Interviewer #1: ... Few things I wanted to, let you know. The first thing is the purpose of this interview is not to judge your ability to set priors, but for us to understand what sorts of interfaces and what sorts of information might help people better set priors. So, if something doesn't make sense, or doesn't seem useful, then you should really let us know. And also whether if something seems useful then it is important for us to know as well.

Participant #1: Okay.

Interviewer #1: So this document that I shared with you it has three pages. The first page is similar, exactly what you saw in the survey, the second page of the survey. You saw the prior probability density parameters?

Participant #1: Yep.

Interviewer #1: And...

Participant #1: Looks like he froze.

Interviewer #2: Oh.

Participant #1: Oh, disappeared.

Interviewer #2: Oh, shoot. Oh, he's back.

Participant #1: Oh, wait. There you go.

Interviewer #2: We lost you for a second there, I1.

Interviewer #1: Resolving network issues. Okay. Is it fine now?

Interviewer #2: Yeah, it's fine now. It was a just after you said which version of the visualization he saw.

Interviewer #1: Ah, okay. Cool. I've been having network issues. You saw this visualization which is the probability density of the prior. And you set the prior as a normal distribution with mean of 3.52 and standard deviation of 0.24. So I guess looking at this interface again, and the prior that it shows, will you walk us through what you did with the interface and what was your strategy in deciding to choose this prior?

Participant #1: Sure. Well, I should say from the outs I don't think I have it open now, but when I was going through this survey I happen to have RStudio open at the time. So I use that to do a quick transformation of some of the information that you gave me initially, looked at it on the log scale to kind of give me a sense of what would be informative, not informative, that sort of thing.

Participant #1: I don't think I have R open at the moment, but that was a part of what happened.

Participant #1: But in terms of how I use this, so I scroll down, grab this, and got a sense of, all right, so for the intercept it didn't take me long to figure out that you had this initially centered approximately about where I would expect the intercept to be on the transform scale. And I had a sense that, just going up and down, that up was clearly more informative, tighter density. On the scale that it was on it seemed like I could go pretty tight density and the limit seemed like it was still pretty permissive. So that's where I ended up.

Participant #1: But I didn't play around much at all. I mean, ultimately I looked at the student, went down to the normal, looked at that. I could go up and I went up, and that seemed pretty reasonable to me.

Interviewer #1: Could you scroll up to the first one?

Participant #1: Yeah, sure.

Interviewer #1: Okay. So, here, how did you decide what was reasonable, what was unreasonable? You mentioned you did some calculations in RStudio, could you describe your thought process? What sort of calculations were you trying to do?

Interviewer #2: Would it help to hit the "show description" button so you can see the-

Participant #1: Oh, yeah, that's probably what-

Interviewer #2: Yeah.

Participant #1: Yeah, that worked because why we were relying on memory and that is a weak thing to rely on.

Interviewer #2: Exactly.

Participant #1: Okay. So I went through here... So, for me, average number of bumps I'm getting a sense of the kind of range I might expect. It's between, you know, about 25 and 44. I took that, took the log of that, to get a sense of what range we're looking at. I don't have R open at the moment. I mean, we could wait for me to do that. But I looked at the transform to get a sense of what neighborhood I'm working in. And on the log scale I'm guessing that this is putting me about in this neighborhood. It looked like you had it pretty near centered where I would expect it based upon this up here, so I didn't feel the need to move that around. And then, of course, there's just the experimental knowledge that you're likely to center something around the approximate range that you thought was reasonable. So it seemed reasonable to stay within that.

Participant #1: In terms of width, since we're working on the log scale, plus or minus even one is pretty permissive and so I felt very comfortable going all the way down... going all the way up once I saw the sense, go all the way up. This is putting me within about the 95 intervals, pretty close to plus or minus one. I felt pretty good to go.

Interviewer #2: I think the other question there is the choice between the normal or the student t.

Participant #1: Sure.

Interviewer #2: If you scroll back up to that one the drop down box there lets you make that selection. Did you-

Participant #1: I went to normal in... Open the past year, so I've been moving in the direction of playing around with the normal. I certainly started using the student t a lot a couple years ago. And I'm just more comfortable with the extra regularization from the normals. Especially if I'm... I often times I work on standardized data sometimes with data that's log transformed and that's... I tend to work with very small effects, small effect sizes and, man, you can... those thinner tails on the normal still are pretty permissive on most of the instances that I work in. And this seemed to be not the case.

Participant #1: But, yeah, if you had given me this about a year ago, I would probably gone with student t.

Interviewer #2: That's fair. Yeah, it looks like I1 is still having some network issues. So I think I'll just keep going and he'll join back in if he can.

Participant #1: Sure.

Interviewer #2: Would there... Let's see, I just need to pick up where we are. Okay, so that was the prior for the intercept parameter and then if you scroll down we have the prior for the mean difference parameter with the same interface that you saw before.

Participant #1: Yep.

Interviewer #2: And if you could just do that same thing, walk through how you made the decision for the prior that you set here, which looks like was the normal(0, 0.2).

Participant #1: Sure. Yeah, it was just, I tried to keep it centered on zero, went up because it just seemed like a regularizing prior that's suggesting I'm not going big effects one way or the other. With this being on the log scale, even negative to positive .5, is still pretty permissive. So I thought going all the way up is still not terribly strong, especially if we have a reasonable amount of data.

Interviewer #2: Mm-hmm (affirmative). Okay, so then thinking about the process you went through with setting this prior and with setting the previous prior, were there any challenges that you faced with the interfaces? Things that weren't working the way you would have expected or something that might have been helpful that wasn't there?

Participant #1: No, I think overall the interface that it was pretty apparent how to use the box and dot portion of the interface. That made sense. It's scaled intuitively with the density. The toggle made sense, student t to normal. There's a moment when I realize that the student t, when I was constrained, to a particular new value that I felt a little more constrained than I would like to have been. But it was fine especially since I went normal anyways.

Participant #1: The only thing that felt like it would have been more helpful is if there are a couple markers on common interval widths, something like that. You know, like a typical 95 or even a 50% interval or something like that. But, I could have a basic sense of what that was like. It gets pretty close to where the density hits the axis anyways.

Interviewer #2: Mm-hmm (affirmative). Okay, great. So, I think that's it for this page and if you could click the "next page" button on the bottom there, we'll go to the second page. Which I believe takes a minute or two to load.

Participant #1: Okay.

Interviewer #2: So this is the second of three pages, so it'll be this and then one more after it.

Participant #1: Okay.

Interviewer #2: And so here we're going to show different variants of the same sort of interface you saw before. And this one is, I believe, the prior for the intercept. Is this one on the response scale?

Interviewer #1: No, this is not. You can skip this one.

Interviewer #2: Oh, sorry. Oh, okay, yeah.

Participant #1: Next page?

Interviewer #1: No, no, no. There are two visualizations, the second one.

Participant #1: Here?

Interviewer #1: Yes.

Interviewer #2: So this will be showing you the... So the first visualization was the one that you saw in the survey. The second one here is that prior transformed back on to the response scale.

Participant #1: Okay.

Interviewer #2: And so, what we'd like you to do is take a look at this version, the prior transformed on to the response scale, play around with it a little bit. Again, verbalizing what you're thinking. And then go ahead and tell us if there's any information there that you think would affect the way you've chosen your priors. If there is something that you've learned here that might be different from what you saw.

Participant #1: Okay, so the prior's still on the scale it was before, but it's just the visualization itself is what you asked for?

Interviewer #2: Exactly.

Participant #1: All right. So let's see. But first, I'm just going through and getting a sense of about what it would have looked like... what it looks like compared to what I used before. I'm now thinking that I'm going to go back up real quick and double check those original values. And to get that here would "show description"?

Interviewer #2: Yeah.

Participant #1: Okay. 25 to 44. Yep. To my eyes it still looks pretty good. That's 25 to 44, that range, were right in here. That's well within the center of the density. I still feel good.

Interviewer #2: Okay. If you were to contrast this with the other interface, which of these do you think you would find more useful in practice?

Participant #1: If I had to choose only one in particular where I was going to set a prior on a model that was on the log scale, I'd go for the first one because the prior matches the visual. But, if I could be greedy and ask for both I think I'd like both because this is great. It gets me on the response scale, but it gives you that extra complexity because now I have to map on a response to a prior, a transform prior space, which would be difficult unless I had access to R and I could plot that out really quick on my own.

Interviewer #2: Right.

Interviewer #1: Can you elaborate on that? What would you plot on R?

Participant #1: Sure, so if I only had access to what we see right here, then it might be nice to just plot the distribution of the prior out itself, on its own scale. On the log transform scale.

Interviewer #1: I see.

Participant #1: I might want to see that just so it's very clear to me what it looks like there. It's nice that there's a transformation here, but I like to see both.

Interviewer #1: Hmm. Interesting.

Interviewer #2: When you... So you said before that you often work with models on the log scale. How have you set these sorts of priors in the past? What sorts of approaches have you used visualizing things, transforming things, anything else?

Participant #1: Well, I should say I work on log scale a bit. I typically just work with standardized, you know, Gaussian data. When I'm on the log scale usually it's some sort of a Poisson regression, something that like. Usually for that, historically I've been even less regularizing just because it's the kind of a model I don't use that often. I'd rather be more permissive so maybe a normal within an s key of even two, centered usually around zero often times just because I know. Plus or minus four s keys on the log scale, it's not flat but it's pretty flat in any application.

Participant #1: The other things that I keep in mind are just, you know, is review number two going to stop me on that permissive of a scale? I think you'd have to be pretty picky to object to that. So that's the kind of stuff I keep in mind.

Interviewer #2: Hmm. So you're thinking about how you can defend the prior?

Participant #1: Oh, for sure.

Interviewer #2: Yeah.

Participant #1: Yep. Yeah, anything that I'm going to put for peer review, yes, I'm going to have to fight. And so usually in that case I'll default to kind of a weekly regularizing version because especially in my field we just generally don't have a lot of high quality prior information for the exact same model.

Participant #1: [crosstalk] With the exception of if I'm working with Gaussian data I can always, if I can think in terms of my head, in terms of effect sizes, well, everything in psychology is a small, to me, fact so I can just put a prior with that log. But I cut you off, go ahead.

Interviewer #1: Oh, so I was just wondering have you ever been asked to defend your choice of priors?

Participant #1: Not yet. I'm just... trying to think. I think at the moment I only have one peer reviewed paper that's Bayesian. You know, I've got a couple. One under review and another one that's about ready to go in to review. And the first one was couple years ago and I just used default m plus down to formative priors. And nobody in psychology is going to object to that. Nowadays my current experience is that the journals that I'm submitting most of the models to, so they're typically like a Bayesian multilevel model. I'm submitting them to substantive journals and most substantive reviewers they're just not going to quibble with priors. They're going to be intimidated that I did a multilevel model, they'll let me get away with anything. That's the shape of it at the moment.

Participant #1: You know, if I was applying to a more methodological journal, then sure, that's going to be a fight I would imagine. But then again, I'm kind of preemptively choosing my priors already, keeping things easy.

Interviewer #1: So, just to confirm, you would preemptively choose less informative priors than more informative priors? Or like less regularizing priors?

Participant #1: Yeah, at the moment that kind of weak to moderately regularizing. So, for example, the manuscript I'm planning on submitting next week, it's a multilevel model time series, Gaussian. And so, we have a couple covariates and the response variable is on a standardized scale. And some of the covariates are just dichotomous and so that puts the effect sizes on roughly a Cohen's d metric. And so I can already think in my head, okay, in psychology in Cohen's d we just almost never see anything above plus or minus one. And so I just use normal 01 priors on those and the effect sizes were way smaller than that. And I don't expect any pushback on that.

Interviewer #1: Mm-hmm (affirmative).

Interviewer #2: Hmm. Okay. I1, do you have any other questions about this bit?

Interviewer #1: Uh, no.

Interviewer #2: Okay. Then we can move down to the third visualization on this page which is showing you the prior predictive distribution for the two different conditions there, the constrictive and the expansive condition in two different colors. For this, the mean difference is fixed and you're just manipulating the prior on the intercept, so that same prior os above.

Participant #1: Nice. Okay.

Interviewer #2: It's the same sort of thing so, you know, play around with it, verbalize what you're thinking, and anything you might have about how this would influence your prior selection.

Participant #1: So, the first thing I'm thinking is I'm impressed at how fast this responds. Almost disoriented in how fast it responds, but wow, that's impressive.

Participant #1: So that's pretty cool.

Interviewer #2: And we definitely appreciate that you noticed that because it took us a while to get there.

Participant #1: I bet. I guess the first thing I'm noticing is that it's a little hard to differentiate between the colors of the lines and so I'm finding myself wishing this is faceted. Maybe like with one atop the other, something like that. But I'm also quickly noticing that they're almost perfectly superimposed one on another, so it looks like it doesn't matter that much.

Participant #1: Otherwise, I guess the other thing I'm noticing is that it's all pretty stable considering the overall distributions.

Interviewer #2: Can you elaborate on that a little bit?

Participant #1: Sure. Well, for like right here, they're all here. I don't have one that's over here, for example. So things are nice and stable.

Participant #1: All I got at the moment. Other questions?

Interviewer #2: So, looking at this and the prior that you chose, again, is there anything that you would [crosstalk] change or does it seem reasonable?

Participant #1: Okay. Take a look... No, I think things still seem reasonable.

Interviewer #1: And what made you... How are you deciding what seems reasonable or not?

Participant #1: So things are still centered around the range where I expected the data to be based upon, you know, the information you all gave me. I expected, you know, to be centered around a small effect. I guess the only thing I would add is... The only thing that's frustrating with the current visual is that, my guess, is that... Okay, pointing at hypothetical experiments. So we have 20 draws, one for the expansive, one for the constructive, and I'm assuming that given the differences that were encoded in my priors that there's a connection between that each of these green lines is connected with one of the orange lines, correct? With one of the iterations?

Participant #1: Okay, so I see I2 nodding.

Interviewer #2: I'm pretty sure that's true. I1 would be the one to make sure that that's true.

Interviewer #1: I mean, so it's like the same... it's like one experiment you have two conditions. So there are 40 lines in total. And each line, so two lines, one green and one orange, has been generated from one draw from the prior predictive distribution.

Participant #1: Okay, good. So that's what I was thinking. So then the only thing that is frustrating about the visual for me is that, within the given, across iterations I would expect sometimes the orange and green lines will be closer or farther apart from one another based upon the degree of difference. That's encoded in the culmination of the two parameters and this doesn't allow me to see that. And so there's the... it's hard for me to get a good sense of the distribution of the differences. And that would be something that if I could see something like that I would like to see something like that.

Interviewer #1: So, by that do you mean the differences between the two conditions?

Participant #1: The two. Yep. So, for example, other than having, gosh, like 20 facets, which might be kind of terrible... you know, maybe it would be nice. I'm also finding myself wanting, like, maybe if there was a second box that gave me a distribution of the different scores. And then I can see what that looked like. That would be reassuring or informative in some way.

Interviewer #2: Mm-hmm (affirmative). If potentially use animation to do it as well. It'd be basically be hops of distributions. You could have that plot and another plot on the other side that was showing you, just cycling through one pair at a time. Then you'd be able to get a sense of how often one was greater than the other. And, yeah.

Participant #1: Yeah, that could be great.

Interviewer #2: Yeah. That's really helpful for us to think about. Thank you.

Interviewer #2: Okay. Anything else about this one, I1?

Interviewer #1: I don't have any other questions.

Interviewer #2: Okay. So, if you could hit the "next page" button we'll move on to the last page. But we're basically going to go through the same thing again, but for the mean difference parameter.

Participant #1: Okay.

Interviewer #2: First distribution-

Participant #1: What I was wanting the whole time. Okay.

Interviewer #2: The first plot would be the one that you've seen. And then the next one will be, once it loads...

Interviewer #1: The file is like seven megabytes.

Interviewer #2: Oh, yeah.

Interviewer #1: Unfortunately.

Interviewer #2: This is why that last visualization didn't take very long. It was smoothly interacting, right? You pay for it up front. Yeah, so if you could skip that first visualization and go to the second one.

Participant #1: Here?

Interviewer #2: Yeah.

Interviewer #1: Yeah.

Interviewer #2: So now you're seeing the prior for the difference now transformed in to that multiplicative scale, right?

Participant #1: Okay. So the first thing I'm just noticing is I don't quite get the ticks on the axis with the x.

Interviewer #1: I see.

Interviewer #2: Right. So that's trying to communicate how many times change, right? Because of the differences on the log scale correspond to multiplicative differences on the response scale, that's trying to tell you how many times different that lambda parameter is. Right?

Participant #1: Got it. Okay. Now I follow.

Participant #1: Okay. I was like this. [inaudible] me...

Interviewer #1: As you're thinking, if you could verbalize it to us that would be great. Thank you.

Participant #1: Say it out loud? Sure. I'm just doing the quick orienting in my head, like, okay, so the null hypothesis would be one times because one times x is still one. So, okay, now I'm centered on null hypothesis and I'm getting the sense that... Okay, so my prior would have allowed me up to two times greater. It's easier for me to think in terms of on the right hand side of the density than the left hand side. I get that there's a symmetry there.

Participant #1: That's for something like social science that seems like that's pretty big. That still seems pretty permissible, all things considered. I'm still feeling good about having a prior that was, I guess, within the context of this experiment maximally regularizing. My mind is kind of maximally regularized prior still, it's still pretty liberal. So I'm feeling good.

Interviewer #2: So then thinking about, again, that sort of question of how you might use this versus the other visualization that you saw, so the one above. Do you think one or the other might be more useful or can you contrast what you might use one or the other then for?

Participant #1: I think, for me, for someone who only uses Poisson once in a blue moon, thinking in terms of the multiplicity or nature of the model. It's one level of abstraction than what I typically work on, so I have to work harder with this. Once I do the couple seconds of hard work I get, oh, yeah, of course that's what it means. With the previous ones I don't have to do that. So this is... If I had to choose between the two I'd choose some of the earlier versions. This now, I put in the work it makes sense. But, I would say it's... yeah, I would just say it's less useful because I have to work harder on it. I'm imagining if I was fitting Poisson models all day long I might have a different answer.

Interviewer #1: Mm-hmm (affirmative). So, like, contrasting it, this visualization, which is showing the multipliers, instead of one that you saw on the survey, which is just showing a [inaudible] distribution. How are you actually thinking about the mean difference parameter when you just saw the probability density of the parameter? You did not see the transformation.

Interviewer #2: And it might help that if you scroll up that's the visualization just above is that you would have seen in the survey.

Interviewer #1: Yeah.

Participant #1: Okay. For something like this where it's a mean difference so we've got a dichotomous variable so it's... Like, in my head I think in terms of standardized mean differences. So, for me, I'm imagining the dummy variable. Of course this is a log transform instead of a standard score, but logs are, I mean, in order of magnitudes, pretty big. At least in my domain that's really big. And so, when I see that... I'm trying to articulate this. I see this in terms of a different score, whereas here this is in terms of it's multiplicative and I get, of course, a different score with a dummy is, algebraically it's the same thing, but I tend to think more in terms of this subtraction nature of a... I tend to think of a dummy variable more as like a subtraction thing. That makes sense?

Interviewer #2: Mm-hmm (affirmative).

Participant #1: I guess that's part of why this, to me, it's just a little bit, it feels closer to how I tend to think about things.

Interviewer #1: So, just to make sure that I'm understanding what your process is like. Do you look at the first visualization, do you look at the tails and then add that to the intercept and then do the transformation of-

Participant #1: Yeah, you can think about it that way. Like, to me, with the dummy variable this is as different score. I'm just thinking I'm subtracting one from the other. So that, to me, just feels intuitive. Whereas, here, I'm not subtracting. This is like, well, this is me multiplying the coefficient to the dummy, which is, of course, entailed in the formula, but it's not the [inaudible] I tend to use.

Interviewer #1: Mm-hmm (affirmative). Interesting.

Interviewer #2: Right. Yeah.

Interviewer #1: I don't have any questions regarding this one.

Interviewer #2: Yeah, I think we can move on to the last one.

Participant #1: Down here?

Interviewer #2: Yep. And so like before this is showing you the prior predictive with the two conditions except now you're manipulating the mean difference parameter and we fixed the intercept. So, again, if you could speak out loud as you play with it.

Participant #1: Okay. Well, I'm definitely liking how I can see the differences in the distributions. Again, I'm frustrated in that I don't know... what I want to do is compare iteration to iteration. And I still can't do that. But somehow this feels more satisfying that I'm seeing them separate the two distributions.

Participant #1: So now I want to go in and compare the implications from my prior. Okay.

Interviewer #2: So you're moving back and forth across now. What are you doing there?

Participant #1: I'm just trying to get a sense of making sure that I understand, you know, watching the... making sure that indeed the distributions are crossing the way that I would expect and that appears to be the case. Wanted to make sure I'm interpreting everything how I expected. But in terms of going back up I just wanted a sense of, okay, what is my model predicting about this? Things still seem reasonable to me.

Interviewer #2: And, so, reasonable how?

Participant #1: Reasonable... well, yeah, I'm still torn because it's I want to say things are reasonable but, still, it's the fundamental thing that I still want to do I can't do yet.

Interviewer #2: Right. Yeah. That compares within iteration.

Participant #1: Yep.

Interviewer #2: Yep.

Participant #1: That's the one I'm lusting after. I guess things still seem reasonable only in the sense that the distribution of the data for both conditions is pretty, it's centered around the distribution that was given to me, with the substantive knowledge that you gave me at the vignette. So that's still doing that. I'm centering my difference parameter on a null. These effects are still indicating that. So based on what I am allowed to see, things are still looking about what I would expect.

Participant #1: And also reasonable in the sense that I'm not... these distributions aren't going off in to outlandish portions of the parameter space. Nothing is bunched up against zero. Nothing is hanging around in the hundreds or thousands. So I'm feeling good.

Interviewer #2: Mm-hmm (affirmative). Great. So-

Participant #1: I'm imagining that prior generations who are trained on the Gibbs sampler would be shocked at how informative this is, but I'm not among those generations.

Interviewer #2: Neither am I. So, great. I1, do you have any other questions about this one?

Interviewer #1: Not specifically, but I think you mentioned that you would want to see the iteration by iteration thing?

Participant #1: Yeah.

Interviewer #1: I was wondering have you ever done something like that previously?

Participant #1: A different score. For me, not much. I've only done a little bit of prior predictive checks, only a tiny bit. So, in fact, I'm eagerly awaiting the second edition of the [McElreath] text because he's clearly moving in that direction where he's going to be pushing those. And so I'm kind of waiting for that, which will give me just a lot of natural practice. What I'm looking at... When I tend to look at models I just tend to... Since I'm using weekly regularizing I don't tend to have to think about it very hard. And especially in this case where I want to see these iterations for the different scores, I mean, I wouldn't need to see frame by frame iterations, you know, I could just look at the prior for the different score itself. But oftentimes I would just do that as a continuous distribution rather than as prior draws.

Participant #1: But if I have to use a prior draw, something like this, I'm kind of finding myself wanting to see the iteration to iteration on the fly. There's like something else lurking in the edges of my memory and it's just not coming to the fore, unfortunately.

Interviewer #2: That's fine.

Participant #1: I'll let you know if it pops up.

Interviewer #2: Yeah. Even if after the interview if it pops up and you want to drop us a note that would be much appreciated.

Participant #1: Sure.

Interviewer #2: Yeah. So, I guess that kind of leads in just to the last couple of questions, which really were, besides the seeing iteration by iteration, which you already mentioned, if there's any other information that you think would be helpful. But if you can't now recall what that is, that's fine if you...

Participant #1: If I were doing something like this for a personal project, I would want the ability to mark off the values from the vignette on to the plot somewhere. Because I keep, from memory, thinking, oh okay, what was the range in that vignette again. It was something like 25 to 45, or 50, some number like that. I just want to put like a, you know, two vertical lines there or something. Or an alternative would be if I was working with some sort of a meta-analysis and if I had a meta-analytic mean then a standard deviation around that mean I'd want a maybe plot that in the background. Something like that.

Interviewer #2: Mm-hmm (affirmative). Yeah. Great. So then last question, can you think of any other instances in the past where you've been choosing priors where there was some useful information that you considered that was kind of different from the things that we've looked at here? Like a model you've worked on recently, yeah.

Participant #1: So, in order to kind of help me choose all my priors?

Interviewer #2: Yeah.

Participant #1: I think other than I was going with the defaults... Yeah, I would say my actual work, not yet. I'm still... substantive in clinical psychology days is still so underused that I don't foresee myself in the future using, at least in the next couple years, anything other than pretty kind of run-of-the-mill default weekly regularizing priors. Because just doing basing stuff is enough to grab people's attention. I don't imagine we will be using more informative priors for another five, 10, 20 years. I mean, I would be shocked if we were. It's too novel.

Interviewer #2: Right.

Participant #1: We're still convincing people that the repeated measure ANOVA isn't good enough. So it's, you know, we have to go step by step.

Interviewer #2: Right. Makes sense. Okay. I1, I don't know if you had any other-

Interviewer #1: Nope, I'm good.

Interviewer #2: No? Great. Then, thanks so much for this. I think this has already generated a number of interesting ideas of things that we could do.

Participant #1: Great.

Interviewer #2: And also, just thanks for your time and, more generally, thanks for all the documents you've put out in to the world. Especially the BRM rewrite of McElreath is great. I hope that you find the time to do it for the second edition, but, you know, we all have bided time, right?

Participant #1: Yes. Yes, but the luxurious amount of time in grad school is gone. I only have a year left of post doc and eventually I have to gird up and become a busy big boy pretty soon. So we'll see what happens. Maybe in the future I'll be able to coerce grad students or someone like that.

Interviewer #2: Yeah. That's what I'm trying to do.

Interviewer #1: I really like the text, the documents that you put out, it's like [crosstalk 00:45:44]. The other one on writing the lmer syntax is difficult and then interpreting the intuitiveness of the Michael Raker, like the prms syntax helps a lot.

Participant #1: I read. Well, thank you. I surely appreciate y'all's work. Tidy base is a nice contribution.

Interviewer #2: Thank you. Yeah. Great, well, this was lovely. I hope that we run in to each other again at some point in the future and thanks again for doing the survey and for also doing the interview.

Participant #1: Right on. Thanks a lot, guys. Appreciate it.

Interviewer #2: Thanks.

Interviewer #1: Thank you.

Participant #1: Take care.

Interviewer #2: Talk to you later.

Interviewer #1: All right, bye.

Interviewer #2: Bye.

Interviewer #1: Well, let's stop the recording.