Innovations

Adapting Agile Methodologies to the Scientific Research Environment

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Abstract

Purpose: To provide a framework for the application of Agile methodology in the scientific research environment. This review establishes how Agile methodology can be modified to fit the research environment and how to implement it. Design/Methodology/Approach: A literature review of Agile methodology in other fields and applied to science. A potential impact review of Agile in science, based on the current performance of scientists. Results: Agile may be applicable in scientific research and may alter the laboratory environment and the publication environment. Agile application may pay dividends for science in responding to a highly uncertain informational environment.

Introduction

Agile methodologies are a widely accepted means of project management for software product management[1]. The methodology consists of 'scrums', which are short meetings, strictly enforced to under 15 minutes, occurring frequently, usually daily; 'Sprints', which are weeklong work blocks set to accomplish specific tasks, or 'user stories' which are programming functionalities to implement, phrased in the format 'As a user, I want to [functionality]' [2].

Scrum is intensely team oriented, and sprints, while the work is typically accomplished in isolation, are capable of building comraderies and otherwise synchronizing objectives. The team focus element of agile makes it enjoyable to employee participants, despite typically increased work demands during the sprint.

After two decades of agile implementation, it has percolated into other industries beyond software development, achieving wide acceptance [3–7]. Technologies such as additive manufacturing and 3D printing have enabled rapid prototyping and testing and have shrunk the timescale required for physical products to approach the development timescales as characterized by Agile[8].
Projects with a modular component are well suited to having their work packages split up into independent and parallel user stories. Modularity makes Agile easier to implement, but it is not explicitly necessary[9]. One can borrow the 'sprint' work structure from agile without largely modular work packages. In this case, work follows a pattern of defining the tasks to be completed in a sprint and then implementing those in a focused manner during sprints, and reviewing the previous sprint once completed.
This is similar to the implicit structure of most employee-supervisor relationships, whereby certain tasks are assigned and then the supervisor and employee meet for progress reporting and Agile makes the process of task accomplishment and reporting more explicit by defining work packages in the context of the wider project. Furthermore, most employee-manager assignments lack concrete definition, and can benefit from the increased clarity that is expected of projects under agile management with modular arrangements.

Science and Agile

Scientific articles have a relative degree of modularity, in that an article may involve several groups performing more or less independent measurements. There can be some co-dependencies, such as when one lab provides an important reagent (such as a purified protein) to another. Where there are dependencies and process flows, these are areas where the Theory of Constraints (ToC), put forth by Eliyahu Goldratt [10], can be useful, as it manages production flows. Agile development has different focuses from the Theory of constraints, and typically avoids production dependencies through the modularity of software architecture. However, one correspondence between ToC and Agile development is the focusing of efforts on the software functionalities which provide value. Here, the role of the Agile framework can be divided into two parts; one for product development, i.e. choosing which functionalities to build, and project management, i.e. managing the efforts of the people working on the project. Both aspects are revolutionary.
Taking the analogy of software development to science, the final output would be the scientific article, published in a journal. However this format largely comes about by historical happenstance and other considerations besides the production and dissemination of scientific knowledge (more on this in the penultimate section). While work packages in software are defined in terms of user stories, (or more granularly, modules, subroutines, etc.), work packages for scientific articles usually culminate in a figure or set of figures to represent data and analysis. The body of the paper is analogous to the user interface of software, with figures comprising the 'meat' of the article, as that is where the final results

of experimental data collection and analysis are presented. Written sections typically restate these findings and importantly provide interpretation and context. One 'Agile' trend on display is the use of 'Living Documents' which are updated regularly and sections may be added to. Like software, these also have different 'releases' and typically sections are added, edited or removed a few at a time.

To make a scientific figure, one must typically perform an analysis of experimental data, and possibly integrate data from different experiments. Here, work packages can be defined in both analysis steps, as well as data visualization to create a scientific figure. One would expect an almost automatic analysis process, given the ubiquity of scientific software, though it is not always straightforward. For cases of review papers as well as cases where the data already exists, the authors are not limited by the comparatively slow generation of experimental data (in most cases). Analyses can typically be described in definitive terms and applied objectively on experimental data test a hypothesis. While there is a significant degree of idealization in this example, the process of scientific production can be modularized for streamlining.

Furthermore, definition of a task is pivotal in sprint meetings which is something to consider in scientific research setting as often valuable research time is being lost because tasks for each scientific member or researcher on the project such as academic article are ill defined. Such meetings and precise task definitions have the potential to minimise failure and increase support for task work pre-emptively. With the definition of a research project, there are tasks which must be completed, forming a backlog of tasks or user stories, which people can take on at the beginning of a sprint. Tasks are not only defined once; in the example of software development, tasks come in from user suggestions to where value can be provided. The framework of updating the user stories allows for new and unexpected discoveries to shape research directions, instead of locking into a fixed project management structure.

The so-called scrum meetings, can in effect (and judging from software and other industries where scrum is deployed) lower confusion in terms of requests for clarification. For example, graduate students, or postdocs waste time going in an unproductive direction which could have been remedied by a short meeting where tasks are well defined and where support and help is sought during this meeting already precisely because students are aware in advance of all its components and feasibility. Usually, we enter scientific explorations serendipitously, which often acts as a reason why strict project management might not be suitable for science, however, clear, and precise definition of tasks which are relevant to accomplish to bring about elements of scientific research project as well as support needed to accomplishthem at the very start of the project, but then also throughout the project can be very beneficial. It avoids unnecessary confusion and procrastination which plague many of current research projects.

One other aspect of agile workplaces is that they typically adopt communication tools such as slack, which serve as a public forum. Resources are made available for everyone on the project such that most questions are answerable by reference to a wiki. The wiki represents a shared corpus of work, and its accessibility allows many questions to be accessed and answered readily with a minimum of productivity loss as the question is answered by a wiki query rather than requiring someone to answer.

Agile Adoption in Science

In principle, the scientific field is more collaborative than business. While this ideal is not met, scientific researchers are in cooperation towards a common goal of improving the understanding of nature. Of course, there are significant deviations from this ideal, where careerist considerations take precedence over providing value, and fields can become siloed and lose touch with reality.

Going from submission to acceptance and publication is a major source of delay for a project to be brought to completion. While it is submitted, it exists in a liminal zone of whether it will be accepted with minor or major revisions. Fields that have adopted a widespread practice of using preprint servers greatly reduce this issue. The article is out in the public domain, and can be cited [11].

One survey of the nursing literature found a delay of almost 3 years between the end of data collection and publication [12]. More than half of students worry about finishing on time [13], and only around 20% of postgraduate students in low-income countries publish during their education [14]. Publication during one's student education is highly associated with future success[15]. One survey of Norwegian academics found that the average postdoc in the natural sciences published 0.65 article equivalents per year[1][16]. Scientific productivity follows a power law distribution, for number of articles published[17], number of citations[18], and funding[19]. Also, we observe cases of extremely productive individuals within science, publishing over 70 articles per year [20]. While much of this productivity is due to not following authorship norms[20], still, there exists significant possibilities for productivity improvement within the sciences.

An additional source of waste in research is that much work remains uncited[21]; early and oft-cited estimates put the number of uncited articles at approximately half [22]. More recent research puts this number at approximately 12% of research remaining uncited after 10 years[23]. While this effort isn't entirely wasted[21], still, it does is an unimpactful use of (often public) resources[24].

Despite these lackluster results, little literature actually exists on improving scientific productivity[14]. PhD attrition rates ranged from 36% to 45% in engineering, mathematics and the sciences [25–27], a significant waste of time, effort and resources. Goal setting, especially when performed with a mentor[28], results in a significantly more positive PhD experience[29] and lower dropout probability[30].

[1]Defined by calculating one's 'share' of an article by dividing by the number of co-authors.

Given the positive impacts of goal setting for academics[31], explicit goal setting can greatly improve student outcomes, given that a minority (30%) of students have defined goals before beginning a doctoral program[32].

Despite the ubiquity of goal setting in industry[33], goal setting for improved performance in academia is still a novel field[34–36]. Given that burnout is a pressing issue in academia[35,37], and is related to feelings of low self-efficacy[37], the practice of goal setting (ideally with a mentor) can increase feelings of control[38], as long as care is taken to not overload work[37].

The question of resource allocation in the sciences can be politically fraught. US higher education research and development expenditures increased from roughly 10 billion US dollars in 1971 to over 70 billion US dollars in 2018 (US dollars 2012 equivalent)[39].

Still, research on the determinants of research productivity is minimal, despite the stakes. Determinants of research productivity (summarized in [40]) include self-efficacy[41,42], research skills[43], entrepreneurial orientation[44], mentorship[45], motivation [46], technology[47] and continuos improvement [48]. Typically, most major scientific conferences will host a panel on career management for (typically young) scientists, encouraging non-conventional career paths in industry or self employment, typically consultancy. Boosting the effectiveness of pupils throughout their career can be an effective use of resources. Approximately 6% of postdocs recommend against others going into a career in academia[49]. Some of the most common complaints are financial insecurity coupled with high expectations and overwork[50]. These issues can be remedied with peer support, opportunities for career progression, and mentorship[50,51], though pervasive issues still remain[52,53].

Chronic stress has deleterious impacts on productivity[54,55], though lack of stress can also be deleterious to performance [56,57]. Technological distraction is a common source of reduced productivity[58]. States of flow, as defined by Mihaly Csikszentmihalyi require, among other factors, clear goals, concentration, clear and immediate feedback, a balance between challenge and skills, a sense of control, an intrinsic sense of reward from the activity and absorption in the activity[59]. Given that this state of flow is highly productive and highly pleasurable, it is highly desirable to cultivate[60]. Agile workflows are ideally constructed for optimal productivity and include many of the elements which support flow. The below items are the nine conditions of flow as defined by Csikszentmihalyi [59].

Principles of Flow by Mihaly Csikszentmihalyi	**Correspondences in Agile Development**
Clear Goals	Well-defined user stories and sprint objectives
Concentration on the Task at Hand	Focusing on a single task during a sprintt, other tasks/concerns are kept outside the sprint
Clear and Immediate Feedback	Frequent feedback loops, including retrospectives. Tasks are brought to completion, creating reward.
Skills Match the Task	Individuals self-assign tasks.
Action and Awareness Merge	Sprint ideally supports mindfulness through eliminating distractions.
Sense of Control	Empowering self-organizing teams. Individuals choose their tasks/user stories
Loss of Self-Consciousness	Sprints can be periods of intense teamwork and bonding.
Timelessness	Focus is kept to the task within the user story within the sprint, and not the entire project timeline.
Autotelic Experience	Individuals choose tasks for themselves, ideally with intrinsic motivation for creativity or mastery.

Table 1: Correspondences between principles of Flow as defined by Mihaly Csikszentmihalyi [59] and current Agile practices. When there is not a strong correspondence between the Flow principle and Agile practice, the correspondence is italicized.

The correspondence between Agility and Flow is supported by the higher rates of job satisfaction on Agile teams compared with non-Agile teams [61,62]. Also, more frequent experiences of flow are associated with higher life satisfaction[63]. Agile may be a system which helps to facilitate flow in organizations. Given the massive issues of mental health, job satisfaction and sense of lack of control among academics[53], Agile practices which support flow may improve the satisfaction and productivity of scientific researchers.

Though in principle Agile transformation does not induce any large capital costs, it does require a significant reshaping of work practice and culture where it is applied [64]. This goes double for academia, where there is less emphasis on productivity improvement as evidenced by low use of coaching in the educational sector as compared to other industries [65], where those working with coaches typically see positive results on productivity[66].Another significant shift in the business world is the adoption of coaching as a vital part of business operations. Coaching is listed as one of the top skills for leaders to develop[67].

While not obviating personal responsibility, it creates a culture of continuous betterment and commitment to teamwork, rather than a narrow, individualized focus.

Another issue is that only half of completed research projects get published[68,69]. Within life sciences, it is estimated that approximately 85% of research investment, $200 billion USD in 2010, is wasted [70,71]. This is highly analogous to development time and resources going into products and features that the user ignores, with a high degree of failure to deliver. An Agile approach should minimize the wasted work; there is a relevant maxim to "maximize the amount of work not done." In software this refers to only creating software features which provide definite value to clients. In science this corresponds to only embarking on projects with an expected finish and defining the project scope beforehand.

Barriers to Agile adoption in research

Agile adoption in research faces similar barriers as in industry. Barriers preventing adoption are cultural resistance, lack of awareness and desire to change, procedural norms, collaboration and communication challenges and stakeholder resistance.

Training is a significant barrier to Agile transformation in research. Managers need to justify funding decisions, and many managers will perceive training in Agile to be unrelated to the project. Furthermore, adopting new work practices takes time in the near term. Fortunately, academics tend to have much less time pressure than their peers in industry, and even 'fixed' article deadlines are quite flexible. Changing one's work practices can have positive impacts for the rest of one's career and is far more beneficial than allocating that time to tasks which one spends the majority of their time doing anyways, usually with limited success.

Individual ego is an issue with any collaborative project. Conflict around rewards, recognition, and contributions are often arise in groups working tightly together on shared projects, but can be overcome[72]. Long term projects which have succeeded are characterized by an explicitly stated conflict-resolution process[73,74], with strong overlaps with non-violent communication (NVC) [75].

Education, especially technical education, often de-prioritizes 'soft-skills' development in favor of technical skills [76]. Soft skills have a significant impact on job performance and earnings, and are vital for the most highly skilled jobs [77]. Working in an Agile team requires a greater level of intrinsic motivation, one is expected to select the tickets that they will complete and bring them to completion during the sprint. Agile team members must demonstrate a greater level of communication, accountability, and self-direction than a traditional employee relationship where one is assigned tasks to perform in isolation. The necessary personal development required for an Agile workspace is an important barrier to adoption.

Other barriers include publishing norms, which prioritize delivering finished, unshakeable results in a publication. Typically, this results in on average three years between the end of data collection and publication[12], during which time the data and its interpretation is unavailable to the public. As mentioned, preprint servers are a step towards greater agility in scientific publishing, the community gets access to results sooner and can use the data and analysis to shape decisions[11]. However, the downside is that the data out in the public domain is not subject to the same quality controls that published research would undergo[78,79]. However, considering future publication as a mark of preprint quality, a study found that never-published preprints were cited a median of zero times and on average 1.99 times, compared to a median of 9 citations and a mean of 72.12 citations for preprints later published [80]. This significant difference suggests that researchers are capable of distinguishing quality research and making the decision to cite or not to cite accordingly.

The examples of Wikipedia and Linux operating system both were cases of community projects creating robust and error-correcting systems, whose accuracy rivaled their top-down counterparts (commissioned encyclopedias[81] and closed software[82]).

One deterrent of data sharing is the fear of the data being used to publish before the sharer can publish their own results[83]. Proper attribution practices can assuage these fears.

Operationalized, this looks like defining the experiments and proper controls beforehand. This should be apparent from the outset, though often some factor may emerge as important that requires controlling for. In situations where data collection is difficult or non-trivial, it is necessary to define the number of measurements to perform. This can be determined in advance based on the expected effect size and the sample size needed to demonstrate a statistically significant result.

Once tasks are defined, it lends itself well to an Agile way of working with Kanban boards for tasks. In the article guidelines for Nature, four display items (Figures and Tables) are recommended for a typical six page article[84]. This serves as a constraint on the scope of an article. Expansion is possible in terms of the number of panels, as well as the inclusion of supplementary information.

In advance of drafting an article, the project team can plan figure panels and associated data collection. Experimental design follows from the hypothesis that one is evaluating. Furthermore, there can be a branching logic that determines the subsequent experiments depending on if the results support the hypothesis or not.

Agile coordination, communication and publication

Another significant source of delay in science is the switching costs between roles. Laboratory experiments require reagents and often specialized material (e.g., purified proteins) to run. Setting up an experiment takes trial and error. Ideally, continuous data collection could be employed. In typical scenarios, the person taking the data also analyzes it, which can create inefficiencies; a preferable alternative is that the researcher analyze data semi-continuously (which can be automated) or share the data with someone capable and willing to analyze data. Sharing project folders between members of the group and delegating responsibilities is valuable for project organization and efficacy. To avoid confusion over the data, communication needs to be robust.

Here, standardized workflows are important in the development of Agile science. Standardization improves the quality level of the data and increases the level at which tasks can be automated and delegated. Standardization of workflows is also a crucial step in ensuring both reproducibility and objectivity in measurement.

Presently, the proliferation of preprint servers is one example of agility practiced within the scientific community. Instead of waiting for publication, data is shared beforehand. As an example, during the Iraq War, special warfare units requested fast access to raw satellite data from the National Security Agency (NSA). The NSA did not want to issue this, instead preferring to provide analyzed reports, which were delayed by at least one week (ref Age of Agile).

One common criticism levied against preprint servers is that the data may not be ready for publication, and the findings can be wrong and misused. While this is a possibility, during the coronavirus pandemic, significant stakes existed motivating very fast scientific production cycles.

The agility of combat units is especially important, as the on-the-ground situation can change extremely rapidly and requires constant adaptation. In the end, the NSA did release the raw reports early before following up with analyzed reports, which helped the special operations forces.

Going beyond preprint servers, researchers may choose to continuously upload raw experimental data as they run experiments. This also capitalizes on trends in broader digital transformation, namely those of elastic cloud computing, continuous software release, and open source frameworks. Elastic cloud computing allows the data to be accessible, and solves extant issues of adherence to FAIR principles (findable, accessible, intra operative and reusable). Furthermore, it provides an unparalleled level of transparency.

Currently, the main barriers to scientific teams continuously uploading their raw data are doubts as to the usefulness and practicality of this. While it requires some initial investment, cloud-based architectures ensure that this can be accomplished without any additional work. Furthermore, it also greatly expands the possibilities for remote collaboration, and analysis specialization. If data is publicly accessible, i.e. there has been a 'release', then other researchers can use it for meta-analysis or machine learning.

In the current research system, data remains in siloes at least until the publication of an article. Some journals require the raw data be published with the article, but in most cases it remains siloed.

In terms of field governance, moves towards mandatory deposition greatly aid the agility of science and the collaborative aspect of it. Great experimentalists can focus on generating results and have collaborators analyse it. In the present system, an individual researcher, particularly if they are a PhD student, is expected to design the experiment, carry out the experiment, analyse the data and write a paper. While exposure to all these domains can be important to one's development as a scientist, what can improve the broader productivity of the scientific field (and in turn the knowledge base of humanity) is a system where the participants leverage their individual strengths to improve total system productivity by comparative advantage.

Agile brought continuous release to the field of software. It can potentially be brought into science by going beyond the practice of using preprint servers and moving to continuous raw data uploading for experiments. Using the tools provided by digital transformation, this can become easy and automatic, and require less work than the current situation of each lab (and each research team) being its own data silo.

Conclusion

Agile has yet to achieve significant adoption in research, though some teams are implementing it with success[85–90]. Agile adoption in science promises to transform the field, not only in terms of efficiency, but also in the fundamental practice of science. Agile brings new formats for performing and disseminating research. Widely adopted, Agile can fundamentally revolutionize knowledge production and even the implicitly held epistemologies of researchers.

It is unlikely that a sclerotic scientific establishment will welcome Agile with a warm embrace, at least at first. Fortune favors the brave, and boldness and innovation are essential qualities for a volatile, uncertain, complex, and ambiguous world. Change is the only constant.

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