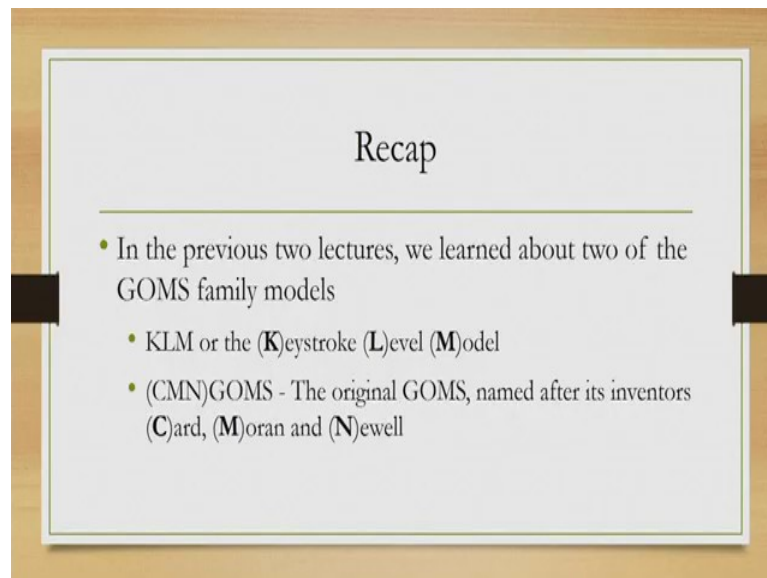


**User-Centric Computing for Human-Computer Interaction**  
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**Lecture - 16**  
**The Fitt's Law**

Hello and welcome to lecture number 16, in the course User-Centric Computing for Human-Computer Interaction. Let us first recall what we have done so far. So, in the previous two lectures, we learned about two models of human behavior, user behavior in the context of interactive system design.

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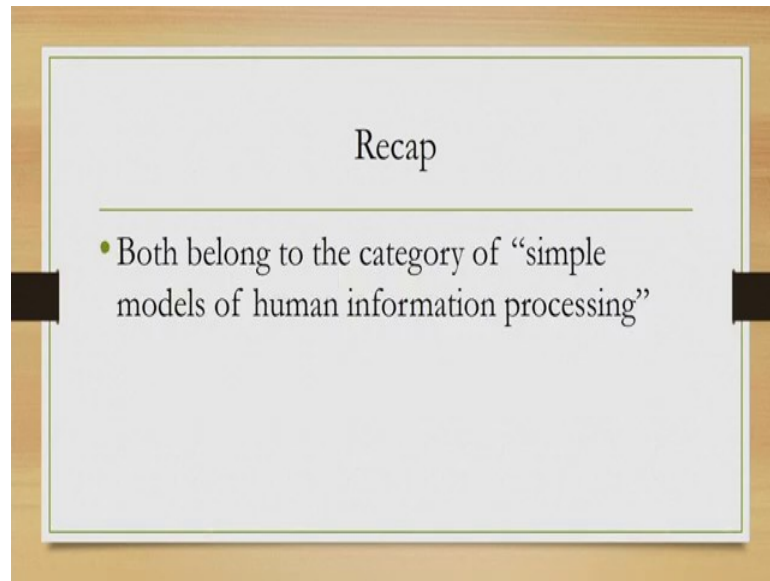


Recap

- In the previous two lectures, we learned about two of the GOMS family models
  - KLM or the (K)eystroke (L)evel (M)odel
  - (CMN)GOMS - The original GOMS, named after its inventors (C)ard, (M)oran and (N)ewell

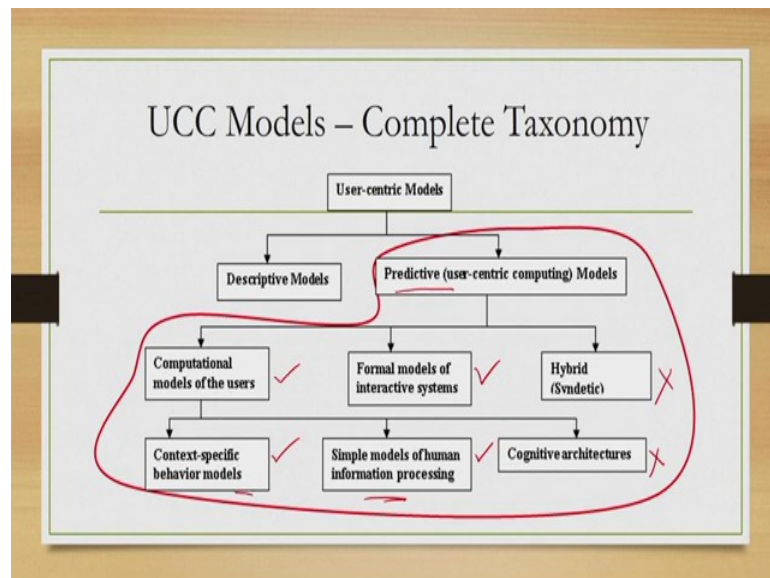
One is the KLM, other one is the CMN GOMS; both belong to the broader GOMS family of models.

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Now, this, these two models are part of a class of models that earlier we labeled as simple models of human information processing.

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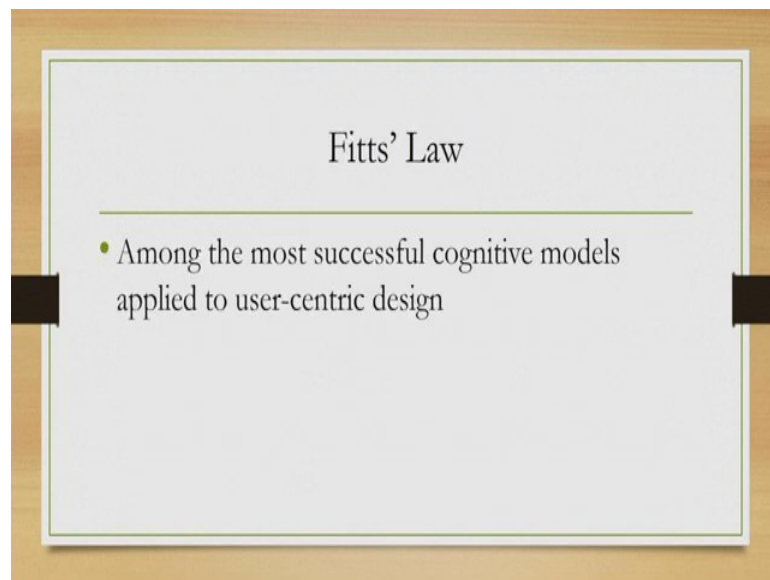


Now, if you can recollect earlier we talked about a taxonomy of user-centric models, so in this taxonomy we are interested in the predictive models among the different predictive models, there are three broad classes, computational user model, formal model and hybrid model. Hybrid model we are not going to discuss any further. Now, under

computational user models, there are context specific behavioral model, simple models of human information processing and cognitive architectures.

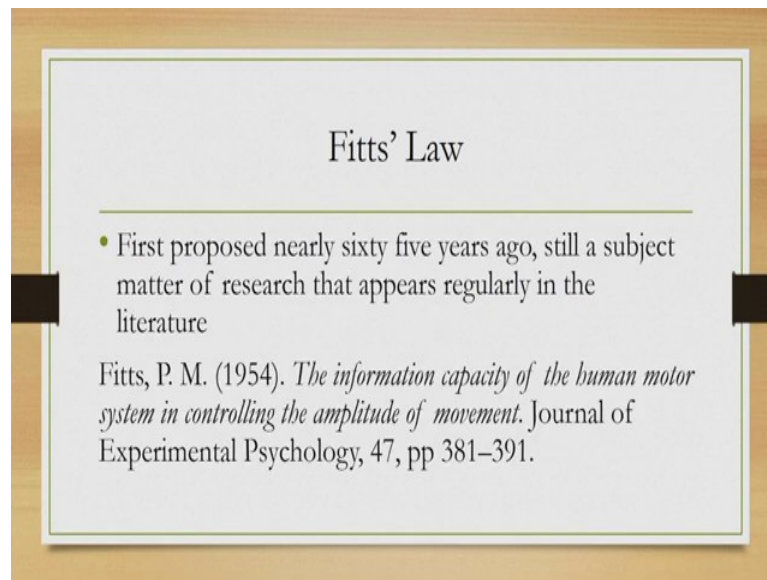
Cognitive architectures like the hybrid models we are not going to discuss any further. So, in the previous two lectures we talked about two models namely KLM and GOMS that are part of this group of models simple model of human information processing. In this lecture, we are going to talk about one model that belongs to this other group namely context specific behavioral models that comes under computational models of the user.

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This model is popularly known as the Fitts' law this is one of the most successful models cognitive models that has been applied to user-centric design.

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Fitts' Law

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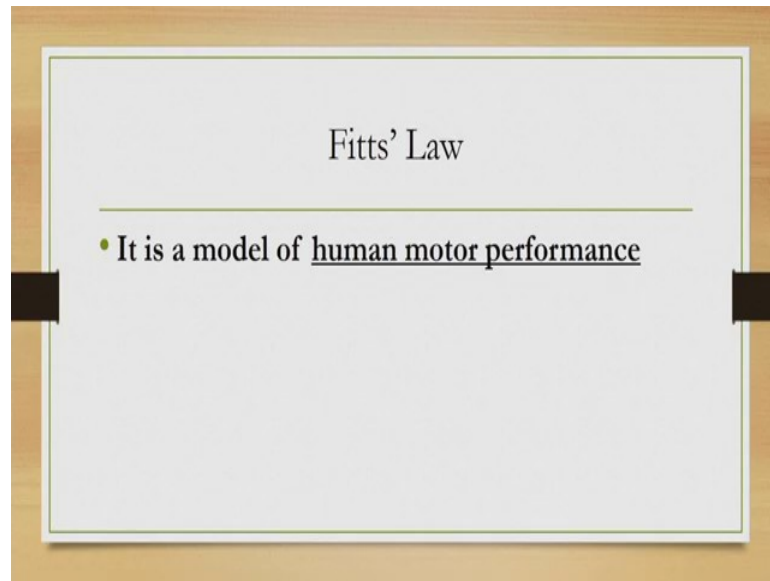
- First proposed nearly sixty five years ago, still a subject matter of research that appears regularly in the literature

Fitts, P. M. (1954). *The information capacity of the human motor system in controlling the amplitude of movement*. Journal of Experimental Psychology, 47, pp 381–391.

It was first proposed nearly 65 years ago in this article by P. M. Fitts in 1954, the model was first proposed. And the article name was The information capacity of the human motor system in controlling the amplitude of movement. It was published in Journal of Experimental Psychology, volume number 47.

It may be noted that this work was not related to the design of user-centric systems, instead it was a general work in the field of cognitive psychology, but the model found wide use in the design of interactive systems and it is still a subject matter of research which appears regularly in the literature.

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Now, what is this Fitts' law? It is a model of human motor performance. So, when we are talking of Fitts' law, we are essentially talking of a model of human motor performance, the way we our motor organs behave that is represented by this model.

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Now, when we are using the term motor performance, it actually refers to many human activities that include hand movement, that include finger movement, eye movement, facial muscle movement, leg movement and so on, so anything that is related to our motor organs.

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However in the context of this discussion and in the context of Fitts' law the motor performance specifically refers to manual or a hand or finger movement. So, in other words, we may say that the Fitts' law is a model of human manual movement. In the human manual movement, two things are there hand or finger.

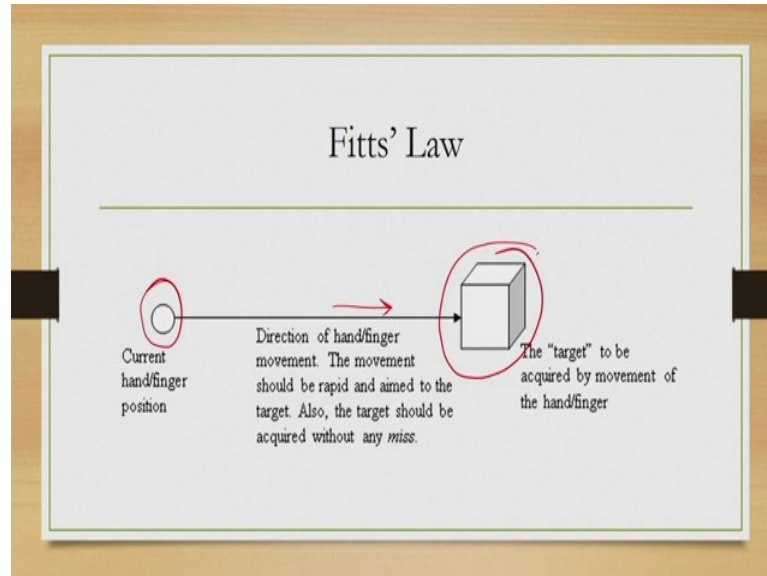
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And this model is a model of human motor performance in a specific context that is the target acquisition task. In other words, we want to acquire a target at some distance from

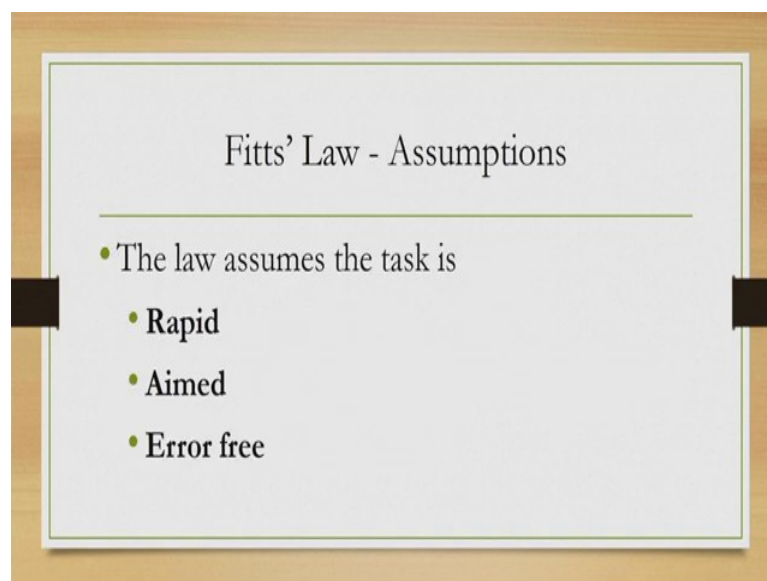
the current hand or finger position, and this, the task of acquiring the target is modeled by the Fitts' law.

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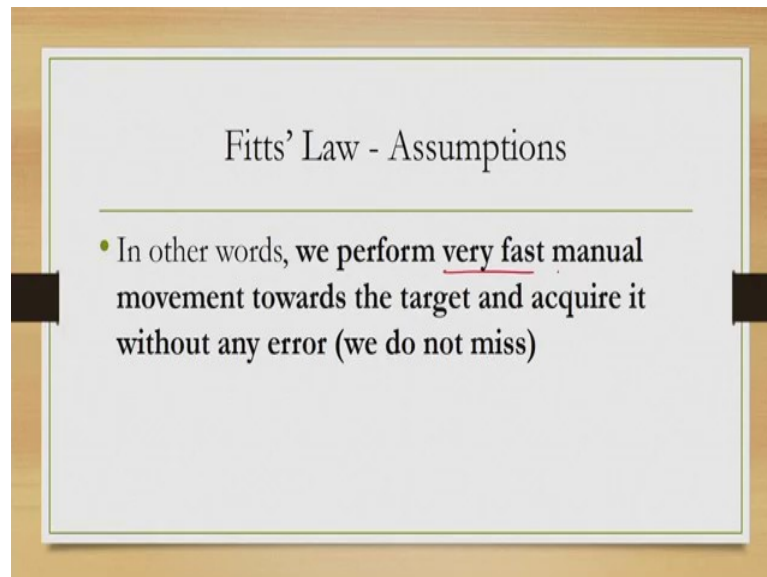
So, the situation is illustrated with this diagram. As you can see this cube represents the target, and our current hand position is here somewhere here, this is the direction of movement. The arrow shows the direction of movement and from here we want to acquire the target this behavior how we acquired the target is modeled by the Fitts' law.

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But there are few assumptions. Before we can say that the Fitts' law models, target acquisition task, there are three assumptions, namely that the task or the target acquisition task is rapid, aimed and error free. So, unless these three conditions are met, we cannot assume that the Fitts' law represent the target acquisition task.

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Fitts' Law - Assumptions

- In other words, we perform very fast manual movement towards the target and acquire it without any error (we do not miss)

So, what these assumptions imply, these assumptions indicate that we perform very fast manual movement towards the target and acquire it without any error or we do not miss in our task. So, we are trying to acquire the target very fast and without any miss.

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Fitts' Law - Assumptions

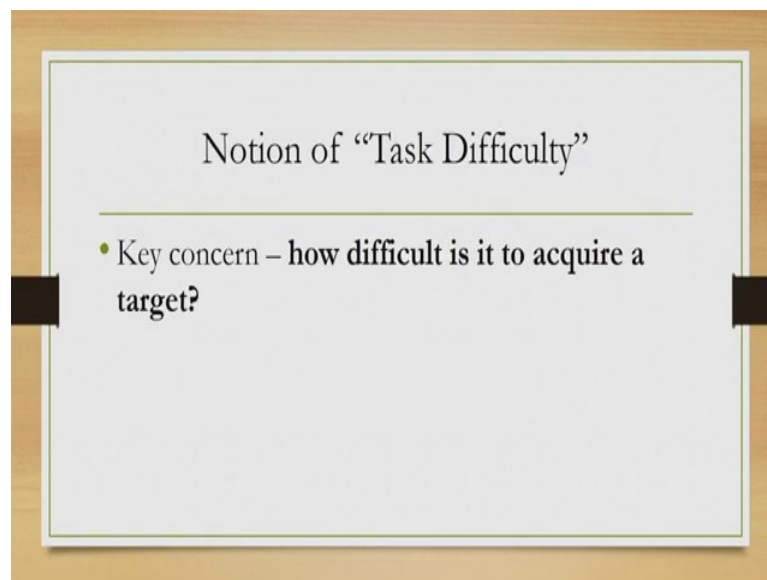
- Fast movement ensures there is **no time to think before acquiring the target**
- Eliminates need to take into account any other cognitive activities other than the manual movements



Now, why this assumption is important? So, here we are trying to model a particular behavior that is target acquisition task. Now, this behavior may involve some thinking as well as a motor action. Motor action is actual movement of the finger towards the target or movement of the hand towards the target. And thinking may involve the decision making process how to move in which path to follow and so on.

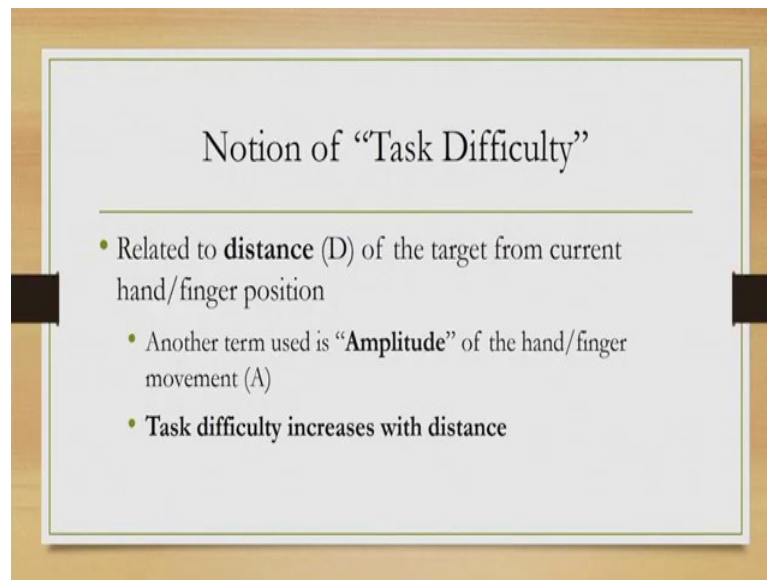
Now, if we are assuming that the movement is rapid, then this thinking part can be dispensed to it. So, we no longer need to think before we move. So, in that case, we can actually model this moment just by considering the motor action rather than the cognition or thinking, so that is the idea of assuming that the movement is fast.

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Now, when we are saying that we want to model this movement, what we are trying to model we are essentially trying to model the difficulty, how difficult it is to acquire the target.

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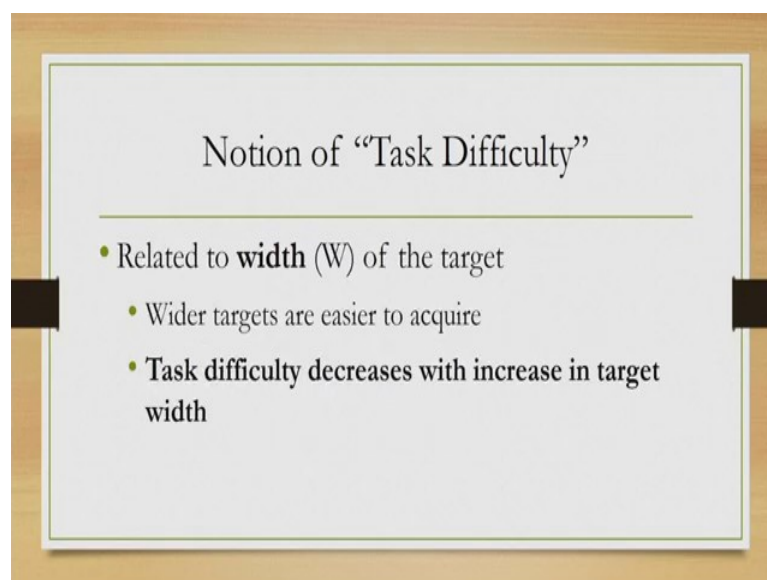


Notion of “Task Difficulty”

- Related to **distance** (D) of the target from current hand/finger position
  - Another term used is “**Amplitude**” of the hand/finger movement (A)
  - **Task difficulty increases with distance**

Now, this difficulty is actually related to two factors. The first one is distance, how far is the target from my current hand position or finger position. And this distance is sometimes also referred to as amplitude, amplitude of movement. And the law states that the difficulty of target acquisition increases with distance. So, the more the distance is the more is the difficulty.

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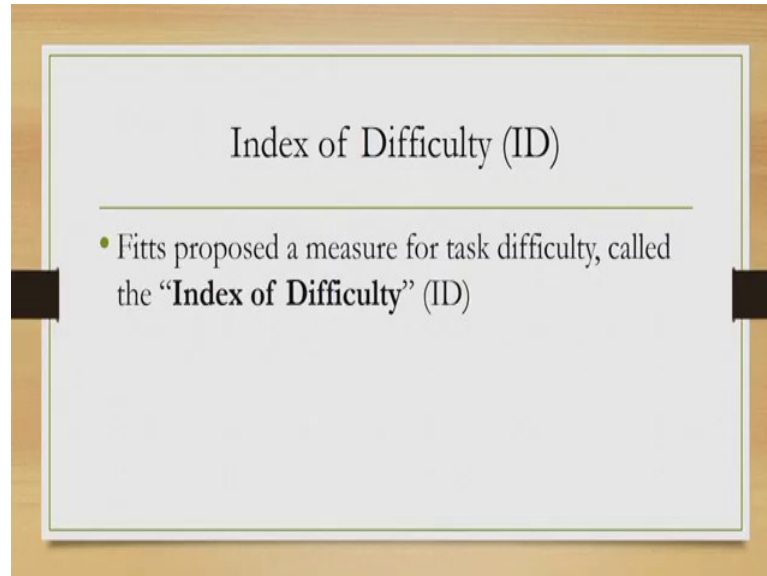
Notion of “Task Difficulty”

- Related to **width** (W) of the target
  - Wider targets are easier to acquire
  - **Task difficulty decreases with increase in target width**

The second factor is width, width of the target. Now, as is obvious or intuitive wider targets are easier to acquire. So, it essentially says that difficulty decreases with the

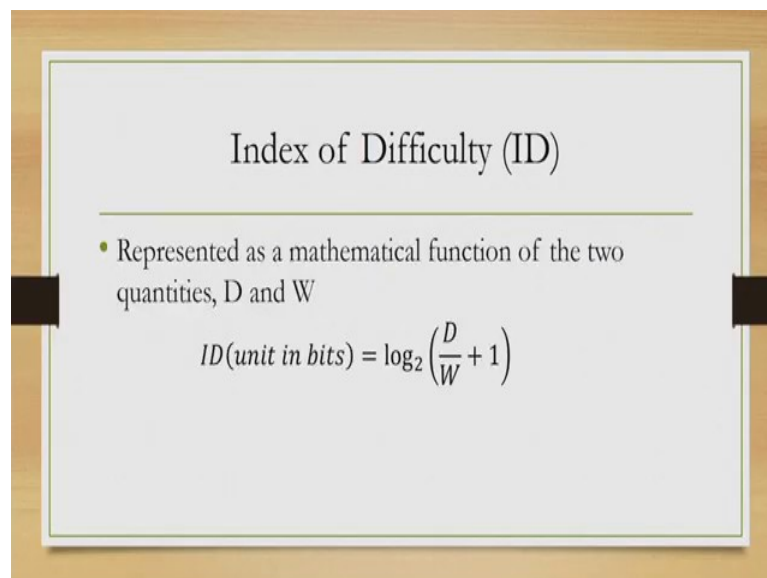
increase in target width. So, there are two things distance and width. And the law states that the difficulty of target acquisition increases with distance and decreases with width.

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So, the more the more wide the target is the less difficult it is to acquire Fitts proposed a major of difficulty which is called index of difficulty or ID.

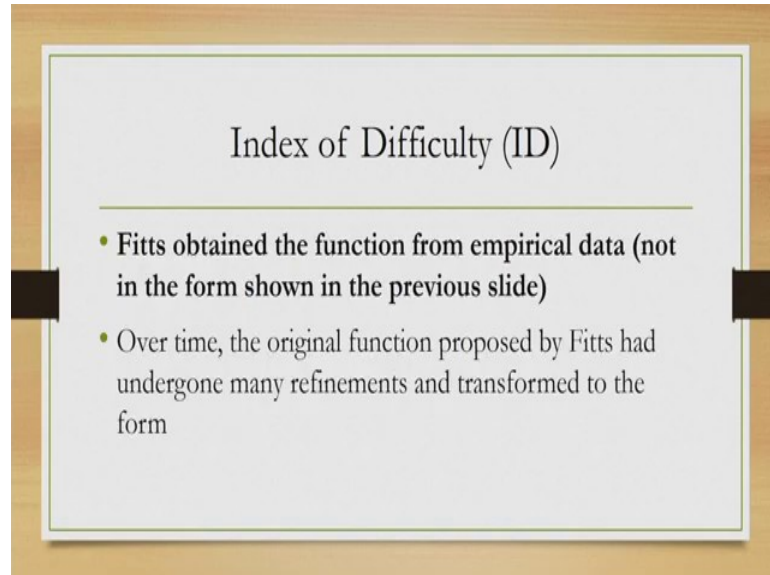
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Now, this major is represented as a mathematical function of the two quantities D and W. so this is a mathematical function of the distance and width, and its unit is in bits. So, ID is essentially represented as a function of D and W, in this form.

$$ID(\text{unit in bits}) = \log_2 \left( \frac{D}{W} + 1 \right)$$

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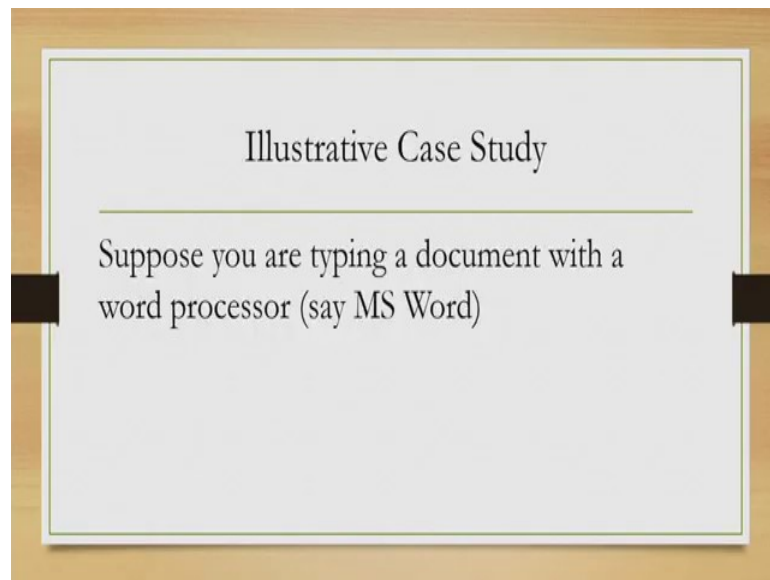
Index of Difficulty (ID)

- Fitts obtained the function from empirical data (not in the form shown in the previous slide)
- Over time, the original function proposed by Fitts had undergone many refinements and transformed to the form

Now, these function how it came it came through empirical studies. So, Fitts conducted lots of studies and performed regression analysis to come up with this with this mathematical function. However, it may be noted that the original function that was proposed by Fitts was not the same as soon previously, over time lots of further research took place and lots of refinement took place, and the equation that we just saw is the outcome of this long history of research.

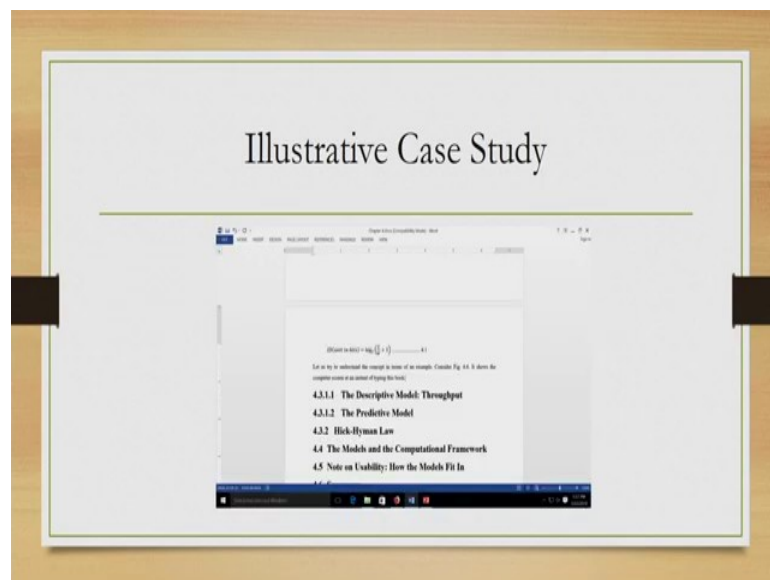
So, this is the equation that is used at present, although it was not originally proposed by Fitts. Now, let us try to understand how to apply this model of difficulty in practical scenario.

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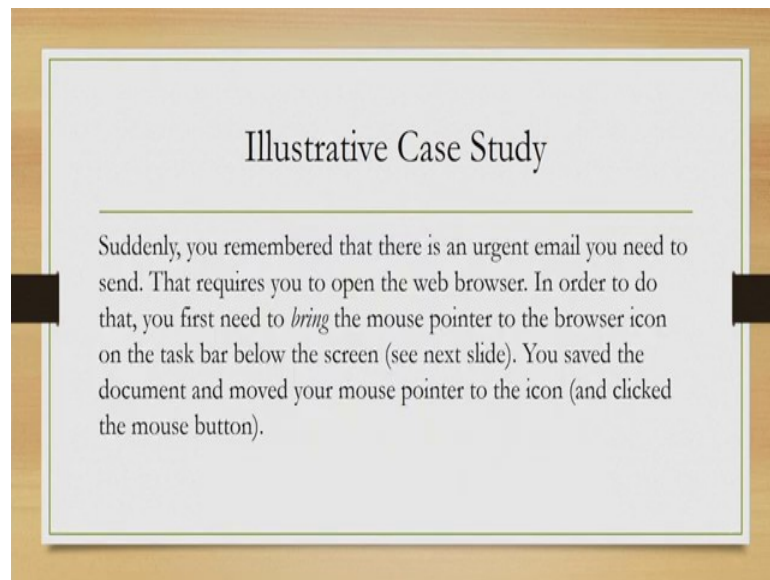
Suppose you are typing something in a text editor. Say for example, you are using MS Word, and typing something on the screen which is being displayed on the screen.

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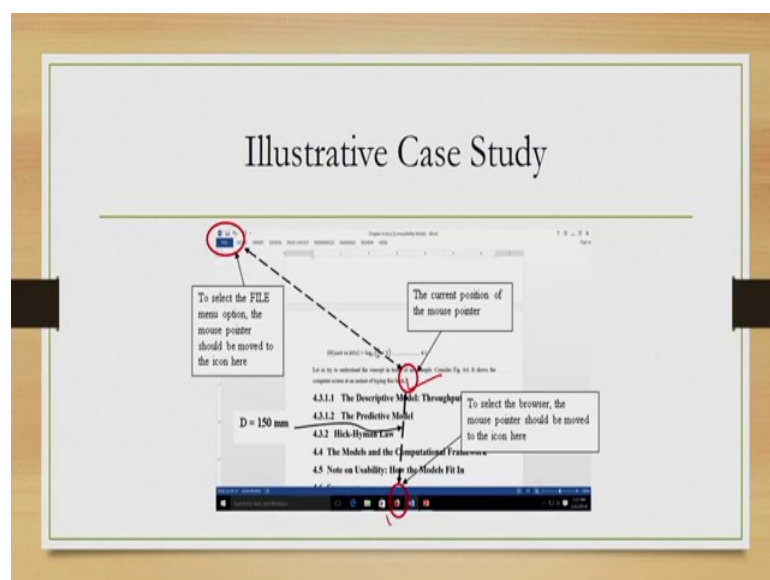
Something like this as shown in this figure. So, this is the MS Word interface and you are typing now at this stage.

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Suddenly you remembered that there is an urgent email you need to send. So, in order to do that, you need to open the web browser essentially you need to bring the mouse pointer to the browser icon, and click on it to open it. Now, the browser icon is located on the task bar below the screen. So, before you do that you saved your document and moved your mouse pointer to the icon.

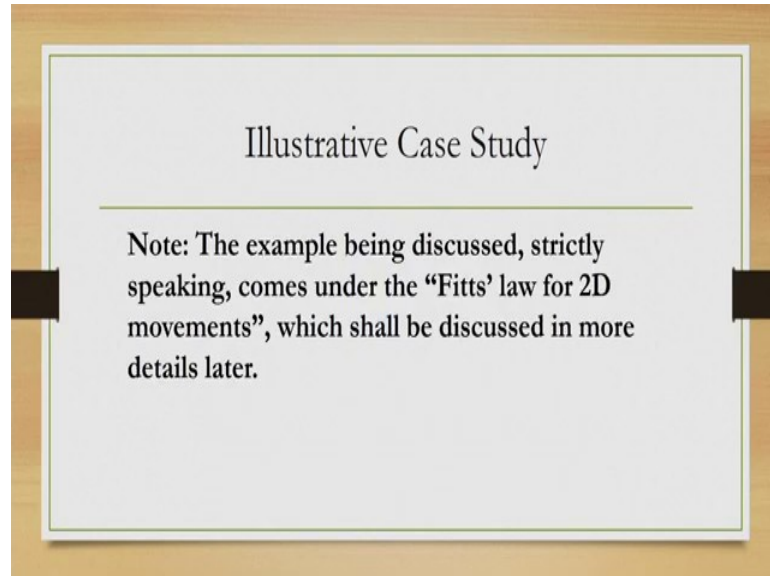
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Something like this. So, you were here at this stage, at that point you remember that you need to send an email. So, you went the file option. And then from the file menu sub

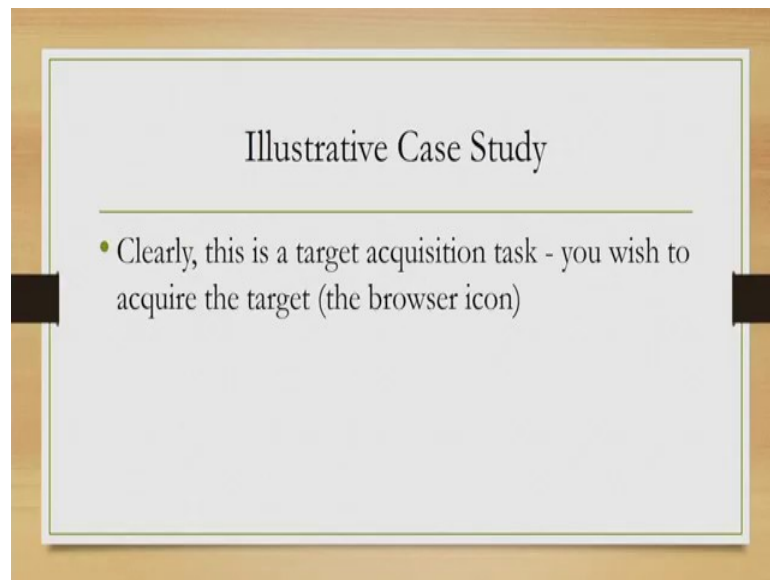
options, you selected the save option and saved your file, then you selected the browser icon which is located here.

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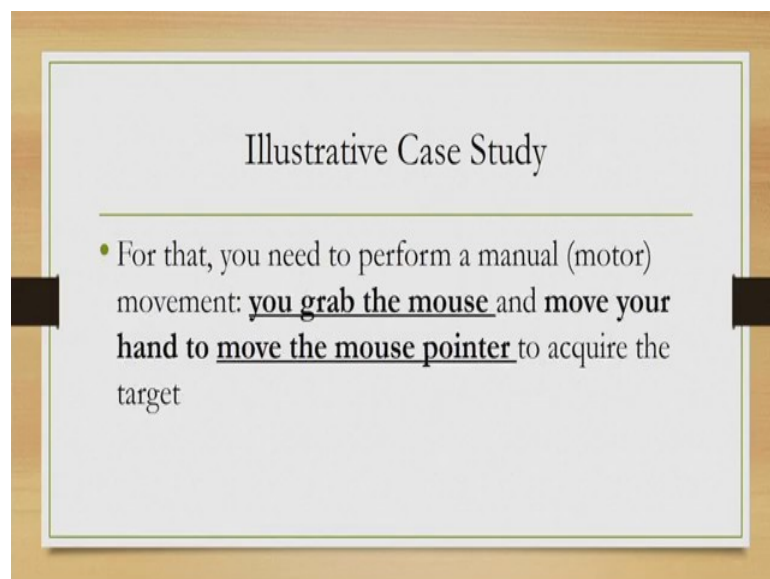
However, there is a note of question. You should remember that in this example although we are going to use Fitts law, but strictly speaking this is not a situation where we can apply the classical Fitts law, it requires certain modification and comes under 2D pointing task where some modified Fitts law is required. But for simplicity, we will assume that we can apply the classical Fitts law in this situation as well, in a subsequent lecture you will get to know about this 2D pointing task and the modified Fitts law in more details.

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Now, let us come back to the example again. So, here we are faced with a target acquisition task. Here our target is to acquire either the file menu option or the browser icon.

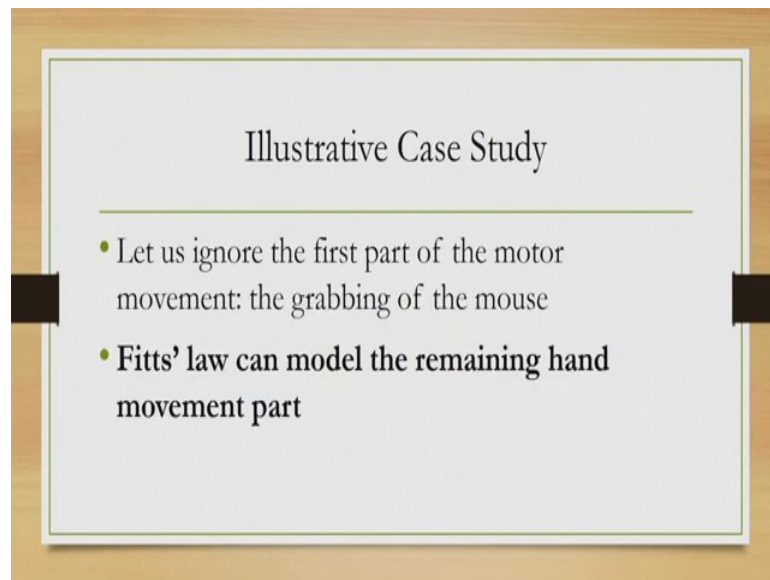
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So, in order to perform the activity, you need to do few more things. First thing is you grab the mouse and then move your hand to move the mouse pointer to acquire the target.



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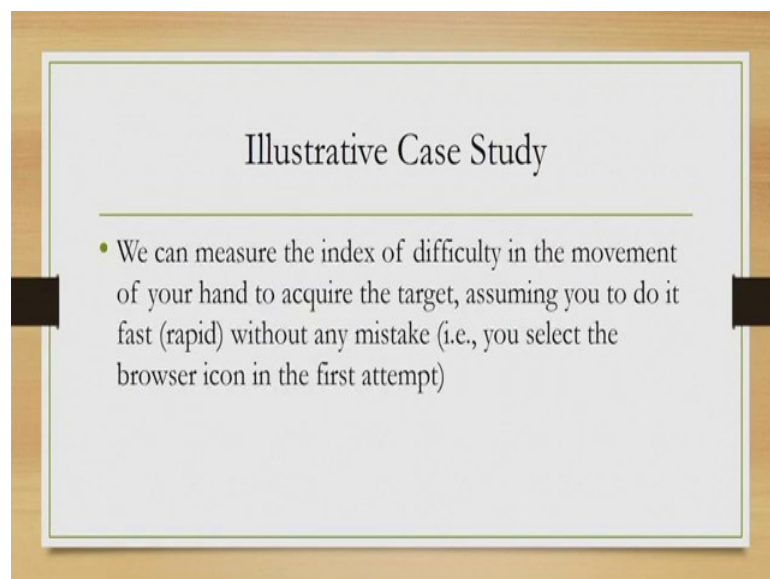
Illustrative Case Study

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- Let us ignore the first part of the motor movement: the grabbing of the mouse
- **Fitts' law can model the remaining hand movement part**

Now, let us ignore the first part that is grabbing the mouse. The second part is move your hand to move the mouse pointer to capture or select the target with Fitts law we can model this activity.

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The slide is titled "Illustrative Case Study" and is set against a light gray background with a thin green border. It is presented on a wooden-textured surface with two black rectangular markers on the left and right sides. The text is as follows:

Illustrative Case Study

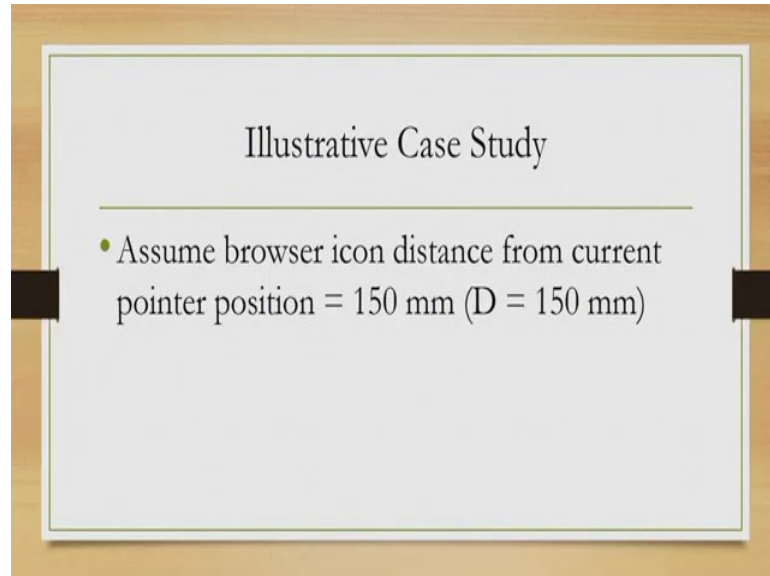
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- We can measure the index of difficulty in the movement of your hand to acquire the target, assuming you to do it fast (rapid) without any mistake (i.e., you select the browser icon in the first attempt)

And we can measure the index of difficulty of this task that is to select the browser icon using the Fitts law, but here the assumption is important. What are the assumptions, that you move very fast you move your hand very fast to acquire the target that is the browser

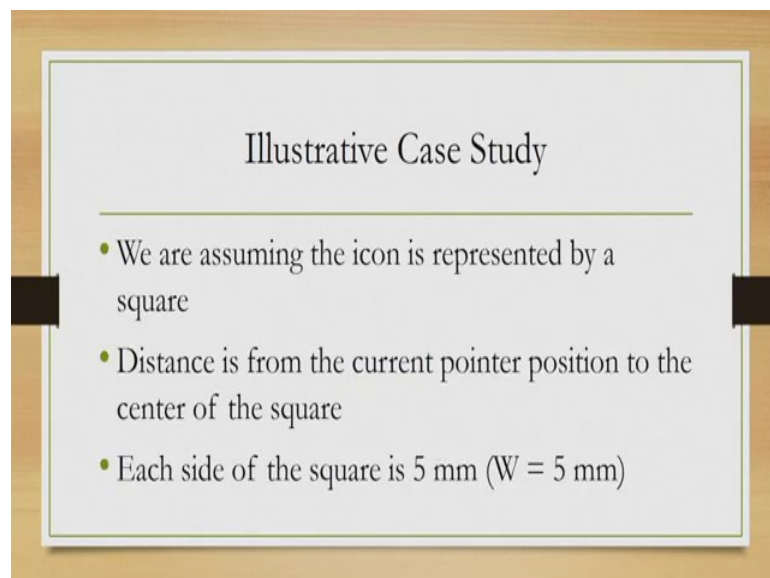
icon and secondly, you do not miss, that means, in the very first attempt you select the icon. So, there is no miss.

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Now, let us assume that the browser icon distance from the current pointer position is 150 millimeter or D is 150 millimeter.

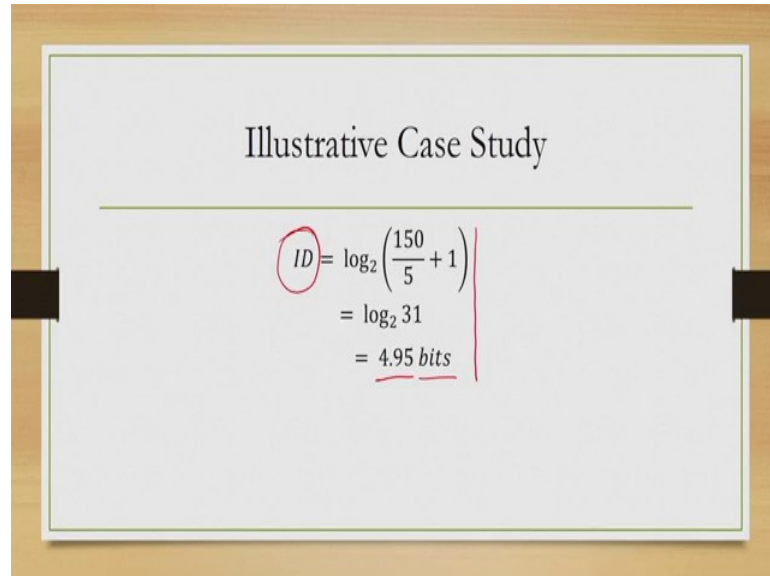
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Let us further assume that the icon is represented by a square, and the distance is actually the distance from the current position to the center of the square, and the square side

length is 5 millimeter or W equal to 5 millimeter. So, these are the assumptions that we are making before we illustrate the use of the law.

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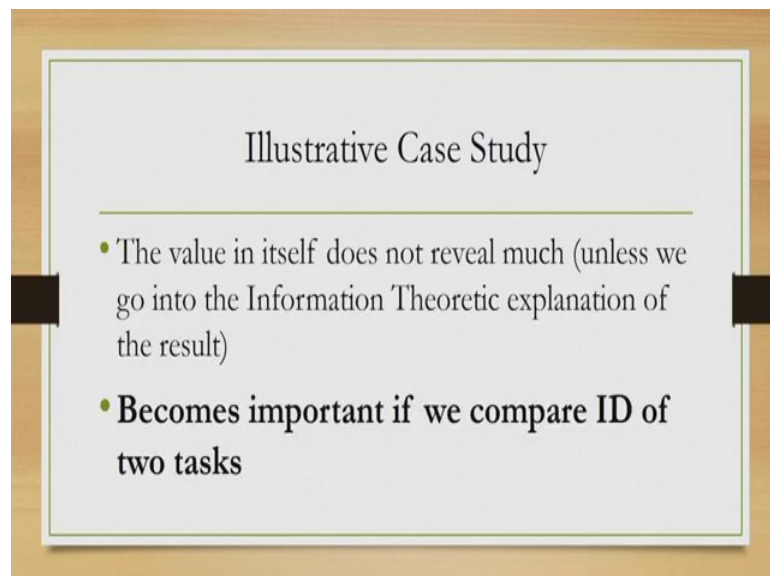
Illustrative Case Study

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$$\begin{aligned} ID &= \log_2 \left( \frac{150}{5} + 1 \right) \\ &= \log_2 31 \\ &= \underline{4.95 \text{ bits}} \end{aligned}$$

Now, with this knowledge, so we have D equal to 150, W equal to 5. If we put these values in the mathematical equation for index of difficulty, we will get the overall value as 4.95 and the unit is bits. So, essentially the major of difficulty or the index of difficulty for the particular task of selecting the browser icon is 4.95 bits which we obtained by applying the equation of index of difficulty.

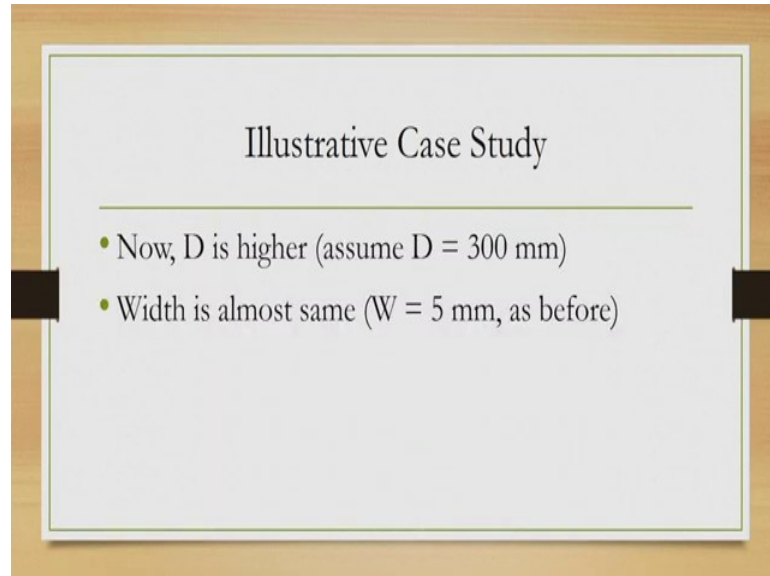
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- 
- Illustrative Case Study
- 
- The value in itself does not reveal much (unless we go into the Information Theoretic explanation of the result)
  - **Becomes important if we compare ID of two tasks**



distance of the browser icon from the current hand or finger position is which is here is 150 millimeter.

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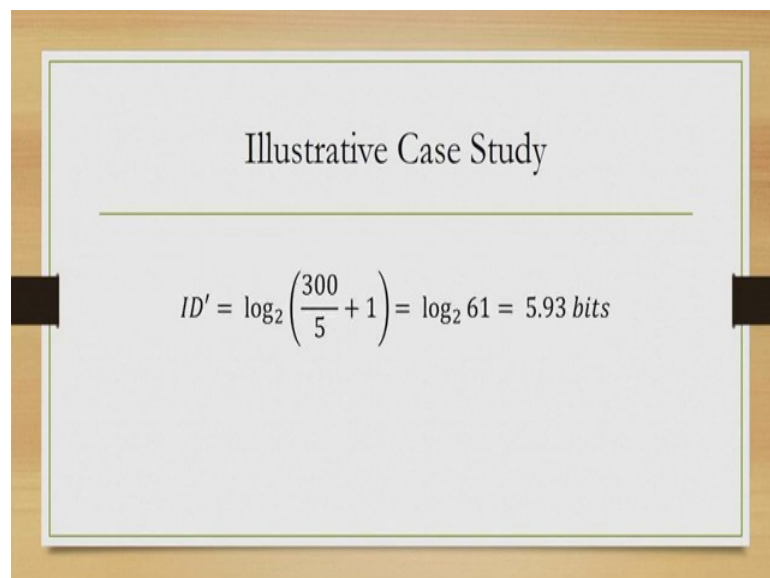


Illustrative Case Study

- Now, D is higher (assume D = 300 mm)
- Width is almost same (W = 5 mm, as before)

Now, in both the cases, we are assuming that the width remains more or less the same which is 5 millimeter.

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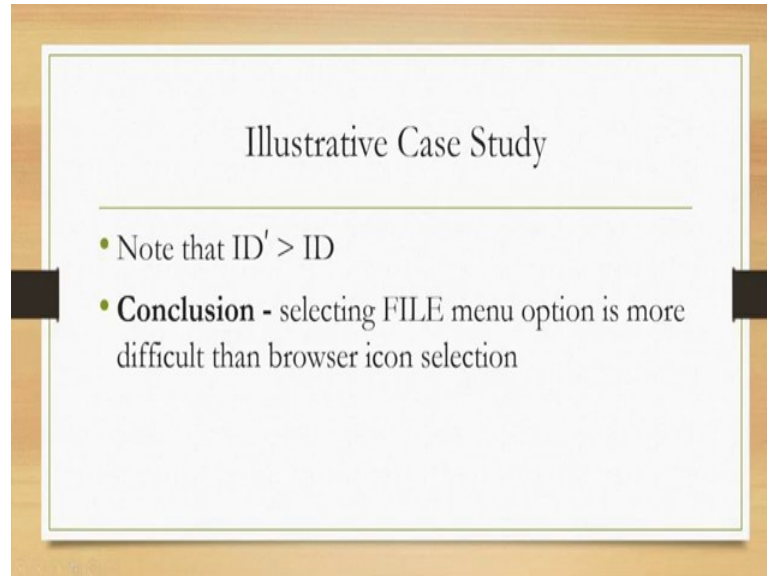
Illustrative Case Study

$$ID' = \log_2 \left( \frac{300}{5} + 1 \right) = \log_2 61 = 5.93 \text{ bits}$$

So, then we have two tasks in one task we are selecting the browser icon; in the other task we are selecting the file menu option. In the case of file menu option, the index of

difficulty can be computed with the help of the equation in this way where let us call it ID dash, which is 5.93 bits which you obtained by applying the equation.

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So, then if we compare with the other thing the index of difficulty of the other tasks that is selection of the browser icon, we can see that ID dash is greater than ID. In other words, the selection of the file menu option is more difficult than the browser icon selection. You are typing something and you want to open the browser icon and send an urgent mail. So, in that case, earlier we said that ideally we should save it then come back to the browser icon, open it and open the mailbox and send the mail.

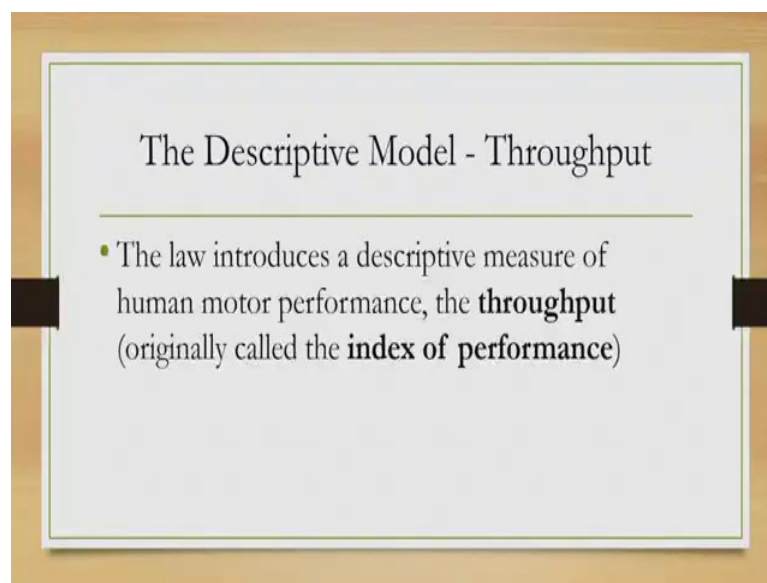
So, if I follow this sequence, then probably I will be losing some time. In stead from the current position. If I directly go to the browser icon open the icon and send the mail probably I will be able to save some time, because this task will be less difficult then actually trying to first save and then open the browser icon as illustrated by the major of difficulty.

So, let me explain it once more. Our calculations show that the difficulty level of selecting the file menu option is more than selection of the browser icon. What it implies? It implies that if we decide to send a mail during in the middle of text editing task where the current hand or finger position or cursor position is where we have shown in the figure earlier, then probably it will make more sense to select the browser icon then trying to save the file as that will a less difficult task compared to first saving the

file, and then selecting the icon, that is of course, one qualitative explanation. And we can do much better as we will see later.

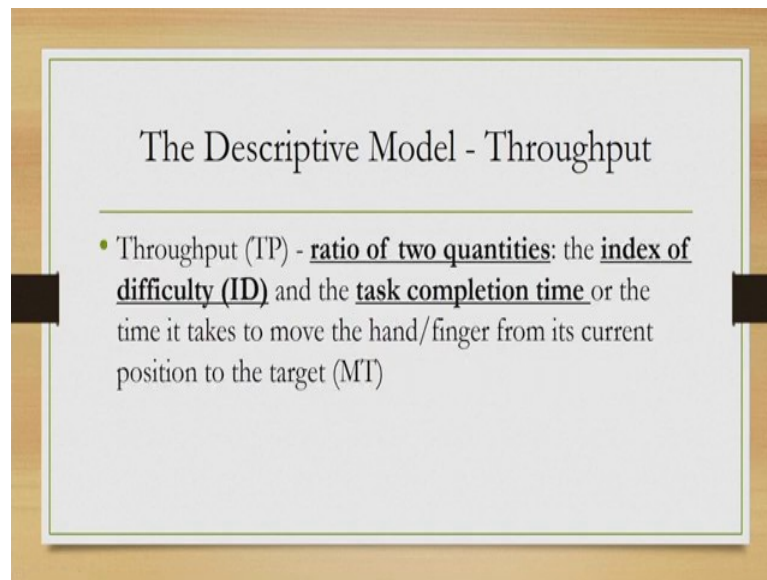
Before that, let us see the different use of the law. So, the Fitts' law can be used in multiple ways one major use is as a descriptive model. Remember from our earlier lectures that descriptive models are essentially used to explain certain behavior rather than predict anything. And Fitts' law can be put to such use it can be used to explain certain interactive behavior without any prediction.

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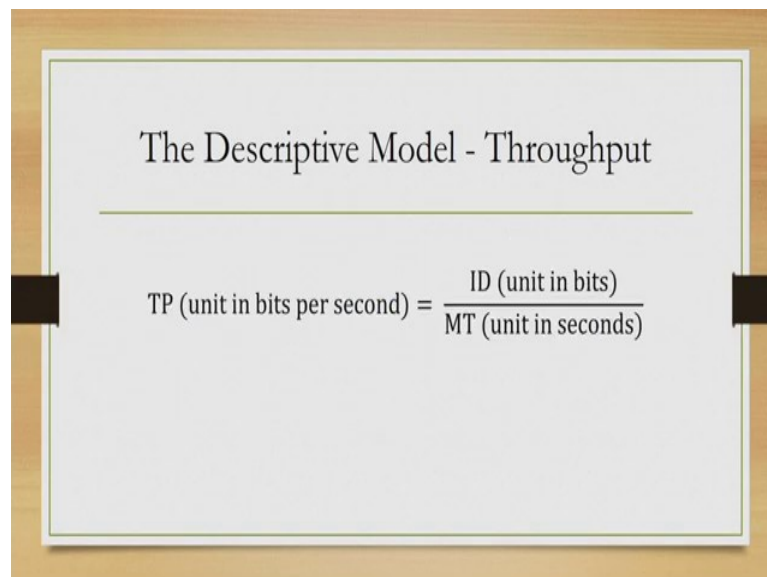
Now, in order to do that, it introduces a descriptive measure of human motor performance which is called the throughput earlier the same measure used to be called the index of performance or IP. Now, it is called throughput.

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The major throughput is a ratio it is a ratio of two quantities, one is the index of difficulty or ID which we have seen earlier, and the other one is the task completion time. This is essentially the time it takes to move the hand or finger from its current position to the target. So, generally it is represented by the symbol MT.

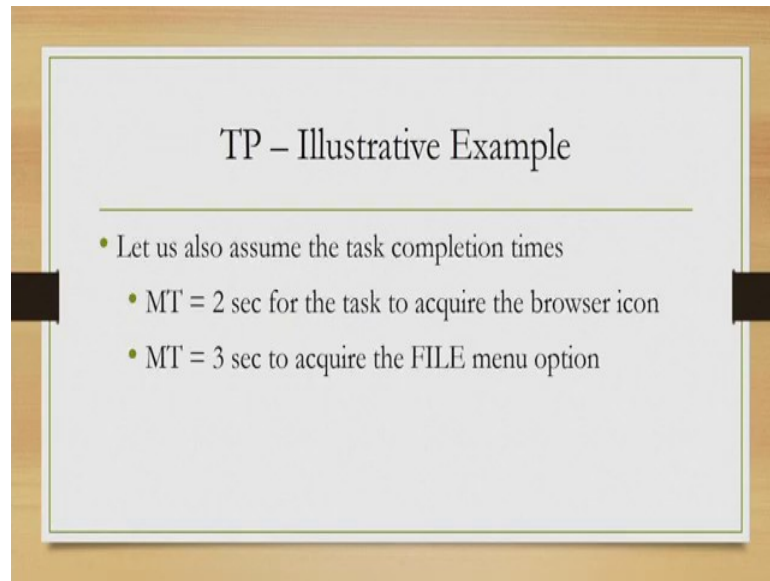
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So, in other words TP or the throughput is the ratio of id or the index of difficulty and MT of the task completion time. So, the unit of ID is bits; unit of MT is typically in seconds. So, the unit for TP is bits per second.



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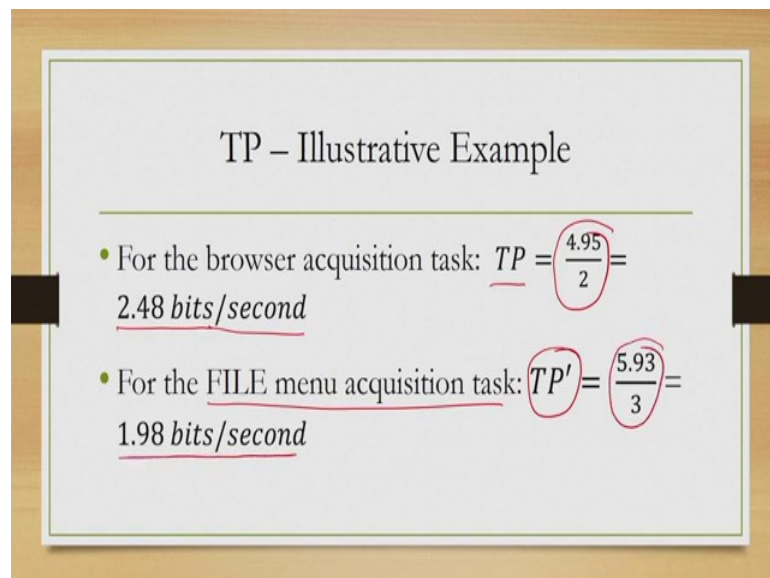


TP – Illustrative Example

- Let us also assume the task completion times
  - MT = 2 sec for the task to acquire the browser icon
  - MT = 3 sec to acquire the FILE menu option

So, then how to make use of this descriptive model that is the throughput. So, let us consider the previous example again. In that example we are having two tasks; one task is to select the browser icon, the other task is to select the file menu option for ultimate objective of saving the file. Now, let us assume that the movement time or time to complete the task is 2 second for acquiring the browser icon and 3 second for acquiring the file menu option.

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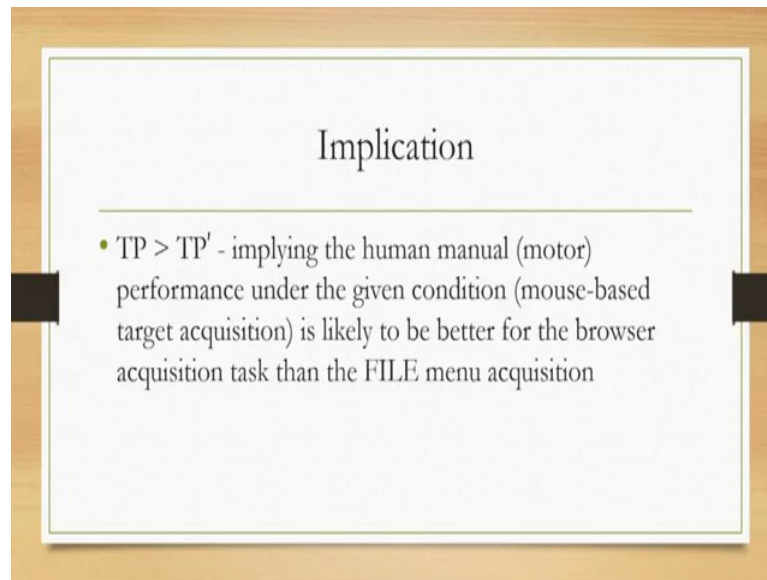


TP – Illustrative Example

- For the browser acquisition task:  $TP = \frac{4.95}{2} =$   
2.48 bits/second
- For the FILE menu acquisition task:  $TP' = \frac{5.93}{3} =$   
1.98 bits/second

Then for browser acquisition task we can calculate throughput as 2.48 bits per second by using the formula. And similarly we can compute the throughput for the file menu of acquisition task which we are referring to as TP dash by using the formula as 1.98 bits per second.

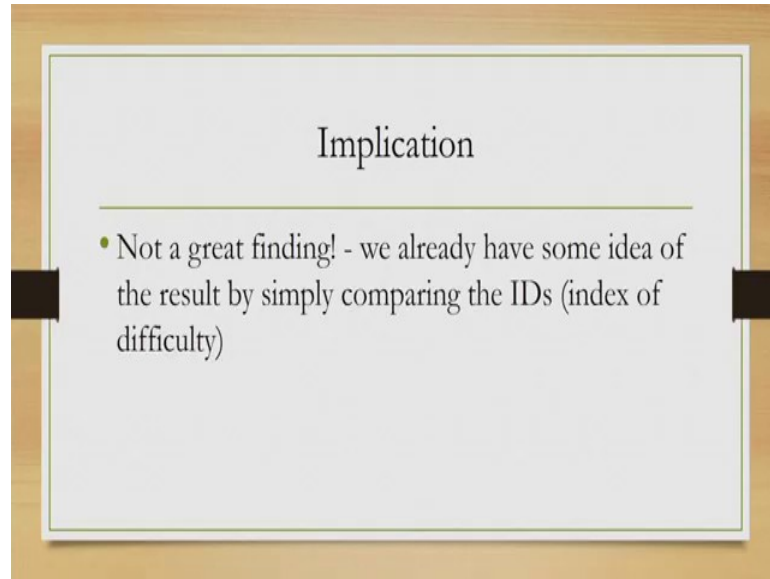
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In other words TP is greater than TP dashed which implies that human manual performance under the given condition that is mouse-based target acquisition is likely to be better for the browser acquisition task than the file menu acquisition task. So, with the calculation of throughput, we can actually conclude about the quality of a particular interaction. We can say that if the throughput of a particular interaction is higher compared to alternative ways of interactions, then the one with higher throughput is having better human performance.

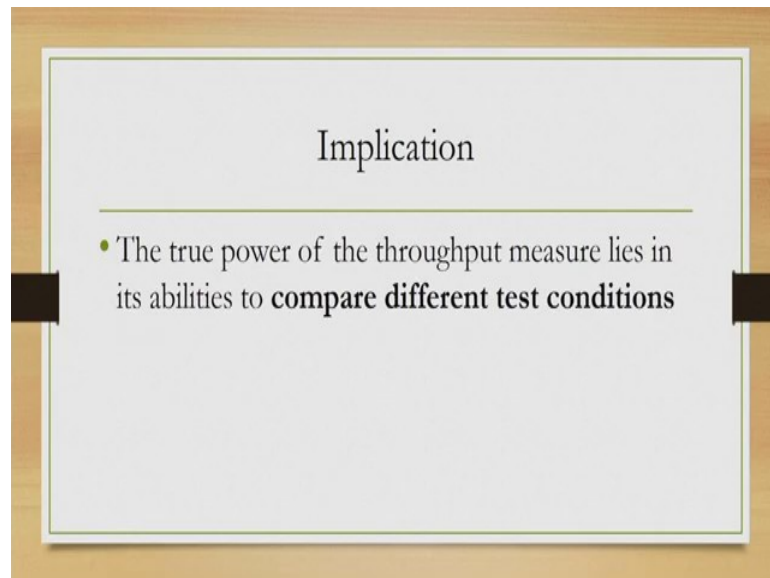
But this conclusion we have already arrived at earlier with the computation of index of difficulty. Earlier we have seen that the index of difficulty of browser icon acquisition task is less than file menu option acquisition task. So, in other words, browser icon acquisition task is having less difficulty than the file menu acquisition task.

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So, then already that gave us some idea of the quality of these two interaction tasks. So, then is there anything new that the idea of throughput keeps us. Actually in this context we may not get anything new because here we are comparing between two tasks under the same test condition.

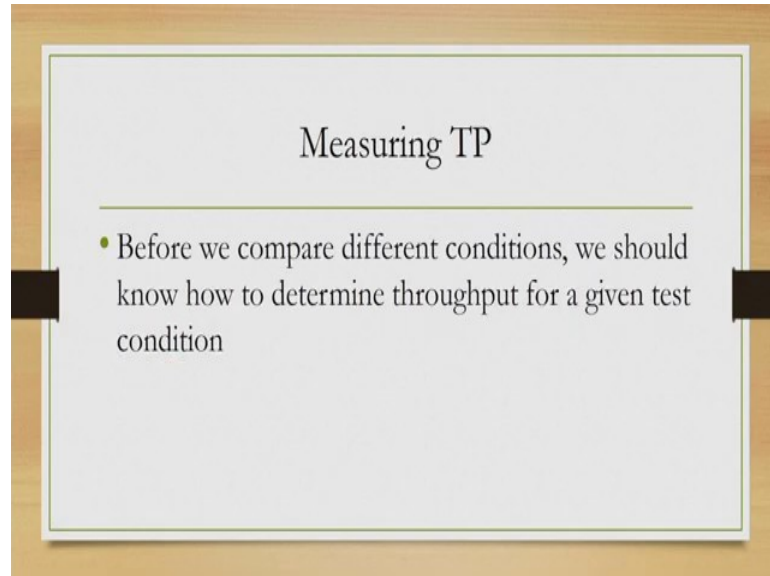
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So, what is the test condition? Test condition is essentially the mouse-based interaction. The true power of throughput measure lies in its abilities to compare different test conditions. So, when we are presented with different test conditions, then we can use the

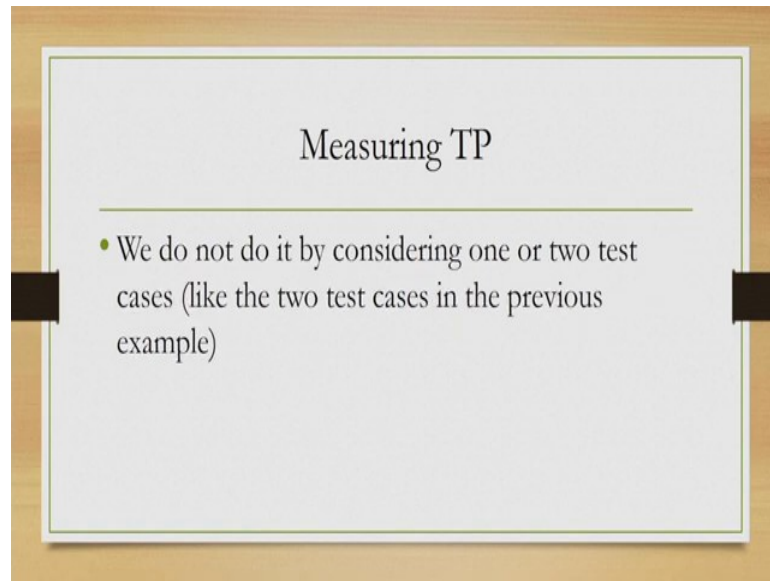
major of throughput to basically give a judgment on the quality of interaction under specific test conditions.

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But before that before we can explain that idea of using throughput to compare test conditions, we need to know how to measure throughput. Earlier in the examples, we have shown very simple way of measurement that is we have chosen one task and one set of values, and then based on that we calculate it throughput. But in reality that is not the case. In reality, we need to go for more extensive empirical studies to identify throughput for a given test condition.

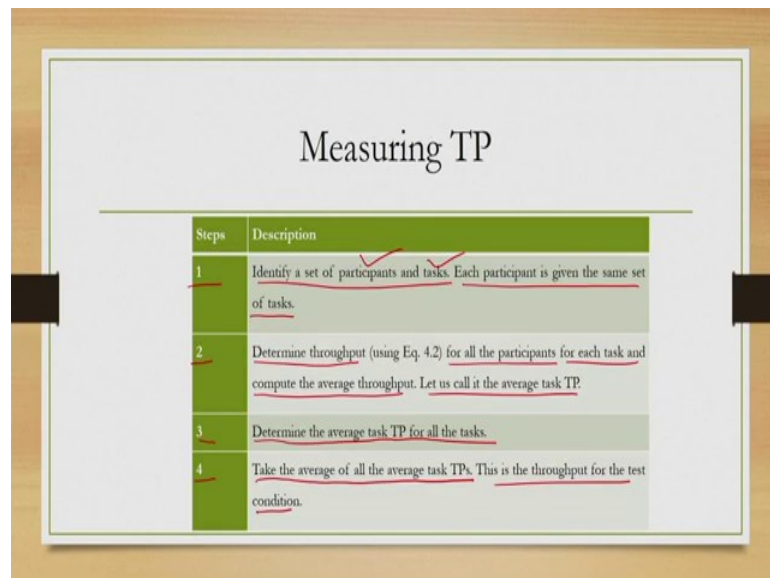
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The slide is titled "Measuring TP" and contains a single bullet point. The text of the bullet point is: "We do not do it by considering one or two test cases (like the two test cases in the previous example)".

We do not do it by considering one or two tasks, or one or two sets of values, we do it for much larger number of tasks and participants.

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The slide is titled "Measuring TP" and contains a table with four steps. The table has two columns: "Steps" and "Description".

Steps	Description
1	Identify a set of participants and tasks. Each participant is given the same set of tasks.
2	Determine throughput (using Eq. 4.2) for all the participants for each task and compute the average throughput. Let us call it the average task TP.
3	Determine the average task TP for all the tasks.
4	Take the average of all the average task TPs. This is the throughput for the test condition.

So, essentially we need to follow four steps. The first step is, step 1 is to identify a set of participants and tasks; each participant is given the same set of tasks that is preferable. Step number 2 is determined throughput using the equation which we have shown earlier for all the participants, for each task, and compute the average throughput, let us called the average as TP.

In step 3, we determine the average task for all the tasks average task throughput for all the tasks. And in step 4, we take the average of all the average task throughputs this is the throughput for the test condition. So, to repeat in the first stage, we identify set up participants and tasks. Each participant is given the same set of tasks. In step 2, we determine the throughput using the equation for all the participants for each task and compute the average throughput.

So, for each task, different participants are given the tasks and we calculate their throughputs, and then we take the average that is the average task throughput for each task. In the next stage step 3, we determine the average task throughput for all the tasks. And finally, we take the average of all the average task throughputs this is the throughput for the entire test condition.

This is quite extensive way of computing the throughput. Then once we compute the throughput what we can do essentially for each test condition, we can compute the throughput following those first steps and then we can compare between the throughputs.

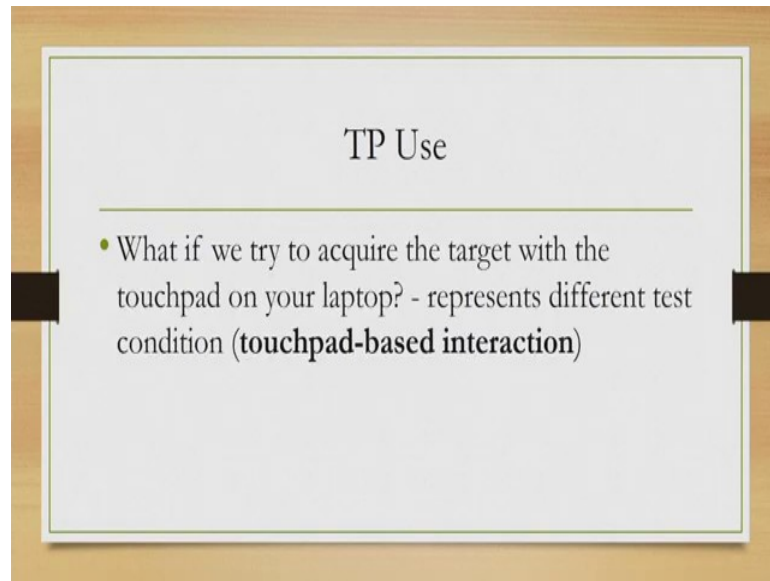
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TP - Use

- Consider the previous example again
- We acquired targets (browser icon or FILE menu icon) with a mouse - **test condition is mouse (to be more precise, the test condition is mouse-based interaction)**

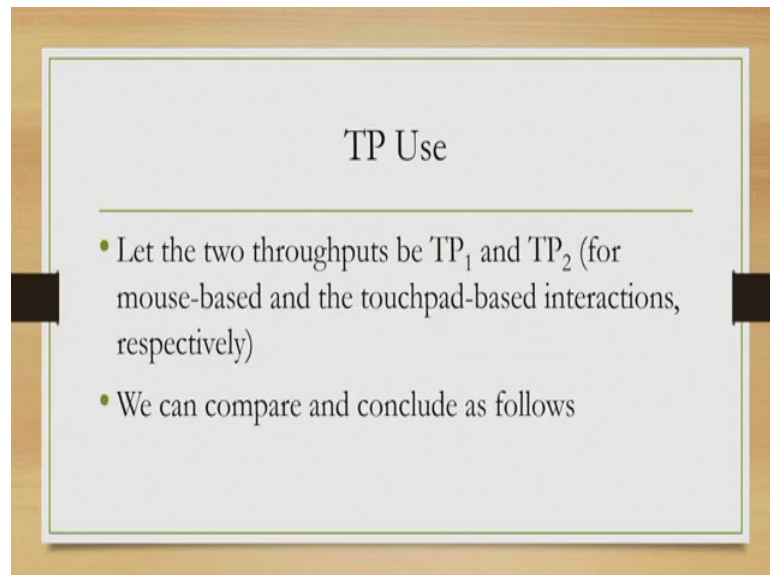
For example, we can compare between the test conditions where one is mouse-based interaction, the other one is touch based interaction.

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So, if we want to compare say which interaction is more difficult whether for a particular task, say we want to select the file menu option, now whether with mouse it is easier compared to a touchpad that is there in your laptop, then we can compute the throughput for each test condition and then compare between them.

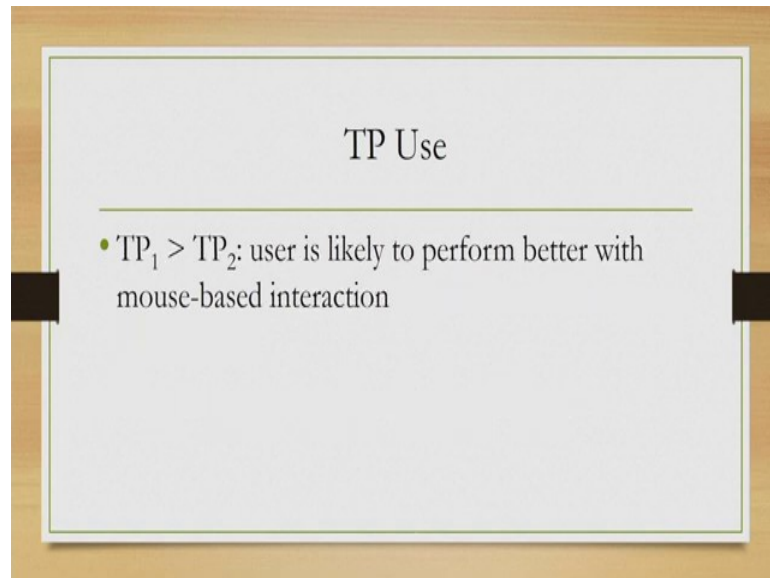
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Suppose, we are comparing between mouse-based interaction and touchpad-based interaction these two are our test conditions and we compute it throughput. The two

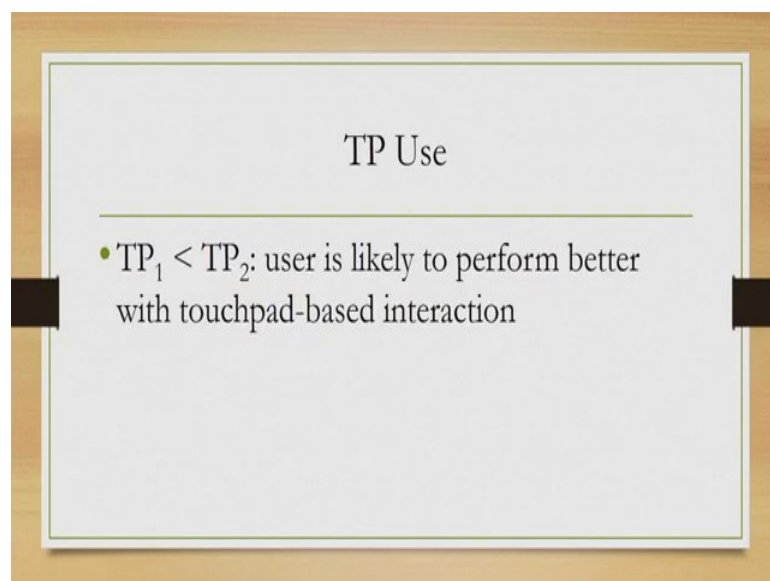
throughputs can be referred to as TP 1 and TP 2. And there can be relationships between them based on the relationship we can come to a conclusion.

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So, first relation is TP 1 greater than TP 2. In other words, the throughput for mouse-based interaction is greater than throughput for touchpad-based interaction. It indicates that the user is likely to perform better with mouse-based interaction than touchpad-based interaction.

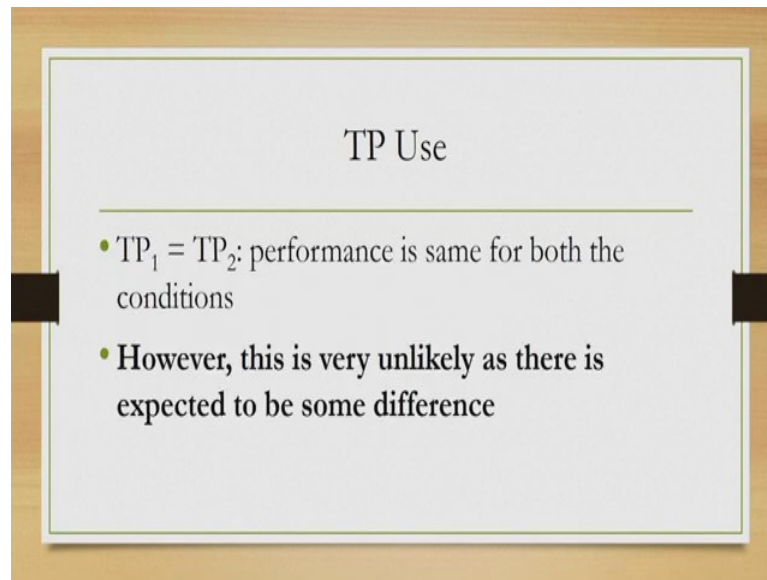
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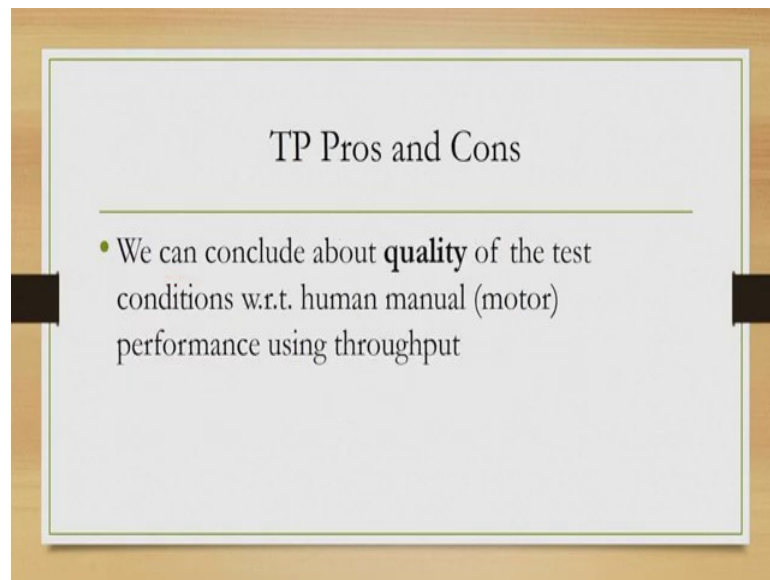
Second condition can be  $TP_1$  is less than  $TP_2$ . In other words, mouse-based interaction is giving less throughput than touchpad-based interaction. So, then of course, our conclusion would be just the opposite that is user is likely to perform better with touchpad-based interaction than mouse-based interaction.

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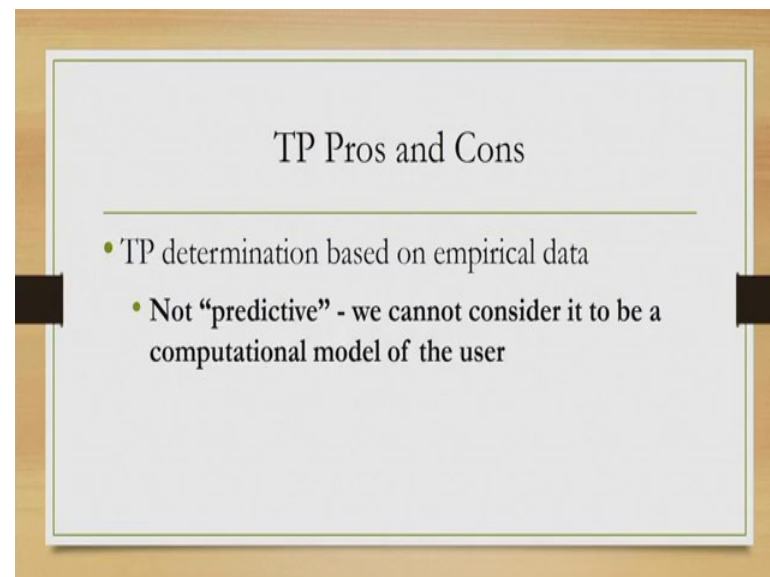
And theoretically there is also a third condition that is both are equal, but of course, it is very unlikely because we are dealing with natural numbers ratios where exactly same value may not occur in practice, it is very very unlikely. But if it happens, then the conclusion can be that the performance is same for both the conditions. Now, when we are talking of performance, we are talking of motor or manual performance.

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So, then what we can do with throughput and what we cannot do. So, throughput essentially helps us to conclude about quality of test conditions with respect to human manual performance. So, it tells us how a human is or a user is likely to perform given a particular test condition, but this throughput determination is based on empirical data.

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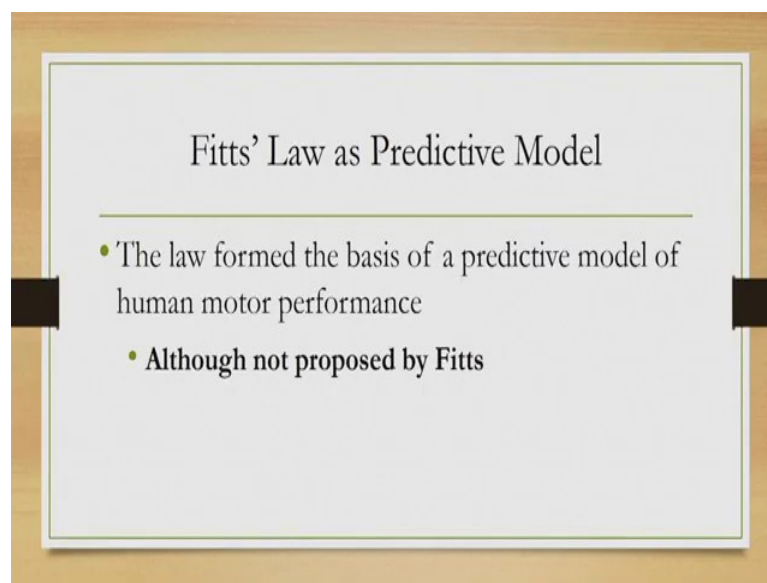


So, every time you want to conclude something about test conditions then you have to go for empirical study, you have to collect the data and then based on that you have to compare and conclude. So, it is not predictive, it is descriptive in that sense it explains

the behavior, but it does not predict anything, so that is the drawback of the throughput measure. On the positive side, we have a measure which allows us to compare between test conditions; on the negative side, we have a measure which requires extensive empirical study every time we want to use it.

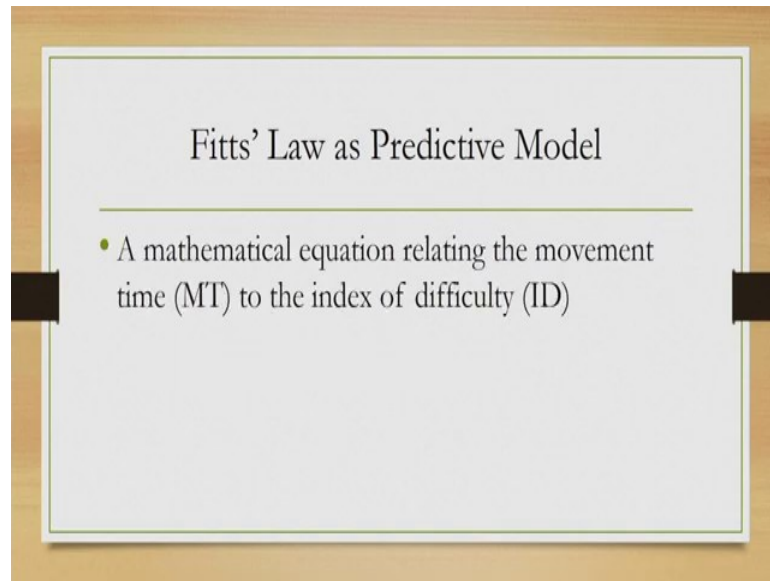
Now, Fitts' law can also be used as a predictive model. So, throughput is not a predictive model it is a descriptive model, but we can use the Fitts law as a predictive model as well.

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Now, this law forms the basis of a predictive model which of course, was not originally proposed by Fitts' but it was derived in subsequent research.

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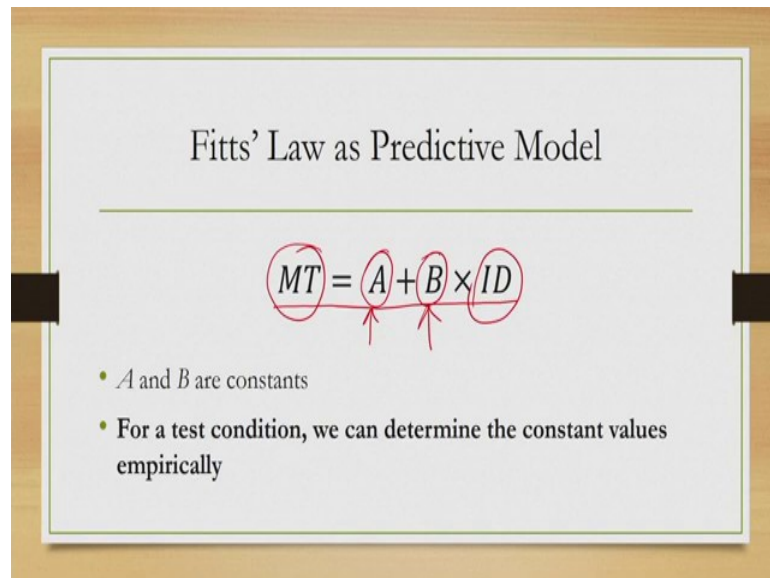


Fitts' Law as Predictive Model

- A mathematical equation relating the movement time (MT) to the index of difficulty (ID)

What is the model here? The model is a mathematical equation. The equation actually is a relationship between two quantities the movement time and the index of difficulty. So, we have a model which is a mathematical equation that relates the movement time or the time to execute a manual target acquisition task to the index of difficulty of that task.

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Fitts' Law as Predictive Model

$$MT = A + B \times ID$$

- *A* and *B* are constants
- For a test condition, we can determine the constant values empirically

And the equation is of the form,

$$MT = A + B \times ID$$

where A and B are constants, MT is the movement time and ID is the index of difficulty. For a given test condition we have to actually conduct some empirical studies to determine the values of A and B, and then we can use it for prediction of the movement time for any task under the given test condition. So, in that sense, it is predictive. It predicts it allows us to predict the movement time given the distance and width.

However, for a given test condition, we have to perform some empirical study to find out the constant values only then we will be able to use it to predict the movement time for any task under that particular test condition. So, what are the steps to determine these values of the constants A and B, this is similar to the way we can determine the throughput.

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Steps	Description
1	Identify a set of participants and tasks. Vary the task difficulty by varying the target distance and widths.
2	Determine the index of difficulty for each task.
3	Empirically determine the movement time for each task (may be using a stopwatch) for each participant. Take the average of all the participants.
4	Thus, you get the MT (average for all participants) and ID for each task. Plot these values in a MT-ID plot (MT along the Y-axis and ID along the X-axis).
5	Use <u>linear regression</u> on the <u>data points</u> to relate the <u>MT</u> and <u>ID</u> with a <u>line equation</u> (in the <u>slope-intercept</u> form). The <u>intercept</u> and <u>slope</u> values in the equation are the values for the constants <u>A</u> and <u>B</u> , respectively.

Essentially the first step is to identify a set of participants and tasks we need to vary the task difficulties by varying the target distance and width. In the second stage, we need to compute that index of difficulty for each task. Step 3 requires as to empirically determine the movement time for each task, you are free to use anything even as stopwatch to actually obtain the time it took for each participant to perform a task. For each task and each participant, we need to do this, and then we need to take the average of all the participants to come up with the average movement time for a task.

Then it leaves us with two values, the MT or average movement time for all participants for a task and the index of difficulty for each task. Now, we need to plot these values in a

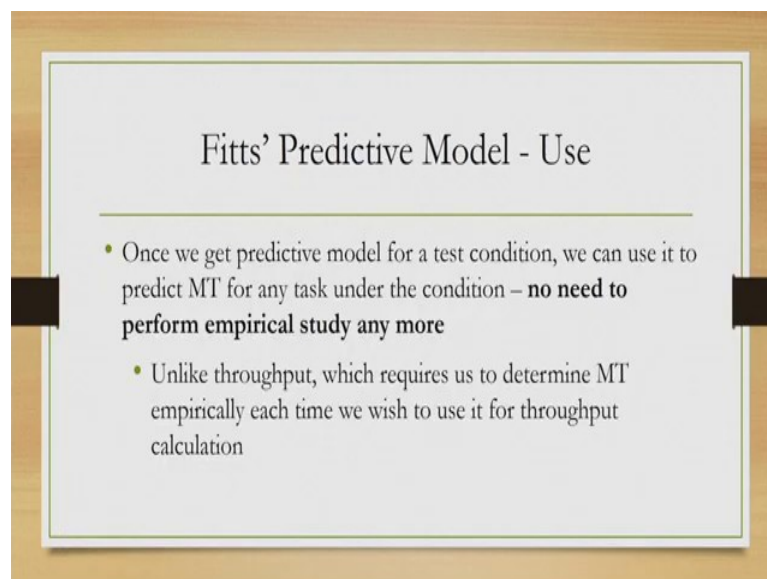
MT ID plot in a graph, and then in the graph you plot the MT values along the y-axis, and ID values along the x-axis. And then use the linear regression technique on the data points to relate the MT and ID with a line equation in the slope intercept form.

If you have noticed in the earlier equation, it is essentially a linear equation in the form of a slope and intercept. The intercept value and the slope value are the constant values A and B respectively. So, A refers to the intercepted value and B refers to the slope value in the equation. So, to repeat, so first you identify setup participants and tasks and vary the tasks, then determine the index of difficulty for each task using the equation.

Empirically determine the movement time for each task using stopwatch or any other such device and take the average of all participants for each task, then you get the average for all participants, the movement time average for all participants and index of difficulty for each task. So, plot this in a MT ID plot, and then use linear regression on the data points to relate MT and ID with a line equation in the slope intercept form, where the intercept is the constant A, and the slope value is the constant B.

So, in this way, you can obtain the constant values which are the model parameter through empirical studies. And once you get that you can use the equation with the known values for predicting the movement time of any task under the given condition.

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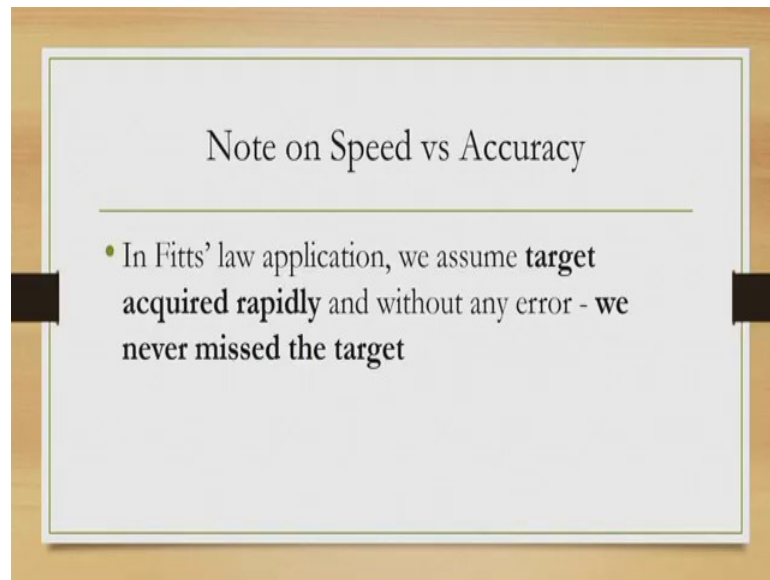


### Fitts' Predictive Model - Use

- Once we get predictive model for a test condition, we can use it to predict MT for any task under the condition – **no need to perform empirical study any more**
- Unlike throughput, which requires us to determine MT empirically each time we wish to use it for throughput calculation

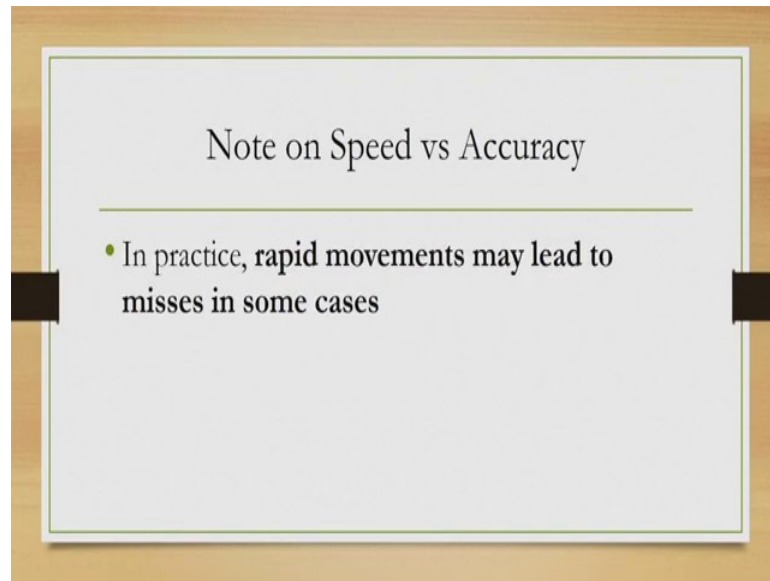
We no longer need to perform any more empirical studies. This is unlike the throughput measure where every time we want to use it we need to perform an empirical study. So, in that sense, the predictive model is more flexible and more beneficial. Now, there is one concept that we should note here.

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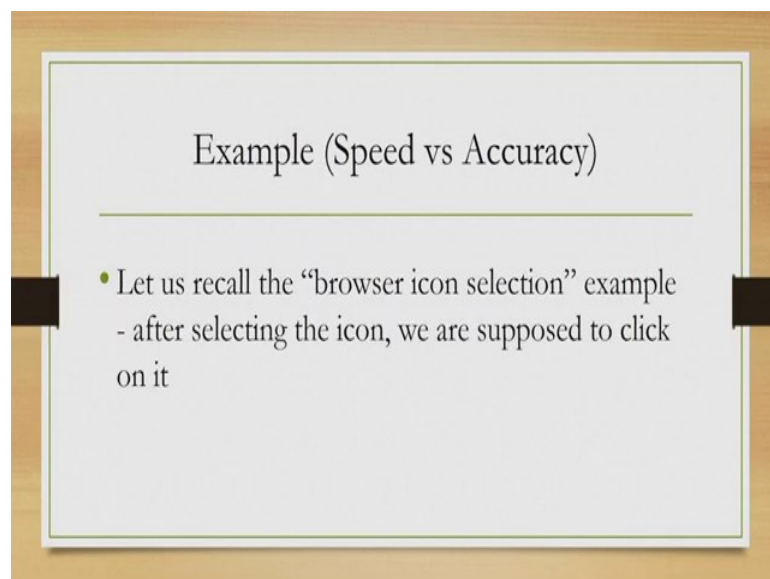
So, we started with the assumption that we acquired the target rapidly and without any error we never missed the target. So, this is the crucial assumption when we want to apply the Fitts law that target acquired is rapid and there is no error or we never missed the target.

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In reality this assumptions may not hold true simultaneously. In fact, if you try to acquire a target rapidly, if you perform rapid movements, then you are likely to make some errors you are likely to miss in some cases.

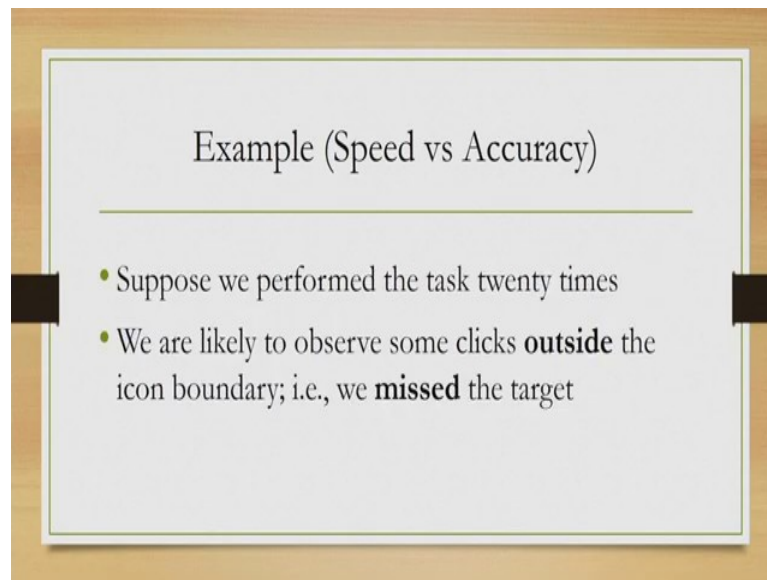
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So, then the question is how to take care of that scenario. So, as an example of what may happen let us recollect the browser icon selection example. So, after selecting the icon, we are supposed to click on it.



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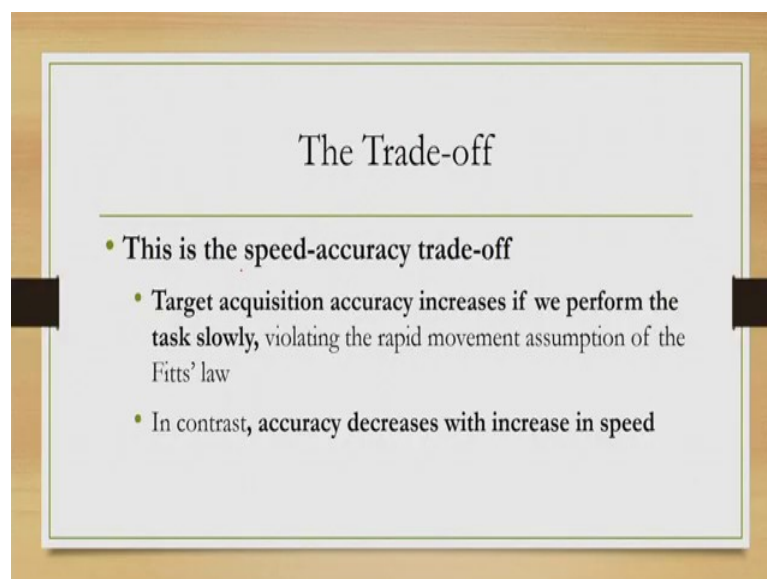


Example (Speed vs Accuracy)

- Suppose we performed the task twenty times
- We are likely to observe some clicks **outside** the icon boundary; i.e., we **missed** the target

Now, we have to perform the task more than ones. Suppose we performed it 20 times and we recorded the point of selection. So, where we took the mouse pointer and clicked when we are doing it rapidly. If you actually plot these points in a graph centered around the center point of the icon, then you will see that some of these points lie outside the boundary of the icon. In other words, in few cases you actually missed to select the icon. Now, this is called the speed accuracy trade off.

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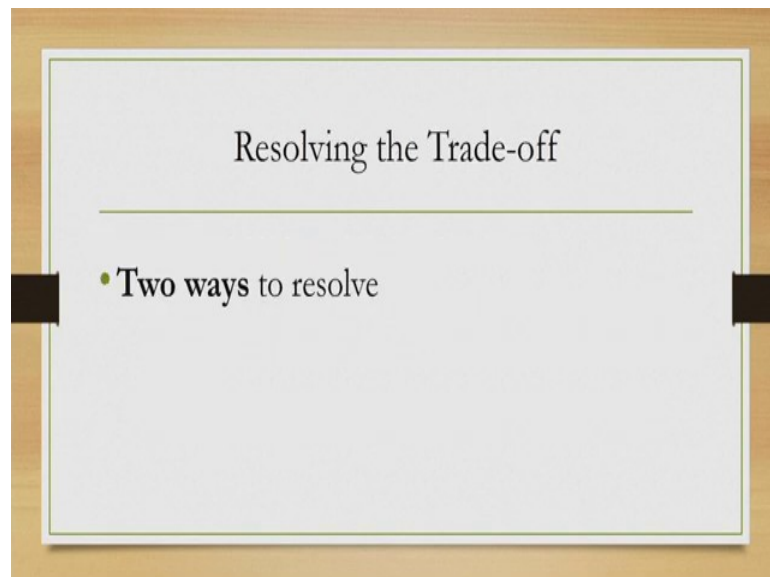
The Trade-off

- **This is the speed-accuracy trade-off**
  - Target acquisition accuracy increases if we perform the task **slowly**, violating the rapid movement assumption of the Fitts' law
  - In contrast, **accuracy decreases with increase in speed**

When you are having high speed, then your accuracy gets compromised. So, you likely to make errors, and when you are moving in slow speed then your accuracy will be higher. But then the problem is that if you are moving slowly if the rapid movement assumption is not adhered to, then we are actually introducing an element of thinking or some cognitive process.

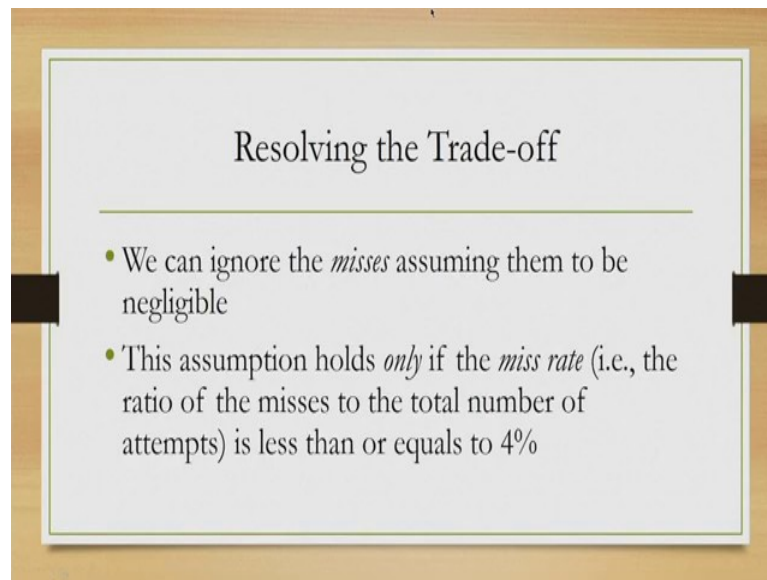
So, in that case, the task no longer remains only a motor activity, their motor plus cognition gets inward and we will not be able to model it with Fitts law in its classical form. So, then we have a trade-off which is called speed accuracy trade-off.

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Now, how to resolve this? So, there are two ways to do this.

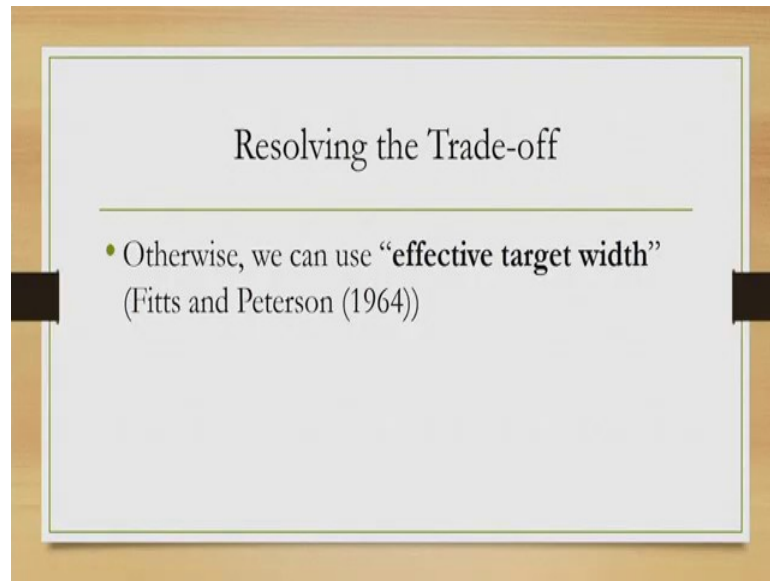
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The first one is that we can ignore the misses assuming them to be negligible. So, in a set of trials, consisting of 20 trials if only in 2 cases we missed, an 18 cases we succeeded, then we may consider these two misses to be negligible and we may simply ignore those. Now, these assumption holds only when we can actually ignore the misses and that is possible only when the number of misses is negligible compared to the total number of attempts.

In general it is said that if the number of misses is less than or equals to 4 percent of the total number of attempts, then we can actually ignore this, and assume that that trade-off is not there and we can simply apply the Fitts law without bothering anything about the misses. In the other case, if the number of misses exceeds this threshold of 4 percent of the total number of attempts, then we can no longer ignore it and in that case some alternative approach needs to be followed.

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That alternative approach is known as concept called effective target width. It was also proposed by Fitts and Peterson in 1964.

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Now, the idea is simple. Here the idea of width of a target is redefined. Earlier we are saying width to be just the boundary. Now, in this case when we are talking of effective target width we are not restricting ourself to the boundary. Instead we are drawing a boundary which covers all the points in a large number of trials including both hits and misses. So, as we mentioned in our earlier example of browser icon selection, if we

perform 20 trials and recorded the points of selection, then all these points if we plot we will get a region.

The maximum width of this region is the effective target width. This region may or may not be equated with only the boundary of the target. So, it may include points where we missed along with the points where we succeeded. So, the points where we succeeded in selecting the item, I likely to be inside the boundary of the icon, and the points where we missed are of course outside the boundary.

But when we are considering the entire region then we are having a larger region than the actual region of the target, in other words we are having a larger width than the actual target width.

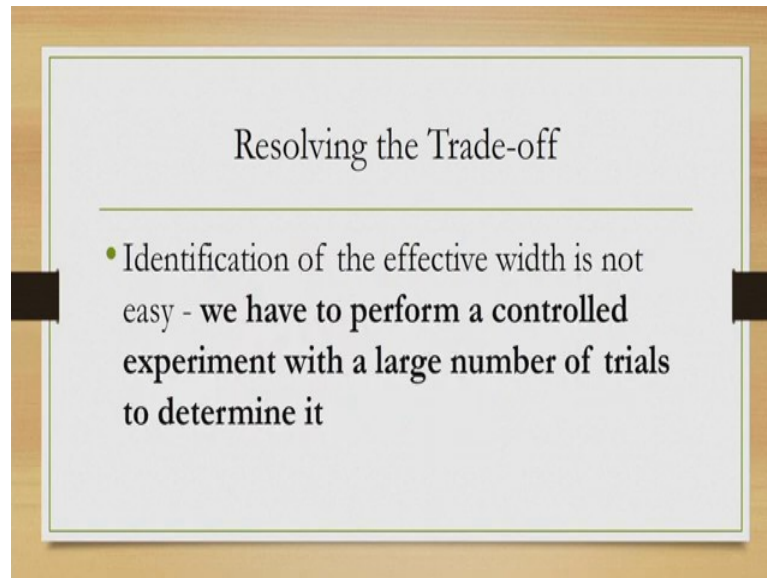
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The slide is titled "Resolving the Trade-off". It contains a single bullet point: "• This larger width is called the 'effective target width'". Below the text is a hand-drawn diagram in red ink. It shows a horizontal line with a small circle at the left end. To the right of the circle is a rectangular box representing a target. The width of this box is labeled 'W'. To the right of the box is a larger, wider rectangular region, also labeled 'W<sub>e</sub>'. The text 'N=20' is written to the right of the diagram. The entire slide content is enclosed in a white box with a thin green border, set against a light brown background.

And this larger width is the effective target width. So, to illustrate this suppose we have our current hand position here, and we are moving in this direction and this is the target. In the classical model, this width is called  $W$ . Now, when we perform this selection tasks n number of time, where  $N$  say 20 in as in our earlier example, and we record the points where we selected, but then these points may look something like this, few will succeed, few will miss, something like this.

So, this entire thing we consider now, and the maximum width of this zone which may be somewhere here. This is the effective width  $W_e$ , and it is likely to be more than  $W$ , since we are considering the attempts where we failed as well.

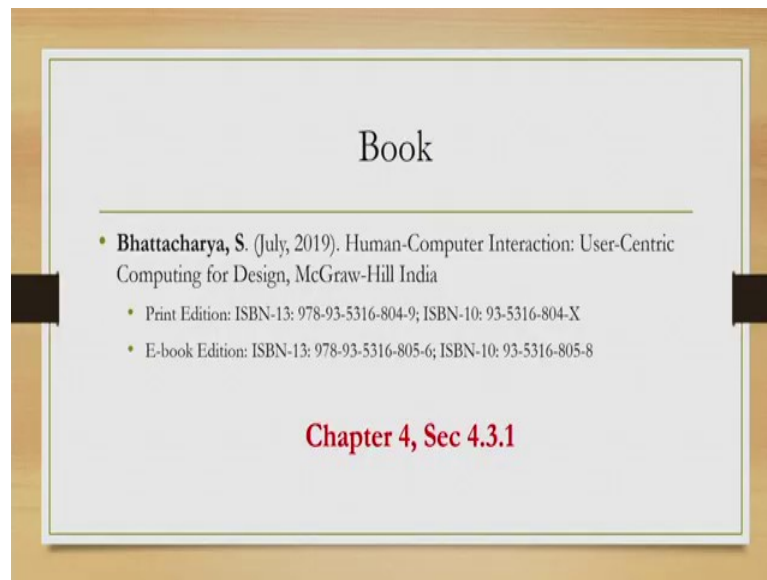
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But clearly identification of this effective width is not easy, it again requires some empirical study. You need to basically perform a set up trials to identify all the points, and then draw a boundary around those points, and then find out the largest width of that region, and that will be your effective target width. However, if we want to consider Fitts law and balanced of speed accuracy tradeoff, then consideration of effective target width is recommended.

In many situations, we can actually restrict ourself to less than 4 percent threshold of misses. So, in that case anyway we do not need to bother about the effective target width, we can simply work with the width of the target.

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So, whatever we have discussed so far can be found in this book. You are advised to refer to chapter 4, section 4.3.1 of this book. There you will get all the details about the model the descriptive model and the predictive model that we discussed today, and the corresponding references.

Thank you and goodbye.