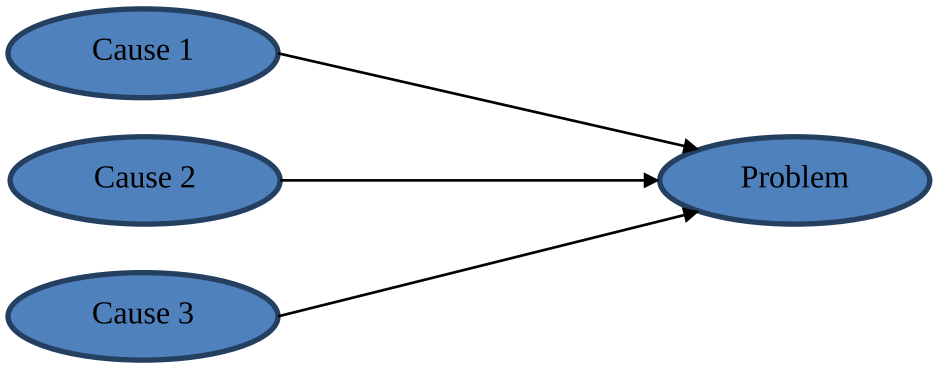
CAUSALITY IN RESEARCH

In the previous chapter we already discussed about the nature of relationship between concepts. In this chapter we will go into detail about the most important aspect of relationship, which is *causality* or *causal relationship*. The issue about causality is basically the main focus in research in every area. Because the prime objective of research is to study the causality between phenomena of interest, identifying the true causality is therefore the crucial task that the researchers have to achieve.

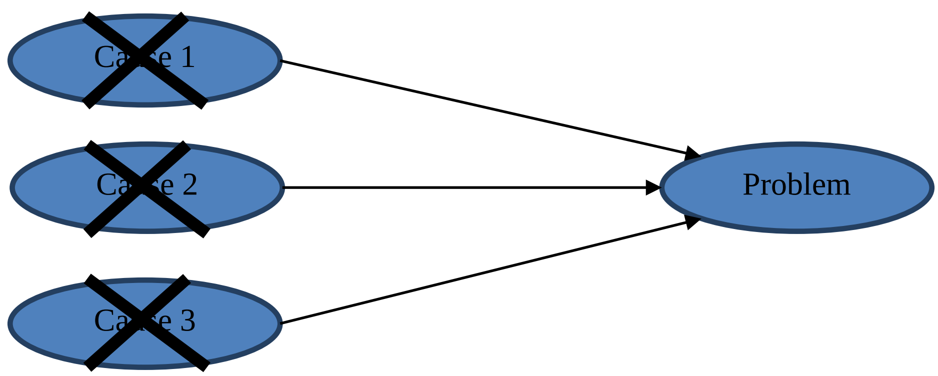
But why the researchers have to be so serious about causality? Remember that the fundamental reason that we have to conduct a research is to solve the problem that we have; and usually the problem that we have involves the effect of one thing on another thing. For example, if we concern about the behavior of employees who like to access social media sites (such as Facebook or LINE) during work and we would like to prevent this behavior, we have to understand first about some major reasons that lead to this behavior. In particular, conventional wisdom suggests that in order to solve a specific problem effectively, it is important that we have to identify some major causes of the problem first. If we can identify correctly what are the valid factors that cause that problem, we can prevent the problem from happening by reducing or eliminating the causes. Using the example given above, if we discover that the true reason why employees like to use social media is because doing so makes them relax from unavoidable work-related stress, from this finding we can offer some intervention to help employees lessen stress at work so that they can reduce social media use intensity as a result.

However, the conclusion about whether one thing actually a true cause of another thing cannot be make superficially. There are many issues that need to be justified before making such decision. Referring to the previous chapter, you already knew that causality implies that one thing will cause another thing to increase (positively related) or cause another thing to reduce (negatively related). But how can you make sure that it is a real cause-and-effect relationship, not just simply a coincidence. There are some issues that need to consider.

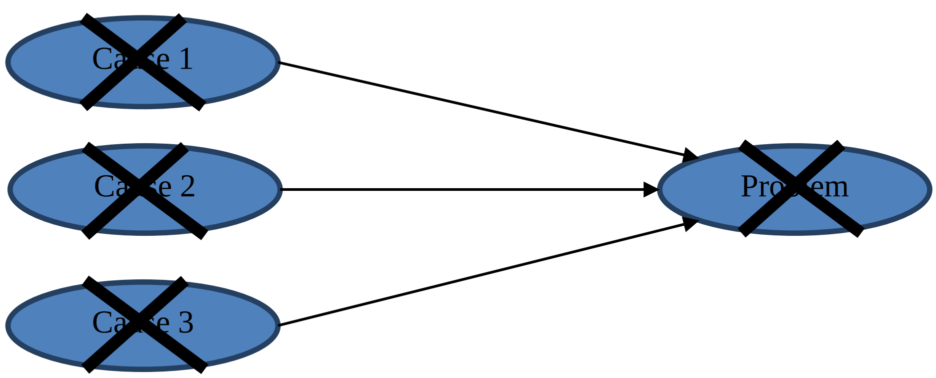
Figure: The importance of causality in research



researchers to correctly identify and confirm the true causes of the problem.



If we eliminate the causes of the problem,



…then the problem can be effectively solved.

Association does not imply causation

The phrase "*association does not imply causation*" is a classic phrase in research. If you observe that two things have a positive relationship (e.g., when one thing increases, another thing also increases), can you assume that one thing causes another thing? Well, the right answer for a prudent researcher is *may be* or *may not be*.

Let's consider this example. I assume that all of you must know about what is global warming. Global warming is a climate problem that has become more severe over the past decades. Media usually portrayed that the global temperature has been increasing year-after-year and it is projected to keep rising exponentially in the future. Now, let consider another circumstance. When years have passed, what will happen to your age? Of course, you get older. Considering the nature of relationship between your age and global temperature, you can see that two thing apparently move in the same direction. As you become older, the average global temperature gets warmer as well. However, does it mean that your age causes global temperature to increase?

If this causal relationship is true (that is, your age actually causes global warming), I think you can have some good excuse to buy face-treatment courses in order to save the world; because if you got older, the world would come to demise sooner from the severe global warming problem that is caused by your age. Unfortunately, you cannot make that excuse to buy face-treatment courses because the causality is not real in this case. People's age always increases as a function of time, whereas average global temperature increases due to other factors such as deforestation, the emission of greenhouse gas, air pollution, and so on. However, two things are just correlated by a coincidence; it does not make any sense to believe in their causal relationship. Basically, there are many things in this world that correlate with each other. Therefore, when you see that two things correlate, you cannot make a quick judgment that one thing causes another thing. In the language of research, *correlation* is the term we use to indicate that two things may just relate by chance; we justify the causality between them.

Reverse causation

Another issue that the researchers seriously concern when they examine the causality between two things is the problem of reverse causality or reverse causality. As the name implies, reverse causality means that the direction of causality between two factors may be opposite from what we expect (Maxwell & Cole, 2007). By the way, reverse causality does not mean that the causality does not exist; but it is the misperception about which factor is a cause which factor is a consequence. In this regards, what we think it is a cause is actually an effect; what we think it is an effect is actually a cause.

For example, one of the popular topics that research is organizational behaviors usually investigates is about employee job satisfaction. Basically, scholars believed that employees who are happy with their job tends to be more productive and can work more effectively for the organization. As a result, many researchers tended to regard job satisfaction as a cause and job performance as an effect. Many studies also found that the relationship between job satisfaction and job performance is positively and significantly associated, and they concluded that the organization should promote job satisfaction to make employee increase work performance.

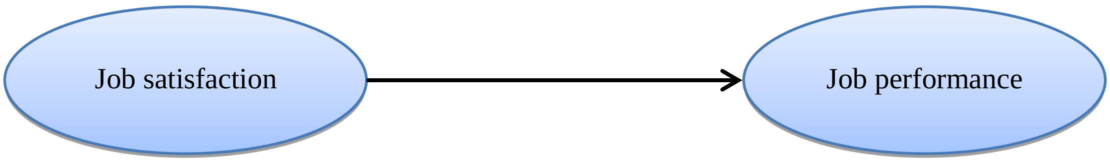
Based on the findings, can you conclude that job satisfaction is actually a true cause that leads to job performance? Is it possible that the causality might move in the opposite direction? In this case, is it possible that job performance might be a cause and job satisfaction is an effect? If you think carefully, that makes sense. If you have a very good performance at work, it could make you become happy with your job as well. This is one example of the reverse causation issue that actually presents in research. You think that one thing will cause another thing, but in reality, it can be the other way around.

In fact, the question whether job satisfaction will lead to higher job performance or whether higher job performance will lead to higher job satisfaction is the issue that has been argued extensively in academic field (Iaffaldano & Muchinsky, 1985; Judge et al, 2001; Lawler & Porter, 1967; Petty et al, 1984; Wanous, 1974). To date, there is no final conclusion about the true causal direction between these two phenomena. However, scholars suggest that the direction of causality might be individual- and context-specific (Judge et al, 2001). In other words, it depends on individual differences and the nature of the environment from which a research is conducted that might determine the causal relationship between job satisfaction and job performance. For some individual or for some organization, job satisfaction will lead to job performance; but in different individual or in other organization, job performance may lead to job satisfaction.

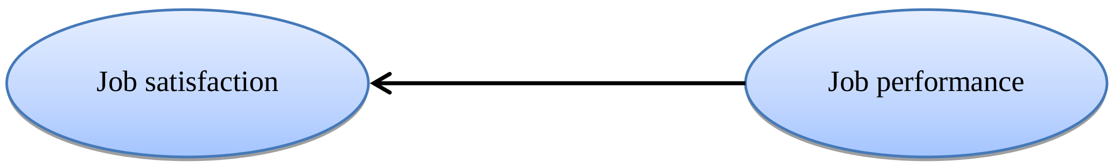
Please note that the reverse causation problem can seriously affect the implications that are inferred from data analysis. Remember that one of the main objectives of research is to come up with the solutions to solve the problem. If the direction of causality that we predicted is incorrect, we can end up with a wrong policy that does not accurately solve the problem. Considering the example that we just discussed, if we believe that employee satisfaction is a cause of job performance and the result that we got from correlation analysis showed that these two factors are positively related, we would recommend that the company should boost satisfaction of employees in order to enhance their performance. However, correlation analysis can only suggest that two things are related somewhat; but it cannot tell which one is a cause which one is a consequence. If, in reality, job performance is actually a cause that leads to job satisfaction and not *vice versa*, the policy implication that we suggest the organization to boost employee satisfaction might not work to generate higher work performance, because we fail to identify the true cause of the problem.

Therefore, when you predict the causal relationship between the concepts in your study, you have to consider carefully whether it is possible that the direction of causality can be opposite from what you think. In this case, using a sound theory as a support for the cause-and-effect relationship can somehow alleviate the concern about the causality issue. But still, using a theatrical support alone cannot prove that the reverse causality problem does not present in the analysis. Some remedy that is widely used in social sciences research to deal with reverse causality problem is to use longitudinal data collection or to collect the data at different time periods. Alternatively, the researchers can use advanced statistical techniques known as *two-stages-least-square regression* to tackle the reverse causality issue in the data analysis.

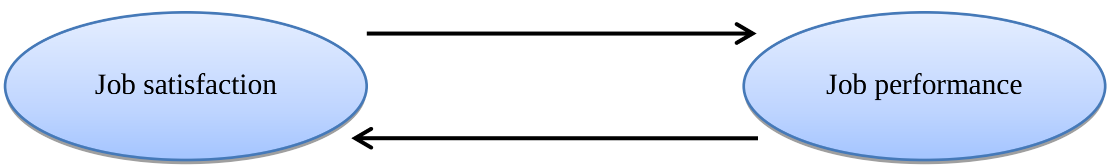
Reverse causality example Every problem has its causes. It is crucial for



Job satisfaction makes employees have better job performance



Having good job performance will make an employee satisfied more with a job



Reverse causality makes it difficult for researchers to infer the direction of causality between job satisfaction and job performance

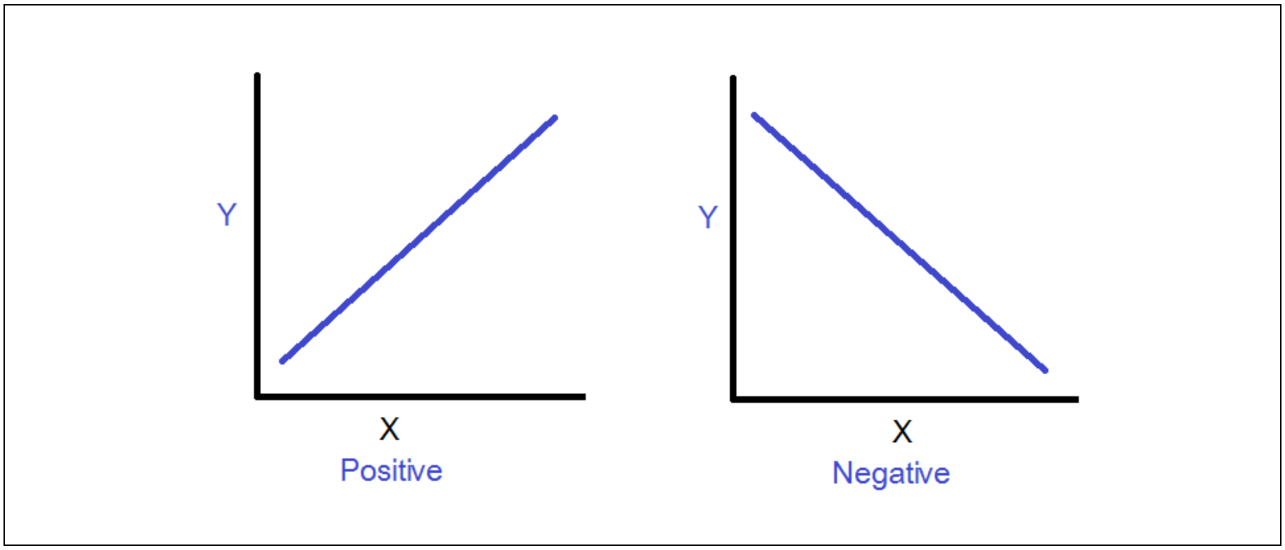
Anyway, reverse causality problem tends to be a common problem in quantitative research because findings from this type of research are based on the relationships inferred from statistical data. In qualitative research, reverse causality problem is less serious because the researchers can ask informants to clarify in detail about the nature of relationship between phenomena of interest. Therefore, incorporating the interview data from qualitative research into statistical evidence found in quantitative research can help address the concern about the reverse causality issue that may present in pure quantitative findings as well.

CRITERIA TO JUSTIFY CAUSALITY

There are three main criteria that can be used to justify the existence of causality between concepts. To justify the causality, it is important for these three criteria to be supported. This section will explain each of them in more detail.

Concomitant variations

Concomitant variation is the first criterion to justify causality between two things. It suggests the cause-and-effect relationship can happen only if two things covary or correlate. In other words, if one phenomenon changes, you must see the change in another phenomenon as well. This covariation or correlation can be either positive or negative. If one thing keeps changing and another thing is still unchanged, there is no reason to believe that they have causal relationship. For causality to occur, one thing must bring about change to another thing.



To test whether two factors covary or correlate, there are some techniques that can be performed. The most convenient method is to use the scatter plot of the data between two phenomena on the X and Y axis to derive the pattern of relationship. However, the most reliable method to confirm the covariation or correlation is to use statistical techniques such as correlation analysis or regression analysis to determine the relationship pattern between phenomena.

Temporal sequence

Another criterion in which the researchers can use to justify causality between two phenomena is to consider the time sequence that they occur. Basically, the phenomenon that is a cause must occur before the phenomenon that is an effect. Generally speaking, we use the past to predict the future. It is difficult to believe that what happens to you today is the result of what you will do in the future (unless you used a time-machine to change something in the future in hope that it will change your present).

In practice, there are some data collection techniques that can be used to satisfy the temporal sequence requirement of causality. Because this criterion require that a cause must happen before the consequence, researchers can conduct the *longitudinal data collection* whereby the data are collected from the same people across time (Huselid & Becker, 1996). By using this method, we can observe the phenomenon regarded as a cause during the current period (time t), and then observe the phenomenon regarded as an outcome in the next period (time t+1). In this case, you claim that you use the phenomenon that occurs in the present to predict the phenomenon that occurs in the future. For example, if we want to examine the effect that X (cause) has on Y (outcome) and we want to make sure that X will cause Y, but not the other way around, we can rule out the reverse causation issue by collect the data of X at the time period before the time we collect the data of Y. In this case, if we collect the data of X in the year 2000, we collect the data of Y in the year 2001. The logic behind this method is that it is impossible for the event that happens in the future to be a cause of the event that already happened in the past.

	Year from which the data are collected:			
X (Cause)	2000	2001	2002	2003
Y (Consequence)	2001	2002	2003	2004

Note that it is not necessary for the time-lapse between the two phenomena to be large. The time-lapse can be a month, a day, a minute, or even a second. The most important thing is that the data of the phenomenon regarded as a cause must be observed before the data of the phenomenon regarded as an outcome. For example, in a study by Haar (2006), the researcher aimed to prove the causal relationship between work-related stress and the attitude that employees have toward the organization. The authors claimed that stress is a cause that affect attitude of employees. As a solution to avoid the reverse causality problem in the analysis, the authors reported that they collected the data of the work-related stress from employees four week before they recollect the data of the attitude toward the organization from the same employees.

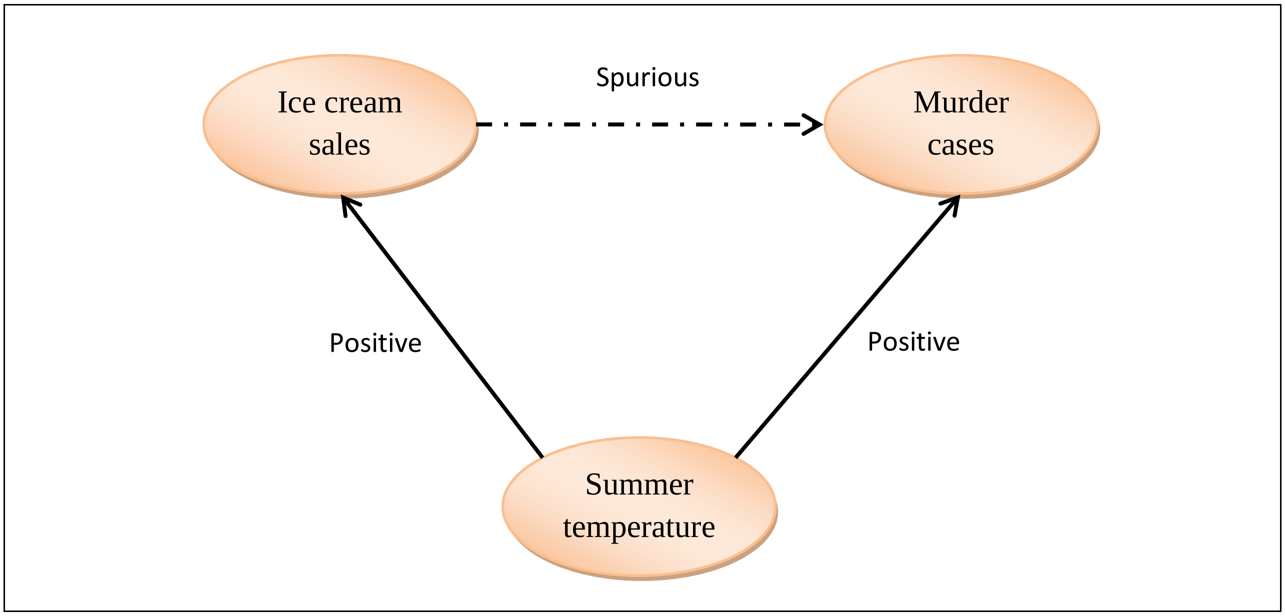
In the area of economics research, the time-lapse data can be classified into *lag variables* and *lead variables*. Lag variables are the data that are measured at one period before the current period. For example if the current period is year 2000, the lag variables are the data that are measured in year 1999. Normally, we use the subscripted t-minus-one as the expression of the lag variable (e.g.. variable $_{t-1}$). On the other hand, lead variables are the data that are measured at one period following the current time period. Normally, we use the subscripted t-plus-one as the expression of the lead variable (variable $_{t+1}$). In particular, using the time-lapse data to study about causality not only reduces the reverse causality issue that may present in the analysis, this method is also appropriate in the situation when the cause tends to take some time to bring about the consequence. For example, the benefits of employee training in the current period may take some time to take effect on employee productivity, as employees may need some time to adapt what they learn in the real work situation. In this regards, measuring the cause before the outcome can help the researchers evaluate the significance of the effect more accurately.

Non-spurious relationship

The last criterion to justify causality is that the association between phenomena that we observe must not be spurious. Literally, the word “spurious” means fake; therefore, non-spurious in this sense means that the association between two occurrences should not be fake. However, what does it means by fake or real relationship? The example about the association between your age and global climate that was discussed earlier is a good example about the association that is considered spurious or fake. They move in the same direction just by coincidence; they just correlate; there is fundamental logic to support the cause-and-effect relationship between them.

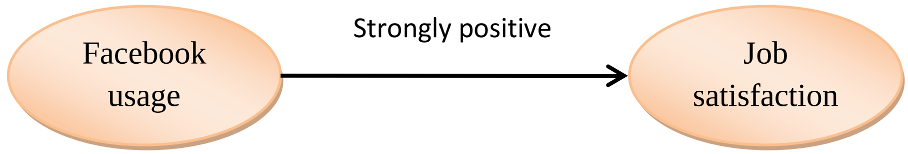
Another reason that explains spurious relationship is that the correlation that we observed between two occurrences is actually caused by the unobserved factor that appears to associate with both of them. To understand this possibility, let's consider this example. There is one shocking report about the positive relationship between ice-cream sales and the report of murder cases. This positive relationship suggests that as more ice cream sales increased, more people also got killed as well.

Oh mine, this is really shocking. Does it mean that ice-cream is a reason that causes people to kill each other? Well, before you decide to ban ice-cream sales, let's answer these questions. First, do you think in which season that ice-cream is sold a lot? Of course, it is sold the best in summer. Hot weather makes people crave for cold drinks and snacks. That's why ice-cream sales increases in summer. Then another question, do you think hot weather in summer can easily cause people to have unstable emotions? Yes, it really makes sense. During hot summer people easily lost temper and that can easily cause them to hurt other people. Now, you can see that ice-cream sales and murder cases have nothing fundamentally connects. They tend to move up together not because of they cause each other. Both of them are caused by the same thing that is increasing temperature. In the end, the causality between ice-cream sales and murder cases that we previously thought is spurious at best.



To deal with spuriousness when analyzing causality between phenomena, normally we have to introduce the control variables in the data analysis in addition to the cause variable that we are interested. The control variables can be any phenomenon that might lead to the outcome variable as well. The objective of incorporating the control variables in the analysis is to prove that the cause variable that we are interested still significantly relate with the outcome variable. In order to verify that the relationship between the cause variable and the outcome variable is not spurious, the relationship between the cause variable and the outcome variable must remain significant even though other control variables are incorporated.

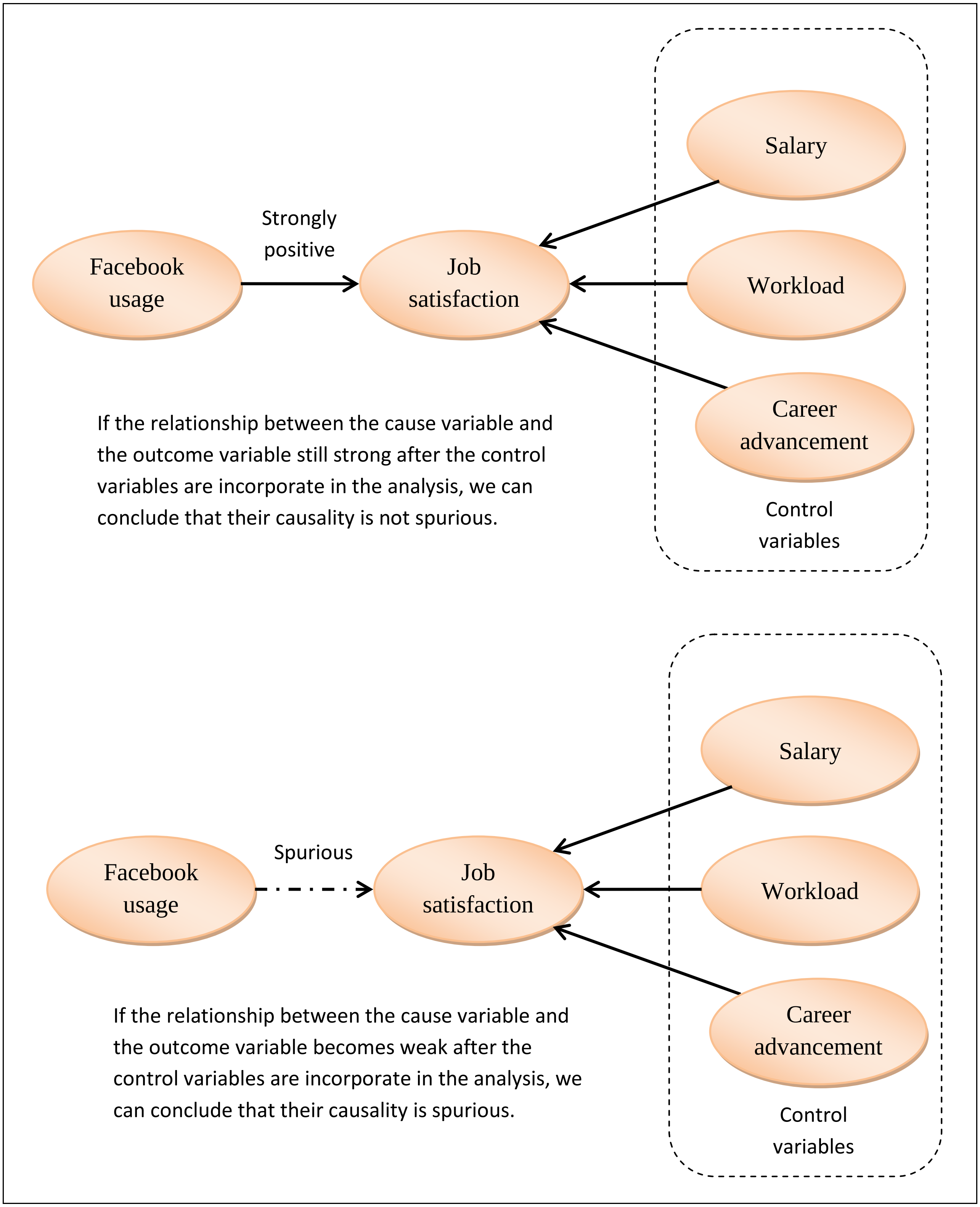
For example, if we conducted a study to investigate whether using Facebook in the workplace can increase job satisfaction, the cause variable in this case would be Facebook use at work and the outcome variable is job satisfaction. Assume that you already collected Facebook usage data in the current period and then collected job satisfaction data in the next period (temporal sequence). When you analyze the correlation between these two variable, you found that they are positive relate (concomitant variation). At this point, you already satisfied two criteria of causality. However, just because you found that Facebook usage and job satisfaction positively correlate is still not sufficient to conclude that the causality between them exists. You have to verify whether this positive relationship is spurious or not.



At this point you found that Facebook usage and job satisfaction are positively related. But how can we confirm that their association is not spurious?

In order to test if the causality between Facebook usage and job satisfaction is spurious, we need to incorporate some control variables in the analysis. In reality, you cannot assume that Facebook usage is the only factor that affects job satisfaction. There might be other factors that affect job satisfaction as well. Although there are a lot of things that affect job satisfaction, let's come up with three factors including (1) salary, (2) workload, and (3) career advancement. These three factors are considered the control variables in the analysis. We need to incorporate these control variables into the analysis to determine what will happen to the relationship between Facebook usage and job satisfaction.

Because the three control variables we have are expected to cause job satisfaction, we also need to draw an arrow pointed from each control variable to job satisfaction in the conceptual model. After the control variables are incorporate in the analysis, then we observe the strength of the relationship between Facebook usage and job satisfaction. If their relationship is still positive and significant after the control variables are incorporated, then we can conclude that the causality is not spurious. This implies that although there are other factors that cause people to be satisfied with their job, the effect of Facebook usage on job satisfaction is still strong. Although good salary, low workload, and opportunity for career advancement are the important factors that cause job satisfaction, Facebook usage is still matter for employees to be satisfied with their job. And because right now the three criteria of causality (temperate sequence, concomitant variation, and non-spurious association) are finally verified, we can finally confirm that Facebook usage is a cause that leads to job satisfaction.



However, if it turns out that the relationship between Facebook usage and job satisfaction becomes weak after all three control variables are incorporated in the analysis, then we can conclude that the positive relationship between Facebook usage and job satisfaction that we got earlier is spurious at best. In this case, it implies that the control variables that we incorporate appear to be more relevant factors that affect job satisfaction rather than Facebook usage does. The reasons that actually make employees to be satisfied with their job are good salary, low workload, and the opportunity for career advancement; not because Facebook usage. When you incorporate these three control factors, Facebook usage is irrelevant for employees' satisfaction. In this situation, we cannot conclude that Facebook usage is a cause that leads to job satisfaction. Although the other two criteria of causality are met, if it turns out that the relationship between the phenomena is spurious, then the causality cannot be confirmed at last.

MODERATING EFFECT AND MEDIATING EFFECT

Moderating effect

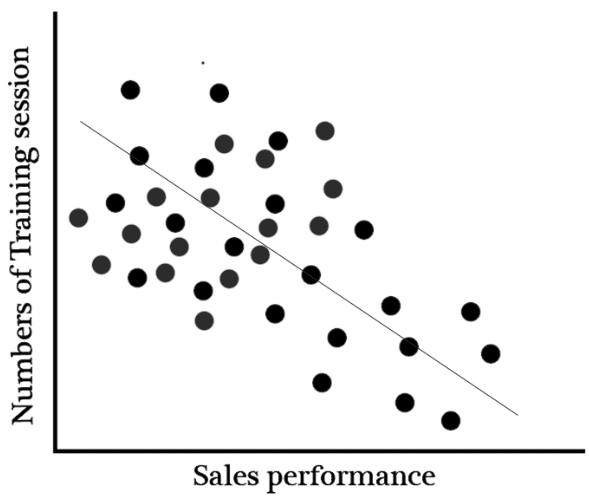
The *moderating effect* (or *interacting effect*) suggests that the effect of the cause variable on the outcome variable is contingent on the third factor which can either enhance or suppress the effect. The third factor that influences the relationship between the cause variable and the outcome variable is called *moderator*. Generally, one particular research question that can be addressed by analyzing the moderating effect is whether the relationship that we observe tends to differ in different circumstances or not.

To have a clear picture of the moderating effect, let's look at this example. One company offered a training program to sales representatives to help them improve sales performance. Basically, the company expected that employees who had attended more training sessions would achieve higher sale performance than those who had attended a few sessions. The training program consisted of many sessions that were held in one month. All employees were required to attend as many sessions as they could. After the training program had ended, the company hired the analyst to evaluate the effectiveness of the training program.

In order to obtain an overview of the relationship between the number of training session and sale performance, the analyst performed a data plot between those two factors. Surprisingly, the finding appeared to contradict the company's expectation, as the data plot revealed that the relationship between the number of training session and sale performance is apparently negative, as shown in the figure below. This implies that more session employees had attended subsequently lowered their sales performance. OMG!! Does it mean that the training program that the company had poured a lot of money and effort into it turned to be a disaster? Does it mean that the company should take the training program off their corporate policy because the analysis showed that it reduce sales performance?

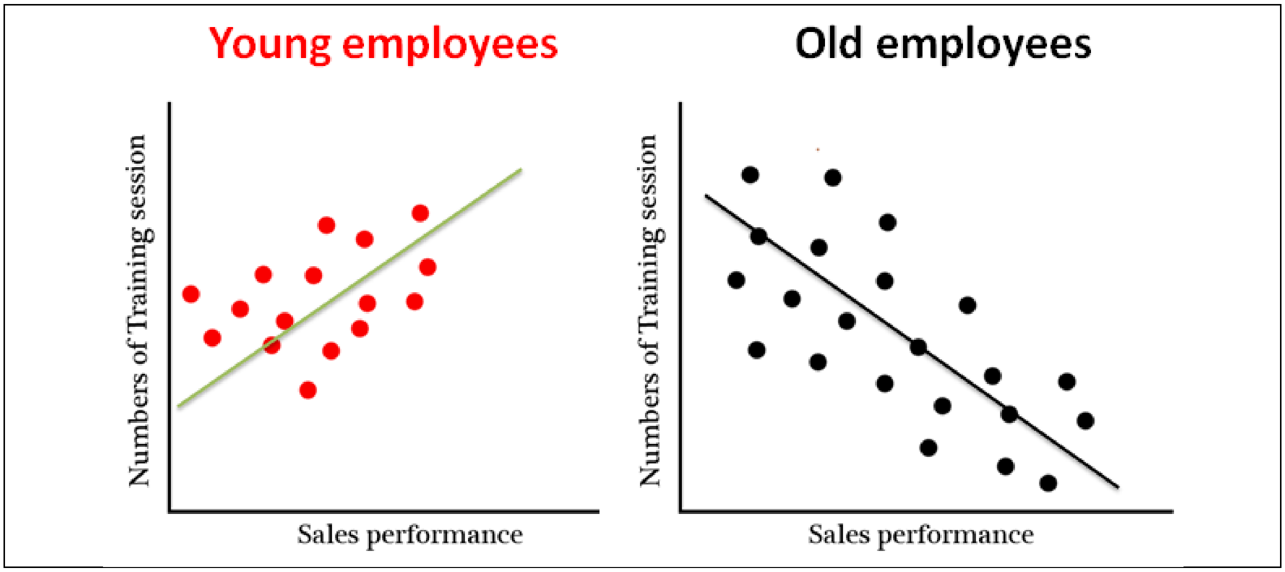
If you were the analyst of that company and you got the result like that, what would you do? Would you go straight to report the bad news to the executive and suggested that the training program is a waste of money? If you decided to do that, please stop and think carefully for a while. Although the result reveals that more training sessions causes employees to have lower sale performance, do you think that this would occur to every employees? In other words, do you think there might be some group of employees who actually benefited from the training?

Data plot between numbers of training session and sales performance



If you think carefully, there must be some factors that might influence the effect of the training program on sale performance. One demographic factor that can influence the finding is "age" of employees. When thinking about age, we may classify people into two broad groups: younger people and older people. Now, please stop and think for a while. Do you think the effect of the training program on sale performance will be the same when you compare between younger employees and older employees?

To clarify the doubt, the analyst separated the data between younger employees and older employees and then performed the data plot separately. The data plots reveal the truth behind the story. For older employees, the result shows a negative relationship like what we saw earlier. However, for younger employees, it appears that there is a positive relationship between the number of training sessions and sales performance. Now the results obtained separately from these two age groups contradict each other. What is a key conclusion that can be drawn from the findings?



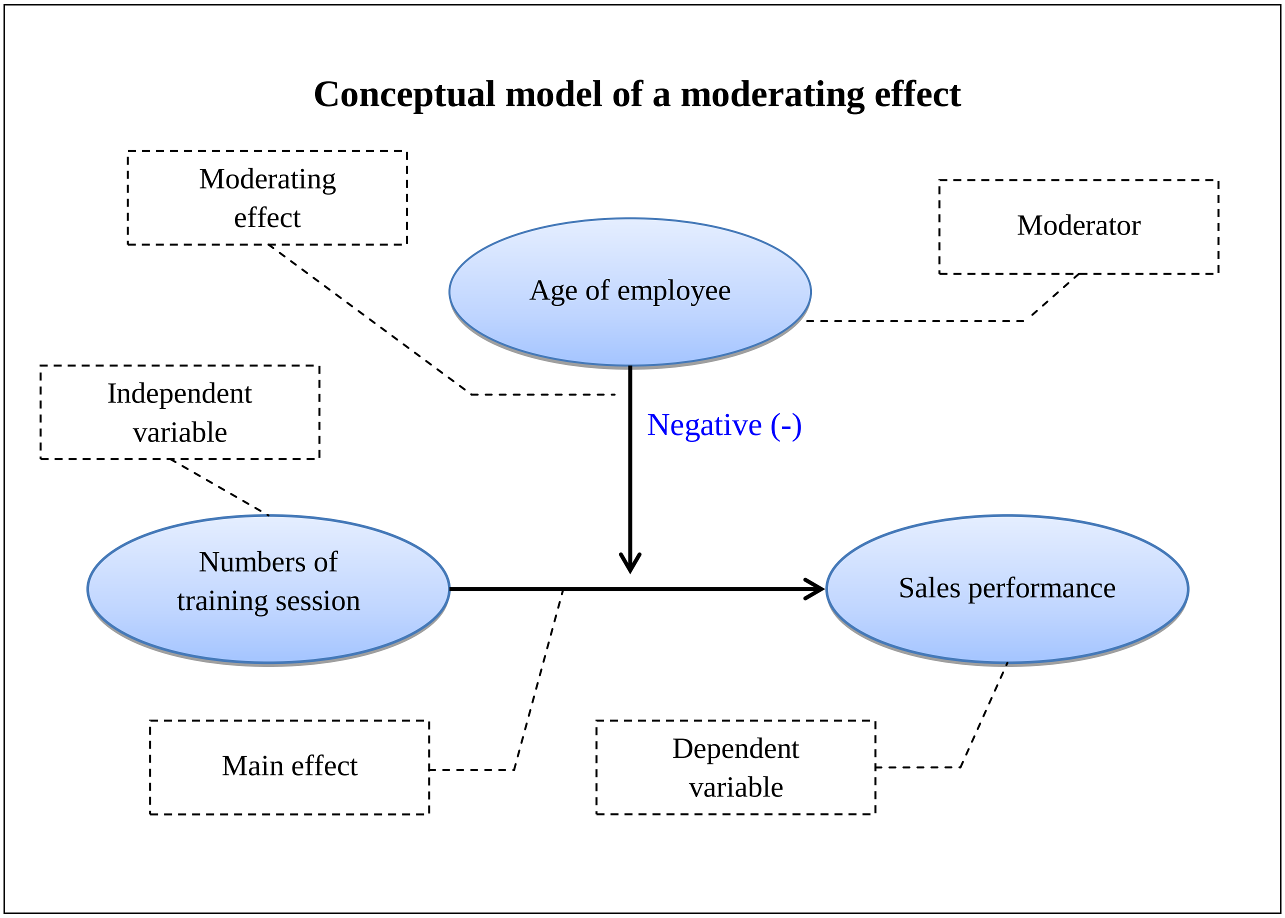
For younger employees, attending more training sessions successfully resulted in higher sales performance as the company expected; but for older employees, attending more training sessions lowered their sales performance. Do these findings make sense to you? Yes, make sense. There are some reasons to support the findings. First, most of the younger employees were in the early stage of their career and they normally lacked solid experience in selling. Thus, the training program tended to provide greater benefit to this group of employees because they were able to learn more about the selling techniques they didn't know before. As a result, they could use what they learned to help them improve sales performance. On the other hand, older employees had been in their career for a longer period of time and most of them already had solid experience in selling. They knew already what they had to do. In addition, extant research has found that age can be an obstacle for effective learning; in particular, older people may have more difficulty in learning as compared to younger people (Charness et al, 1992; Kubeck et al, 1996). This can be an additional explanation why older employees did not benefit from training. For this reason, the training program may not have any effect on their performance. But because the company required employees to attend as many sessions as they could, it is possible that older employees who attended more sessions may waste times that should have been spent to do their job. This could explain why more training sessions turned to lower sales performance of older employees.

From this example, you can see that the effect of one factor (e.g., the number of training sessions) on another factor (e.g., sales performance) may not necessarily be absolute; but it can depend on the third factors or the moderator (e.g., age of employees). In this case, we can conclude that effect of training session on sales performance is moderated by (or is contingent on) the age of employees; while the effect is negative for older employee, it is positive for younger employees. The result can also be summarized by a 2 x 2 matrix as shown in the table below.

	Less training session	More training session
Older age	Higher performance	Lower performance
Younger age	Lower performance	Higher performance

Note that the easy way to make sense of the moderating effect is to consider whether the effect of one factor on another factor will be the same if we classify the subjects into two groups based on some characteristic. A moderator can be discrete or categorical factors such gender (male and female), position (boss and subordinate), employment status (employed and unemployed). Also, it can be specific conditions characterized by high magnitude and low magnitude such as the level of stress (low stress and high stress) and level of knowledge (less knowledge and more knowledge).

The figure below illustrates how a moderating effect is expressed in a conceptual model for the example case. The arrow drawn from number of training session to sales performance is called a "main effect". Age of employee is a moderator (or moderating variable) that influences the effect that number of training session (independent variable) has on sales performance (dependent variable). To express the moderating effect, the arrow from the moderator has to point to the line that represents the main effect. The influence of age that makes the relationship between number of training session and sales performance to differ between two sample grounds is called the moderating effect.

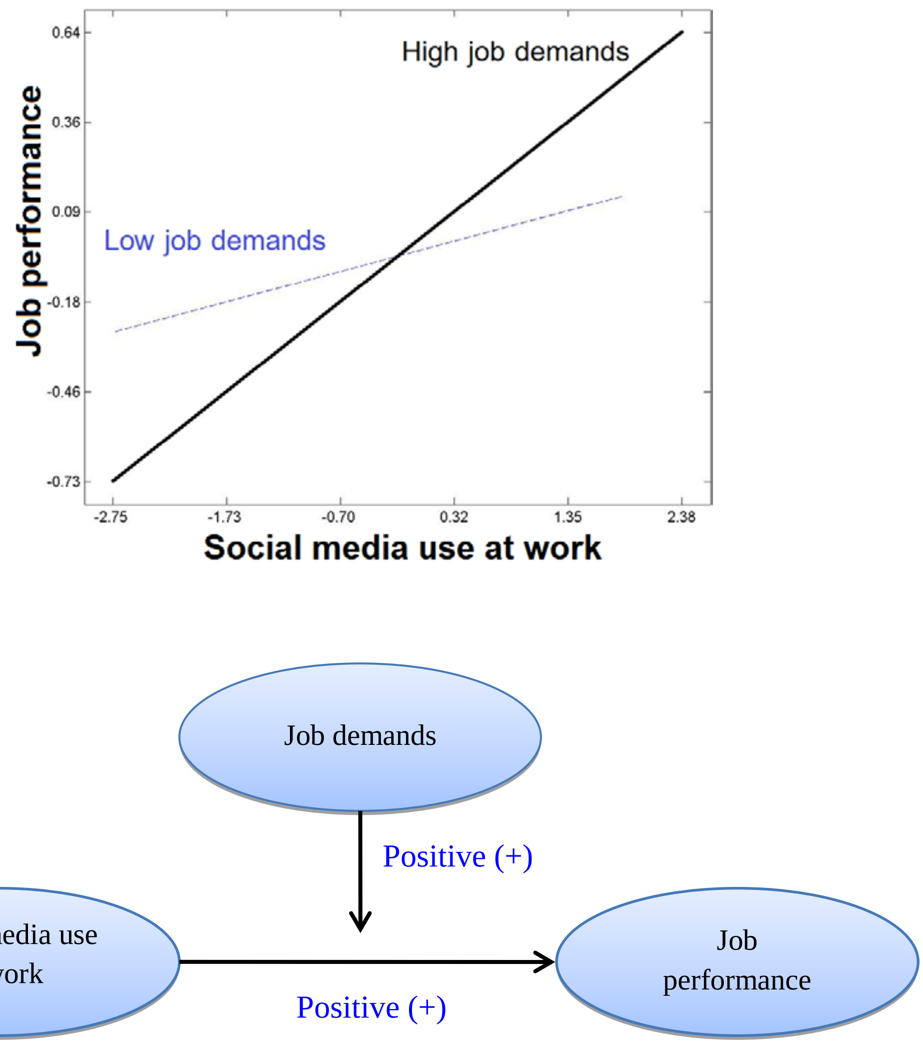


The moderating effect also has a sign (positive or negative). In the conceptual model you can see that the sign of the moderating effect that points to the link between the independent variable and the dependent variable is negative. How to interpret the sign of the moderating effect is similar to how to interpret the sign between variables. But instead of comparing between two variables like the examples in the previous chapter, when interpreting the sign of the moderating effect we need to compare between the "moderator" and "the relationship between the variables where the moderator points to". In this example, the negative sign of the moderating effect means that as age increases, the effect of training session on sales performance will reduce.

Note that the moderating effect does not mean that the effect that one factor have on another factor has to be opposite between groups (positive in one group and negative in another group). The effect of one group may be highly positive while the effect of another group may be less positive or neutral.

For example, a study about the effect of social media use intensity on job performance that the author investigated found that employees who used more social media tended to have higher job performance. However, the author was skeptical whether this benefit would be the same for every employee. Thus, the moderating effect analysis was performed to explore the conditions that might cause some employees to benefit more or less from using social media at work.

Moderating effect of job demands on the relationship between social media use at work and job performance



The author found that employees who faced with high job demands tended to benefit more from using social media during work. Job demands are characterized by highly quantitative workloads that easily make employees expose to job stress. Therefore, this finding implies that using social media in the group of employees who suffered from high job demands allowed them to relax from quantitative workload that they had to encounter. When employees could relax, it helped them maintain productivity. This is why the benefit of social media use intensity at work tended to be more positive for employees who inevitably involved with high job demands, as compared to employees who did not encounter the job demands issue.

As shown in the top part of the figure above, the slope of the relationship between social media usage and job performance appears to be steeper for the group of employees who faced with high job demands (solid line) as compared to the group of employees who didn't face with high job demands (dash line). In the conceptual model at the bottom of the figure you can see two signs: one is the sign between social media usage and job performance; another one is the sign of the moderating effect that points to the link between social media usage and job performance. Both of them are positive. In particular, the positive sign between social media usage and job performance can be interpreted that: as employees use more social media, their job performance increase. The positive sign of the moderating effect that points to the link between social media usage and job performance can be interpreted that: as employees encounter *more* job demands, the relationship between social media usage and job performance also *increases*. In other words, higher job demands substantiate the positive effect of social media usage on job performance.

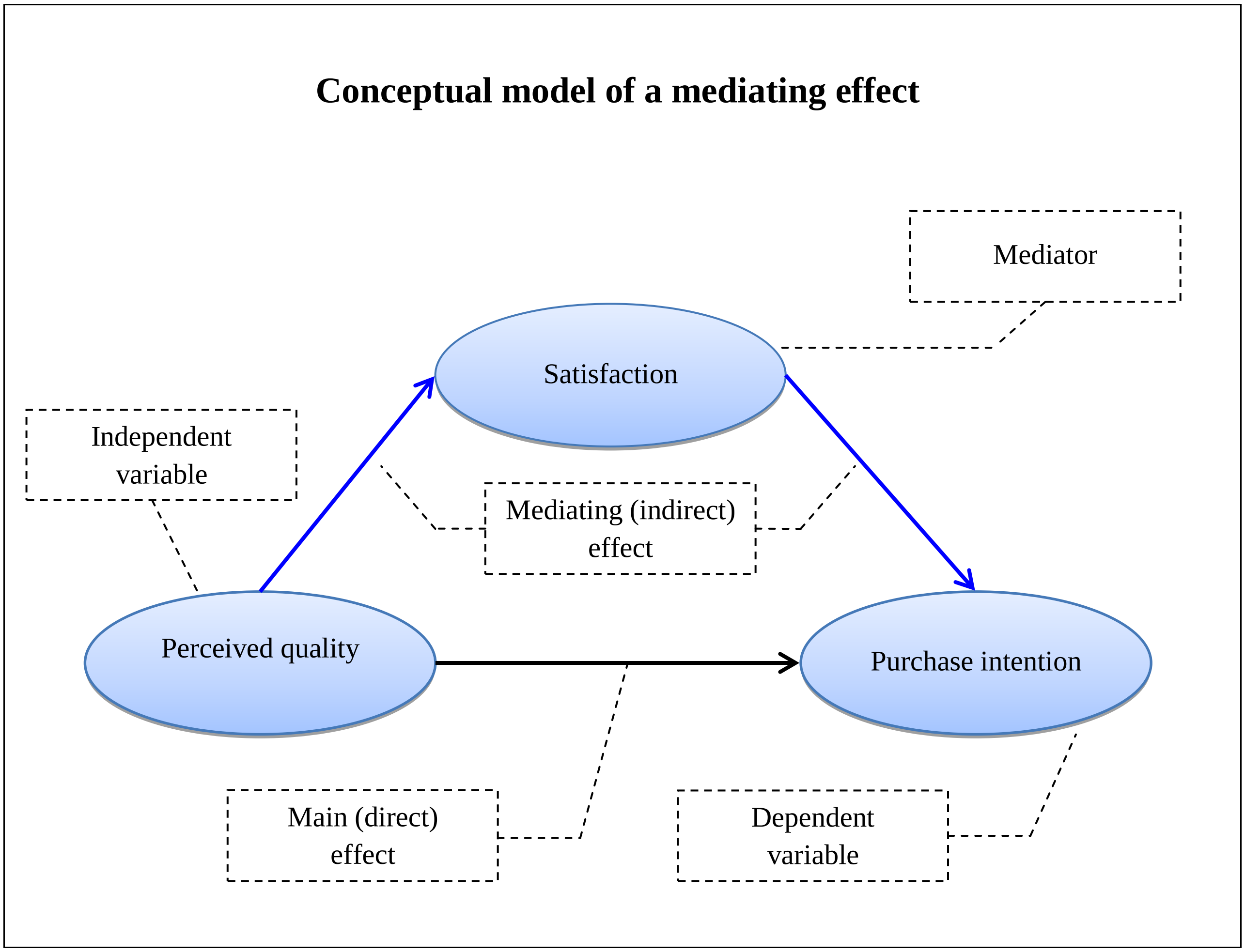
Generally, the analysis of moderating effect provides an additional insight that allows the researchers to discover the conditions that make the relationship between phenomena of interest differ among groups of samples. Researchers have to identify the third factors that can influence the relationship between phenomena of interest. The ration behind using moderating effect is consistent with the *contingency theory* in management which posits that there is no one best method that can lead to success (Feldman, 1976; Tosi & Slocum, 1984). The effectiveness of a method depends on situations; the method that is effective in one situation may be less effective or even ineffective in another situation.

Mediating effect

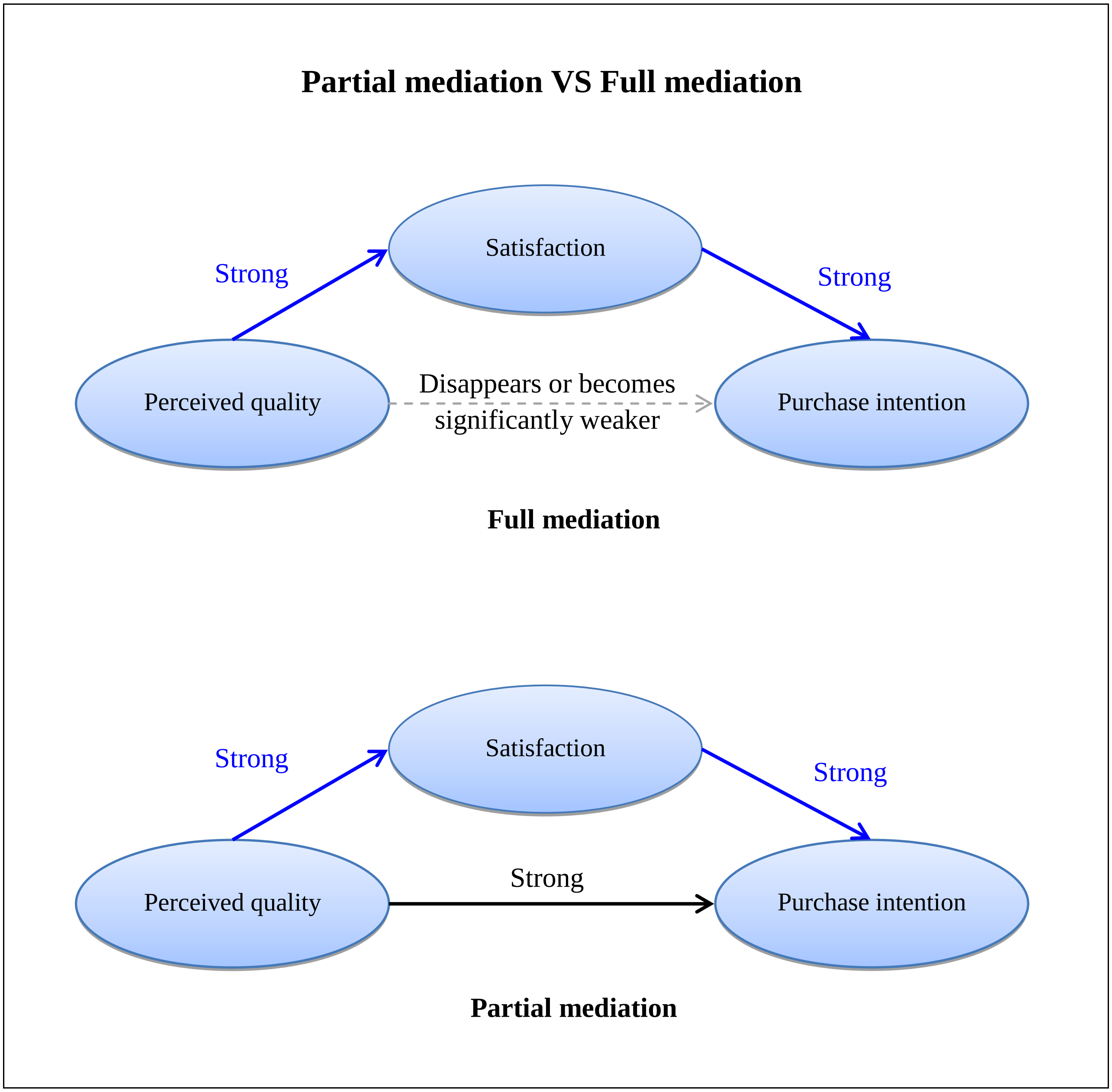
The mediating effect suggests that the effect that the cause variable exerts on the outcome variable does not happen direct; but the effect is transferred through the third factor called a *mediator* or *mediating variable*. In another words, the mediating effect represent the indirect effect that the cause variable have on the outcome variable.

To get some practical example of the mediating effect in research, let's consider some theoretical model in marketing that explains why consumers decide to purchase a particular product/service. Anyway, let's stop for a while and ask yourself have you ever recognized the psychological process that happen to you before you decide to buy a particular product? When you came across a particular product, let's say a computer tablet, would you buy it right away without thinking. Well, unless you were super rich, you would take some time to let your brain evaluate some information at least for a while before you take action.

In marketing, one key factor that determines purchase intention of consumers is "perceived quality of a product/service" (Patterson & Spreng, 1997). Perceived quality involves consumers' judgment about overall excellence or superiority of a particular product/service (Snoj et al, 2004). However, do you think perceived quality is the only reason that is sufficient to motivate consumers to make a purchase? It may not be necessary. Some people prefer to buy low cost products and they are willing to give up the quality for the cheaper price they pay. Before consumers decide to make a purchase because of the quality, consumers may need to be satisfied with the quality of a product/service first. Satisfaction is important because if we think the quality of the product is good but we don't satisfied with it, we don't want to buy the product anyway. In marketing research, customer satisfaction has been found as an influential factor that motivates consumers to make a purchase (Fornell et al, 2010; Yu et al, 2014; Yuksel et al, 2010). In this case, the effect of perceived quality may not directly influence consumers to make a purchase, but its effect can be transferred indirectly through the role of customer satisfaction. In other words, perceived quality can lead to customer satisfaction; customer satisfaction, in turn, can lead to purchase intention. Customer satisfaction in this case is the mediator in the analysis.



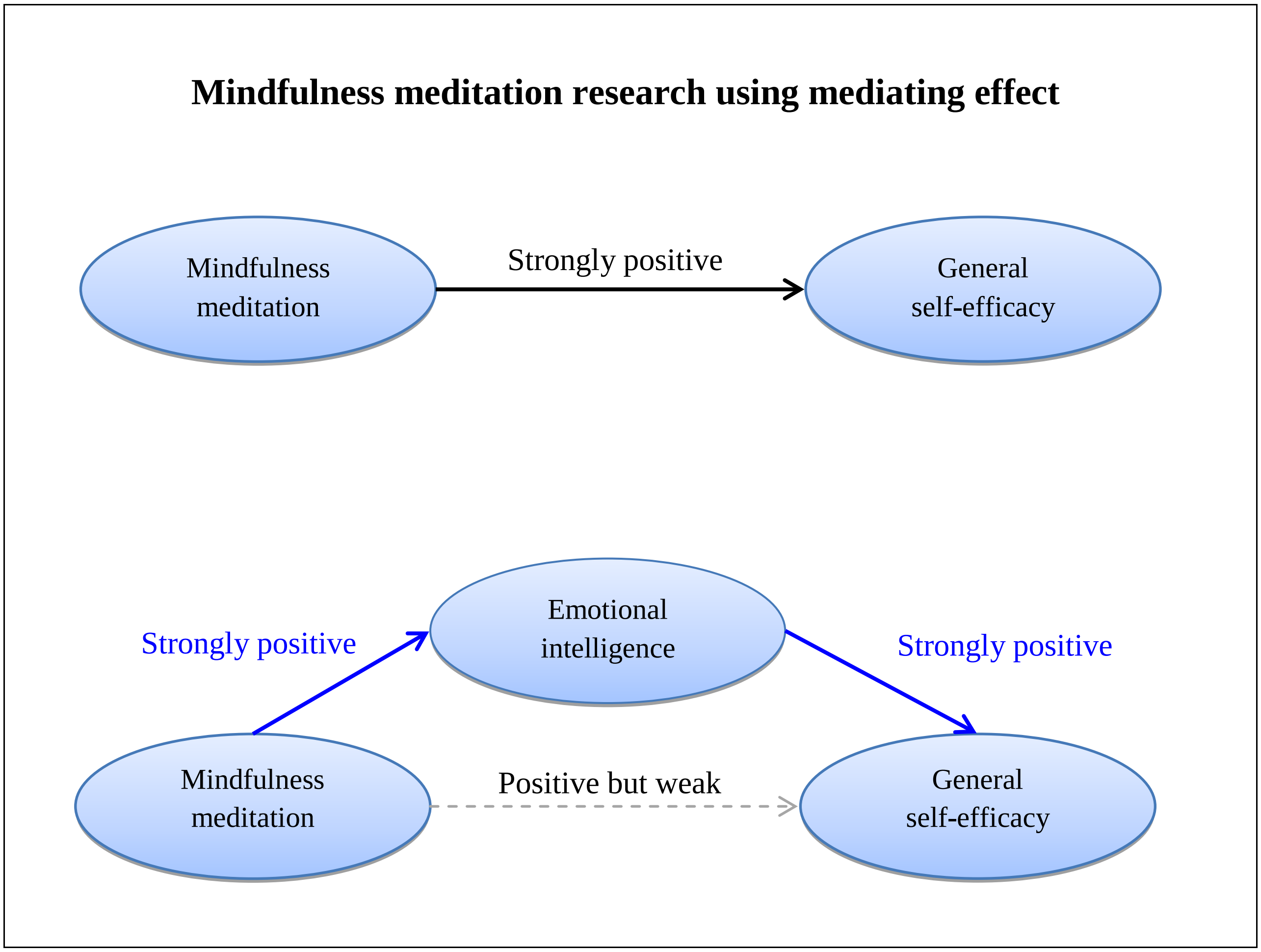
The figure below illustrates how the mediating effect is expressed in a conceptual model. The arrow drawn from perceived quality to purchase intention is called a "main effect" (sometime it is called a "direct effect"). This is a direct influence that perceived quality (independent variable) has on purchase intention (dependent variable). Satisfaction is a "mediator" or "mediating variable" that provides some underlying logic that explains why perceived quality affects purchase intention. Therefore, the mediator is placed at the middle between the independent variable and the dependent variable, with one arrow pointed from the independent variable to it and another arrow pointed from it to the dependent variable. The arrow in the black color represents the directly effect that perceived quality exert on purchase intention. The arrows in the blue color represent the indirect effect that perceived quality exert on purchase intention through the mediating role of satisfaction.



Mediating effect can fully or partially explain the relationship between the independent variable and the dependent variable. "*Full mediation*" occurs when the strength of relationship between the independent variable and the dependent variable is nullified when the mediator is introduced into the analysis. This suggests that the moderator can fully explain why the independent variable leads to the dependent variable. In this case, we assume that the direct effect between the independent variable and the dependent variable does not exist. The independent variable only affects the dependent variable indirectly through the mediator. Using the previous example, if the direct relationship between perceived quality and purchase intention is nullify or becomes significantly weaker, it can be concluded that customer satisfaction fully mediates the relationship between perceived quality and purchase intention. This means that without customer satisfaction, perceived quality cannot lead to purchase intention. No matter how much customers perceive that the product has good quality, if they are not satisfied with it, they will not buy it. The conceptual model that represents full mediation is presented in the top part of the figure above.

On the other hand, "*partial mediation*" occurs when the strength of relationship between the independent variable and the dependent variable is still strong even when the mediator is introduced into the analysis. This suggests that although the mediator can explain why the independent variable affects the dependent variable, it can only explain partially; the direct influence of the independent variable on the dependent variable still exists. Using the same example, if the direct relationship between perceived quality and purchase intention is still strong even when the moderator is included in the analysis, it can be concluded that customer satisfaction partially mediates the relationship between perceived quality and purchase intention. While satisfaction can explain why perceived quality affects buying intention, perceived quality itself can still exert a direct influence on customer intention to buy the product. The conceptual model that represents partial mediation is presented in the bottom part of the figure.

Generally, the analysis of the mediating effect is useful for researchers to provide an explanation why one phenomenon affects another. For example, in the study about the benefits of mindfulness meditation that the author conducted (Charoensukmongkol, 2014), the statistical analysis showed that people who had practiced mindfulness meditation more intensively tended to exhibit higher level of general self-efficacy. Simply put, this implies that people who meditated a lot tended to develop more self-confidence. But what can explain this relationship?



In order to investigate the mechanism that made people who regularly practiced meditation to develop higher self-confidence, the author conducted the mediating effect analysis. Based on the literature review, the author found that one particular benefit of mindfulness meditation practice is to help people effectively regulate and stabilize emotions. When people meditate regularly, it helps them easily cultivate peace of mind especially when they encounter with a stressful situation. Being able to regulate emotions can play an important role for people to develop self-confidence because when people are in a negative mood (sadness), it is more likely for them to see things pessimistically. This uncontrolled emotion, in turn, can cause people to lose confidence in their ability to be successful. On the other hand, when people are in a positive mood (happiness), they tend to be more optimistic about their competencies.

According to the information from literature review, the author additionally hypothesized that the ability to regulate emotions might be the mediator that explains why meditation practice can promote self-confidence. Thus, the ability to regulate emotions was conceptualized in the study by using emotional intelligence. As expected, the analysis of the mediating effect supported the hypothesis about the mediating effect of emotional intelligence. In this regard, the author found that mindfulness meditation has a positive relationship with emotional intelligence; emotional intelligence also has a positive relationship with self-efficacy. Plus, these positive relationships are very strong. Furthermore, after emotional intelligence was incorporated into the analysis as the mediator, the positive relationship between mindfulness meditation and self-efficacy now turned to be very weak. What happens here can be interpreted that emotional intelligence fully mediates the relationship between mindfulness meditation and self-efficacy. Thus, the overall results can be concluded that practicing mindfulness meditation does not directly make people develop self-confidence, but it is emotional intelligence that people obtain from practicing mindfulness meditation that actually helps people develop self-confidence.

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