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TEACHING A MODELING PROCESS: REFLECTIONS FROM AN ONLINE COURSE

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ABSTRACT

The outbreak of the COVID-19 pandemic in 2020 posed unique challenges for academic and professional education, while at the same time offering opportunities related to the mass switching of the delivery of courses to the online mode. In this paper, we share the experience of organizing and delivering an online doctoral-level course on Agent-Based Modeling for Social Research. Our aim was to teach interdisciplinary content on various elements of the modeling process in a coherent and practical way. In the paper, we offer a critical assessment of different aspects of the course, related to content as well as organization and delivery. By looking at the course in the light of the current knowledge on good teaching and learning practices from the educational and psychological literature, and reflecting on the lessons learned, we offer a blueprint for designing and running complex, multi-thread simulation courses in an efficient way.

1 INTRODUCTION

Disruption to educational activities has been but one of the many impacts of the COVID-19 pandemic on the different aspects of social life. The many associated challenges aside, the forced switch to online delivery has been often relatively smooth. Thanks to the proliferation of online communication technology and ubiquity of e-learning tools and remote teaching methods, this switch has even brought about some unexpected opportunities. In this paper, we reflect on the experiences from running a PhD-level course, entitled Agent-Based Modeling for Social Research, which was carried out in late 2020, in the place of a week-long residential summer course that had to be canceled due to the pandemic. By doing so, we aim to provide a blueprint for designing, organizing and delivering complex simulation courses in an online environment, while reflecting on those aspects of the course that could have been done differently.

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From the point of view of teaching simulation techniques, two challenges were particularly important for online delivery. First, we aimed to coherently cover interdisciplinary material, catering to a diverse audience with a range of programming skills, in an online-only framework. Second, we focused on the methods and practices related to the different aspects of the modeling *process* rather than on a specific technique or application. The underlying modeling process itself has been detailed elsewhere (Bijak et al. 2020), and in this paper we present just the aspects that are relevant for achieving our educational objectives.

This paper is aimed at two partially overlapping audiences: (1) researchers who convene and deliver online courses on modeling and simulation, in particular on Agent-Based Modeling (ABM), and (2) organizers and administrators of online courses on modeling and simulation, but also other (formal) topics. The remainder of the paper is structured as follows. Section 2, relevant for both audiences, presents the state of the art in the relevant aspects of learning, from high-level remarks on the psychology of learning and good practice in online education, to a discussion of the teaching of simulation methods. Section 3 presents the case study of our online course on agent-based modeling, with focus on course design and content, aimed at course conveners (Sections 3.1 and 3.2), as well as practical aspects, relevant for organizers and administrators (Section 3.3). Section 4 includes critical reflections and lessons learned from running the course, as well as suggestions of changes for future editions, again relevant for both audiences.

2 STATE OF THE ART

2.1 Psychology of E-learning: General Remarks

The use of digital technology in society is now ubiquitous. It is no surprise, then, that e-learning (learning via digital resources) in education, health, and corporate settings has now taken center stage. For example, virtually no student anywhere in the developed world now earns a post-secondary degree purely via conventional face-to-face teaching any more: e-learning, in various forms, nearly always plays a part, ranging from the basic opportunity to review recorded live lectures through to courses offered entirely online. This trend has only been intensified by the COVID-19 pandemic, which has seen many educators having to convert their courses to an online format in a very short time period (Szegedine Lengyel 2020).

A great deal of research has attempted to evaluate the efficacy of e-learning. Some studies have found that e-learning is as good as, if not better than, conventional teaching methods (e.g., Pei and Wu 2019; Rakic et al. 2019; Yuwono and Sujono 2018), particularly if it is combined with some face-to-face teaching (blended learning; Means et al. 2013). However, the particular benefits of e-learning over face-to-face teaching are not always clear cut, and some studies have even found it to be inferior, particularly if pure e-learning is compared to conventional teaching rather than blended teaching (e.g., see Means et al. 2013).

Part of the challenge of evaluating e-learning is that it typically deviates from conventional teaching on myriad dimensions. These dimensions include, but are not limited to, (1) student motivation, (2) opportunities to interact with instructors and/or peers, (3) time-on-task, (4) forms of assessment, (5) presence of interactive elements, and (6) student satisfaction, to name a few. Hence, understanding whether and why e-learning is better or worse than conventional teaching is a particularly complex task.

Experimental cognitive and metacognitive psychology offers a potentially useful framework that can be used to navigate this complex situation. The concept of desirable difficulty (Bjork 1994; Bjork and Bjork 2020) suggests that if learning is to be durable, it should incorporate obstacles for learners to overcome. For example, many studies have shown that learners who engage in effortful retrieval of previously learned information retain that information for longer compared to learners who merely restudy it or who engage in effortless retrieval (e.g., Pyc and Rawson 2009; see Rowland 2014 for review). In other words, learning must be hard work to be durable, but, of course, not all difficulties are desirable. For example, distraction during learning makes learning difficult, but it does nothing to enhance it (Mendoza et al. 2018). What is critical is that the difficulties engender cognitive processes conducive to long-term memory retention.

In addition to the retrieval example, there are many studies that suggest desirable difficulty is a generalizable principle. To cite a few examples, learning is better if (1) it is spaced over several learning sessions versus massed in one learning session (Benjamin and Tullis 2010), (2) it involves active engagement versus passive listening (Deslauriers et al. 2019), (3) practice problems of different types are interleaved rather than grouped in blocks (Kornell and Bjork 2008), and (4) the conditions of learning are varied rather than held constant (Smith and Rothkopf 1984). In all these cases, the superior method creates difficulties for the learner, thereby slowing the learning process compared to the inferior one.

While desirable difficulties are good for durable learning, their effectiveness is not typically appreciated by learners. In fact, several studies show the opposite: learners tend to believe that fluent, easy learning conditions produce the most durable memories. In a recent study on mathematics learning, school-aged children were asked to assess their own learning when practicing Venn diagram and permutation problems according to either a spaced or massed practice schedule (Emeny et al. 2021). Unsurprisingly, the children's actual performance was much better with the spaced schedule, but their predictions strongly favored the massed schedule. Presumably, massed learning was easier because the method needed to solve the problems was applied to all the problems within the same session rather than having to be retrieved for multiple practice sessions. However, this accessibility misled the children into believing their mathematical knowledge was relatively permanent when, in fact, it was often forgotten soon afterwards. Analogous results to these have also been obtained with adults (e.g., Simon and Bjork 2001; Zechmeister and Shaughnessy 1980).

For e-learning, the principle of desirable difficulty provides a reasonable way to understand whether an online mode of delivery is likely to be effective. One potential danger of this delivery mode is that spontaneity in delivery may be lost. Instead, instructors may work very hard preparing lecture videos in which material is presented in a slick, errorless manner. However, spontaneous delivery may constitute a desirable difficulty. For example, an instructor correcting herself when defining a concept may cause her students initial confusion, but it also informs students about the easily made types of confusions. Moreover, highly fluent online lecture delivery could potentially lead learners into a false sense of mastery over the material. This metacognitive illusion, in turn, could undermine learners' future attempts to revisit the material and learn it properly. Thus, if e-learning is to truly live up to people's expectations as a superior educational method, it must incorporate desirable difficulties for learners that promote memory retention.

2.2 Teaching Simulation Modeling: What Works

Knowledge about and expertise in applying diverse mathematical methods, as well as in-depth knowledge about the application domain, are needed to build a suitable abstraction of the system (the simulation model), and to execute simulation experiments, that reveal insights into the system behavior. Therefore, modeling and simulation has been considered a science and also an art (Shannon 1998). Simulation studies are intricate processes, in which modeling, designing, executing experiments, and interpreting their outcomes are intertwined. As modeling and simulation is applied in nearly all areas of science and engineering, any course on modeling and simulation requires specific focus. A plethora of courses and approaches to teach modeling and simulation exist (Altiok et al. 2001; Molnar et al. 2009), including on agent-based modeling (Macal and North 2013). These approaches reflect the scientific culture of the application and the purpose(s) of modeling and simulation and depend on answers to the following questions:

- What is the goal of the course: shall the students learn basic concepts of modeling and simulation (Schriber et al. 2013), about one modeling technique in more depth, e.g., DEVS (Van Tendeloo and Vangheluwe 2017), to apply a specific tool (North et al. 2007), about one type of task in simulation studies, e.g., experiment design, or shall oversee the conduction of entire simulation studies (Loper et al. 2019), or grasp broader scientific concepts, e.g., system thinking (Hung 2008)?
- What is the format of the lectures? Are these 90-minute tutorials, e.g., to be held at a conference, lectures including practical exercises spanning over a week, or lectures taught at a University over a twelve-week period? This will have an impact on the level of detail that can be captured.
- What role do practical exercises play? Are tools available to capture all aspects of modeling, or shall students receive first-hand experience in implementing simulation algorithms?

- What is the background of the students? What is their age, e.g., is the lecture give at a school (Grgurina et al. 2018) or as part of a University curriculum (Loper et al. 2019), and what is their education, e.g., have students a background in computer science (Kashefi et al. 2018) or biology (Bodine et al. 2020), and how homogeneous is the audience in that regard?
- How shall the success of the course be measured? This will also depend on the format, e.g., whether it is a tutorial held at a conference, or an obligatory course in a computer science curriculum. In addition, different goals of a modeling and simulation course provide different challenges for measuring the success, e.g., if students shall be taught in the process how to develop conceptual models as crucial part of the modeling and simulation life cycle (Loper et al. 2012).

How one question is answered constrains answers to other questions: e.g., if diverse aspects of continuous time agent-based modeling and simulation shall be captured both theoretically as well as by practical exercises within a four-week remote course, then the students need a solid background in modeling and simulation, and some experience in applying modeling and simulation methods. Thus, a thorough selection of students (and a moderate number of attendees) is key in enabling the intended learning progress.

3 CASE STUDY: AN ONLINE COURSE ON AGENT-BASED MODELING

3.1 Background, Course Aims and Learning Objectives

This section presents details on the course of Agent-Based Modeling for Social Research, organized as one deliverable of the Bayesian Agent-Based Population Studies project, funded by the European Research Council. The course took place virtually, on 3–25 November 2020, with plenary sessions held online every week, interspersed with small-group activities and tutorials, as discussed in detailed below.

The main aim of the course was to familiarize the participants with the most recent advances in building, analyzing and documenting agent-based models of social processes. The course covered different aspects related to the choice of modeling language and environment, tailoring models for specific research purposes, statistical analysis of model results and key principles of experimental design, inclusion of realistic cognitive assumptions in models, and documenting the modeling endeavors by using alternative approaches. The course was aimed at PhD level students and early career researchers with some prior experience with coding and interest in computational modeling in social science. The course was financed from the project, and as such was free to attend, but entry was competitive, and the number of participants was capped at 25.

The intended learning objectives of the course were six-fold. In line with the broader program of work underpinning the course (Bijak et al. 2020), the participants were expected to learn how to:

1. Discuss different principles of agent-based modeling and apply them in practice
2. Reflect on the history and uses of agent-based models in social sciences
3. Evaluate the relative merits of different approaches for implementing agent-based models
4. Analyze the results of agent-based models by using selected statistical methods
5. Include psychologically and cognitively realistic assumptions in agent-based models
6. Document models by using documentation standards and provenance-based approaches

The main innovations of the course in comparison with other similar courses on agent-based modeling were therefore the focus on different elements of the modeling process, as well as its interdisciplinary outlook. To that end, modeling itself provided a backbone to the course structure, expanded by adding elements from other relevant scientific disciplines. The guiding principles, translating the different elements of the modeling and simulation life cycle (Robinson 2014) onto the course structure and sequence, are shown in Figure 1. The specific ingredients of the scientific content of the course and the logic of its organization are discussed next, followed by a review of practical aspects of the course delivery. All these elements and the underlying principles can serve as a blueprint for designing, organizing, running and reflecting on similar courses on modeling and simulation.

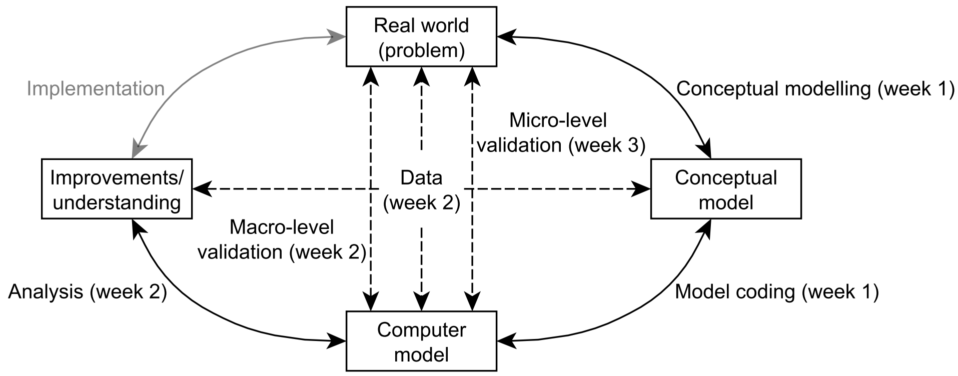

Figure 1: Mapping of the course content to a modeling and simulation life cycle (after: Robinson 2014).

3.2 Course Content and Logic

The first week of the course was dedicated to the theory of modeling and the practicalities of implementing agent-based models in Julia. For the theoretical part we pre-recorded a general introduction, followed by two short lectures, with a general **introduction to modeling**, introducing the concept of explanatory vs. predictive modeling and general advice on best practices, as well as a condensed overview of behaviors in complex systems that can make prediction or understanding difficult. We used the first live session to discuss questions the participants had concerning these two video lectures.

As a preparation for the second part, participants had been given an **interactive Jupyter notebook** (Kluyver et al. 2016) to work through, which was intended to give them a quick introduction to the most important aspects of the Julia language (Bezanson et al. 2017). In the live session we built on that by demonstrating the step-wise implementation of a simple agent-based model in Julia from scratch, without any pre-defined libraries. Again taking advantage of the interactive nature of Jupyter notebooks we went through the necessary coding steps together with participants, starting off with defining and creating simple agents and ending with running a full simulation and displaying some results. We interspersed that process with a few simple coding "quizzes" that participants were encouraged to solve on the spot.

In the video lecture on **model implementation** we emphasized the topic of discrete event simulation. While most agent-based models are based on discrete time steps, the potential for bias to be introduced in discrete time models (see for example Özmen et al. 2016) is well known. Hence, we aimed to enable the participants to judge the potential risks of discrete time models, and to apply discrete event simulation when necessary. We showed an example of a rule-based approach with the continuous-time Markov chain (CTMC) semantics (Warnke et al. 2017), and demonstrated the simulation algorithm for such a model. We prepared example models in both variants, to serve as the starting point for model implementation.

Preparation for the second session on **data quality and describing uncertainty** included a video introducing some of the problems with social data, and a proposed framework for quality assessment. This was followed by a discussion of probabilistic description of sources, with focus on the bias or variance of data. Participants were then asked to use the framework to assess an example data source. During the live session a Vevox live poll provided a tool for participants to share their individual quality assessments and discuss the results in real time. These interactive elements allowed the key messages to be consolidated and highlighted the challenges around data quality and incorporating uncertainty into the model.

The session on **model analysis** focused on introducing the notion of a model as a tool for simulation experiments, enabling the use of statistical techniques of experimental design. In a pre-recorded video, and a live follow-up session, we covered both descriptive methods, as well as key principles of statistical meta-modeling, sensitivity and uncertainty analysis, with examples. This aspect was later to be developed in the context of the group projects towards the end of the course. To help reinforce learning, before this session, the students were asked to watch the video and solve two introductory tasks related to the topic.

The **psychological experiments** session focused on the role that individual level empirical data, collected via experiments and surveys, can play in agent-based modeling The pre-recorded lecture discussed the information that can be gained using psychological experiments and surveys, as well as some of the key challenges in formalizing and applying these types of data. Participants also completed a demonstration psychological study prior to the live session to provide them with an engaging and interactive task and improve their understanding of psychological studies. This was accompanied by an active discussion during the live session about the advantages and disadvantages of applying findings from psychological studies to agent-based models, further followed up in the group projects in the context of the models being developed.

In the final session we discussed **model documentation**, as an essential part of the modeling process and of communicating the model. We presented the ODD+D template (Grimm et al. 2020), as the most relevant standard for documenting ABMs, and discussed both its advantages and its shortcomings. In addition, we suggested provenance models for formal description of the model documentation (Ruscheinski and Uhrmacher 2017) as an alternative, or indeed complementary, approach. The structure of the course and flow of its main activities and outcomes are shown in Figure 2.

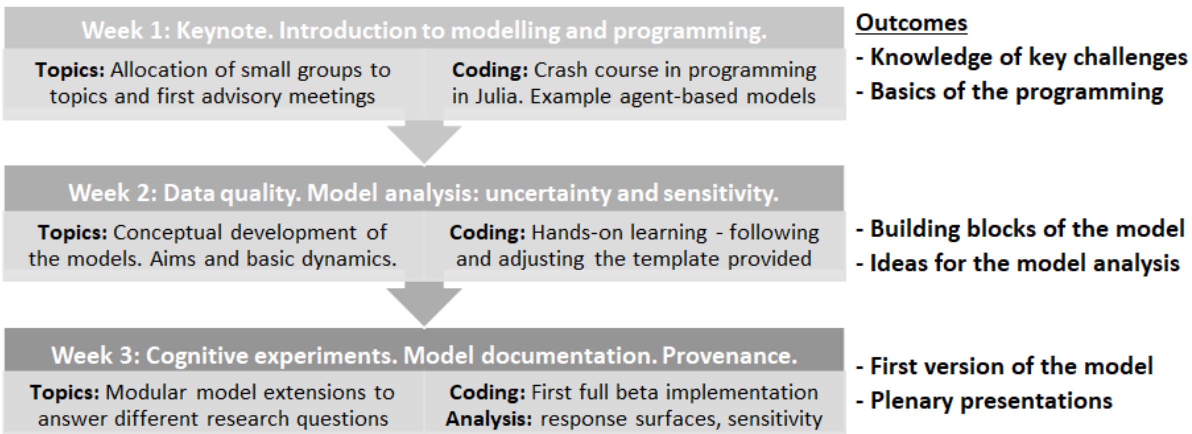

Figure 2: Flow of the learning activities in the successive weeks of the course and their key outcomes.

3.3 Practicalities

The course ran across just over three weeks in November 2020 and was delivered using Microsoft Teams as the **virtual learning environment (VLE)**. Delivery was originally planned as a five-day intensive residential course in Southampton, UK, to learn and work in a small group environment. It was a conscious decision to choose a virtual learning environment which could recreate the collaborative feel and allow both synchronous and asynchronous learning. Participants could also contact tutors directly via the chat function, personal email or the dedicated course email address which was redirected directly to the organizers

The main **live sessions** – plenary lectures and interactive practicals – were held for two hours a day, with plenaries at 15:00–17:00 GMT, during a window that allowed participants from various time zones (South America, Europe and Asia) to join during waking/working hours. Participants sometimes struggled to arrange their group sessions at a time which suited everyone. The disadvantage of not being together in a computer laboratory was most strongly felt in the live interactive sessions, as using modeling software alongside the tutor was difficult, and issues took longer to troubleshoot remotely. The scheduled practical sessions often overran. In the final live session, participants were invited to present reports on their group work, and then were directed to complete an online feedback form, embedded into the VLE through

Microsoft Forms. Finally, participants who attended the live sessions and contributed to project work were offered a certificate of completion for 24 hours of Continuous Professional Development (CPD). The timetable and sequencing of different types of sessions during the course are shown in Figure 3.

Course day	**1**	**2**	3	4	5	6	7	8	**9**	10	11	12	13	14	15	**16**	17	18	19	20	21	22	**23**
Activities	**K**	**L**	T	T	W	W	C	C	**L**	T	T	W	W	C	C	**L**	T	T	W	W	C	C	**P**

K = Keynote and opening; L = Lectures; T = small groups: topics; C = small group: coding; P = presentations

W = Weekend | Plenary sessions **in bold**

Figure 3: Schematic timetabling of the course, including plenary sessions (keynote lecture and the opening session, interactive lectures, group presentations) and small-group activities.

Even though the **formal prerequisites** included experience with computer programming and statistical analysis, no prior knowledge of agent-based models was assumed. This was intended to provide a desirable level of difficulty for the participants – not too high to avoid being detrimental, but still challenging. The course had thus to be designed to account for participants with varying knowledge and experience levels of programming, and the added pressures of their work and home-life commitments and working from home during a pandemic. All participants who signed up to the original in-person course agreed to attend the postponed virtual delivery. Several participants dropped out during the delivery of the course due to either increased work pressure or for health reasons. We started the course with 25 participants enrolled, selected from the original pool of 35 applicants, and finished with 21. The profile of participants spanned several disciplines, from social to biological and health sciences, as well as engineering.

The participants were selected based on the alignment to the entry criteria. The shortlisted participants were asked to rank the topic choices by preference, and were then assigned to five equal tutor-led project groups for the duration of the course. To facilitate learning through an adequately-spaced schedule (see Section 2.1), the course consisted of five structured sessions, ten hours in total. The participants were expected to make up further 14 hours of work through self-study, one-to-one and small group meetings, both with tutors and self-organized The course started with a virtual keynote lecture by an expert in the field (Prof. Alexia Prskawetz, Vienna University of Technology), followed by an icebreaker with group activities. Course materials included nine pre-recorded short lectures (2hrs 15mins in total), a reading list with 21 articles or book chapters, and three self-paced demonstration tasks. The pre-recorded lectures were uploaded to the VLE a month prior to the start of the course. Participants also needed access to coding software (JupyterLab, Julia) and one person per team was asked to upload group project work to GitHub.

The participants were sent **advance instructions** on: (1) Technical guidance and tips on how to use the VLE; (2) How the course materials and VLE would be structured; (3) How they would be expected to interact with the VLE and each other via a meeting etiquette document. The use of built-in 'Tags' allowed posting notifications to specific groups of participants. Communications were not reliant on access to the VLE, as participants were emailed three times a week during the course delivery, first, with a reminder of the work and session content for the week, second, with a reminder for time and link of the live meeting on the day, and third, with a summary of live meeting actions, and work set for the following week.

Participants were added to the VLE in advance of the course, to encourage early engagement and iron-out any technical difficulties before the start of the live sessions. The front page of the VLE served as a notice board. As the breakout room functionality had not yet been implemented at this point, we used channels to create distinct areas for small groups to manage their projects. In these, participants could create their own threaded discussions, store and manage files, and organize ad-hoc meetings.

There was no formal assessment, but **informal (formative) assessment** took place throughout the course. Participants were asked to complete self-paced tasks in their own time, and then report back their issues and answers to the group in the next plenary session. Tutors also utilized the polling application Vevox to allow participants to answer questions during the live session anonymously and quickly. A secondary benefit of using the polling app was that varying the mode of teaching delivery fostered engagement, which can be a challenge during online teaching, and the anonymity of the application removed a social barrier if the learner would be too self-conscious to answer questions incorrectly. This encouraged a dialogue and allowed the tutors to assess the learning of the group as a whole. Such retrieval practices (quizzing) and varying the conditions of learning both constitute desirable difficulties mentioned in Section 2.1.

4 REFLECTIONS AND LESSONS LEARNED

4.1 Reflections on the Online Agent-Based Modeling Course

To aid reflections on the course and help prepare for any future editions, we have solicited **feedback from participants**, through a short survey with 15 questions, which was completed by 17 participants. Qualitative feedback was also gathered from written comments in emails and the chat areas in the VLE. Overall, participants enjoyed the course. No respondent to the feedback form indicated disappointment with the course, and the majority rated it 5 out of 5 ("I very much enjoyed attending the course") on the five-point Likert scale. All participants indicated that the course had increased their interest in the subject, and 15 (88%) stated that they would share knowledge learned on the course with a colleague.

The course was successful in advancing the knowledge of agent-based modeling and related topics among the participants, 13 of whom (76%) said that the course increased their knowledge on the subject, three (18%) responded neutrally, and only one responded that they had learned a little. Most participants planned to use their learning from the course towards a future publication or thesis, and some hoped to use their new knowledge to benefit public policy. Two participants remained in contact with their tutor after the course, to pursue their modeling project further, with the aim of incorporating it into their research.

The highest-rated asset from the course was the tutors' knowledge and expertise, with the interactive tutor sessions scoring the highest in terms of quality and usefulness to the participants. Participants also appreciated the accessibility and dedication of the tutors, also in terms of the additional time spent on small-group tuition. They have indicated a solid grounding of the concepts of agent-based modeling, but some also hoped for an opportunity for a follow-up, as indicated for example by the following comment: *"I really do hope there is a continuation to this course as there is still a lot to learn."*

In terms of the **course shortcomings**, several participants were disappointed with their progression when using a new programming language, e.g. *"The whole setup was pretty good really, given the circumstances – just marred for me by the fact that I could not really get off the ground with the programming"*. Additionally, participants underestimated their initial knowledge and the involved nature of the course. While some found the course and materials "well-pitched", or even too superficial, most comments suggested that participants struggled to keep up, with comments like "challenging" and "intense" recurring in the feedback. This suggests a slightly too high level of difficulty, at least for a part the group – not surprising, given that the participants had to learn a new programming language and the principles of modeling at the same time.

In Section 2 we mentioned the desirable difficulty of tasks and learning techniques. While the feedback suggests that that this was partially achieved, the difficulty of the course may have felt exacerbated by the workload, combined with additional pressures of the COVID-19 environment, e.g. in *"The pandemic makes it hard as we had a lot to cope with and reduces our time to engage"*. Still, even where participants have not contributed working code to their group projects or achieved the desired levels of progression, they still reported increased confidence and understanding of ABMs and the modeling process. This suggests that the inclusion of challenges and obstacles might have had a desirable effect on learning, the durability aspect of which, however, is difficult to judge without carrying out dedicated follow-up tests and experiments.

Many participants also struggled with the **intensive nature of the course** and the expected workload, many trying to fit the course around full-time jobs or study. Some 82% of responders confirmed that they spent 24 hours or more on the course in total, particularly participants without previous experience who took longer to familiarize themselves with the software. Several participants recognized that the workload was reasonable when compared to a 5-day in-person course, but one stated that they would not have signed up, had they understood the time commitment. Five (29%) participants indicated that they would have preferred a longer course with increased spacing, to allow more time for self-study and content absorption.

Despite the challenges, on the whole, the six course goals summarized in Section 3.1 were achieved. Participants left the course with a better, holistic understanding of ABMs, when the models could be applied, appropriate model structure and theoretical assumptions, and basics of an appropriate programming language in which to build the model. Importantly, the course fostered a positive learning environment and encouraged participants to continue their learning in the future, as witnessed by the following comment: *"This is one of the best courses I have been too. Thank you for your time and sharing your knowledge!"*

4.2 Lessons Learned and Ideas for Future Editions

From the feedback we solicited from participants, and our post-course reflections, it appeared that the participants struggled most with the actual **implementation of the model**. For many of them the difficulty of translating their model into working code prevented them from progressing as fast or as far in the course as they would have liked. There are a number of potential reasons for this. First, it appears that our attempts to filter participants by coding experience did not work, in the sense that potential participants' self-assessment was a lot more optimistic than we expected. Another reason, supported by some of the feedback we received, may have been that coding in a new (for them) language is a lot harder for inexperienced programmers than we accounted for. Finally, overestimation of the participants' abilities on the side of the tutors might have led to inefficient tutoring especially during the first week of the course. Even though Julia seems to be a good choice of a language for such a course, in particular in terms of the long-term value the participants can get out of learning it, these issues need to be addressed, so that the course can reach its full potential here. There are clear trade-offs between the accessibility of the programming language used and ability to implement and analyze the more sophisticated aspects of modeling and simulation experiments.

This issue could be addressed in a number of different ways. To make sure that participants' coding experience is sufficient for them to profit from the course, the pre-screening could be more stringent. Alternatively, the programming and modeling aspects can be separated, so that the modeling course is preceded by a dedicated programming course (either by the same team or outsourced e.g. to the IT department) or participants are urged to take part in an existing self-study program Another (not exclusive) option would be to have very intensive programming tuition in the first week, with a lot of attention especially to the less experienced participants. If that is not possible, the language/coding barrier could be reduced by letting at least the less experienced participants use either a language they are comfortable with (such as Python or NetLogo, Wilensky 1999), pseudo-code, or a framework that provides most of the infrastructure necessary for agent-based modeling (such as `Agents.jl`). This would limit the course material in terms of coding and implementing models, but would allow the participants to at least learn the more general modeling principles and higher-level conceptual aspects of modeling. Changes to these aspects of course design and delivery could help us adjust and reflect on the possibility of incorporating additional desirable difficulties in any successive editions, and to fine-tune the course blueprint in that way.

At the same time, there need to be **clearer expectations about workload and time commitment**, including on the tasks and reading – for the next edition of the course, we plan to use an open-access monograph, which would act as a textbook (Bijak 2021). Ideally, we would also recommend that participants block a day a week to work on their projects, but realistically this may not be possible given other commitments. From that point of view, running the course over a longer period to allow for greater comprehension is an appealing option. To some extent, the participants can be also involved in the planning of the course, with a pre-course survey asking them about topics to focus on. In terms of VLE choice, additional considerations include the privacy of communication: in our case, this required recording consent to share data and messages from all participants, but absent that, a different VLE might have been preferable.

Finally, as a general point, more attention needs to be paid to **accessibility**: for example, some platforms now include automatic live closed captions, and the same could be introduced for pre-recorded videos. Course materials created using Microsoft Office (for example, the PowerPoint slides used in presentations) can utilize the built-in accessibility checker tool. As even well-designed slides cannot be read by screen readers within a live video, the presentation slides could be shared in advance, ideally along with the transcripts, with images described verbally or notes added to the chat bar. Visual accessibility and awareness of color blindness and other visual impairments are additional considerations here.

On the whole, as discussed throughout this paper, the course has benefited not only the participants through their learning, but also the teaching team, through enabling a higher-level reflection on online teaching provision, with focus on modeling and simulation. The proposed blueprint achieved its aims, but as documented above, the lessons learned from this edition of the course can help design and run the next editions more efficiently, and paying closer attention to the various aspects of (online) learning and the associated best practice. This will be facilitated by some of the content being already made freely available online (Bijak et al. 2021). Some of the lessons learned are of general nature and are likely to be transferable to other remote educational contexts. As the world emerges from the COVID-19 pandemic, they will be especially important to address the new challenges of the rapidly-changing educational landscape.

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