Interviewer #1: Okay, so this document consists of three pages. The first page is what you already saw in the survey, and in this survey you saw this the prior ... So you saw this prior probability density on the parameter scale. And you set the prior as for the intercept as a normal 3.42 and the standard deviation 0.69.

Participant #8: Yeah.

Interviewer #1: So I guess my question is looking at this interface again and the prior that you chose, like would you walk me through what you did with the interface and how you decided to choose this prior?

Participant #8: It's actually been a while ... So I think, yeah, it was basically like I just moved around the dot. Like the first one was fairly straightforward, because I just looked for the 3.42, and then it was good that like you have in the parentheses the values too for which. It took me a bit to understand how moving the dot actually would work, so if I would just look at the gray part, it's at least for me, I guess I was pre-guessing that is ... Like I'm using ... Like I have used priors in like this kind of approach for quite a bit during my PhD, but I've not been doing that permanently the last two years too much, so maybe it's all in part on myself that I'm a bit like out of touch with like how those it work properly?

Participant #8: But I also like, where like using that gray box, I think it's making sense once I look at the prior part down here, like I wasn't entirely sure how to interpret the numbers here.

Interviewer #1: I see.

Participant #8: But it became here when I actually saw what's presented in this field down here. Then it made more sense to me. But again, that might just be my lack of in the last, and where it's just like being a bit rusty in those things, but once I actually saw this part down here, it made more sense for me again.

Participant #8: Which is of course the great help is the figure. Like so once you see the figure, you actually know what moving the dot gives you, and the...it then helps you understand what the two different parts, like how they interact actually.

Interviewer #1: Mm-hmm (affirmative), I see. Okay, so could you tell me about like the values that you chose? You said, like you chose a location for the prior as 3.42. Could you talk a little bit about that?

Participant #8: Yeah, that was based ...

Interviewer #1: Indicate you ...

Participant #8: ... on the description.

Interviewer #1: Oh, sorry. So if you scroll up you can see the description, if that like you need some reminding, because it's probably been a while.

Participant #8: Yes, it's been a while. Where was ...

Interviewer #1: By the Show Description button.

Participant #8: Yeah, so like it's showing up. I thought it was the mean, but I don't know if I had to calculate it somehow or not. I really don't remember why I said that. Was it ... No, it's not there. No, I don't remember, sorry. I probably should have looked at this.

Interviewer #1: No, no, that's fine, because I mean ... So you don't remember what you did, or how you arrived at that value, or was it something else that you're forgetting?

Participant #8: No, I just don't remember. It could be that because it varies between the 24.6 and 44, so that the mean between those two would be like three four two, and then I used the standard deviation, but ... I think that's what I did.

Interviewer #1: So you calculated ... Just to make sure I'm understanding it correctly, so you calculated the mean between 24 and 44?

Participant #8: Yeah.

Interviewer #1: And then could you, like what did you do after that to get like 3.42?

Participant #8: I think it's ... And again, like I'm not like quite sure, I think, but I think that's what ... Yeah. So it was ... I don't know why I have ... So I guess it's just being the range of the values that are there. I just divided it by 10. I don't know why. But again, I'm not sure if I remember it correctly. But I think it was that. So that's like frequently [inaudible 00:05:27].

Interviewer #1: Mm-hmm (affirmative), interesting. I'm just curious, did you happen to take the log of the mean, by any chance?

Participant #8: No.

Interviewer #1: Because the log of ...

Participant #8: I could have.

Interviewer #1: ... 34, it's close to like 3.5, 3.4.

Participant #8: Yeah, no, I don't think I did the log, but ... No, I really don't remember.

Interviewer #1: That's perfectly fine. Okay. Could you tell me like why you chose the scale value of 0.59?

Participant #8: Yeah, I think that was then just related ... [inaudible] so that when I ... Let's see, I think I had like the mean between those two, I just did the standard deviation, and for some reason probably divided it by ten as well. Like that blue one's showing me what I said, I guess.

Interviewer #1: Right.

Participant #8: Yeah, so for some reason divided that by 10.

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

Participant #8: Like it's usually ... Let's see, maybe I should have done the positions like one over that, but ...

Interviewer #1: Did you ... I guess my other question is, did you factor in like the information presented in the model description there, which is like I guess sort of the likelihood function, that was written in the description? Did you take it maybe down from that information?

Participant #8: You mean this part. Yeah, probably not, because otherwise I would have taken the log. I didn't.

Interviewer #1: I see. Okay, I guess like we can move on to the next one, the mean difference parameter, the second visualization over there.

Participant #8: Is there, okay.

Interviewer #1: Again, the same question, it's like could you tell me how you decided to choose this prior?

Participant #8: That's related to this example too or no? Yes. Oh, I remember. So this one, I didn't think there was any information ... Yeah, I remember. Because like I didn't think there was enough information for me in the example text above to actually have an informative prior, so that's why I set it to like the means of zero at the [inaudible 00:08:19], like basically just saying I'll make it as uninformative as I can. And I think, I don't know if there was probably X part to where I said I would choose an uninformative prior, but that was just not possible with that like distribution that was there.

Interviewer #1: Mm-hmm (affirmative), yeah, so if ... Sorry, go ahead.

Participant #8: I was just going to say, like I would ... If I don't have any information on the parameters I'm interested in, you just start with the uniform, so like uniform distribution and just like just try to set the bounds for something that's reasonable. Like I know that's a bit questionable in terms of what's reasonable, but just set it to something that's not informed.

Interviewer #1: So if, just to make sure I'm understanding this correctly, so if you were not constrained by this box, then you'd have chosen a uniform distribution?

Participant #8: Yes.

Interviewer #1: Okay, could you like briefly like think about what kind of limits would you set for that distribution?

Participant #8: So like if it's related to like the log link plot there, so with the Poisson distribution, like if ... I mostly work with logistic, and so like with logistic, what I see is if you go a variable beyond like an absolute value, like 5, like maybe even 10, then it just gets really uninformative, so I usually bind between minus 5 and plus 5, but I would probably do the same. No, maybe I'd go with maybe -10 and +10, just to be sure I'm inclusive for like different values, but that's pretty much the bounds that I would usually set.

Interviewer #1: I see, cool. So I guess I just wanted to follow up like on what you just said. So when you use a logistic regression model, is there a reason you don't use like a normal prior like centered at zero but like with a standard deviation of 2 or 3 or something, which would roughly put most of the limits like probably mass within the minus 5 to 5 bound?

Participant #8: Yeah, so like it depends which of the parameters I would set the prior for. What I often do for like if I go back to the equation, is if it is a beta parameter, I usually use a uniform... Like I understand that you could do it normally. It might make sense in some ways. But also I would probably have to set the standard deviation wide enough to actually capture the greatest of values, so it would allow for high values, but I find ... And that's very specific for the modeling that I do or that I did. What I found is once you actually allow the parameters to go outside of the plus-minus 10 bounds, it just makes the whole model fairly unstable, and that's partly because there's often 5 to 10 factors, like beta factors in the models too, and that data's a bit messy. But that's why I sometimes just bound it by those kind of strict bounds.

Interviewer #1: I see. I guess like if you scroll down to the mean difference visualization, could you tell me like how you think your prior is ... Like what is the implication of your prior on your model?

Participant #8: So like this one, and so I was just trying to get as uninformative as possible, because I thought that there was not enough information for me to set the prior from the description that was given above, so that was why I tried to make it flat and really inclusive of the outside values. And so the main reason was that I was restricted in the choices of priors that I could use, like of the prior distributions.

Interviewer #1: Is that also why you chose student's t versus the normal, because you wanted fatter tails?

Participant #8: Yeah.

Interviewer #1: Okay. I guess we can move onto the next page.

Participant #8: Okay.

Interviewer #1: This one takes a while to load, but this page is some visualizations. So the first one you've already seen, so you can scroll down to the second one.

Participant #8: Okay.

Interviewer #1: So the second one shows the same density, but it transforms it onto the log scale, so that's the response scale ...

Participant #8: Okay, right.

Interviewer #1: ... because our model uses this log transform for the Poisson model, so this is the density that you would see if you do the log transform, so yeah, could you interact with this visualization and tell me how you would use this information if at all, and what do you think of the information presented here versus the one in the previous visualization?

Participant #8: I guess that the first thing that I noticed was that, because I'm already familiar with the box, I kind of get the connection between the two but that they should, as I guess for most people, but [inaudible] with it ... Let's just say for most people, it's probably hard to do the log, the [inaudible] log on the select, just setting the values and then seeing them presented on a different scale. That is a bit complicated, I think.

Participant #8: I mean, one thing ... Yeah, that's probably not ... So it might be good to have the same values on both, because now, no, it's unless the description's really informative ... It just I think needs to be really clear that what you see on the gray box is the log of the values down there, and in some ways it's in the description, but I think it would also be good to also be in the figure legend, but that it's really clear how those things interact.

Interviewer #1: I see.

Participant #8: But I think yeah, that's the main thing.

Interviewer #1: How would you contrast like this information to the previous one, like if you were to chose a prior?

Participant #8: I think with the previous one, if I would have actually caught on to the log part for setting the prior ... I guess it depends on like the audience, too. So for me, what I usually like to do, I like to actually work on the links selected, if I find about regressions, I like to work on parameter space with options pulling into there ...

Interviewer #1: Mm-hmm (affirmative).

Participant #8: ... but that means of course for the priors they would have to have taken the log already. But in general it's at least to me, and that's my bias, because I like to look at the and think about the modeling parts, and then also, like especially if I say for example look at beta prior distributions or something, I want to compare them between like variables, too. So I primarily work on the linearised form of the regression, meaning like before I back-transform them.

Interviewer #1: Okay. Cool, but like if you saw this visualization, what prior would you choose, given this information? You can just like interact and set to something.

Participant #8: Does it show? I guess it ... So I guess I would again try to get to the main ... But then it really is about the visual part, because like if you set the priors there, they're now disconnected from this part, unless I do take the log of them.

Participant #8: For me it's mainly that the first part is more intuitive to set the prior than this part, just the background there, like original scale, because then if I just did it visually here, I don't know ... I don't know, I think it's not as intuitive as the one before.

Interviewer #1: Mm-hmm (affirmative), interesting. Okay, I mean, just like to play along with this interface, what prior would you choose if you just saw this?

Participant #8: What I would do is I would try to, like if I think about those values again, select the one in the beginning of the example, I would again just put it at the mean. So it's, and then again just play with it visually. It's just I would probably given that those values are now log scale, I would probably just use the visual parts to try to like bigger like kind of get it to the mean between those two [student's t(3.35, 0.5)]. But I think it's harder to do.

Interviewer #1: Mm-hmm (affirmative), I see. Cool. I guess like one request I have is going back is going back to the previous visualization, the first one.

Participant #8: This one?

Interviewer #1: Yeah. So I'm still curious, like because in the survey you missed the log part, now how would you choose this prior? If you don't mind, could you talk about that a little? Like what prior would you choose?

Participant #8: I would probably go with the mean between the two. It's like, again, have the mean between the two and then take the log of the value, because it's ... What?

Interviewer #1: The mean is 34 point something, so the log is like 3.5, so you choose, you center the prior at 3.5?

Participant #8: Yeah.

Interviewer #1: And how would you choose the scale?

Participant #8: I would probably do it at the log of the standard deviation here.

Interviewer #1: So that is 5.93, so the log of the standard deviation is 1.8. Okay, so that's outside. So you'd set something more diffuse.

Participant #8: Yeah.

Interviewer #1: So you'd then just go down as much as you can?

Participant #8: Right, and then like what ... Let's see. The 3.5 ... Yeah, I guess if that visualization doesn't make that much sense anyway ... Yeah, I know that usually, so when I do ... What I usually work with is a, like in R and WinBUGs and stuff, and then instead of the standard deviation you do the precision for those things, like for the parabolas. Yeah, that's what I usually do. So like it says one over the standard deviation.

Interviewer #1: Mm-hmm (affirmative), right. Okay, so let's move on to the third visualization on this page. So this is the prior predictive distribution. That's twenty ... So we're generating from the parabolic distribution, so this is what twenty have with particular experiments would look like. So again, could you interact with this and tell me like how you would use this information if at all, if you were to chose priors based off of this information?

Participant #8: So what's predictive predictive probability. I guess is that that's not the posterior.

Interviewer #1: No, it's ... If you assumed your priors were the data generating process, then what kind of data would your model be predicting?

Participant #8: I don't think I've ever used it, I think. No.

Interviewer #1: Mm-hmm (affirmative).

Participant #8: It's basically saying so that the priors that you use are like what I do is the thought and then if I use like those 20 experiments, that's the distribution that I will get.

Interviewer #1: Wait, I didn't catch that. Could you repeat that?

Participant #8: So let's say I set my priors in that gray box again, and then you used as the priors for your prior experiments, so that's the distributions you would get.

Interviewer #1: If I use the prior that you said as the data generating process, so I sample data from your prior and I pass it through the model, so then this is what the prior ... So because your prior distribution is basically a description of what the data looks like, right, the prior should resemble the data in some format. So this is telling you like what, based off of your prior distributions, what the data would look like before you've collected any actual data

Interviewer #1: And then in this case, you're just changing the intercept parameter, and the mean difference parameter has been fixed at zero. So this is showing you like ...

Participant #8: Oh, okay.

Interviewer #1: ... what the model would predict, just based off of the prior information.

Participant #8: Yeah, no, like I have now just kind of this. So I guess the commenting on this, like so it's the student's t distribution is like narrower, but I don't know, I don't like ... I'm not sure that I know enough about it, this, to actually comment meaningfully.

Interviewer #1: I guess what you could do more is tell me how you would use this information, like how you would choose a prior based off of this information.

Participant #8: Oh okay. I don't know if it [inaudible 00:25:17]. I'm not sure. If I go at a normal, like, I know that there's more variation and like the way that those things looked, but I'm not sure if that actually helps me much in terms of choosing my parameter. Like I'm just not sure how cases more informative for me ... I mean, it's basically like it's noise compared to the previous visualizations, and I don't know that it's really that useful. But again, I'm not familiar with this.

Interviewer #1: Okay. I guess like what prior would you choose, given this information, given this visualization.

Participant #8: I would probably go with ... So just let me up to this vision, I'd probably go to this t, and that's mainly because it's like definite lines, so there's just more ... It's like they don't spread as much as with the normal distribution, and then I would probably go back to setting the priors similar to what I did before. So I'm not sure if I would change much compared to the previous examples. The only thing is ...

Interviewer #1: Okay, cool. Let's move on to the next page.

Participant #8: Okay.

Interviewer #1: Okay, and this takes a while to load. The first one ... This is the last page of this document, and this is just the same as the pervious one except that we're looking at the main difference parameter instead of [inaudible] parameter, so if you just scroll down to the second visualization.

Participant #8: This one?

Interviewer #1: Yeah.

Participant #8: Okay, yeah.

Interviewer #1: This is showing you the density under response scale. My question is like looking at this information, how are you interpreting it, and how if at all would you use this information?

Participant #8: This plot, it does make sense to me, but like setting the prior for the beta parameter, the thing of the ... Pardon?

Interviewer #1: No, go ahead.

Participant #8: I was just going to say the part with the figure, I am not quite sure how to interpret it.

Interviewer #1: Interesting.

Participant #8: No, I don't know what I would do with ...

Interviewer #1: So I mean, I guess like just to, since our model is on the log scale, because we are doing the log transformation, so basically your parameters alpha and beta are not additive. They are interacting ... So basically if you look at like lambda is equal to exponential of alpha plus beta x, basically your beta is multiplying your intercept. This is what this visualization is showing you. So if you select, say, if you move the density, yeah, the probability density to like zero comma whatever this default set is, then it's saying that you don't expect any difference between the two conditions, but then you expect on average but you are accepting, you are assigning some probability mask to like ... In the test condition there could be an effect of two times that of the control conditions, or in this case right now you're saying that on average you'd expect the effect to be in the test condition one-third of the control condition. So basically this is how ...

Participant #8: It's interesting, but I've never seen the beta presented this way, and that might just be like because different fields, difference definitely, but like I guess it depends on like what field people work in. So I just know in at least in the ecology part that I work in, it's not common at all to present information this way. Like I think it's really useful, and especially once you understand what it actually shows, it also kind of lets people get away from like thinking that whatever like scale that x, like in this case the log scale, that's informative, but for sure, I'm not quite sure, but it's like once I have more and more beta, things get way more complicated.

Interviewer #1: Right, yeah.

Participant #8: So I guess back to your question, I think I would primarily use this information from the previous one up, where it is on the log scale, like the beta on the log scale, because it's just for me the way I'm thinking, I usually think on the linear as to where's the equation. But I can see this is useful. I don't know how I would set the prior, given that though. Because back to your question with like how to set the prior on this one, I guess I would set the mean to like zero and then like do the same thing with the values like having it high, but yeah, it's harder to imagine how I would use this kind of thing.

Interviewer #1: Could you tell me like, so if you set this prior, could you tell me like what kind of an effect you're expecting, like what is your prior belief and the size of the effect?

Participant #8: It's essentially going with the uninformative way. It's just, given that I'm not sure where I would set things ... I wasn't sure where I would set things, given the description that I had before, I would just set it as like the prior to zero and one, so and just then on the figure it would be like 1 times [inaudible 00:33:04].

Interviewer #1: Mm-hmm (affirmative), okay. Cool. Let's move on to the next visualization.

Participant #8: I guess that's really the same as before, so like if I hadn't seen it before but I would probably stay with the student's t again, because it's such not as available as the normal one, and yeah, you can do, let's see, because this one is back on the original scale again, but I would just stay with like the uninformative prior.

Interviewer #1: Mm-hmm (affirmative). Okay. So I guess like other questions we have, did you face any challenges in using this interface in any way?

Participant #8: No, it was just when I looked at the first one, it took like making the connection between the gray box and the figure ... Like it was very clear once like I saw the text under the box, because then it was really easy to actually get there, and especially when the values in the ... It's like with the x's are still I did before, like in the like [inaudible 00:34:36], it was really clear, like the link between the values that I have in the box and the figure, which when the values in the figure transform, so like, going back to the non-log scale, that connection, if you know the previous one, you can infer that, but it's just I think being really clear that why there's differences in the values that you see, that's important.

Participant #8: And I guess from mine, it's just like I had a bit of an issue with understanding. Like I just overlooked the log part, which then just made my relative choice weird, I think? Yeah.

Interviewer #1: No, that's fine. Yeah, I mean, there's definitely better ways that this information could have been presented. Cool.

Interviewer #1: So I guess like, was there other information that you would have liked to use like while setting these priors?

Participant #8: No, I think it was good. Like you mentioned, because like you do let people set the priors individually, and in the end it would also be interesting to see how the two interact, but I don't know if it's beyond the scope of what you guys are doing, but basically having the visualization in a way that you can set both the priors, but you can also see the result, like what they would look like for the results coming up.

Interviewer #1: How do you mean like ... What do you mean by the results, like a prior predictive distribution, or something else?

Participant #8: Yes, it's basically so when you have that, like you built that model, so what the output of the models, like I guess similar to what you have here with the upper vertical, like the experiments, but instead of fixing one of the parameters, actually allowing for both of them to be set and then seeing what the outcome.

Interviewer #1: I see. Okay, so I guess like the other questions are taking your, I mean in your field, like in your past experience, have you ... You said you used like logistic models, so what kind of information do you consider when choosing priors? I think you mentioned something about choosing uniform distributions, but besides that.

Participant #8: Yeah, so like oftentimes when you use uniform distributions, what like the best part is ... Like in some studies we did was we actually had prior information from other studies, so you actually have an informative prior and we usually used, we then used normal distributions for those, because we didn't have any other assumptions for the distribution there, and those previous values then just informed modeling part, but for most part I would use uniform class.

Participant #8: Like depending on ... I mean, that's mostly for the parameters on the right. Then of course on the y side of the equation, it depends on what distribution you choose, but like for the beta parameters it's usually uninformative if I don't have any other information. And the intercept is then usually normal, in most cases, yeah.

Interviewer #1: So could you talk a little bit more about like that instance where you had prior research and you set informative priors. How did you like take that prior information, and how did you translate that into an informative prior?

Participant #8: It's essentially, and so that says at the framework that I'm familiar with is like so I usually use on ... Like at that point if I knew it was [inaudible] box, so in there you can actually set your priors, and the way we did it there was ... Like it depended on how much information you had from the previous studies. If you had like an estimate on the standard error, then we were actually able to use those parameters so that you have your ... We would just use the estimate as the mean, and then we would also use like so the standard error ... We had also the standard error for the precision of the beta parameter. But that's kind of like the way we did it, and in that case it was fairly straightforward.

Interviewer #1: So you used the standard error almost exactly? Like you did not add uncertainty to it?

Participant #8: No.

Interviewer #1: Okay. And how did you ... Like using that prior, like what was your results? Were those results ... I guess, how influenced were the results based on those priors [inaudible 00:40:11]?

Participant #8: It was for like a number of bird species, and it depend on the species. It was ... No, negatively dependent. Like so there was no generalities, because some of them were [inaudible] and there was probability of returns for bird species, and some of them were getting like actually lower estimates, because we compared including and not including priors, and so some of them were then like in results in lower probabilities, but they're usually to some extent go on to the priors, but not all that much. And it's in most cases also they're more drawn to the prior if we had less data for the new datasets. So it's just kind of like what we expect would happen.

Interviewer #1: Yeah.

Participant #8: So, yeah.

Interviewer #1: And was it like a hierarchical model, or was it just ...

Participant #8: Yeah.

Interviewer #1: ... simple logistical regression. Okay.

Participant #8: The first situation was logistic, and the next situation was hierarchical.

Interviewer #1: Okay, cool. I don't think I have any other questions.

Participant #8: Great.

Interviewer #1: All right, Richard, thank you so much for giving us, like taking the time to take this survey, and also like ... Let me just stop the recording.