User-Centric Computing for Human-Computer Interaction
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Lecture - 22
Model for touch performance (FFitts' law)

Hello and welcome to the 22nd lecture in the course User-Centric Computing for Human-Computer Interaction. So, in the previous lectures, we started our discussion on some contemporary models of user performance, in the context of interactive systems and so far whatever we have discussed let us first have a quick recap on those models.

So, first we started with in the category of contemporary user models for user centric design, we started with 2D pointing models and 3D pointing models or in other words bivariate and trivariate pointing models. This was followed by a discussion on constrained navigation and related models, namely the steering law and the menu selection model. Then we discussed about mobile typing behavior models, two models we have discussed; one is a performance model for single finger typing and the other one is a model for two thumb typing. The single finger typing model is also popularly known as the Fitts digraph model.

So, we will continue with the discussion on contemporary models and today we are going to discuss a performance model for touch interaction. So, when you talk of touch interaction, what we refer to? There are actually few interactions in the context of touch screen interfaces which we can refer to as fundamental interactions. So, any touch interaction can be represented as a combination of this fundamental touch interactions.

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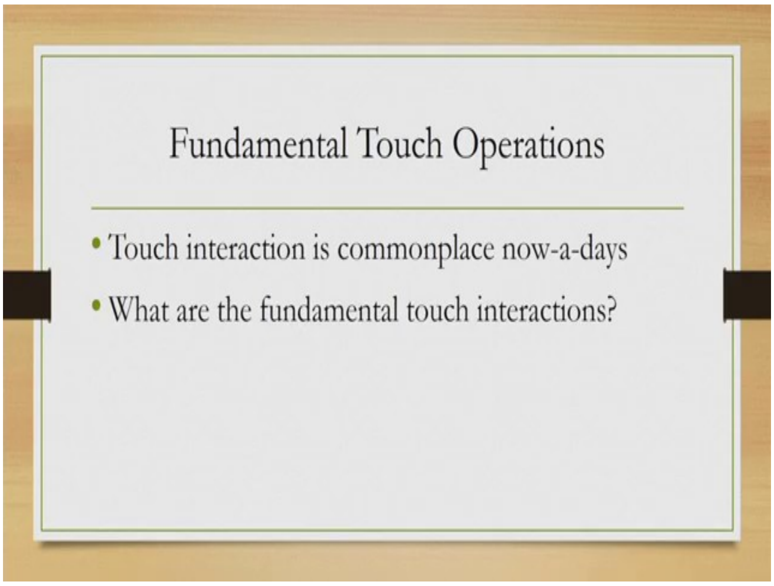

So, what are these fundamental touch interactions? There are roughly three such fundamental interactions. One is tap that is when we tap our finger on a particular screen area or screen object. One is scroll. So, in the scroll operation on a touch screen device, what we do? We typically touch our finger at a particular position and perform a single finger gesture upward, downward, left, right. So, this is a scrolling operation, either vertical or horizontal. So, this is another fundamental operation.

And the third operation can be considered to be a combination of tap and gesture that is gesture with multiple fingers or multi-touch gesture, that is we are touching the screen surface at multiple points with multiple fingers and then performing some finger gesture for each of those finger to carry out some interaction task.

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For example, you are watching a photo and you want to zoom it. So, in that case you touch at different places of the photo and then perform a multi task gesture to zoom it, similarly zoom out also requires multi task gesture. So, this is the third fundamental operation.

You may be wondering why multi task gesture is a fundamental operation, because we can always break it down into two fundamental operations that is tap and single finger scroll operation or single finger gesture operation. In fact, that is not the case, in case of multi task gesture these two operations do not take place sequentially rather they take place simultaneously and it is better to consider these type of combination as a unique fundamental gesture as a unique fundamental interaction rather than a composite interaction.

So, to repeat in the context of touch interaction we can have three fundamental interactions one is tap, one is single finger gesture for scrolling and the other one is multi-touch gesture. Now, we are saying that these are fundamental operations. On the basis of what we are saying this, let us try to understand that in terms of an example. Suppose, you are asked to perform a web browsing task. So, you are asked to perform a task which involves browsing the internet. So, what you are likely to do? What is the sequence of operations that you are likely to do?

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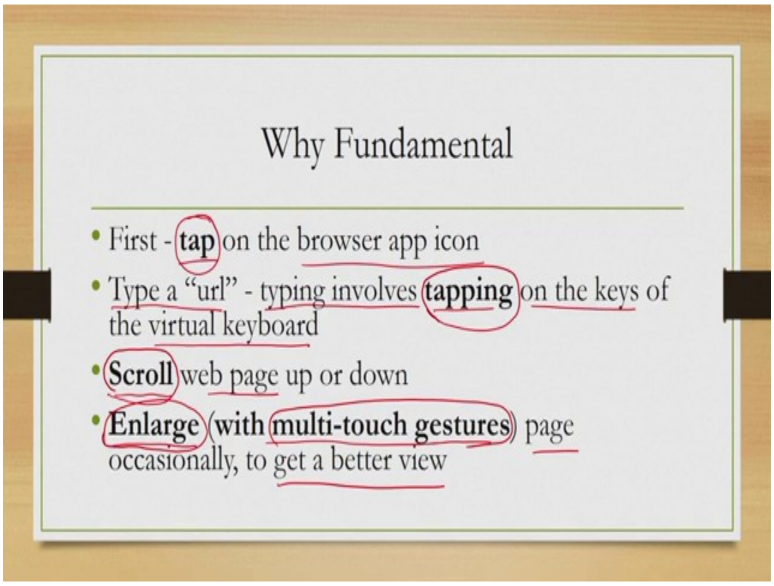

Let us quickly go through the sequence that you are most likely to do in order to perform this web browsing activity. First you tap on the browser, app icon. Then, you type a url or uniform resource allocator which is essentially a typing task and typing involves tapping on the keys. These keys are present on a virtual keyboard layout as we have discussed in our last lecture.

Then, it may be followed by a scrolling operation, you may like to scroll up down to see different portions of the web page. And finally, you may like to enlarge. So, this is also another optional operation you may like to enlarge the page to get a better view and here you require multi-touch gesture.

So, essentially what this sequence tells us is that this entire web browsing activity can be represented as a sequence of fundamental touch activities. Namely, tap, we have already seen or we have already discussed that the first step is tapping on the browser icon. This is followed by url typing which again requires a series of tapping, so this typing can be represented as a sequence of fundamental operation that is typing. This is followed by a scrolling operation another fundamental operation and optionally there may be enlarging task which involves multi-touch gesture another fundamental touch interaction.

If you do it if you do this analysis for any interaction task on a touch screen device, you will find out that all these tasks can be represented as a combination of these three basic tasks, namely tap, scroll and multi-touch gestures. So, that is why we are calling these three activities these three touch interactions as fundamental touch interactions and any other interaction as a combination of these fundamental touch interactions.

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Now, there are models which are built to compute performance of a user for each of these fundamental touch interaction. Namely, there is a performance model for scrolling behavior and there is a performance model for multi-touch gestural interaction. In fact, there is not one, but many such models available for this fundamental touch operations. In this lecture, we are going to discuss one such model that is the performance model for tap behavior modeling. Let us try to understand the tapped behavior first. So, when we say we want to tap on a particular screen area or on a particular screen object in order to select it what we refer to.

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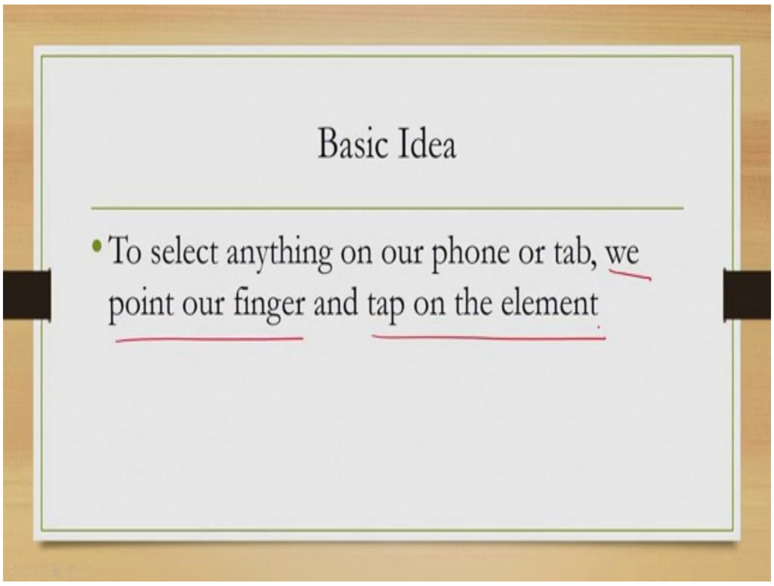

So, essentially it refers to that we point our finger and tap on that element or the screen area.

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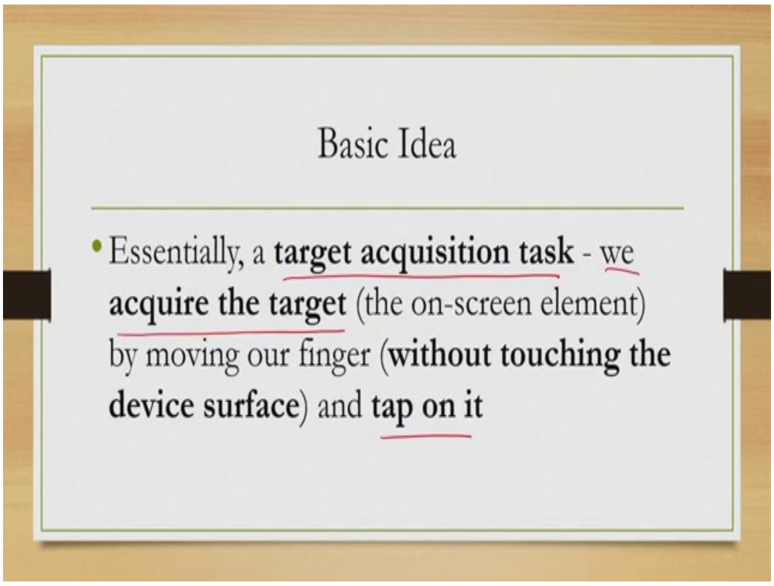

So, this means that what we are doing is nothing, but a target acquisition task. We acquire the target and tap on it. Now, this target acquisition does not involve moving that finger on the screen, instead the finger is moved off screen and then once we position our finger just on top of the target we tap on it. So, the finger movement does not require touching the surface, but tapping requires touching the surface. So, this is nothing but a task similar to a target acquisition task. So, then the natural question come why this is a difficult problem, because we have already seen that any target acquisition task can be modeled with the Fitts law provided they adhere to few conditions.

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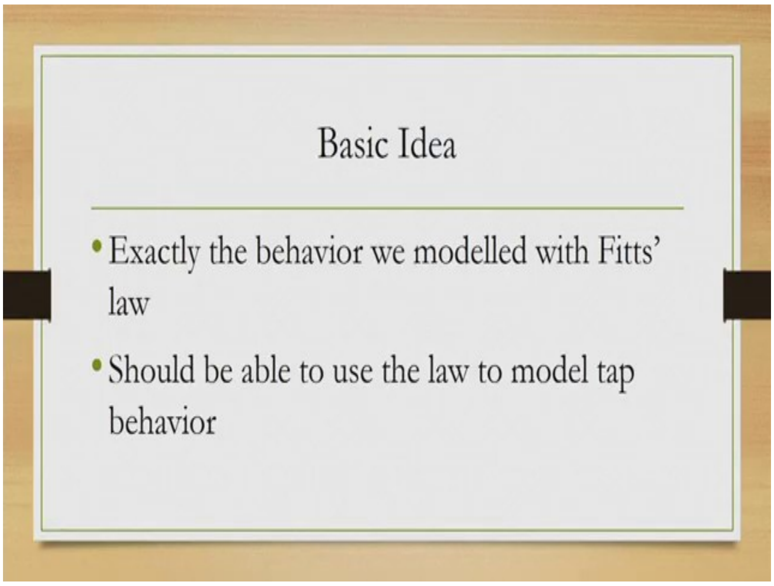

Now, in this case why then we cannot apply Fitts law or can we apply Fitts law in this particular problem? Can we apply the law to come up with a model of tap performance? The answer is not possible.

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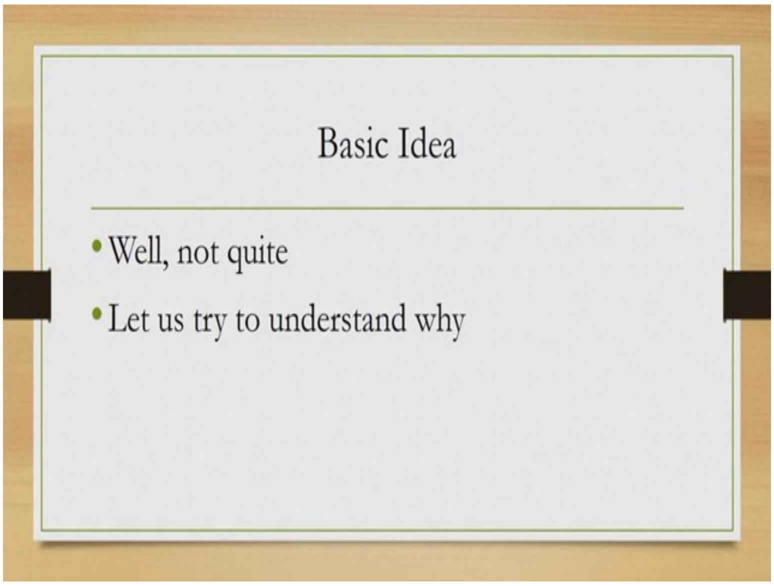

So, we will not be available to use the Fitts' law in its current form because of several reasons. Let us try to understand those reasons. So, when we say we want to apply Fitts law or when we say that the Fitts law model targets acquisition task what we assumed implicitly is that we are using mouse or stylus or any other pointing device to apply the model.

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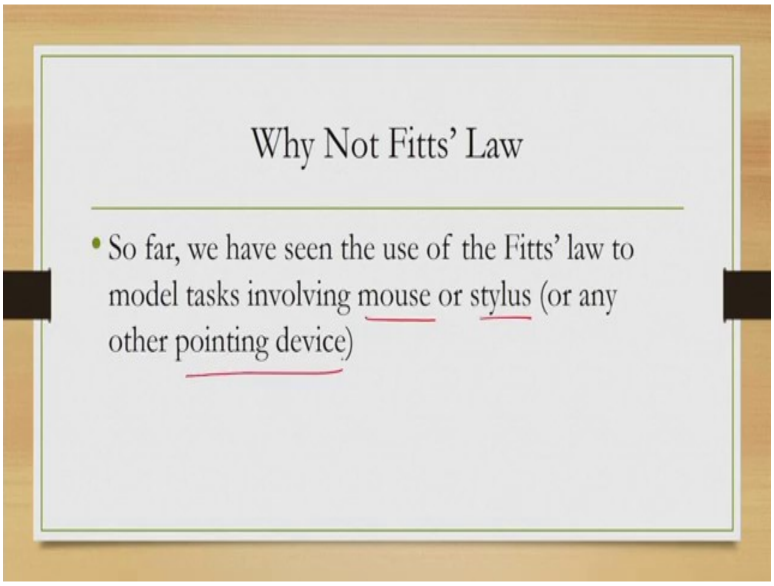

Although, that was not strictly the case when the Fitts law was proposed originally, but in the context of application of the law, in interactive system design for analysis it is the most common assumption and the application domains are mostly related to mouse based interaction. So, essentially we can think of application of Fitts law as equivalent to modeling target acquisition performance when interacting with a mouse or stylus based pointing mechanism.

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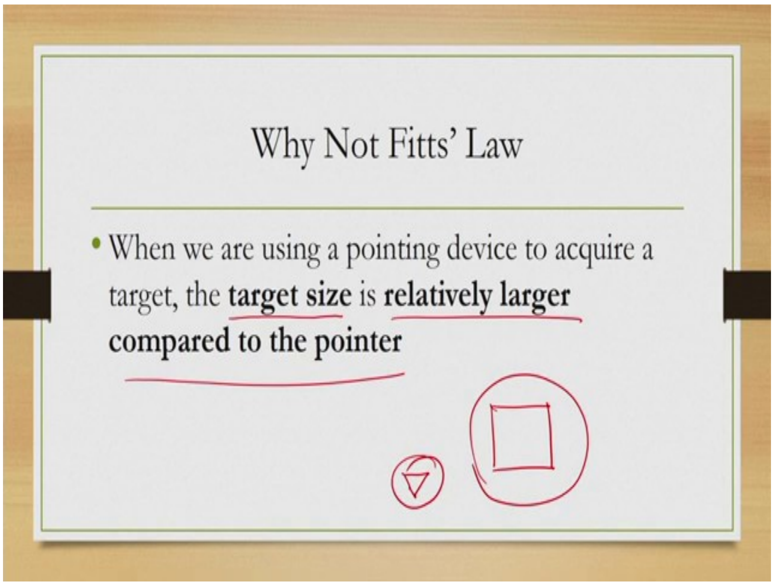

Now, one characteristic of such input mechanism is that the target size, the object that we want to select with the pointer is relatively larger compared to the pointer size. Now, this is important. So, if I have an object like this and I have a pointer size which is small, so this size is much smaller compared to this over all object size and that is an implicit assumption we have made so far in our application of Fitts law. That, the onscreen pointer that we are using to acquire a target is having much less width or much less size compared to the overall target size.

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Now, why that is important? In the context of application of the Fitts law, the assumption is that it should be rapid aimed and error free. Now, the consideration of error is important as we have already discussed during the discussion on Fitts law. So, when we are assuming that the pointer size is much less than the target size, then actually it is easier to adhere to this condition of errors.

So, we will be able to keep the error rate low if we are assuming that we have a pointer which is used to acquire a target which is having much less size compared to the target size. So, if we can keep the error at low then we can manage the speed accuracy tradeoff without any problem or without much problem.

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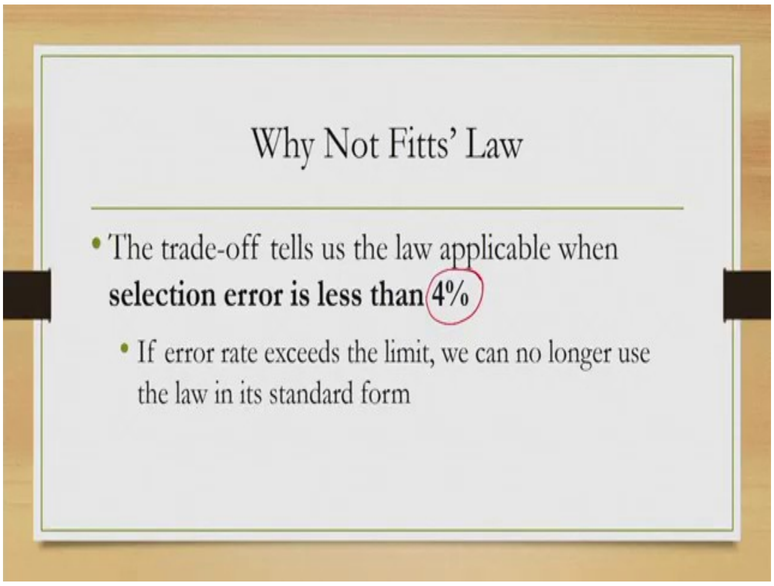

In case, it is not possible to keep the error rate low. Remember, from our earlier discussion on Fitts law when we discussed about the speed accuracy tradeoff we mentioned that if the error rate remains less than 4 percent then we can ignore this error and can simply apply the classical law in its original form.

However, if the error rate is more compared to the accuracy, accuracy, if the error rate is more than 4 percent then we will not be able to do that. We will not be able to apply the Fitts law in its original form and there we need to do some modification in the application of the law.

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What is that modification? If you we can recall it we can no longer use the original target width in the formulation of the law instead we have to take into account effective target width and the index of difficulty has to be recalculated or recomputed accordingly.

So, what is that effective target width? That is the maximum size of the area encompassing all the points of selection. So, all these points need not be within the target area it may be outside the area also and all this points will define a region and we will take the maximum width of that region that is the effective target width.

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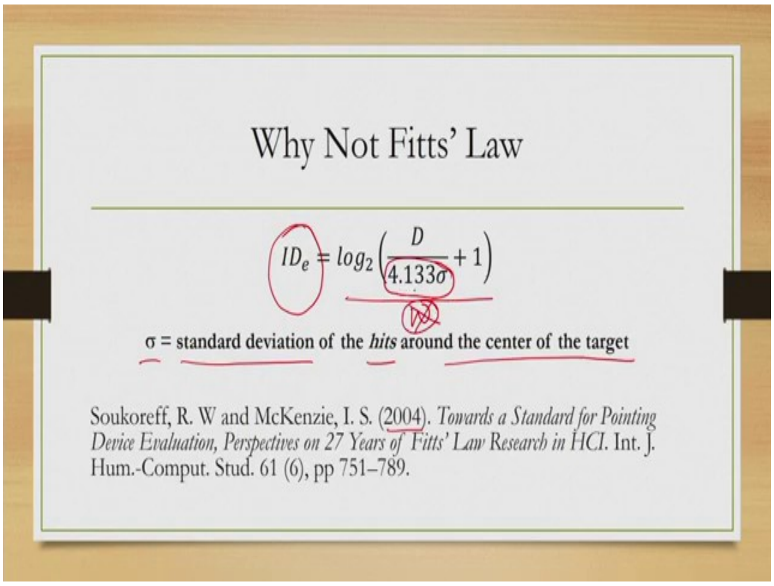

Now, Sukoreff and McKenzie in 2004 proposed one formulation for computing this index of difficulty when error rate is more than 4 percent. They, according to their formulation we can compute the index of difficulty of such tasks with this expression where instead of W or the target width we are using this term 4.133 sigma. Now, sigma is the standard deviation of the hits around the center of the target.

So, if we plot the hits around the center of the target it represents a distribution of points, so hit distribution. And sigma indicates the standard deviation of that particular hit distribution and when error rate exceed 4 percent, we have to calculate index of difficulty using the modified formulation proposed by Sukoreff and McKenzie in this paper in 2004 and we cannot use the classical form of the Fitts law. So, we cannot use the width instead we have to use this term 4.133 sigma. Now, what happens in the context of tapping with a finger on a touch screen device?

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Here the assumption does not hold, that is the target size is much larger than the pointer size which is used to acquire the target. In this case, the pointer is the finger and the target may be smaller than the finger. So, we cannot implicitly assume that the pointer is having much less size than the target size. So, the surface area of the finger tip may be larger compared to the target size. In other words, the target is partially occluded from our view. So, when that happens then it becomes difficult to locate the exact poison of that target, to locate the exact position where we need to touch to select the target and that in turn increases the likelihood of target misses.

So, we are touching, but we are unable to see where we touch. So, in that case we may touch at a wrong place than the one required to select a particular object and so we are likely to miss in our selection task. Now, this problem where we may miss because we are unable to view the target properly due to the relatively larger size of the fingertip is known as fat finger problem.

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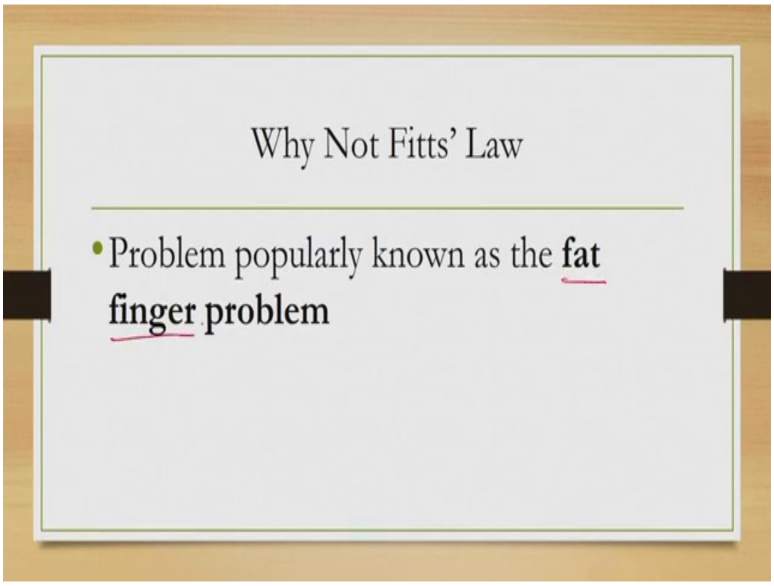

This is a very common problem found in interaction with touch devices where the screen size is relatively small. If we are dealing with a very large screen touch device then of course, this problem does not occur. However, for Smartphone interactions or tap interactions this is a very common problem.

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So, what is the consequences of having a fat finger problem? Now, on a small screen device we may see many elements packed within a small region. Now, if we touch a place which is not the desired one then in that place there may be some other element which we do not want to select, but we may inadvertently select that element. It may also happen that in the small area we are not having many elements and so we touched at a point which is not required, but there is nothing happens. So, effectively we wasted the effort and time required to perform that touch operation.

So, in one case due to our error some other objects got selected in other case nothing happens and we wasted the time and effort. In either case the point to note is that the overall error rate overall target miss rate is likely to be more than 4 percent. So, if that is the case then as we have already discussed we will not be able to apply the Fitts law, we have to go for a modified target acquisition model based on a modified law.

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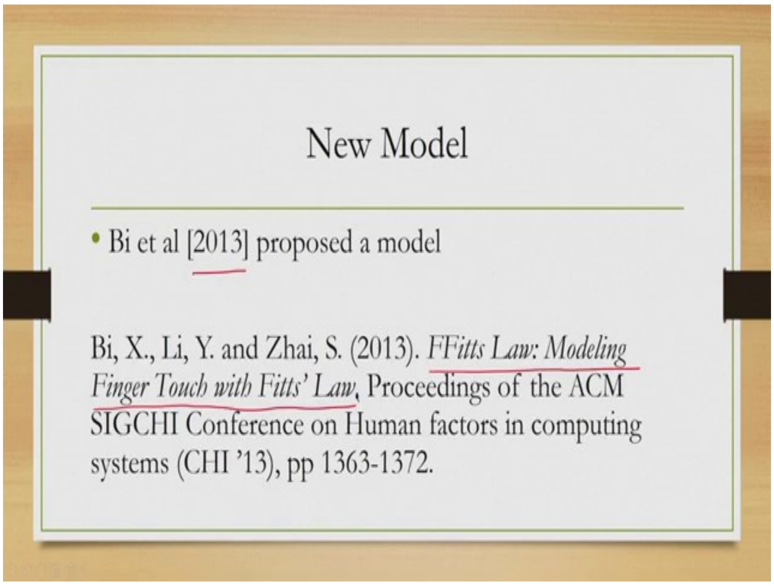

So, we require a new model now in 2013 Bi et al proposed one such model which was published in the proceedings of CHI, 2013, a FFitts Law Modeling Finger Touch with Fitts Law. So, what is the basic idea behind this model? The most fundamental assumption that is there behind this model is that the distribution of touch points is the sum of two independent distribution.

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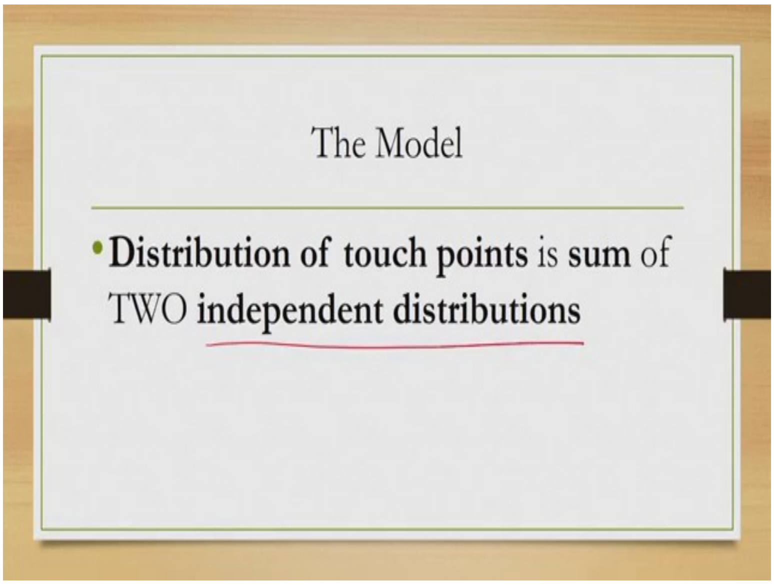

So, earlier we talked of the distribution of hits. So, this distribution of hits represent the touch points within the target area or outside the target area. Now, outside the target area of course, indicates the miss points and when the touch points are within the target area they represent the points when we hit the target. Now, together they represent a distribution, distribution of touch points. In the model proposed by Bi et al it is assumed that these distribution is actually a composition of two independent distributions.

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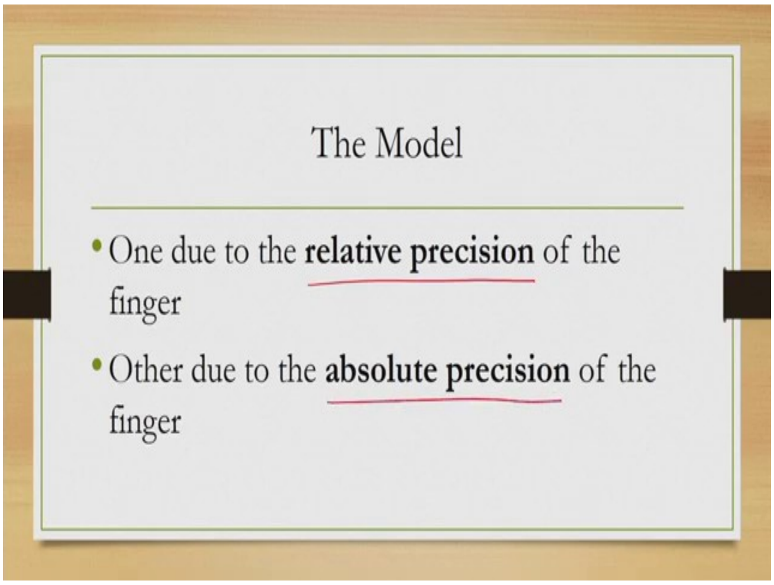

So, what are these two independent distributions? One distribution appears because of something known as relative precision of the finger and the other distribution appears because of something else known as the absolute precision of the finger. So, let us try to understand what these terms mean.

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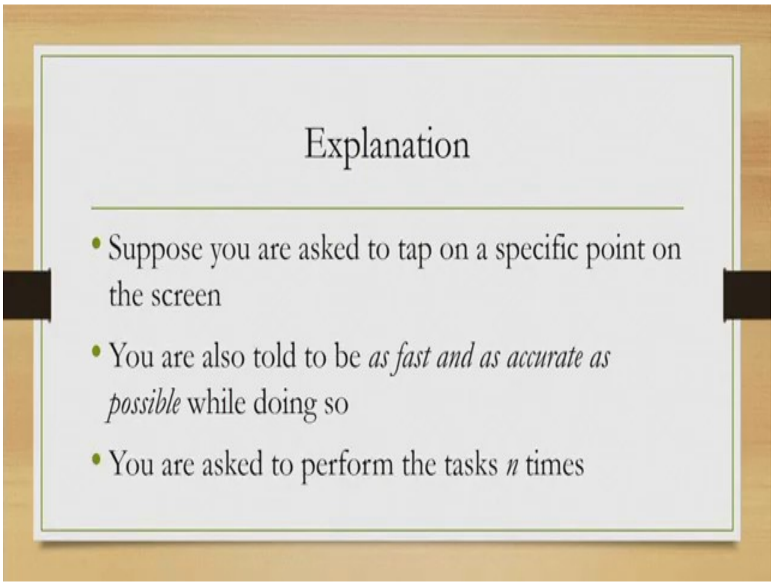

Suppose you are asked to tap on a target. So, you are given a task that this is a target and you are asked to select the target by tapping on it and you are finger is there at a initial position from there you have to acquire the target and tap on it. However, you are also told that you have to select the target as fast as possible and as accurate as possible. So, these two conditions are given to you. And you are asked to select the target may be say 20 times.

So, at the end of the 20 trials each target selection task is a trial and there are 20 trails. So, at the end of this 20 trials what you are likely to find? You are likely to find 20 touch points. Now, some of these points as I said earlier will be within the target area and some will be outside; that means, you are likely to find some target misses.

Now, why that happens? Because while you are asked to select the target you are also asked to select the as fast and as accurate as possible. So, this is the speed accuracy tradeoff you are asked to manage. If you are not told about this tradeoff, if you are simply told to select the target without bothering about speed and accuracy then probably you would not have missed the targets. So, the misses occurred due to the speed accuracy tradeoff.

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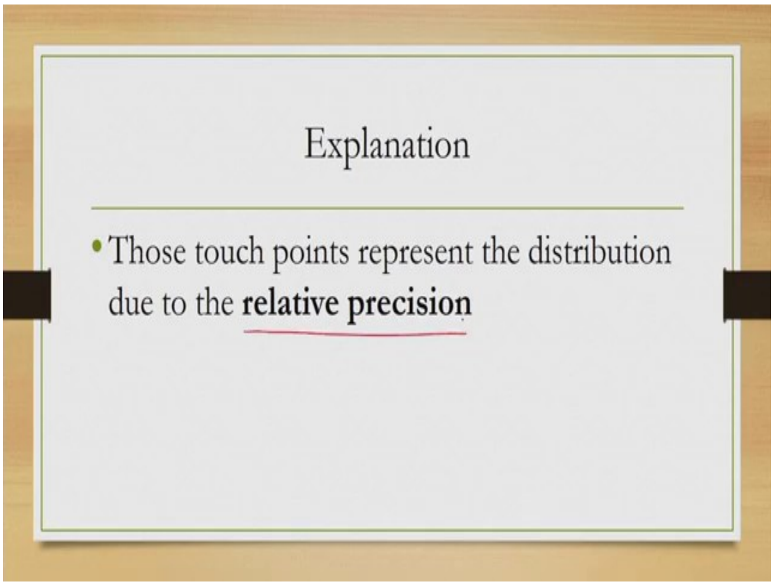

Now, this touch points which lie outside the target and which happened because you are told to balance the tradeoff these points are due to relative precision. So, the distribution that you will get of the points outside the target represents the distribution due to relative precision of the finger. When we try to balance the speed accuracy tradeoff while acquiring a target, we are likely to encounter some selection error, we are likely to miss the target sometimes. Now, this misses the distribution of the points which represent this misses is due to the relative precision of the finger.

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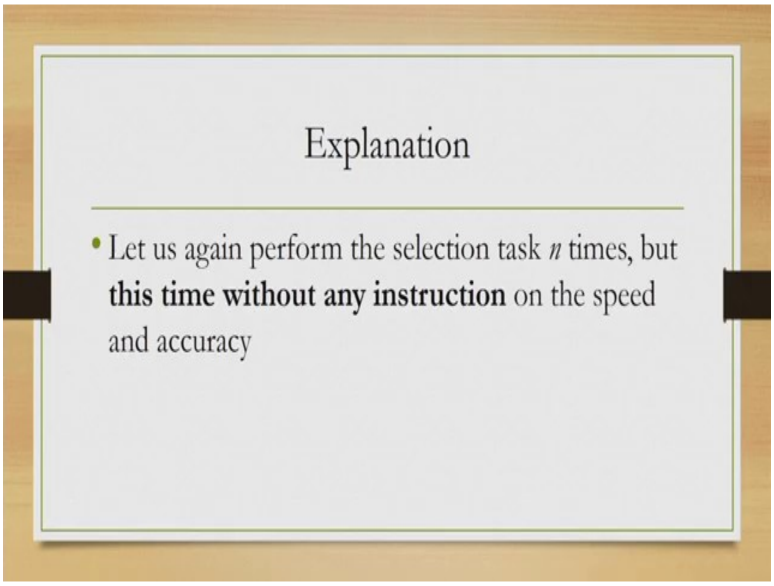

Now, let us consider the trail again. This time you are asked to again select the target may be 20 times; however, this time you are not told to balance the speed accuracy tradeoff. So, you are not told that you have to be as fast as possible and as accurate as possible and you are asked to do it 20 times like before. So, at the end of it what you are likely to find if you expect that you will find that all points are within the target region then you are mistaken. Actually, if you are asked to do this trial on a small screen mobile device where your finger size is relatively larger than the fingertip size is relatively larger than the target size then you are likely to find still some points which are outside the target region.

Now, why this misses occurred? So, when your touch points are outside the target region it indicates that you have missed the target. In this case, why this misses occurred? Here you are not asked to balance the tradeoff between speed and accuracy, but still the misses occurred, this is due to the fat finger problem. So, you are getting a distribution of miss due to fat finger problem and that distribution is known as the absolute precision of the finger.

So, earlier we have seen the distribution due to the relative precision of the finger which happens because we want to balance the tradeoff between speed and accuracy. Now, any encounter a distribution of miss points due to absolute precision of the finger it refers to the miss points which happen due to fat finger problem not due to the requirement to balance the speed accuracy tradeoff.

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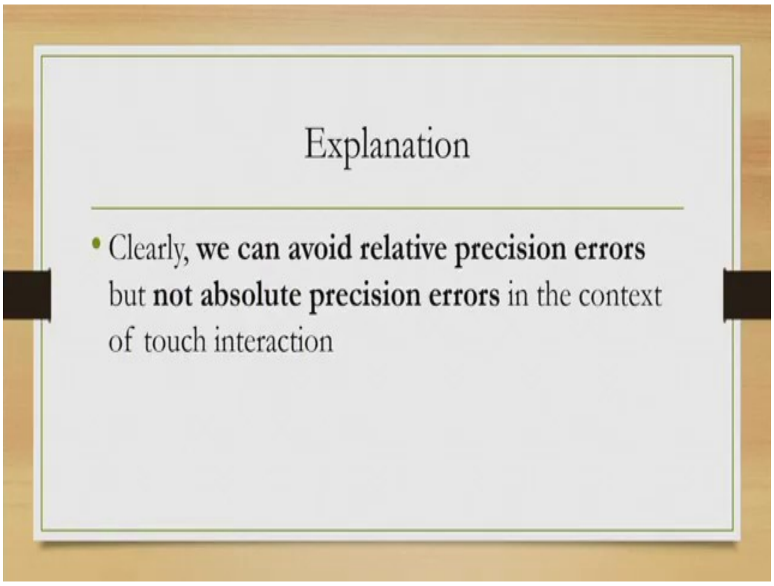

So, if you have understood the concepts then it might have been clear, that if we are not asked to balance the tradeoff between speed and accuracy on a device where the target size is relatively larger than the size of the pointer or the finger that is used to acquire it then we may completely avoid relative precision errors.

However, we will never be able to completely avoid errors that occur due to absolute precision because in a small screen there will always be fat finger problem and we are going to have this error irrespective of whether we are asked to balance the tradeoff between speed and accuracy or not. So, with this basic knowledge of this two distributions let us try to understand what the modified model for touch performance is. Let us try to understand its derivation.

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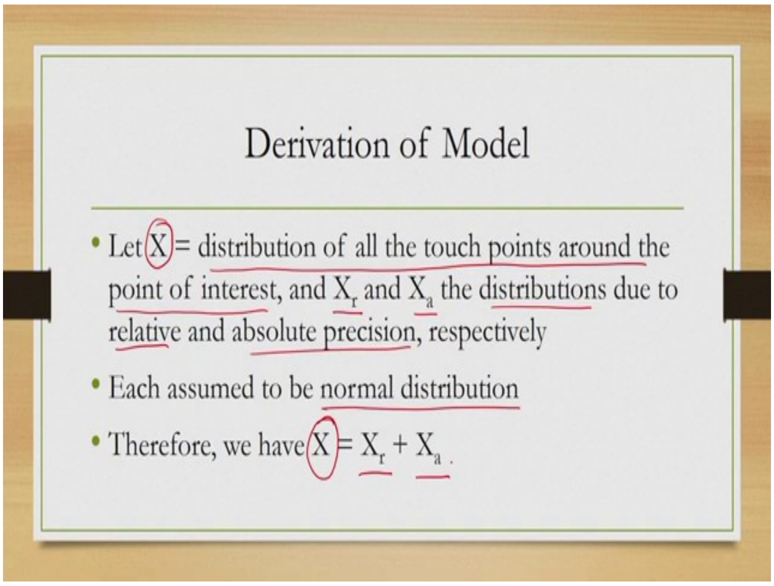

Let us denote by X, the distribution of all the touch points around the point of interest and by X r and X a the distributions due to relative and absolute precision. We are also assuming that all these distributions are normal distributions. So, then we can represent X as a combination of X r and X a as we have already stated.

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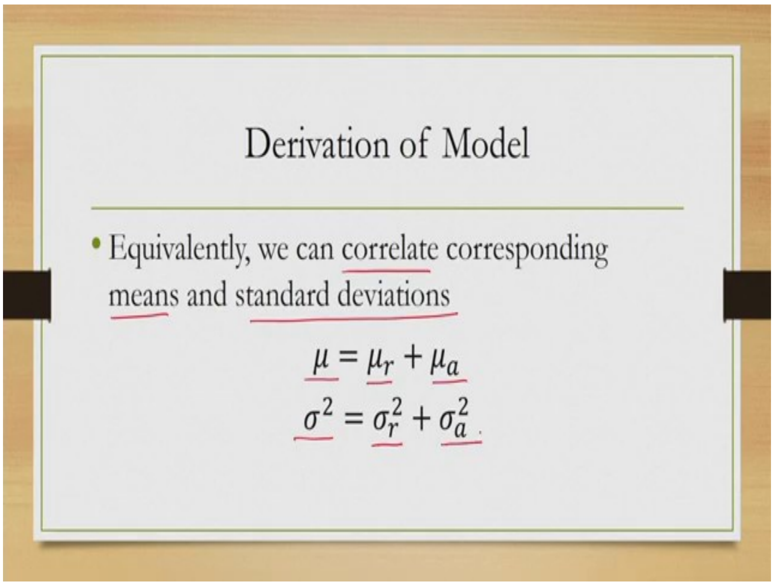

Equivalently, we can correlate the corresponding means and standard deviations. If mu represents mean of the overall distribution, mu r represent mean of the distribution due to relative precision and mu a represent mean of the distribution due to absolute precision, then mu can be represented as summation of mu r and mu a. Similarly, the standard deviation of the overall distribution can be represented as a summation of the standard deviation of the distribution due to relative precision and standard deviation of the distribution due to absolute precision.

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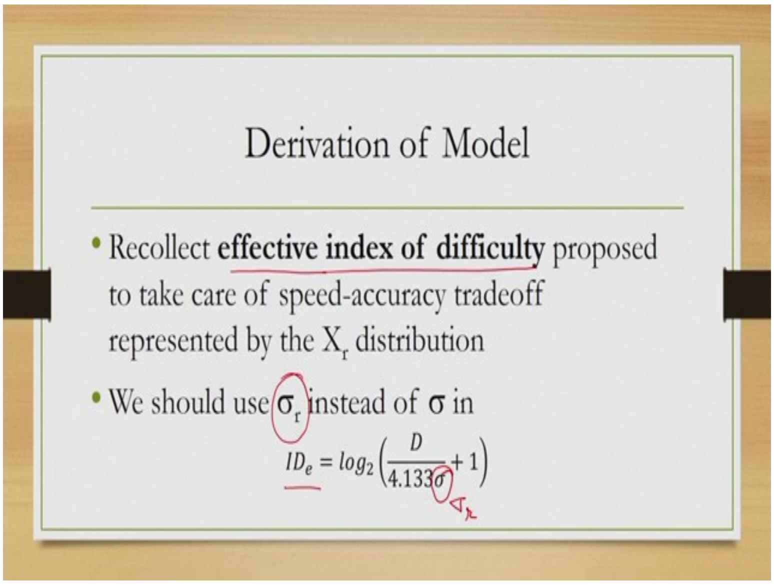

Now, earlier we have shown the formulation for computation of index of difficulty when we are considering the effective target width and that index of difficulty we are calling as effective index of difficulty, when instead of the original target width we are considering effective target width.

Now, the original formulation that we have seen earlier uses the term sigma, that is the standard deviation of the distribution representing all the touch points. But now, we have this knowledge that this entire distribution of touch point is a combination of this two distributions, one due to relative precision, one due to absolute precision and the effective target width actually refers to the width of the hit points that happened due to speed accuracy tradeoff.

So, in that case we clearly have to consider only the distribution due to relative precision which happens due to speed accuracy tradeoff and the corresponding standard deviation. So, instead of sigma here we are supposed to use sigma r to compute the index of difficulty for interactions or interactive tasks where the error rate is more than 4 percent.

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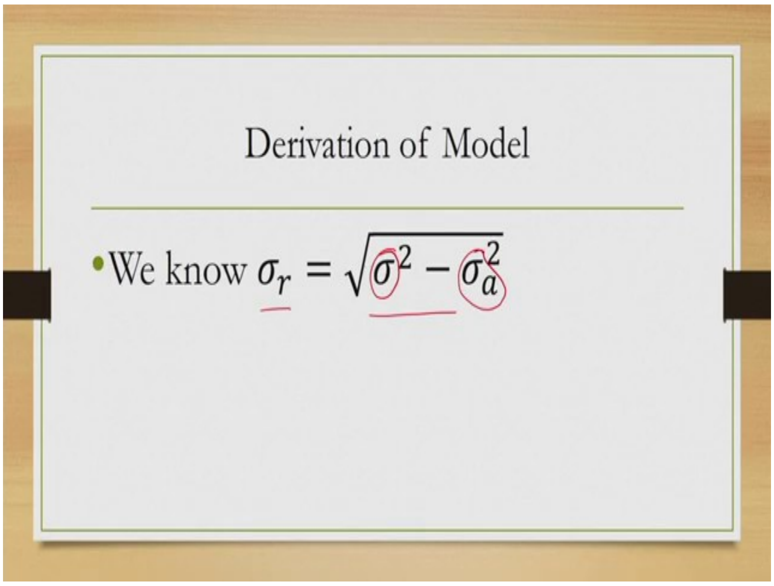

Now, we already know based on our earlier knowledge of the two distributions and the overall distribution as a combination of this two distributions, that sigma r can be represented in this way, the standard deviation of the entire distribution minus the standard deviation of the distribution due to absolute precision.

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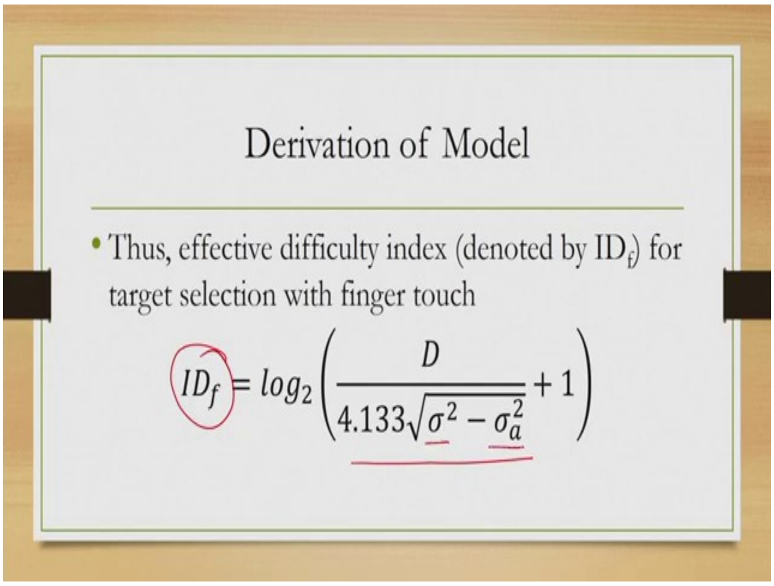

So, we can replace sigma r with this new formulation and then get the effective difficulty index in this form. So, instead of sigma r we are using sigma and sigma a.

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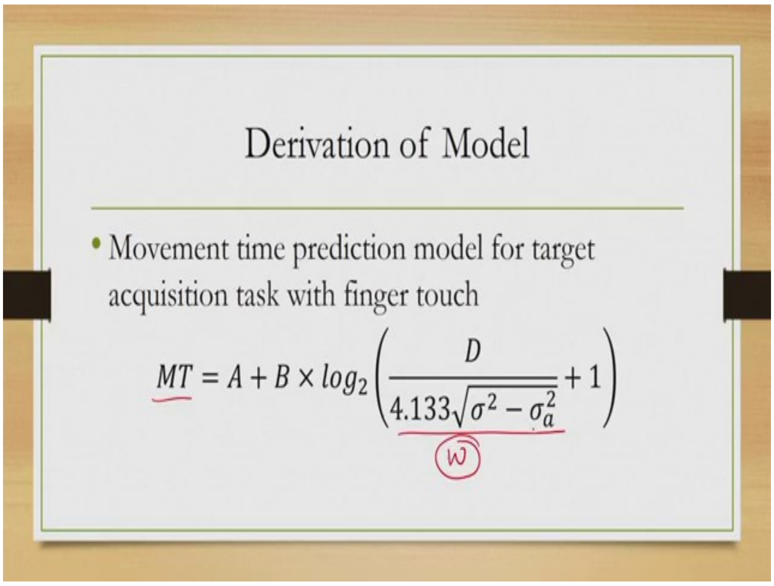

And once we have this then we can go for the overall model which is the movement time prediction model in the form of Fitts law, but here instead of W or the target width we are using this term 4.133 square root of sigma square minus sigma a square, where sigma is the standard deviation for the overall touch point distributions and sigma is the standard deviation for the touch point distributions that happened due to absolute precision. So, this is the model for touch performance prediction. And as you probably can relate this is the model we can use to predict performance of tap behavior one of the fundamental touch interaction.

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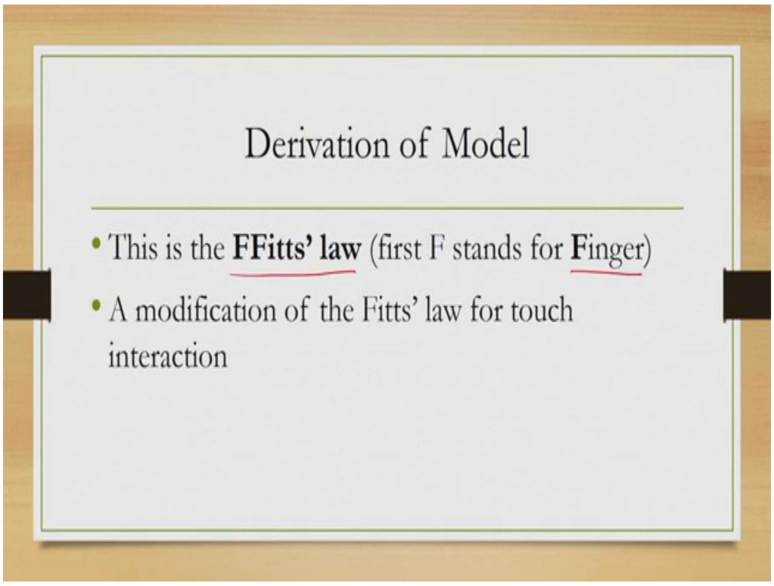

Now, this model is often referred to as the FFitts law, where the first F refers to finger. So, essentially it indicates Fitts law modified, Fitts law in a modified form when we are using finger to select or tap on a small screen display area.

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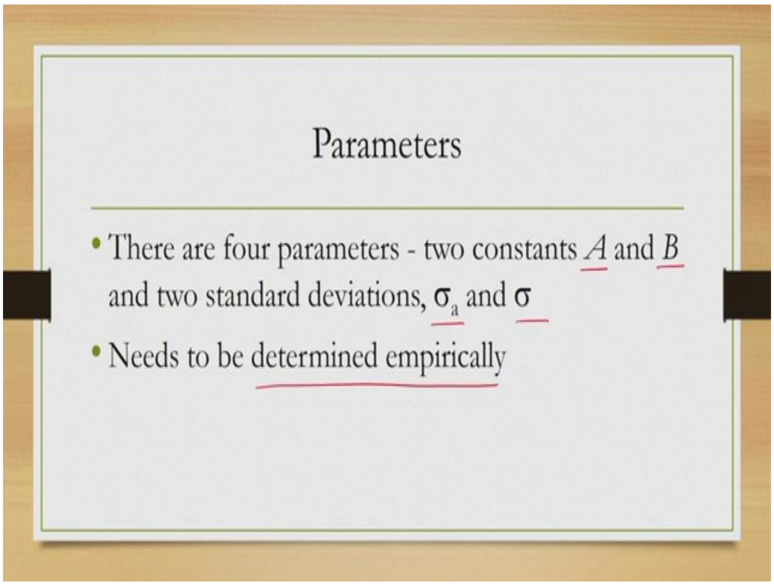

Now, there are few model parameter which require some clarification. Fitts law as we have already discussed in the Fitts law in the model derived from the Fitts law there are this two constants A and B and along with that there are two standard deviations sigma a and sigma.

Now, we have already discussed how to empirically determine this constants A and B the two standard deviations also have to be determined empirically however, it is not a very straight forward approach. Let us quickly go through the method for determining these two standard deviations. Now, let us first discuss the determination of the standard deviation for the overall distribution of touch points.

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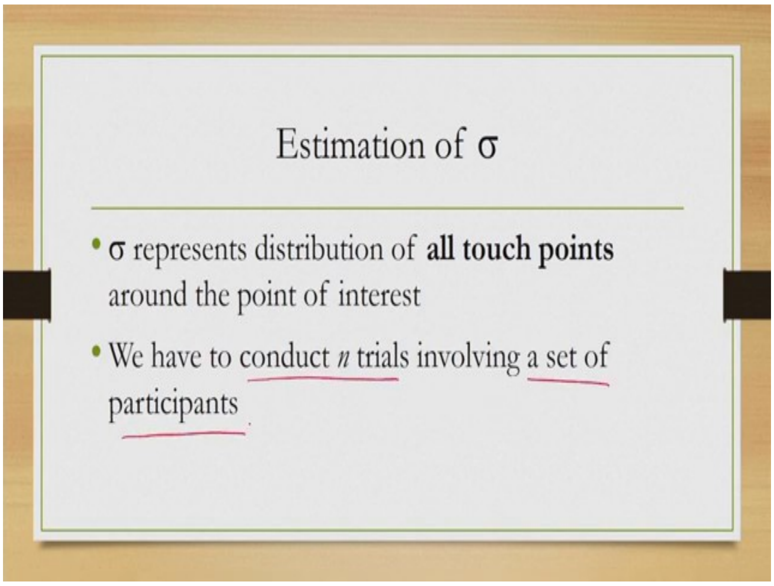

So, in this case what we need to do? We need to conduct n trails involving a set of participants which is common for all empirical studies.

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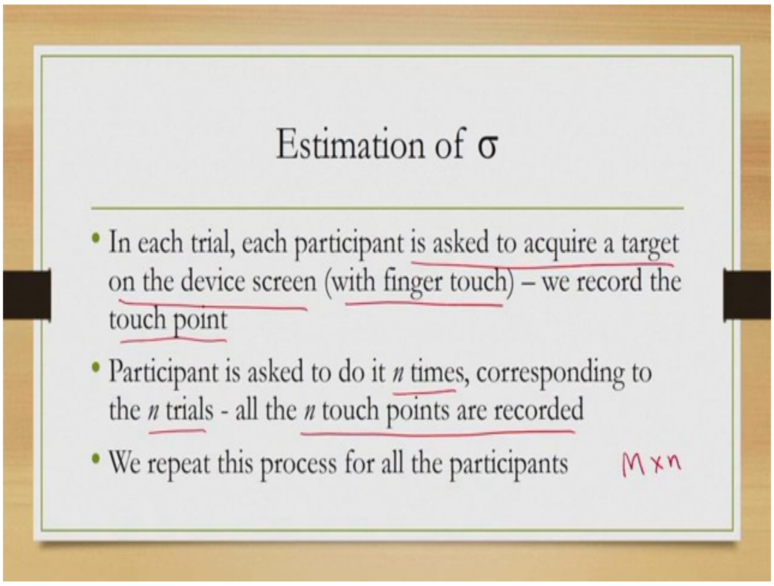

Then, in each trial each participant is asked to acquire a target on the device screen which of course, as to be done with finger touch and we record the touch point. So, each participant is asked to acquire the target n times corresponding to the n trails and all the n touch points we are recording and we repeat this process for all the participants. So, if there are m participants each performing n trails then we get m into n points.

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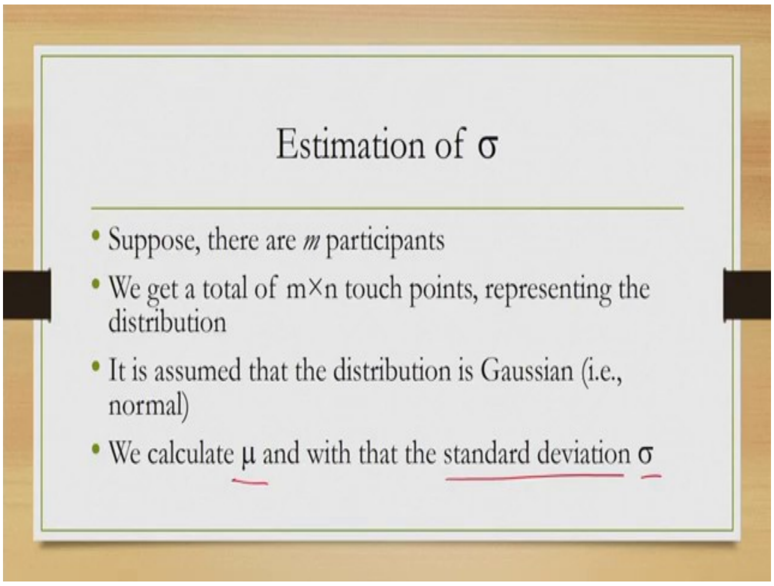

These points represent the distribution for all the touch points and we calculate mu or the mean for this overall distribution and with that we calculate the standard deviation sigma. So, that is how we estimate sigma for the overall distribution.

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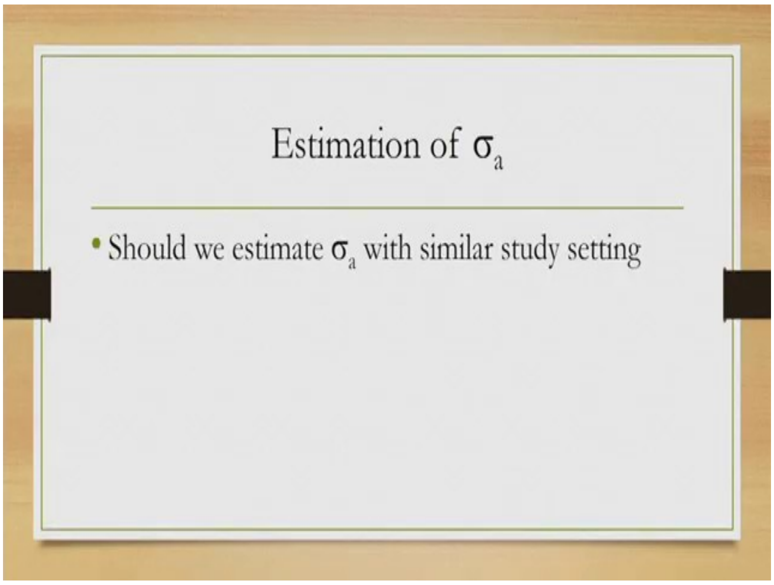

In case of estimation of the standard deviation for the distribution that occurs due to absolute precision of the finger we have to adopt a slightly different approach. So, in this case what we need to do is that we have to change the procedure a bit.

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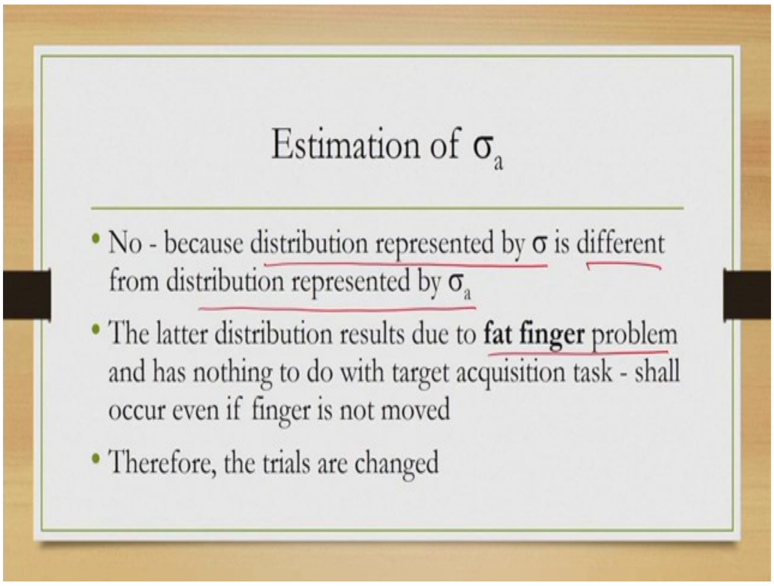

We cannot simply use the similar setting which we have used to estimate sigma because distribution represented by sigma is different from distribution represented by sigma a. Now, sigma a distribution occurs due to the fat finger problem and it will occur irrespective of whether we are balancing the speed accuracy tradeoff or not. So, in other words the distribution occurs not because of the finger movement, so in this empirical study the tasks need not involve movement of the finger.

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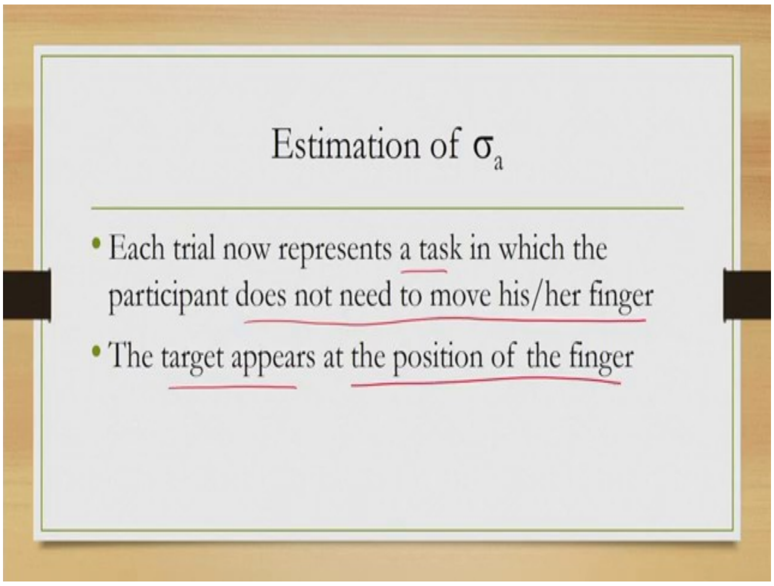

So, we change the tasks in the trails. Now, in each trail there is a task in which the participant does not need to move his or her finger the target appears at the position of the finger.

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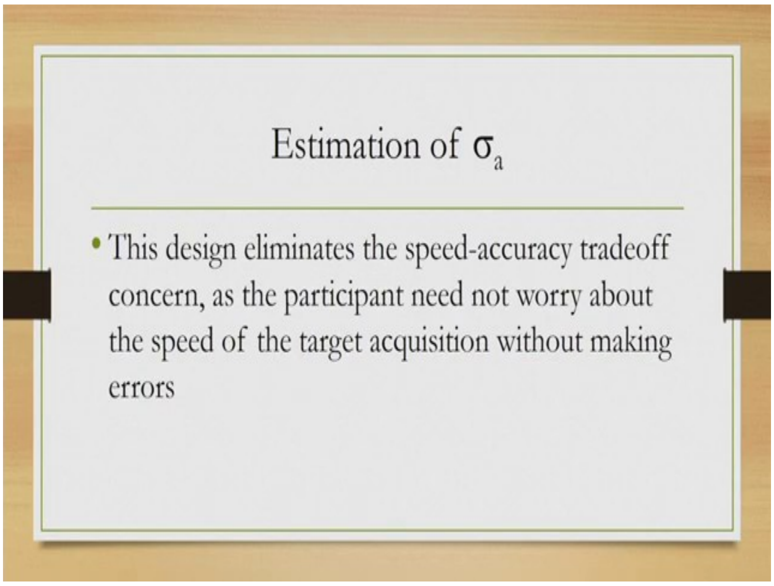

So, if we design it, design the empirical study in this way then we are eliminating the speed accuracy tradeoff because we are not asking the participant to move their finger. So, there is no question of missing a target due to the finger movement. So, they are likely to miss the target only due to the fat finger problem and that is going to reveal the distribution for absolute precision of the finger.

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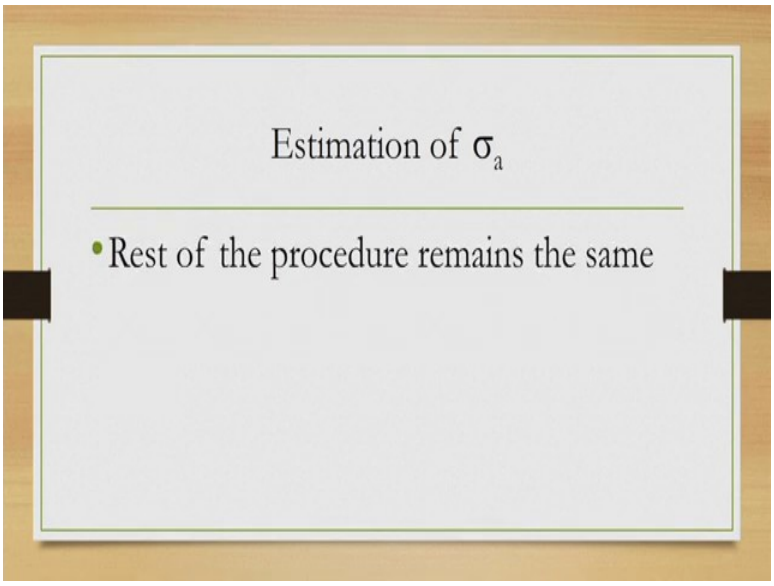

Once we get those points with that we compute the mean and then from there the sigma and this sigma is the parameter sigma a in this modified model for touch performance that is the FFitts law. So, to repeat. So, there are 4 parameters A, B, sigma and sigma a. Now, A and B has to be derived empirically in the same way that we have already discussed earlier.

In case of sigma and sigma a, we need to set up the study carefully. So, for determination of sigma in the study what we need to do is we conduct n trials for each of m participants, participants are asked to acquire a target by moving a finger and we record all their touch points, then from those touch points we estimate the sigma.

In case of determination of sigma a, or the standard deviation of the distribution due to the absolute precision of the finger what we do is in the empirical study we ask each participant to acquire a target without moving the finger. So, the target appears near the finger position. So, there is no need for the participants to move their fingers.

So, with that we eliminate the possibility of target acquisition error occurring due to speed accuracy tradeoff and we can get only the touch points that happen due to absolute precision of the finger. Once we get that distribution we can actually estimate the mean and subsequently the standard deviation of that distribution. So, in that way we estimate all the model parameters and once we estimate that we ready with our prediction model. So, that is the idea.

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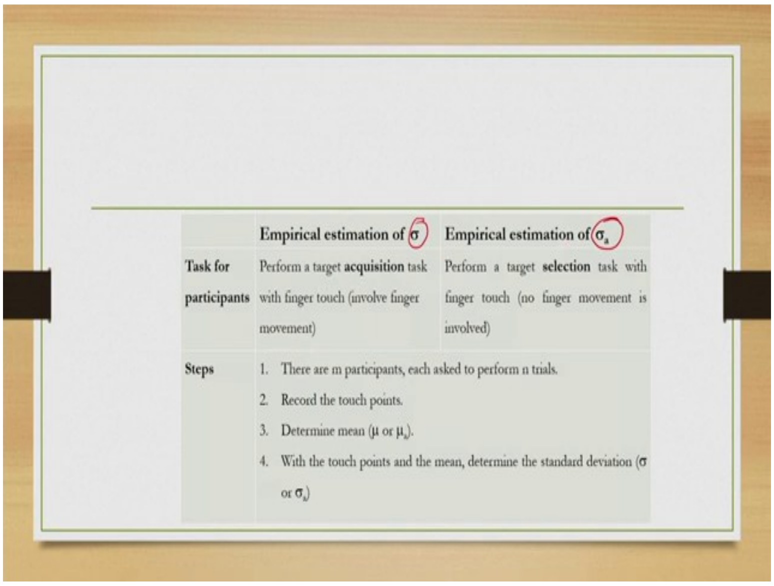

So, in this table I have summarized the details of the empirical studies required to estimate sigma and sigma a, which I have already discussed.

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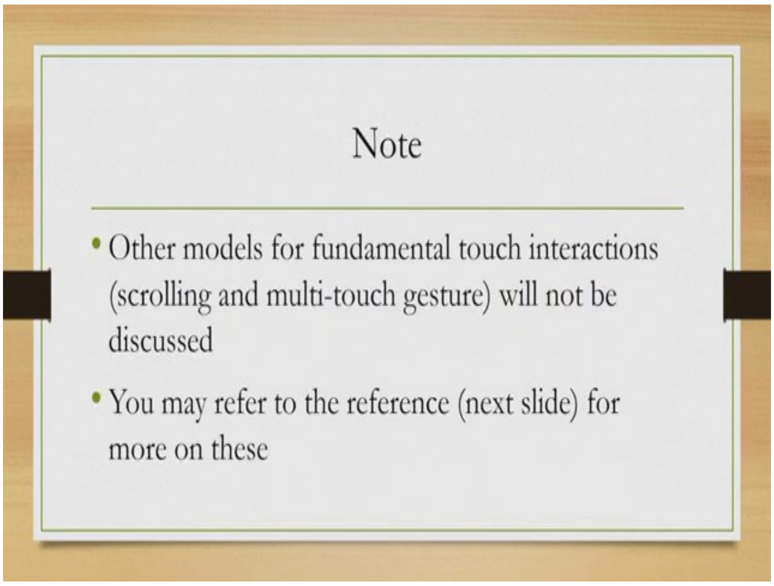

Now, this is one of the models that are there to compute performance of all the fundamental touch interactions. So, if we recollect we mentioned three fundamental touch interactions, namely, tap, scroll and multi-touch gestures. The model that we discussed in this lecture can be used to model the performance of tap behavior. There are models for scrolling behavior as well as multi-touch gestural behavior in the context of touch interaction. However, we are not going to discuss those models in this course. The interested readers are advised to refer to the chapter of the book that I have used to get the material of this lecture.

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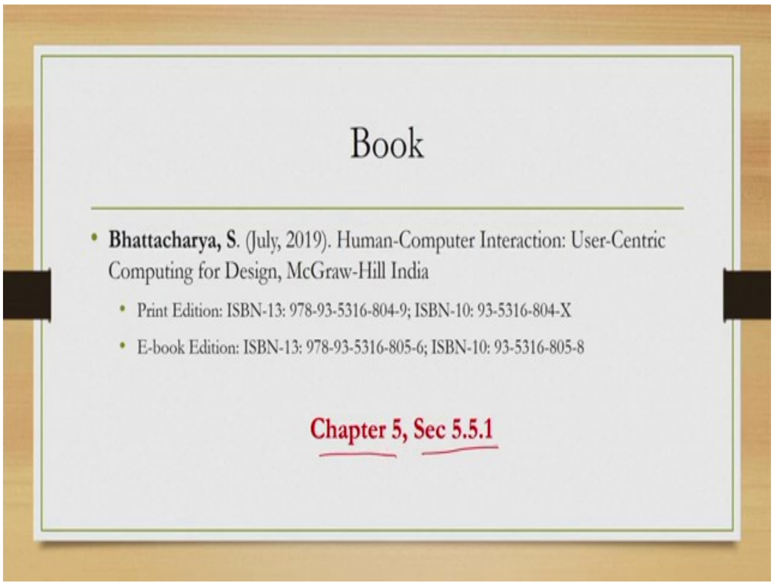

So, the material that I have used is from chapter 5 of this book. Now, the lecture pertains to section 5.5.1. However, in the same chapter you can find the other models related to the other fundamental touch interactions. So, if you are interested you are advised to refer to this chapter and the other sections which contains more details on the models for other fundamental touch interactions along with the model that we discussed today.

Thank you and goodbye.