A framework for implementing a modular open source health economic model (MOSHEM) in youth mental health that is accountable, reusable and updatable

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Abstract

Summary: Health economists make limited use of the modular and open source approaches to model building that other disciplines use to make large modelling projects more transparent, efficient and sustainable. We propose a framework for a modular open source health economic model (MOSHEM) in youth mental health. The framework includes of set of 20 standards for implementing a MOSHEM that is accountable (seven standards), reusable (nine standards) and updatable (four standards). We provide a rationale for each standard. The framework also includes a modelling toolkit of open access repositories and six R packages for authoring MOSHEM modules (data structures and algorithms), supplying those modules with data and using the modules to implement reproducible modelling analyses. We describe an early application of the framework to developing utility mapping models that currently meet 18 framework standards. We discuss the potential benefits and challenges of extending this initial work to develop a more extensive MOSHEM for undertaking a range of economic analyses in youth mental health.

Code: Visit https://www.ready4-dev.com for more information about how to find, install and apply the framework and model.

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1 Introduction

Computational models, particularly those addressing economic topics, have become essential tools for health policy development [1,2]. Although influential and widely used, health economic models typically have a number of limitations that at best restrict their usefulness and which in some cases may facilitate harmful misuse.

There is a strong case for making health economists more accountable for the appropriate use and social acceptability of their models. Users of models should be able to assess their adequacy for a particular purpose [3]. This goal is difficult to achieve in the current context of the poor reproducibility [4–6] and frequently insufficient validation [7] of health economic models. Many health economic models are released with undeclared errors [8]. The value judgments that strongly shape health economic analyses are rarely made explicit, omissions that may lead to socially unacceptable policy recommendations [9]. A modelling team's value judgments about what questions to address, the most important features of a system to represent and the weighting of different types of evidence may be poorly aligned with those of the people impacted by decisions informed by model analyses [10]. As health economic models adopt more sophisticated techniques, the need for accountability grows. More complex models may be more prone to propagation errors [11] and models designed to address multiple questions should be expected to meet more onerous verification and validation obligations [12,13]. The nature and extent of individual model authorship contributions may be less clear in models implemented over longer time-frames with a large and changing group of collaborators [10].

The resource and skills intensive undertaking of modelling could be made more tractable if it was easier for health economists to re-use each other's models [14]. However, as many health economic models are owned by pharmaceutical companies and consultancies, commercial considerations can limit the reuse of models and their constituent code and data [13]. Legal and ethical issues such as privacy and confidentiality requirements further limit public release of some model artefacts [15]. Transferring a health economic model developed for one jurisdiction for application in another typically involves retaining some features and updating others [16]. However, models do not always make implementation choices (for example, use of concepts with standardised meanings across jurisdictions, supplying context specific data as replaceable data-packs and distributing source code under licenses that allow derivative works) that facilitate model transferability.

Health economic models should be updated and refined as new evidence emerges and decision contexts change [17], but this occurs infrequently [18]. Funding for health economic modelling projects rarely extend to provision of medium term support for model updates and improvements. The career trajectories of health economists can also mitigate against adequate maintenance of a model, it being relatively common for model authors to have moved on from the team that owns the model and / or from working on the health condition for which the model was developed.

A potential strategy for improving model accountability, reusability and updatability is to make models both modular and open-source.

A modular model is constructed from multiple reusable and replaceable sub-models (modules) [19]. Modules can share inputs and outputs with other modules or can be run as independent models [20]. Advantages of modular models include feasibility (large projects are broken into smaller tasks, with each component independently developed and tested) and flexibility (making it easier to selectively replace or update specific parts of a model and to scale up or down the level of granularity) [19]. Modular approaches are currently being used to facilitate the development of complex computational models in disciplines such as biology [19], neuroscience [21] and ecology [20]. In health economics the related and enabling concept of reference models has been recommended [22], but peer reviewed studies describing modular health economic models remain relatively rare, though examples exist in infectious disease [23] and cardiology [24].

Modular models provide an opportunity for multiple modelling teams to contribute to, test and reuse models. To enhance this capacity, modular models may be implemented as open source projects that give others liberal permissions to access and use model source code and data [19–21]. Although there appears to be in principle support from many health economists for greater use of open source health economic models (OSHEMs) [15], actual implementations are rare [13,25,26]. Barriers to adoption of OSHEMs include concerns about intellectual property, confidentiality, model misuse and the resources required to support open source implementations [15,27]. Adherence to good practice guidance is an essential requirement for healthcare modelling [2], but guidelines for implementing OSHEMs remain scarce, piecemeal and need improving [28].

Our interest in modular and open source source approaches developed when we began seeking am appropriate framework for undertaking and validly synthesising diverse types of economic research in mental health. Mental disorders impose high health, social and economic burdens worldwide [29,30]. Much of this burden is potentially avertable [31], but poorly financed and organised mental health systems are ill-equipped for this challenge [32,33]. A substantial economic literature already exists to assess the affordability and value for money of mental health interventions [34]. This economic evaluation work is an essential prerequisite for improving allocative efficiency in mental health, but could be of greater value to systems planners if integrated with a broader program of economic research.

We are developing ready4 (https://www.ready4-dev.com), a modular OSHEM (MOSHEM) on the mental health of young people aged 12 to 25. We are initially applying ready4 to four of the twelve domains of health economics identified by Wagstaff and Culyer [35]:

- *health and its value* (our projects: utility mapping models);
- *determinants of health and ill-health* (our projects: models for creating rich and representative synthetic household populations from survey data);
- *demand for health and health care* (our projects: spatial epidemiology and help-seeking choice models); and
- *supply of health services* (our projects: a model of primary mental health care services).

Once these projects are completed, our aim is to flexibly combine these models to answer questions in two additional Wagstaff and Culyer domains:

- *efficiency and equity* (our goal: assess the distributional impacts and identify the optimal targeting of care provision); and
- *economic evaluation* (our goal: assess the cost-utility of competing policy options).

To undertake this work we first needed to develop a framework for standardisation. Standardisation is an essential enabler of automation, collaboration, interoperability and transferability in modular and open source approaches, but as MOSHEMs remain rare it is unclear what standards are most appropriate to specify. A MOSHEMs is a computational modelling project, so standards developed for ready4 will need to be verified and implemented by software, some of which will need to be developed for this specific purpose.

In this paper, we:

(i) describe a framework comprised of:
  - a set of standards for implementing an accountable, reusable and updatable MOSHEM; and
  - a modelling toolkit (online repositories and software) for applying those standards to the authoring of ready4 modules, datasets and analyses.

(ii) provide a worked example of how we used the framework to develop and apply ready4 modules for utility mapping.

2 Framework

To help us implement a MOSHEM in youth mental health, we have developed a framework that:

- specifies a set of standards for MOSHEM development and use; and
- provides a modelling toolkit (repositories and software) for authoring model modules, managing data and implementing reproducible analyses consistent with those standards.

2.1 Standards

Based on published guidance on computational modelling in health economics and other disciplines and our own experience, we have identified 20 standards that we believe are important for implementing a MOSHEM that is accountable (seven standards), reusable (nine standards) and updatable (four standards). The standards are specified in Table 1 and are discussed below.

2.1.1 Standards for an accountable MOSHEM

Guidance on transparency in health economic modelling published over ten years ago [12] made recommendations on documenting models but notably did not include recommendations on sharing model

Table 1: Framework standards

Characteristic	Standard	Meaning
Accountable - it is easy to see who developed, tested and applied a model and how they did it.		
	A1	Open online repositories are used to permanently archive, uniquely identify and transparently record development history and authorship of model code and data.
	A2	Model code and data are documented.
	A3	Model code uses consistent syntax, with abstraction used for analysis code.
	A4	Literate programming is used to implement model analyses.
	A5	Code coverage is reported.
	A6	All parts of a study analysis and reporting workflow can be reproduced and/or replicated.
	A7	Model code and data are distributed with tools to support appropriate citation.
Reusable - a model and its components can be used in other models and by other modellers.		
	R1	Model code is made available for re-use under copyleft or permissive licenses.
	R2	Non-confidential model data is licensed for liberal re-use (potentially subject to ethical use terms).
	R3	Model code and data are stored and managed separately.
	R4	Module data structures are encapsulating and inheriting.
	R5	Module algorithms are implemented as functions and linked to module data-structures as methods.
	R6	Model module data-structures and algorithms are distributed as code libraries.
	R7	Test data is available to demonstrate generalised applications of model code.
	R8	Statistical models are distributed with tools to support their safe and appropriate re-use.
	R9	Simple user-interfaces allow non-technical users to configure and run models.
Updatable - a model and its components are maintained and continuously improved.		
	U1	Model code and data are version controlled.
	U2	The signficiance and status of model and code updates are indicated with semantic versioning and release types.
	U3	Continuous integration is used to verify model code updates.
	U4	Deprecation conventions are used to retire model code and data.

code and data. However, more recent and multidisciplinary healthcare modelling guidance [2] recommends using existing digital repository services to these types of digital model artefacts. Some types of repository such as GitHub [36] provide tools for disseminating work in progress code and providing highly transparent records of the complete development history and individual authorship contributions of a software project, while others such as Zenodo [37] and Dataverse [38] provide persistent storage solutions that generate a Digital Object Identifier (DOI) for each code and data collection.

Model code and data should be clearly documented, potentially with different versions for technical and non-technical users [12]. Consistent use of meaningful naming conventions when authoring code is recommended [39,40]. Code can be made easier to follow by using the practices of abstraction [41], where only simple, high level commands are routinely exposed to reviewers, and polymorphism [42], where the same command (e.g. "simulate") can be reused to implement different algorithms of the same type. Programs to implement model analyses can be made comprehensible to even non-technical users through the use of literate programming techniques and tools like RMarkdown [43] that integrate computer code with plain English descriptions.

An essential component of quality assuring health economic models is verification - ensuring that calculations are correct and consistent with model specifications [44]. One useful concept for informing model users about the extensiveness of verification checks is code coverage [45] - the proportion of model code that has been explicitly tested. Transcription errors - mistakes introduced when transferring data between sources, models and reports - are very common in health economic models [8]. The risk of these errors might be lower if there was full transparency across all steps in a study workflow. Scientific computing tools now make it relatively straightforward to author programs that reproducibly execute all steps in data ingest, processing and reporting [39].

Code and data should be distributed with tools that make it easy for potential users to appropriately cite each model artefact.

2.1.2 Standards for a reusable MOSHEM

To make model code and data widely re-usable by others, it is important to provide users with appropriate and explicit permissions. In the context of open source models, there are two broad categories of licensing options. Some guidance strongly recommends the use of permissive licensing [39] that provides users with great flexibility as to the purposes (including commercial) for which the content could be re-used. An alternative approach is to use copyleft licenses [46] that can require content users to distribute any derivative works they create under similar open source arrangements. For code, it may be appropriate to adopt the prevailing open source licensing practice within the programming language being used. For data, it may not be sufficient to simply choose between a permissive license like the Public Domain Dedication (CC0) [47] or a copyleft option such as the Attribution-Share Alike (CC-BY-SA) [48]. In addition to ensuring that data is ethically appropriate for disseminate in open access repositories, responsible custodianship of some de-identified or aggregated data may involve using or adapting template terms of use [49] which have a number of ethical clauses (for example, prohibiting efforts to re-identify research participants).

Storing model code and data in separate files and locations (as opposed to hard coding - embedding data into source code) can make it easier to apply models to different decision contexts and, when necessary, to selectively restrict access to data that are confidential, while disseminating all other model artefacts. Clear distinctions should be made between model modules (code that defines abstract data structures and the algorithms that can be applied to data described by these structures), model datasets (digital information such as parameter values, unit records, etc) and model analyses (code that links model datasets to model modules and specifies the algorithms to apply to the data associated with each module).

The coding practice of encapsulation [41] can be used to help ensure that model modules continue to work as intended even when they are combined [50]. In some cases, combining modules may mean new versions of modules have to be created to better account for interaction effects. The coding concept of inheritance [41] can be used to efficiently achieve this objective as well as to facilitate selective editing of modules when transferring models to different decision contexts [50]. Writing algorithms as collections of functions (short, self-contained and reusable software routines that each perform a discrete task) is recommended as good practice for scientific computing [39]. Functions to implement model algorithms can be associated with module data structures (also known as a class) via a special type of function called a method. Model modules of a similar type or purpose can be efficiently distributed and documented by bundling them as code libraries. It is good practice to make available test or toy data to demonstrate the use of model algorithms [39].

Statistical models are a common output of health economic evaluations, but they are often not reported in a format that enables others to confidently and reliably re-use them [51]. Open source approaches can help address this by disseminating code artefacts that enable easy and appropriate use of a statistical model to make predictions with new data. However, great care must be exercised when doing so if models are derived from data on human subjects as some software artefacts by default contain a copy of the source dataset. Such dataset copies must therefore be replaced (for example, with synthetic data) and the amended artefact's predictive performance then retested before any public release. Another way to make MOSHEMs easier to use is to develop simple user-interfaces for non-technical users. In the open source R language, such user-interfaces are typically developed with the Shiny package, for which a tutorial aimed at health economists is available [52].

2.1.3 Standards for an updatable MOSHEM

To avoid MOSHEMs going stale - losing validity and usefulness with time - they should be routinely updated. Each update of code and data should be uniquely identifiable and retrievable, a goal that can be facilitated by use of version control tools [2].

Potential users of model code and data should be able to easily identify which version is most appropriate to their needs. Using semantic versioning [53] conventions can signal the potential importance of an update to users of model code and data. Also informative is to clearly label the type of code hosted in a repository as either:

- "development" (typically the most comprehensive and up to date source code, but potentially not yet sufficiently well documented and tested for potential users to apply to purposes other than testing);
- "production" (code that has been released with a view to it being applied to its stated purposes and therefore typically required to meet defined documentation and testing standards); or
- "archive" (permanent copies of code at key milestones in its development - potentially useful if seeking to use older versions of code to reproduce analyses).

Continuous integration [54] tools can help verify that each code update passes multiple quality tests. Finally, using deprecation conventions that take an informative and staged approach to retiring old code and data reduces the risk that model revisions have unintended consequences on third party users. The package lifeycle [55] provides tools for R developers to consistently deprecate their code.

2.2 Modelling toolkit

We developed a toolkit to help us develop and use ready4 modules, datasets and analyses that meet the standards listed in Table 1. The toolkit is comprised of online repositories and software.

2.3 Repositories

We created a GitHub organisation (a collection of code repositories) where all our development code is stored and version controlled [56]. We linked our GitHub organisation to an account we established at codecov [57] to track our code coverage. We configured the repositories in our GitHub organisation to use GitHub actions to support continuous integration.

For hosting documentation websites for the code libraries we create, we enabled GitHub Pages in each library's repository. We also developed a consolidated project documentation website [58], using the Hugo framework [59] and Docsy theme [60]. To host that website we established an account with Netlify [61] and linked that service to our GitHub organisation so that the website would automatically update whenever the source code in its GitHub repository was edited.

We also created a Zenodo community [62] - a collection of permanent, unbiquely identified repositories. We then linked our Zenodo community and GitHub organisation so that every time we create a new “release” in a GitHub repository, a copy of that code is automatically created on Zenodo with a DOI. Finally, to manage model datasets, we created a dedicated collection within the Harvard Dataverse installation [63].

2.4 Software

We created six development version R libraries to help us author model modules, supply them with data and implement reproducible modelling analyses. The six libraries, their primary focus, the standards they support and the third-party packages they depend on are summarised in Table 2.

The foundation for ready4 is provided by a library called ready4 [64] that defines a template module (using R’s S4 type class) from which all model module data structures will inherit features and a novel syntax for implementing the algorithms attached to model modules. The ready4 library also contains tools for retrieving web based information on model modules, datasets and analysis programs and for partially automating updates to the project website.

Three R libraries are designed to standardise and partially automate workflows for authoring new model modules. The ready4pack library [65] provides tools for authoring module libraries that are:

- documented (with a website, a manual itemising selected contents and a manual itemising all contents);
- licensed (with GPL-3 by default);
- easily citable (citation information can be retrieved within an R session or from hosting repositories); and
- quality assured (triggering continuous integration workflows, including any unit tests created by module library authors).

The ready4pack library is designed to integrate with our GitHub organisation and depends on the other two module authoring libraries. Methods from the ready4fun library [66] are used to verify that functions for implementing module algorithms are written in a consistent house style and to use their standardised format to automatically generate basic documentation for each function. Methods from the ready4class [67] library are used to streamline and standardise the authoring of module data-structures. Like ready4fun, the ready4class library uses standardised naming conventions to automatically generate basic documentation for each module data-structure.

The ready4use library [68] contains modules for ingesting model datasets from online repositories (hosted on a Dataverse installation or on GitHub), labelling model datasets and sharing model datasets via online repositories. The ready4show library [69] contains tools to help author analyses programs that are either self-documenting or which trigger the creation of a scientific summary.

When used in conjunction with repositories, the six R libraries provide strong support for implementing 17 framework standards. However, the software only weakly supports implementing the standards relating to safe dissemination of statistical models (R8) and user-interface development (R9) and does not yet provide any workflow tools to help implement the standard for deprecation conventions (U4). Standards not supported or weakly supported by our software can be met with existing developer tools in R.

Table 2: Modelling toolkit R packages for developing and using MOSHEMs that meet framework standards

Package	Focus	Standard	Depends on these R libraries
ready4	Foundation	A3 R4	assertthat bib2df dataverse dplyr fs Hmisc kableExtra knitr lifecycle magrittr methods natmanager piggyback purrr readr readxl rlang rmarkdown rvest stats stringi stringr testit testthat tibble tidyRSS tools utils zen4R
ready4fun	Module algorithms	A2-3 R5	desc devtools dplyr generics gert Hmisc knitr lifecycle lubridate magrittr methods piggyback pkgdown purrr readxl ready4 ready4show ready4use rlang sinew stats stringi stringr testit testthat tibble tidyr tools usethis utils xfun
ready4class	Module structures	A2 R4-5	devtools dplyr fs gtools Hmisc knitr lifecycle magrittr methods purrr ready4 ready4fun ready4show rlang stats stringi stringr testit testthat tibble tidyr usethis utils
ready4pack	Module libraries	A1-2,5,7 R1,3,6 U1-3	dataverse dplyr knitr lifecycle magrittr methods purrr ready4 ready4class ready4fun rlang stringr testthat tibble tidyr utils
ready4use	Datasets	A1-2,7 R3,7 U1	data.table dataverse dplyr fs Hmisc knitr lifecycle magrittr methods piggyback purrr readxl ready4 ready4show rlang stats stringi stringr testit testthat tibble tidyr utils
ready4show	Analyses	A4,6	dataverse DescTools dplyr flextable grDevices here Hmisc kableExtra knitr knitrBootstrap lifecycle magrittr methods officer purrr ready4 rlang rmarkdown stringi stringr testthat tibble tidyr utils xtable

Table 3: Framework checklist applied to utility mapping study

	Standard	Met?	Description
A1	Public	Yes	Datasets are available at https://doi.org/10.7910/DVN/DKDIB0 and https://doi.org/10.7910/DVN/HJXYKQ. For details of where to find Development and Archive code see: https://www.ready4-dev.com/docs/getting-started/software/libraries/types/module/ https://www.ready4-dev.com/docs/getting-started/software/executables/programs/ https://www.ready4-dev.com/docs/getting-started/software/executables/subroutines/
A2	Documentation	Yes	All code libraries have documenting websites with URLs that concatenate 'https://ready4-dev.github.io/' and the library name (e.g. https://ready4-dev.github.io/youthvars). All three Markdown programs are self-documenting, with one [70] including additional instructions in a README file. Only one sub-routine [71] is documented with a meaningful README file. All datasets have meaningful metadata descriptors.
A3	Syntax	Yes	All libraries are authored with ready4pack [65] to ensure a consistent house style. All libraries except [72] use framework syntax, as does one program [70].
A4	Literate programming	Yes	All programs use literate programming.
A5	Code coverage	No	No current reporting of code coverage.
A6	Reproducibility	Yes	All parts of the study workflow from raw data ingest through to data processing, analysis, reporting and dissemination of study outputs can be reproduced (if granted access to source data) or replicated (using supplied synthetic data) with one program [70].
A7	Citation tools	Yes	All libraries can return citation details when running R's 'citation' function. All code and data repositories have tools to generate citation details.
R1	Code licenses	Yes	All code libraries, programs and sub-routines use GPL-3 licenses.
R2	Data terms	Yes	Datasets use amended version of template provided by Harvard Dataverse [49].
R3	Separation	Yes	All development code is stored on repos in a GitHub organisation [56] and all archived releases are available in a Zenodo community [62]. All non-confidential data is stored in repositories within a Harvard Dataverse collection [63].
R4	Encapsulated, inheriting	Yes	Four [73–76] out of five libraries include encapsulating and inheriting modules. See: https://www.ready4-dev.com/docs/model/finding-modules/
R5	Functions	Yes	All code libraries include functions. The most complete list of functions for each library is available by clicking the 'Manual - Developer (PDF)' link on each package's documentation homepage (see item A2 above)
R6	Libraries	Yes	All module data-structures and algorithms are distributed as code libraries.

	Standard	Met?	Description
R7	Test data	Yes	Two synthetic datasets and their data dictionaries are publicly available in a data repository [77]. One (ymh_clinical_tb.RDS) closely resembles the study dataset and was released so that the main study algorithm [70] can be rerun by those without access to the confidential study dataset. The other (eq5d_ds_dict.RDS) is deliberately different to the source dataset in both variable naming convention and the concepts used for predictors and outcome measures. It was created to demonstrate generalised applications of study algorithms.
R8	Prediction tools	Yes	Model catalogues (PDF files beginning with 'AAA_TTU_MDL_CTG') are available in the study results dataset [78] and describe the predictive performance of all models under a variety of usage regimes (including when the source dataset in the R model object is replaced with fake data). The youthu library [72] includes tools for searching for and applying models compatible with different types of input data. An example program to demonstrate this functionality is available in both RMarkdown [79] and rendered PDF formats (the 'Application.pdf' file in the study results dataset [78]).
R9	User interface	No	No user interface has yet been developed.
U1	Version controlled	Yes	All code is version controlled using Git and GitHub. All source code is available in a GitHub organisation [56].
U2	Semantic versioning	Yes	Semantic versioning is used in all code. As no code library has yet been submitted to CRAN, only the development version extensions of each version number have been incremented to date.
U3	Continuously integrated	Yes	All six libraries use continuous integration (CI). CI results for each library can be viewed at a URL that concatenates 'https://github.com/ready4-dev/', the library name and '/actions' (e.g. https://github.com/ready4-dev/youthvars/actions)
U4	Deprecation	Yes	Retired code is deprecated using tools from the lifecycle R library (e.g. everything after "## DEPRECATED FNS" in https://github.com/ready4-dev/youthvars/blob/main/data-raw/fns/add.R). Package vignettes and datasets are also deprecated e.g. https://ready4-dev.github.io/youthvars/articles/Replication_DS.html)

3 Application

We applied the framework to develop modules for developing utility mapping models, supplying those modules with data and implementing utility mapping analyses. The study for which these tools were developed and which applied them to developing utility mapping models for a clinical mental health sample of young people has been previously described [80]. The outputs we authored using the framework's modelling toolkit include:

- development version module libraries for describing and validating youth mental health human record datasets [73], scoring health utility [74], specifying utility mapping models [75] and implementing reproducible utility mapping studies [76];
- a development version library of functions for finding and using utility mapping models developed with these tools [72];
- data collections of synthetic populations for testing model modules [77] and study input and results data [78];
- programs for replicating all steps from data ingest to manuscript reporting [70], applying utility mapping models to new data [79] and generating a synthetic representation of the study dataset [81];
- subroutines for creating a catalogue of utility mapping models [82] and generating a draft scientific manuscript [71] for studies implemented with these modules.

When we assesses these study outputs against each framework standard, we conclude that 18 standards were wholly or mostly met (see Table 3). The two standards where the study outputs currently fall short are in reporting code coverage and including a user-interface. Both these items are scheduled to be addressed when we release production versions of the code libraries.

4 Discussion

In this article we introduced a framework that we developed to help us implement ready4 - a MOSHEM in youth mental health. We outlined framework standards for an accountable, reusable and updatable MOSHEM and described the modelling toolkit we created for applying those standards to the development and use of ready4. We also provided an overview of an initial set of ready4 modules developed with the framework to implement a utility mapping study. We reviewed the modules, datasets and analyses generated by that study against framework standards.

The strengths, limitations and issues raised by this work can be discussed in terms of relevance to future development of ready4, to health economists interested in undertaking other MOSHEMS and to funders of health economic research.

4.1 Implications for the development of the ready4 MOSHEM

One of the main novel contributions of the framework we have developed is that it declares an explicit set of standards for the implementation and use of a MOSHEM. A practical benefit of specifying these standards is that it enabled us to develop a modelling toolkit to partially automate workflows for authoring, documenting and disseminating ready4 modules, datasets and analyses. The modelling toolkit's practical utility has been demonstrated through its application in creating all ready4 components used in a utility mapping study [80] and the automation it facilitates makes the development and curation of a large and growing number of ready4 digital assets more tractable. The interoperability of the ready4 modules we have developed today is demonstrated in multiple example literate programs on the ready4 documentation website [58] and in the program used to implement the utility mapping analysis [70].

The framework's standards also provide a mechanism to assess the extent to which ready4 meets explicit accountability, reusability and updatability goals.

Open source approaches have been recommended to help develop the mental health modelling field [83] but only one mental health related model (in Alcohol Use Disorder [84]) is currently indexed [RECHECK] in the

Open Source Models Clearinghouse [25,85]. We are aware of just one other open source mental health model - a reference model in Major Depressive Disorder - that is currently in development [86].

However, the framework represents a technical capacity and is not a behavioural outcome. Having features to facilitate accountability, reuse and updating does not guarantee being that our OSHEM will be meaningfully held accountable, reused and updated. Making code and data publicly available may make limited impact on error detection unless third parties begin to use these artefacts in their own projects. Currently all the framework and module libraries we have developed are available only as "development" releases. Further development, testing and documenting before we submit production versions of each library to the Comprehensive R Archive Network (CRAN) [87]. Having these libraries available on CRAN is a likely prerequisite of significant levels of reuse.

Estimating the potential uptake of these tools is difficult. Mental health topics accounted for about 268 of 2829 (10%) economic evaluations undertaken during 26 month period in 2012-2014 identified in a previous review [88].

Developing networks of modellers working on common health conditions has been recommended as a strategy for improving model validity [28] and some of us are part of a nascent initiate of this type in mental health [89].

Similarly, developing partnerships between modellers and decision-makers across the life-cycle of a modelling project can help ensure models are appropriately conceptualised, implemented and have practical utility as decision aids [90,91].

- Community building (feasibility)
- Funding contingent directions - replications / transfers

4.2 Implications for health economists

Output by health economists [35,88,92]

4.3 Implications for research funders

- unreasonable to expect more accountability without more resources

Major mental health reform programs, can involve the identification, prioritisation, sequencing, targeting and monitoring of multiple interdependent initiatives.

The significant deficits in our understanding of the systems in which mental disorders emerge and are treated [93] suggest that there is ample scope for mental health systems models to progressively improve their validity over time. Prospective work could address the weak theoretical underpinnings for understanding complex mental health systems [94]. For example, it remains unclear why increased investments in mental health care have yet to discernibly reduce the prevalence and burden of mental disorders[95]. The literature, and evidence base, regarding how the requirements, characteristics and performance of mental health services are shaped by spatiotemporal context needs to be further developed [96]. There is also a need for better evidence to identify the social determinants of mental disorders most amenable to preventative interventions, and for which population sub-groups such interventions would be most effective [97].

The development, validation and updating of more complex mental health economic models implemented over longer time frames may be too onerous a burden for a single modelling team.

5 Conclusion

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Availability of data and materials

The most up to date and comprehensive source of documentation on our framework and model is available at https://www.ready4-dev.com . Development versions of all code repositories referenced in this article are available in https://github.com/ready4-dev/ . Archived code releases are available in https://zenodo.org/communities/ready4 . All data repositories referenced in this article are available in https://dataverse.harvard.edu/dataverse/ready4 .

Ethics approval

Framework development did not involve human subject research and was not ethically reviewed. The utility mapping worked example is a previously reported study that was reviewed and granted approval by the University of Melbourne's Human Research Ethics Committee, and the local Human Ethics and Advisory Group (1645367.1).

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Conflict of Interest

None declared.

References

1. Dakin H, Devlin N, Feng Y, Rice N, O'Neill P, Parkin D. The influence of cost-effectiveness and other factors on nice decisions. Health economics. Wiley Online Library; 2015;24: 1256–1271.
2. Erdemir A, Mulugeta L, Ku JP, Drach A, Horner M, Morrison TM, et al. Credible practice of modeling and simulation in healthcare: Ten rules from a multidisciplinary perspective. Journal of translational medicine. 2020;18: 369. doi:10.1186/s12967-020-02540-4
3. Thompson EL, Smith LA. Escape from model-land. Economics. De Gruyter Open Access; 2019;13.
4. Jalali MS, DiGennaro C, Guitar A, Lew K, Rahmandad H. Evolution and reproducibility of simulation modeling in epidemiology and health policy over half a century. Epidemiologic Reviews. 2021;43: 166–175. doi:10.1093/epirev/mxab006
5. McManus E, Turner D, Sach T. Can you repeat that? Exploring the definition of a successful model replication in health economics. Pharmacoeconomics. 2019;37: 1371–1381. doi:10.1007/s40273-019-00836-y
6. Bermejo I, Tappenden P, Youn J-H. Replicating health economic models: Firm foundations or a house of cards? PharmacoEconomics. 2017;35: 1113–1121. doi:10.1007/s40273-017-0553-x
7. Ghabri S, Stevenson M, Möller J, Caro JJ. Trusting the results of model-based economic analyses: Is there a pragmatic validation solution? Pharmacoeconomics. 2019;37: 1–6. doi:10.1007/s40273-018-0711-9
8. Radeva D, Hopkin G, Mossialos E, Borrill J, Osipenko L, Naci H. Assessment of technical errors and validation processes in economic models submitted by the company for NICE technology appraisals. International Journal of Technology Assessment in Health Care. 2020;36: 311–316. doi:10.1017/S0266462320000422
9. Duckett S. A journey towards a theology of health economics and healthcare funding. Theology. SAGE Publications Sage UK: London, England; 2022;125: 326–334.
10. Thompson E. Escape from model land: How mathematical models can lead us astray and what we can do about it. New Yourk: Basic Books; 2022.
11. Saltelli A. A short comment on statistical versus mathematical modelling. Nature Communications. 2019;10: 3870. doi:10.1038/s41467-019-11865-8
12. Eddy DM, Hollingworth W, Caro JJ, Tsevat J, McDonald KM, Wong JB. Model transparency and validation: A report of the ISPOR-SMDM modeling good research practices task force-7. Med Decis Making. 2012;32: 733–43. doi:10.1177/0272989x12454579
13. Feenstra T, Corro-Ramos I, Hamerlijnck D, Voorn G van, Ghabri S. Four aspects affecting health economic decision models and their validation. PharmacoEconomics. 2022;40: 241–248. doi:10.1007/s40273-021-01110-w
14. Arnold RJG, Ekins S. Time for cooperation in health economics among the modelling community. PharmacoEconomics. 2010;28: 609–613. doi:10.2165/11537580-000000000-00000
15. Pouwels X, Sampson CJ, Arnold RJG. Opportunities and barriers to the development and use of open source health economic models: A survey. Value Health. 2022;25: 473–479. doi:10.1016/j.jval.2021.10.001
16. Barbieri M, Drummond M, Rutten F, Cook J, Glick HA, Lis J, et al. What do international pharmacoeconomic guidelines say about economic data transferability? Value in Health. Elsevier; 2010;13: 1028–1037.
17. Jenkins DA, Martin GP, Sperrin M, Riley RD, Debray TPA, Collins GS, et al. Continual updating and monitoring of clinical prediction models: Time for dynamic prediction systems? Diagnostic and Prognostic Research. 2021;5: 1. doi:10.1186/s41512-020-00090-3
18. Sampson CJ, Wrightson T. Model registration: A call to action. PharmacoEconomics - Open. 2017;1: 73–77. doi:10.1007/s41669-017-0019-2

19. Pan M, Gawthrop PJ, Cursons J, Crampin EJ. Modular assembly of dynamic models in systems biology. PLoS computational biology. Public Library of Science San Francisco, CA USA; 2021;17: e1009513.
20. Barros C, Luo Y, Chubaty AM, Eddy IM, Micheletti T, Boisvenue C, et al. Empowering ecological modellers with a PERFICT workflow: Seamlessly linking data, parameterisation, prediction, validation and visualisation. Methods in Ecology and Evolution. Wiley Online Library; 2023;
21. Frazier-Logue N, Wang J, Wang Z, Sodums D, Khosla A, Samson AD, et al. A robust modular automated neuroimaging pipeline for model inputs to TheVirtualBrain. Frontiers in Neuroinformatics. Frontiers Media SA; 2022;16: 883223.
22. Afzali HH, Karnon J, Merlin T. Improving the accuracy and comparability of model-based economic evaluations of health technologies for reimbursement decisions: A methodological framework for the development of reference models. Med Decis Making. 2013;33: 325–32. doi:10.1177/0272989x12458160
23. Trauer JM, Ragonnet R, Doan TN, McBryde ES. Modular programming for tuberculosis control, the “AuTuMN” platform. BMC Infectious Diseases. 2017;17: 546. doi:10.1186/s12879-017-2648-6
24. Urach C, Zauner G, Endel G, Wilbacher I, Breitenecker F. A modular simulation model for assessing interventions for abdominal aortic aneurysms. 2013 winter simulations conference (WSC). 2013. pp. 66–76. doi:10.1109/WSC.2013.6721408
25. Emerson J, Bacon R, Kent A, Neumann PJ, Cohen JT. Publication of decision model source code: Attitudes of health economics authors. PharmacoEconomics. 2019;37: 1409–1410. doi:10.1007/s40273-019-00796-3
26. Michalczyk J, Clay E, Pochopien M, Aballea S. PRM123 - AN OVERVIEW OF OPEN-SOURCE MODELS IN HEALTH ECONOMICS. Value in Health. 2018;21: S377. doi:10.1016/j.jval.2018.09.2243
27. Wu EQ, Zhou Z-Y, Xie J, Metallo C, Thokala P. Transparency in health economic modeling: Options, issues and potential solutions. PharmacoEconomics. 2019;37: 1349–1354. doi:10.1007/s40273-019-00842-0
28. Sampson CJ, Arnold R, Bryan S, Clarke P, Ekins S, Hatswell A, et al. Transparency in decision modelling: What, why, who and how? PharmacoEconomics. 2019;37: 1355–1369. doi:10.1007/s40273-019-00819-z
29. Bloom DE, Cafiero ET, Jané-Llopis E, Abrahams-Gessel S, Bloom LR, Fathima S, et al. The global economic burden of noncommunicable diseases. 91-93 route de la Capite,CH-1223 Cologny/Geneva,Switzerland: World Economic Forum.; 2011.
30. Global, regional, and national burden of 12 mental disorders in 204 countries and territories, 1990–2019: A systematic analysis for the global burden of disease study 2019. The Lancet Psychiatry. 2022;9: 137–150. doi:10.1016/S2215-0366(21)00395-3
31. Chisholm D, Sweeny K, Sheehan P, Rasmussen B, Smit F, Cuijpers P, et al. Scaling-up treatment of depression and anxiety: A global return on investment analysis. The Lancet Psychiatry. 2016; doi:10.1016/s2215-0366(16)30024-4
32. Saxena S, Thornicroft G, Knapp M, Whiteford H. Resources for mental health: Scarcity, inequity, and inefficiency. The Lancet. 370: 878–889. doi:10.1016/S0140-6736(07)61239-2
33. Whiteford H, Ferrari A, Degenhardt L. Global burden of disease studies: Implications for mental and substance use disorders. Health Affairs. 2016;35: 1114–1120. doi:10.1377/hlthaff.2016.0082
34. Knapp M, Wong G. Economics and mental health: The current scenario. World Psychiatry. 2020;19: 3–14. doi:10.1002/wps.20692
35. Wagstaff A, Culyer AJ. Four decades of health economics through a bibliometric lens. Journal of health economics. Elsevier; 2012;31: 406–439.
36. github. GitHub [Internet]. 2007. Available: https://github.com/
37. European Organization For Nuclear Research, OpenAIRE. Zenodo [Internet]. CERN; 2013. doi:10.25495/7GXK-RD71

38. Quantitative Social Science I for. Dataverse [Internet]. Harvard University; 2007. Available: https://dataverse.org
39. Wilson JAC Greg AND Bryan. Good enough practices in scientific computing. PLOS Computational Biology. Public Library of Science; 2017;13: 1–20. doi:10.1371/journal.pcbi.1005510
40. Alarid-Escudero F, Krijkamp EM, Pechlivanoglou P, Jalal H, Kao S-YZ, Yang A, et al. A need for change! A coding framework for improving transparency in decision modeling. PharmacoEconomics. 2019;37: 1329–1339. doi:10.1007/s40273-019-00837-x
41. Hourani H, Wasmi H, Alrawashdeh T. A code complexity model of object oriented programming (OOP). 2019 IEEE jordan international joint conference on electrical engineering and information technology (JEEIT). 2019. pp. 560–564. doi:10.1109/JEEIT.2019.8717448
42. Milojkovic N, Caracciolo A, Lungu MF, Nierstrasz O, Röthlisberger D, Robbes R. Polymorphism in the spotlight: Studying its prevalence in java and smalltalk. 2015 IEEE 23rd international conference on program comprehension. 2015. pp. 186–195. doi:10.1109/ICPC.2015.29
43. Xie Y, Allaire JJ, Grolemund G. R markdown: The definitive guide. Chapman; Hall/CRC; 2018.
44. Büyükkaramikli NC, Rutten-van Mölken MPMH, Severens JL, Al M. TECH-VER: A verification checklist to reduce errors in models and improve their credibility. PharmacoEconomics. 2019;37: 1391–1408. doi:10.1007/s40273-019-00844-y
45. Eric Wong W, Debroy V, Choi B. A family of code coverage-based heuristics for effective fault localization. Journal of Systems and Software. 2010;83: 188–208. doi:https://doi.org/10.1016/j.jss.2009.09.037
46. Foundation TFS. What is copyleft? [Internet]. Available: https://www.gnu.org/copyleft/
47. Commons C. CC0 1.0 universal [Internet]. 2022. Available: https://creativecommons.org/publicdomain/zero/1.0/legalcode
48. Commons C. Attribution-ShareAlike 4.0 international [Internet]. 2022. Available: https://creativecommons.org/licenses/by-sa/4.0/legalcode
49. Quantitative Social Science I for. Sample data usage agreement [Internet]. 2022. Available: https://support.dataverse.harvard.edu/sample-data-usage-agreement
50. Hamilton M. Apply an object-oriented paradigm to computational models of mental health systems [Internet]. 2022. Available: https://ready4-dev.github.io/ready4/articles/V_03.html
51. Kearns B, Ara R, Wailoo A, Manca A, Alava MH, Abrams K, et al. Good practice guidelines for the use of statistical regression models in economic evaluations. PharmacoEconomics. 2013;31: 643–652. doi:10.1007/s40273-013-0069-y
52. Smith R, Schneider P. Making health economic models shiny: A tutorial. Wellcome Open Res. 2020;5: 69. doi:10.12688/wellcomeopenres.15807.2
53. Preston-Werner T. Semantic versioning 2.0.0 [Internet]. 2022. Available: https://semver.org
54. Shahin M, Ali Babar M, Zhu L. Continuous integration, delivery and deployment: A systematic review on approaches, tools, challenges and practices. IEEE Access. 2017;5: 3909–3943. doi:10.1109/ACCESS.2017.2685629
55. Henry L, Wickham H. Lifecycle: Manage the life cycle of your package functions [Internet]. 2021. Available: https://CRAN.R-project.org/package=lifecycle
56. Orygen. ready4: A suite of authoring, modelling and prediction tools for exploring topics in young people's mental health [Internet]. 2022. Available: https://github.com/ready4-dev/
57. Codecov [Internet]. Available: https://about.codecov.io/
58. Orygen. ready4 - a modular computational model in youth mental health [Internet]. Available: https://ready4-dev.com/

59. Hugo: The world's fastest framework for building websites [Internet]. Available: https://gohugo.io

60. Docsy [Internet]. Available: https://www.docsy.dev

61. Netlify [Internet]. Available: https://www.netlify.com

62. Orygen. ready4: Open and modular mental health systems models [Internet]. 2022. Available: https://zenodo.org/communities/ready4

63. Orygen. ready4: Open and modular mental health systems models [Internet]. 2022. Available: https://dataverse.harvard.edu/dataverse/ready4)

64. Hamilton MP. ready4: Implement open science computational models of mental health systems [Internet]. 2021. doi:10.5281/zenodo.5606250

65. Hamilton M. ready4pack: Author r packages that extend the Ready4 framework [Internet]. 2022. doi:10.5281/zenodo.5644322

66. Hamilton M, Wiesner G. ready4fun: Author and document functions that extend the Ready4 framework [Internet]. 2022. doi:10.5281/zenodo.5611779

67. Hamilton M, Wiesner G. ready4class: Author Ready4 framework modules [Internet]. 2022. doi:10.5281/zenodo.5640313

68. Hamilton M, Wiesner G. ready4use: Author, label and share Ready4 framework datasets [Internet]. 2022. doi:10.5281/zenodo.5644336

69. Hamilton M, Wiesner G. ready4show: Author literate programs to share insights from applying the Ready4 framework [Internet]. 2022. doi:10.5281/zenodo.5644568

70. Hamilton M, Gao C. Complete study program to reproduce all steps from data ingest through to results dissemination for a study to map mental health measures to AQoL-6D health utility [Internet]. Zenodo; 2022. doi:10.5281/zenodo.6212704

71. Hamilton MP. ready4-dev/ttu_lng_ss: Create a Draft Scientific Manuscript For A Utility Mapping Study [Internet]. Zenodo; 2022. doi:10.5281/zenodo.5976988

72. Hamilton MP, Gao CX. Youthu: Transform youth outcomes to health utility predictions [Internet]. Zenodo; 2022. doi:10.5281/zenodo.6210978

73. Hamilton M, Gao C. youthvars: Describe and Validate Youth Mental Health Datasets [Internet]. Zenodo; 2022. doi:10.5281/zenodo.6084467

74. Hamilton M, Gao C. Scorz: Score questionnaire item responses [Internet]. Zenodo; 2022. doi:10.5281/zenodo.6084824

75. Hamilton M, Gao C. specific: Specify Candidate Models for Representing Mental Health Systems [Internet]. Zenodo; 2022. doi:10.5281/zenodo.6116701

76. Gao C, Hamilton M. TTU: Implement Transfer to Utility Mapping Algorithms [Internet]. Zenodo; 2022. doi:10.5281/zenodo.6130155

77. Hamilton MP. Synthetic (fake) youth mental health datasets and data dictionaries [Internet]. Harvard Dataverse; 2021. doi:10.7910/DVN/HJXYKQ

78. Hamilton MP, Gao CX, Filia KM, Menssink JM, Sharmin S, Telford N, et al. Transfer to AQoL-6D Utility Mapping Algorithms [Internet]. Harvard Dataverse; 2021. doi:10.7910/DVN/DKDIB0

79. Hamilton M, Gao C. aqol6dmap_use: Apply AQoL-6D Utility Mapping Models To New Data [Internet]. Zenodo; 2022. doi:10.5281/zenodo.6416330

80. Hamilton MP, Gao CX, Filia KM, Menssink JM, Sharmin S, Telford N, et al. Mapping psychological distress, depression and anxiety measures to AQoL-6D utility using data from a sample of young people presenting to primary mental health services. medRxiv. Cold Spring Harbor Laboratory Press; 2022; doi:10.1101/2021.07.07.21260129

81. Hamilton MP. aqol6dmap_fakes: Generate fake input data for an AQoL-6D mapping study [Internet]. Zenodo; 2022. doi:10.5281/zenodo.6321821

82. Hamilton M. ttu_mdl_ctlg: Generate a template utility mapping (transfer to utility) model catalogue [Internet]. Zenodo; 2022. doi:10.5281/zenodo.6116385

83. Long KM, Meadows GN. Simulation modelling in mental health: A systematic review. Journal of Simulation. 2017; doi:10.1057/s41273-017-0062-0

84. Clearinghouse C. Basu, kim: Alcohol use disorder [Internet]. OSF; 2018. Available: osf.io/jvayu

85. Evaluation of Value C for the, Health R in. Open-source model clearinghouse [Internet]. Tufts Medical Center; Available: http://ghcearegistry.org/orchard/open-source-model-clearinghouse

86. Innovation T, Initiative V. IVI-MDD value model [Internet]. 2022. Available: https://www.thevalueinitiative.org/ivi-mdd-value-model/

87. Statistical Computing RF for. The comprehensive r archive network [Internet]. 2022. Available: https://cran.r-project.org

88. Pitt C, Goodman C, Hanson K. Economic evaluation in global perspective: A bibliometric analysis of the recent literature. Health Economics. Wiley Online Library; 2016;25: 9–28.

89. Mental Health Research QC for. National mental health systems modelling network [Internet]. 2022. Available: https://qcmhr.org/research/research-streams/mental-health-services-research/national-mental-health-systems-modelling-network/

90. Zabell T, Long KM, Scott D, Hope J, McLoughlin I, Enticott J. Engaging healthcare staff and stakeholders in healthcare simulation modeling to better translate research into health impact: A systematic review. Frontiers in Health Services. 2021;1. doi:10.3389/frhs.2021.644831

91. Squires H, Chilcott J, Akehurst R, Burr J, Kelly MP. A framework for developing the structure of public health economic models. Value in Health. 2016;19: 588–601. doi:https://doi.org/10.1016/j.jval.2016.02.011

92. Muñoz JAM, Munoz CMM, Serrano AIP, Antón DML, Espejo ALS. Health economics: Identifying leading producers, countries relative specialization and themes. Revista de Estudios Empresariales Segunda época. Facultad de Ciencias Sociales y Juridicas; 2020; 7–19.

93. Fried EI, Robinaugh DJ. Systems all the way down: Embracing complexity in mental health research. BMC Medicine. 2020;18: 205. doi:10.1186/s12916-020-01668-w

94. Langellier BA, Yang Y, Purtle J, Nelson KL, Stankov I, Diez Roux AV. Complex systems approaches to understand drivers of mental health and inform mental health policy: A systematic review. Administration And Policy In Mental Health. 2018; doi:10.1007/s10488-018-0887-5

95. Jorm AF, Patten SB, Brugha TS, Mojtabai R. Has increased provision of treatment reduced the prevalence of common mental disorders? Review of the evidence from four countries. World psychiatry : official journal of the World Psychiatric Association (WPA). 2017;16: 90–99. doi:10.1002/wps.20388

96. Furst MA, Gandré C, Romero López-Alberca C, Salvador-Carulla L. Healthcare ecosystems research in mental health: A scoping review of methods to describe the context of local care delivery. BMC Health Services Research. 2019;19: 173. doi:10.1186/s12913-019-4005-5

97. Alegría M, NeMoyer A, Falgàs Bagué I, Wang Y, Alvarez K. Social determinants of mental health: Where we are and where we need to go. Current Psychiatry Reports. 2018;20: 95–95. doi:10.1007/s11920-018-0969-9