9.2: Purpose of Factorial Designs

Factorial designs let researchers manipulate more than one thing at once. This immediately makes things more complicated, because as you will see, there are many more details to keep track of. Why would researchers want to make things more complicated? Why would they want to manipulate more than one IV at a time.

Before we go on, let's clarify what we mean by manipulating more than one thing at once. When you have one IV in your design, by definition, you are manipulating only one thing. This might seem confusing at first, because the IV has more than one level, so it seems to have more than one manipulation. Consider manipulating the number of coffees that people drink before they do a test. We could have one IV (coffee), with three levels (1, 2, or 3 coffees). You might want to say we have three manipulations here, drinking 1, 2, or 3 coffees. But, the way we define manipulation is terms of the IV. There is only one coffee IV. It does have three levels. Nevertheless, we say you are only doing one coffee manipulation. The only thing you are manipulating is the amount of coffee. That's just one thing, so it's called one manipulation. To do another, second manipulation, you need to additionally manipulate something that is not coffee (like time of day in our previous example).

Returning to our question: why would researchers want to manipulate more than one thing in their experiment. The answer might be kind of obvious. They want to know if more than one thing causes change in the thing they are measuring! For example, if you are measuring people's happiness, you might assume that more than one thing causes happiness to change. If you wanted to track down how two things caused changes in happiness, then you might want to have two manipulations of two different IVs. This is not a wrong way to think about the reasons why researchers use factorial designs. They are often interested in questions like this. However, we think this is an unhelpful way to first learn about factorial designs.

We present a slightly different way of thinking about the usefulness of factorial designs, and we think it is so important, it get's its own section.

Factorials manipulate an effect of interest

Here is how researchers often use factorial designs to understand the causal influences behind the effects they are interested in measuring. Notice we didn't say the dependent variables they are measuring, we are now talking about something called effects. Effects are the change in a measure caused by a manipulation. You get an effect, any time one IV causes a change in a DV.

Here is an example. We will stick with this one example for a while, so pay attention… In fact, the example is about paying attention. Let's say you wanted to measure something like paying attention. You could something like this:

1. Pick a task for people to do that you can measure. For example, you can measure how well they perform the task. That will be the dependent measure
2. Pick a manipulation that you think will cause differences in paying attention. For example, we know that people can get distracted easily when there are distracting things around. You could have two levels for your manipulation: No distraction versus distraction.
3. Measure performance in the task under the two conditions
4. If your distraction manipulation changes how people perform the task, you may have successfully manipulated how well people can pay attention in your task.

Spot the difference

Let's elaborate this with another fake example. First, we pick a task. It's called spot the difference. You may have played this game before. You look at two pictures side-by-side, and then you locate as many differences as you can find. here is an example:

Figure \(\PageIndex{1}\): Spot the differences between the two images.

How many differences can you spot? When you look for the differences, it feels like you are doing something we would call “paying attention”. If you pay attention to the clock tower, you will see that the hands on the clock are different. Ya! One difference spotted.

We could give people 30 seconds to find as many differences as they can. Then we give them another set of pictures and do it again. Every time we will measure how many differences they can spot. So, our measure of performance, our dependent variable, could be the mean number of differences spotted.

Distraction manipulation

Now, let’s think about a manipulation that might cause differences in how people pay attention. If people need to pay attention to spot differences, then presumably if we made it difficult to pay attention, people would spot less differences. What is a good way to distract people? I’m sure there are lots of ways to do this. How about we do the following:

1. No distraction condition: Here people do the task with no added distractions. They sit in front of a computer, in a quiet, distraction-free room, and find as many differences as they can for each pair of pictures
2. Distraction condition: Here we blast super loud ambulance sounds and fire alarms and heavy metal music while people attempt to spot differences. We also randomly turn the sounds on and off, and make them super-duper annoying and distracting. We make sure that the sounds aren’t loud enough to do any physical damage to anybody’s ear-drums. But, we want to make them loud enough to be super distracting. If you don’t like this, we could also tickle people with a feather, or whisper silly things into their ears, or surround them by clowns, or whatever we want, it just has to be super distracting.

Distraction effect

If our distraction manipulation is super-distracting, then what should we expect to find when we compare spot-the-difference performance between the no-distraction and distraction conditions? We should find a difference!

If our manipulation works, then we should find that people find more differences when they are not distracted, and less differences when they are distracted. For example, the data might look something like this:

```
library(ggplot2)
df <- data.frame(Distraction = c("No distraction","Distraction"),
                 Mean_diffs = c(10,5))
ggplot(df, aes(x=Distraction, y=Mean_diffs))+
  geom_bar(stat="identity")+
  theme_classic()+
  ylab("Mean differences spotted")+
  xlab("Distraction Condition")+
  ggtitle("The distraction effect")
```

run restart restart & run all

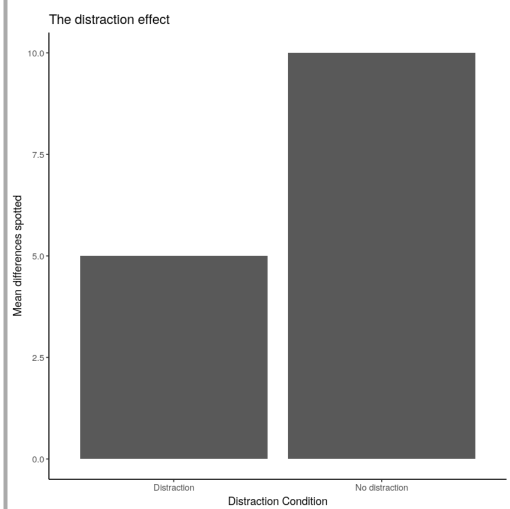

Figure \(\PageIndex{2}\): Example data from pretend experiment showing number of differences spotted in a distraction versus no distraction condition.

The figure shows a big difference in the mean number of difference spotted. People found 5 differences on average when they were distracted, and 10 differences when they were not distracted. We labelled the figure, “The distraction effect”, because it shows a big effect of distraction. The effect of distraction is a mean of 5 spot the differences. It’s the difference between performance in the Distraction and No-Distraction conditions. In general, it is very common to use the word effect to refer to the differences caused by the manipulation. We manipulated distraction, it caused a difference, so we call this the “distraction effect”.

Manipulating the Distraction effect

This is where factorial designs come in to play. We have done the hard work of finding an effect of interest, in this case the distraction effect. We think this distraction effect actually measures something about your ability to pay attention. For example, if you were the kind of person who had a small distraction effect (maybe you find 10 differences when you are not distracted, and 9 differences when you are distracted), that could mean you are very good at ignoring distracting things while you are paying attention. On the other hand, you could be the kind of person who had a big distraction effect (maybe you found 10 differences under no distraction, and only 1 difference when you were distracted); this could mean you are not very good at ignoring distracting things while you are paying attention.

Overall now, we are thinking of our distraction effect (the difference in performance between the two conditions) as the important thing we want to measure. We then might want to know how to make people better at ignoring distracting things. Or, we might want to know what makes people worse at ignoring things. In other words we want to find out what manipulations control the size of the distraction effect (make it bigger or smaller, or even flip around!).

Maybe there is a special drug that helps you ignore distracting things. People taking this drug should be less distracted, and if they took this drug while completing our task, they should have a smaller distraction effect compared to people not taking the drug.

Maybe rewarding people with money can help you pay attention and ignore distracting things better. People receiving 5 dollars every time they spot a difference might be able to focus more because of the reward, and they would show a smaller distraction effect in our task, compared to people who got no money for finding differences. Let's see what this would look like.

We are going to add a second IV to our task. The second IV will manipulate reward. In one condition, people will get 5 dollars for every difference they find (so they could leave the study with lots of money if they find lots of differences). In the other condition, people will get no money, but they will still have find differences. Remember, this will be a factorial design, so everybody will have to find differences when they are distracted and when they are not distracted.

The question we are now asking is: Will manipulating reward cause a change in the size of the distraction effect. We could predict that people receiving rewards will have a smaller distraction effect than people not receiving rewards. If that happened, the data would look something like this:

```
library(ggplot2)
df <- data.frame(Distraction = c("No distraction","Distraction",
                                 "No distraction","Distraction"),
                 Mean_diffs = c(10,5,11,9),
                 Reward = rep(c("No Reward","Reward"),each=2))
ggplot(df, aes(x=Distraction, y=Mean_diffs, group=Reward, fill=Reward))+
  geom_bar(stat="identity", position="dodge")+
  theme_classic()+
  ylab("Mean differences spotted")+
  xlab("Distraction Condition")+
  ggtitle("The distraction effect as a function of reward")
```

run restart restart & run all

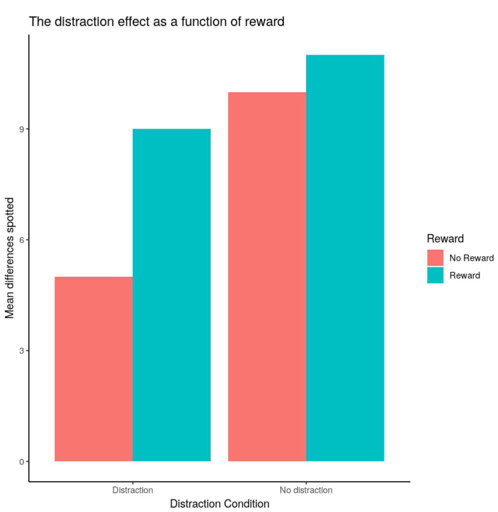

Figure \(\PageIndex{3}\): Example data showing how the distraction effect could be modulated by a reward manipulation. Distraction condition plotted on the x-axis, makes it more difficult to compare the changes in the distraction effect between reward conditions.

I've just shown you a new kind of graph. I apologize right now for showing this to you first. It's more unhelpful than the next graph. What I did was keep the x-axis the same as before (to be consistent). So, we have distraction vs. no distraction on the x-axis. In the distraction condition, there are means for spot-the-difference performance in the no-reward (red), and reward (aqua) conditions. The same goes for the no-distraction condition, a red and an aqua bar for the no-reward and reward conditions. We can try to interpret this graph, but the next graph plots the same data in a different way, which makes it easier to see what we are talking about.

```
library(ggplot2)
df <- data.frame(Distraction = c("No distraction","Distraction",
                                 "No distraction","Distraction"),
                 Mean_diffs = c(10,5,11,9),
                 Reward = rep(c("No Reward","Reward"),each=2))
ggplot(df, aes(x=Reward, y=Mean_diffs, group=Distraction, fill=Distraction))+
  geom_bar(stat="identity", position="dodge")+
  theme_classic()+
  ylab("Mean differences spotted")+
  xlab("Reward Condition")+
  ggtitle("The distraction effect as a function of reward")
```

run restart restart & run all

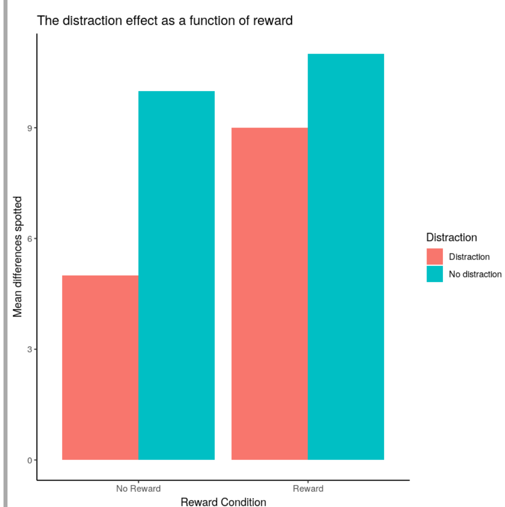

Figure \(\PageIndex{4}\): Example data showing how the distraction effect could be modulated by a reward manipulation. Reward condition plotted on the x-axis, makes it easier to compare the changes in the distraction effect between reward conditions.

All we did was change the x-axis. Now the left side of the x-axis is for the no-reward condition, and the right side is for the reward condition. The red bar is for the distraction condition, and the aqua bar is for the no distraction condition. It is easier to see the distraction effect in this graph. The distraction effect is the difference in size between the red and aqua bars. For each reward condition, the red and aqua bars are right beside each other, so can see if there is a difference between them more easily, compared to the first graph.

No-Reward condition: In the no-reward condition people played spot the difference when they were distracted and when they were not distracted. This is a replication of our first fake study. We should expect to find the same pattern of results, and that's what the graph shows. There was a difference of 5. People found 5 differences when they were distracted and 10 when they were not distracted. So, there was a distraction effect of 5, same as we had last time.

Reward condition: In the reward condition people played spot the difference when they were distracted and when they were not distracted. Except, they got 5 dollars every time they spotted a difference. We predicted this would cause people to pay more attention and do a better job of ignoring distracting things. The graph shows this is what happened. People found 9 differences when they were distracted and 11 when they were not distracted. So, there was a distraction effect of 2.

If we had conducted this study, we might have concluded that reward can manipulate the distraction effect. When there was no reward, the size of the distraction effect was 5. When there was reward, the size of the distraction effect was 2. So, the reward manipulation changed the size of the distraction effect by 3 (5-2 =3).

This is our description of why factorial designs are so useful. They allow researchers to find out what kinds of manipulations can cause changes in the effects they measure. We measured the distraction effect, then we found that reward causes changes in the distraction effect. If we were trying to understand how paying attention works, we would then need to explain how it is that reward levels could causally change how people pay attention. We would have some evidence that reward does cause change in paying attention, and we would have to come up with some explanations, and then run more experiments to test whether those explanations hold water.
