a decrease in condom use and safe syringe use increases the probability of an increase in *Incidence* by 26.88% and 26.04% respectively.

The research question for this model was 'What impact do changes in funding have on HIV incidence in the *MSM, IDU, FSW* and *Non-MARP* population groups Philippines?'. The resulting model has shown that effects on incidence has a certain pathway - that is, by changing funding levels on primary prevention programs, behaviour changes are impacted, and hence incidence. The implications of these findings could be that, for the Philippines, and investment in primary prevention programs and programs that focus on behavioural changes in the *MSM, IDU, FSW* and *Non-MARP* pop-

ulations may provide more impact on the reduction of incidence of HIV for the country than investing funding in testing and treatment programs. The plausibility of such a finding would not seem completely out of the question; as more knowledge and awareness of HIV is made at the education level, the more people would be aware on how to prevent disease transmission. However, it needs to be acknowledged that there has recently been strong clinical evidence of the preventative effect of treatment (the HPTN052 trial showed 96% efficacy among heterosexual discordant couples) [10]. It remains to be assessed how this efficacy in ideal conditions will translate to real-world effectiveness, considering lack of adherence and other factors, and biological differences in infectiousness for people who inject drugs and MSM. When effectiveness studies measure such levels, and they can be translated to appropriate assumptions for the Philippines, the model can be re-run to determine whether the same findings hold or the evidence suggests greater emphasis should be placed on testing and treatment.

The results for this research has obvious implications for the decision makers in the Philippines, and how HIV funding in the country is allocated. While there is, of course, the necessary funding the needs to go towards treatment and testing, this research shows that extra funding towards primary prevention programs has a greater impact on HIV incidence. The funding allocation decisions then need to be made in terms of how much extra funding should be contributed towards this activity? Should the current levels of funding for treatment and testing programs stay the same and any extra funding be directed towards primary prevention programs? If any extra funding is obtained, how would this be allocated between the three programs: treatment, testing, and primary prevention.

The model proposed in this thesis has shown the impact of funding primary prevention programs on HIV incidence. The funding-incidence pathway and the results from this research is important in making the case for funding not only treatment and testing programs, but also the importance of funding activities like primary prevention programs. It could be used to persuade decision makers to invest more in these programs in order to make a greater impact on HIV incidence in the Philippines in the coming years.

The importance of primary prevention programs has been recognised in Australia. In the country's Seventh National HIV Strategy for 2014 - 2017 [3], an importance is placed on education and prevention programs, with

prevention being the number one area priority of area for action. An example of how such programs have been successful include the prevention of HIV among sex workers in Australia due to effective implementation of safer sex practices by sex workers, supported by effective peer education, and a culture of high levels of condom use [3]. Additionally, investment in primary prevention programs such as Needle Syringe Programs (NSPs) have been shown to have a large impact on HIV infections. From 2000 - 2009, Australia invested $243m in NSPs, which yielded a saving in healthcare costs of $1.28 billion and resulted in an estimated 32,050 HIV infections being averted [23]. While these results are from Australia, it provides evidence that validates the findings of this research.

A strength of this model is that it provides knowledge of the probability that a particular change in policy (or funding) will have on outcomes, which is useful in informing policy when used with current HIV modelling techniques. The HIV-BN that was developed has been able to answer the research question. The model in its current form is complementary to the current suite of HIV models being used and is designed to be used as a management and decision support tool.

The model can be further extended to include more factors, however this increases the complexity substantially. A way in which to handle this would be to turn the BN into an Object-Oriented Bayesian Network. OOBNs are BNs which have interface (input and output nodes) and instance nodes (nodes that represent another network or network fragment). The extension of BNs in to the Object Oriented paradigm allows information flow into and out of the BN from, or to, other OOBNs [17]. In doing this, more complex and dynamic models can be constructed where traditional BNs are often found inadequate or limited [41]. By extending the current model into an OOBN, a more detailed, but easier to handle model whose sub-networks can be validated and quantified by personnel in the Philippines can be formulated.

The development of a dashboard-style GUI for the results of the BN (and any subsequent OOBN that may be developed) would allow end-users to undertake their own scenario-testing without an in-depth understanding of the BN modelling methodology, and without the inevitable clutter of nodes that will occur with the development of a more detailed BN or OOBN.

The model presented in this chapter represents a new way in which to

investigate factors that impact on HIV incidence and prevalence. While the results of this model are qualitative in nature, more quantitative results can be obtained with the development of an OOBN.

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A1: Conditional Probability Tables for the HIV-BN

The conditional probability tables for the network are displayed in the following pages. The conditional probability table entries were populated from discussions with staff at Kirby. These discussions included getting staff to fill in conditional probability tables, as well as scenario based questions.

Treatment Programs

Funding	Increas	Decrea:
Increase	0.95	0.93333
Decrease	0.05	0.06666

ART

Testing Prc	Increase		Decrease	
Treatment	Increas	Decrea:	Increas	Decrea:
Yes	0.3	0.99	0.25	0.99
No	0.7	0.01	0.75	0.01

Behavioural Changes

Testing Prc	Increase		Decrease	
Primary Pr	Increas	Decrea:	Increas	Decrea:
Increase Ir	0.16304	0.05	0.12	0.01
No Change	0.04347	0.1	0.06	0.07
Decrease I	0.01087	0.05	0.02	0.12
Increase Ir	0.15217	0.05	0.1	0.02
No Change	0.04347	0.12	0.08	0.14
Decrease I	0.02173	0.03	0.02	0.04
Increase Ir	0.02173	0.05	0.07	0.04
No Change	0.17391	0.12	0.11	0.09
Decrease I	0.02173	0.03	0.02	0.07
Increase Ir	0.01087	0.01	0.01	0.004
No Change	0.09782	0.18	0.18	0.184
Decrease I	0.02173	0.01	0.01	0.012
Increase Ir	0.02173	0.01	0.03	0.04
No Change	0.08695	0.17	0.09	0.14
Decrease I	0.10869	0.02	0.08	0.02

Detectable Viral Load

ART	Yes	No
Increase	0	0
Remains th	0.25	1
Decrease	0.75	0

MSM Infections

Behavioural	Increase in Testing			No Change in Testing			Decrease in Testing			Increase in Condom Use MSI			No Change in Condom Use I			Decrea:
Detectable	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas
Increase	0.33333	0	0.55	0.33333	0.33333	0.6	0.33333	0.1	0.65	0.33333	0.05	0.05	0.33333	0.33333	0.1	0.33333
No Change	0.33333	0.95	0.35	0.33333	0.33333	0.25	0.33333	0.9	0.25	0.33333	0.35	0.25	0.33333	0.33333	0.45	0.33333
Decrease	0.33333	0.05	0.1	0.33333	0.33333	0.15	0.33333	0	0.1	0.33333	0.6	0.7	0.33333	0.33333	0.45	0.33333

Behavioural	Decrease in Condi		Increase in Condom Use FSV			No Change in Condom Use F			Decrease in Condom Use FS			Increase in Condom Use Nor			No Change in Con	
Detectable	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain
Increase	0.85	0.75	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333
No Change	0.1	0.15	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333
Decrease	0.05	0.1	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333

Behavioural	No Cha	Decrease in Condom Use Nc			Increase in Use of Contamir			No Change in Use of Contan			Decrease in Use of Contami		
Detectable	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:
Increase	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333
No Change	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333
Decrease	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333

Funding

Increase	0.5
Decrease	0.5

Primary Prevention Programs

Funding	Increas	Decrea:
Increase	0.7	0.01
Decrease	0.3	0.99

Testing Programs

Funding	Increas	Decrea:
Increase	0.95	0.7
Decrease	0.05	0.3

Non-MARP Infections

Behavioural	Increase in Testing			No Change in Testing			Decrease in Testing			Increase in Condom Use MSI			No Change in Condom Use I			Decrea:
Detectable	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas
Increase	0.33333	0	0.55	0.33333	0.33333	0.6	0.33333	0.1	0.65	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333
No Change	0.33333	0.95	0.35	0.33333	0.33333	0.25	0.33333	0.9	0.25	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333
Decrease	0.33333	0.05	0.1	0.33333	0.33333	0.15	0.33333	0	0.1	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333

Behavioural	Decrease in Condi		Increase in Condom Use FSV			No Change in Condom Use F			Decrease in Condom Use FS			Increase in Condom Use Nor			No Change in Con	
Detectable	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain
Increase	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0	0.08	0.33333	0.33333
No Change	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.95	0.45	0.33333	0.33333
Decrease	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.05	0.47	0.33333	0.33333

Behavioural	No Cha	Decrease in Condom Use Nc			Increase in Use of Contamir			No Change in Use of Contan			Decrease in Use of Contami		
Detectable	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:
Increase	0.1	0.33333	0.05	0.08	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333
No Change	0.45	0.33333	0.95	0.45	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333
Decrease	0.45	0.33333	0	0.47	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333

FSW Infections

Behavioural	Increase in Testing			No Change in Testing			Decrease in Testing			Increase in Condom Use MSI			No Change in Condom Use I			Decrea:
Detectable	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas
Increase	0.33333	0	0.55	0.33333	0.33333	0.6	0.33333	0.1	0.65	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333
No Change	0.33333	0.95	0.35	0.33333	0.33333	0.25	0.33333	0.9	0.25	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333
Decrease	0.33333	0.05	0.1	0.33333	0.33333	0.15	0.33333	0	0.1	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333

Behavioural	Decrease in Condi		Increase in Condom Use FSV			No Change in Condom Use F			Decrease in Condom Use FS			Increase in Condom Use Nor			No Change in Con	
Detectable	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain
Increase	0.33333	0.33333	0.33333	0.05	0.05	0.33333	0.33333	0.1	0.33333	0.45	0.35	0.33333	0.33333	0.33333	0.33333	0.33333
No Change	0.33333	0.33333	0.33333	0.6	0.5	0.33333	0.33333	0.45	0.33333	0.5	0.55	0.33333	0.33333	0.33333	0.33333	0.33333
Decrease	0.33333	0.33333	0.33333	0.35	0.45	0.33333	0.33333	0.45	0.33333	0.05	0.1	0.33333	0.33333	0.33333	0.33333	0.33333

Behavioural	No Cha	Decrease in Condom Use Nc			Increase in Use of Contamir			No Change in Use of Contan			Decrease in Use of Contami		
Detectable	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:
Increase	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333
No Change	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333
Decrease	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333

IDU Infections

Behavioural	Increase in Testing			No Change in Testing			Decrease in Testing			Increase in Condom Use MSI			No Change in Condom Use I			Decrea:
Detectable	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas
Increase	0.33333	0	0.55	0.33333	0.33333	0.6	0.33333	0.1	0.65	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333
No Change	0.33333	0.95	0.35	0.33333	0.33333	0.25	0.33333	0.9	0.25	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333
Decrease	0.33333	0.05	0.1	0.33333	0.33333	0.15	0.33333	0	0.1	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333

Behavioural	Decrease in Condi		Increase in Condom Use FSV			No Change in Condom Use F			Decrease in Condom Use FS			Increase in Condom Use Nor			No Change in Cor	
Detectable	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain
Increase	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333
No Change	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333
Decrease	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333	0.33333

Behavioural	No Cha	Decrease in Condom Use Nc			Increase in Use of Contamir			No Change in Use of Contan			Decrease in Use of Contami		
Detectable	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:	Increas	Remain	Decrea:
Increase	0.33333	0.33333	0.33333	0.33333	0.33333	0.95	0.55	0.33333	0.33333	0.1	0.33333	0.1	0.05
No Change	0.33333	0.33333	0.33333	0.33333	0.33333	0.05	0.35	0.33333	0.33333	0.45	0.33333	0.3	0.3
Decrease	0.33333	0.33333	0.33333	0.33333	0.33333	0	0.1	0.33333	0.33333	0.45	0.33333	0.6	0.65

5

Conclusion and Further Work

This thesis has examined the HIV epidemic in the Philippines and has identified factors which could account for the previously 'low and slow' development of the epidemic. A review of some commonly used HIV/AIDS models was made in Chapter 1 of the thesis. Each of these models has its advantages and disadvantages. The EPI Model, which is no longer used, is a simple tool that can be used to make insights into likely trends and numbers of AIDS cases in a short time period [8]. However it should not be used for periods longer than four years, and it cannot provide insight about the epidemiological features of a pandemic. The EPP can be used to construct national and sub-national epidemic curves by making full use of all available surveillance data, however data used may not be representative of sub-populations [24]. Spectrum is a user-friendly program that can provide a range of outputs such as the number of people who need ART however it is somewhat of a 'black-box' which does not allow users to see the underlying governing equations or change them easily [2, 10]. The Goals Model is part of Spectrum and can provides a tool to link program goals and funding, but it requires a lot of data, it does not incorporate macroeconomic conditions in its calculations, and it does not calculate an 'optimum' allocation pattern

[1, 17]. The UNAIDS Modes of Transmission Model can model the incidence distribution in key populations and can calculate the number of new infections per year, however due to the crude grouping of populations, the results obtained are heavily reliant on the quality of the data used [19, 21]. The UNAIDS Workbook estimates adult HIV prevalence from surveillance data, however the quality of the data used when making estimates is a weakness in this method [20, 22]. The Asian Epidemic Model is a semi-empirical process model that replicates the transmission dynamics of HIV in Asian settings, however it requires a lot of data, which most countries are unable to supply [6, 15].

Chapter 3 of the thesis investigated the reasons why the Philippines has not faced a large HIV epidemic until recently. These reasons include the geography of the Philippines, the low number of IDUs, and a culture of relative sexual conservatism. There were factors present, however that indicated the potential for a large and increasing HIV epidemic to take place. These factors include low condom use (around 20% to 30% among high risk groups [3, 5, 7, 11, 13, 18, 23]), an increasing level of casual sex and extremely high risk behaviours among IDUs, and the large number of overseas filipino workers who may be a bridge population for the spread of HIV and other STIs [4, 12, 16].

This thesis has also proposed a management and decision tool, the HIV-BN, for investigating the impact of funding changes on HIV incidence in four populations of interest (MSM, IDU, FSW, Non-MARP). Chapter 2 provided an overview of the Bayesian Network methodology and highlighted the advantages of this methodology and its applicability to modelling the incidence and prevalence of HIV/AIDS in the Philippines. This method has provided the basis of the model proposed in Chapter 4. The novel model proposed in this chapter provided a management and decision tool that is able to answer the research question of 'What impact do changes in funding have on HIV incidence in the MSM, IDU, FSW and Non-MARP population groups Philippines?'. In the process of building the model and undertaking the inference required, it was found that the greatest impact on funding related to changes in funding levels on primary prevention. These changes impacted behavioural changes, and hence incidence.

This thesis was centred on investigating the HIV epidemic in the Philippines and developing a model to that could investigate the impact of funding

changes on HIV incidence in MSM, FSWs, IDUs and Non-MARPs. While the HIV-BN presented here provides a new management and decision tool to complement the current suite of HIV models in use, there are opportunities for future research. The first opportunity would be to extend the HIV-BN to the Object-Oriented (OO) paradigm for BNs. This would allow for more detail to be incorporated in the model, including further demographic details and epidemiological variables. The OO paradigm has the advantage that parts of the network can be handed to experts to construct the structure of the relevant sub-network, discretise the nodes, and parameterise them. Once completed, the resulting sub-networks are then able to be put together to create an overall Object Oriented Bayesian Network (OOBN) for investigating the impact of funding changes on HIV incidence.

The OO paradigm will also allow for the extension of the model in order to link it with more specific spending data. This would allow for further inference regarding the impact of spending changes on HIV incidence and prevalence. Additionally, such a HIV-OOBN can be used as part of a suite of tools that can be used in health economics and to investigate optimal allocations.

Extending the HIV-BN dynamically is also another area of further research. Dynamic Bayesian Networks (DBNs) allow variables in a Bayesian network to be time dependent in order to model time series or sequences [9, 14]. While DBNs have generally been used in robotics and computer science [14], they have also been used outside these fields, for example gene expression [25] and speech recognition [26] research. The DBN methodology can also be extended to the OO paradigm to create Dynamic Object Oriented Bayesian Networks (DOOBNs).

Another opportunity for future research is to incorporate the results of the current HIV models into a HIV-OOBN. In doing this, it would be possible to use the strengths of the current models, with the strengths of the OO and BN methodologies to create a model that could provide more insight into the relationships between funding, behaviour, epidemiology, and incidence of HIV.

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