State of the Practice for Medical Imaging Software Based on Open Source Repositories

Spencer Smith[a], Ao Dong[a], Jacques Carette[a], Michael Noseworthy[b]

[a]*McMaster University, Computing and Software Department, 1280 Main Street West, Hamilton, L8S 4K1, Ontario, Canada*

[b]*McMaster University, Electrical and Computer Engineering, 1280 Main Street West, Hamilton, L8S 4K1, Ontario, Canada*

Abstract

We present the state of the practice for Medical Imaging (MI) software based on data available in open source repositories. We selected 29 projects from 48 candidates and assessed 9 software qualities (installability, correctness/ verifiability, reliability, robustness, usability, maintainability, reusability, understandability, and visibility/transparency) by answering 108 questions for each. Using the Analytic Hierarchy Process (AHP) on the quantitative data, we ranked the MI software. The top five are *3D Slicer*, *ImageJ*, *Fiji*, *OHIF Viewer*, and *ParaView*. This is consistent with the community's view, with four of these also appearing in the top five using GitHub metrics (stars-per-year). The quality and quantity of documentation present in a project correlates quite well with its popularity. Generally, MI software is in a healthy state as shown by the following: in the repositories we observed 88% of the documentation artifacts recommended by research software development guidelines, 100% of MI projects use version control tools, and developers appear to use the common quasi-agile research software development process. However, the current state of the practice deviates from the existing guidelines because of the rarity of some recommended artifacts (like a test plan, requirements specification, code of conduct, and code style guidelines), low usage of continuous integration (17% of the projects), low use of unit testing (about 50% of projects), and room for improvement with documentation. From interviewing the developers, we identified 6 concerns: lack of development time, lack of funding, technology hurdles, correctness, usability, maintainability, and reproducibility. Recommendations for improving the state of the practice include the following: increase documentation, increase testing by enriching datasets, increase continuous integration usage, move to web applications, employ linters, use peer reviews, and design for change.

Keywords: medical imaging, research software, software engineering, software quality, analytic hierarchy process

1. Introduction

We study the state of software development practice for Medical Imaging (MI) software using data available in open source repositories. MI tools use images of the interior of the body (from sources such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron

Emission Tomography (PET) and Ultrasound) to provide critical information for diagnostic, analytic, and medical applications. Given its importance, we want to understand the merits and drawbacks of the current development processes, tools, and methodologies. We use a software engineering lens to assess the quality of existing MI software.

1.1. Research Questions

As well as state of the practice (SOP) for MI software, we would like to understand the impact of the often cited gap (chasm!) between recommended software engineering practices and that used for most research software [1]. Although scientists spend a substantial proportion of their working times on software development [2, 3], few are formally trained [2].

Our investigation is based on the following four research questions:

RQ1: What MI open source software projects exist? (Section 2)

RQ2: Based on quantitative measurements of each project's development practices, which projects follow best practices? (Section 2)

RQ3: How similar are the top projects identified in RQ2 to the most popular projects as viewed by the community? (Section 3.1)

RQ4: How do MI projects compare to general research software with respect to the artifacts (documents, scripts and code) present in their repositories? (Section 3.2)

RQ5: How do MI projects compare to research software in general with respect to the use of tools (Section 4) for:

- RQ5.a development; and,
- RQ5.b project management?

RQ6: How do MI projects compare to research software in general with respect to principles, processes, and methodologies used? (Section 5)

RQ7: What are the pain points for developers working on MI software projects? (Section 6)

RQ8: How do the pain points of developers from MI compare to the pain points for research software in general? (Section 6)

RQ9: For MI developers what specific best practices are taken to address the pain points and software quality concerns? (Section 6)

RQ10: What research software development practice could potentially address the pain point concerns identified in RQ7? (Section 7)

1.2. Scope

We only cover MI visualization software. We exclude other categories of MI software, including segmentation, registration, visualization, enhancement, quantification, simulation, plus MI archiving and telemedicine systems (compression, storage, and communication). We also exclude statistical analysis and image-based physiological modelling and feature extraction, classification, and interpretation. Software that provides MI support functions is also out of scope; therefore, we have not assessed the toolkit libraries VTK and ITK. Finally, Picture Archiving and Communication System (PACS), which helps users to economically store and conveniently access images, are considered out of scope.

1.3. Methodology

We have a standard set of questions designed to assess the qualities of any research software project. [blind review redacted details on the author's previous studies using the same methodology.] We maintain the previous constraint that the work load for measuring a given domain should take around one person-month's worth of effort (20 working days at 8 person-hours per day).

We identify a list of potential packages (through online searches) which is then filtered and vetted by a domain expert. We aim for roughly 30 packages. For each remaining package, we measure its qualities by filling in a grading template [citation redacted for double blind]. This data is used to rank the projects with the Analytic Hierarchy Process (AHP). We summarize further details on the interaction with the domain expert, software qualities, grading the software and AHP below and in longer form in [redacted for double blind].

1.3.1. Domain Expert

The Domain Expert vets the proposed list because online resources can be inaccurate. The expert also vets the AHP ranking. For the current assessment, our Domain Expert is [details of our domain expert removed for double-blind].

In advance of the first meeting with the Domain Expert, they are asked to independently create a list of top software packages in the domain. This helps get the expert's knowledge refreshed in advance of the meeting.

1.3.2. Software Qualities

Quality is defined as a measure of the excellence or worth of an entity. As is common practice, we do not think of quality as a single measure, but rather as a set of measures. That is, quality is a collection of different qualities, often called "ilities." For this study we selected 9 qualities to measure: installability, correctness/ verifiability, reliability, robustness, usability, maintainability, reusability, understandability, and visibility/transparency. With the exception of installability, all the qualities are defined in Ghezzi et al. (2003) [4]. Installability is defined as the effort required for the installation and/or uninstallation of software in a specified environment [5].

1.3.3. Grading

We use an existing template [citation redacted] that is designed to measure the aforementioned qualities. To stay within our given measurement time frame, each package gets up to five hours of time. Project developers can be contacted for help regarding installation, if necessary, but we impose a cap of about two hours on the installation process. Figure 1 shows an excerpt of the measurement spreadsheet. The rows are the measures and the columns correspond to the software packages. [The full data is available on Mendeley; link will be provided after refereeing.]

Summary Information						
Software name?	3D Slicer	Ginkgo CADx	XMedCon	Weasis	ImageJ	DicomBrowser
Number of developers	100	3	2	8	18	3
Initial release date?	1998	2010	2000	2010	1997	2012
Last commit date?	02-08-2020	21-05-2019	03-08-2020	06-08-2020	16-08-2020	27-08-2020
Status?	alive	alive	alive	alive	alive	alive
License?	BSD	GNU LGPL	GNU LGPL	EPL 2.0	OSS	BSD
Software Category?	public	public	public	public	public	public
Development model?	open source	open source	open source	open source	open source	open source
Num pubs on the software?	22500	51	185	188	339000	unknown
Programming language(s)?	C++, Python, C	C++, C	C	Java	Java, Shell, Perl	Java, Shell
…	…	…	…	…	…	…
Installability						
Installation instructions?	yes	no	yes	no	yes	no
Instructions in one place?	no	n/a	no	n/a	yes	n/a
Linear instructions?	yes	n/a	yes	n/a	yes	n/a
Installation automated?	yes	yes	yes	yes	no	yes
messages?	n/a	n/a	n/a	n/a	n/a	n/a
Number of steps to install?	3	6	5	2	1	4
Numbe extra packages?	0	0	0	0	1	0
Package versions listed?	n/a	n/a	n/a	n/a	yes	n/a
Problems with uninstall?	no	no	no	no	no	no
…	…	…	…	…	…	…
Overall impression (1..10)?	10	8	8	7	6	7
…	…	…	…	…	…	…
Correctness/Verifiability						
…	…	…	…	…	…	…

Figure 1: Grading template example

The full template consists of 108 questions over 9 qualities. These questions are designed to be unambiguous, quantifiable, and measurable with constrained time and domain knowledge.

The grader, after answering questions for each quality assigns an overall score (between 1 and 10) based on the answers. Several of the qualities use the word "surface" to highlight that these particular qualities are a shallow measure. For example, usability is not measured using user studies. Instead, we look for signs that the developers considered usability. We use two freeware tools to collect repository related data: GitStats and Sloc Cloc and Code (scc). Further details on quality measurement are provided in [redacted for double blind].

1.3.4. Analytic Hierarchy Process (AHP)

Developed by Saaty in the 1970s, AHP is widely used to analyze multiple criteria decisions [6]. AHP organizes multiple criteria in a hierarchical structure and uses pairwise comparisons between alternatives to calculate relative ratios [7]. AHP works with sets of n *options* and m *criteria*. In our project $n = 29$ and $m = 9$ since there are 29 options (software products) and 9 criteria (qualities). With AHP the sum of the grades (scores) for all products for a given quality will be 1.0. We rank the software for each of the qualities, and then we combine the quality rankings into an overall ranking based on the relative priorities between qualities.

2. Results

In this section we answer RQ1 and RQ2.

2.1. *In-Scope Open-Source MI Software*

We initially identified 48 candidate software projects from the literature [8, 9, 10], on-line articles [11, 12, 13], and forum discussions [14]. Then we filtered as follows:

1. Removed the packages with no source code available, such as *MicroDicom*, *Aliza*, and *jivex*.

2. Focused on MI software that provides visualization functions. We removed seven packages that were toolkits or libraries, such as *VTK*, *ITK*, and *dcm4che*, and another three that were for PACS.

3. Removed *Open Dicom Viewer* as it has not received any updates since 2011.

The Domain Expert provided a list 12 software packages. We found 6 packages were on both lists: *3D Slicer*, *Horos*, *ImageJ*, *Fiji*, *MRIcron* (we use its descendant *MRIcroGL*) and *Mango* (we use the web version *Papaya*). The remaining six packages were on our out-of-scope list. The Domain Expert agreed with our final choice of 29 packages. Table 1 summarizes the in-scope open-source MI software that is available at the time of measurement (the year 2020), thus answering RQ1.

In Table 1 the projects are sorted in descending order of lines of code. We found the initial release dates (Rlsd) for most projects and marked the two unknown dates with "?". The date of the last update is the date of the latest update, at the time of measurement. We found funding information (Fnd) for only eight projects. For the Number Of Contributors (NOC) we considered anyone who made at least one accepted commit as a contributor. The NOC is not usually the same as the number of long-term project members, since many projects received change requests and code from the community. With respect to the OS, 25 packages work on all three OSs: Windows (W), macOS (M), and Linux (L). Although the usual approach to cross-platform compatibility was to work natively on multiple OSes, five projects achieved platform-independence via web applications. The full measurement data for all packages is available on [removed for blind review]

The programming languages used in order of decreasing popularity are C++, JavaScript, Java, C, Python, Pascal, Matlab. The most popular language is C++, for 11 of 29 projects; Pascal and Matlab were each used for a single project.

2.2. *Which Projects Follow Best Practices?*

To answer RQ2 we measured the software as described in Section 1.3. In the absence of a specific real world context, we assumed all nine qualities are equally important. Figure 2 shows the overall scores in descending order.

The top four software products *3D Slicer*, *ImageJ*, *Fiji*, and *OHIF Viewer* have higher scores in most criteria. *3D Slicer* has a score in the top two for all qualities; *ImageJ* ranks near the top for all qualities, except for correctness & verifiability. *OHIF Viewer* and *Fiji* have similar overall scores, with *Fiji* doing better in installability and *OHIF Viewer* doing better in correctness &

Software	Rlsd	Updated	Fnd	NOC	LOC	OS			Web
						W	M	L	
ParaView [15]	2002	2020-10	✓	100	886326	✓	✓	✓	✓
Gwyddion [16]	2004	2020-11		38	643427	✓	✓	✓	
Horos [17]	?	2020-04		21	561617		✓		
OsiriX Lite [18]	2004	2019-11		9	544304		✓		
3D Slicer [19]	1998	2020-08	✓	100	501451	✓	✓	✓	
Drishti [20]	2012	2020-08		1	268168	✓	✓	✓	
Ginkgo CADx [21]	2010	2019-05		3	257144	✓	✓	✓	
GATE [22]	2011	2020-10		45	207122		✓	✓	
3DimViewer [23]	?	2020-03	✓	3	178065	✓	✓		
medInria [24]	2009	2020-11		21	148924	✓	✓	✓	
BioImage Suite Web [25]	2018	2020-10	✓	13	139699	✓	✓	✓	✓
Weasis [26]	2010	2020-08		8	123272	✓	✓	✓	
AMIDE [27]	2006	2017-01		4	102827	✓	✓	✓	
XMedCon [28]	2000	2020-08		2	96767	✓	✓	✓	
ITK-SNAP [29]	2006	2020-06	✓	13	88530	✓	✓	✓	
Papaya [30]	2012	2019-05		9	71831	✓	✓	✓	
OHIF Viewer [31]	2015	2020-10		76	63951	✓	✓	✓	✓
SMILI [32]	2014	2020-06		9	62626	✓	✓	✓	
INVESALIUS 3 [33]	2009	2020-09		10	48605	✓	✓	✓	
dwv [34]	2012	2020-09		22	47815	✓	✓	✓	✓
DICOM Viewer [35]	2018	2020-04	✓	5	30761	✓	✓	✓	
MicroView [36]	2015	2020-08		2	27470	✓	✓	✓	
MatrixUser [37]	2013	2018-07		1	23121	✓	✓	✓	
Slice:Drop [38]	2012	2020-04		3	19020	✓	✓	✓	✓
dicompyler [39]	2009	2020-01		2	15941	✓	✓		
Fiji [40]	2011	2020-08	✓	55	10833	✓	✓	✓	
ImageJ [41]	1997	2020-08	✓	18	9681	✓	✓	✓	
MRIcroGL [42]	2015	2020-08		2	8493	✓	✓	✓	
DicomBrowser [43]	2012	2020-08		3	5505	✓	✓	✓	

Table 1: Final software list (sorted in descending order of the number of Lines Of Code (LOC))

verifiability. Given the installation problems, we may have underestimated the scores on reliability and robustness for *DICOM Viewer*, but we compared it equally for the other seven qualities.

[Summary description list]

2.3. Installability

We found installation instructions for 16 projects, but two did not need them (*BioImage Suite Web* and *Slice:Drop*) as they are web applications. 10 of the projects required extra dependencies:

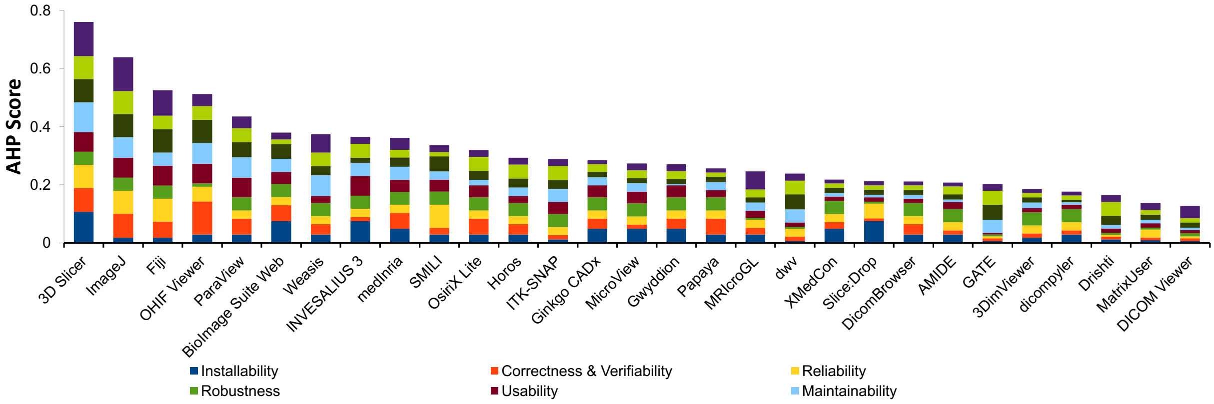

Figure 2: Overall AHP scores with an equal weighting for all 9 software qualities

Five depend on a specific browser; *dwv*, *OHIF Viewer*, and *GATE* needs extra libraries to build; *ImageJ* and *Fiji* need an unzip tool; *MatrixUser* needs Matlab; *DICOM Viewer* needs a Nextcloud platform.

The scores are based on the ease of following the installation instructions, and automated installation and uninstallation process. There were no issues for all but the bottom four, just various degrees of ease and automation. *GATE*, *dwv*, and *DICOM Viewer* showed severe installation problems. We were not able to install them, even after a reasonable amount of time (2 hours). For *dwv* and *GATE* we failed to build from the source code, but we were able to proceed with measuring other qualities using a deployed on-line version for *dwv*, and a virtual machine version for *GATE*. For *DICOM Viewer* we could not install the NextCloud dependency, and thus could not measure reliability nor robustness for it.

MatrixUser depends on Matlab, whose installation is not easy. For users who already have Matlab, this score should be higher.

2.4. *Correctness & Verifiability*

The packages with higher scores for correctness and verifiability used a wider array of techniques to improve correctness, and had better documentation to witness this. For instance, we looked for evidence of unit testing, and found evidence for only about half of the projects. We identified five projects using continuous integration tools: *3D Slicer*, *ImageJ*, *Fiji*, *dwv*, and *OHIF Viewer*.

Even for projects with well-organized documentation, requirements specifications and theory manuals were still missing. The only requirements-related document we found was a road map of *3D Slicer*, which contained design requirements for upcoming changes.

2.5. *Surface Reliability*

We were able to follow the steps in the tutorials that existed (seven packages had them.) However, *GATE* could not open macro files and became unresponsive several times, without any descriptive error message. We found that *Drishti* crashed when loading damaged image files, without showing any descriptive error message.

2.6. *Surface Robustness*

The packages with higher robustness scores gracefully handled unexpected or unanticipated inputs, typically showing a clear error message. We may have underscored *OHIF Viewer*, since we needed further customization to load data.

According to their documentation, all 29 software packages should support the DICOM standard. To test robustness, we prepared two types of image files: correct and incorrect formats (with the incorrect format created by relabelling a text file to have the ".dcm" extension). All software packages loaded the correct format image, except for *GATE*, which failed for unknown reasons. For the broken format, *MatrixUser*, *dwv*, and *Slice:Drop* ignored the incorrect format, did not show any error message and displayed a blank image. *MRIcroGL* behaved similarly except that it showed a meaningless image. *Drishti* successfully detected the broken format of the file, but the software crashed as a result.

2.7. *Surface Usability*

The software with higher usability scores usually provided both comprehensive documented guidance and a good user experience. *INVESALIUS 3* provided an excellent example of a detailed and precise user manual. *GATE* also provided numerous documents, but unfortunately we had difficulty understanding and using them. We found getting started tutorials for only 11 projects, but a user manual for 22 projects. *MRIcroGL* was the only project that explicitly documented expected user characteristics.

2.8. *Maintainability*

We gave *3D Slicer* the highest score for maintainability because we found it had the most comprehensive artifacts. Only a few of the 29 projects had a product, developer's manual, or API (Application Programming Interface) documentation, and only *3D Slicer*, *ImageJ*, *Fiji* included all three documents (see Table 2 for the full data). Moreover, *3D Slicer* has a much higher percentage of closed issues (92%) compared to *ImageJ* (52%) and *Fiji* (64%).

Twenty-seven of the 29 projects used git for version control, with 24 of these using GitHub. *AMIDE* used Mercurial and *Gwyddion* used Subversion. *XMedCon*, *AMIDE*, and *Gwyddion* used SourceForge. *DicomBrowser* and *3DimViewer* used BitBucket.

2.9. *Reusability*

We have assumed that smaller code files are likely more reusable – see Table 3 for the details.

2.10. *Surface Understandability*

All projects had a consistent coding style with parameters in the same order for all functions, modularized code, and, clear comments that indicate what is done, not how. However, we only found explicit identification of a coding standard for 3 out of the 29: *3D Slicer*, *Weasis*, and *ImageJ*. We also found hard-coded constants (rather than symbolic constants) in *medInria*, *dicompyler*, *MicroView*, and *Papaya*. We did not find any reference to the algorithms used in projects *XMedCon*, *DicomBrowser*, *3DimViewer*, *BioImage Suite Web*, *Slice:Drop*, *MatrixUser*, *DICOM Viewer*, *dicompyler*, and *Papaya*.

Software	Prod. Roadmap	Dev. Manual	API Doc.
3D Slicer	✓	✓	✓
ImageJ	✓	✓	✓
Weasis		✓	
OHIF Viewer		✓	✓
Fiji	✓	✓	✓
ParaView	✓		
SMILI			✓
medInria		✓	
INVESALIUS 3	✓		
dwv			✓
BioImage Suite Web		✓	
Gwyddion		✓	✓

Table 2: Software with the maintainability documents (listed in descending order of maintainability score)

2.11. Visibility/Transparency

Generally speaking, the teams that actively documented their development process and plans scored higher. Table 4 shows the projects that had documents for the development process, project status, development environment, and release notes.

3. Discussion

We first compare our ranking to a (proxy for) the community's ranking. We then compare the state of the practice for MI with that of other research software. In particular we provide details on recommended artifacts that are rarely observed for MI software. [other new sections] Section 10.1 presents threats to the validity of our data and conclusions.

3.1. Comparison to Community Ranking

We use GitHub stars, number of forks and number of people watching the projects are proxies for community ranking – see Table 5 for statistics collected in July 2021. Recall that 24 projects use GitHub. Our ranking and GitHub popularity, at least for the top five projects, seems to line up fairly well.

We ranked some popular packages fairly low, such as *dwv*. This is because we were unable to build it locally, even though we followed its installation instructions. However, we were able to use its web version for the rest of the measurements. Additionally, this version did not detect a broken DICOM file and instead displayed a blank image (Section 2.6). *DICOM Viewer* ranked low as we were unable to install the NextCloud platform.

Another likely reason for discrepancies is that we weighted all qualities equally. This is not likely how users implicitly rank the different qualities. This would require a broader user study to properly assess. Furthermore our measures of popularity are only *proxies* which are biased towards past rather than current preferences [44], as these are monotonically increasing quantities.

Finally there are often more factors than just quality that influence the popularity of "consumer" products.

Although both rankings are imperfect measures, they nevertheless suggest a correlation between best practices and popularity. We don't know if this is causal, in either direction (i.e. if best practices enable popularity or if popularity increases the need for using more software development best practices).

3.2. *Software Artifacts*

We use nine research software development guidelines to compare recommended software artifacts versus those present in MI software. These guidelines are:

- United States Geological Survey Software Planning Checklist [45],
- DLR (German Aerospace Centre) Software Engineering Guidelines [46],
- Scottish Covid-19 Response Consortium Software Checklist [47],
- Good Enough Practices in Scientific Computing [48],
- xSDK (Extreme-scale Scientific Software Development Kit) Community Package Policies [49],
- Trilinos Developers Guide [50],
- EURISE (European Research Infrastructure Software Engineers') Network Technical Reference [51],
- CLARIAH (Common Lab Research Infrastructure for the Arts and Humanities) Guidelines for Software Quality [52], and
- A Set of Common Software Quality Assurance Baseline Criteria for Research Projects [53].

In Table 6 each row corresponds to an artifact. For a given row, a checkmark in one of the columns means that the corresponding guideline recommends this artifact. The last column shows whether the artifact appears in the measured set of MI software, either not at all (blank), commonly (C), uncommonly (U) or rarely (R). We did our best to interpret the meaning of each artifact consistently between guidelines and specific MI software, but the terminology and the contents of artifacts are not standardized. The challenge even exists for the ubiquitous README file. The content of README files shows significant variation between projects [54]. Although some content is reasonably consistent, with 97% of README files contain at least one section describing the 'What' of the repository and 89% offering some 'How' content, other categories are more variable. For instance, information on 'Contribution', 'Why', and 'Who', appear in 28%, 26% and 53% of the analyzed files, respectively [54].

Table 7 presents our measurements for MI software. The table groups the artifacts by frequency into categories of common (20 to 29 (>67%) packages), uncommon (10 to 19 (33-67%) packages), and rare (1 to 9 (<33%) packages). Tables 2 and 4 show the details on which projects use which types of artifacts for documents related to maintainability and visibility, respectively.

Note that "popularity" in Table 6 does no imply that these oft recommended artifacts are the most important. Guidelines are often brief, to encourage adoption, and thus even guidelines that mention the need for installation instructions rarely mention uninstallation instructions. Two items in Table 7 do not appear in any guidelines: *Troubleshooting guide* and *Developer's manual*. However the information within these documents overlaps with the recommended artifacts. Troubleshooting information often can be found in a User Manual, while the information in a "Developer's Manual" is often scattered amongst many other documents.

Three of the 26 recommended artifacts were never observed in the MI software: i) Uninstall, ii) Test plans, and iii) Requirements. It is possible that some of these were created but never put under version control.

Neglecting requirements documentation is unfortunately common for research software, and MI software is no exception to this trend. Although such documentation is recommended by some [46, 50, 55], in practice this is rare [56]. Sanders and Kelly [57] interviewed 16 scientists from 10 disciplines and found that none of the scientists created requirements specifications, unless regulations in their field mandated such a document. Requirements are the least commonly produced type of documentation for research software in general [58].

This is unfortunate as when scientific developers are surveyed on their pain points, Wiese et al. [59] found that software requirements and management is the software engineering discipline that most hurts them, accounting for 23% of the technical problems reported by study participants. Further adding to the misfortune, there is a widespread perception that up-front requirements are impossible for research software [60, 61]. Fortunately a more agile approach to requirements is feasible [62], and research-software specific templates exist [63].

A theme emerges amongst the artifacts rarely observed in practice: they are developer-focused (a list of library dependencies, a contributor's guide, a developer Code of Conduct, coding style guidelines, product roadmap, design documentation and API documentation).

Other communities use checklists to help with best practices. Examples include checklists for merging branches [64], for saving and sharing changes to the project [48], for new and departing team members [65], for processes related to commits and releases [50] and for overall software quality [51, 66].

MI projects fall somewhat short of recommended best practices, but are not alone amongst research software projects. This gap has been documented before [1, 67], and is known to cause sustainability and reliability problems [68], and to waste development effort [69].

3.3. Interview Methods

The repository-based measurements summarize the information we can collect from on-line resources. This information is incomplete because it doesn't generally capture the development process, the developer pain points, the perceived threats to software quality, and the developers' strategies to address these threats. Therefore, part of our methodology involves interviewing developers.

We based our interviews on a list of 20 questions, which can be found in [70]. Some questions are about the background of the software, the development teams, the interviewees, and how they organize their projects. We also ask about the developer's understanding of the users. Some questions focus on the current and past difficulties, and the solutions the team has found, or plan to try. We also discuss documentation, both with respect to how it is currently done, and how it is perceived. A few questions are about specific software qualities, such as maintainability, understandability, usability, and reproducibility. The interviews are semi-structured based on the question list; we ask follow-up questions when necessary. The interview process presented here was approved by the McMaster University Research Ethics Board under the application number MREB#: 5219.

We sent interview requests to all 29 projects using contact information from projects websites, code repository, publications, and from biographic pages at the teams' institutions. In the end nine developers from eight of the projects agreed to participate: *3D Slicer*, *INVESALIUS 3*, *dwv*, *BioImage Suite Web*, *ITK-SNAP*, *MRIcroGL*, *Weasis*, and *OHIF*. We spent about 90 minutes for each interview. One participant was too busy to have an interview, so they wrote down their answers. In one case two developers from the same project agreed to be interviewed. We held the meetings on-line using either Zoom or Teams, which facilitated recording and automatic transcription. The full interview answers can be found in [71].

4. Comparison of Tool Usage Between MI and Other Research Software

Developers use software tools to support the development, verification, maintenance, and evolution of software, software processes, and artifacts [4, p. 501]. MI software uses tools for CI/CD, user support, version control, documentation, and project management. To answer RQ5 we summarize the tool usage in these categories, and compare this to the usage by the research software community.

Table 8 summarizes the user support models by the number of projects using each model (projects may use more than one support model). We do not know whether the prevalent use of GitHub issues for user support is by design, or whether this just naturally happens as users seek help. The common use of GitHub by MI developers is not surprising, given that GitHub is the largest code host in the world, with over 128 million public repositories and over 23 million users (as of roughly February 26, 2020) [72].

From Section 2.8, 27 of the 29 projects used git as the version control tool, one used Mercurial and one used Subversion. The hosting is on GitHub for 24 packages, SourceForge for three and BitBucket for two. Although teams may have a process for accepting new contributions, no one discussed this during their interviews. However, most teams (eight of nine) mentioned using GitHub and pull requests to manage contributions from the community. The interviewees generally gave very positive feedback on using GitHub. Some teams previously used a different approach to version control and eventually transferred to git and GitHub. The past approaches included contributions from e-mail (three teams), contributions from forums (one team) and e-mailing the git repository back and forth between developers (one team).

The common use of version control for MI software illustrates considerable improvement from the poor adoption of version control tools that Wilson lamented in 2006 [73]. The proliferation of version control tools for MI matches the increase in the broader research software community. A little over 10 years ago [58] estimated that only 50% of research software projects use version control, but even at that time [58] noted an increase from previous usage levels. A survey in 2018 shows 81% of developers use a version control system [74]. [75] has similar results, showing version control usage for alive projects in mesh generation, geographic information systems and statistical software for psychiatry increasing from 75%, 89% and 17% (respectively) to 100%, 95% and 100% (respectively) over a four-year period ending in 2018. (For completeness the same study showed a small decrease in version control usage for seismology software over the same time period, from 41% down to 36%). A recent survey by [76] shows version control use among practitioners at over 95%, with 83/87 survey respondents indicating that they use it. All but one of the software guides cited in Section 3.2 includes the advice to use version control. (The USGS guide [45] was the only set of recommendations to not mention version control.) The high usage of version control tools in MI software matches the trend in research software in general.

As mentioned in Section 2.4, we identified five projects using CI/CD tools (about 17% of the assessed projects). We found which projects used CI/CD by examining the documentation and source code of all projects. The count of CI/CD usage may actually be higher, since traces of CI/CD usage may not always appear in a repository. This was the case for a study of LBM software, where interviews with developers showed that more projects used CI/CD than was evident from repository artifacts alone [77]. The 17% utilization for MI software contrasts with the high frequency with which research software development guidelines recommend continuous integration [47, 64, 51, 78, 52]. Although there is currently little data available on CI/CD utilization for research software, our impression is that CI/CD is not yet common practice, despite its recommendation. This is certainly the case for LBM software, where usage numbers are similar to MI software, with only 12.5% of 24 LBM packages showing evidence of CI/CD in their repositories [77]. The survey of [76] suggests higher use of CI/CD with 54% (54/100) of respondents indicating that they use it. However, that survey measures something different from the current one by surveying practitioners, rather than assessing projects. Additional information on CI/CD is given in the recommendations (Section 7.1).

For documentation tools and methods mentioned by the interviewees, the most popular (mentioned by about 30% of developers) were forum discussions and videos. The second most popular options (mentioned by about 20% of developers) were GitHub, wiki pages, workshops, and social media. The least frequently mentioned options (about 10% of developers) included writing books, and google forms. In contrasting MI software with LBM software, the most significant documentation tool difference is that LBM software often uses document generation tools, like doxygen and sphinx [77], while MI does not appear to use these tools.

Some interviewees mentioned the project management tools they used. Generally speaking, the interviewees talked about two types of tools: i) trackers, including GitHub, issue trackers, bug trackers and Jira; and, ii) documentation tools, including GitHub, Wiki page, Google Doc, and Confluence. Of the specifically named tools in the above lists, interviewees mentioned GitHub 3 times, and each of the other tools once each.

Based on information provided by [79], tool utilization for MI software has much in common with tool utilization for ocean modelling software. Both use tools for editing, compiling, code management, testing, building, and project management. From the data available, ocean modelling differs from MI software in its use of Kanban boards for project management.

5. Comparison of Principles, Process, and Methodologies to Research Software in General

We answer research question RQ6 by comparing the principles, processes, and methodologies used for MI software to what can be gleaned from the literature on research software in general. In our interviews with developers the responses about development model were vague, with only two interviewees following a definite development model. In some cases the interviewees felt their process was similar to an existing development model. Three teams (about 38%) either followed agile, or something similar to agile. Two teams (25%) either followed a waterfall process, or something similar. Three teams (about 38%) explicitly stated that their process was undefined or self-directed.

Our observations of an informally defined process, with elements of agile methods, matches what has been observed for research software in general. Scientific developers naturally use an agile philosophy [80, 60, 81, 82, 56], or an amethododical process [83], or a knowledge acquisition driven process [84]. A waterfall-like process can work for research software [62], especially if the developers work iteratively and incrementally, but externally document their work as if they followed a rationale design process [85].

No interviewee introduced any strictly defined project management process. The most common approach was following the issues, such as bugs and feature requests. Additionally, the *3D Slicer* team had weekly meetings to discuss the goals for the project; the *INVESALIUS 3* team relied on the GitHub process for their project management; the *ITK-SNAP* team had a fixed six-month release pace; only the interviewee from the *OHIF* team mentioned that the team has a project manager; the *3D Slicer* team and *BioImage Suite Web* team do nightly builds and tests. The *OHIF* developer believes that a better project management process can improve junior developer efficiency while also improving internal and external communication.

We identified the use of unit testing in less than half of the 29 projects. On the other hand, the interviewees believed that testing (including usability tests with users) was the top solution to improve correctness, usability, and reproducibility. This level of testing matches what was observed for LBM software [77] and is apparently greater than the level of testing for ocean modelling software. [79] reports that ocean modellers underemphasize testing.

As the observed artifacts in Table 7 show, none of the 29 projects emphasize documentation. None of them had theory manuals, although we did identify a road map in the *3D Slicer* project. We did not find requirements specifications. Table 9 summarizes interviewees' opinions on documentation. Interviewees from each of the eight projects thought that documentation was essential to their projects, and most of them said that it could save their time to answer questions from users and developers. Most of them saw the need to improve their documentation, and only three of them thought that their documentations conveyed information clearly enough. Nearly half of developers also believed that the lack of time prevented them from improving documentation.

As Table 6 suggests, an emphasis on documentation, especially for new developers, is echoed in research software guidelines. Multiple guidelines recommend a document explaining how to contribute to a project, often named CONTRIBUTING. Guidelines also recommend tutorials, user guides and quick start examples. [49] suggests including instructions specifically for on-boarding new developers. For open-source software in general (not just research software), [86] recommends providing tutorial style examples, developer guidelines, demos, and screenshots.

6. Developer Pain Points

Based on interviews with nine developers (described in Section 3.3), we answer three research questions (first mentioned in Section 1.1): RQ7) What are the pain points for developers working on research software projects?; RQ8) How do the pain points of developers from MI compare to the pain points for research software in general?; and RQ9) For MI developers what specific best practices are taken to address the pain points and software quality concerns?

Our interviews identified pain points related to a lack of time and funding, technology hurdles, improving correctness, and improving usability. In this section, we go through each pain point and contrast the MI experience with observations from other domains. We also cover potential ways to address the pain points, as promoted by the community. (Later, in Section 7, we propose additional pain mitigation strategies based on our experience.) In addition to pain points, we summarize MI developer strategies for improving maintainability and reproducibility. Although the interviewees did not explicitly identify these two qualities as pain points, we did discuss threats to these qualities and ways to improve them as part of our interview process [70]. The interviewee's practices for addressing pain points and improving quality can potentially be emulated by other MI developers. Moreover, these practices may provide examples that can be followed by other research software domains.

[87] lists some pain points that did not come up in our conversations with MI developers: interruptions while coding, scope bloat, lack of user feedback, hard to collaborate on software projects, and aloneness. [59] also mention two research software pain points that did not explicitly arise in our interviews: reproducibility, and software scope determination. To the list of pain points not discussed for MI, our study of LBM software [88] adds lack of software experience for the developers, technical debt, and documentation. We did not observe any pain points for MI that were not also observed for LBM. From the pain points mentioned above, although the topics of reproducibility and technical debt did not come up in our MI interviews, we covered these two topics as part of the discussion of software qualities, as summarized at the end of this section. Although previous studies show pain points that were not mentioned by MI developers, we cannot conclude that these pain points are not relevant for MI software development, since we only interviewed nine developers for about an hour each.

P1: **Lack of Development Time:** Many interviewees thought lack of time, along with lack of funding (discussed next), were their most significant obstacles. Other domains of research software also experience the lack of time pain point [87, 89, 59]. Our study of LBM software [88] also highlighted lack of time as a significant pain point.

Potential and proven solutions suggested by the interviewees include:

- Shifting from development to maintenance when the team does not have enough developers for building new features and fixing bugs at the same time;
- Improving documentation to save time answering users' and developers' questions;
- Supporting third-party plugins and extensions; and,
- Using GitHub Actions for CI/CD (Continuous Integration and Continuous Delivery.)

P2: **Lack of Funding:** Developers felt the pain of having to attract funding to develop and maintain their software. For instance, the interviewees from *3D Slicer* and *OHIF* said getting funding for software maintenance is more challenging than finding funding for research. The interviewee from *ITK-SNAP* thought more funding was a way to solve the lack of time problem, because they could hire more dedicated developers. On the other hand, the interviewee from *Weasis* did not feel that funding could solve the same problem, since they would still need time to supervise the project.

Funding challenges have also been noted by others [90, 91, 92, 88]. Researchers that devote time to software have the additional challenge that funding agencies do not always count software when they are judging the academic excellence of the applicant. [59] reported developer pains related to publicity, since publishing norms have historically made it difficult to get credit for creating software. As studied by [93], research software (specifically biology software, but the trend likely applies to other research software domains) is infrequently cited. [87] also mentions the lack of formal reward system for research software.

An interviewee proposed an idea for increasing funding: Licensing the software to commercial companies to integrate it into their products.

P3: **Technology Hurdles:** The technology hurdles mentioned by MI developers include: hard to keep up with changes in OS and libraries, difficult to transfer to new technologies, hard to support multiple OSes, and hard to support lower-end computers. Developers expressed difficulty balancing between four factors: cross-platform compatibility, convenience to development and maintenance, performance, and security.

The pain point survey of [59] highlights that technology hurdles are an issue for research software in general. Some technical-related problems mentioned by [59] include dependency management, cross-platform compatibility (also mentioned by [87]), CI, hardware issues and operating system issues. From [88] technology pain points for LBM developers include setting up parallelization and CI.

The solutions proposed by the MI developers include the following:

- Adopting a web-based approach with backend servers, to better support lower-end computers;
- Using memory-mapped files to consume less computer memory, to better support lower-end computers;
- Using computing power from the computers GPU for web applications;
- Maintaining better documentations to ease the development and maintenance processes;
- Improving performance via more powerful computers, which one interviewee pointed out has already happened.

As the above list shows, developers perceive that web-based applications will address the technology hurdle. Table 10 shows the teams' choices between native application and web application. Most of the 29 teams (24 of 29, or 83%) chose to develop native applications. For the eight teams we interviewed, three of them were building web applications, and the *MRIcroGL* team was considering a web-based solution.

The advantage for native applications is higher performance, while web applications have the advantage of cross-platform compatibility and a simpler build process. These web advantages mirror the native disadvantages of difficulty with cross-platform compatibility and a complex build process. The lower performance disadvantage of web applications can be improved with a server backend, but in this case there are disadvantages for privacy protection and server costs. These issues are discussed further in the recommendations (Section 7.2).

P4: **Ensuring Correctness:** Interviewees identified multiple threats to correctness. The most frequently mentioned threat was complexity. Complexity enters the software by various means, including the large variety of data formats, complicated data standards, differing outputs between medical imaging machines, and the addition of (non-viewing related) functionality. Other threats to correctness identified include the following:

- Lack of real world image data for testing, in part because of patient privacy concerns ([59] mentions that the pain point of privacy concerns also arises for research software in general);
- Tests are expensive and time-consuming because of the need for huge datasets;
- Software releases are difficult to manage;
- No systematic unit testing; and,
- No dedicated quality assurance team.

As implied by the above threats to correctness, testing was the most often mentioned strategy for MI developers for ensuring correctness. Seven teams mentioned test related activities, including test-driven development, component tests, integration tests, smoke tests, regression tests, self tests and automated tests. With the common emphasis on testing to improve correctness, MI software is ahead of some other scientific domains. For scientific software in general [87] mention the problem of insufficient testing and [94] show that more developers think testing is important than the number that believe they have a sufficient understanding of testing concepts. Our study of LBM software suggests that this domain shares the challenges of insufficient testing and insufficient understanding of testing concepts [88]. Automated testing is a specific challenge for LBM software since free testing services do not offer adequate facilities for large amounts of data [88]. Although not specifically mentioned during our interviews, the large data sets for MI likely also cause a challenge for using free testing services, like GitHub Actions.

Research software in general often struggles with the oracle problem for testing because for many potential test cases the developer doesn't have a means to judge the correctness of their calculated solutions [94, 95, 96, 59]. The MI developers did not allude to this challenge, likely because for a give image (test case) it is possible to determine, potentially by using other software, the expected analysis results.

A frequently cited strategy for building confidence in correctness (mentioned by 3 interviewees) is a two state development process with stable releases and nightly builds. Other strategies for ensuring correctness that came up during the interviews include CI/CD, using de-identified copies of medical images for debugging, sending beta versions to medical workers who can access the data to do the tests, and collecting/maintaining a dataset of problematic images. Some additional strategies used by MI developers include:

- Using open datasets.
- If (part of) the team belongs to a medical school or a hospital, using the datasets they can access;
- If the team has access to MRI scanners, self-building sample images for testing;
- If the team has connections with MI equipment manufacturers, asking for their help on data format problems;

The feedback from the interviewees makes it clear that increased connections between the development team and medical professionals/institutions could ease the pain of ensuring correctness via testing.

P5: **Usability:**

The discussion with the developers focused on usability issues for two classes of users: the end users and other developers. The threats to usability for end users include an unintuitive user interface, inadequate feedback from the interface (such as lack of a progress bar), users being unable to determine the purpose of the software, not all users knowing if the software includes certain features, not all users understanding how to use the command line tool, and not all users understanding that the software is a web application. For developers the threats to usability include not being able to find clear instructions on how to deploy the software, and the architecture being difficult for new developers to understand.

At least to some extent the problems for MI software users are due to holes in their background knowledge. The survey of [59] for research software in general also mentioned that users do not always have the expertise required to install or use the software. [88] observes a similar pattern for LBM software, with several LBM developers noting that users sometimes try to use incorrect method combinations. Furthermore, some LBM users think that the packages will work out of the box to solve their cases, while in reality computational fluid dynamics knowledge needs to be applied to correctly modify the packages for a new endeavour.

To improve the usability of MI software, the most common strategies mentioned by developers are as follows:

- Use documentation (user manuals, mailing lists, forums) (mentioned by 4 developers)

- Usability tests and interviews with end users; and, (mentioned by 3 developers)
- Adjusting the software according to user feedback. (mentioned by 3 developers)

Other suggested and practiced strategies include a graphical user interface, testing every release with active users, making simple things simple and complicated things possible, focusing on limited number of functions, icons with clear visual expressions, designing the software to be intuitive, having a UX (User eXperience) designer, dialog windows for important notifications, providing an example for users to follow, downsampling images to consume less memory, and providing an option to load only part of the data to boost performance. The last two points recognize that an important component of usability is performance, since poor performance frustrates users.

Up to this point, we have covered the pain points that came up in interviews with MI developers, along with a summary of the techniques that are currently used to address these pain points. Although the developers did not explicitly identify the qualities of maintainability and reproducibility as pain points in our interviews, as part of our interview questions (Section 3.3) they did share their approaches for improving these qualities, as discussed below.

Q1: **Maintainability:** [58] rate maintainability as the third most important software quality for research software in general. The push for sustainable software [69] is motivated by the pain that past developers have had with accumulating too much technical debt [97]. For LBM software, [88] identifies technical debt as one of the developer pain points.

To improve maintainability, the most popular (with five out of nine interviewees mentioning it) strategy is to use a modular approach, with often repeated functions in a library. Other strategies that were mentioned for improving maintainability include supporting third-party extensions, an easy-to-understand architecture, a dedicated architect, starting from simple solutions, and documentation. The *3D Slicer* team used a well-defined structure for the software, which they named as an "event-driven MVC pattern". Moreover, *3D Slicer* discovers and loads necessary modules at runtime, according to the configuration and installed extensions. The *BioImage Suite Web* team had designed and re-designed their software multiple times in the last 10+ years. They found that their modular approach effectively supports maintainability [98].

Q2: **Reproducibility:** Although the MI developers did not mention reproducibility explicitly as a pain point, they did mention the need to improve documentation. Good documentation does not just address the pain points of lack of developer time (P1), technology hurdles (P3), usability P5, and maintainability. Documentation is also necessary for reproducibility. The challenges of inadequate documentation are a known problem for research software [87, 59] and for non-research software [99].

In our interviews, we discussed threats to reproducibility and strategies for improving it. The threats that were mentioned include closed-source software, no user interaction tests, no unit tests, the need to change versions of some common libraries, variability between CPUs, and misinterpretation of how manufacturers create medical images.

The most commonly cited (by 6 teams) strategy to improve reproducibility was testing (regression tests, unit tests, having good tests). The second most common strategy (mentioned by 5 teams) is making code, data, and documentation available, possibly by creating open-source libraries. Other ideas that were mentioned include running the same tests on all platforms, a dockerized version of the software to insulate it from the OS environment, using standard libraries, monitoring the upgrades of the library dependencies, clearly documenting the version information, bringing along the exact versions of all the dependencies with the software, providing checksums of the data, and benchmarking the software against other software that overlaps in functionality. Specifically one interviewee suggested using *3D Slicer* as the benchmark to test their reproducibility.

7. Recommendations

In this section we provide recommendations to address the pain points from Section 6 to answer RQ10. Our recommendations are not lists of criticisms for what should have been done in the past, or what should be done now; they are suggestions for consideration in the future. We expand on some of the ideas that came out of our interviews with developers (Section 6), including continuous integration, moving to web applications, and enriching the test data sets. We also bring in new ideas from our experience like employing linters, peer review, design for change and assurance cases. Our aim is to mention ideas that are at least somewhat beyond conventional best practices. The ideas listed here have the potential to become best practices in the medium to long-term. We list the ideas roughly in the order of increasing implementation effort.

7.1. Use Continuous Integration

Continuous integration involves frequent pushes to a code repository. With every push the software is built and tested [100, p. 13], [101, 102]. CI can take significant time and effort to set up and integrate into a team's workflow, but the benefits are significant, as follows:

- Elimination of headaches associated with a separate integration phase [102], [100, p. 20]. If developers postpone integration, integration problems are inevitable. Continuous integration means that problems are immediately obvious and the source of the problem can be isolated to the small increment that was just committed.

- Detection and removal of bugs [102] via automated testing. To improve productivity, defects are best discovered and fixed at the point where they are introduced [100, p. 23]. Code is not the only source of errors; they are also found in the files and scripts related to configuration management [100, p. 18].

- Everyone is always working on a stable base, since the rejection of inadequate commits means that the main branch will always be working. A stable base will always pass all tests. If the CI system uses generators and linters, it will also have current documentation and standard compliant code. A stable base improves developer productivity, allowing them to focus on coding, testing, and documentation.

CI consists of the following elements:

- A version control system [102]. To be effective, all files should be under version control, not just code files. Anything that is needed to build, install and run the software should be under version control, including configuration files, build scripts, test harnesses, and operating system configuration files [100, p. 19]. Fortunately for the MI, as shown in Section 2.8 all our measured projects use version control.

- A fully automated build system [102]. As [100, p. 5] point out, deploying software manually is an anti-pattern. For MI software, Table 7 shows 18 of 29 packages (62%) were observed to include build scripts. Projects without a build system will need to add one to pursue using CI.

- An automated test system [102]. Building quality software involves creating automated tests at the unit, component, and acceptance test level, and executing these tests whenever someone makes a change to the code, its configuration, the environment, or the software stack that it runs on [100, p. 83]. As Table 7 shows, test cases are in the uncommon category for MI software artifacts, which means that some MI projects will need to increase their testing automation if they wish to pursue CI.

- An automated system for other tasks, such as code checking, documentation building and web-site updating. These other tasks are not essential to CI, but they can be incorporated to improve the quality of the code and the communication between developers and users. For instance, a static analysis (possibly via linters) of the code may find poor programming practice or lack of adherence to adopted coding standards.

- An integrated build system to pull everything together. Every time there is a check-in (for instance a pull request), the integration server automatically checks out the sources onto the integration machine, starts a build, runs tests, and informs the committer of the results.

To enable incorporation into a team's workflow, [100, p. 60] explain that the usual approach for CI is to keep the build and test process short. Since MI files are large, the tests run with every check-in may need to focus on simple code interface tests, saving large tests for less frequent execution. A more sophisticated option to address the bottleneck for merges is CIVET (Continuous Integration, Verification, Enhancement, and Testing), which solves this problem by intelligently pinning, cancelling, and if necessary, restarting jobs as merges occur [103]. A more sophisticated process management system can also enforce rules for pull requests, like checking that a test specification includes the test's motivation, a test description, and a design description for all changes [103].

Setting up a CI system has never been easier than it is today. A dedicated CI server (either physically or virtually) can be installed with tools such as Jenkins, Buildbot, Go, and Integrity. However, installation on your own server is often unnecessary since there are many hosted CI solutions, such as: Travis CI, GitHub Actions and CircleCI. All that is required to begin using a hosted CI is to select the service and then edit a few lines of a YAML configuration file in the project's root directory.

[101] highlights the following challenges for adopting CI: lack of awareness and transparency, lack of expertise and skills, coordination and collaboration challenges, more pressure and workload for team members, general resistance to change, scepticism and distrust on continuous practices. The most common reason given for not adopting CI is that developers are not familiar enough with CI [104]. [101] observes that these problems can be mitigated via improving testing activities, planning and documentation, promoting a team mindset, adopting new rules and policies, and decomposing development into smaller units.

Continuous integration and delivery helps with addressing several pain points. For instance, CI/CD helps reduce development time (P1) by removing the need for a time-consuming integration stage and by automating regression testing. Automated regression tests also help with ensuring correctness (P4) and the quality of reproducibility (Q2).

7.2. *Move To Web Applications*

Section 6 describes the pain point of technology hurdles (P3), which motivates considering the use of web applications. Here we give further advice to help with deciding whether to adopt a web application. The decision will be based on whether, on balance, the web application improves the four factors identified by developers: compatibility, maintainability, performance, and security. To enable decision-making, a team will need to prioritize between these factors, based on their objectives and experience. The suggestions are intended to provide ideas and avenues for exploration; a web application will not be the right fit for all projects and all teams.

- **Modern technologies may improve frontend performance.** Web applications with only a frontend usually perform worse than native applications. However, new technologies may ease this difference. For example, some JavaScript libraries can help the frontend harness the power of the computer's GPU and accelerate graphical computing. In addition, there are new frameworks helping developers with cross-platform compatibility. For example, the Flutter project enables support for web, mobile, and desktop OS with one codebase. Other options include Vue, Angular and React, and Elm.

- **Backend servers can potentially deliver high performance.** Web applications with backend servers may perform even better than native applications. If a team needs to support lower-end computers, it is good to use back-end servers for heavy computing tasks. For backend servers where traffic and latency is not an issue, options include Django, Laravel and Node.js. The advantage of Django is that it provides access to Python libraries. For backend servers where traffic and latency is an issue, Gin is an option.

- **Backend servers can have low costs.** Serverless solutions from major cloud service providers (like Amazon Web Services (AWS) and Google Cloud Platform) may be worth exploring. Serverless solutions still use a server, but the server provider only charges the team when they use the server. The solution is event-driven, and costs the team by the number of requests processed. Thus, serverless can be very cost-effective for less intensively used functions.

- **Web transmission may diminish security.** Transferring sensitive data on-line can be a problem for projects requiring high security. Regulations for some MI applications may forbid doing web transmissions. In this case, a web application with a backend may not be an option.

7.3. *Enrich the Testing Datasets*

As described in Section 6, ensuring correctness (P4) via testing can be problematic because of limited access to real-world medical imaging datasets. We build on the suggestions we heard from our interviewees as follows:

- **Build and maintain good connections to datasets.** A team can build connections with professionals working in the medical domain, who may have access to private datasets and can perform tests for the team. If a team has such professionals as internal members, the process can be simplified.

- **Collect and maintain datasets over time.** A team may face problems caused by various unique inputs over the years of software development. This data should be collected and maintained over time to form a good, comprehensive, dataset for testing.

- **Search for open data sources.** In general, there are many open MI datasets. For instance, there are Chest X-ray Datasets by National Institute of Health [105], Cancer Imaging Archive [106], MedPix by National Library of Medicine [107], and datasets for liver [108] and brain [109] tumor segmentation benchmarks. A team developing MI software should be able to find more open datasets according to their needs.

- **Create sample data for testing.** If a team can access tools creating sample data, they may also self-build datasets for testing. For example, an MI software development team can use an MRI scanner to create images of objects, animals, and volunteers. The team can build the images based on specific testing requirements.

- **Remove privacy from sensitive data.** For data with sensitive information, a team can ask the data owner to remove such information or add noise to protect privacy. One example is using de-identified copies of medical images for testing.

- **Establish community collaboration in the domain.** During our interviews with developers in the MI domain, we heard many stories of asking for supports from other professionals or equipment manufacturers. However, we believe that broader collaboration between development teams can address this problem better. Some datasets are too sensitive to share, but if the community has some kind of "group discussion", teams can better express their needs, and professionals can better offer voluntary support for testing. Ultimately, the community can establish a nonprofit organization as a third party, which maintains large datasets, tests Open Source Software (OSS) in the domain, and protects privacy.

7.4. *Employ Linters*

A linter is a tool that statically analyzes code to find programming errors, suspicious constructs, and stylistic inconsistencies [110]. Linters can be used as an ad hoc check for code files, but they really come into their own when used as part of a CI system, as discussed in Section 7.1. Almost none of the research software guidelines that we consulted, summarized in Section 3.2, mention linters. The one exception is [51]. Despite the lack of mention in the guidelines, we believe that linters have the potential to improve code quality at a relatively low cost.

Linters have the following benefits: finding potential bugs, finding memory leaks, improving performance, standardizing code with respect to formatting, removing silly errors before code reviews, and catching potential security issues [111]. Most popular programming languages have an accompanying linter. For example, Python has the options of PyLint, flake8 and Black [78].

We recommend the use of linters because they are relatively easy to incorporate into a developer's workflow, and they address several MI pain points (Section 6). For instance, linters address the lack of development time (P1) by increasing the developer's productive time via guarding against making frustrating, time-consuming, mundane mistakes. Moreover, since a linter can include rules that capture the wisdom of senior programmers, it can help newer developers avoid common mistakes. With respect to the technology hurdle pain point (P3), linters can assist with the move toward web applications (Section 7.2). For instance, ESLint in React is a pluggable linter that lets the developer know if they have imported something and not used it, if a function could be short-handed, if there are indentation inconsistencies, etc. [112]. By insisting on code standardization linters can reduce technical debt and thus improve maintainability (Q1). Although linters are tools for code analysis, the idea of statically checking for adherence to basic rules can be extended to check documentation. [113] shows how the use of tools to enforce documentation standards partially explains the relatively higher quality of statistical tools that are part of the Comprehensive R Archive Network (CRAN).

7.5. *Conduct a Mix of Rigorous and Informal Peer Reviews*

We advocate incorporating peer review into the development process, as frequently recommended for research software [50, 114, 53, 45]. In most cases a modern, lightweight review, should be adequate. Modern code review is informal, tool-based, asynchronous, and focused on reviewing code changes [115]. Managing a project via GitHub pull requests is an example of a modern approach to reviewing code. Software development organizations have moved to this lightweight style of code review because of the inefficiencies of rigorous inspections [116]. However, for important parts of the code, developers may benefit from mixing in a more rigorous approach.

[117] began work on rigorous review via code inspection. Elements of a typical inspection include reviewing the code against a checklist (checking the consistency of variable names, look for terminating loops, etc.), performing specific review tasks (such as summarizing the code's purpose, cross-referencing the code to the technical manual, creating a data dictionary for a given module, etc.) Rigorous inspection finds 60-65% of latent defects on average, and often tops 85% in defect removal efficiency [118]. The success rate of code inspection is generally higher than most forms of testing, which average between 30 — 35% for defect removal efficiency [119, 118]. For research software, [120] show a task based inspection approach can be effective. Task based

inspection is an ideal fit with an issue tracking system, like GitHub. The review tasks can be issues, so that they can be easily assigned, monitored and recorded. Potential issues include assigning junior developers to test getting-started tutorial and installation instructions.

As indicated in Section 5 some MI projects use modern code review, via issue tracking and the use of GitHub. Those MI projects not incorporating modern code review would likely benefit by adopting it. Although a rigorous code inspection is likely not worth the required resources, for critical parts of the code, developers may want to adopt a more rigorous approach. For instance, developers may drop the modern trend of asynchronous review and instead occasionally use synchronous review to help uncover errors and disseminate best practices throughout the team. For instance, teams could periodically meet, either in-person or virtually, and have junior members walk through their code. In-person reviews will likely help realize the benefits of modern code review noticed by [121]: defect detection, knowledge transfer, increased team awareness, and creation of alternative solutions to problems.

Due to improving code quality and increasing knowledge transfer, peer review addresses the same pain points and qualities as linters (Section 7.4): P1, P3, and Q1. Peer review can potentially find misunderstandings in how the code implements the required theory, which will improve the software's correctness (P4). The benefits of peer review for addressing pain points can be increased by extending the review from just code, to also reviewing all software artifacts, including documentation, build scripts, test cases and the development process itself.

7.6. Design For Change

In our "state of the practice" assessment exercise for LBM software [88], we noticed that LBM developers implicitly used modularization based on the principle of design for change to improve maintainability (Q1). We recommend that MI developers use the same principle for their modularizations. Although the advice to modularize research software to handle complexity is common [122, 123, 1], specific guidelines on how to divide the software into modules is less prevalent. Not every decomposition is a good design for supporting change, as shown by [124]. For instance, a design with low cohesion and high coupling [4, p. 48] will make change difficult. Especially in research software, where change is inevitable, designers need to produce a modularization that supports change. [79] points out that ocean modelling software is currently feeling the pain of not emphasizing modularization in legacy code.

Specific examples of design for change for LBM software [88] include the following:

- pyLBM has decoupled geometries and models of their system using abstraction and modularization of the source code, to make it easy to add new features. The pyLBM design allows for independent changes to the geometry and the model. pyLBM also redeveloped data structures to ease future change.

- TCLB [125] is designed to allow for the addition of some LBM features, but changes to major aspects of the system would be difficult. For example, "implementing a new model will be an easy contribution", but changes to the "Cartesian mesh … will be a nightmare" [88]. The design of TCLB highlights that not every conceivable change needs to be supported, only the likely changes.

As the LBM examples above illustrate, developers can accomplish design for change by first identifying likely changes, either implicitly or explicitly, and second by hiding each likely change behind a well-defined module interface. This approach mirrors the recommendations from [124]. Section 3.2 lists ideas for how to document the design, including the likely changes, so that they are more visible to others.

8. Threats to Validity

Below we categorize and list the threats to validity that we have identified. Our categories come from an analysis of software engineering secondary studies by [126], where a secondary study analyzes the data from a set of primary studies. [126] is appropriate because a common example of a secondary study is a systematic literature review. Our methodology is a systematic software review — the primary studies are the software packages, and our work collects and analyzes these primary studies. We identified similar threats to validity in our assessment of the state of the practice of Lattice Boltzmann Solvers [88].

8.1. Reliability

A study is reliable if repetition of the study by different researchers using the original study's methodology would lead to the same results [127]. Reliability means that data and analysis are independent of the specific researcher(s) doing the study. For the current study the identified reliability related threats are as follows:

- One individual does the manual measures for all packages. A different evaluator might find different results, due to differences in abilities, experiences, and biases.
- The manual measurements for the full set of packages took several months. Over this time the software repositories may have changed and the reviewer's judgement may have drifted.

In [128] we reduced concern over the reliability risk associated with the reviewer's judgement by demonstrating that the measurement process is reasonably reproducible. In [128] we graded five software products by two reviewers. Their rankings were almost identical. As long as each grader uses consistent definitions, the relative comparisons in the AHP results will be consistent between graders.

8.2. Construct Validity

[127] defines construct validity as the adopted metrics representing what they are intended to measure. Our construct threats are often related to how we assume our measurements influences the various software qualities, as summarized in Section 1.3.3. Specifically, our construct validity related threats include the following:

- We make indirect measurement of software qualities since meaningful direct measures for qualities like maintainability, reusability and verifiability, are unavailable. We follow the usual assumption that developers achieve higher quality by following procedures and adhering to standards [129, p. 112].

- As mentioned in Section 2.3, we could not install or build *dwv*, *GATE*, and *DICOM Viewer*. We used a deployed on-line version for *dwv*, a VM version for *GATE*, but no alternative for *DICOM Viewer*. We might underestimate their rank due to these technical issues.

- Measuring software robustness only involved two pieces of data. This is likely part of the reason for limited variation in the robustness scores (Figure **??**). We could add more robustness data by pushing the software to deal with more unexpected situations, like a broken Internet connection, but this would require a larger investment of measurement time.

- We may have inaccurately estimated maintainability by assuming a higher ratio of comments to source code improves maintainability. Moreover, we assumed that maintainability is improved if a high percentage of issues are closed, but a project may have a wealth of open issues, and still be maintainable.

- We assess reusability by the number of code files and LOC per file. This measure is indicative of modularity, but it does not necessarily mean a good modularization. The modules may not be general enough to be easily reused, or the formatting may be poor, or the understandability of the code may be low.

- The understandability measure relies on 10 random source code files, but the 10 files will not necessarily be representative.

- As discussed in Section **??**, our overall AHP ranking makes the unrealistic assumption of equal weighting.

- We approximated popularity by stars and watches (Section 3.1), but this assumption may not be valid.

- As mentioned in Section 3.3, one interviewee was too busy to participate in a full interview, so they provided written answers instead. Since we did not have the chance to explain our questions or ask them follow-up questions, there is a possibility of misinterpretation of the questions or answers.

- In building Table 6 some judgement was necessary on our part, since not all guidelines use the same names for artifacts that contain essentially the same information.

8.3. Internal Validity

Internal validity means that discovered causal relations are trustworthy and cannot be explained by other factors [127]. In our methodology the internal validity threats include the following:

- In our search for software packages (Section **??**), we may have missed a relevant package.

- Our methodology assumes that all relevant software development activities will leave a trace in the repositories, but this is not necessarily true. For instance, the possibility exists that CI usage was higher than what we observed through the artifacts (Section 4). As another example, although we saw little evidence of requirements (Section 4), maybe teams keep this kind of information outside their repos, possibly in journal papers or technical reports.

- We interviewed a relatively small sample of 8 teams. Their pain points (Section 6) may not be representative of the rest of their community.

8.4. External Validity

If the results of a study can be generalized (applied) to other situations/cases, then the study is externally valid [127]. We are confident that our search was exhaustive. We do not believe that we missed any highly popular examples. Therefore, the bulk of our validity concerns are internal (Section 10.1.3). However, our hope is that the trends observed, and the lessons learned for MI software can be applied to other research software. With that in mind we identified the following threat to external validity:

- We cannot generalize our results if the development of MI software is fundamentally different from other research software.

Although there are differences, like the importance of data privacy for MI data, we found the approach to developing LBM software [88] and MI software to be similar. Except for the domain specific aspects, we believe that the trends observed in the current study are externally valid for other research software.

9. Future Work

The following recommendations for future state of the practice measurement exercises, for MI or for other domains, could address some threats to validity mentioned above. Moreover, some ideas may make the data collection more efficient.

- We would like to make surface measurements less shallow. For example:
  - Surface reliability: our current measurement relies on the processes of installation and getting started tutorials. However, not all software needs installation or has a getting started tutorial. We could devise a list of operation steps (with the help of the Domain Expert), perform the same operations with each software, and record any errors.
  - Surface robustness: we used damaged images as inputs for this measuring MI software. This process is similar to fuzz testing [130], which is one type of fault injection [131]. We may adopt more fault injection methods, and identify tools and libraries to automate this process.
  - Surface usability: we can design usability tests and test all software projects with end-users. The end-users can be volunteers and domain experts. Ideas for getting started are available in [70].
  - Surface understandability: our current method does not require understanding the source code. As software engineers, perhaps we can select a small module of each project, read the source code and documentation, try to understand the logic, and score the ease of the process.

- Maintainability: we can add a measure modifiability as part of the measurement of maintainability. An experiment could be conducted asking participants to make modifications, observing the study subjects during the modifications, testing the resulting software and surveying the participants [70].

- We can further automate the measurements on the grading template. For example, with automation scripts and the GitHub API, we may save significant time on retrieving the GitHub metrics through a GitHub Metric Collector. This Collector can take GitHub repository links as input, automatically collect metrics from the GitHub API, and record the results.
- We can improve some interview questions. Some examples are:
  - In one question we ask, "Do you think improving this process can tackle the current problem?" The problem is that this is a yes-or-no question, which is not informative. We could change the question to "By improving this process, what current problems can be tackled?";
  - We can ask for more details about the modular approach, such as "What principles did you use to divide code into modules? Can you describe an example of using your principles?".
- We can better organize the interview questions. Since we use audio conversion tools to transcribe the answers, we should make the transcription easier to read. For example, we can order them together for questions about the five software qualities and compose a similar structure for each.
- We can mark the follow-up interview questions with keywords. For example, say "this is a follow-up question" every time asking one. Thus, we record this sentence in the transcription, and it will be much easier to distinguish the follow-up questions from the 20 designed questions.

10. Conclusions

We analyzed the state of the practice for the MI domain with the goal of understanding current practice, answering our ten research questions (Section 1.1) and providing recommendations for current and future projects. Our methods in Section **??** form a general process to evaluate domain-specific software, that we apply to the specific domain of MI software. We identified 48 MI software candidates, then, with the help of the Domain Expert selected 29 of them to our final list.

Section 2 lists our measurement results for ranking the 29 projects for nine software qualities. Our ranking results appear credible since they are mostly consistent with the ranking from the scientific community implied by the GitHub stars-per-year metric. As discussed in Section 3.1, four of the top five software projects appear in both our list and in the GitHub popularity list. Moreover, our top five packages appear among the first eight positions on the GitHub list. The noteworthy discrepancies between the two lists are for the packages that we were unable to install (*dwv* and *Dicom Viewer*).

Based on our grading scores *3D Slicer*, *ImageJ*, *Fiji* and *OHIF Viewer* are the top four software performers. However, the separation between the top performers and the others is not extreme. Almost all packages do well on at least a few qualities, as shown in Table 12, which summarizes the packages ranked first and second for each quality. Almost 70% (20 of 29) of the software packages appear in the top two for at least two qualities. The only packages that do not appear in Table 12, or only appear once, are *Papaya*, *MatrixUser*, *MRIcroGL*, *XMedCon*, *dicompyler*, *DicomBrowser*, *AMIDE*, *3DimViewer*, and *Drishti*. The shortness of this list suggests parity with respect to adoption of best practices for MI software overall.

For insight into devising future methods and tools, we interviewed nine developers (from eight teams) to learn about their pain points (Section 6). We also discussed qualities of potential concern. The identified pain points and qualities of concern include:

P1 Lack of development time,

P2 Lack of funding,

P3 Technology hurdles,

P4 Ensuring correctness,

P5 Usability,

Q1 Quality of maintainability, and

Q2 Quality of reproducibility.

Despite the pain points, overall MI software is in a healthy state for software development practices. In our survey of the selected projects we observed 88% of the documentation artifacts recommended by research software development guidelines (Section 3.2). With respect to tools, MI is keeping pace with other research software with 100% of the projects using version control (with 93% specifically using git) (Section 4). We observed that the MI developers tend to follow the typical research software trend of using a quasi-agile software development process (Section 5).

Although the state of the practice for MI software is healthy, we did notice areas where practice seems to lag behind the research software development guidelines. For instance, the guidelines recommend three artifacts that were not observed: uninstall instructions, test plans, and requirements documentation. We observed the following recommended artifacts, but only rarely: contributing file, developer code of conduct, code style guidelines, product roadmap, design documentation, and API documentation (Section 3.2). Although software development tool use seems healthy, we found the use of CI/CD behind typical usage rates (17% of the projects used CI/CD) (Section 4). With respect to the development process, developer identified areas for improvement included testing (only 50% of projects were identified to have unit testing) and documentation (only three out of nine developers felt their documentation was clear enough) (Section 5).

Our interviewees proposed strategies to improve the state of the practice, to address the identified pain points, and to improve software quality. To their list (Section 6) we added some of our own recommended strategies (Section 7). Below we summarize the proposed strategies, with traceability to where we discuss the strategy, and to the relevant pain points.

1. Increase documentation to address P1, P3, P5, Q1, Q2 (Section 6)
2. Increase testing by enriching datasets to address P4, Q2 (Section 6, 7.3)
3. Increase modularity to address Q1 (Section 6)
4. Use continuous integration to address P1, P4, Q2 (Section 6, 7.1)
5. Move to web applications to address P3 (Section 6, 7.2)
6. Employ linters to address P1, P3, Q1 (Section 7.4)
7. Peer reviews to address P1, P3, P4, Q1 (Section 7.5)
8. Design for change to address Q1 (Section 7.6)
9. Assurance case to address P4, Q2 (Section **??**)
10. Generate all things to address P1, P3, P4, P5, Q1 and Q2. (Section **??**)

10.1. Threats to Validity

We follow Ampatzoglou et al. [126]'s analysis of threats to validity in software engineering secondary studies.

10.1.1. Reliability

A study is reliable if repeating it by another researcher, using the same methodology, would lead to the same results [127]. We identify the following threats:

- One individual does the measures for all packages. A different evaluator might find different results, due to differences in abilities, experience, and biases.
- The measurements for the full set of packages took several months (of elapsed time). Over this time the software repositories may have changed and the reviewer's judgement may have drifted.

The measurement process used has previously been shown to be reasonably reproducible. [citation redacted] reports grading five software products by two reviewers. Their rankings were almost identical. As long as each grader uses consistent definitions, the relative comparisons in the AHP results will be consistent between graders.

10.1.2. *Construct Validity*

Construct validity is when the adopted metrics represent what they are intended to measure [127]. We have identified the following potential issues:

- We make indirect measurement of software qualities since meaningful direct measures for qualities like maintainability, reusability and verifiability, are unavailable. We follow the usual assumption that developers achieve higher quality by following procedures and adhering to standards [129, p. 112].

- We could not install or build *dwv*, *GATE*, and *DICOM Viewer*. We used a deployed on-line version for *dwv*, a virtual machine version for *GATE*, but no alternative for *DICOM Viewer*.

- Robustness measurements involve only two pieces of data, leading to limited variation in the robustness scores (Figure **??**). Our measurement-time budget limited what we could achieve here.

- Our maintainability proxies (higher ratio of comments to source, high percentage of closed issues) have not been validated.

- While smaller modules tend to be easier to reuse, small modules are not necessarily good modules, nor understandable modules.

- The understandability measure relies on 10 random source code files, but the 10 files will not necessarily be representative.

- Our overall AHP ranking makes the unrealistic assumption of equal weighting.

- We approximated popularity by stars and watches.

- Table 6 required judgement as not all guidelines use the same names for artifacts that contain essentially the same information.

10.1.3. *Internal Validity*

Internal validity means that discovered causal relations are trustworthy and cannot be explained by other factors [127]. We identify the following:

- Our search (Section 2) could have missed a relevant package.

- Our methodology assumes that development activities will leave a trace in the repositories, but this is not necessarily true. For instance, we saw little evidence of requirements (Section 3.2), but teams might keep this kind of information outside their repos.

10.1.4. *External Validity*

If the results of a study can be generalized to other situations, then the study is externally valid [127]. In other words, we cannot generalize our results if the development of MI software is fundamentally different from other research software. Although there are differences, like the importance of data privacy for MI data, we found the approach to developing [other software (citation redacted)] and MI software to be similar. Except for the domain specific aspects, the trends observed in the current study are similar to that for other research software.

11. Conclusions

Our analysis of the state of the practice for MI domain along nine software qualities strongly indicates that "higher quality" is consistent with community ranking proxies. Although our quality measures are rather shallow, we see this as an advantage. The shallow measures are a proxy for the importance of *first impressions* for software adoption.

Our grading scores indicate that *3D Slicer*, *ImageJ*, *Fiji* and *OHIF Viewer* are the overall top four. However, the separation between the top performers and the others is not extreme. Almost all packages do well on at least a few qualities, as shown in Table 12, which summarizes the packages ranked first and second for each quality. Almost 70% (20 of 29) of the software packages appear in the top two for at least two qualities. The only packages that do not appear in Table 12, or only appear once, are *Papaya*, *MatrixUser*, *MRIcroGL*, *XMedCon*, *dicompyler*, *DicomBrowser*, *AMIDE*, *3DimViewer*, and *Drishti*.

While we did find a reasonable amount of documentation, especially when consider all MI projects, there were definitely some holes. Some important documentation (test plans and requirements documentation) was missing, and other (contributors' guide, code of conduct, code style guidelines, product roadmap, design documentation, and API documentation) (Section 3.2) were rare.

A deeper understanding of the needs of the MI community will require data beyond what is available in repositories. Future work should involve interviewing MI developers to better understand their "pain points".

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Conflict of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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Software	Text Files	Total Lines	LOC	LOC/file
OHIF Viewer	1162	86306	63951	55
3D Slicer	3386	709143	501451	148
Gwyddion	2060	787966	643427	312
ParaView	5556	1276863	886326	160
OsiriX Lite	2270	873025	544304	240
Horos	2346	912496	561617	239
medInria	1678	214607	148924	89
Weasis	1027	156551	123272	120
BioImage Suite Web	931	203810	139699	150
GATE	1720	311703	207122	120
Ginkgo CADx	974	361207	257144	264
SMILI	275	90146	62626	228
Fiji	136	13764	10833	80
Drishti	757	345225	268168	354
ITK-SNAP	677	139880	88530	131
3DimViewer	730	240627	178065	244
DICOM Viewer	302	34701	30761	102
ImageJ	40	10740	9681	242
dwv	188	71099	47815	254
MatrixUser	216	31336	23121	107
INVESALIUS 3	156	59328	48605	312
AMIDE	183	139658	102827	562
Papaya	110	95594	71831	653
MicroView	137	36173	27470	201
XMedCon	202	129991	96767	479
MRIcroGL	97	50445	8493	88
Slice:Drop	77	25720	19020	247
DicomBrowser	54	7375	5505	102
dicompyler	48	19201	15941	332

Table 3: Number of files and lines (by reusability scores)

Software	Dev. Process	Proj. Status	Dev. Env.	Rls. Notes
3D Slicer	✓	✓	✓	✓
ImageJ	✓	✓	✓	✓
Fiji	✓	✓	✓	
MRIcroGL				✓
Weasis			✓	✓
ParaView		✓		
OHIF Viewer			✓	✓
DICOM Viewer			✓	✓
medInria			✓	✓
SMILI				✓
Drishti				✓
INVESALIUS 3				✓
OsiriX Lite				✓
GATE				✓
MicroView				✓
MatrixUser				✓
BioImage Suite Web			✓	
ITK-SNAP				✓
Horos				✓
dwv				✓
Gwyddion				✓

Table 4: Software with visibility/transparency related documents (listed in descending order of visibility/transparency score)

Software	Comm. Rank	Our Rank	Stars/yr	Watches/yr	Forks/yr
3D Slicer	1	1	284	19	128
OHIF Viewer	2	4	277	19	224
dwv	3	19	124	12	51
ImageJ	4	2	84	9	30
ParaView	5	5	67	7	28
Horos	6	12	49	9	18
Papaya	7	17	45	5	20
Fiji	8	3	44	5	21
DICOM Viewer	9	29	43	6	9
INVESALIUS 3	10	8	40	4	17
Weasis	11	7	36	5	19
dicompyler	12	26	35	5	14
OsiriX Lite	13	11	34	9	24
MRIcroGL	14	18	24	3	3
GATE	15	24	19	6	26
Ginkgo CADx	16	14	19	4	6
BioImage Suite Web	17	6	18	5	7
Drishti	18	27	16	4	4
Slice:Drop	19	21	10	2	5
ITK-SNAP	20	13	9	1	4
medInria	21	9	7	3	6
SMILI	22	10	3	1	2
MatrixUser	23	28	2	0	0
MicroView	24	15	1	1	1
Gwyddion	25	16	n/a	n/a	n/a
XMedCon	26	20	n/a	n/a	n/a
DicomBrowser	27	22	n/a	n/a	n/a
AMIDE	28	23	n/a	n/a	n/a
3DimViewer	29	25	n/a	n/a	n/a

Table 5: Software ranking by our methodology versus the community (Comm.) ranking using GitHub metrics (Sorted in descending order of community popularity, as estimated by the number of new stars per year)

	[45]	[46]	[47]	[48]	[49]	[50]	[51]	[52]	[53]	MI
LICENSE	✓	✓	✓	✓	✓		✓	✓	✓	C
README		✓	✓	✓	✓		✓	✓	✓	C
CONTRIBUTING		✓	✓	✓	✓		✓	✓	✓	R
CITATION				✓				✓	✓	U
CHANGELOG		✓		✓	✓		✓			U
INSTALL					✓		✓	✓	✓	U
Uninstall								✓		
Dependency List			✓		✓			✓		R
Authors							✓	✓	✓	U
Code of Conduct							✓			R
Acknowledgements							✓	✓	✓	U
Code Style Guide		✓					✓	✓	✓	R
Release Info.		✓				✓	✓			C
Prod. Roadmap						✓	✓	✓		R
Getting started					✓		✓	✓	✓	R
User manual			✓				✓			C
Tutorials							✓			U
FAQ							✓	✓	✓	U
Issue Track		✓	✓		✓	✓	✓		✓	C
Version Control		✓	✓	✓	✓	✓	✓	✓	✓	C
Build Scripts		✓		✓	✓	✓	✓		✓	U
Requirements		✓				✓			✓	R
Design Doc.		✓	✓		✓		✓	✓	✓	R
API Doc.					✓		✓	✓	✓	R
Test Plan		✓				✓				
Test Cases	✓	✓	✓		✓	✓	✓	✓	✓	U

Table 6: Comparison of Recommended Artifacts in Software Development Guidelines to Artifacts in MI Projects (C for Common, U for Uncommon and R for Rare)

Common	Uncommon	Rare
README (29)	Build scripts (18)	Getting Started (9)
Version control (29)	Tutorials (18)	Developer's manual (8)
License (28)	Installation guide (16)	Contributing (8)
Issue tracker (28)	Test cases (15)	API documentation (7)
User manual (22)	Authors (14)	Dependency list (7)
Release info. (22)	Frequently Asked Questions (FAQ) (14)	Troubleshooting guide (6)
	Acknowledgements (12)	Product roadmap (5)
	Changelog (12)	Design documentation (5)
	Citation (11)	Code style guide (3)
		Code of conduct (1)
		Requirements (1)

Table 7: Artifacts Present in MI Packages, Classified by Frequency (The number in brackets is the number of occurrences)

User Support Model	Num. Projects
GitHub issue	24
Frequently Asked Questions (FAQ)	12
Forum	10
E-mail address	9
GitLab issue, SourceForge discussions	2
Troubleshooting	2
Contact form	1

Table 8: User support models by number of projects

Opinion on Documentation	Num. Ans.
Documentation is vital to the project	8
Documentation of the project needs improvements	7
Referring to documentation saves time to answer questions	6
Lack of time to maintain good documentation	4
Documentation of the project conveys information clearly	3
Coding is more fun than documentation	2
Users help each other by referring to documentation	1

Table 9: Opinions on documentation by the numbers of interviewees with the answers

Software Team	Native Application	Web Application
3D Slicer	✓	
INVESALIUS 3	✓	
dwv		✓
BioImage Suite Web		✓
ITK-SNAP	✓	
MRIcroGL	✓	
Weasis	✓	
OHIF		✓
Total number among the eight teams	5	3
Total number among the 29 teams	24	5

Table 10: Teams' choices between native application and web application

Quality	Ranked 1st or 2nd
Installability	3D Slicer, BioImage Suite Web, Slice:Drop, INVESALIUS
Correctness and Verifiability	OHIF Viewer, 3D Slicer, ImageJ
Reliability	SMILI, ImageJ, Fiji, 3D Slicer, Slice:Drop, OHIF Viewer
Robustness	XMedCon, Weasis, SMILI, ParaView, OsiriX Lite, MicroView, medInria, ITK-SNAP, INVESALIUS, ImageJ, Horos, Gwyddion, Fiji, dicompyler, DicomBrowser, BioImage Suite Web, AMIDE, 3DimViewer, 3D Slicer, OHIF Viewer, DICOM Viewer
Usability	3D Slicer, ImageJ, Fiji, OHIF Viewer, ParaView, INVESALIUS, Ginkgo CADx, SMILI, OsiriX Lite, BioImage Suite Web, ITK-SNAP, medInria, MicroView, Gwyddion
Maintainability	3D Slicer, Weasis, ImageJ, OHIF Viewer, ParaView
Reusability	3D Slicer, ImageJ, Fiji, OHIF Viewer, SMILI, dwv, BioImage Suite Web, GATE, ParaView
Understandability	3D Slicer, ImageJ, Weasis, Fiji, Horos, OsiriX Lite, dwv, Drishti, OHIF Viewer, GATE, ITK-SNAP, ParaView, INVESALIUS
Visibility and Transparency	ImageJ, 3D Slicer, Fiji
Overall Quality	3D Slicer, ImageJ

Table 11: Top performers for each quality (sorted by order of quality measurement)

Quality	Ranked 1st or 2nd
Installability	3D Slicer, BioImage Suite Web, Slice:Drop, INVESALIUS
Correctness and Verifiability	OHIF Viewer, 3D Slicer, ImageJ
Reliability	SMILI, ImageJ, Fiji, 3D Slicer, Slice:Drop, OHIF Viewer
Robustness	XMedCon, Weasis, SMILI, ParaView, OsiriX Lite, MicroView, medInria, ITK-SNAP, INVESALIUS, ImageJ, Horos, Gwyddion, Fiji, dicompyler, DicomBrowser, BioImage Suite Web, AMIDE, 3DimViewer, 3D Slicer, OHIF Viewer, DICOM Viewer
Usability	3D Slicer, ImageJ, Fiji, OHIF Viewer, ParaView, INVESALIUS, Ginkgo CADx, SMILI, OsiriX Lite, BioImage Suite Web, ITK-SNAP, medInria, MicroView, Gwyddion
Maintainability	3D Slicer, Weasis, ImageJ, OHIF Viewer, ParaView
Reusability	3D Slicer, ImageJ, Fiji, OHIF Viewer, SMILI, dwv, BioImage Suite Web, GATE, ParaView
Understandability	3D Slicer, ImageJ, Weasis, Fiji, Horos, OsiriX Lite, dwv, Drishti, OHIF Viewer, GATE, ITK-SNAP, ParaView, INVESALIUS
Visibility and Transparency	ImageJ, 3D Slicer, Fiji
Overall Quality	3D Slicer, ImageJ

Table 12: Top performers for each quality (sorted by order of quality measurement)