5-2018

A Measure of Human-Integrated System Performance under Time-Varying Circumstances

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A MEASURE OF HUMAN-INTEGRATED SYSTEM PERFORMANCE UNDER TIME-VARYING CIRCUMSTANCES

by

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A Dissertation

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Doctor of Philosophy

School of Industrial Engineering

West Lafayette, Indiana

May 2018

THE PURDUE UNIVERSITY GRADUATE SCHOOL
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Dedicated to the memory of my parents,

And in honor of my aunt

and my sister,

All for their love and support

ACKNOWLEDGMENTS

I could not have completed this work without the support of many. First and foremost, I would like to express my special thanks to my advisor, Dr. Steve Landry, for his guidance, advice and support throughout my PhD life. Dr. Landry inspired me to explore a new approach in the field of human factors, and I owe a debt of gratitude to him for his time and careful guidance. I also would like to thank my committee members, Drs. Sara McComb, Karen Marais and Denny Yu for their tremendous help. I would like to express my thanks to Dr. McComb who always encourages me and supports me. Additionally, I would like to thank Dr. Marais and Dr. Yu for appreciating my research and patiently encouraging me to improve my weak aspects.

I owe a deep debt of appreciation to VEF (Vietnam Education Foundation) for giving me a fellowship opportunity to study at one of the nation's leading research institutions. To take this opportunity, I'd like to extend warm thanks to my VEF friends who have shown interest and given encouragement. I am deeply grateful to my peers at Purdue University have provided wonderful support and special thanks go to Yul Kwon, Julian Archer and Harsh Aggarwal. They checked on me, empathized with me, and offered help. I am also thankful to my friend, Loc Nguyen, for his unconditional friendship and for supporting me when I need it.

None of this would have been possible without the love and support of my family. My parents, especially my mom, instilled in me the significance of education at a very young age and was always giving me the freedom to make my life choices. I am particularly grateful for my aunt and my sister, who are supportive in every way and have taken care of my family when I have been absent from home. Lastly, I would like to show my appreciation to master Minh-Niem who taught me the simple but insightful lessons of self-balancing and living in true happiness. His lessons have changed my thought patterns and my views on many subjects of life.

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LIST OF ABBREVIATIONS

$A_i(x)$	Cumulative average performance time of each of the *x* cumulative task-units completed in time-varying circumstances
CIR	Circumstance
C_i	Condition *i*
{C_1=Inside}	Condition inside
{C_2=Outside},	Condition outside
{C_3=Gloves},	Condition with gloves
{C_4=No-gloves}	Condition without gloves or no-gloves
{IN}, {OG}, {ON}	Individual circumstances

ABSTRACT

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Degree Received: May 2018
Title: A Measure of Human-Integrated System Performance under Time-Varying Circumstances
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There are many methods to evaluate a system from given options in discrete or fixed situations ('circumstance'). However, most systems are operated under time-varying circumstances and it's not known how to evaluate the best system design when the operator in that system moves between time varying circumstances. In this dissertation, an adaptability model has been formalized using symbolic notion, which is based on learning curve theory and the adaptability measures are proposed.

In the first study ('the demonstration study'), the measures proved that they could be calculated and the learning curves could be plotted in continuous varying-circumstances. In the second study ('the empirical study'), we tested two systems under three varying-circumstances. The primary purpose of this experiment was to study whether the order and delay of changing circumstances affect the adaptability measures, in which influential circumstances are randomly arranged. The statistical tests showed that order and delay do not have effects on adaptability measures. However, the results from the graphical analysis provide useful information to adjust the setting of circumstances regarding the levels of order and delay factors in practice.

The findings are expected to provide an insight into understanding how human operators adapt to changing circumstances while still continuing to achieve the goal. The results also are envisioned to provide new metrics for evaluating the effectiveness of alternatives in system design.

1. INTRODUCTION

One way to evaluate a system design is to evaluate the performance of humans integrated in that system design. The system design is a notion that defines a physical model of a system being created. For example, the system design could have the small dimension of a smartphone or a care device, or have the large dimension of a car or a factory. There are several methods that can be used to quantify the performance characteristics of the system regarding human subjects. Specifically, scientists developed mathematical models to structure human behaviors in the loops while the operators are performing tasks (Pietro Carlo Cacciabue, 2004; Dick, Bittner, & Harris, 1989; R. A. Hess, 1987; Leamon, 1980; Macadam, 2003; McRuer, 1980; N. Moray, 1981; Oliver, Pentland, & Verly, 2000; William B. Rouse, 1981). Another method is to evaluate the system holistically from the context in which humans run the system to perform a specific task. Scientists apply a variety of disciplines, concepts, frameworks and measures to develop the specific methods for evaluating the specific system designs (Camerer & Weber, 1992; Firth-Cozens, 2001; Neville Moray, 1994; Stanton, Salmon, & Rafferty, 2013; Strauch, 2017).

Currently, these methods or measures are most often being applied in discrete working environments. The ‘discrete’ term is referred to as typical, normal or optimal, and a working environment is called a set of conditions (i.e. ‘circumstance’). For example, a new phone design is normally tested on a particular task under perfect laboratory conditions such as good lighting conditions and stable background noise. However, the measures could also be applied during atypical or non-normal circumstances. By testing under imperfect conditions, the scientist tried to learn if a system design could accommodate human operators to complete a task when they reach their limitations.

Many real world systems are operated in dynamic environments, where the humans running the system have experienced the continuous changes in conditions of working environments (i.e. ‘circumstance’). Let’s consider an example of using a smart phone, the device that we use every day. We know that different phones provide different functions and user experience. There is a difference when you're trying to use the phone in the dark versus in the light or using the phone in your quiet room versus in a crowd. Some phones support users very well in these conditions, and help them do their work better in the dark or better in the crowd. For instance, some phones have noise cancellation and some do not. In a dynamic situation, when a user walks from inside (your quiet and normal lighting room) to outside (very sunny and noisy area), how does his/her phone support the user to do his/her work, such as typing emails, searching for a flight, talking to customers or controlling a drone? And then, what phones would a user choose to do his/her job effectively in dynamic conditions like this? In fact, disruptions in human performance due to environmental changes might happen. Furthermore, we haven't yet known the way to evaluate the performance of humans who operate a system design under such dynamic situations and how we could quantify the disruptions in human performance.

With the rapid development of new high-tech system designs applied in dynamic environments, the need for a measure of system performance in continuous circumstances for evaluating system designs is obvious. None of the current methods are capable of detecting the transitions in performance when the circumstances change. This problem is especially pronounced when varying circumstances occur continuously in a series (Neville Moray, 1999). Due to the difference between the traditional approaches and the proposed approach to evaluating system design, the context of circumstances differs for each purpose. For the traditional approach, a system design generally is evaluated in a discrete circumstance or evaluated discretely in several circumstances (See Figure 1.1a, and Figure 1.4a). The methods of evaluating human performance in this system design also are treated individually in discrete circumstances. On the other hand, for the proposed approach, a system design is evaluated in a continuous series of time-varying circumstances. Throughout this work, the term 'continuous series of time-varying circumstances' refers to a set of discrete circumstances happening one after another in a temporal order of succession. The term 'time-varying' refers to the variations of the conditions of particular circumstances in a series (See Figure 1.1b, Figure 1.2 and Figure 1.4b). In other words, a time-varying circumstance means that certain conditions constituting this circumstance vary with the conditions in the precedent circumstance and the conditions in the subsequent circumstance in time order. However, within a specific discrete circumstance, conditions are unchanging or consistent within the boundary of this circumstance. The continuation of circumstantial occurrences is the essential feature of the proposed approach.

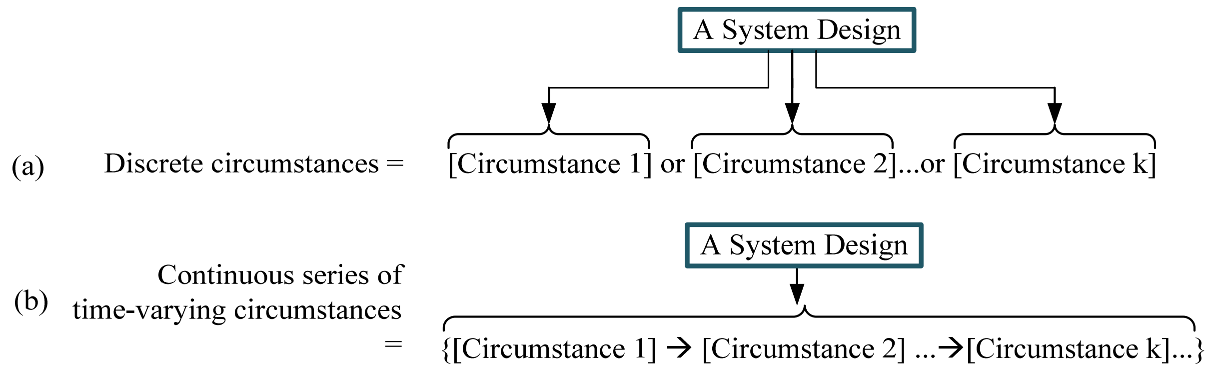


Figure 1.1 Contexts of circumstances. (a) The context of discrete circumstances, (b) The context of continuous series of time-varying circumstances. The point down arrow (↓) indicates a direction that a system design can be tested under a circumstance or a series of circumstances. The right point arrow (→) stands for the continuation of circumstantial occurrences.

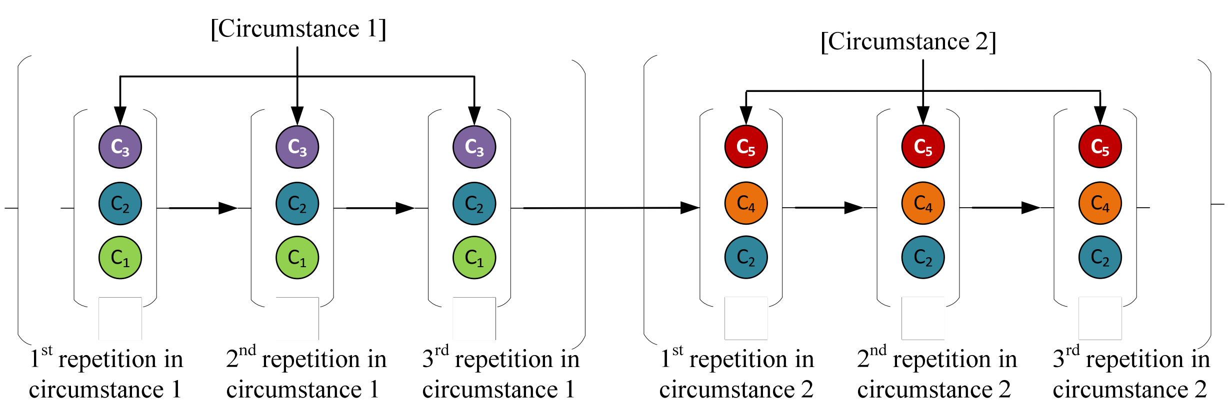


Figure 1.2 An illustration of time-varying circumstances. Within a circumstance, the conditions are unchanging or consistent within the boundary of this circumstance. R_i stands for the i^{th} repetition in a circumstance. C_i stands for the condition in a circumstance. The condition C_i only changes in a new circumstance.

Still, knowledge gaps in the proposed approach may exist. There is no method to measure the human performance in continuous series of time-varying circumstances. This situation is commonly explained: When circumstances dynamically change, the operators go from one circumstance to another circumstance. There's a transition between circumstances that might cause a disruptive effect in human performance and change the performance improvement rate. Out of this experimental setup, the questions emerge:

- How well does a system design accommodate human operators who adapt to changing circumstances?
- Could we measure the adaptability parameters to know how a human-integrated system adapts to time-varying circumstances?
- From that sense, given several system designs, to select a system that works best over time varying circumstances, the systems will be tested by running the systems through a task across different orders of time- varying circumstances. The human performance would be collected and analyzed to see how the performance is affected under changing circumstances.

An obvious idea arose about the performance of human operators over a number of replications that is close to the concept of learning curves. The concept of learning curves explains the learning ability of human operators in a system and is a reliable tool for modeling the human performance. This theory explains the particular criteria of human performance when the operators repeat a task over time, and the shape of the curve gradually leads into an asymptote at the long end. This new method has been built based on the learning curve theory, and it is expected to address the answer to the research questions because it is not known how humans adapt to time-varying circumstances.

1.2 Research Gap

Currently, most systems operate under time-varying circumstances and scientists do not know how to evaluate the best system design when the operator in that system moves between time varying circumstances. For instance, a person usually looks for a method that helps him/her select a smart phone that will work effectively in continuous time-varying circumstances rather than in non-time-varying ('fixed' or 'discrete') circumstances. As a matter of fact, different phones provide different functions and user experience. Some phones help users use the phone better in the dark versus under the sunlight or vice versa. Some phones support users effectively in a crowd better than in a quiet room. These phones help users very well in these individual circumstances. However, let's consider these situations dynamically when a user uses a GPS navigation app on your phone navigating directions from tunnels to open highway. In this case, his/her car is moving from a dark area to an outside area. How does the user know that the device enables him/her to navigate the direction due to environmental changes like this? Is the user's device effective to regain the loss-GPS connectivity? Is the user's device effective to allow him/her see the map on the phone after exiting the tunnels because it takes approximately five minutes for the eyes to adapt from darkness to bright sunlight? What phones would the user choose to do his/her job effectively in dynamic conditions like this? This is a practical example of the theoretical concept provided above.

The evaluation of human-integrated system designs is commonly based on some measure of operator performance under one, often "typical" or "optimal," set of conditions (i.e., one "circumstance") (See Figure 1.4a). Although various measures of human performance have been developed, these techniques are still applied in discrete circumstances. In the Figure 1.4a) we will describe the context of discrete circumstances and the relationships between factors in this context. In the Figure 1.4a):

1) There are three separate graphs in Figure 1.4a): each graph depicts the human performance curve under each individual circumstance: circumstance 1 (CIR_1), circumstance 2 (CIR_2) and circumstance 3 (CIR_3). In other words, each curve

describes the human performance separately from others. The occurrences of those circumstances do not relate to others in terms of a temporal sequence.

2) The x-axis is the repetitions of the task (x), where $x \in N_{>0}$. This is the independent variable, i.e. the "cause", where we could directly control.
3) The y-axis is the values of human performance versus the independent variable x. This is the dependent variable, i.e. the "effect". The relationship between two variables is inverse ('negative'); That is, when x increases, y decreases. Graphically, the curve on the performance graph moves from left to right, it falls as a negative slope. The shape of the curve represents the principle: the performance improves (the curve falls) when the repetition of x increases.
4) The dots on curves are the completion time values which are observed at each repetition of x. The higher the dots, the worse the performance; the lower the dots, the better the performance.
5) In general, the performance improvement rate is described as the slope of the curve. The slope of a human-performance curve can be negative or can equal zero. Thus the shape of the curve can be decreasing or remaining constant. Figure 1.3illustrates the shapes of the several curves according to the values of the slopes of the curves. In this figure, the curves start from the repetition 1 (R_1) to repetition 5 ($R_{n=5}$). The curve with a smaller slope will be better (negative number between 0 and 1) than the curve with a larger slope. For example, the blue curve (slope = -1) will be better than the red curve (slope = -0.8); those curves are better than the orange curve (slope = 0).

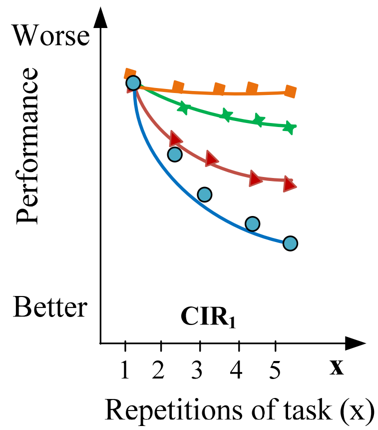
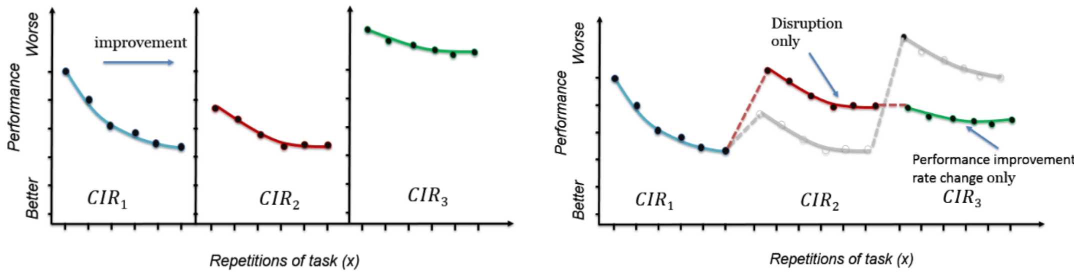


Figure 1.3 Slopes of a human-performance curve

However, most systems operate under time-varying circumstances (See Figure 1.4b), and there exists no measure to evaluate how well different designs accommodate operators' ability to adapt to these changing circumstances. In Figure 1.4, we will describe the context of time-varying circumstances, the relationship between factors in this context and the issues that need to be studied. In Figure 1.4b):

1) Discrete curves in three individual graphs are concatenated to create a new curve. This curve represents a continuous series of time varying circumstances (CIR_i). That means, the curve will depict human performance in a series of time varying circumstance CIR_1, CIR_2, CIR_3;
2) The transitions between two time varying circumstances raise the issues that are affecting human performance. In this figure, the data points are the completion times of a task; the vertical distance between the final data point in a CIR_i and the first data point in the subsequent CIR_{i+1} indicates the disruption because of the transition. In the figure, the color curve shows a significant disruption between CIR_1 to CRI_2 but shows no disruption between CIR_2 to CIR_3. The grey curve which has the same slope with the color curve in CIR_2 has the smaller disruption than the color curve has. However, the grey curve has quite a large disruption from CIR_2 to CIR_3 while the color curve has no disruption.



(a) (b)

Figure 1.4 Human performance in individual circumstances (a), and in time-varying circumstances (b). The curves in figure a) describe human performance in discrete circumstances. There are no relations or connections among these curves; The curves in Figure b) describe human performances in continuous series of time-varying circumstances

Look closely into the difference between the current and the proposed approaches, what happens if an operator does their task under a continuous set of time-varying circumstances rather than a discrete set of individual/one-at-a-time set of circumstances? Transitions to new circumstances might affect human performance, or might not. In addition, transitions not only might affect the shapes of the performance curves but also influence the shift levels of human performance (short or high or no-shifting). These influences cause the interruptions to human performance in a series of time varying circumstances. Moreover, the transition duration is also taken into account when human operators interact with the changing conditions under time-varying circumstances. Therefore, there are at least two effects on human performance that could be of interest: disruption and performance improvement rate change ('slope'). That is, if an operator encounters a sudden change in circumstance, there might be some disruption to their performance, and they may not be able to recover their performance well.

Those effects might be system-dependent in that some systems may have more or less disruption and more or less of a performance improvement rate change. If we change the y-axis to time as a measure of performance, the curves we see are learning curves, and we can compute parameters for disruption and learning slope changes. A log-linear pattern of the learning curve describes a stable process and it will improve its productivity open-endedly. The pattern of the improvement could last beyond expected output of the process (Raccoon, 1996)

The proposed method is an additional option for the decision makers to select a desired system design with reference to using the design in time-varying circumstances. However, the transitions between time varying circumstances raise several issues that could affect human performance. In addition, the time delays of the transitions also need to be studied to find out if they have effects on human performance in subsequent circumstances. These are the fundamental issues that drive the development of the proposed model for measuring human performance in time-varying circumstances and evaluating system designs.

1.3 Problem Statement

The system designs are currently evaluated based on measures of human performance on one, typical or normal circumstance. The circumstance is typically perfect so that the "good" or "bad" outcomes of human performance only should be considered "good" or "bad" in such perfect circumstance. Also, the system designs are evaluated under discrete circumstances, the results of human performance should be properly considered as separate evaluations.

In fact, the system designs are operated under imperfect circumstance, specially under a transition from a normal ('good') circumstance to a non-normal ('bad') circumstance, or vice versa. There is no measure to show how well system designs support human operators to adapt to these changing circumstances. Transitions between circumstances can cause disruptions, and the changing circumstances can influence the slope of the performance curve in the subsequent circumstance. Exploration of how the changing circumstances affect human performance and how to capture these effects is needed. The developed measures in this study are expected to quantify these effects on human performance. This understanding will contribute to the overall knowledge of human performance and provide an additional option to evaluate system designs.

1.4 Research Objectives

This research is about developing a way to measure the performance of humans using a system (‘human integrated system’) such as a computer or a machine under time-varying situations (‘circumstances’). In summary, the research consists of the following objectives:

- develop a symbolic model to describe the human-integrated system performance under time-varying circumstances
- characterize adaptability parameters including disruption and performance improvement rate under time-varying circumstances
- develop metrics to measure human adaptability and system effectiveness
- demonstrate that the above-mentioned measures are feasible and they can be calculated.
- Identify characteristics/distributions of adaptation measures
- Identified whether measures are order dependent or not:
    i. Does sequential (within subjects) presentation affect adaptability parameters?
    ii. What amount/length of delay in between transitions affects adaptability measures?

The purpose of this study is to contribute to this understanding by developing the measures for evaluating the performance of humans integrated system in a continuous series of time-varying circumstances.

1.5 Structure

The dissertation is divided into six chapters. The first chapter introduces the research gaps, the problem statements and the research objectives. The second chapter discusses background on evaluations of systems regarding human performance and learning curves. The third chapter introduces the theoretical work used to develop the adaptability model, and to build the adaptability parameters and system effectiveness. This chapter also describes in detail the proposed measures used in capturing the various aspects of the transitions between continuous time-varying circumstances. A mathematical model of adaptability is also presented in this chapter. Chapter four discusses the first part of the experimental work in which the demonstration experiment was conducted to portray that the measures are feasible and that they can be calculated. Chapters five discusses the second part of the experimental work in which an empirical experiment was conducted to explore the characteristics of adaptability measures. The method and the results of this experiment are also included in this chapter. The implications of the results are then discussed in chapter six. Chapter seven summarizes research results and recommends the future work.

2. LITERATURE REVIEW

This chapter discusses the history of learning curves, the concepts of learning curves and typical models of learning curves. Log-linear models are introduced with a comparison of two typical models of learning curves and an emphasis of using the cumulative average model in our research. We also introduce the learning curve components such as learning slope, learning rate and learning percentage and their relationships. The family of learning curves and learning curves applications are briefly presented in this section but the details will be discussed in the Appendix A and Appendix B. Lastly, learning curves in time-varying circumstances will be proposed. It is a fundamental component for building the adaptability model which is presented in the theoretical work section in chapter 3.

2.1 Overview of learning curves

2.1.1 Learning curve history

Learning curves initially studied by Edward Throndike in 1898 on the learning behavior of a group of cats. The idea was that cats learned how to escape by activating the latch through a number of trial and error experiments. However, the term of “learning curve” was first used by Ebbinghaus in 1913 (Barrett, 1970).

Later, the learning curves (LC) explain resource (cost or time) reductions in some industry. The conceptual foundation of learning curves arose from airframe manufacturing production in aircraft industry (T. Wright, 1936). Conventionally, studies showed that each direct labor input was used to produce a series of orders for a particular aircraft model, which was reduced at a constant rate. The direct labor unit cost was one of the evaluation criteria. The other criteria were human performance time or production time to produce each item. Other versions of the learning curves are the experience curves, which are used to estimate the magnitude of reduction cost.

However, they are not widely used as the learning curves (Abernathy & Wayne, 1974; Adler & Clark, 1991)

2.1.2 Concept of learning curves

The term *learning curve* is first used to represent the knowledge that is learned over time when the assigned task is repeated in a number of trials (Ebbinghaus, 1913). It has been a graphical representation of the outputs of the learning process. Since 1913, it had many applications in a variety of areas such as modeling modern business, forecasting the performance of business structures, measuring workers' learning process (Antunes, Coito, & Duarte-Ramos, 2012; Pietro C Cacciabue, 2011; Fogliatto & Anzanello, 2011; R. Hess & Modjtahedzadeh, 1990; Leamon, 1980; A. Liu & Salvucci, 2001; Macadam, 2003; Patil, 2008; Tian, Wu, Wang, & Zhao, 2011). One of the notable applications is in the aircraft industry (Antunes et al., 2012; Anzanello & Fogliatto, 2011; Baloff, 1971; Crawford, 1944; Fogliatto & Anzanello, 2011; Liao, 1988; McRuer, 1980). In addition, the learning curve shows a crucial principle: the more times a task has been performed, the less time is required for subsequent tasks (See Figure 2.1) (Pietro Carlo Cacciabue, 2004; Ebbinghaus, 1913; T. P. Wright, 2012).

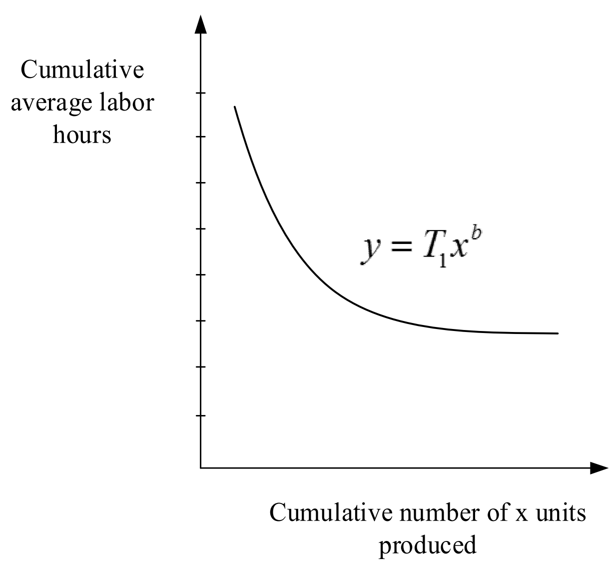


Figure 2.1 Learning curve with learning period and time

A univariate learning curve standard model is the conventional learning curve which presents the ability of learning of human agents to implement an assigned task under one circumstance. The most renowned and widely used model is Wright's model, also called as "log-linear" model. In this model, the criterion is the average labor hours to make x units of a product. Generally, a mathematical representation for learning curve model (Anzanello & Fogliatto, 2011; Teplitz, 1991; T. P. Wright, 2012) is described as follows:

$$y = T_1 x^b \qquad (1.1)$$

where

y = cumulative average labor hour (or cost) to produce or assemble x units

T_1 = labor hour (or cost) to produce or assemble the first unit

b $(-1 \le b \le 0)$= slope of the learning curves. The b coefficient is used to measure the operators' learning slope. If b is close to -1, the operators have fast learning slopes and vice versa.

Learning curves theory explains how a resource becomes more effective after a sequence of the repetitive task. The original contribution to learning curves theory is credited to T.P. Wright in the article "Factors affecting the cost of airplanes" (Barrett, 1970). The learning curve theory includes three assumptions (Chase, Aquilano, & Jacobs, 2001):

1. The assumption of the amount of the completion time: The time to complete a given task will reduce each time the given task is repeated.
2. The assumption of the learning rate: The completion time per unit will decrease at a constant rate.
3. The assumption of the prediction pattern: The reduction time will follow a predictable pattern.

These assumptions were found true in the airplane industry and other industries. Wright (1936) described a learning theory that showed how direct labor costs of making an airplane decreased while the number of airplanes increased at a constant rate. Learning curves has applied not only to labor hours but also to a variety of other costs, including materials and purchased items.

Today, the learning curve theory has a variety of applications such as calculating batch production performance, estimating the capital requirements, reducing direct labor cost components in the construction and installation of the power plants, testing projects in industrial software for validation, analyzing the performance of an organization, plant or factory, describing the technological learning in energy system models, building strategic environmental policy models and evaluating better outcome quality in service organizations (Hentschker & Mennicken, 2015; Mugerwa & Blomen, 1993; Rogner, 1998; Shafiei, Saboohi, & Ghofrani, 2005; Towill & Cherrington, 1994; Tüzün & Tekinerdogan, 2015; Yamane et al., 2015; Ziesemer & Michaelis, 2011).

2.1.3 Concept of *learning*

Learning in the context of operation management refers to advancing effectiveness from a number of the repetitions of a production operation. In addition, learning is time dependent and could be controlled externally. L.E. Yell and D.R. Sule confirmed that human performance enhances through repetitions. Therefore, learning curves have the difference names such as progress curves, improvement curves, performance curves, experience curves or efficiency curves (Sule, 1978; Yelle, 1979). Basically, learning in this context yields the following important principles:

The 1st principle of learning curves: If we perform tasks repetitively, the time that we take to complete subsequent tasks reduces. The learning curve concept is based on doubling principles (Brookfield, 2005). According to Wright (1936), the average direct labor cost (or labor hour) for the cumulative total output is reduced by 20% when the produced items double. In other words, the learning curve effect of the 1st principle of learning curves is *the time per repetition decreases as the number of repetitions increases*.

The 2nd principle of learning curves: The workers are not purposefully taught how to be more efficient. They merely learn how to perform the task better by doing the given task over and over (Leslie & Holloway, 2006).

The relation between the learning and performance constitutes the basic concept of learning curves: *Workers learn while they are working; the more they repeat the operation, the more efficient they become*. Then, the direct labor resource (time, cost) per unit decreases. This reduction in labor time per unit achieves improved productivity. The time spent to produce the 2nd unit, 3rd unit and so on will decrease at a constant rate. The phenomenon is called learning and is a result of repetition (Andress, 1954).

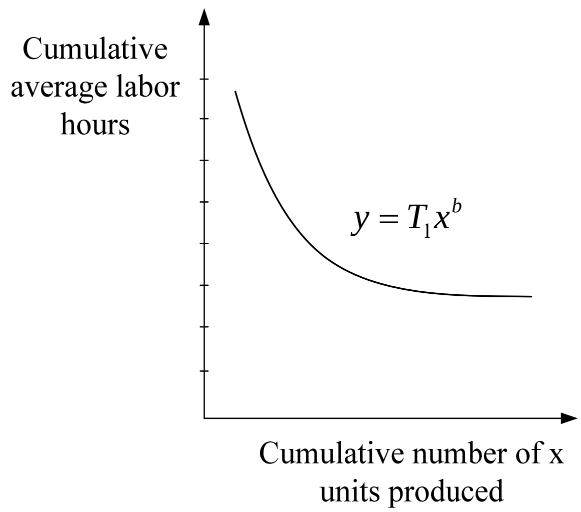
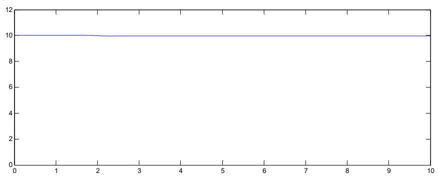
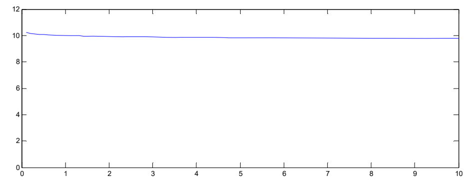


Figure 2.2 A basic learning curve

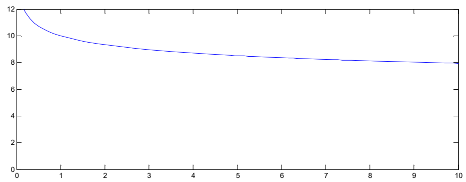
In the following figure, the figures show different "speed" of leaning. The horizontal axis represents any units related to replication such as the number of trials. The vertical axis represents learning criteria such as human proficiency, learning time. Regarding types of learning curves, the steep curve indicates an easy learning task or the operator quickly masters the assigned task, which is finished in a short period of time; the shallow curve denotes a more difficult task in which the operator takes a longer time to complete.



T=10, x=10, b=-0.001



T=10, x=10, b=-0.01



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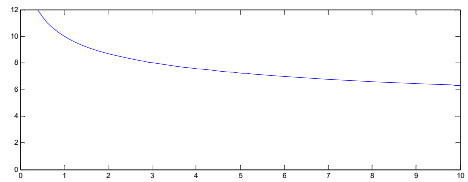
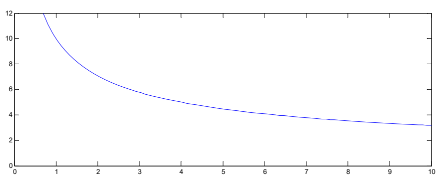


T=10, x=10, b=-0.2



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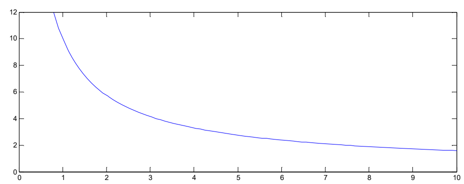
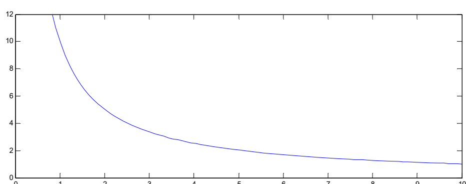
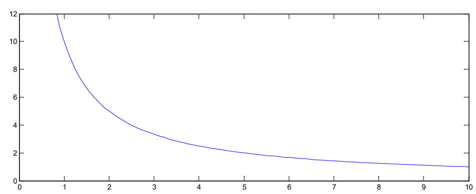


T=10, x=10, b=-0.8



T=10, x=10, b=-0.99



T=10, x=10, b=-1

Figure 2.3 An illustration of different types of the learning curve $y = Tx^{(b)}$ from difficult tasks to easy tasks (left-right and top-down) at Y-axes scale from 0 to 12

2.1.4 Log-linear models

This section will discuss the log-linear learning curve model, which has been widely developed and used in many industries and organizations. Log-linear is the initial model of learning curves, which was introduced first by T. Wright (1936). It indicates a constant improvement in human performance regardless of the final production amount.

There are two types of log-linear learning curves: *Wright's model* and *Crawford's model*. Wright (1936) observed that the cumulative number of aircraft produced doubles; the cumulative cost/hour to produce aircraft reduces at a constant rate. This is known as the cumulative average theory or Wright's model (T. Wright, 1936). On the other hand, J.R. Crawford (1944) observed that the constant rate which describes the decrease in cost should be related to the current unit cost/hour instead of the cumulative average cost/hour. This is known as the incremental unit cost/hour theory, Crawford's model or Stanford model, because Crawford was a researcher at Stanford Research Institute and worked on learning curve theory (Crawford, 1944; Liao, 1988).

Both models use the same equation which is described as the following standard learning curve equation:

$$y = Tx^b$$

where y = cumulative average labor hour (or cost) to produce or assemble x units

T = the first unit hour

b = the learning curve exponent, measured by $\frac{log(r)}{log(2)}$; r is learning rate.

Table 2.1 The meaning of y and x are different under two concepts (Crawford, 1944; Liao, 1988)

Wright' model	**Crawford's model**
y = the cumulative average hour (or cost) of each of the x cumulative produced units x = the cumulative number of produced units	y = the incremental unit hour (or cost) of the x^{th} produced unit x = the algebraic midpoint of a particular production lot

2.1.4.2 Cumulative-average learning curve model (Wright' model)

The cumulative-average learning curve model aims to model the relationship between the cumulative costs per unit and cumulative produced units. This relationship indicates the learning effect: the cumulative cost per unit will decrease by a constant percentage when cumulative production units double. The cumulative average model, which has a geometric form, is expressed as

$$y_x = y_1 x^b$$

where

y_x: cumulative average time per unit or per batch; The learning curve is explained in percentage terms which are depending on the relationship between cumulative average times when the cumulative quantities doubles.

y_1: the time to produce the first unit. In this section, we use y_1 instead of T_1 for easy calculation of learning slope and learning rate.

x: the cumulative units of production or the cumulative number of units/batches

b: the learning coefficient or learning slope which is calculated by $\frac{log\ (learning\ rate)}{log(2)} = \frac{log\ (learning\ curve\ percentage)}{log(2)}$. For the 80 percent curve, we get $b = \frac{log 0.8}{log 2} = -0.322$

<u>Log-linear learning curve</u>

To present the log-linear learning curve in the shape of a hyperbola (See Figure 2.4), we construct the log-log learning curve in the form of the straight-line equation as follow (See Figure 2.5).

$$\log y_x = \log y_1 + b \log x$$

where b is a constant slope of the line

y_x = cumulative average labor hour (or cost) to produce x units

y_1 = labor hour (or cost) to produce the first unit

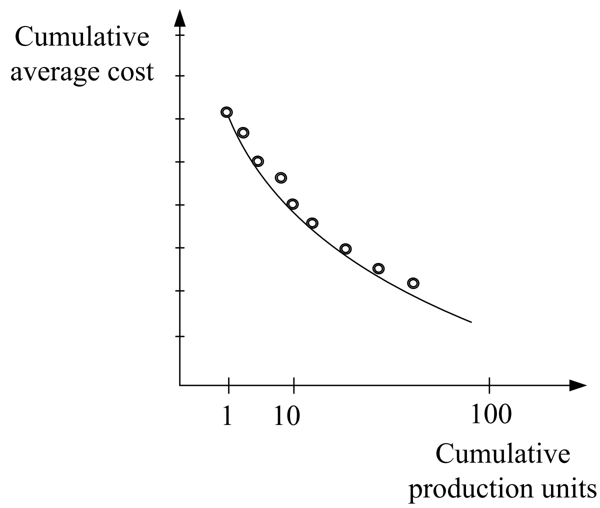


Figure 2.4 Log-linear learning curve

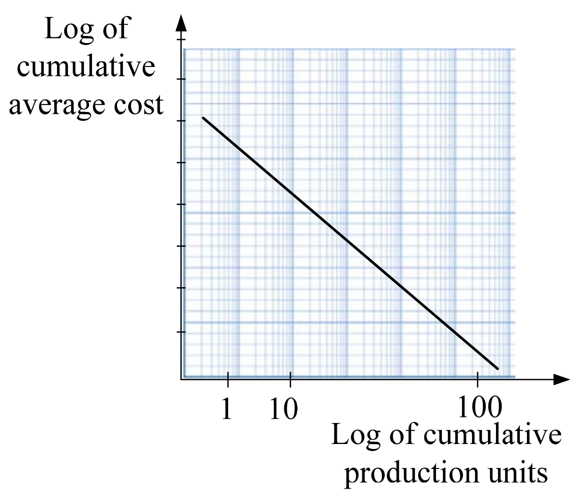


Figure 2.5 Log-log learning curve

Learning rate, total cost, unit cost and marginal cost

The learning rate *r* is determined by diving to consecutive production levels in which one level is a double of the first one:

$$x_2 = 2x_1$$

$$y_{x_1} = y_1 x_1^b$$

$$y_{x_2} = y_1 \left(2x_1\right)^b$$

The percent production or learning rate is computed by

$$r = \frac{y_{x_2}}{y_{x_1}} = \frac{y_1\left(2x_1\right)^b}{y_1\left(x_1\right)^b} = 2^b$$

Formulas for total cost:

$$T_y = \left(x\right) y_x = y_1 x^{b+1}$$

Formulas for unit cost:

$$U_y = y_1 x^{b+1} - y_1 (x-1)^{b+1}$$

Formulas for marginal cost which is the marginal hour (or cost) of producing xth unit:

$$M_y = \frac{d\left(T_y\right)}{dx} = \left(b+1\right) y_1 x^b$$

Many years ago, some disagreement observed over the interpretation of Wright's idea (Barrett, 1970):

- Wright was dealing with the cost of one extra unit of output or the average of some given amount of cumulative output
- According to Wright, "This eighty percent has a definite meaning in that it represents the factor by which the average labor cost in any quantity shall be multiplied in order to determine the average labor cost for a quantity of twice that of airplanes".

Despite the observed disagreement, we could explain this difference because of the usage of the measuring unit. While a unit cost measures the cost of each individual unit (a marginal cost concept), a cumulative average cost measures the average cost per unit of the cumulative output produced (Barrett, 1970).

Example calculations of learning rate

In airframe manufacturing industry, the first unit takes 1000 hours to produce; it is expected that the 80 percent learning curve will fit the performance model. Therefore,

$$b = \frac{log(\ learning\ percentage)}{log(2)} = \frac{log\ (0.8)}{log(2)} = -0.322$$

Table 2.2 Cumulative average vs. cumulative average time (Brookfield, 2005)

Cumulative quantity, units	Production time per unit	Cumulative production time	Cumulative average production time per unit
1	1000	1000	1000
2	600	1600	$800 = \frac{1600}{2} \approx 1000(2)^{-0.322}$
4	960	2560	$640 = \frac{2560}{4} \approx 1000(4)^{-0.322}$
8	1536	4096	$512 = \frac{4096}{8} \approx 1000(8)^{-0.322}$

Let's do simple math to illustrate the principles of learning curve. If we have collected the data from a product production, it takes 1000 hours to produce the first unit; 600 hours to produce the second unit; 960 hours to produce the third and fourth units; 1536 hours to produce the remaining four units (Brookfield, 2005). Then, the learning curves show the relationship between cumulative quantities and cumulative average work hours as the cumulative quantity doubles, the cumulative average time reduces by 20 percent:

1000 (1 unit) → 800 (2 units) → 640 (4 units) → 512 (8 units)

where 640 = 800(80%) and 512 = 640(80%)

In other words, subsequent cumulative average times can be calculated by multiplying the previous cumulative average time by the learning rate of 80 percent. This is an example of an 80 percent learning curve.

2.1.4.3 Unit model (Crawford's model)

Unit model is another way to describe the principles of learning curves. To compare the difference between Wright's model and Crawford's model, two significant observations are brought up as follows (Liao, 1988)

- Each production lot is periodically (annually, monthly, daily, and hourly) different.
- Even built on the same data set, two models produce similar but not identical results.

Therefore, the two models are not interchangeable. The unit cost model is normally used to describe the specific cost to produce x^{th} unit. The equation of the unit cost model is the same with the equation of the cumulative average model except for the method of interpretation (Badiru, 1992, 2011).

2.1.4.4 Cumulative vs. unit models

In the figure below, there are two lines which represent the cumulative average learning curve (upper line) and the unit learning curve (lower line). The unit curve describes the direct labor hours for a specific unit and the cumulative average curve describes the average direct labor hours for all produced units up to a particular cumulative point (Andress, 1954). For example, at 100^{th} unit, the unit curve indicates that it needs 156 hours to produce the 100^{th} unit whereas the cumulative average learning curve shows that it requires about 230 hours to produce each of the cumulative 100 units.

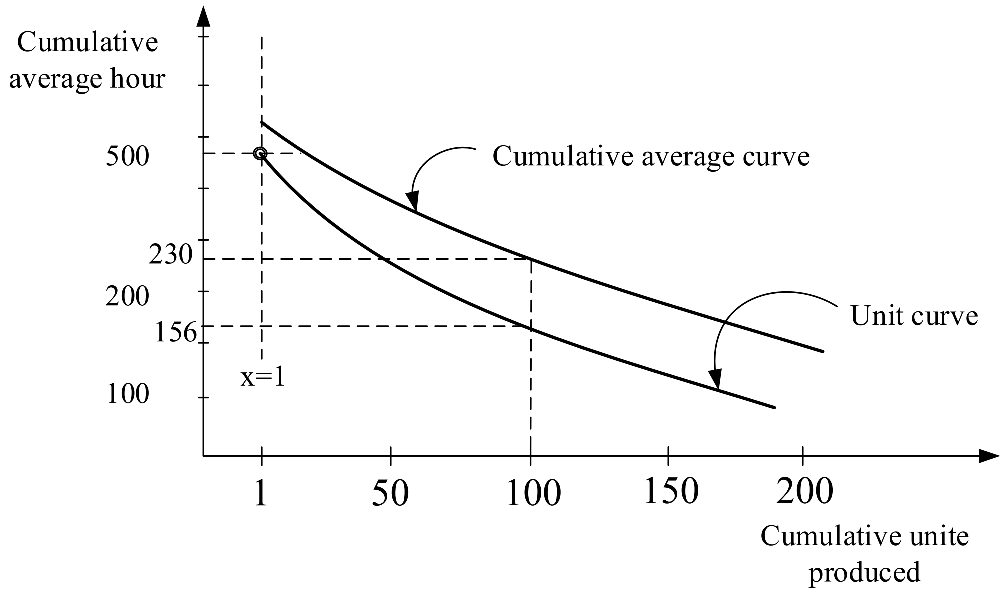


Figure 2.6 A presentation of cumulative average and unit curves on the log-log coordinate

Contrasting to curvilinear functions which can have any shape of slopes, parameter b in the power function of the learning curves implies that y value descends at a constant rate every time x-value doubles. In other words, in the Wright's model, the cumulative average hour decreases at a constant rate while the incremental unit hour decreases at a variable rate. On the other hand, in Crawford's model, the incremental unit hour decreases at a constant rate and the cumulative average hour decreases at a variable rate (Liao, 1988).

If so, which model is better? From a mathematical view, there is no reason for choosing one model over the other. But which model reflects better the true learning patterns in the real world? Liao (1988) stated that 92 percent of businesses used unit model in a study in 1972. According to Liao, several reasons that make the incremental unit model have the advantage over Wright's model (Liao, 1988).

- First, Crawford's model is a "current" figure which offers the operational senses how the decisions are made. On the other hand, Wright's model includes the labor hours of the previous time units (day, month, year) that makes it impossible for the process to be quickly handled. The operators hardly communicate or inform the problem instantly with the other operating employees.

- Second, Crawford's model uses data directly from the records, whereas Wright's model requires additional data manipulation before use.
- Third, Wright's model tends to hide the changes in a production process. For this point, they are dependent on the cumulative average, i.e. all the past production history. If a significant change in the production process occurs, it would reflect a significant change in the cumulative average model.

However, the other researches indicated that the cumulative average curve has the advantage to smooth out the unit data to the unit model. The first figure right below shows that there is no clear relationship among variable unit data. The next figure shows the same data set but displayed by cumulative average data. The cumulative average data shows that it has the capability to predict the improvement. (Thomas, 2009; Thomas, Mathews, & Ward, 1986).

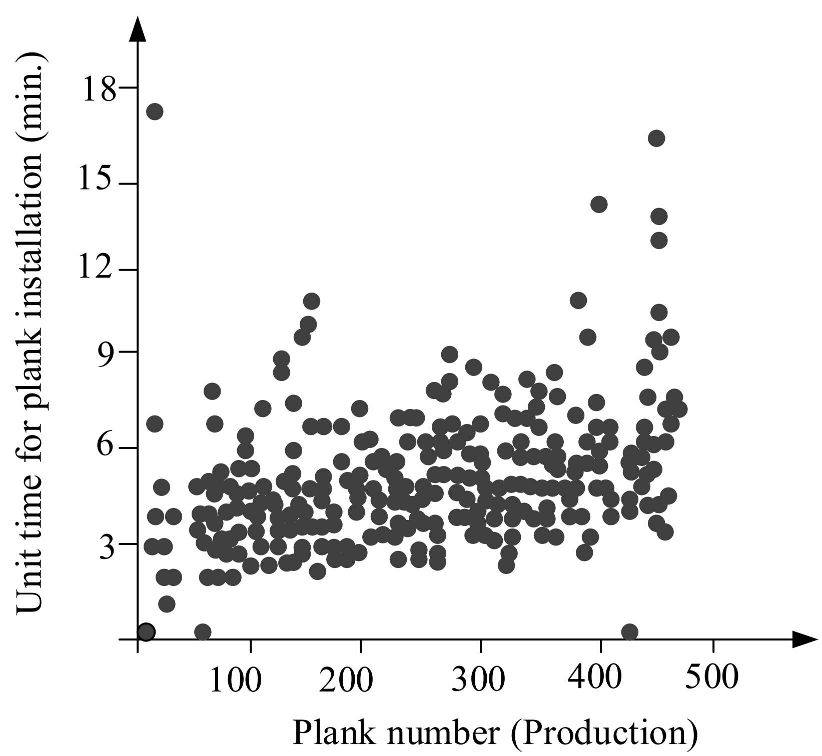


Figure 2.7 Unit data plotted for setting concrete floor planks (Thomas et al., 1986)

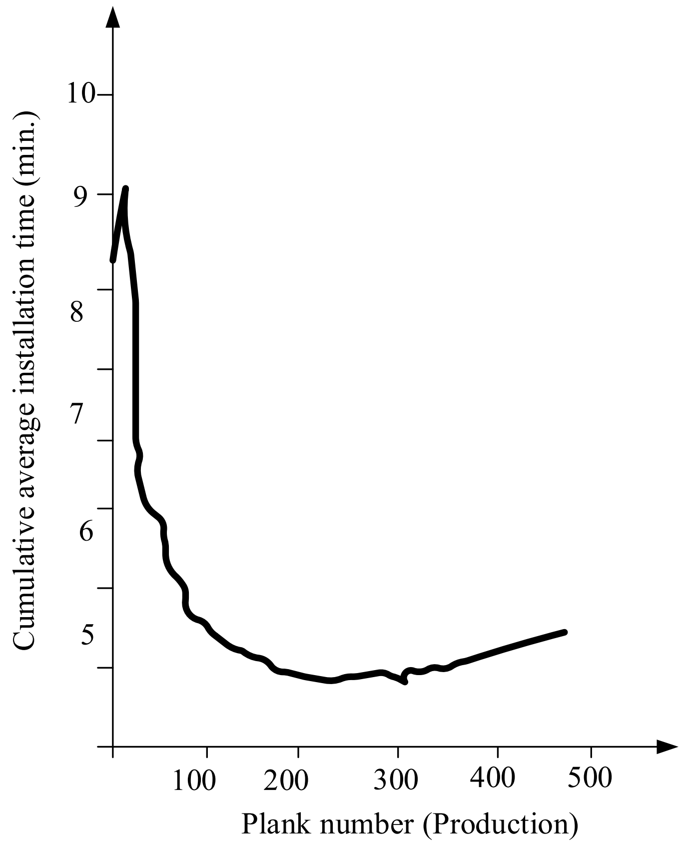


Figure 2.8 Cumulative average plot for setting concrete floor planks (Thomas et al., 1986)

2.2 Estimating the learning rate

Learning rate or learning percentage is generally computed from production records. However, most companies did not start to collect data because the issues might occur in the early stages of production. If the company store records longer, it is more accurate to estimate learning percentage (Stump, 2002).

The learning rate is determined depending on the percentage spent on manual work versus the percentage spent on machine-controlled work. Several estimated learning rates in particular industries are listed as follows

Aerospace = 85 percent learning

Ship building = 80-85 percent learning

Complex machine tools for new models = 75-85 percent learning

Repetitive electronics manufacturing = 90-95 percent learning

Repetitive machining or punch-pass operations = 90-95 percent learning

Repetitive electrical operations = 75-85 percent learning

Repetitive welding operations = 90 percent learning

Raw material manufacturing = 93-96 percent learning

2.3 Learning improvement, learning rate and progress ratio

Regarding the learning curves, does the performance (y-axis) stabilize or continue improvement? In the large-scale system, some industries improve continually over decades such as computers, electronic devices, auto manufacturing, washing machines, and other manufactured goods. Otherwise, high-automated systems may have a near zero learning slope because they have little human's involvement in production.

A log-linear pattern of the learning curve describes a stable process and it will improve its productivity open-endedly. For example, factories, mines and chemical plants are expected to improve their productivities over time and their performance improvement could last beyond expected performance of the process (See Figure 2.9) (Raccoon, 1996).

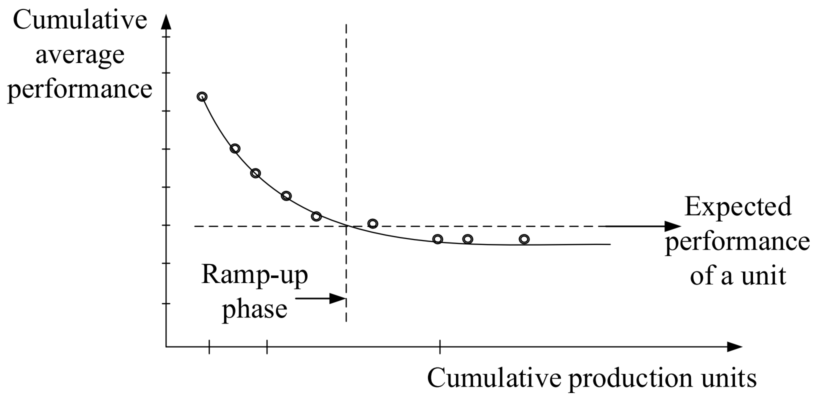


Figure 2.9 Expected vs. actual performance (cost, hour)

Regarding the learning curves, the learning slope and the learning rate can be explained in terms of each other's. The learning rate describes how the unit hour or cumulative average unit hour adjusts every time the cumulative performance doubles (Raccoon, 1996). The learning slope and the learning rate relate to each other by the following equation:

$$Slope = \frac{log(learning\ rate)}{log(2)} = log_2(learning\ rate)$$

We could say, the smaller the learning rate is, the faster the learning happens. A 75% learning rate indicates that the productivity increases very fast. A 99% learning rate means that the productivity improves very slowly. A learning rate greater than 100% means that the productivity gets worse. Actually, many industries have the learning rates between 80% and 90% (Raccoon, 1996).

Operators with a high degree of human involvement have steeper learning slopes than operators with a high degree of machine (Yelle, 1979). Therefore, the higher the learning rate is, the smaller the progress ratio is. The following table describes the relationship between the machine-labor and learning rate:

Table 2.3 The relationship between the machine- labor and learning rate

Machine –Labor (as a percent of total labor)	Learning rate	Progress ratio
25%	80%	20%
50%	85%	15%
75%	90%	10%

In Table 2.3 and Figure 2.10, the uniform learning rates (90%, 80%, and 70%) of the learning curves are subject to manufacturing industry. In the airframe manufacturing industry, it was found that the x^{th} airframe required 80% direct labor hours of the $\frac{x^{th}}{2}$ airframe. For example, the 16^{th} airframe required only 80% labor hours of the eighth airframe. The 20^{th} airframe required 80% labor hours of the 10^{th} airframe, and so on (Yelle, 1979). This reflects the doubling principle that we discussed in the section “Concept of learning” in this chapter.

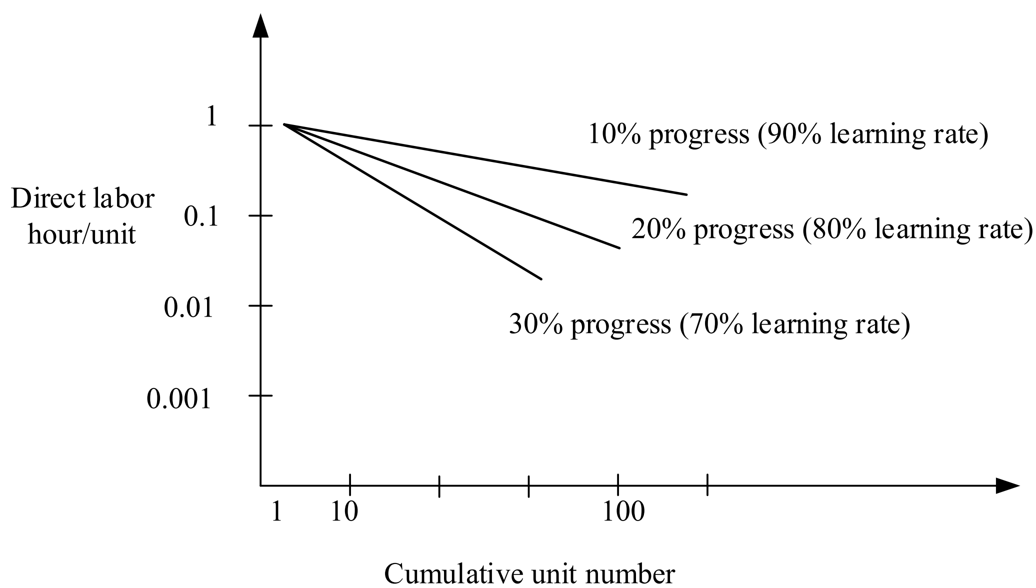


Figure 2.10 The uniform rates (90%, 80%, 70%) of learning curves (Yelle, 1979)

2.3.2 Levels of learning rates

The task mentioned in the learning curves includes two parts used for constructing the learning curve. They are human-paced tasks and machine-paced tasks (Raccoon, 1996).

- Regarding the human-paced task, humans are very flexible and very good at adapting. The more human-paced percentage involved, the steeper the learning curve is.
- Regarding the machine-paced task, machines basically don't improve. In other words, merely mechanical operations cannot be enhanced in learning.

Table 2.4 Levels of typical learning rates

Learning rate	Percent human-paced	Percent machine-paced	Levels
70%-75%	99%	1%	Fast learning rate (*)
80%	75%	25%	Moderate learning rate
90%	25%	75%	Moderate learning rate
98%-99%	1%	99%	Slow learning rate (**)

(*) The learning curve in this case could be improved if the learning continues without disruption.

(**) The learning curve in this case could be improved if the machines facilities need an investment

2.3.3 Learning phases and process stability

A learning curve could be divided into two phases: an initial operation learning phase or build-up phases and the production phase. Build-up phases describe the closed point between actual performance values and the expected performance. When the productivity tends to gradually improve in the first phase, the operators acquire more knowledge. In the second phase, human operators have more familiarity with the given tasks and the learning curve levels off without further productivity improvement (Raccoon, 1996). This happens beyond the last point of the production phase and the following typical characteristics were observed in terms of business investments:

- Short-term losses: the startup stage will need more investments or capital than the "expected performance".
- Long-term gains: The long-term phase will continue to improve open-endedly and exceed the expected performance since production will obtain the returns.

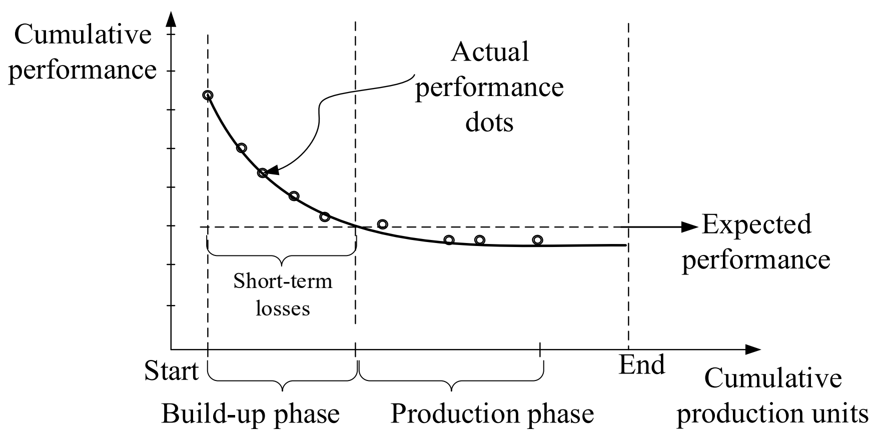


Figure 2.11 Interpreting the learning curves: short-term losses vs. long-term gains

An important criterion of the long-term gain of many learning curves is the *process stability improvement*. For this reason, in order to maintain stability, we should control the instabilities. In the manufacturing industry, the instabilities includes disruptions, bottlenecks and inconsistent motivation (Raccoon, 1996) as follows:

- Disruptions: Disruptions happen when the process involves replacing a worker by another, moving offices, switching products, reorganizing the process, or installing new tools and resources.
- Bottlenecks: Bottleneck happens when the process involves outdated and slow production facilities, or inexperienced workers (See Figure 2.13)
- Inconsistent motivation: If the incentive relaxes when marginal costs fall, the inconsistency might happen. It may affect the productivity and the shape of the learning curve will go up. Human performance may improve under pushing but decline during slack times. Therefore,

the administrators should maintain the incentive to workers before the process is down and up at the other times (See Figure 2.14).

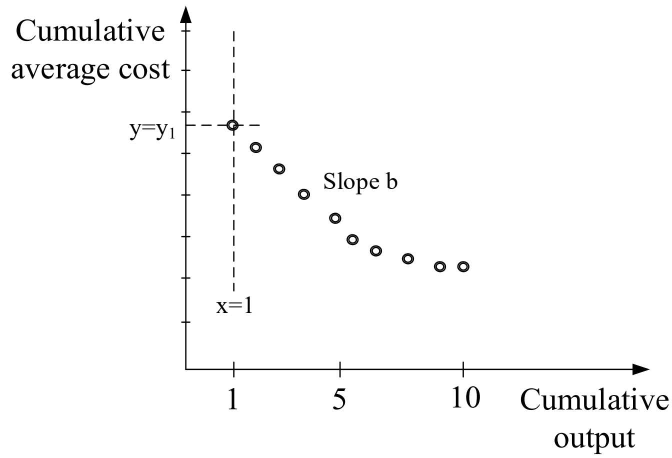


Figure 2.12 A conventional log-linear learning curve

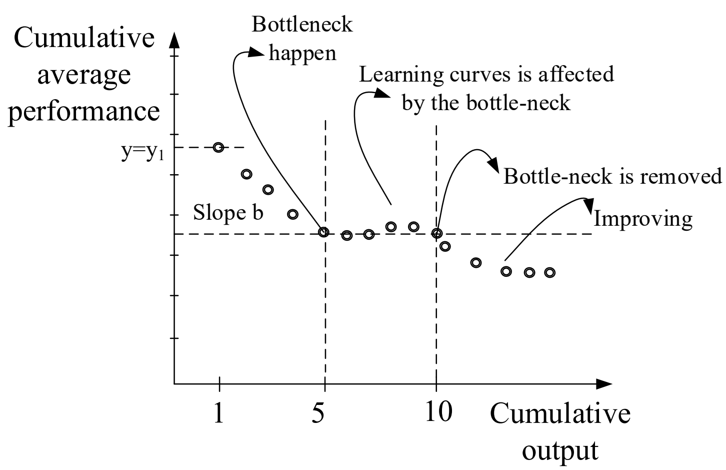


Figure 2.13 Bottlenecks affect the learning curve

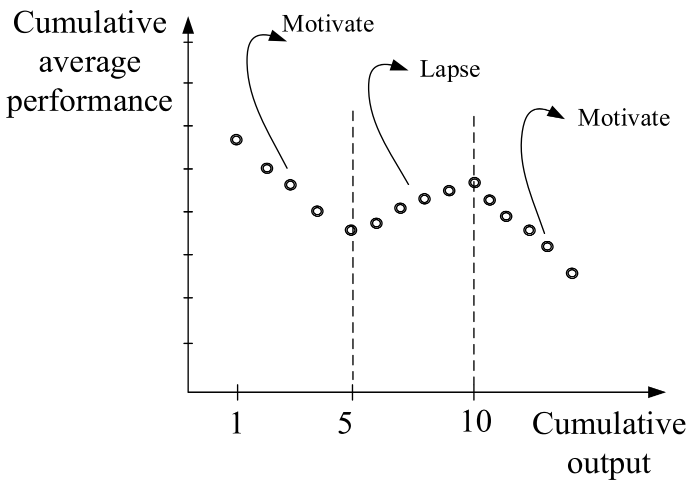


Figure 2.14 Inconsistent motivation

2.4 Individual and organizational learnings

2.4.1 Individual learning

Individual learning is related to the learning of individual human operators. If we would like to compare the skills of human operators, two elements are used. They are learning slope and the initial starting level. These two factors are used to compare the performance times between two workers who performs a simple assembly task. The performance time is the time to perform the given tasks. In Figure 2.15, worker A has a lower starting point and a slower learning slope. In Figure 2.16, worker B has a higher starting point but has a faster learning slope. Chase et al. said that worker B obtains the better skills than worker A because worker B has a faster learning slope and better performance time (Chase et al., 2001). However, it’s hard to tell the amount of the difference just by looking at the learning curves. In this research, we came up with a quantitative method to solve this issue with a different approach to the problem.

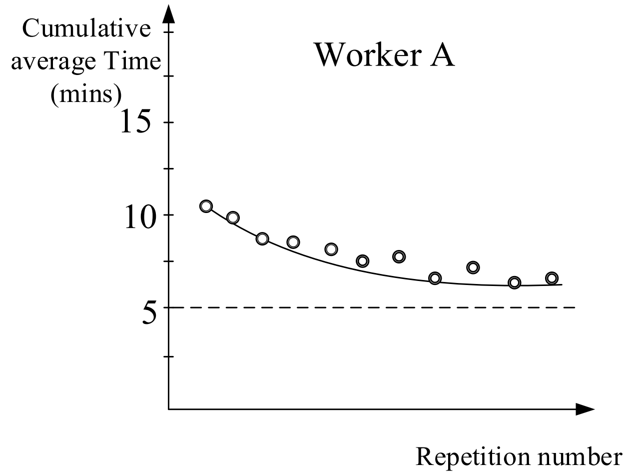


Figure 2.15 The learning curve of the worker A

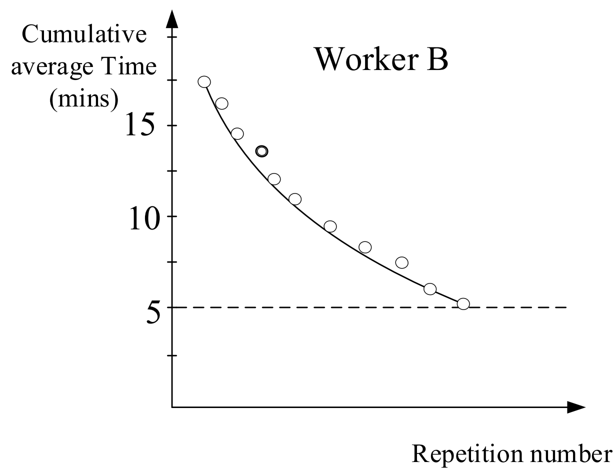


Figure 2.16 The learning curve of the worker B

To consider the problem practically, these are some recommendations to enhance individual performance depending on learning curves:

1. Select appropriate workers
2. Apply appropriate trainings
3. Set motivation

4. Apply work specialization
5. Do one or few jobs at a time
6. Use supporting tools or equipment to support performance

2.4.2 Organizational learning

Organizational learning is related to group or team learning. Organizations often learn to maintain their competitive advantages. Organizational learning is constituted by individual learning of humans in the systems. In addition, the organizations could acquire knowledge from technologies or documents. However, the acquired knowledge can depreciate if individual members leave and organizations or technologies become inaccessible or difficult to use (Chase et al., 2001).

2.5 Graphical presentations of human performance with learning curves

The performance could improve through practice because practice helps to gain knowledge and competency (Ritter & Schooler, 2001). To describe the gaining, there are two graphical ways to present the improved performance that goes with learning curves (Badiru, 1992; Chase et al., 2001; Liao, 1988; Stump, 2002)

- Cumulative average time vs. unit number: cumulative average time shows the cumulative average performance when the production units increase. This type of learning curve is called progressive or product learning (See Figure 2.17).
- Output per time period vs. time: average output during a time period is called average industry learning. It is usually applied to high volume production or in short cycle time (See Figure 2.18).

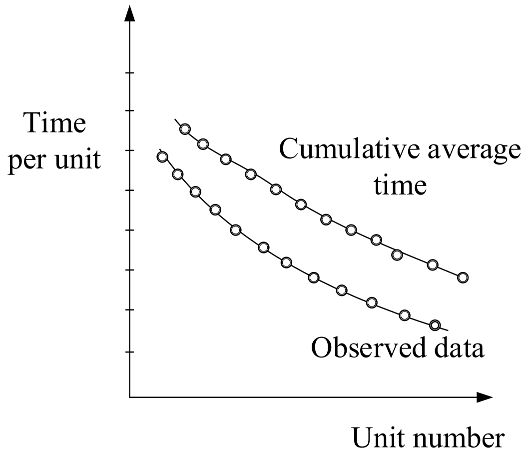


Figure 2.17 Labor time per unit vs. unit number represents the cumulative average performance curve

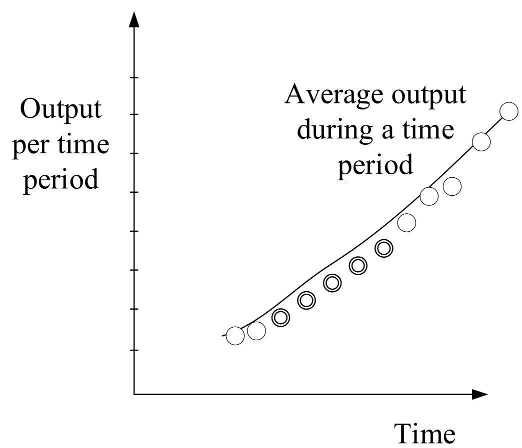


Figure 2.18 Output per time period vs. time represents the industry learning curve

At a comprehensive level, the learning curve concept could apply for individual labor learning or organizational learning (Yelle, 1979). *Individual learning* is the advancement when people repeat a task and gain the proficiency through learning experience. *Organizational learning* is also the improvement through practice, but it derives from changes in administrations, technology, equipment and product design (Chase et al., 2001).

Learning curves are very influential and powerful. It has been broadly applied in strategic decisions regarding employment performance, cost, capacity and pricing (Raccoon, 1996; Sule, 1978). For instance, the learning curves can assist the decision makers to forecast the labor-hour requirements for a product production. It also helps determine suppliers' prices in order to deal with cost negotiations or strategic planning (Raccoon, 1996).

2.6 Family of learning curves models

The conventional univariate learning curve models describe the relationship of one dependent variable (e.g. cumulative average production cost, cumulative average labor hour) and an independent variable (e.g. cumulative production units). These are popular univariate models of learning curves (Badiru, 1992):

1. Log-linear model
2. DeJong's learning formula
3. Glover's learning formula
4. Knecht's upturn model
5. Levy's adaptation function
6. Multiplicative power model (Cobb-Douglas)
7. Pegel's exponential function
8. Plateau model
9. S-curve model
10. Stanford-B model
11. Yelle's product model

As we discussed in the earlier section, log-linear is the initial model which first was introduced by T. Wright. It indicates a constant improvement in human performance regardless the final production quantity. There are two forms of the log-linear model: cumulative average cost/hour model (Wright' model) and unit cost model (Crawford's model). According to Baridu, the cumulative-average learning curve model is more widely used today than the unit cost model. (Badiru, 1992). Log-linear curve is well-known because it offers the best fit model in most situations and be able to predict production performance based on repetitive tasks. (Blancett, 2002). The popular univariate models are discussed in detail in Appendix A.

2.7 Applications of Learning curves

The learning curves originated in the aircraft industry. It discovered that the total output of a given type of aircraft was increased, while the direct labor input per unit regularly declined. This is a very first application of learning curves in industry (T. Wright, 1936).

The learning curve is used to predict the time required to complete a given task. The slope of the learning curve is defined by the ratio between the direct labor hours at any unit of output and the human hours at twice that output (Hartley, 1965).

The learning curve is also used to identify a direct influence on the process of learning which is workers' skills and efficiency versus the standard time (See Figure 2.19). This could be the crucial interest because learning curves consider the other factors such as the complexity of the designs, discontinuities in the production, production control, inspection and organization of the factory as a holistic learning factor (Hartley, 1965).

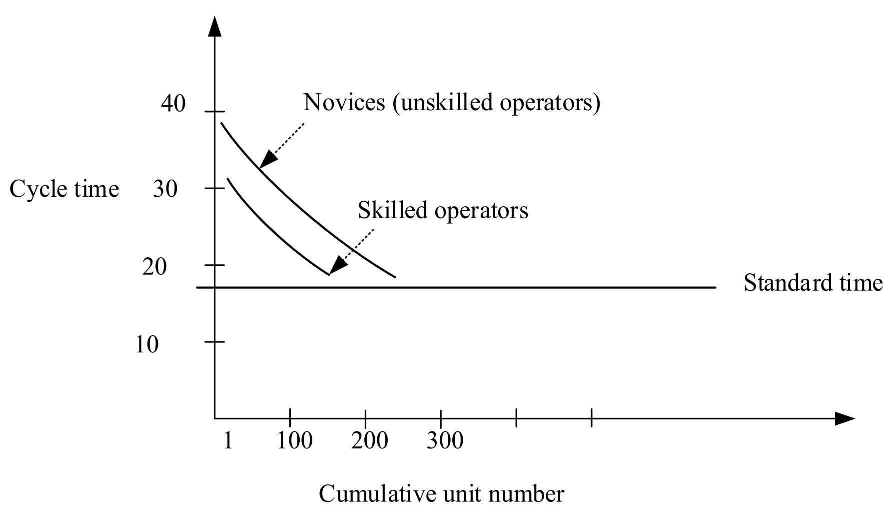


Figure 2.19 Learning curves of novices and skills operators

In some practices, learning curves are used to identify the labor standards. For example, the novices would be assigned more times to learn and take time to be familiar with the task (See Figure 2.19). However, in many cases, the operators achieve the specific levels of skills from performing the other tasks. This makes the standard time identification procedure become fairly complex (Yelle, 1979).

The other summary of learning curves application is discussed in Appendix B.

2.8 Learning curves with time-varying circumstances

Generally, the concept of learning curves has been researched in the assembly manufacturing domain and used for exploring the concept of the adaptability of the human operator when the working conditions have changed. In the first circumstance, if the human operator is able to adapt to the conditions of the circumstance, the learning curve will genuinely decrease with a learning slope, which is uniquely characterized by each human operator. When moving to the next circumstance, the human operator has to learn to adapt to new conditions in the new circumstance. Therefore, the adaptability curve might start a new circumstance at a higher point than the latest point in the previous circumstance, which means the operator spends more time to adapt to uncomfortable conditions while trying to complete the assigned task. This starting point also might be lower than or equal to the last point in the previous circumstance because the operator is not affected by the uncomfortable conditions. The human performances in these two moves are evaluated as the successful adaptation. However, if the human operator is unable to learn to adapt to new conditions, the learning curve will no longer maintain its power curve and it could go in any unidentified shapes (See Figure 2.20).

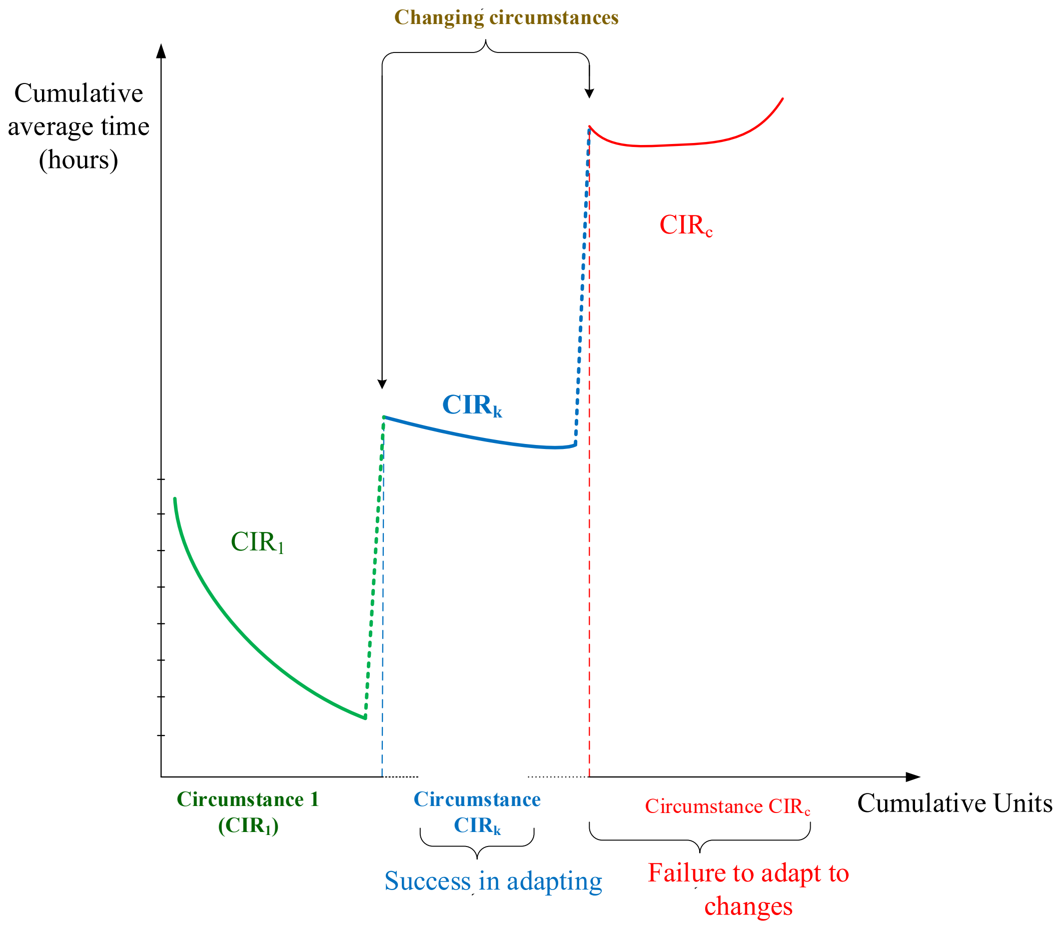


Figure 2.20 The concept of human performance in time-varying circumstances

3. THEORETICAL WORK: THE ADAPTABILITY MODEL

3.1 Concept

An operator does their task under a continuous set of time-varying circumstances (See Figure 3.1). The development of a measure of how well the system allows the operator to handle these transitions between a process of continuous time-varying circumstances. This process is described as the human operator implements the assigned task through c circumstances. As shown in Figure 3.1, the vertical axis represents the cumulative average performance time of each of the x cumulative task-units completed in varying circumstances and the horizontal axis represents the cumulative number of task-units completed in a range of c circumstances. The circumstances are separated by the vertical dash lines. When moving from one circumstance to another, the learning curve will shift-up or –down due to the changing conditions in a new circumstance. This behavior characterizes the adaptability of humans in the integrated system in time-varying circumstances. The learning curves with their changing shapes according to changing conditions will be discussed in more details in the later sections.

Figure 3.1 depicts a human performance curve in c time-varying circumstances. The first circumstance often consists of a set of conditions. To evaluate a system under a circumstance, the human operators run it in several trials. They do the task for the first time, the completion time is recorded, and they do the task the 2nd time, the completion time is recorded, and so on. The collected data is used to model the performance in individual circumstances. The curves show how well human operators do the task in a single circumstance. Then in the following circumstances, the conditions change. The human operators in the system in order to execute the task, must adjust to the new conditions and keep adapting or fail to adapt. This means the learning process is not an event solely happening in fixed conditions; instead, it happens in altered/new conditions and changing circumstances.

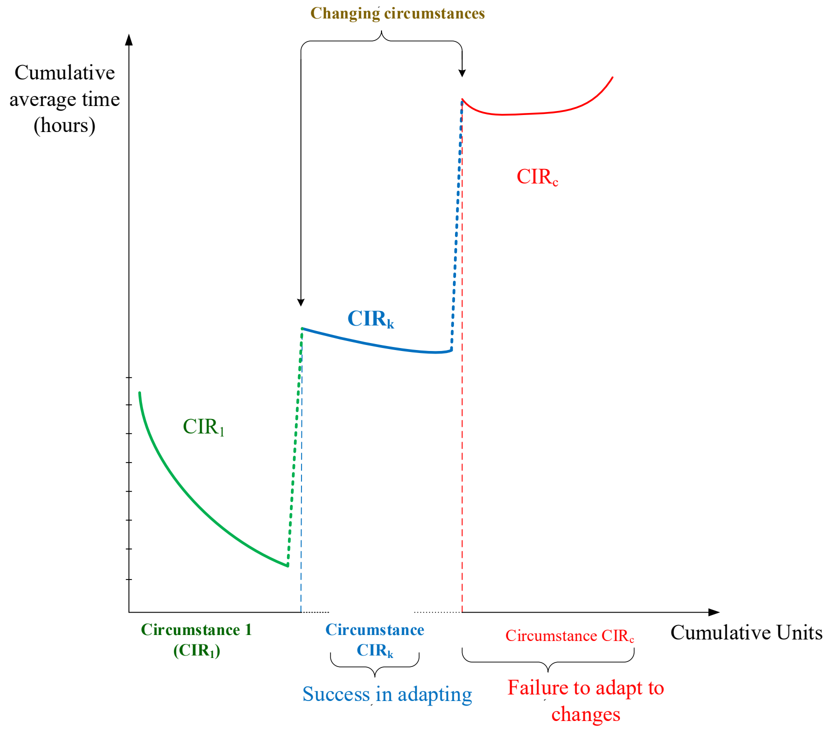


Figure 3.1 The concept of human performance in time-varying circumstances

3.2 Definition

The model of human performance in time-varying circumstances was built on the following definitions:

Definition 1: A *condition* is a singular aspect of the working environment. This condition could be a characteristic or restriction of the working environment and it affects human performance. A condition is denoted by $C_i, i = 1 \rightarrow n$ where n stands for the total number of system conditions, and a condition value is dependent on the actual characteristic or restriction. For example, conditions of a working environment might be lighting, temperature, background noise, indoor or outdoor.

Definition 2: A *nominal condition* is a condition where its characteristic value does not influence the outcomes of human performance. In contrast, a non-nominal condition is a condition where its characteristic value does not influence the outcomes of human performance. For example: C1='*nominal* lighting level if the illumination is equal to 500 lux'. At this level, the condition is expected to not affect the human performance (Konz & Johnson, 2004); C2='*non-nominal* (low) lighting level if the illumination is less than 50 lux'.

Definition 3: A *circumstance* is a process of the working environment that happens in a period of time and may influence human operator performance, or influence the system that produces changes in human performance, or the performance of human-integration in a system. A circumstance consists of a set of multiple conditions which condition values and are consistent across a circumstantial period of time. A circumstance is denoted by $CIR_k = \{C_i\}$, $i = 1 \rightarrow o_k$ *and* $k = 1 \rightarrow c$; where $o_k \leq n$ stands for the number of conditions in circumstance CIR_k, and c is the number of observable circumstances. For example: CIR_1= {C1='normal lighting level at 500 lux-750 lux', C2='normal temperature at 27°C-30°C', C3='noise level below 70 dBA and greater than 60 dBA'}; CIR_2= {C1='low lighting level where C1 value below 500 lux', C2='low temperature where C2 value lies in a range of 10°C-12°C', C3='noise level below 85 dBA and greater than 75 dBA'};

Definition 4: The *time-varying circumstances* describes a process of different working environments that occur in a sequence that affect human performance. Each circumstance might have different periods of time and condition values in an individual circumstance which are consistent across this circumstantial period of time. *That means* when a system is in a circumstance, the condition values are constant through this circumstantial period of time; the conditions only change to new values when the system moves into a new circumstance.

Definition 5: The *adaptability* of a human-integrated system is the capability of the human operator to retain the learning ability and to complete the task when the circumstances change.

3.3 Model formulation

A model of human performance in time-varying circumstances is based on Wright's model of learning curves (Liao, 1988; T. Wright, 1936) and is represented in a form of piecewise learning curve equations as follows:

$$A_i(x) = T_i(x - U_{i-1})^{b_i},\ x \in [L_i, U_i] \tag{1.1}$$

where

$A_i(x)$ = the *cumulative average performance time* of each of the x cumulative task-units completed in circumstance *i*. For convenience, I will refer to this as 'performance time'. For example, in manufacturing, $A_i(x)$ could be the cumulative average man-hours of each of the cumulative units produced in circumstance *i*.

T_i = the *first* performance time in circumstance i, $i = 1, \ldots, c$.

x = the *cumulative number of task-units* completed in c time-varying circumstances; $x \in [L_i, \mathrm{U}_i]$ where i refers to an individual circumstance i, L_i and U_i are lower bound and upper bound that form an interval for circumstance i and $x \geq 1$.

b_i = learning curve exponent $(-1 \leq b_i \leq 0)$, or *learning slope* in circumstance i, measured by $\dfrac{\log(r)}{\log(2)}$. This means the value of $A_i(x)$ decreases at a constant rate when x is doubled. The value of b close to -1 means the operator has a fast learning ability.

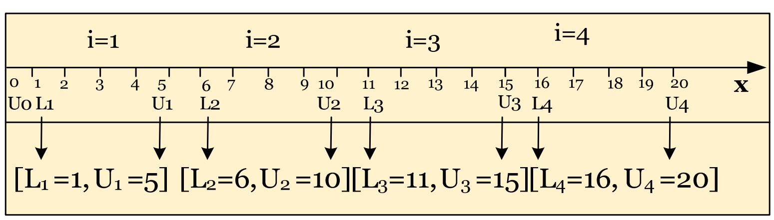


Figure 3.2 An illustration of the cumulative number of task-units completed in c=4 time-varying circumstances

In the figure above, the x-axis represents the cumulative number of 20 task-units in four circumstances. A range of lower bound L_i and upper bound U_i defines each circumstance. The bound ranges of these circumstances are illustrated in Figure 3.2.

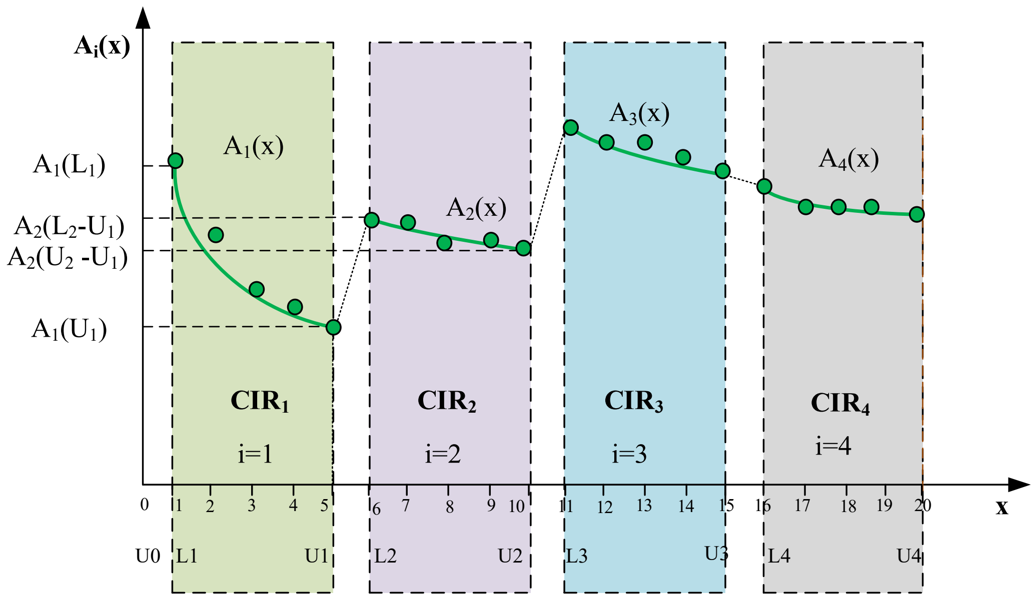


Figure 3.3 The lower- and upper-bound ranges in four time-varying circumstances

Figure 3.3 describes the performance of a human operator who runs a system design in four time-varying circumstances. Each circumstance is formed by a range of lower bound L_i and upper bound U_i. For example, CIR_1 is bounded by a range of $[L_1 = 1,\ U_1 = 5]$, CIR_2 is bounded by a range of $[L_2 = 6,\ U_2 = 10]$ …and so on. A dynamic process of time-varying circumstances is discussed as follows:

- In CIR_1, an operator starts the first replication, where $x=1$, and obtains the performance time at ($x=1$, $A_1(x) = L_1$). From the formula (1.2), we have $A_1(x=L_1=1) = T_1(x-U_0)^{b1} = T_1$, where $U_0=0$, $x=1$. In repetitions that follow, the performance times decrease at a constant rate along the learning curve C_1 every time x is doubled. U_1 signifies the total amount of repetitions that the operator has undergone in CIR_1. The steeper the curve is, the quicker the operator completed the task.

- In the next step, the operators face a new circumstance. The transition between two circumstances might cause a disruption. It affects the human operator's performance time. Therefore, the performance time at $x=L_2-U_1$, for example, might be higher than the last value in the previous circumstance, and the learning slope b_2 is also less steep than b_1 in CIR_1.
- The operator's performance time in these circumstances are represented by the piecewise learning curves with learning slopes of b_1, b_2, b_3 *and* b_4, respectively. Hypothetically, it might be the case that the performance is unstable and the learning slopes becomes unpredictable, which means the operator is unable to adapt to a new circumstance.

3.4 Measures of adaptability

3.4.1 Learning slope

Learning slope b_k is a measure of the performance improvement rate in a single circumstance. There are several mathematical methods that could be used to estimate learning coefficient b_k, in which a widely used method is the least-squares method (LSM). This method aims to minimize the summed square of residuals by using least-square errors algorithm or least-square linear regression to predict the learning curve parameters (Lerch & Buck, 1975; Y.-T. Liu, Mayer-Kress, & Newell, 2003; Roessingh & Hilburn, 2000). Many software packages that offer flexible LSM methods are used to estimate the learning coefficient b_k.

3.4.2 Learning index

The learning index is a measure of performance improvement rate. This measure of the operator kth in a set of p operators is calculated by averaging learning slopes in c circumstances. The formula of learning index is defined as follows:

$$LI_k = \frac{\sum_{i=1}^{c} b_i}{c} \tag{1.2}$$

where LI_k = learning index. In terms of statistical presentation, this index is denoted by $\bar{b}$

b_i = learning slope in circumstance *i*, *i=1...c*;

c = the number of observable circumstances;

In this case, the smaller the LI_k, the faster the human operator learns. In addition, comparing the learning indexes' standard deviations (*SD*) among the operators also gives us the information about the levels of the variability among the learning slopes.

3.4.3 Adaptability coefficient

The adaptability coefficient $\gamma_{i,i+1}$ is used to measure the disruption between two continuous time-varying circumstances. It describes how fast the human operator adapts to a new time-varying circumstance and is calculated by dividing the last performance value in a preceding circumstance to the first performance value in a subsequent circumstance. The formula of adaptability coefficient is defined as follows:

$$\gamma_{i,i+1} = \frac{A_i\left(U_{i+1} - U_i\right)}{A_{i+1}\left(L_{i+1} - U_i\right)} \qquad for\ 1 \le i \le c \tag{1.3}$$

where $A_i(U_{i+1}-U_i)$ and $A_{i+1}(L_{i+1}-U_i)$ are cumulative average performance times of each of *x* units in two consecutive circumstances;

$\gamma_{i,i+1}$ = adaptability coefficient of an operator from CIR_i to CIR_{i+1}

By default, $\gamma_{0,1} = 1$ for $i = 0$

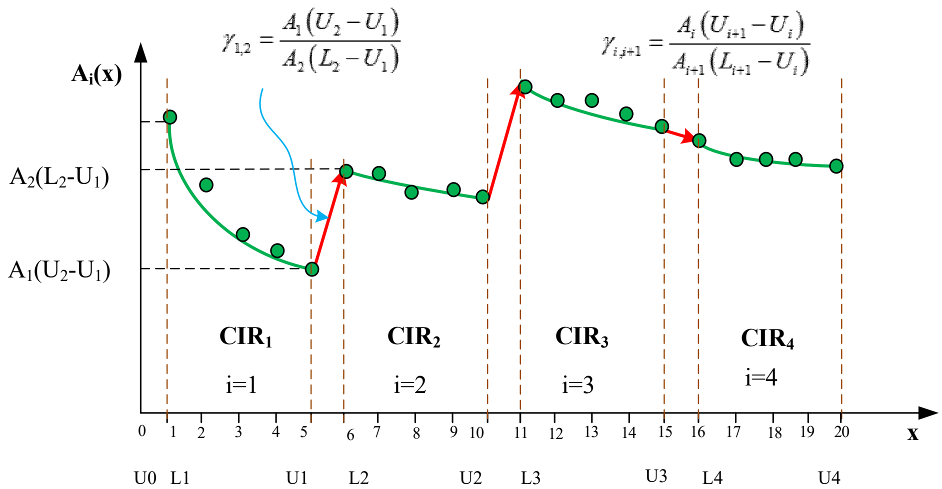


Figure 3.4 Adaptability coefficients of an operator from CIR_i to CIR_{i+1}

3.4.4 Adaptability index

The adaptability index is a measure of the disruption of a human operator in c circumstances. The adaptability index of an operator *k* is calculated by averaging individual adaptability coefficients $\gamma_{i,i+1}$ in c circumstances. The formula of adaptability index is defined as follows:

$$AI_k = \frac{\sum_{i=1}^{c-1} \gamma_{i,i+1}}{c-1} \qquad (1.4)$$

where AI_k = adaptability index. In terms of statistical presentation, this index is denoted by $\overline{\gamma}$

$\gamma_{i,i+1}$ = adaptability coefficient of an operator in CIR_{i+1}

c = number of observable circumstances

In this case, the larger the AI_k, the better the human operator adapts. In addition, comparing the adaptability indexes' standard deviations (*SD*) among the operators also gives us information about the levels of the variability among the adaptability coefficients.

3.4.5 Learning index of human operators tested in a system

Given n designs of a system, D_1, D_2..., D_j... D_n. LI_{D_j} is a measure for measuring the performance improvement rate of human integrated system D_j. The formula of this measure is described as follows:

$$LI_{D_j} = \frac{\sum_{k=1}^{p_j} LI_k}{p_j} \tag{1.5}$$

where LI_{D_j} = learning index of system design D_u; In terms of statistical presentation, this index is denoted by $\overline{\overline{b}}_{D_j}$

LI_k = learning index of operator k

p_u = number of operators tested in system design D_u

3.4.6 Adaptability index of human operators tested in a system design

Given n designs of a system, D_1, D_2, D_u…D_n. AI_{D_u} is a measure for measuring the adaptability coefficient of human integrated system D_u. The formula of this measure is described as follows:

$$AI_{D_u} = \frac{\sum_{k=1}^{p_u} AI_k}{p_u} \tag{1.6}$$

where AI_{D_u} = adaptability index of system design D_u ; In terms of statistical presentation, this index is denoted by $\overline{\overline{\gamma}}_{D_j}$

AI_k = adaptability index of operator k

p_u = number of operators tested in system design D_u

3.4.7 Effectiveness of a system design (E_{Du}/PS)

To compare the *n* designs of a system, $D_1, D_2, D_u \ldots D_n$, we developed a measure to evaluate the system's effectiveness. This is *a performance score* (PS) and is calculated by averaging total human performance of every operator tested in design D_u, $u=1...n$ across time-varying circumstances. In other words, performance score is the average of total performance time in time-varying circumstances that human operators successfully complete the task by using the given system. The formula of the effectiveness score is defined as follows:

$$E_{D_u} = \frac{\sum_{k=1}^{p_u}\left[\sum_{i=1}^{c}(U_i - U_{i-1})A_i(U_i - U_{i-1})\right]}{p_u} = \frac{\sum_{k=1}^{p_u}\left[\sum_{i=1}^{c}(U_i - U_{i-1})[T_i(U_i - U_{i-1})^{b_i}]\right]_k}{p_u} \qquad (1.7)$$

where E_{D_u} = *effectiveness of system design* D_u

p_u = number of operators tested in design D_u

c = number of circumstances

U_i = upper bound of circumstance i

The design with the lowest effectiveness will be considered within the framework the best:

$$E^* = \min\left(E_{D_1}, E_{D_2}, \ldots E_{D_u} \ldots, E_{D_n}\right)$$

In a case where a learning curve model does not fit observed data, in other words the human operator may fail to complete the task in a repetition in a particular circumstance, the function of $\left[xA_i(x)\right]$ is replaced by

$$\sum_{j=L_i}^{U_i} y_j \qquad (1.8)$$

where $\sum_{j=L_i}^{U_i} y_j$ = the cumulative average performance gains in a circumstance and

y_j = performance time at the repetition j

3.4.8 Usability/preference subject score (SS)

The preference score is an index to reflect the extent to which a system over a set of continuous circumstances influences human performance. From here on, after subjects run a system through sets of circumstances, they are asked how the circumstances affect their performance, how they perform the task under these circumstances and how the system supports humans to complete the task. For example, here are the questions that subjects are asked about their performance and the system: If it is 'Strongly agree,' it is scored 1; if it is = Mostly agree,' then it is scored 2 and so on; and if it is ‘Strongly disagree,' it is scored 7. This measure is termed the preference of the participants. The total preference scores for each system design in time-varying circumstances is denoted by SS_{Dj}.

In our research, The Post Study System Usability Questionnaire (PSSUQ) was applied to evaluate usability or subject preference choice. The PSSUQ in this study includes a 16-item questionnaire which was given to a subject at the end of each experiment. The PSSUQ presented subjects with a set of statements in 7-point Likers scales. The PSSUQ applies the following scale: 1 = Strongly agree, 2 = Mostly agree, 3 = Agree, 4 = Neither agree nor disagree, 5 = Disagree, 6 = Mostly disagree, and 7 = Strongly disagree (For specific questionnaire used in our research, see Appendix M. Questionnaire form).

3.5 System design evaluation regarding adaptability parameters

In this section, we introduce classification of the evaluation of system designs regarding adaptability parameters. Given that we have several system designs, D_u where $u=1, 2, 3\ldots m$; m = number of system designs. See Appendix C-Classification of adaptability coefficient for more detail.

Table 3.1 System designs with adaptability parameters

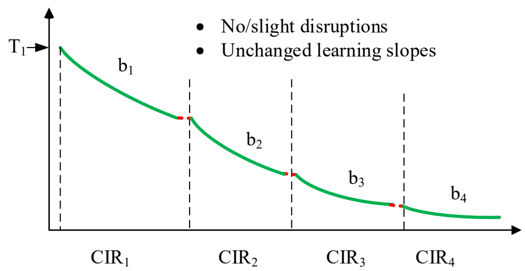
Parameters	Classification	Evaluation
$\gamma_{i,i+1} \approx 0$ and $A_i(U_{i+1}-U_i) \ll A_{i+1}(L_{i+1}-U_i)$	No adaptability	Design D_u does not support the adaptability in circumstance CIR_{i+1}
$0<\gamma_{i,i+1}<1$ and $A_i(U_{i+1}-U_i) < A_{i+1}(L_{i+1}-U_i)$	Passive adaptability	Design D_u supports passively the adaptability in circumstance CIR_{i+1}
$\gamma_{i,i+1}=1$ and $A_i(U_{i+1}-U_i) \approx A_{i+1}(L_{i+1}-U_i)$	Perfect adaptability	Design D_u supports perfectly the adaptability in CIR_{i+1}
$\gamma_{i,i+1}>1$ and $A_i(U_{i+1}-U_i) > A_{i+1}(L_{i+1}-U_i)$	Active adaptability	Design D_u supports actively the adaptability in CIR_{i+1}
$b_{i+1} \geq 0$ and $-1 \leq b_i < 0$	No learning	It is no learning ability in circumstance CIR_{i+1}
$-1 \leq b_i < b_{i+1} < 0$	Learning decreases = lower performance	It is lower learning ability in circumstance CIR_{i+1} than in circumstance CIR_i
$-1 \leq b_i \leq b_{i+1} < 0$	Learning is unchanging = performance does not change	Learning ability does not change in circumstance CIR_{i+1}
$-1 \leq b_{i+1} < b_i < 0$	Learning increases = higher performance	It is higher learning ability in circumstance CIR_{i+1} than in circumstance CIR_i

3.6 Some cases of adaptability parameters

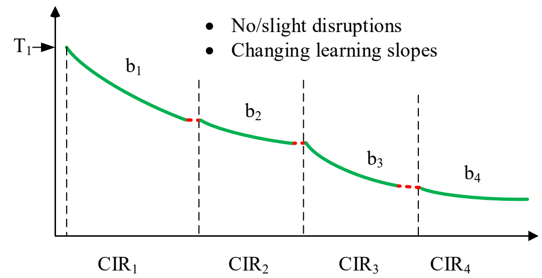
The conditions of circumstances are factors of working environments that might affect the performance of human integrated systems. Thus, the operators in the system have to adapt to the new conditions if they want to finish the assigned task; otherwise, they would fail to adapt to new circumstances.

When transitioning to new circumstances, the learning curve might shift up or shift down due to the influences of new conditions. If the learning curve shifts down, that means the conditions of the current circumstance tend to well support the adaptability at the first trial, and the learning process would attain promising performance improvement at the following trials in the same circumstance. On the other hand, when the learning curve shifts up, that means the conditions do not well support the learning activity at the first trial. It's likely that the operator needs more time to adapt to the new conditions and perform the task. The steeper the upward shift, the farther the distance from the last performance value in the previous circumstance, and the less chance for the operators to continue to succeed at the later trials. To know what's good and what's bad about the measures, see the table below which lists some cases of adaptability parameters in time-varying circumstances. For additional analysis on adaptability parameters, see Appendix C. Classification of adaptability coefficient and Appendix D. Some patterns of adaptability parameters.

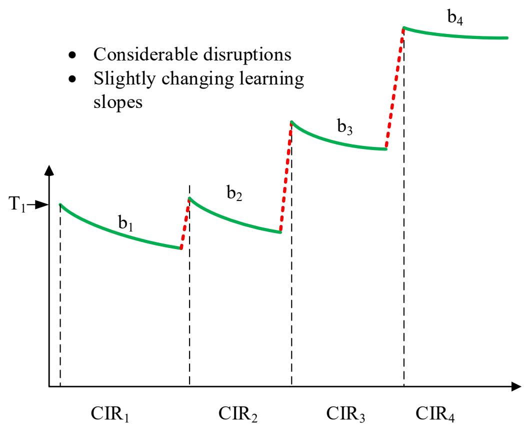
Table 3.2 Some cases of the adaptability parameters in time varying circumstances



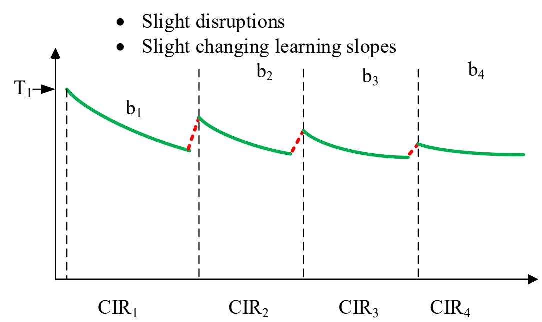
a) Disruptions and learning slopes are unaffected by changing circumstances



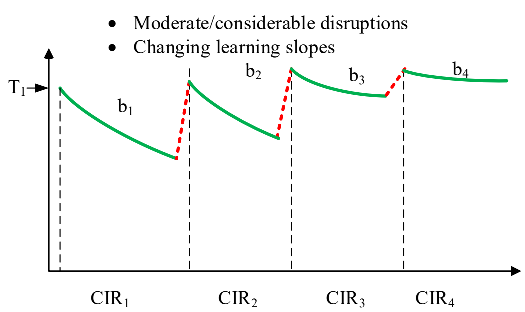
b) Disruptions show no change but learning slopes could be affected by changing circumstances



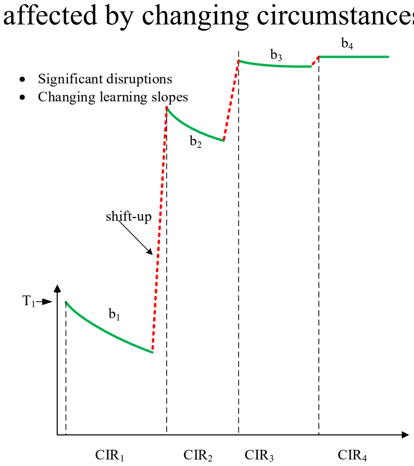
c) Disruptions and learning slopes are affected by changing circumstances



d) Disruptions and learning slopes are affected by changing circumstances



e) Disruptions and learning slopes are affected by changing circumstances



f) Disruptions and learning slopes are significantly affected by changing circumstances

4. EXPERIMENTAL WORK: DEMONSTRATION STUDY

The experiment work was designed to test and prove the proposed measure with respect to time-varying circumstances. It includes the demonstration study and an empirical experiment. This chapter discusses the demonstration study and its results. Chapter 5 will be the empirical experiment and the results of the experiment are discussed based on the findings on chapter 5.

4.1 Purpose

The purpose of the demonstration study is to determine that the measures can be calculated and if the task is able to be performed across time-varying circumstances.

4.2 Method

4.2.1 Participant

A group of four students in our lab voluntarily joined the study representing a variety of gender, age or academic backgrounds.

4.2.2 Demonstration task

The demonstration task is to search and isolate objects in a series of time varying circumstances in a short amount of time. Search-and-isolate is an integral part of search-and-rescue operations where humans cannot enter the scene. The human operator is part of a human-machine system who remotely operates the robot's mechanical arms and carries out the assigned task.

In my experiment, I test the use of a human-robot design for the task search and isolate an object in a series of time varying circumstances (See Figure 4.1). The objective is to search a certain area, find and isolate a target, in this case a ball, at different positions. The robot is controlled through a radio transmitter, receiver and mounted camera. Robot components include one servo motor, two wheels, two controlled arms, two arm motors and a central control circuit. The operator can control the robots to move in both forward and reverse directions and to move left and right if there are any obstacles.

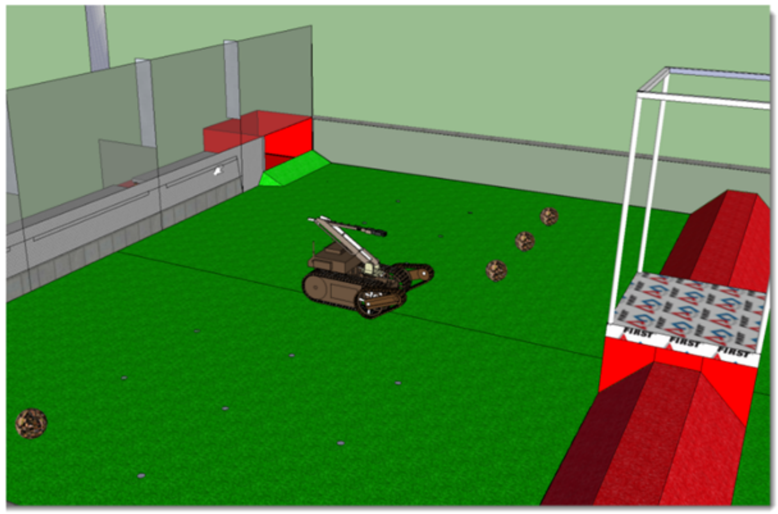


Figure 4.1 The search-and-isolate task

4.2.3 Experimental circumstance

The context for the search-and-isolate task is established by constructing a time varying circumstance experiment area (See Figure 4.2). To set up different conditions, the installed equipment or materials will be manipulated (See Table 4.1 Setting values of experiment conditions). The experimental facilitator is responsible for monitoring and adjusting the condition values regarding particular circumstances (See Appendix E. Validity procedure for the settings of demonstration experiment and Appendix F. Literature review: validities in research process).

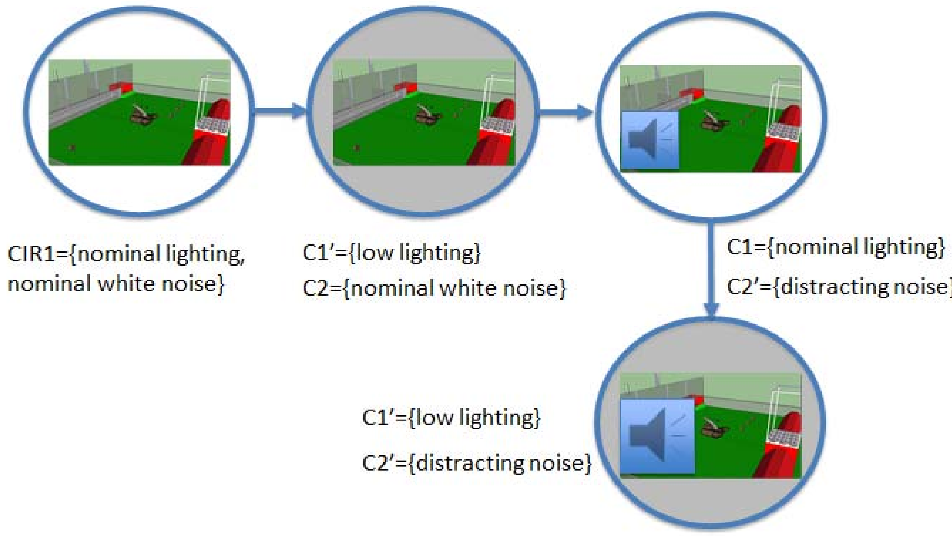


Figure 4.2 Four time-varying circumstances

In our studies, the circumstances are constructed by including one or a set of conditions as follows:

1) Circumstance 1 consists of a set of nominal condition Ci. For instance, CIR1= {C1, C2}, where C1= {nominal lighting} and C2= {nominal white noise}
2) Circumstances 2 and 3 consist of one nominal condition and one non-nominal condition, respectively Ci and Ci'. For instance,
    a. Circumstance 2 = {C1', C2}, where C1'= {low lighting} and C2= {nominal white noise}
    b. Circumstance 3 = {C1, C2'}, where C1= {nominal lighting} and C2'= {distracting background noise}
3) Circumstance 4 consists of a pair of two non-nominal conditions Ci'. For instance, Circumstance 4 = {C1', C2'}, where C1'= {low lighting} and C2'= {distracting background noise}

Table 4.1 Setting values of experiment conditions

Conditions	Description	Condition value
C_1	Nominal condition: *normal* and *continuous lighting* and *white noise*	For the performance of visual tasks of high contrast and small size, the condition value is equal to 500 lux (Konz & Johnson, 2004) The recommended values of noise criteria (NCB) at factory and shop areas is about 55–70 dBA. The background noise value is equal the upper limit, 70 dBA (Barron, 2002; Konz & Johnson, 2004)
C_2	Non-nominal condition: *low* lighting	Lighting for public spaces, the condition value equals 50 lux (Konz & Johnson, 2004)
C_3	Non-nominal condition: *factory background noise*	Because noise legislation permitting is 85 dBA for 16 hours of exposure, the condition value equals 85 dBA. This value also lies between the mean of noise levels of city traffic or garbage disposal (80 dBA) and wood cutting or truck traffic (90 dBA) (Konz & Johnson, 2004).

4.2.4 Apparatus

The equipment that we used is a 3ch Radio Control Robot Construction. In the demonstration study, we exercise the adaptability with design 1 of the robot. This design is equipped with two handles to enable grasping the target object. For the same reason, two types of handles are applied in design 2 and design 3, respectively. However, due to the purpose of the demonstration study, we applied the design 1 to test the method and the other two designs will be applied in the pilot study.

The experimental setup mainly consists of the following components described in Table 4.2. Every element of the experimental setup will be described in this section.

Table 4.2 Settings of the demonstration study

Experiment task	The subjects will perform the same searching task in three circumstances
Experiment circumstances	C1 Nominal condition: normal and continuous lighting and white noise C2 Non-nominal condition: low lighting C3 Non-nominal condition: factory background noise
Preparation	Setting up devices, data collection sheets, instruction sheets

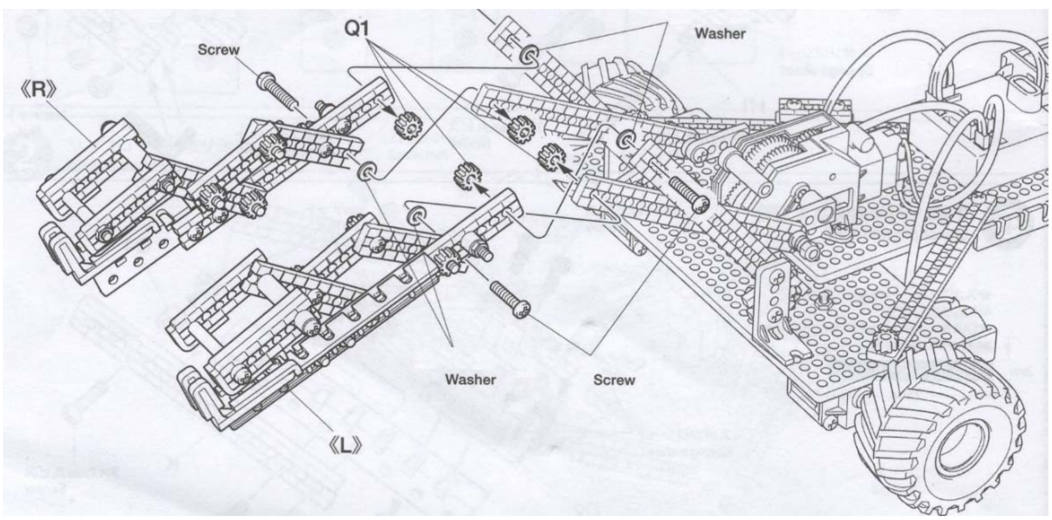


Figure 4.3 Design 1 – Twin Arm type (Tamiya 3ch Radio Control Robot Construction Set)

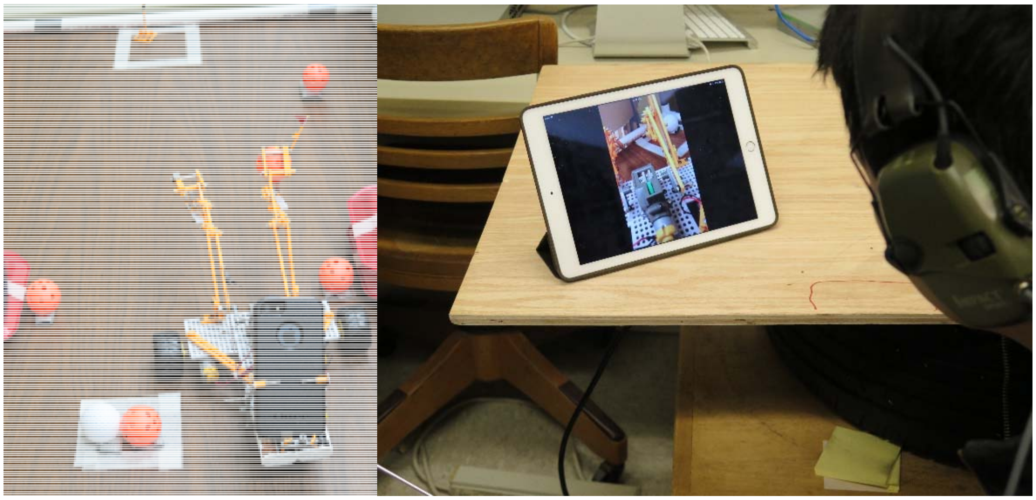


Figure 4.4 An experiment setting for the demonstration study

4.2.5 Procedure

The subjects will perform the same searching task in three circumstances. Given a set of conditions in a searching human-machine system. The experiments are designed based on the measurable conditions including normal lighting, white background noise, low and continuous lighting, factory background noise (See Appendix E- Validity procedure for the settings of demonstration experiment).

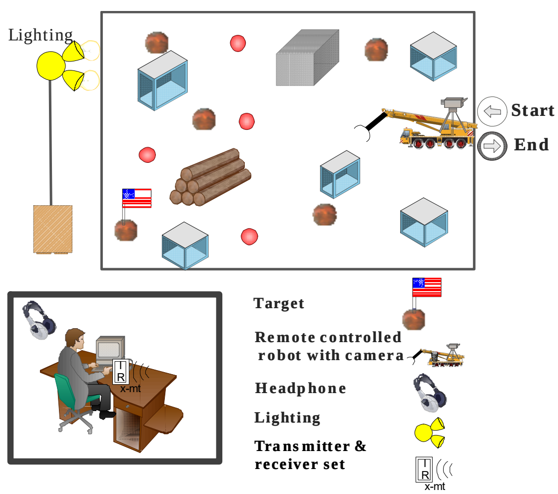


Figure 4.5 Searching area for the demonstration study

The procedure is described as follow:

1. The experiment facilitator will tell the operator when to begin the experiment.
2. The operator then starts to learn how to use the transmitter & receiver set to remotely control the robot. The operator also learns how to move the robot arms and become familiar with the movements of the arms.
3. The operator moves the robot from its starting position and searches for the target ball in the enclosed area.
4. Once locating the target ball through the camera, the operator moves the robot close to the target, controls the arms to grasp the ball, retreats the robot and places the target in the designated location.
5. Searching times are collected at each repetition. The experiment operator informs the subjects when a test is recorded and observes the subjects conducting the task until the target is transferred to the designated area. The searching time is counted from when the subjects are ready to start the task until the time the subject completes the task.
6. After completing one circumstance, the operator moves to the next circumstance and performs the task in five repetitions.

4.3 Results

In this section, the main results of the experiments in the demonstration study or the demonstration are presented (See Appendix G. Data analysis and calculation details).

Table 4.3 Learning slopes and learning indexes

	b_1	b_2	b_3	b_4	$\bar{b}$ = $\mathbf{LI_k}$
Subject 1	-0.2253	-0.3913	0	-0.014	**-0.158**
Subject 2	-0.4162	-0.1485	-0.2665	-0.3066	**-0.284**
Subject 3	0	-0.0797	-0.0277	-0.0242	**-0.033**
Subject 4	-0.1886	0	0	0	**-0.047**

Table 4.4 Adaptability coefficients and adaptability indexes

	$\gamma_{1,2}$	$\gamma_{2,3}$	$\gamma_{3,3}$	$\bar{\gamma}$ = $\mathbf{AI_k}$
Subject 1	0.765	0.866	0.706	**0.779**
Subject 2	1.851	0.588	0.482	**0.974**
Subject 3	0.742	1.013	1.347	**1.034**
Subject 4	1.621	1.538	0.884	**1.348**

Table 4.5 Design D_1: Performance score (PS), $\bar{\bar{b}}$ and $\bar{\bar{\gamma}}$

$\bar{\bar{b}} = \mathbf{LI_{Du}}$	$\bar{\bar{\gamma}} = \mathbf{AI_{Du}}$	$\mathbf{PS_{D1} = E(x)_{D1}}$
-0.1305	1.034	3564.596

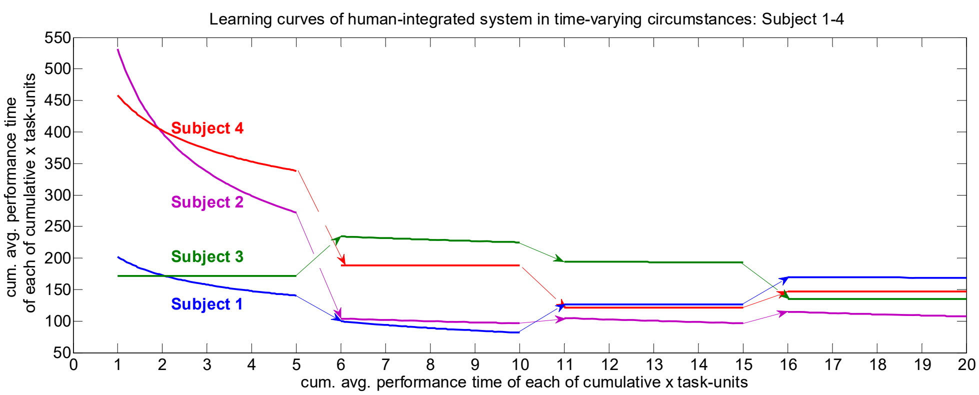


Figure 4.6 Learning curve of human-integrated robot system (Subject 1-4) in four time-varying circumstances

4.4 Discussion

The explanations of the results are presented as follows:

- Under each circumstance, the subjects repeated the task 5 times. The performance time was recorded according to every replication. The collected data was processed as the inputs for the model. Then, the inputs were plugged into the model and the measure metrics were calculated. The graphical results show the subject performances marked with four different colors to indicate the features of the learning slopes and the disruptions in time-varying circumstances.
- The demonstration shows that the metrics in my proposed method could be calculated and plotted.
- The result of demonstration is to consider to change experimental task. The robot task is very difficult to manage.

5. EXPERIMENTAL WORK: EMPIRICAL EXPERIMENT

The research is about developing a measure of the performance of human operators working with a system ('human integrated system') under time varying situations. Specifically, we evaluate this proposed measure by finding the answers to the following questions:

1. What happens when human operators perform tasks under a continuous set of time varying situations?
2. Could we measure the adaptability parameters to know how a human-integrated system adapts to time-varying situations?
3. How does a system accommodate human operators to adapt to time varying situations?

From these motives, two goals that aim to execute the research mission are proposed:

First, a symbolic model of human-integrated-system performance in *time-varying* circumstances was developed. The adaptability parameters and system performance score (PS) are calculated based on the human performance from the proposed model. In addition to this, a demonstration was implemented to show that adaptability parameters, system performance score could be calculated and the performance curves could be plotted.

Second, an empirical experiment was performed to explore characteristics/distribution of the adaptability parameters, and to compare to PS and subject preference score (SS). The preference score is an index to reflect the extent to which circumstances influence the human performance. From here on after, subjects run a system through sets of circumstances, they are asked how the circumstances affect their performance and how they perform the task under these circumstances. For example, here are the questions if subjects are asked about their performance: If it is 'easy,' it is scored 0; if it is 'slightly difficult,' then it is scored 1; if it is 'moderately difficult,' it is scored 2-3; if it is 'difficult,' it is scored 4; and if it is 'extremely difficult,' it is scored 5. This SS measure is termed the preference of the participants.

5.1 Introduction

Getting to grips with the second goal of the empirical experiment requires finding answers to the following fundamental questions:

1. What happens when human operators perform tasks under a continuous set of time varying situations?
2. Could we measure the adaptability parameters to know how a human-integrated system adapts to time-varying situations?
    a. Furthermore, what is a method that we can use to measure the disruption and system-dependent effects ('adaptability parameters') of a system?
    b. Does the sequential order in between transition (within subject's design) presentation affect PS, SS?
    c. Does delay between circumstances affect adaptability parameters?

5.2 Experiment consideration

The subjects participated in a study of human working with an electronic device. They were given an electronic device such as a smartphone or a tablet. They didn't need to attend a training session because the research aims to observe the learning ability of the participant after a number of task repetitions. If the task is repeated in a fixed/discrete circumstance, the completion time could improve. They also did not need to perform a demo task because the subjects learned how to use the device while carrying out the task. This is also the purpose of our study.

Pretend that subjects are a quality control (QC) staff of a grocery store. Their duty is to inspect the quality of fruit delivered in front of the docking site or what is already moved inside the checking area indoors. The fruit comes in different varieties and in a large amount of cardboard cases. The QC staff count the numbers of cartons, to check if the whole quantity is matched. Then the QC staff randomly selects three cartons, opens them and inspects them. In fact, the samples are taken randomly from each of a particular produce type. These samples are checked thoroughly for visual damages. The statistical rules set maximum levels for each type of damage. The inspectors also enter their observations onto a web form and describe/rate each situation associated with any damages/errors and illustrate them with photos. The QC staff finally submits the report about the presented quantity, visual damages, and attached photos.

5.3 Purposes and research questions

The experiment aims to identify characteristics/distribution of $\overline{\gamma}$ and $\overline{b}$, and to compare to PS, SS. It will contribute to answer the following main questions:

- Does the sequential order in between transition (within subject's design) presentation affect PS, SS?
- Does delay affect $\overline{\gamma}$ and $\overline{b}$?

5.4 Method

5.4.1 Participant

For this study, humans participated but the data collected is not about the individual. All subjects must be at least 18 years old, a student enrolled at Purdue University and cannot be color-blind to participate in the study. The subjects were asked to use a device (phone, and tablet) to complete the visual fruit inspection task that will measure some values that are external to the person. No identifiable data is collected about the person.

5.4.2 Empirical task

In this study, the subjects carried out an abstract task of fruit visual inspection. It is not a real industrial visual inspection task in which they have to process and make physical contact with real fruit. Instead of working with real fruit, the subjects will participate in a visual checking procedure with colored balls. There are a number of containers which contain identical colored balls. The identical colored balls represent a typical type of fruit. For example, the green color ball represents a green Granny Smith apple. From now on, I will use the term “fruit visual inspection” for the experimental task.

5.4.3 Experimental circumstances

According to the purpose of the experiment, the data was collected in the experimental circumstances which were created as follows:

1. The visual fruit inspection task was performed under a specific order of three continuous circumstances. The experimenter will set up this order of circumstances depending on four conditions: {C1= Inside}, {C2= Outside}, {C3= Gloves} and {C4= No-gloves}. From these conditions, three individual circumstances are created: {IN=Working Inside with No-gloves}, {OG = Working Outside with Gloves}, {ON= Working Outside with No-gloves}. From these three circumstances, six orders of continuous circumstances are generated as follows

Order 1:	IN	OG	ON
Order 2:	IN	ON	OG
Order 3:	OG	IN	ON
Order 4:	OG	ON	IN
Order 5:	ON	IN	OG
Order 6:	ON	OG	IN

2. The completion time per repetition in three circumstances will be collected. The questionnaires also will be collected after finishing the experiment.
3. The experiments were conducted at Landry Lab, B20, Potter Engineering Center, Purdue University, and West Lafayette, Indiana. For condition C1 (inside), the experiment was conducted in Landry Lab, B20 which is located in the basement of the Potter Building. For condition C2 (outside), the experiment was handled at the secondary entrance area shown in this picture (See Figure 5.1 below).

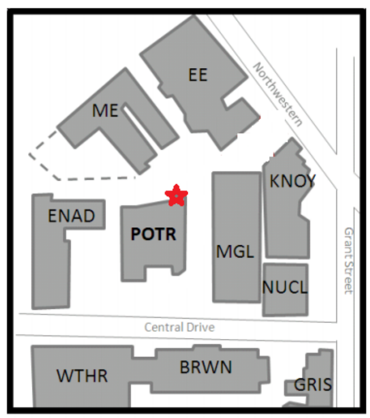


Figure 5.1 The (outside) pedestrian area is located by the Potter Building entrance (illustrated by a red star)

5.4.4 Apparatus

The subjects were given a smartphone (D1) or a tablet (D2), printed instructions regarding task guidelines, printed instructions regarding inspection procedures and an inspection kit (gloves, color checking chart) to perform the inspection task on a number of cases of colored balls (See Figure 5.2 and Figure 5.3). After the experiment, they were asked to fill out questionnaires about the experience in different circumstances.

Figure 5.2 Inspection kit (gloves and color checking chart). The gloves are RUCPAC Professional Tech brand with weather resistant and touchscreen compatible features.

Figure 5.3 Cases of colored balls

5.4.5 Procedure

In the procedure, the participants were given an instruction document where the subjects can learn the purpose of the experiment, read the task description and follow the task guidelines to perform the mission. The experimenter recorded the completion time per repetition until the subjects complete three circumstances. Specifically, a participant was in three stages:

1) In the preparation stage:
    a. Sign the consent form (See Appendix H. Research participant consent form)
    b. Read the experiment instruction (See Appendix I. Task instruction)
    c. Receive inspection tools (an assigned electronic device, instruction sheets, an inspection kit) (See Appendix L. Standard color chart)

2) In the first experiment stage (the first circumstance):
    a. Be provided verbal instruction throughout the experiment
    b. Perform a task repetition in the first circumstance by following the *inspection procedure* in a web-form in the given device (See Appendix J. Inspection procedure and Appendix K. Inspection web-form)
    c. Notify the experimenter when completing a repetition of the task
    d. Repeat the task four more times in the first circumstance
    e. Be notified by the experimenter when completing the task in the first circumstance
    f. Answer the questionnaire. (See Appendix M. Questionnaire form)
    g. Take a rest break ('delay between circumstances') of a duration defined by the design of the experiment

3) At the second and third experiment stages (the continuous circumstances):
    a. Continue to perform the steps (a-g) as in stage 2
    b. Repeat the task 5 times in a new circumstance.
    c. Answer the questionnaire.

The inspection task is based on physical attributes of fresh fruit. When working on specific types of fruit, the inspectors should follow exhaustive guidelines on fruit inspection. For inspecting fruit, the inspectors need to check the following: color and physical characteristics (size of the fruit). The subject opens the inspection web form and follows the instructions and inspection procedures in the web form.

Figure 5.4 Subjects perform the inspection task in circumstance OG (outside with gloves) with iPhone (left) and tablet (right)

Figure 5.5 The subject performs the inspection task in circumstance IN (inside and no-gloves)

5.5 Experimental Design

In order to collect data, a full factorial design of experiment with a number of treatment combinations and one replicate for each treatment is considered. For designing the experiment, we identify factors, factor levels, number of participants, number of circumstances and dependent variables. A profile of experiments was tested including time-varying circumstances. In this profile, the response variable is performance completion time, and factors are system, order of circumstances and delay between circumstances (See Table 5.1). The orders of time-varying circumstances are sets of individual circumstances that are arranged orderly, and they are given in Table 5.2.

5.5.1 Independent Variables

The independent variables include system (system I-iPhone, system II-Tablet), order and delay. What are we interested in if the measures are able to capture the differences between the factors? We are not specifically interested in the effects of order on the performance or what the differences are between system designs in this experiment. Human operators can run any system through any orders of time-varying circumstances to perform a task. We care about whether the proposed methods could detect the differences. Therefore, there are six orders of time-varying circumstances and we randomly selected three orders into the experiment. The selected orders are O2, O3 and O5 (See 0).

We do want to know the effects of delays on the performance and we want to quantify these effects ($\overline{\gamma}$ and $\overline{b}$). What are effects on $\overline{\gamma}$ and $\overline{b}$ of the delay when switching over between circumstances? We want to know what is the shape of the effect between the levels of delays. As a part of that, we are not concerned about the long delays between circumstances because after along breaks, for example days, the task is taken over. So, if we want to find the effects on the order of delays in minutes, then these delays could be considered as disruption, rather than the forgetting effects. In addition, the studies of forgetting curves were conducted in fixed circumstances over a long observation time (such as days, months). This is different than what was set up in this experiment where the task was run through dynamic circumstances. The proposed measure of adaptability over the disruption is about something happening continuously not a day or a week later. For that reason, we are not concerned about the long delays because the measures are not intended for the long delays, but the short delays.

5.5.2 Dependent Variables

The dependent variables include $\overline{\gamma}$, $\overline{b}$ PS and SS. The adaptability index $\overline{\gamma}$ is the average of individual adaptability coefficients and the learning index $\overline{b}$ is the average of learning slopes. The performance score (E_D/PS) is the average of total human performance of every operator tested in design. Usability/preference subject score (SS) is the preference score which reflects the extent to which the system influences human performance (See Table 5.1).

Table 5.1 Experimental variables

Factors	**Levels**	**Subject**	**Circumstance**	**Dependent Variables**
Order	3 (out of 6)	p = 18	c = 3	$\overline{\gamma}$, $\overline{b}$
System	1, 2			
Delay	L=1, M=5, H=10			

Table 5.2 Orders of Circumstances

Order 1: O1	A	B	C
Order 2: O2*	**A**	**C**	**B**
Order 3: O3*	**B**	**A**	**C**
Order 4: O4	B	C	A
Order 5: O5*	**C**	**A**	**B**
Order 6: O6	C	B	A

** Selected orders*

5.5.3 Experimental design table

We apply a full factorial design to create an experimental design table to detect the effects of factors in the model. The system, order and delay are the factors of the model. There are six orders of circumstances (O1, O2, O3, O4, O5 and O6) and two system designs (system I-iPhone, system II-Tablet). Three orders were randomly taken from six orders (O2, O3 and O5). The factor order is a nuisance factor and we are not interested in the factor interactions. We have a third factor, delays, with three levels. Combining these factors, we get (system)x(order)x(delay) = (2)x(3)x(3)= 18 runs. Thus, a full design includes all factors that have true effects and noise factors are shown in Table 5.1.

Table 5.3 Experimental Design

Run Order	**System**	**Order**	**Delay**
1	Sys II	O2= IN→ON→ OG	5
2	Sys I	O2= IN→ON→ OG	5
3	Sys I	O5 = ON→ IN→ OG	1
4	Sys I	O2= IN→ON→ OG	10
5	Sys II	O5 = ON→ IN→ OG	1
6	Sys I	O3= OG → IN→ ON	10
7	Sys II	O5 = ON→ IN→ OG	5
8	Sys I	O3= OG → IN→ ON	1
9	Sys II	O5 = ON→ IN→ OG	10
10	Sys II	O3= OG → IN→ ON	1
11	Sys I	O5 = ON→ IN→ OG	10
12	Sys II	O3= OG → IN→ ON	5

13	Sys I	O2= IN→ON→ OG	1
14	Sys II	O2= IN→ON→ OG	10
15	Sys II	O3= OG → IN→ ON	10
16	Sys I	O5 = ON→ IN→ OG	5
17	Sys I	O3= OG → IN→ ON	5
18	Sys II	O2= IN→ON→ OG	1

5.6 Data Analysis

There are two system designs that are used in this experiment: D_1 (iPhone) and D_2 (tablet). The experimental task is fruit quality inspection. The test will be conducted by randomly assigning subjects to different orders of the sets of circumstances. The performance time is the completion time and each subject repeats the task 5 times in each circumstance. In addition, we have 4 conditions: Indoor (I), Outdoor (O) with Gloves (G) and No-Gloves (N). From these conditions, we form three individual circumstances: {IN}, {OG}, {ON} (See Figure 5.1, Table 5.1 and Table 5.2). The dependent variables (DV) are disruption, learning slope, PS and SS, and the independent variables (IV) are order, delay and system.

Because the purpose of this study is to explore the $\overline{\gamma}, \overline{b}$ and their effects on human performance, we don't know the distributions of $\overline{\gamma}, \overline{b}$ and the following questions are aiming to discover what the distributions of adaptability parameters look like:

Question 1: What is a method that we can use to measure the disruption ($\overline{\gamma}$) and system-dependent effects ($\overline{b}$) ('adaptability parameters' = ($\overline{\gamma}, \overline{b}$)) of a system?

Question 2: What happens when human operators perform tasks under a continuous set of time varying circumstances?

Question 3: Could we measure the adaptability parameters to know how a human-integrated system adapts to time-varying circumstances?

Question 4: Does the sequential order in between transitions (within subject's design) presentation affect $\overline{\gamma}$ and $\overline{b}$?

Test $\overline{\gamma}$ and $\overline{b}$ on the sequential order	Ho: $\overline{\gamma}$ equal across the orders of circumstances Ha: $\overline{\gamma}$ do not equal across the orders circumstances
	Ho: $\overline{b}$ equal across the orders of circumstances Ha: $\overline{b}$ do not equal across the orders of circumstances

Question 5: Does delay between circumstances affect adaptability parameters?

Test $\overline{\gamma}$ and $\overline{b}$ on the delay	Ho: $\overline{\gamma}$ equal across the delay between circumstances Ha: $\overline{\gamma}$ do not equal across the delay between circumstances
	Ho: $\overline{b}$ equal across the delay between circumstances Ha: $\overline{b}$ do not equal the delay between circumstances

Question 6: How does a system accommodate human operators to adapt to time varying circumstances?

Question 7: How does one select the best system design depending on human performance *within* and *between* varying circumstances?

In future research, if we want to evaluate system designs, for example comparing two systems in which we know one system is known apparently better than the other system, by applying the adaptability measure, we need more information about the distributions of $\overline{\gamma}$ and $\overline{b}$. This is necessary to figure out how many observations are needed in this validation experiment which is dependent on what the differences on each adaptability parameters are, what the standard deviations are and what the distributions are. Therefore, in the limitation sense of this exploratory experiment, we don't add interactions in this exploratory experiment and need only one observation per cell. In addition, the order and system are treated as nuisance factors. Besides, the delay factor is added to this experiment to test the delay levels between circumstances.

Depending on the research questions and data collection methods, we suggest the appropriate data analysis as follows:

Part 1: Perform the exploratory data analysis.

In this part, we plot the learning curves in time-varying circumstances and focus on analyzing box-plots and interval plots. The boxplots show the ranges and the central tendency (mean, median) that helps to evaluate intuitively the relation between the independent variables and dependent variables. Besides, the interval plots help to examine the center of the distribution by displaying the confident interval of the observed mean. The purpose of graphing is to describe the data patterns, explore the data, make comparisons among a dependent variable vs independent variables and provoke necessarily statistical analysis on the data.

a) In this Part 1.a), we will plot the learning curves in time-varying circumstances and find the answers to

- Question 2: Observe human performance under time-varying circumstances

b) In this Part 1.b), we come up with the calculations on the adaptability parameters and fit calculated data to distributions. This Part 1.b) will find the answers to
    - Question 1: Formulas used to calculate the adaptability parameters
    - Question 3: Calculations on the adaptability parameters

a) In this Part 1.c), we analyze box-plots and interval plots. In addition, we also fit the data of adaptability parameters to distributions. This Part 1.c) will find the answers to
    - Question 2: Observe from the plots to see if the order has any effects on adaptability parameters and formulate a hypothesis about the order factor.
    - Question 2: Observe from the plots to see if the delay has any effects on adaptability parameters and

Part 2: Perform the statistical analysis to test the hypothesis for confirming the observation in the Part 1.a). Formulate hypotheses about the order and delay factors.

- Question 4: Perform the statistical analysis about the effects of order on adaptability parameters
- Question 5: Perform the statistical analysis about the effects of delay on adaptability parameters

Part 3: Calculate Performance scores and usability/preference scores for comparing two system designs (See 0). Part 3 will find the answers to Question 6 and Question 7.

Table 5.4 Comparison of different metrics for two systems

	System 1- iPhone			**System 2-Tablet**		
	Indoor	Outdoor/ No gloves	Outdoor/ with gloves	Indoor	Outdoor/ No gloves	Outdoor/ with gloves
Performance score	E_{D1}			E_{D2}		
Usability/ preference score	SS_{D1}			SS_{D2}		
Disruption	$\overline{\overline{\gamma}}_{D1}$= AI_{D1}			$\overline{\overline{\gamma}}_{D2}$= AI_{D2}		
Learning slope	$\overline{\overline{b}}_{D1}$= LI_{D1}			$\overline{\overline{b}}_{D2}$= LI_{D2}		

6. RESULTS AND DISCUSSION

In this section, the results of human performance will be displayed by the learning curves in time varying circumstances. The calculated adaptability parameters will be presented together with the explanatory data analysis to explore the distribution and the confidence interval for the mean of calculated data. To study the effects of adaptability parameters, we conducted the statistical analysis of the effects of the influential factors such as orders and delays on the adaptability parameters. And lastly, the performance scores PS (effectiveness scores) will be compared regarding system usage. The user preference scores SS are also presented to provide the user-favored systems for the inspection task.

6.1 Part 1: Visual examination of data

6.1.1 Learning curves under time varying circumstances

The learning curves charts are classified into two groups according to two systems (device 1=iPhone, device 2= Tablet). The calculated data used for plotting these graphs can be found at Appendix P. In Figure 6.1 and Figure 6.2, the x-axis represents the repetitions in each circumstance (1 to 5) and these repetitions add up to 15 repetitions in three continuous circumstances. The y-axis represents the cumulative average completion time (second). The dash-lines indicate the continuation of the learning curves in a sequence of circumstances. The upper right portion of the figure shows the chart legends in which their colors and symbols indicate participants' performance curves in the charts.

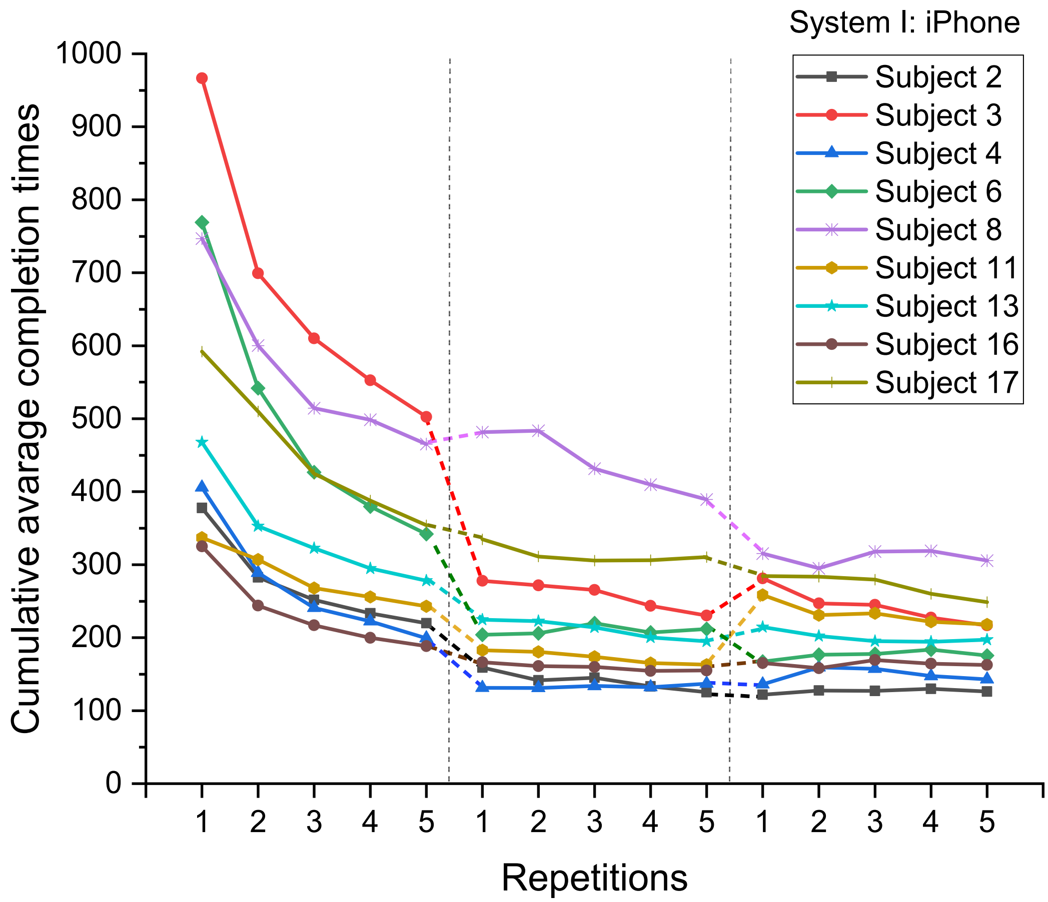


Figure 6.1 Learning curves of subjects using System I – iPhone

Both Figure 6.1 and Figure 6.2 describe human performance as learning curves in time unit under three continuous circumstances. Overall, the curves decrease over the repetitions. This is an obvious evidence of the learning curve principle in which human performance decreases at specific rates when humans repeat the task. In addition, the curves have different shapes in each 5-repetition circumstance. This represents human performance variation due to the transitions between circumstances. That means, the curves of a specific subject vary over circumstances. For example, for subject 1, the slopes of the curves change in time-varying circumstances. In circumstance 1, b equals -1; in circumstance 1, b equals -0.4957 and circumstance 3, b equals -0.4072. Besides, these shapes of the curves have been fit into the basic learning curve equation to look for the learning slope of each subject in each circumstance (See Appendix T).

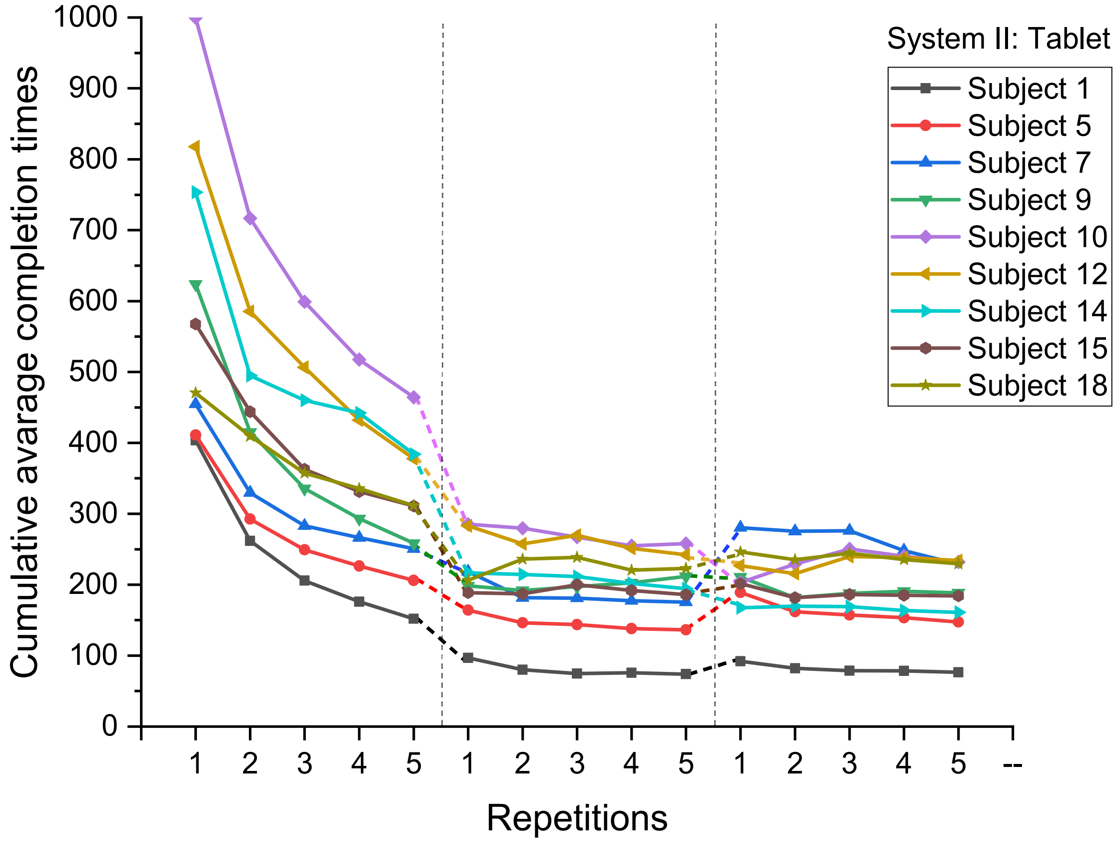


Figure 6.2 Learning curves of subjects using System II - Tablet

Regarding the transition which causes the disruptions in human performance, we can observe it as the dash-lines which connect two consecutive learning curves in two continuous circumstances. Here are several observations on the disruptions based on the graph:

- There is an obvious evidence that time-varying circumstances have the disruptive effects on human performance. This is due to the curves shifted between circumstances.
- The order of circumstances might affect the disruptions of the curves. For example, in the graph for System II-Tablet, with the order 5 (O5), the disruptions of the subject 5 and subject 7 tend to go down from CIR1 to CIR2 but then go up from CIR2 to CIR3. However, the subject 1 with the order 2 (O2) and subject 15 with order 3 (O3) also have this trend on their disruptions. On the other hand, in the graph for the system I-

iPhone, with the order 5 (O5), the disruptions of the subject 3, subject 11 and subject 16 tend to go down from CIR1 to CIR2 but then go up from CIR2 to CIR3. Only subject 13 has this trend. From this observation, the order of circumstances might not affect the disruptions though a statistical test is necessary to confirm this observation. Over and above, the order is not our main interest and it is a nuisance factor in our research. In fact, human operators may run a system through random and unexpected orders of continuous time-varying circumstances.

- The delay between circumstances might raise a concern about whether it affects the disruption and the shapes of the learning curves. However, the learning curves do not show this information in their shape. Therefore, we will look for this evidence in the interval plots and boxplots in the section of descriptive statistics.

Regarding the learning curves, Figure 6.1 and Figure 6.2 show that subjects who used the System I-iPhone spent less time to complete the task than the subjects who used System II-Tablet. Specifically, Figure 6.2 shows that there are more learning curves of System I lie close to the x-axis than the curves of System II. This might indicate that System I-iPhone is more effective than System II-Tablet regarding the working time. However, this observation is not obvious and we need specific numbers, the performance score (PS), to confirm or refute it. The performance score (PS) presented in section 6.3 will address the answers to this concern. In addition, the slopes of the curves in both systems seem to have few differences but it's hard to distinguish just by observing the graph. The proposed measures in this dissertation are expected to capture these differences in learning slopes.

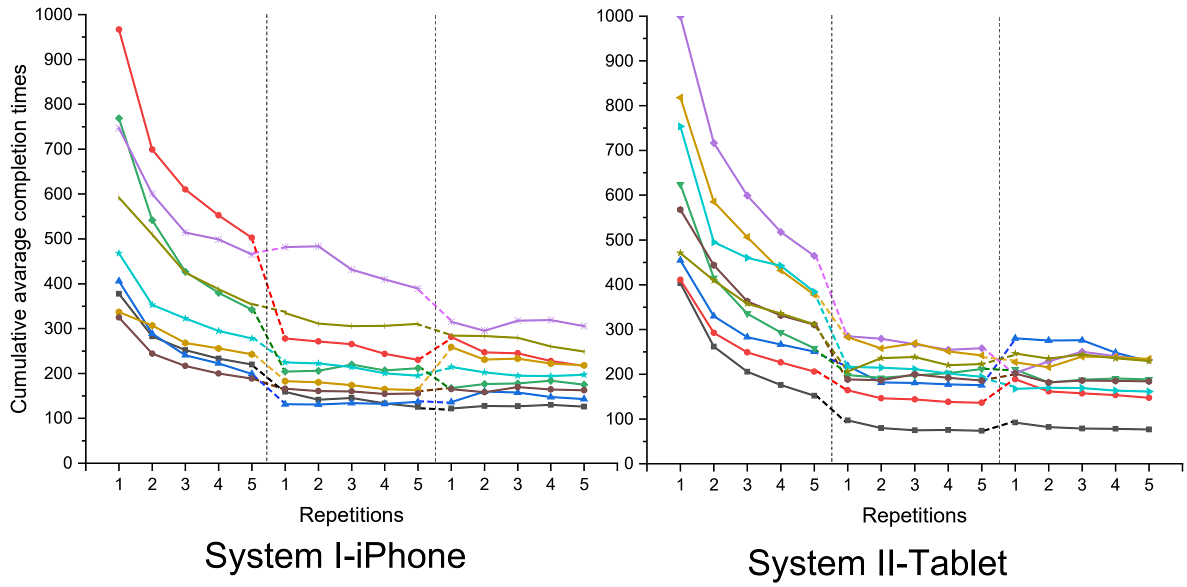


Figure 6.3 Learning curves of System I vs. System II on the same scale of y-axis from 0 to1000 seconds

6.1.2 Calculations on the adaptability parameters

The adaptability parameters comprise two values: adaptability index and learning index. The formulas used for calculating these parameters are described in Table 6.1. The details of these formulas are covered in Section 3.4 - measures of adaptability, Chapter 3.

Table 6.1 Formulas used for calculating adaptability parameters

Adaptability parameters	**Formulas**
Learning index of a subject k, $LI_k = \overline{b}$	Equation (1.2)
Adaptability index of a subject k, $AI_k = \overline{\gamma}$	Equation (1.3)
Learning index of a system design D_j	Equation (1.5)
Adaptability index of a system design D_j	Equation (1.6)

To calculate adaptability parameters, we first calculate the adaptability coefficients and find the learning slopes. The calculations on adaptability coefficient can be found at Appendix P. and the fit values of learning slopes can be seen at Appendix T. Then, by applying the formulation in Table 6.1, we will obtain the Learning index $LI_k = \overline{b}$, Adaptability index $AI_k = \overline{\gamma}$ (See Table 6.2). Specifically, in Table Appx 26 and Table Appx 27 in Appendix P, the adaptability indices of the transitions between two circumstances are shown in columns of Gamma 1,2 and Gamma 2,3. $Gamma_{i,\, i+1}$ value represents the adaptability coefficient of the transition between circumstance i and circumstance i+1. For example, the gamma 1,2 of subject 2 equals 1.38. This means that when shifting from circumstance 1 (IN) to circumstance 2 (ON), the subject 2 gains an adaptability index of 1.38. The adaptability index for each subject is listed in column AI_k and the total score AI_{iphone} of the iPhone device is 1.334. The calculations of these parameters are represented in detail in Appendix P.

Table 6.2 Adaptability parameters

Subject	**Delay**	**Order**	**$AI_k = \overline{\gamma}$**	**$LI_k = \overline{b}$**
Subject 1	5	Order 2	1.57	-0.40
Subject 2	5	Order 2	1.38	-0.63
Subject 3	1	Order 5	1.81	-1.00
Subject 4	10	Order 2	1.46	-0.68
Subject 5	1	Order 5	1.25	-0.72
Subject 6	10	Order 3	1.68	-0.75
Subject 7	5	Order 5	1.15	-0.93
Subject 8	1	Order 3	0.92	-1.00
Subject 9	10	Order 5	1.30	-0.81
Subject 10	1	Order 3	1.63	-0.90
Subject 11	10	Order 5	1.33	-0.85
Subject 12	5	Order 3	1.34	-0.94
Subject 13	1	Order 2	1.24	-0.86
Subject 14	10	Order 2	1.77	-0.77
Subject 15	10	Order 3	1.65	-0.78
Subject 16	5	Order 5	1.13	-0.69
Subject 17	5	Order 3	1.06	-1.00
Subject 18	1	Order 2	1.51	-0.87

6.1.3 Descriptive analysis

In this part, we focus on analyzing boxplots and interval plots. The boxplots show the ranges and the central tendency (mean, median) that helps to evaluate intuitively the relationship between the independent variables and dependent variables. Additionally, the interval plots help to examine the center of the distribution by displaying the confident interval of the observed mean. The purpose of graphing is to describe the data patterns, explore the data, make comparisons among a dependent variable vs independent variables and provoke statistical analysis on the data.

There are two dependent variables (gamma-bar and beta-bar) and three independent variables (system, order and delay). Because of the purpose stated above, we will focus on the plots of dependent variables (gamma-bar and beta-bar) vs independent variables (order and delay). Gamma-bar is the adaptability index and beta-bar is the learning index. In the following section, we'll construct the interval plots and box plots for gamma-bar and beta-bar of system, order and delay. In these plots, the levels of an individual independent variable are lined up side by side on the same scale of a dependent variable (gamma-bar or beta-bar). We can observe the attributes (such as distribution, median, 25th and 75th percentile, outliers) of these factors, compare distributions across different levels all at once and observe the obvious differences. The interval plots show the mean of a dependent variable as a dot. Each interval displays a 95% confidence interval (CI) for the mean of a dependent variable.

In Figure 6.4, the interval plot of 95% CI on the mean of gamma-bar shows that the means of gamma-bar are approximately similar at level O2 and level O5; the mean of gamma-bar is slightly larger in level O2; the boxplot of gamma-bar shows that gamma-bar at level O3 has the largest range, gamma-bar on level O1 is more symmetric and gamma-bars at level O3 and level O5 are left-skew and right-skew. Therefore, the means and variances are graphically displayed in the below figure indicating that the means of gamma-bar at 3 levels of order are approximately equal, and the variances of gamma-bar at 3 levels of order are different. It might be practical differences on the variance of orders. A further statistical investigation is needed to confirm this observation. In addition, there are no obvious outliers in both independent variables.

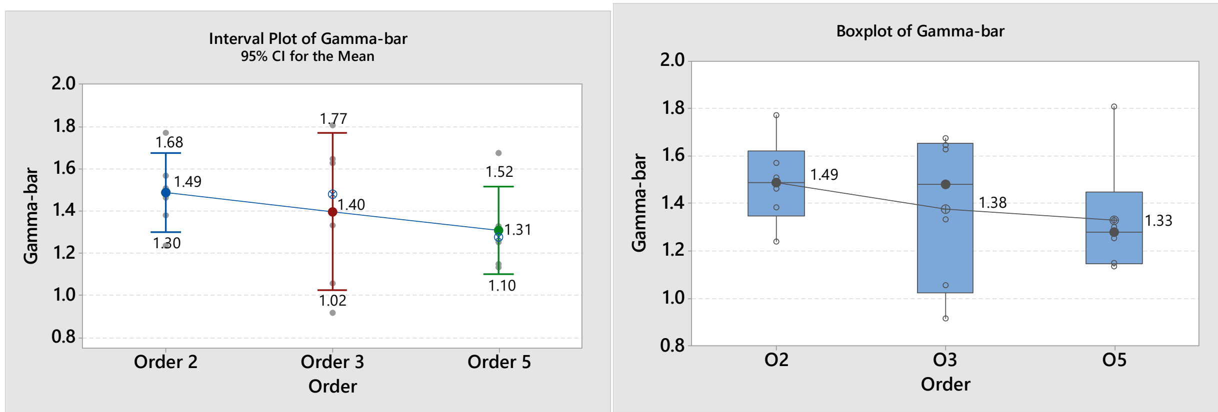


Figure 6.4 Interval plot and boxplot of $\bar{\gamma}$ vs. order

In Figure 6.5, the interval plots 95% CI on the mean of gamma-bar shows that the means of gamma-bar are approximately similar at level 1 and 5, and the mean of gamma-bar is slightly larger at level 10. In the boxplot, gamma-bar at level 1 of delay has the largest range; gamma-bar at level 1 is slightly symmetric; all three boxes appear to have slightly different centers; gamma-bars at levels of 5 and 10 of delay are right-skew and left-skew. In summary, the means and variances are graphically displayed in the below figure indicating that the means of gamma-bar at 3 levels of delay are approximately equal, and their variances are not very different. In addition, there are no obvious outliers in both independent variables.

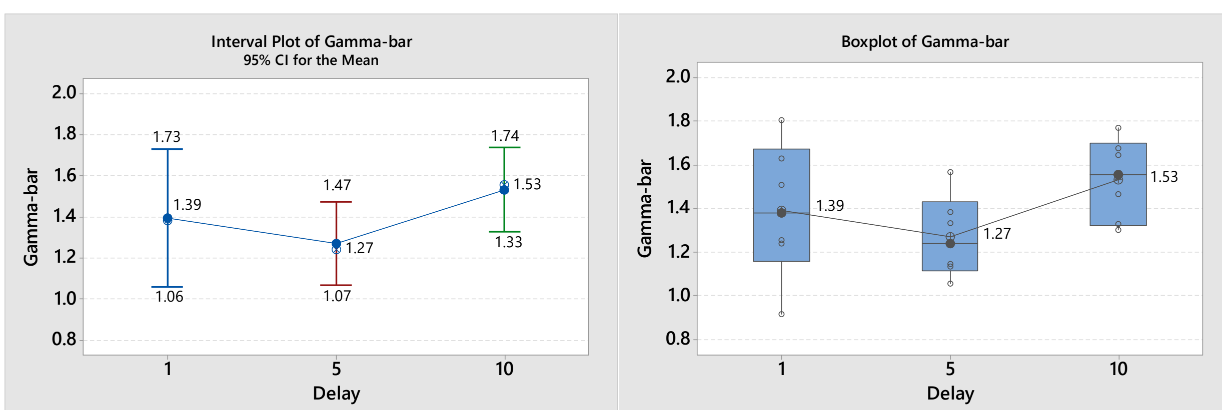


Figure 6.5 Interval plot and boxplot of $\bar{\gamma}$ vs. delay

In Figure 6.6, the interval plot 95% CI on the mean of beta-bar shows that the means of beta-bar are approximately similar at O2 and O5; the mean of beta-bar is slightly lower (or better) at level O3. The box plot shows that beta-bar at O2 has the largest range, beta-bars at O2 and O5 are more symmetric, and beta-bar at O3 is right-skew. In addition, there is an obvious outlier at beta-bar equals -0.4 at O2. In summary, the means and variances are graphically displayed in the above figures indicating that the means of beta-bars at 3 levels of order are not equal and their variances are different. A further statistical investigation is needed to confirm this observation.

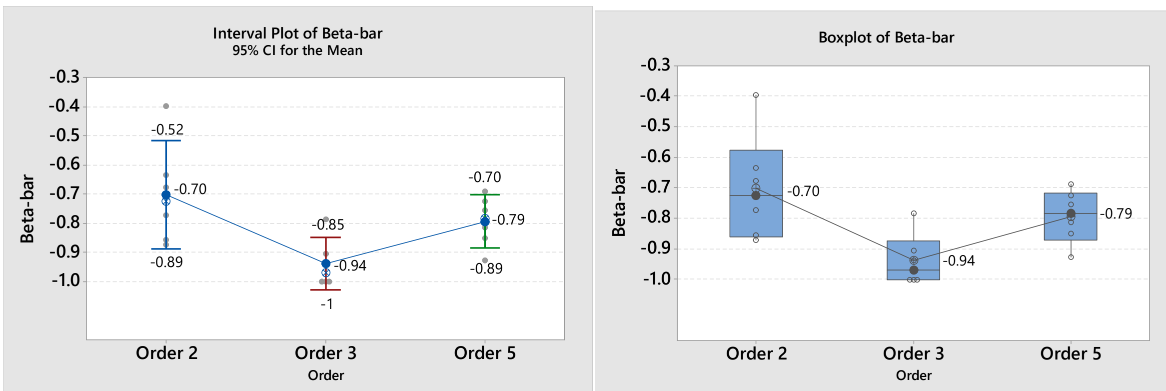


Figure 6.6 Interval plot and boxplot of $\bar{b}$ vs order

In Figure 6.7, the interval plot 95% CI on the mean of beta-bar shows that the means of beta-bar are approximately similar at level 5 and 10 of delay; the mean of beta-bar is slightly lower (or better) at level 1. The box plot shows that beta-bar at level of 5 of delay has the largest range, beta-bar at level 10 is more symmetric, and beta-bars at levels of 1 and 5 of the delay are left-skew and slightly right-skew. In addition, there is no obvious outlier at level 5 of the delay. In summary, the means and variances are graphically displayed in the above figures indicating that means of beta-bar at 3 levels of delay are approximately equal; but their variances are different. A further statistical investigation is needed to confirm this observation.

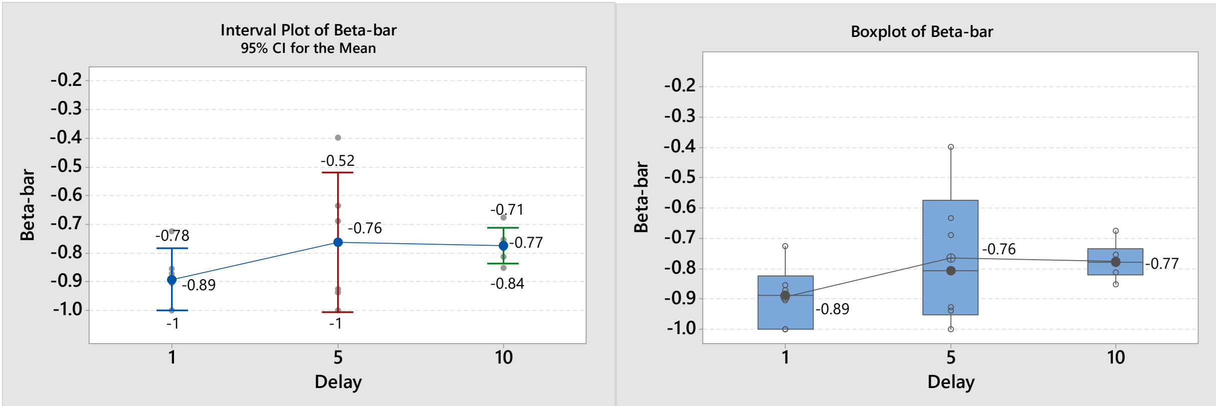


Figure 6.7 Interval plot and boxplot of $\overline{b}$ vs delay

6.1.4 Differences on learning rates

Table 6.3 shows the converted means of learning rates from means of learning slopes. The differences in means of learning rates are calculated and the results are displayed in Table 6.4. In order to make the comparisons between differences of the learning rates and to specify the practical significance regarding the ratio of human/machine in task design, we designed a heuristic table of the differences between learning rates (See Table 6.5). According to this table, the factor beta-bar on order has raised a concern due to slightly high differences between O2-O3, O3-O5. In addition, the amount of 9,43% or even 5.71% brings about a pretty large improvement in performance when their learning rates belong to the range of [50%, 65%], which are very fast learning rates.

Table 6.3 Converted learning rate

	Level	**Mean of learning slope**	**Mean of learning rate, r_{level} (%)**
Beta-bar vs Order	O2	-0.7	61.56
	O3	-0.94	52.12
	O5	-0.79	57.83
Beta-bar vs Delay	delay =1	-0.89	53.96
	delay =5	-0.76	59.05
	delay =10	-0.77	58.64

Table 6.4 Differences $|r_i - r_j|$ where i: row, j: column

		Order	
r_{order}	r_{O2}	r_{O3}	r_{O5}
r_{O2}	0	9.43	3.72
r_{O3}		0	5.71
r_{O5}			0
		Delay	
r_{delay}	$r_{D=1}$	$r_{D=5}$	$r_{D=10}$
$r_{D=1}$	0	5.09	4.68
$r_{D=5}$		0	0.41
$r_{D=10}$			0

Table 6.5 The differences between learning rates regarding the ratio of human/machine in task design

	Human/Machine (%/%):											
Heuristics	2/98	5/95	10/90	55/45	65/35	75/25	90/10	99/1	100/0	100/0	100/0	100/0
Learning slope b	-0.014	-0.059	-0.074	-0.152	-0.234	-0.322	-0.415	-0.515	-0.621	-0.737	-0.862	-1.000
Learning rate r_j (%)	99%	96%	95%	90%	85%	80%	75%	70%	65%	60%	55%	50%
	Popular in many industries											
	Very Slow		Slow	Moderately fast			Fast		Very Fast			
Repetition	**Productivity based on r_j:**											
1st	100	100	100	100	100	100	100	100	100	100	100	100
2nd	99	96	95	90	85	80	75	70	65	60	55	50
4th	98.01	92.16	90.25	81	72.25	64	56.25	49	42.25	36	30.25	25
8th	97.03	88.47	85.74	72.9	61.41	51.2	42.19	34.3	27.46	21.6	16.64	12.5
16th	96.06	84.93	81.45	65.61	52.2	40.96	31.64	24.01	17.85	12.96	9.151	6.25
r_i	**The differences in learning rates** (r_i-r_j):											
65%	-34%	-31%	-30%	-25%	-20%	-15%	-10%	-5%	0%	5%	10%	15%
60%	-39%	-36%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	5%	10%
55%	-44%	-41%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%	5%
50%	-49%	-46%	-45%	-40%	-35%	-30%	-25%	-20%	-15%	-10%	-5%	0%

6.1.5 Fit distributions

Because we do not know the distribution of the collected data, we used Individual Distribution Identification in Minitab to fit these data with all parametric distributions. Table 6.6 and Table 6.7 provides the summary information for the whole data. All the statistics are based on the non-missing (N = 18) values. For gamma-bar, mean = 1.39862 and std = 0.253470. For beta-bar, mean = -0.810483 and std = 0.153682. The output also includes Anderson-Darling (AD) statistics and the p-values for fit distributions.

In these results, we tested the null hypotheses which state that gamma-bar and beta-bar follow a normal distribution. Specifically, if a p-value is greater than the significance level of 0.05, we fail to reject the null hypothesis. That means we cannot conclude that the data do not follow a normal distribution and it suggests that gamma-bar or beta-bar follow a normal distribution. For gamma-bar, p-value of Normal-distribution-fit equals 0.921 indicating that the Normal distribution and the largest extreme value fit the data well. The Box-Cox (p-value = 0.921) also provides a good fit for the data. For beta-bar, p-value of Normal-distribution-fit equals 0.477 indicating that the Normal distribution and the largest extreme value fit the data quite well.

The probability plots in Figure 6.8 and Figure 6.9 also confirm these results. In a probability plot, the middle line is the expected percentile of the distribution. It is created for identifying the likelihood estimates of the distribution's mean. The left-red- and right-red- lines represent the lower and upper bounds of the confidence intervals of the expected percentile. The probability plots show that the data of parameters locate around a straight line and lie within the confidence intervals. This observation is also applied for the 2-parameter Weibull, 3-parameter Weibull, the largest extreme value, and gamma distribution. The other distributions do not satisfy the likelihood estimates of the distribution's mean. To select a distribution that has the best fits our data, we select a distribution having the largest p-value.

Table 6.6 Fitting gamma-bar in distributions

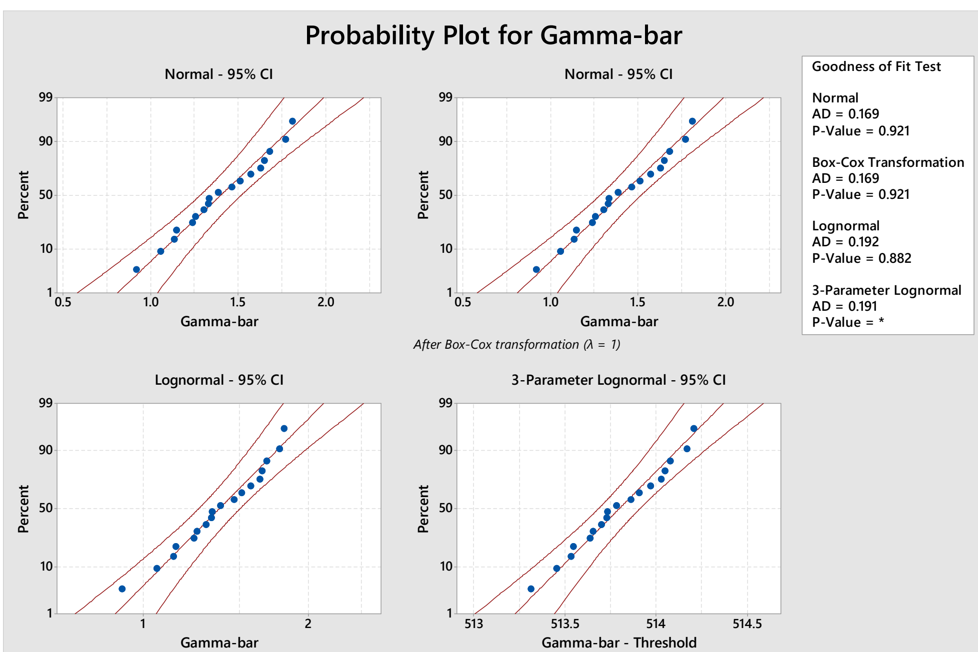
Descriptive Statistics

N	N*	Mean	StDev	Median	Minimum	Maximum	Skewness	Kurtosis
18	0	1.39862	0.253470	1.35894	0.91614	1.8081	-0.0747359	-0.789563

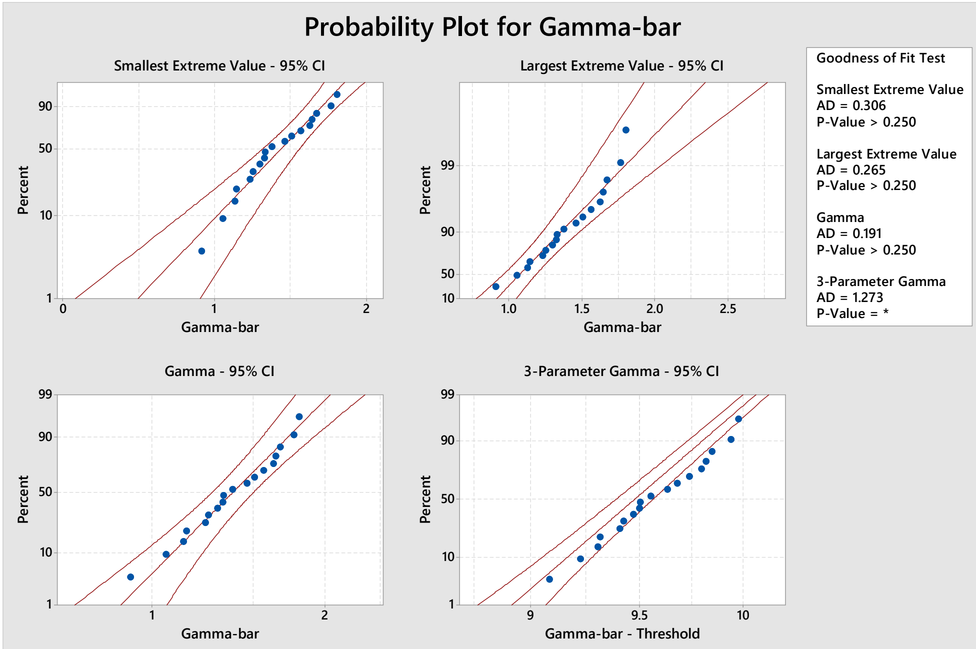
Box-Cox transformation: λ = 1

Goodness of Fit Test

Distribution	AD	P	LRT P
Normal	0.169	0.921	
Box-Cox Transformation	0.169	0.921	
Lognormal	0.192	0.882	
3-Parameter Lognormal	0.191	*	0.417
Exponential	5.612	<0.003	
2-Parameter Exponential	1.948	<0.010	0.000
Weibull	0.219	>0.250	
3-Parameter Weibull	0.184	>0.500	0.514
Smallest Extreme Value	0.306	>0.250	
Largest Extreme Value	0.265	>0.250	
Gamma	0.191	>0.250	
3-Parameter Gamma	1.273	*	1.000
Logistic	0.216	>0.250	
Loglogistic	0.214	>0.250	
3-Parameter Loglogistic	0.216	*	0.583

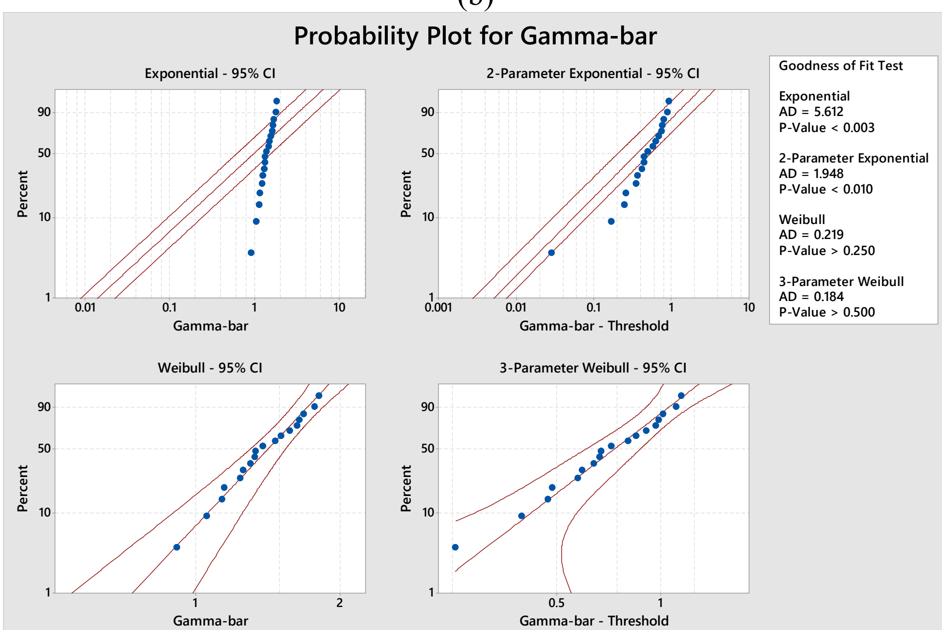


(a)



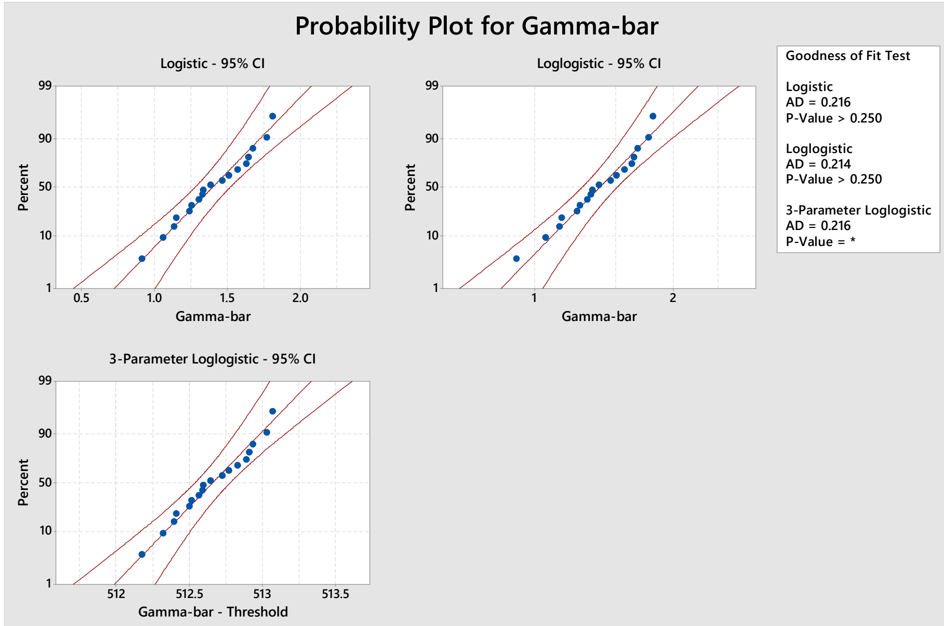
Probability Plot for Gamma-bar
Smallest Extreme Value - 95% CI
Largest Extreme Value - 95% CI
Gamma - 95% CI
3-Parameter Gamma - 95% CI
Percent
Gamma-bar
Gamma-bar - Threshold
Goodness of Fit Test
Smallest Extreme Value
AD = 0.306
P-Value > 0.250
Largest Extreme Value
AD = 0.265
P-Value > 0.250
Gamma
AD = 0.191
P-Value > 0.250
3-Parameter Gamma
AD = 1.273
P-Value = *

(b)



Probability Plot for Gamma-bar
Exponential - 95% CI
2-Parameter Exponential - 95% CI
Weibull - 95% CI
3-Parameter Weibull - 95% CI
Percent
Gamma-bar
Gamma-bar - Threshold
Goodness of Fit Test
Exponential
AD = 5.612
P-Value < 0.003
2-Parameter Exponential
AD = 1.948
P-Value < 0.010
Weibull
AD = 0.219
P-Value > 0.250
3-Parameter Weibull
AD = 0.184
P-Value > 0.500

(c)



(d)

Figure 6.8 Probability plots of fitted distributions for gamma-bar (a-d)

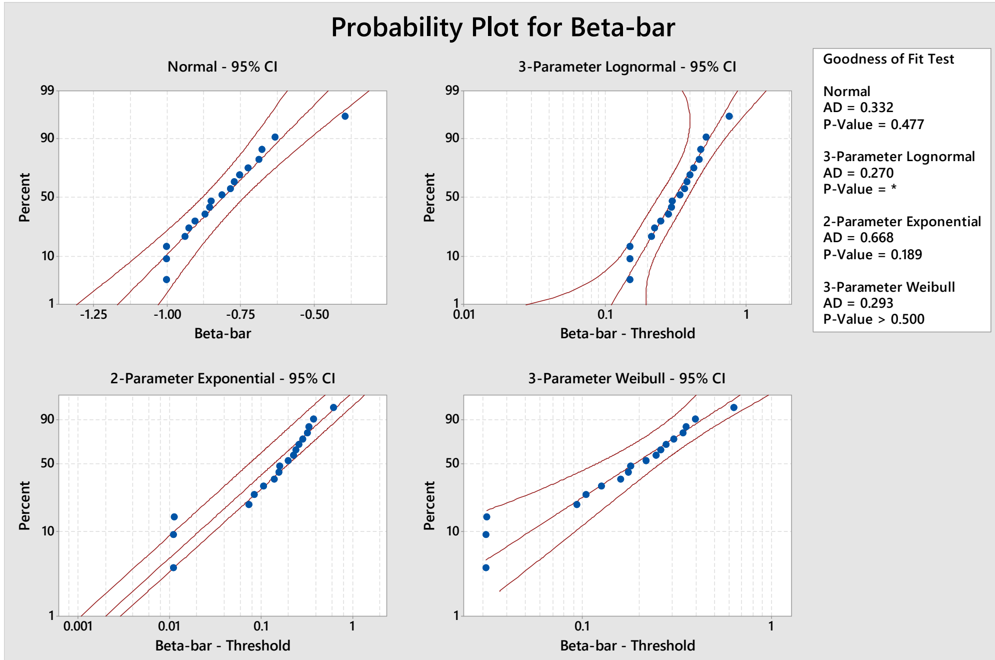
Table 6.7 Fitting Beta-bar in distributions

Descriptive Statistics

N	N*	Mean	StDev	Median	Minimum	Maximum	Skewness	Kurtosis
18	0	-0.810483	0.153682	-0.831735	-1	-0.3966	1.02564	1.69614

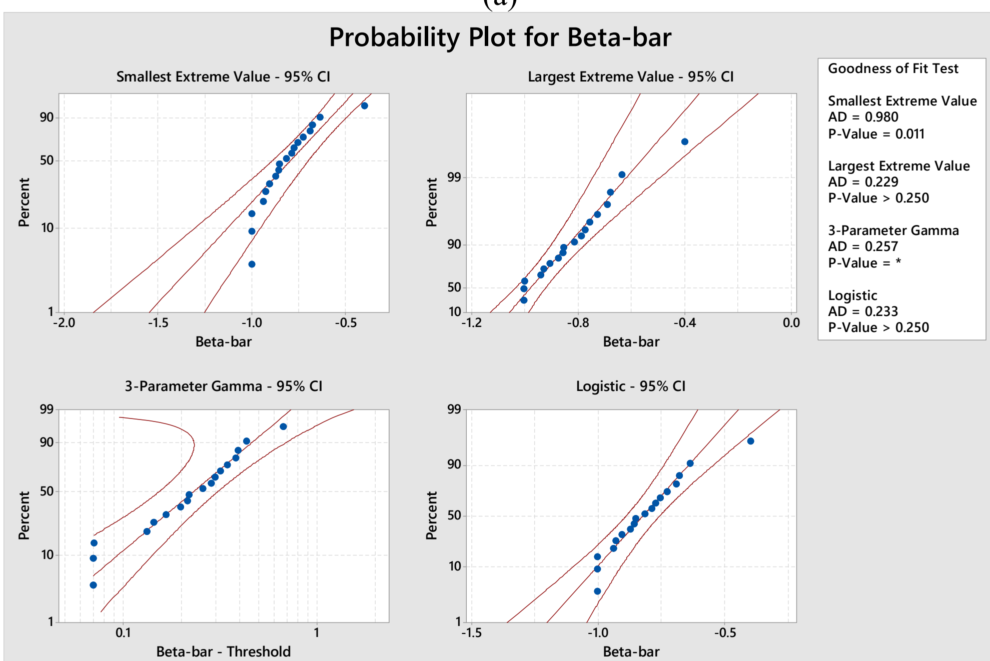
Goodness of Fit Test

Distribution	AD	P
Normal	0.332	0.477
3-Parameter Lognormal	0.270	*
2-Parameter Exponential	0.668	0.189
3-Parameter Weibull	0.293	>0.500
Smallest Extreme Value	0.980	0.011
Largest Extreme Value	0.229	>0.250
3-Parameter Gamma	0.257	*
Logistic	0.233	>0.250
3-Parameter Loglogistic	0.254	*



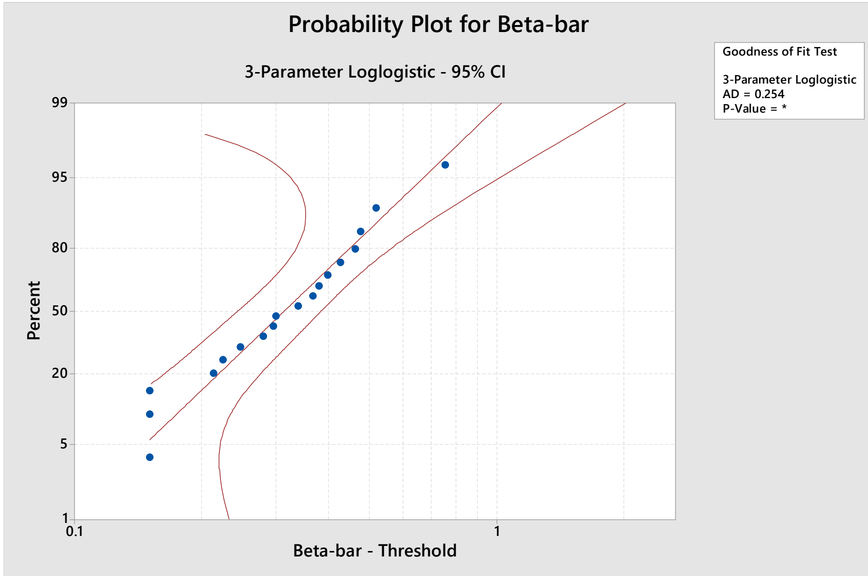
Probability Plot for Beta-bar
Normal - 95% CI
3-Parameter Lognormal - 95% CI
2-Parameter Exponential - 95% CI
3-Parameter Weibull - 95% CI
Percent
Beta-bar
Beta-bar - Threshold
Goodness of Fit Test
Normal
AD = 0.332
P-Value = 0.477
3-Parameter Lognormal
AD = 0.270
P-Value = *
2-Parameter Exponential
AD = 0.668
P-Value = 0.189
3-Parameter Weibull
AD = 0.293
P-Value > 0.500

(a)



Probability Plot for Beta-bar
Smallest Extreme Value - 95% CI
Largest Extreme Value - 95% CI
3-Parameter Gamma - 95% CI
Logistic - 95% CI
Percent
Beta-bar
Beta-bar - Threshold
Goodness of Fit Test
Smallest Extreme Value
AD = 0.980
P-Value = 0.011
Largest Extreme Value
AD = 0.229
P-Value > 0.250
3-Parameter Gamma
AD = 0.257
P-Value = *
Logistic
AD = 0.233
P-Value > 0.250

(b)



(c)

Figure 6.9 Probability plots of fitted distributions for beta-bar (a, b, c)

6.2 Part 2: Statistical examination of data

In this section, we ran a General Linear Model (GLM) to test the effects of gamma-bar and beta-bar upon the order and the delay. The hypotheses are listed in Table 6.8. There are three levels of order and three levels of delay. We're interested in studying the effects of the responses; thus these factors are fixed.

Table 6.8 Hypotheses on the effects of order and delay

Hypotheses about the effects of the order on $\bar{\gamma}$ and $\bar{b}$	Ho: $\bar{\gamma}$ equal across the orders of circumstances Ha: $\bar{\gamma}$ do not equal across the orders circumstances
	Ho: $\bar{b}$ equal across the orders of circumstances Ha: $\bar{b}$ do not equal across the orders of circumstances

Hypotheses about the effects of the delay on $\overline{\gamma}$ and $\overline{b}$	Ho: $\overline{\gamma}$ equal across the delay between circumstances Ha: $\overline{\gamma}$ do not equal across the delay between circumstances
	Ho: $\overline{b}$ equal across the delay between circumstances Ha: $\overline{b}$ do not equal across the delay between circumstances

We ran the GLM on Minitab software. The output displays a table of factors which includes levels and their values. The output also gives a table of ANOVA (Analysis of Variance) which comprises the model terms, degree of freedom, and residual sums of squares, F-statistics and p-values. We also need to check the residual plots for the ANOVA's assumptions. Then, we'll confirm the hypotheses based on the GLM's output.

In the ANOVA table of gamma-bar, we found that

- It needs to check the assumptions of residuals on the residual plots in order to see if they are randomly distributed and have constant variance. In the residuals versus fits plot, the points appear randomly both sides of zero (0) and we don't recognize any patterns of the dots. The residuals versus order plot also shows that the dots fall randomly around the central line. There is no trend or recognized patterns. The normality probability plots also display the residuals falling approximately along the straight line. This is a sign that the residuals are normally distributed.
- All p-values are larger than 0.05. This indicates that there are no statistically significant effects at the level of significance of 0.05 (alpha=0.05). The two-way interactions are not statistical significance in that all their p-values are larger than 0.05. This indicates that the effect of the order factor on the gamma-bar does not depend on the delay factor and vice versa. Above all,

we fail to reject the null hypothesis. We cannot conclude that there is a statistically significant association between gamma-bar and delay, and gamma-bar and order. On the other hand, speaking in statistical significance, the delay and order do not affect the gamma-bar.

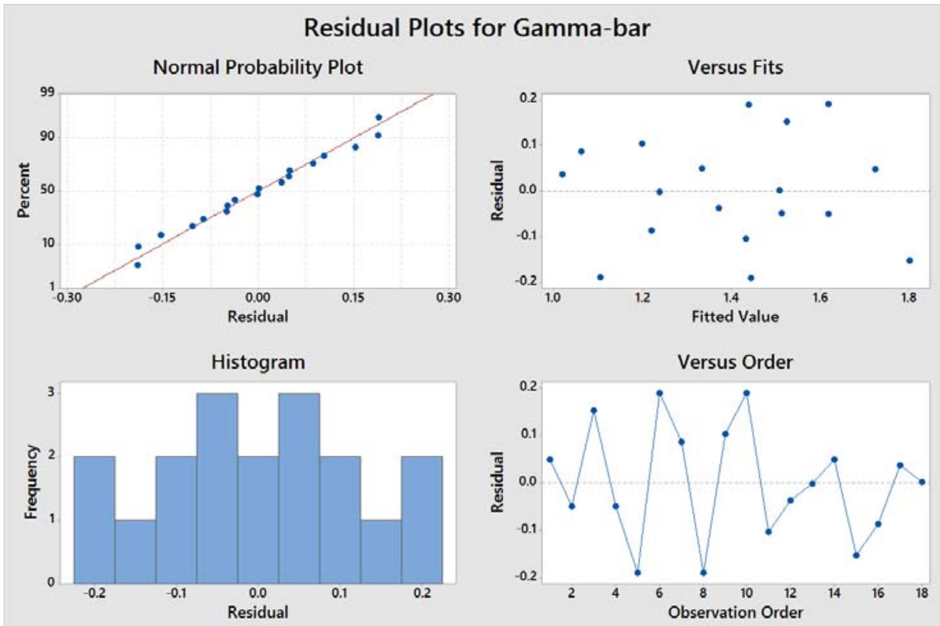


Figure 6.10 Residual plots for gamma-bar

In the ANOVA table of beta-bar, we found that

- It needs to check the assumptions of residuals on the residual plots in order to see if they are randomly distributed and have constant variance. In the residuals versus fits plot, the points appear randomly both sides of zero (0) and we don't recognize any patterns of the dots. Except there are two outliers lying far away from the other dots. This is a sign that the assumptions of residuals are violated. The residuals versus order plot also shows that the dots fall randomly around the central line. There is no trend or recognized patterns. The normality probability plots also display the residuals falling approximately along the straight line.
- All p-values are larger than 0.05. This indicates that there are no statistically significant effects at the level of significance of 0.05 (alpha=0.05). The two-way interactions are not statistical

significance in that all their p-values are also larger than 0.05. This indicates that the effect of the order factor on the beta-bar does not depend on the delay factor and vice versa. Above all, we fail to reject the null hypothesis. We cannot conclude that there is a statistically significant association between beta-bar and delay, and beta-bar and order. On the other hand, speaking in statistical significance, the delay and order do not affect the beta-bar. However, we suspect that the residual plots show that the assumptions associated with the ANOVA model are not violated, except Residuals vs. Fits regarding equal variance. For this reason, we need to use the Kruskal-Wallis test to check the ANOVA's result. In Table 6.14, the Kruskal-Wallis test has confirmed the ANOVA's result.

Table 6.9 Result of GLM on Gamma-bar versus System, Order, Delay

General Linear Model: Gamma-bar versus System, Order, Delay	Factor Type	Levels	Values			
	System Fixed	2	System I, System II			
	Order Fixed	3	O2, O3, O5			
	Delay Fixed	3	1, 5, 10			
	Analysis of Variance					
	Source	DF	Adj SS	Adj MS	F-Value	P-Value
	System	1	0.07465	0.074654	1.25	0.325
	Order	2	0.08099	0.040495	0.68	0.557
	Delay	2	0.20466	0.102330	1.72	0.289
	System*Order	2	0.23023	0.115117	1.94	0.258
	System*Delay	2	0.00480	0.002398	0.04	0.961
	Order*Delay	4	0.25892	0.064729	1.09	0.468
	Error	4	0.23795	0.059486		
	Total	17	1.09220			
	Model Summary					
	S	R-sq	R-sq(adj)	R-sq(pred)		
	0.243898	78.21%	7.41%	0.00%		

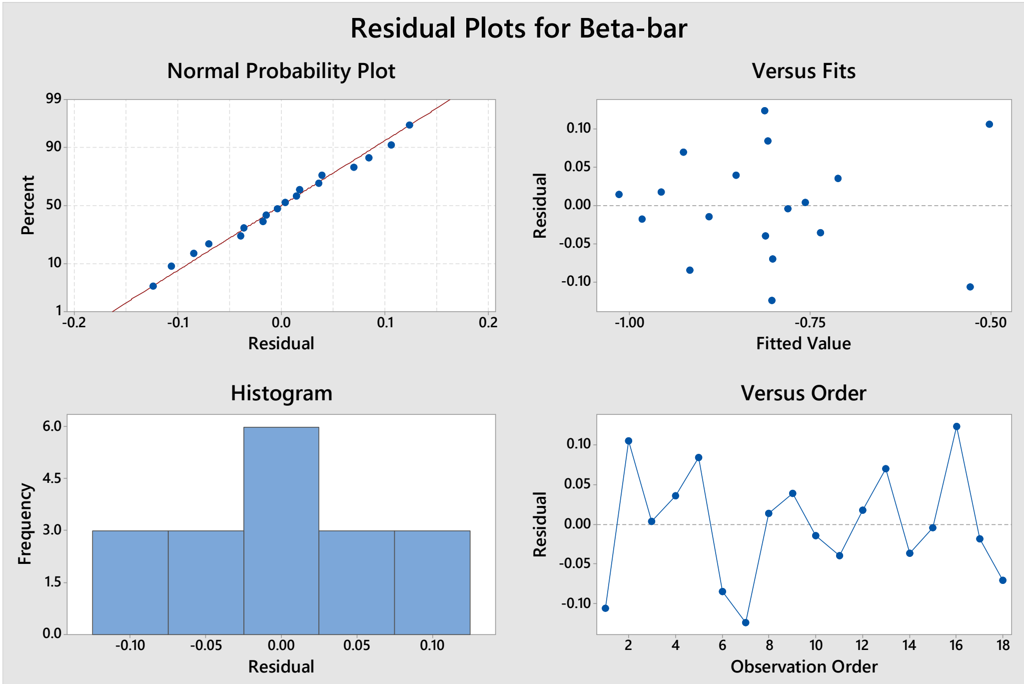


Figure 6.11 Residual plots for beta-bar

Table 6.10 Result of GLM on Beta-bar versus System, Order, Delay

<table>
<tr><td>General Linear Model:
Beta-bar versus
System, Order, Delay</td><td>Factor Information
Factor Type Levels Values
System Fixed 2 System I, System II
Order Fixed 3 O2, O3, O5
Delay Fixed 3 1, 5, 10</td></tr>
<tr><td></td><td>Analysis of Variance

Source DF Adj SS Adj MS F-Value P-Value
System 1 0.006000 0.006000 0.29 0.620
Order 2 0.119681 0.059841 2.86 0.169
Delay 2 0.061058 0.030529 1.46 0.334
System*Order 2 0.000289 0.000144 0.01 0.993
System*Delay 2 0.017029 0.008514 0.41 0.690
Order*Delay 4 0.113899 0.028475 1.36 0.386
Error 4 0.083552 0.020888
Total 17 0.401507

Model Summary
S R-sq R-sq(adj) R-sq(pred)
0.144527 79.19% 11.56% 0.00%</td></tr>
</table>

Table 6.11 Test for Equal Variances of Gamma-bar

Test for Equal Variances: Gamma-bar versus Order

Method

Null hypothesis	All variances are equal
Alternative hypothesis	At least one variance is different
Significance level	α = 0.05

95% Bonferroni Confidence Intervals for Standard Deviations

Order	N	StDev	CI
O2	6	0.179821	(0.067356, 0.79878)
O3	6	0.329578	(0.109888, 1.64470)
O5	6	0.247556	(0.047558, 2.14411)

Individual confidence level = 98.3333%

Tests

Method	Test Statistic	P-Value
Multiple comparisons	—	0.520
Levene	1.37	0.284

Test for Equal Variances: Gamma-bar versus Delay

Method

Null hypothesis	All variances are equal
Alternative hypothesis	At least one variance is different
Significance level	α = 0.05

95% Bonferroni Confidence Intervals for Standard Deviations

Delay	N	StDev	CI
1	6	0.319946	(0.141702, 1.20199)
5	6	0.192504	(0.073992, 0.83333)
10	6	0.195152	(0.101292, 0.62560)

Individual confidence level = 98.3333%

Tests

Method	Test Statistic	P-Value
Multiple comparisons	—	0.472
Levene	1.42	0.272

Table 6.12 Test for Equal Variances of Beta-bar

Test for Equal Variances: Beta-bar versus Delay

Method

Null hypothesis	All variances are equal
Alternative hypothesis	At least one variance is different
Significance level	α = 0.05

95% Bonferroni Confidence Intervals for Standard Deviations

Delay	N	StDev	CI
1	6	0.103184	(0.0420236, 0.42155)
5	6	0.232249	(0.0823666, 1.08963)
10	6	0.059190	(0.0203724, 0.28613)

Individual confidence level = 98.3333%

Tests

Method	Test Statistic	P-Value
Multiple comparisons	—	0.083
Levene	6.17	0.011

Test for Equal Variances: Beta-bar versus Order

Method

Null hypothesis	All variances are equal
Alternative hypothesis	At least one variance is different
Significance level	α = 0.05

95% Bonferroni Confidence Intervals for Standard Deviations

Order	N	StDev	CI
O2	6	0.176460	(0.0548339, 0.944863)
O3	6	0.106096	(0.0413597, 0.452836)
O5	6	0.118197	(0.0561667, 0.413865)

Individual confidence level = 98.3333%

Tests

Method	Test Statistic	P-Value
Multiple comparisons	—	0.633
Levene	0.67	0.526

We performed Kruskal-Wallis tests of the equality of medians for Gamma-bar and Beta-bar on Order and Delay. The Kruskal-Wallis hypotheses are: H_0: the parameters' medians are all equal versus H_1: the parameters' medians are not all equal.

Table 6.13 Kruskal-Wallis Test of Gamma-bar

Kruskal-Wallis Test: Gamma-bar versus Order

Kruskal-Wallis Test on Gamma-bar

Order	N	Median	Ave Rank	Z
O2	6	1.487	11.3	1.03
O3	6	1.482	9.5	0.00
O5	6	1.279	7.7	-1.03
Overall	18		9.5	

H = 1.42 DF = 2 P = 0.493

Kruskal-Wallis Test: Gamma-bar versus Delay

Kruskal-Wallis Test on Gamma-bar

Delay	N	Median	Ave Rank	Z
1	6	1.382	9.3	-0.09
5	6	1.241	6.8	-1.50
10	6	1.556	12.3	1.59
Overall	18		9.5	

H = 3.19 DF = 2 P = 0.203

Table 6.14 Kruskal-Wallis Test of Beta-bar

Kruskal-Wallis Test: Beta-bar versus Order

Kruskal-Wallis Test on Beta-bar

Order	N	Median	Ave Rank	Z
O2	6	-0.7240	13.0	1.97
O3	6	-0.9209	6.2	-1.87
O5	6	-0.8317	9.3	-0.09
Overall	18		9.5	

H = 4.92 DF = 2 P = 0.085
H = 4.93 DF = 2 P = 0.085 (adjusted for ties)

Kruskal-Wallis Test: Beta-bar versus Delay

Kruskal-Wallis Test on Beta-bar

Delay	N	Median	Ave Rank	Z
1	6	-0.8878	6.6	-1.64
5	6	-0.8078	10.1	0.33
10	6	-0.7782	11.8	1.31
Overall	18		9.5	

H = 3.01 DF = 2 P = 0.222
H = 3.01 DF = 2 P = 0.222 (adjusted for ties)

6.3 Part 3: Calculations on Performance score and usability/preference score

6.3.1 Performance score/ Effectiveness

The performance score indicates how effective a system could be for a specific mission. We called it the effectiveness score which was calculated by averaging total human performance time across time-varying circumstances. The smaller the score, the better the system. Table 6.15 and Table 6.16 show results of the effectiveness score for each subject in each circumstance. Equation 1.7 was used to calculate these quantities. The effectiveness score of System I-iPhone equals 1223.845 which was slightly smaller than the score of System II-Tablet of 1262.556. Therefore, System I should be better than System II regarding working time.

Though these measures are able to capture the adaptability information that no current method cannot, they need to test on validation experiments. As we stated before, we focus on exploring the gamma-bar and beta-bar in this dissertation. A comparison of two system designs is not yet your concern because we are not ready to do so. Details of these calculations are displayed in Appendix Q.

Table 6.15 Performance score/ Effectiveness of System I-iPhone

	E_{S1*}	E_{S2}	E_{S3}	E_{S4}	E_{S5}	E_{S6}	E_{S7}	E_{S8}	E_{S9}
CIR1	377.82	966.65	405.87	768.99	746.83	337.09	467.84	325.01	591.89
CIR2	357.96	278.00	376.00	321.72	481.70	337.15	307.99	350.71	334.71
CIR3	368.54	281.28	327.47	349.68	315.22	288.50	314.05	351.65	284.29
SUM	**1104.32**	**1525.93**	**1109.34**	**1440.38**	**1543.75**	**962.74**	**1089.88**	**1027.36**	**1210.89**
$E_{(iPhone)}$	**1223.845**								

subject S_i

Table 6.17 Performance score/ Effectiveness of System II-Tablet

	E_{S1}*	E_{S2}	E_{S3}	E_{S4}	E_{S5}	E_{S6}	E_{S7}	E_{S8}	E_{S9}
CIR1	403.48	411.05	454.70	623.93	999.66	817.72	753.45	567.49	470.66
CIR2	402.93	352.58	311.40	325.83	285.18	282.96	312.33	332.80	320.02
CIR3	407.01	332.63	280.40	316.86	322.47	306.74	349.62	323.52	295.59
SUM	**1213.42**	**1096.26**	**1046.50**	**1266.62**	**1607.31**	**1407.42**	**1415.40**	**1223.81**	**1086.27**
$E_{(tablet)}$		**1262.556**							

**subject S_i*

6.3.2 Usability/preference subject score

In this section, The Post Study System Usability Questionnaire (PSSUQ) was applied to evaluate usability in our research. The PSSUQ in our study comprised a 16-item questionnaire given to a subject at the end of each experiment. The PSSUQ presented subjects with a set of statements in 7-point Likers scales. The PSSUQ uses the following scale: 1 = Strongly agree, 2 = Mostly agree, 3 = Agree, 4 = Neither agree nor disagree, 5 = Disagree, 6 = Mostly disagree, and 7 = Strongly disagree. The details of PSSUQ are shown in the Appendix M and Appendix R.

The four scales to evaluate a system, which are computed by averaging the responses accordingly, including (Lewis, 1991, 1995, 2002):

1. Overall usability: Average the responses from subjects to items 1 through 16.
2. System use: Average the responses from subjects to items 1 through 6.
3. Information quality: Average the responses from subjects to items 7 through 12.
4. Interface quality: Average the responses to items 13 through 16.

Table 6.19 Post-Study System Usability Questionnaire (PSSUQ) Scores

	Lower limit	**Mean**	**Upper limit**
iPhone	Overall scores		
SysUse	2.2	2.556	2.9
InfoQual	1.7	2.000	2.3
IntQual	1.7	2.167	2.6
Overall	2.2	**2.431**	2.6
Tablet	Overall scores		
SysUse	1.4	1.667	1.9
InfoQual	1.6	1.870	2.1
IntQual	1.3	1.667	2.0
Overall	1.7	**1.875**	2.0

According to Table 6.18, System II-Tablet has a score of 1.875 which was better than the score of System I-iPhone of 2.431. The result indicated that the users preferred to use the Tablet to perform the inspection task than the iPhone.

Table 6.20 Scores of two systems

	System design D_1 iPhone	**System design D_2 Tablet**
Performance score (PS)	PS_{D1}=E_{D1}= 1223.845	PS_{D2} = E_{D2}=1262.556
Usability/ preference subject score (SS)	UPS_{D1}/SS_{D1}= 2.43	UPS_{D2}/SS_{D2}= 1.875
Disruption	$\bar{\bar{\gamma}}_{D1}$= AI_{D1} = 1.334	$\bar{\bar{\gamma}}_{D2}$= AI_{D2} = 1.463
Learning slope	$\bar{\bar{b}}_{D1}$= LI_{D1} = -0.823	$\bar{\bar{b}}_{D2}$= LI_{D2} = -0.792

Table 6.20 shows the scores regarding each evaluation item such as performance score (PS), subject score (SS), and disruption and learning slope. The highlighted items under a specific system means that system has a better score over another system. Specifically, System I has a better score, PS_{D1}= 1223.845, on PS. This means system I is better than System II regarding working time. However, system II has a better SS score, SS_{D2}= 1.875. This means users preferred to use System II than System I. Regarding adaptability parameters, System II also has a better adaptability Index/disruption over System I, $\overline{\overline{\gamma}}_{D2}$= AI_{D2} = 1.463; However, users using System I completed the task faster than participants who used system II because the beta-bar-bar of System I, $\overline{\overline{b}}_{D1}$= LI_{D1} = -0.823, is smaller than the beta-bar-bar of System I, $\overline{\overline{b}}_{D2}$= LI_{D2} = -0.792.

Due to the purpose of human subject study, it is not yet possible to compare two systems at this time. Eventually, we can compare systems by using the proposed measures, once we validate the measures. But it's not our goal right now. Because of this reason, the calculations of PS, SS and beta-bar, gamma-bar for comparing systems in the following slide is just for reference. According to the comparison results, the SS score does not align with PS and disruption does not align with learning slope. Regarding human performance, System I- iPhone is better. Regarding users' choice, System II-Tablet is better. Regarding adaptability (disruption), System II-Tablet is better or the system accommodates human operators better. Regarding improvement rate (learning slope), System I- iPhone is better or the operators learned faster when using System I. Above all, we can see that people prefer using the system that has less disruption. In addition, the learning slope reflect a match with the performance score.

7. CONCLUSIONS AND RECOMMENDATION FOR FUTURE WORK

7.1 Conclusion

Currently there are many methods to evaluate systems. However, there is no method to assess a system by evaluating human performance. The method discussed in this dissertation emphasizes human subjects working in a continuous set of time-varying circumstances. A symbolic model was built based on the learning curve theory, and the measures of adaptability parameters under time-varying circumstances were also constructed based on this model. These measures are used for evaluating systems or system designs which are based on human performance. Specifically, the gamma-bar, beta-bar and performance score (effectiveness of system design) are the measures for systems.

Following the measure development, the demonstration study was conducted to show the computations of the proposed measure in an example. The measures were proven to be calculated and the learning curves could be plotted in continuous varying-circumstances. However, the result of the demonstration is to consider changing the experimental task because the robot task is very difficult to manage manually.

In the empirical experiment, a human subject study was conducted to explore the proposed measures. We tested two systems under three varying-circumstances to determine the characteristics of the measures and to see whether they are affected by some experimental choices such as the order of circumstances and delay between circumstances. The statistical tests show that order and delay do not have effects on gamma-bar and beta-bar. However, the graphical analysis shows that there are differences between levels of order on beta-bar. The statistical tests show that order and delay do not have effects on adaptability parameters. However, the results from the graphical analysis provide useful information to adjust the setting of circumstances regarding the order of circumstances in future experiments.

Thess measures are important because they gave us an opportunity to understand how disruption affects human performance in time-varying circumstances. This research explores the characteristics of the adaptability parameters and applies the measures to evaluate systems. The following are the summarized findings with respect to the aim of our studies:

- Before we can design a future validation experiment, we need to understand the characteristics of measures and what types of experimental choices affect the measures that we should take into account. For example, we have to consider whether we need to be concerned about the amount of delays between circumstances, which could be 10 minutes maximum, and whether we need to be concerned about the order of circumstances. This is a beginning step to qualify and quantify how well a system could accommodate human operators to complete a task, in which current methods do not take into account the time-varying circumstances.
- Theoretically, this research expects to provide a novel approach for evaluating systems by measuring human performance in time-varying circumstances. A symbolic model was built based on the learning curve theory and the measures of adaptability parameters (gamma-bar, beta-bar and performance score) under time-varying circumstances were constructed based on this model. Even though humans are unique and complex, the proposed models are expected to characterize the adaptability patterns of human operators by analyzing sets of adaptability parameters and learning slopes in different experimental runs of sets of time-varying circumstances. This research provides an understanding of human adaptability of human-integrated systems in time-varying circumstances without dividing these systems as separate elements.
- Regarding statistical significance, the human subject study shows that order and delay do not have effects on gamma-bar and beta-bar. The result also shows that there is no difference between two systems under the effect of different orders and delays. Furthermore, gamma-bar follows Normal distribution with N (1.39, 0.25) and beta-bar follows Normal distribution with Normal, N (-0.81, 0.154).

- Regarding practical significance, the human subject study shows that order has effects on beta-bar. Because of the differences of learning rates about 10% and 6%, the differences of the beta-bar on the orders are practically significant. The delays at 1, 5 and 10 minutes in transitions between circumstances do not affect adaptability measures and they are not practically significant.
- For evaluating systems, the performance score (PS) and subject score (SS) are used together with adaptability parameters and learning slopes to select the best system working under time-varying circumstances. The higher the scores, the better the chance for the human operators to adapt to changing circumstances, and also for the decision makers to select a best-fit system design. In the human subject study, we have two systems: System I-iPhone and System II-Tablet. The result table shows that System I is better than System II regarding human performance (PS scores); System II is better than System I regarding users' choice (SS scores); System II is better than System I regarding adaptability (gamma-bar); Using System I, the operators performed the task faster when using System II (beta-bar). Above all, System II is better than System I because System II accommodates the operators better and causes less disruption under time-varying circumstances.

The main takeaways are:

1) The proposed measures provide a useful way for potentially measuring how well a system enables human adaptation in dynamic changing circumstances. The proposed measures differ from the previous methods in which the proposed measures deal with the dynamic changing circumstances and were developed in mathematical framework;
2) In addition, the demonstration study showed how the measures could be recorded and implemented;

3) Some experimental aspects were streamlined before running the validation experiment: an experimental choice of order should consider practically a few things. The order has practical effects on learning ability, especially in which the task involves a large percentage of human over machine. We need to be aware of designing the orders of time-varying circumstances, particularly with small sample sizes. We cannot dismiss this observation when the plots from the visual examination indicate the differences or the practical effect, even though the statistical results don't show the differences. Therefore, additional tests with more statistical power are expected to see if the differences persist. The future designs of experiment might not need to be concerned about the delays (up to 10 minutes). However, the delays that go beyond the level of 10 minutes also require further experiments to determine if they have an effect on the measures.

7.2 Limitations and Recommendation for Future Work

Due to the limitation of the studies in an academic environment, we did not have a better opportunity to improve the power of the study by collecting more data or testing the systems under more intense settings. Therefore, the findings have a limited general application because the sample size is small and we need to conduct validation experiments in intense and different continuous time-varying circumstances to extend the generalization of these findings. Specifically, the measures need to be tested in "intense" time-varying circumstances, such as larger delay levels, longer serials of order and various conditions.

Depending on the specific type of task and application situations, the learning curves will be different. For this reason, it is recommended to examine the measures on a variety of task and application situations. Therefore, we could fit the learning curve data into according types of learning curves models with specific task designs or applications. These models mostly are modified from Wright's model and their equations adapted to specific applications.

The findings are expected to provide new measures not only for evaluating the effectiveness of alternatives in singular system design but also for assessing the complex systems under dynamic settings. For example, selecting a system that works best for an organization or a team that runs this system for a particular mission. Therefore, the application zone of this proposed method could be scaled up to larger organizations or teams that use complex systems rather than individual systems. An organization that runs a complex system for a particular mission is a possible object to apply this method.

The measures also could be applied to estimate the cost of producing a unit under dynamic changing circumstances, and estimate the 'cost' of disruption due to shifting working environments. Conventionally, the criteria mostly used in learning curve models are performance time and cost of produced quantities. Therefore, it could bring up a novel idea to observe the disruptions which are computed under cost unit in which we are able to observe the characteristics of disruptions and evaluate them as not only a system-dependent measure but also a self-adjusting index for a system under long observed continuous time-varying circumstances.

The measures could be the extent to apply in the job rotation task which is a very popular arrangement for employee training. For job rotation, the employees are usually required to attend training programs in different departments or workstations at specific training times. In an application context relating to our research, we would like to know which particular systems help the employee rotate among the departments or workstations. To do this, the employee use systems to do a given task in a department, then they are rotated to other departments. The transitions between departments might affect the employees' performance. The systems that the employees use might support them to do the work well or not support them to do the work well. Therefore, besides many purposes of job rotations including controlling the development of trauma disorders or reducing physical workload, in the context of our research, job rotation could apply the measures of disruptions and obtains another way to evaluate the adaptability of employees under changing circumstances. In this case, they are rotating departments.

REFERENCES

Abernathy, W. J., & Wayne, K. (1974). Limits of the learning curve. *Harvard Business Review, 52*(5), 109-119.

Adler, P. S., & Clark, K. B. (1991). Behind the learning curve: A sketch of the learning process. *Management Science, 37*(3), 267-281.

Andress, F. J. (1954). The learning curve as a production tool. *Harvard Business Review, 32*(1), 87-97.

Antunes, R., Coito, F. V., & Duarte-Ramos, H. (2012). Improving Operator Performance through the Use of a Multivariable Human-Machine Control Strategy *Technological Innovation for Value Creation* (pp. 95-104): Springer.

Anzanello, M. J., & Fogliatto, F. S. (2011). Learning curve models and applications: Literature review and research directions. *International Journal of Industrial Ergonomics, 41*(5), 573-583.

Asher, H. (1956). Cost-quantity relationships in the airframe industry.

Badiru, A. B. (1992). Computational survey of univariate and multivariate learning curve models. *Engineering Management, IEEE Transactions on, 39*(2), 176-188.

Badiru, A. B. (2011). 18 Industrial Work Measurement and Improvement through Multivariate Learning Curves. *Learning Curves: Theory, Models, and Applications*, 349.

Baloff, N. (1966). The learning curve--some controversial issues. *The Journal of Industrial Economics*, 275-282.

Baloff, N. (1971). Extension of the Learning Curve--Some Empirical Results. *Operational Research Quarterly*, 329-340.

Barrett, C. F. (1970). *An empirical analysis of learning curves.* ProQuest Information & Learning.

Barron, R. F. (2002). *Industrial noise control and acoustics*: CRC Press.

Blancett, R. S. (2002). Learning from productivity learning curves. *Research-Technology Management, 45*(3), 54-58.

Brinberg, D., & McGrath, J. E. (1985). Validity and the research process *Validity and the Research Process*: Sage Publications.

Brookfield, B. (2005). Management Accounting Decision Management. *Elsevier*.

Caamano Alegre, M. (2009). Experimental Validity and Pragmatic Modes in Empirical Science. *International Studies in the Philosophy of Science, 23*(1), 19-45.

Cacciabue, P. C. (2004). Elements of human-machine systems *Guide to Applying Human Factors Methods* (pp. 9-47): Springer.

Cacciabue, P. C. (2011). *Modelling and simulation of human behaviour in system control*: Springer Publishing Company, Incorporated.

Camerer, C., & Weber, M. (1992). Recent developments in modeling preferences: Uncertainty and ambiguity. *Journal of risk and uncertainty, 5*(4), 325-370.

Chase, R. B., Aquilano, N. J., & Jacobs, F. R. (2001). *Operations management for competitive advantage*: Irwin/McGraw-Hill.

Crawford, J. (1944). Learning curve, ship curve, ratios, related data. *Lockheed Aircraft Corporation, 144*.

De Jong, J. (1957). The effects of increasing skill on cycle time and its consequences for time standards. *Ergonomics, 1*(1), 51-60.

Dick, A. O., Bittner, A. C., & Harris, R. (1989). Design of a MANPRINT tool for predicting personnel and training characteristics implied by system design: ANALYTICS INC WILLOW GROVE PA.

Ebbinghaus, H. (1913). *Memory: A contribution to experimental psychology*: Teachers college, Columbia university.

Firth-Cozens, J. (2001). Cultures for improving patient safety through learning: the role of teamwork. *Quality and Safety in Health Care, 10*(suppl 2), ii26-ii31.

Fogliatto, F. S., & Anzanello, M. J. (2011). 1 Learning Curves: The State of the Art and Research Directions. *Learning Curves: Theory, Models, and Applications*, 1.

Glover, J. (1965). Manufacturing progress functions I. An alternative model and its comparison with existing functions. *International Journal of Production Research, 4*(4), 279-300.

Hartley, K. (1965). The learning curve and its application to the aircraft industry. *The Journal of Industrial Economics*, 122-128.

Hentschker, C., & Mennicken, R. (2015). The Volume-Outcome Relationship and Minimum Volume Standards–Empirical Evidence for Germany. *Health economics, 24*(6), 644-658.

Hess, R., & Modjtahedzadeh, A. (1990). A control theoretic model of driver steering behavior. *Control Systems Magazine, IEEE, 10*(5), 3-8.

Hess, R. A. (1987). A qualitative model of human interaction with complex dynamic systems. *Systems, Man and Cybernetics, IEEE Transactions on, 17*(1), 33-51.

Konz, S., & Johnson, S. (2004). *Work design: occupational ergonomics*: Holcomb Hathaway, Publishers.

Leamon, T. (1980). The organisation of industrial ergonomics—A human: machine model. *Applied Ergonomics, 11*(4), 223-226.

Lerch, J. F., & Buck, J. R. (1975). *An exponential learning curve experiment.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.

Leslie, M., & Holloway, C. A. (2006). The sales learning curve. *Harvard Business Review, 84*(7/8), 114.

Levy, F. K. (1965). Adaptation in the production process. *Management Science, 11*(6), B-136-B-154.

Lewis, J. R. (1991). Psychometric evaluation of an after-scenario questionnaire for computer usability studies: the ASQ. *ACM Sigchi Bulletin, 23*(1), 78-81.

Lewis, J. R. (1995). IBM computer usability satisfaction questionnaires: psychometric evaluation and instructions for use. *International Journal of Human-Computer Interaction, 7*(1), 57-78.

Lewis, J. R. (2002). Psychometric evaluation of the PSSUQ using data from five years of usability studies. *International Journal of Human-Computer Interaction, 14*(3-4), 463-488.

Liao, S. S. (1988). The learning curve: Wright's model vs. Crawford's model. *Issues in Accounting Education, 3*(2), 302-315.

Liu, A., & Salvucci, D. (2001). *Modeling and prediction of human driver behavior.* Paper presented at the Intl. Conference on HCI.

Liu, Y.-T., Mayer-Kress, G., & Newell, K. M. (2003). Beyond curve fitting: A dynamical systems account of exponential learning in a discrete timing task. *Journal of Motor Behavior, 35*(2), 197-207.

Macadam, C. C. (2003). Understanding and modeling the human driver. *Vehicle System Dynamics, 40*(1-3), 101-134.

McRuer, D. (1980). Human dynamics in man-machine systems. *Automatica, 16*(3), 237-253.

Moray, N. (1981). Systems-Engineering Models of Human-Machine Interaction - Rouse,Wb. *Quarterly Journal of Experimental Psychology Section a-Human Experimental Psychology, 33*(May), 210-211.

Moray, N. (1994). Error reduction as a systems problem. *Human error in medicine*, 67-91.

Moray, N. (1999). Digital Systems Evaluation. (10.13140/RG.2.1.3965.3605.).

Mugerwa, M. N., & Blomen, L. J. (1993). Fuel cell system economics *Fuel Cell Systems* (pp. 531-563): Springer.

Oliver, N., Pentland, A., & Verly, J. (2000). Driver behavior recognition and prediction in a SmartCar. *Enhanced and Synthetic Vision 2000, 4023*, 280-290. doi: 10.1117/12.389351

Patil, S. (2008). *Industrial Engineering And Management*: Technical Publications.

Pelham, B., & Blanton, H. (2012). *Conducting research in psychology: Measuring the weight of smoke*: Cengage Learning.

Raccoon, L. (1996). A learning curve primer for software engineers. *ACM SIGSOFT Software Engineering Notes, 21*(1), 77-86.

Ritter, F. E., & Schooler, L. J. (2001). The learning curve. *International encyclopedia of the social and behavioral sciences, 13*, 8602-8605.

Roessingh, J., & Hilburn, B. (2000). *The Power Law of Practice in adaptive training applications*: Citeseer.

Rogner, H.-H. (1998). Hydrogen technologies and the technology learning curve. *International Journal of Hydrogen Energy, 23*(9), 833-840.

Rouse, W. B. (1981). Human-computer interaction in the control of dynamic systems. *ACM Computing Surveys (CSUR), 13*(1), 71-99.

Rouse, W. B. (1981). HUMAN-COMPUTER INTERACTION IN THE CONTROL OF DYNAMIC SYSTEMS. *Computing surveys, 13*(1), 71-99. doi: 10.1145/356835.356839

Shafiei, E., Saboohi, Y., & Ghofrani, M. (2005). *Model for R&D planning in energy.* Paper presented at the Engineering Management Conference, 2005. Proceedings. 2005 IEEE International.

Stanton, N., Salmon, P. M., & Rafferty, L. A. (2013). *Human factors methods: a practical guide for engineering and design*: Ashgate Publishing, Ltd.

Strauch, B. (2017). *Investigating human error: Incidents, accidents, and complex systems*: CRC Press.

Stump, E. (2002). *All about learning curves.* Paper presented at the Society of Cost Estimating and Analysis Conference Paper, Galorath Incorporated., El Segundo, CA.

Sule, D. R. (1978). The effect of alternate periods of learning and forgetting on economic manufacturing quantity. *AIIE Transactions, 10*(3), 338-343.

Teplitz, C. J. (1991). *The learning curve deskbook: A reference guide to theory, calculations, and applications*: Quorum Books New York.

Thomas, H. R. (2009). Construction learning curves. *Practice Periodical on Structural Design and Construction*.

Thomas, H. R., Mathews, C. T., & Ward, J. G. (1986). Learning curve models of construction productivity. *Journal of construction engineering and management, 112*(2), 245-258.

Tian, J., Wu, Y., Wang, X., & Zhao, T. (2011). *Hazard analysis based on human-machine-environment coupling.* Paper presented at the Reliability and Maintainability Symposium (RAMS), 2011 Proceedings-Annual.

Towill, D., & Cherrington, J. (1994). Learning curve models for predicting the performance of AMT. *The International Journal of Advanced Manufacturing Technology, 9*(3), 195-203.

Tüzün, E., & Tekinerdogan, B. (2015). Analyzing impact of experience curve on ROI in the software product line adoption process. *Information and Software Technology, 59*, 136-148.

Watkins, K. E. (1991). Validity in Action Research.

Wright, T. (1936). Learning curve. *Journal of the Aeronautical Sciences, 3*(1), 122-128.

Wright, T. P. (2012). Factors affecting the cost of airplanes. *Journal of the Aeronautical Sciences (Institute of the Aeronautical Sciences), 3*(4).

Yamane, Y., Takahashi, K., Hamada, K., Morikawa, K., Bahagia, N., Diawati, L., & Cakravastia, A. (2015). Developing a plant system prediction model for technology transfer. *International Journal of Production Economics, 166*, 119-128.

Yelle, L. E. (1979). The learning curve: Historical review and comprehensive survey. *Decision Sciences, 10*(2), 302-328.

Ziesemer, T., & Michaelis, P. (2011). Strategic environmental policy and the accumulation of knowledge. *Structural Change and Economic Dynamics, 22*(2), 180-191.

APPENDIX A. LITERATURE REVIEW: FAMILY OF LEARNING CURVE MODELS

Besides the well-known log-linear learning curve model, discussed in the previous literature review section, the following learning curve models are discussed in detail:

1. S-model
2. Stanford-B
3. Dejong
4. Levy's adaptation function
5. Glover's learning formulas
6. Pegel's learning formulas
7. Plateau
8. Yelle's model
9. Multiplicative power model (Cobb-Douglas)

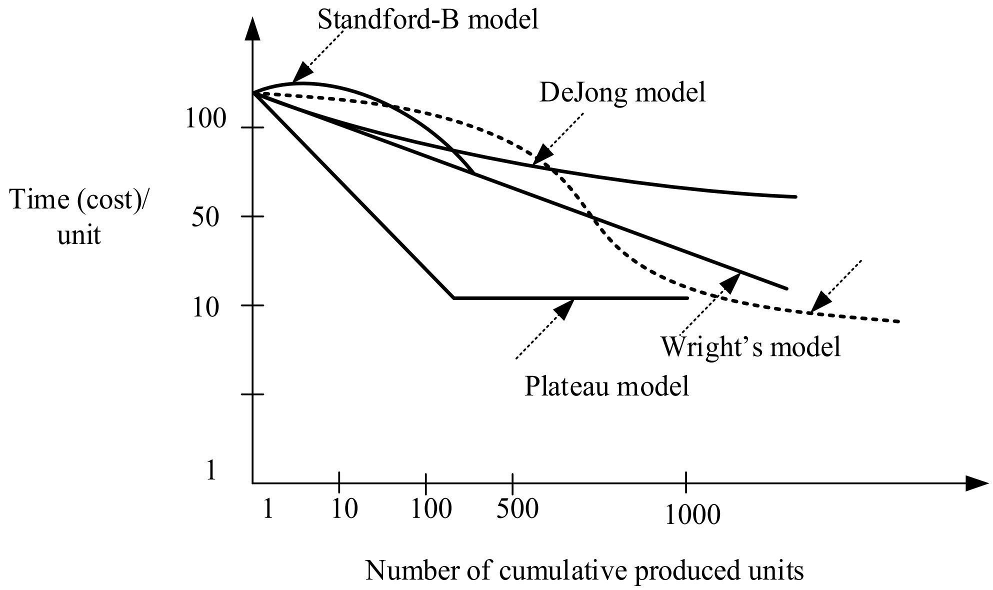


Figure Appx 1. Different learning curves models in the logarithm scale (Anzanello & Fogliatto, 2011; Badiru, 1992, 2011; Yelle, 1979)

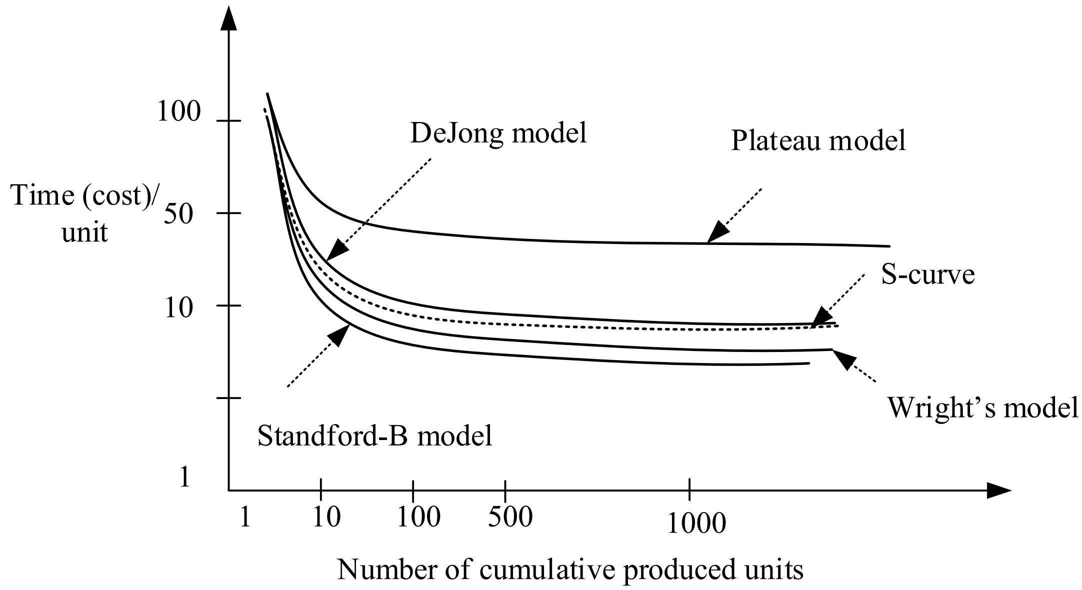


Figure Appx 2. Different learning curves models in the arithmetic scale (Anzanello & Fogliatto, 2011; Badiru, 1992, 2011; Yelle, 1979)

1. S-curve model

The S-shaped learning curve describes a gradual start-up phase and a learning curve stage. In the early stage, the curve has a shape of cumulative normal distribution function and the learning does not actually occur. It might be the case because of replacing tools, applying new methods or design, installing materials, or changing workers. In the later stage, the learning curve has the shape of the operating characteristics function. (Anzanello & Fogliatto, 2011; Badiru, 1992; Yelle, 1979). The form of S-curve formulas is described as follows:

$$y = y_1\left[M + (1-M)(x+B)^b\right]$$

where M: incompressibility factor

B: equivalent experience units

y_1: cost to produce the first unit

2. Stanford-B model

The Stanford B model contains the previous experience factor. In the beginning of the production process, this factor is expected to carry the experience over from a production unit to the next one. After a number of repetitions, the Standford B learning curve switches back to a linear or a plateau shape. This has been the best fit model when applied to in the Boeing 707 manufacturing (Anzanello & Fogliatto, 2011; Asher, 1956; Badiru, 1992; Yelle, 1979). The Stanford B model is expressed as follows:

$$Y_x = y_1 \left(x + B \right)^b$$

where y_x : direct cost to produce the xth unit

y_1: cost to produce the first unit

b: the slope of the curve

B: the experience constant (1<B<10)

3. DeJong's learning formula (DeJong)

DeJong's model includes an incompressible factor M into the conventional log-linear model. This factor represents the man-machine ratio (Anzanello & Fogliatto, 2011; Badiru, 1992; De Jong, 1957; Yelle, 1979). Dejong's model is expressed as follows:

$$M_y = y_1 \left[M + 1 \left(1 - M \right) x^{-b} \right]$$

where M: incompressibility factor;

if M = 0, the manufacturing process is solely manual operation;

if M = 1, the manufacturing process is conducted wholly by machine. In this case, the unit cost becomes y_1 and there is no cost improvement shown during production operations.

y_1: cost to produce the first unit

4. Levy's adaptation function

Levy suggested a learning curve model in a form of learning cost function. The model includes a flattening constant for a large value of x (Anzanello & Fogliatto, 2011; Badiru, 1992; Levy, 1965). Levy's model is expressed as follows:

$$M_y = [\frac{1}{B} - (\frac{1}{B} - \frac{x^b}{y_1})k^{(-kx)}]^{-1}$$

where B: production index for the first unit

K: constant for flattening the learning curve at a large value of x

y_1: cost to produce the first unit

5. Glover's learning formula

Glover's learning model includes a work commencement factor. This model basically attaches the individual learning performances of workers to the factory-based learning curve (Anzanello & Fogliatto, 2011; Badiru, 1992; Glover, 1965). Glover's model is expressed as follows:

$$\sum_{i=1}^{n} y_i + a = Y_1 \left[\sum_{i=1}^{n} x_i \right]^m$$

where Y_i : elapsed time or cumulative quantity

x_i : cumulative quantity or elapsed time

a: commencement factor

m: model parameter

n: index of the curve (=1+b)

6. Pegel's exponential function

Pegel's exponential function is an alternative symbolic model of the learning curve, and it has a form of the power functions (Anzanello & Fogliatto, 2011; Badiru, 1992). This model has a form of the exponential function and is expressed as follows

$$y_x = \alpha(a^{x-1}) + \beta$$

where

α, β, a are empirical parameters

x: cumulative produced quantity

7. Plateau model

In the plateau model, the learning curve reaches a certain level after a specific quantity of repetitions. Therefore, this modified version of the learning curve model represents the divergence of real costs when the produced units exceed a certain number. For this reason, the learning curve has nonconstant slopes. (Anzanello & Fogliatto, 2011; Badiru, 1992; Yelle, 1979). The plateau model is expressed as follows:

$$y_x = y_1 x^b e^{cx}$$

where b, c are modified constants

y_x: the unit cost of x^{th} unit. It approaches zero when x increases to a large number.

x: cumulative produced quantity. x reaches the infinity when the cumulative cost approaches zero

y_1: cost to produce the first unit

In general, the plateau model assumes the production cost will level off once a specific cumulative produced unit will be attained. The unit cost of x^{th} unit is determined by

$$U_{y_x} = \frac{d}{dx}\left[y_1 x^b e^{cx} \right] = y_1 x^b e^{cx} \left(c + \frac{b}{x} \right)$$

where y_1: the cost to produce the first unit when b = 0

y_x : direct cost to produce the x^{th} unit

b, c: modified constants

8. Yelle's product learning curve

Yelle's model is an aggregation of individual learning curves in which the individual learning curves are used to build up an aggregated log-linear equation (Anzanello & Fogliatto, 2011; Badiru, 1992; Yelle, 1979). The Yelle'model is expressed as follows

$$y_x = k_1 x_1^{b_1} + k_2 x_2^{b_2} + \ldots + k_n x_n^{b_n}$$

where y_x: cost of producing x^{th} unit

n: number of operators to produce a product

$k_i x_i^{b_i}$: learning curve of the i^{th} operator

However, according to Howell, Yelle's model has several shortcomings including that the learning curve is created by aggregating different learning curves slopes will not be a straight line; But it could be convex or concave to the origin of the axes (Badiru, 1992).

9. Multivariate learning curve

A multivariate learning curve model is a special model of learning curves. It was originally used to construct the learning ability of human operators under the influence of a variety of factors. Besides the factor of production output (counts, units), there are additional factors that could be included in the learning curve model such as skill ability, experience level, prior training rating, improvement in methods, tolerant levels or the complexity of the task (Baloff, 1966; William B Rouse, 1981). The learning curve model comprising a number of factors is expressed as follows (Badiru, 1992; Baloff, 1966):

$$T_c = K\prod_{i=1}^{n}\left(T_i x_i^{b_i}\right)$$

where

T_c = cumulative time for a given sets of factors

K = model parameter, measured by the time to produce the first unit

n = number of the factors in model

T_i = coefficient of the i^th factor

b_i = learning slope for the i^th factor

x_i = value of i^th factor

APPENDIX B. LITERATURE REVIEW: TYPICAL LEARNING CURVE APPLICATIONS

Table Appx 1. Typical individual learning curve applications

Year	Category	Application	Paper	Author(s)
1940	Psychology	Thorndike's law of effect explains different factors that are responsible for the stamping in and the stamping out	A rational equation of the learning curve based on Thorndike's law of effect	Harold Gulliksen
1971	Mental Health	The study focused on an asymptotic learning curve which reflects the acquisition of the response instead of arbitrary assumption; it could be a better composite measure of learning and performance.	Anxiety and motor behavior: a review	Rainer Martens
1994	Software development process	The learning curves are used to estimate the number of faults in software development process. The curves are mostly applied at the beginning of the test-and-debug phase.	Applying various learning curves to hyper-geometric distribution software reliability growth model	Rong-Huei Hou et al.
1971	Background music	Tie to a number of repetitions, the jobs could be explained by influence of music on human behavior with aiding alertness.	Background music and industrial efficiency: a review	J. G. Fox

Table Appx 2. Typical learning curves application in organizational zone

Order	**Category**	**Application**	**Paper**	**Author(s)**
2010	Energy Industry	The experience curve approach was used for applying renewable and non-renewable energy supply technologies and quantifying the cost dynamics of technologies.	Review of experience curve analyses for energy demand technologies	Martin Weiss et al.
2007	Scheduling	Learning curve is used for scheduling; The scheduling is position-based and its sum-of-processing-time is based on learning effects.	A state-of-the-art review on scheduling with learning effects	Dirk Biskup
1976	Aggregate Planning	Learning curve is used for developing aggregate-output plans in term of changing productivity; The productivity is related to the cumulative output of the organization.	Aggregate planning with learning curve productivity	RONALD J. EBERT
1992	Product Innovation	Learning curve is used to identify organizations' learning skills and how they could relate to new product management.	An organizational learning approach to product innovation	Daryl McKee
2002	Technology assessment	Learning effects are the interest in this research. The learning curves are used for analyzing learning effects in health technology assessment.	Assessing the learning Curve effect in health Technologies	Craig R. Ramsay et al.

APPENDIX C. CLASSIFICATION OF ADAPTABILITY COEFFICICENT

This below classification table does evaluate the disruption factor/adaptability coefficient based on the time spent in the first repetition in the new circumstance and time spent in the latest repetition in the previous circumstance. The table denotes that $\gamma_{i,i+1}$ is the adaptability coefficient in two consecutive circumstances, $A_i(U_{i+1}-U_i)$ and $A_{i+1}(L_{i+1}-U_i)$ are the last and the first performance times in two consecutive circumstances.

Table Appx 3. Classification of adaptability coefficient

Adaptability coefficient	Classification
$\gamma_{i,i+1} \approx 0$ and $A_i\left(U_{i+1}-U_i\right) << A_{i+1}\left(L_{i+1}-U_i\right)$	No adaptability
$0 < \gamma_{i,i+1} < 1$ and $A_i\left(U_{i+1}-U_i\right) < A_{i+1}\left(L_{i+1}-U_i\right)$	Passive adaptability
$\gamma_{i,i+1} = 1$ and $A_i\left(U_{i+1}-U_i\right) \approx A_{i+1}\left(L_{i+1}-U_i\right)$	Perfect adaptability
$\gamma_{i,i+1} > 1$ and $A_i\left(U_{i+1}-U_i\right) > A_{i+1}\left(L_{i+1}-U_i\right)$	Active adaptability

Examples of the classification of adaptability coefficients:

- $\gamma_{i,i+1} \approx 0$: No adaptability. If $\gamma_{i,i+1} = \dfrac{A_i\left(U_{i+1}-U_i\right)}{A_{i+1}\left(L_{i+1}-U_i\right)} \approx 0$, $A_{i+1}(L_{i+1}-U_i)$ is very large in comparison with $A_i(U_{i+1}-U_i)$

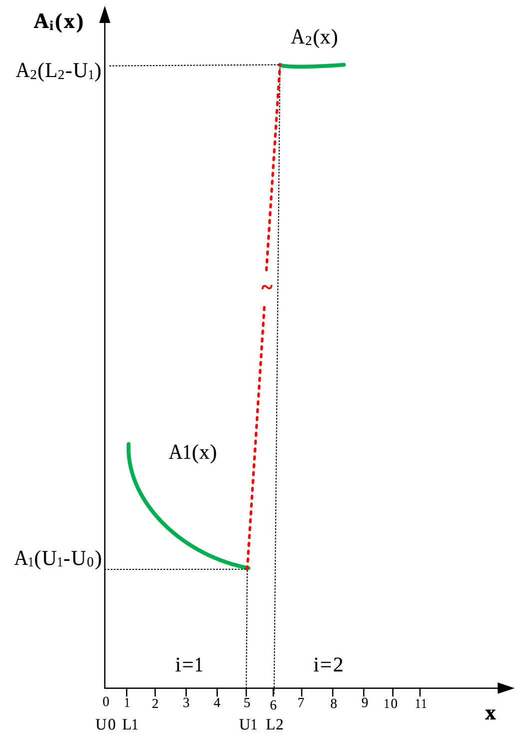


Figure Appx 3. No adaptability: $A_{i+1}(L_{i+1}-U_i)$ is very large in comparison with $A_i(U_{i+1}-U_i)$

- $0 < \gamma_{i,i+1} < 1$: Passive adaptability. If $\gamma_{i,i+1} < 1$ or $\gamma_{i,i+1} = \dfrac{A_i(U_{i+1} - U_i)}{A_{i+1}(L_{i+1} - U_i)} < 1$

  $\rightarrow A_i(U_{i+1}-U_i) < A_{i+1}(L_{i+1}-U_i)$

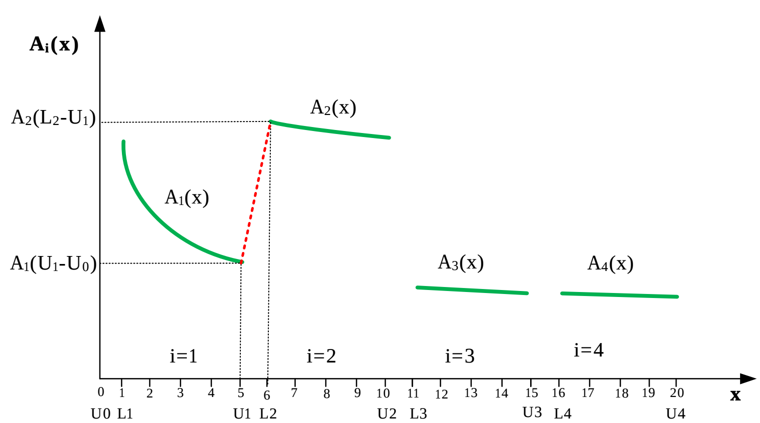


Figure Appx 4. $A_i(U_{i+1}-U_i) < A_{i+1}(L_{i+1}-U_i)$: Passive adaptability

- $\gamma_{i,i+1} \approx 1$: Perfect adaptability. If $\gamma_{i,i+1} \approx 1$ or $\gamma_{i,i+1} = \dfrac{A_i\left(U_{i+1} - U_i\right)}{A_{i+1}\left(L_{i+1} - U_i\right)} \approx 1$

$\rightarrow A_i(U_{i+1}\text{-}U_i) \approx A_{i+1}(L_{i+1}\text{-}U_i)$

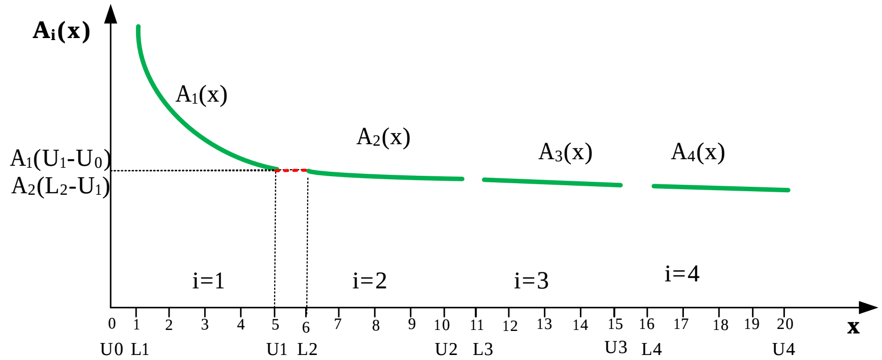


Figure Appx 5. $A_i(U_{i+1}\text{-}U_i) \approx A_{i+1}(L_{i+1}\text{-}U_i)$: Perfect adaptability

- $\gamma_{i,i+1} > 1$: Active adaptability. If $\gamma_{i,i+1} = \dfrac{A_i\left(U_{i+1} - U_i\right)}{A_{i+1}\left(L_{i+1} - U_i\right)} > 1$

$\rightarrow A_i(U_{i+1}\text{-}U_i) > A_{i+1}(L_{i+1}\text{-}U_i)$

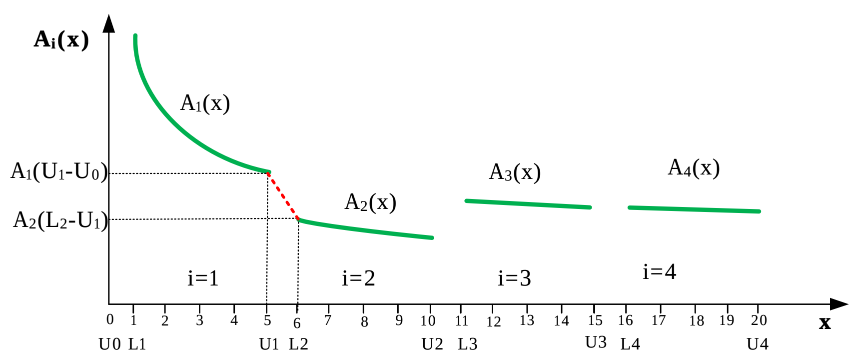


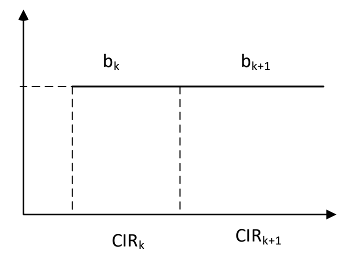
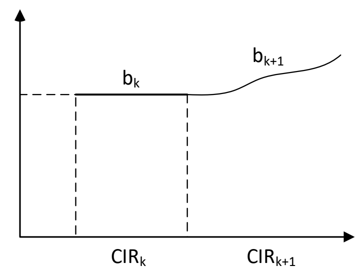
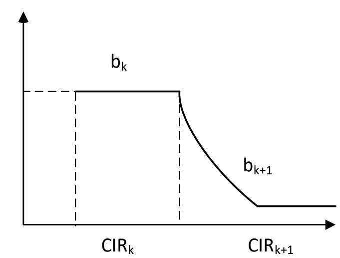
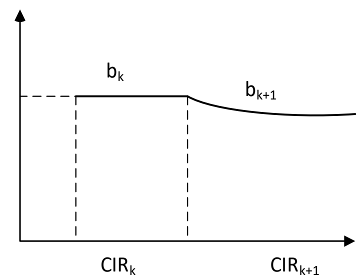
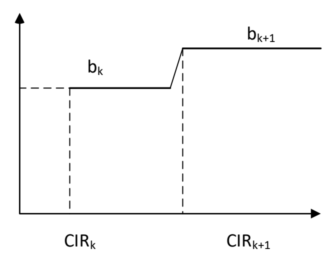
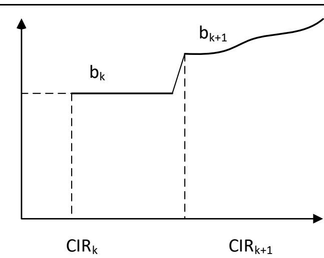
Figure Appx 6. $A_i(U_{i+1}\text{-}U_i) > A_{i+1}(L_{i+1}\text{-}U_i)$: Active adaptability

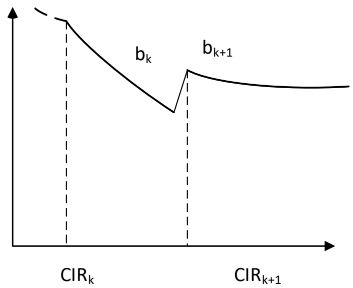
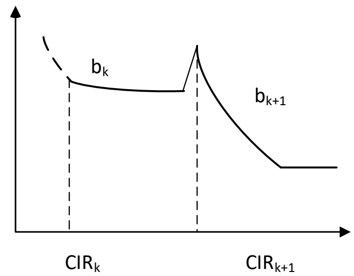
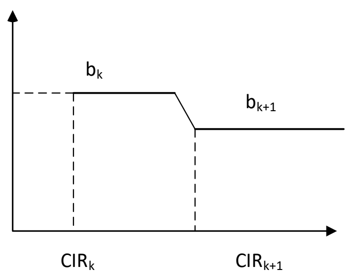
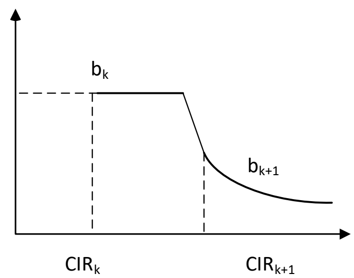
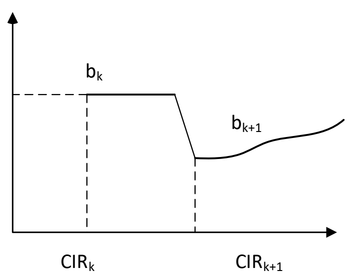
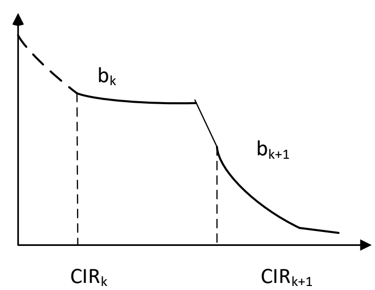
APPENDIX D. SOME PATTERNS OF ADAPTABILITY PARAMETERS

There are two parameters, the adaptability coefficient γ_k and learning slope b_k, which affect the learning process and the adaptability of human integrated systems. The following table illustrates some patterns of the adaptability according to γ_k and b_k in consecutive time-varying circumstances.

In the proposed model, the adaptability coefficient plays a role as a direction indicator to the first trial at a new circumstance, which is shifted from the last trial at the previous circumstance. From this point, the learning process of the operators might take many patterns which depend on the adaptability coefficient γ_k and the learning slope b_k .

Table Appx 4. Some patterns of adaptability parameters

Adaptability coefficient & Learning slope	*Illustration*	*Adaptability coefficient & Learning slope*	*Illustration*
$\gamma_{k,k+1} = 1$ $b_k = 0,$ $b_{k+1} = 0$	 No learning, perfect adaptability	$\gamma_{k,k+1} = 1$ $b_k = 0,$ $b_{k+1} > 0$	 No learning, perfect adaptability
$\gamma_{k,k+1} = 1$ $b_{k+1} << b_k < 0$	 Fast learning, perfect adaptability	$\gamma_{k,k+1} = 1$ $b_k << b_{k+1} < 0$	 Slow learning, perfect adaptability
$\gamma_{k,k+1} < 1$ $b_k = 0,$ $b_{k+1} = 0$	 No learning, passive adaptability	$\gamma_{k,k+1} < 1$ $b_k = 0,$ $b_{k+1} > 0$	 No learning, passive adaptability

$\gamma_{k,k+1} < 1$ $b_k << b_{k+1} < 0$	 Slow learning, passive adaptability	$\gamma_{k,k+1} < 1$ $b_{k+1} << b_k < 0$	 Fast learning, passive adaptability
$\gamma_{k,k+1} > 1$ $b_k = 0,$ $b_{k+1} = 0$	 No learning, active adaptability	$\gamma_{k,k+1} > 1$ $b_k = 0,$ $b_{k+1} < 0$	 Fast learning and active adaptability
$\gamma_{k,k+1} > 1$ $b_k = 0,$ $b_{k+1} > 0$	 Active adaptability at the first trial but fail to adapt later	$\gamma_{k,k+1} > 1$ $b_{k+1} << b_k < 0$	 Fast learning, active adaptability

APPENDIX E. VALIDITY PROCEDURE FOR THE SETTINGS OF DEMONSTRATION EXPERIMENT

Table Appx 5. Validity procedure

Validity types	Validity procedure
Prior validates	**Purpose:** Preparation to select events and phenomena for observation and study; identify these are real, true and important. • Selection of circumstances
Internal validity	**Purpose:** Controlling irrelevant variables • Provide the instructions and explanations for the subject. Provide the same amount of the explanation. Don’t give different people different ways of instruction. • Positions of the objects in the experiment area are fixed and do not change at different times. For example, light hanged at the same position, the objects, obstacles are put at the same areas.
	Purpose: The method captures a specific theoretical construct • The phenomenon being measured actually exists and happens: a system works in different influential working environments.
Construct validity	**Purpose:** The results of a study can be generalized to other settings (ecological validity) or people (population validity) **Validity testing:** • Setting the experiments in a more natural setting • The results show that human performance varies in different circumstances. Some circumstances especially challenge the limitations of human capabilities to finish the task.

APPENDIX F. LITERATURE REVIEW: VALIDITIES IN RESEARCH PROCESS

1. What is validity?

Validity is used for defining the nature of research relationships to be studied. Validity has been used as correspondence, convergence, equivalence, generality, robustness or repeatability. If the validity is considered as correspondence or fit, it is appropriate to test the methodology and procedures for doing a study. If the validity is considered as robustness, it is appropriate to examine the implementation of the data (Watkins, 1991).

Research is the study of relations between context elements. The research could be divided into the following major stages:

1. Restudy stage: Generalize, identify, develop and clarify the problem. The orientations to do research might follow one of these methods:
   - Basic research: Focus on conceptual issues
   - Applied research: Focus on substantive systems
   - Technological research: Focus on methodologies
2. Doing-a-study stage (central stage): Combine some knowledge, ideas, and techniques to arrive at some solutions. In this stage, several approaches could be used to do a study:
   - Experiment path: Design a study, then implement the design
   - Theoretical path: Develop a theory, then test the theory
   - Empirical path: Collect and analyze a set of data, then interpret the data
3. Follow-up stage: Explore the scope of limits of the solutions or findings

The paths and orientations discussed above are valuable and valid parts of the overall research process (Brinberg & McGrath, 1985). However, the research process is usually complex and multifaceted, there is no “correct” and “standard” path that we could apply. Scientists normally use multiple paths to tackle the problem and exploit the potential strengths of each path as well as offset their weaknesses. Furthermore, various paths through the research might encounter the different validity issues that will be discussed in the following parts (Brinberg & McGrath, 1985).

2. Concept of validity

The validity was first defined by Kelly (1927). The validity means that a test is valid if it measures what claims to be measured. To do this, the experiment should be designed to investigate the relationships between independent variables and the control of extraneous variables.

3. Experiment validity

The researchers expect the research study to be valid when it truly measures what it was intended to. Experiment validity will ensure the study having validity not only in the scope within the experiment but also in the generalizability.

Experiment validity is expected to contribute to several major benefits (Caamano Alegre, 2009):

1. Better quality of an experimental procedure
2. No need to select different fundamental views on solving problems, if the views are compatible with the application that has similar valid procedures.
3. Omit the weak ideas that are not supported by experimental practice

4. Statistical conclusion validity

The appropriate usage of statistics infers whether the presumed independent and dependent variables are correlated. It refers to how large and reliable is co-variation between the presumed cause and effect. This type of validity is called criterion-related validity (Caamano Alegre, 2009). This validity is used to evaluate how well one or a set of independent variables predicts the outcomes (dependent variables). The aim of validity testing presumes that independent and dependent variables are correlated.

5. Internal validity

Internal validity refers to the covariation between independent and dependent variables which create a causal relationship (Caamano Alegre, 2009). It brings about the concerns with the causal interpretation of the validity of criteria used in the study.

6. Construct validity

Construct validity refers to whether a test captures a specific theoretical construct. Construct validity expects to provide the evidential basis for test interpretation. It indicates to which extent the independent and dependent variables actually represent the hypothetical relationships of interest (Pelham & Blanton, 2012). With a focus on cause and effect constructs, construct validity underscores the generalization of operations and constructs in order to examine whether a measure is related to other variables as stated in the theory.

7. External validity

External validity refers to the appropriateness of the generalizations from the results in order to obtain the validation from the testing environment to the application. External validity considers if a set of research findings could provide accurate descriptions of what normally happens in the real world (Caamano Alegre, 2009; Pelham & Blanton, 2012).

APPENDIX G. DATA ANALYSIS OF DEMONSTRATION STUDY

1. Raw collected data

Table Appx 6. Raw collected data of four subjects in four circumstances

			Subject 1	Subject 2	Subject 3	Subject 4
			Second	Second	Second	Second
CIR 1	1	1	201.83	531.76	171.74	458.37
	2	2	155.76	351.6	272.21	541.87
	3	3	93.9	140.11	232.13	111.04
	4	4	91.08	127.45	127.54	231.66
	5	5	225.04	105.96	198.65	183.64
CIR 2	6	1	200.75	135.81	270.32	188.31
	7	2	105.5	83.91	328.11	440.97
	8	3	78.66	110.19	205.44	86.93
	9	4	80.5	112.93	130.4	142.29
	10	5	80.37	142.19	119.26	76.87
CIR 3	11	1	126	198.94	207.9	121.65
	12	2	123	108.48	175.15	170.48
	13	3	137.11	155.53	293.04	137.88
	14	4	127.89	94.81	91.37	101.11
	15	5	108.32	90.13	207.74	118.38
CIR 4	16	1	176.18	268.79	144.83	146.88
	17	2	160.34	136	164.15	150.44
	18	3	226.71	146.66	108.75	145.4
	19	4	132.97	163.06	137.14	177.82
	20	5	124.07	167.53	127	495.71

2. Fitted learning slopes

Table Appx 7. Fitted learning slopes in four circumstances

	CIR_1	CIR_2	CIR_3	CIR_4
Subject 1	b = -0.2253 R-square: 0.8529 Adjusted R-square: 0.8529 RMSE: 10.05	b = -0.3913 R-square: 0.9981 Adjusted R-square: 0.9981 RMSE: 1.606	b = 0.00373* R-square: 0.02544 Adjusted R-square: 0.02544 RMSE: 2.049	b = -0.01404 R-square: 0.04565 Adjusted R-square: 0.04565 RMSE: 8.812

Subject 2	b = -0.4162 R-square: 0.954 Adjusted R-square: 0.954 RMSE: 24.68	b = -0.1485 R-square: 0.4102 Adjusted R-square: 0.4102 RMSE: 8.528	b = -0.2665 R-square: 0.9381 Adjusted R-square: 0.9381 RMSE: 6.606	b = -0.3066 R-square: 0.9251 Adjusted R-square: 0.9251 RMSE: 10.59
Subject 3	b = 0.149 R-square: -0.05882 Adjusted R-square: -0.05882 RMSE: 22.08	b = -0.07965 R-square: 0.3496 Adjusted R-square: 0.3496 RMSE: 27.85	b = -0.02768 R-square: 0.05178 Adjusted R-square: 0.05178 RMSE: 14.12	b = -0.0242 R-square: 0.2469 Adjusted R-square: 0.2469 RMSE: 6.308
Subject 4	b = -0.1886 R-square: 0.5966 Adjusted R-square: 0.5966 RMSE: 52.39	b = 0.1312 R-square: -0.3033 Adjusted R-square: -0.3033 RMSE: 60	b = 0.08527 R-square: -0.2333 Adjusted R-square: -0.2333 RMSE: 11.12	b = 0.1397 R-square: 0.3581 Adjusted R-square: 0.3581 RMSE: 26.53

* The highlighted learning slopes indicate that the collected data in a particular circumstance do not fit well the learning curve equations.

3. Calculation Details

Collecting performance time

For each subject, we record the time of the task since the subject is ready to start until the subject completes the requirement of the task. The recorded time unit is minute, second and millisecond (a hundredth of a second) (unit: min.s.ms). The converted raw performance time is returned by using the following equation:

(value in minute) *(60) + (value in second) + (value in millisecond)/100

Table Appx 8. Converted raw performance time

	# of replications	Subject 1	Subject 2	Subject 3	Subject 1
CIR 1	1	201.83	531.76	171.74	458.37
	2	155.76	351.6	272.21	541.87
	3	93.9	140.11	232.13	111.04
	4	91.08	127.45	127.54	231.66
	5	225.04	105.96	198.65	183.64
CIR 2	6	200.75	135.81	270.32	188.31
	7	105.5	83.91	328.11	440.97
	8	78.66	110.19	205.44	86.93
	9	80.5	112.93	130.4	142.29
	10	80.37	142.19	119.26	76.87
CIR 3	11	126	198.94	207.9	121.65
	12	123	108.48	175.15	170.48
	13	137.11	155.53	293.04	137.88
	14	127.89	94.81	91.37	101.11
	15	108.32	90.13	207.74	118.38
CIR 4	16	176.18	268.79	144.83	146.88
	17	160.34	136	164.15	150.44
	18	226.71	146.66	108.75	145.4
	19	132.97	163.06	137.14	177.82
	20	124.07	167.53	127	495.71

Converting collected data to learning curve format

Table Appx 9. Converted collected data

x	$x = L_i, U_i$	$A_i(x)$			
	L_i, U_i	**Subject 1**	**Subject 2**	**Subject 3**	**Subject 4**
1	L_1=1	201.83	531.76	171.74	458.37
2		178.795	441.68	221.975	500.12
3		150.496	341.156	225.36	370.426
4		135.642	287.73	200.905	335.735
5	U_5=5	153.522	251.376	200.454	305.316
6	L_6=6	200.75	135.81	270.32	188.31
7		153.125	109.86	299.215	314.64
8		128.303	109.97	267.956	238.736
9		116.352	110.71	233.5675	214.625
10	U_{10}=10	109.156	117.006	210.706	187.074
11	L_{11}=1	126	198.94	207.9	121.65
12		124.5	153.71	191.525	146.065
13		128.703	154.316	225.363	143.336
14		128.5	139.44	191.865	132.78
15	U_{15}=15	124.464	129.578	195.04	129.9
16	L_{16}=16	176.18	268.79	144.83	146.88
17		168.26	202.395	154.49	148.66
18		187.743	183.816	139.2433	147.573
19		174.05	178.627	138.717	155.135
20	U_{20}=20	164.054	176.408	136.374	223.25

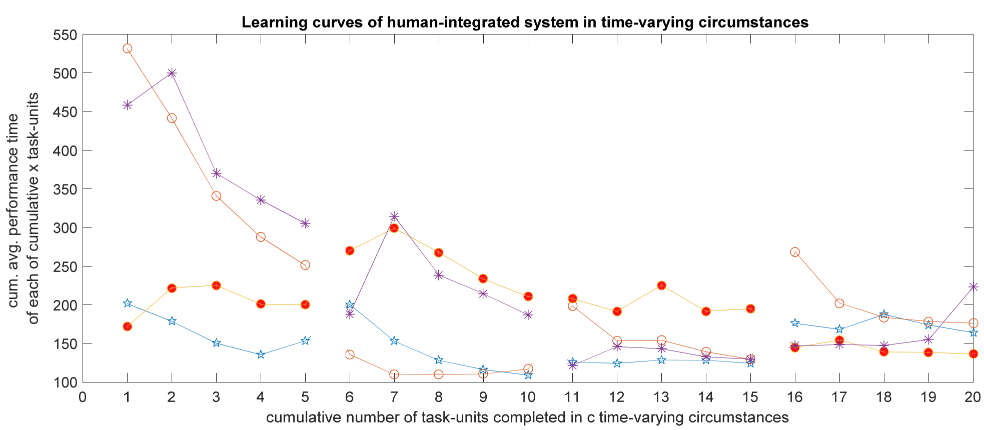


Figure Appx 7. Learning curves of human-integrated system in time-varying circumstances

Subject performance time at each replication is listed on separate columns in Table Appx 6. These performance time are collected across four circumstances in which each circumstance is continuously partitioned by an equal range of five replications from a range of 20 replications. For example, CIR_1 is from replication (rep) 1st to rep 5th, CIR_2 is from rep 6th to rep 10th, CIR_3 is from rep 11th to rep 15th and CIR_4 is from rep 16th to rep 20th. The graphs of Y versus X with converted collected data Y are shown Figure Appx 7.

<u>Fitting curves of each adaptability</u>

To determine learning slopes parameters b_i, there are two ways that we fit the curves in Matlab: to utilize the least square fitting function (lsqcurvefit) or to use the open curve fitting tool (cftool). After fitting, determined parameters area listed in Table Appx 10 below.

Table Appx 10. The fitted learning slopes of four subjects

	CIR_1	**CIR_2**	**CIR_3**	**CIR_4**
Subject 1	b = -0.2253 R-square: 0.8529 Adjusted R-square: 0.8529 RMSE: 10.05	b = -0.3913 R-square: 0.9981 Adjusted R-square: 0.9981 RMSE: 1.606	b = 0.00373* R-square: 0.02544 Adjusted R-square: 0.02544 RMSE: 2.049	b = -0.01404 R-square: 0.04565 Adjusted R-square: 0.04565 RMSE: 8.812
Subject 2	b = -0.4162 R-square: 0.954 Adjusted R-square: 0.954 RMSE: 24.68	b = -0.1485 R-square: 0.4102 Adjusted R-square: 0.4102 RMSE: 8.528	b = -0.2665 R-square: 0.9381 Adjusted R-square: 0.9381 RMSE: 6.606	b = -0.3066 R-square: 0.9251 Adjusted R-square: 0.9251 RMSE: 10.59
Subject 3	b = 0.149 R-square: -0.05882 Adjusted R-square: -0.05882 RMSE: 22.08	b = -0.07965 R-square: 0.3496 Adjusted R-square: 0.3496 RMSE: 27.85	b = -0.02768 R-square: 0.05178 Adjusted R-square: 0.05178 RMSE: 14.12	b = -0.0242 R-square: 0.2469 Adjusted R-square: 0.2469 RMSE: 6.308
Subject 4	b = -0.1886	b = 0.1312	b = 0.08527	b = 0.1397

	R-square: 0.5966 Adjusted R-square: 0.5966 RMSE: 52.39	R-square: -0.3033 Adjusted R-square: -0.3033 RMSE: 60	R-square: -0.2333 Adjusted R-square: -0.2333 RMSE: 11.12	R-square: 0.3581 Adjusted R-square: 0.3581 RMSE: 26.53

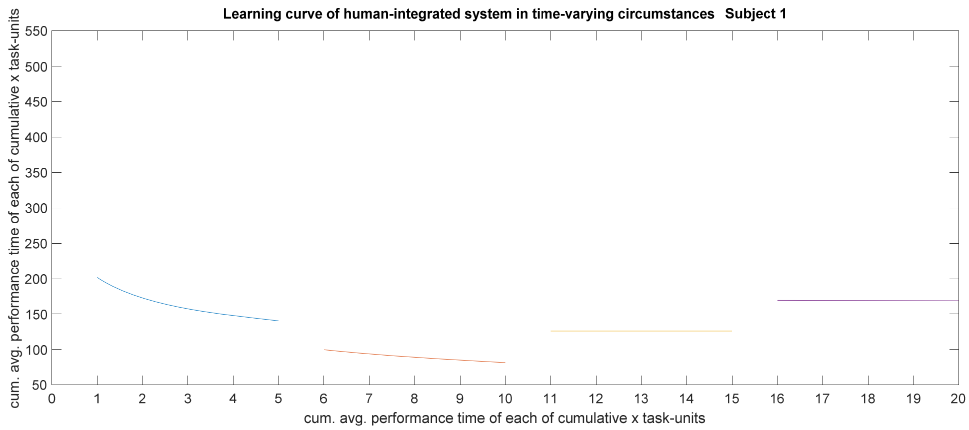


Figure Appx 8. Learning curve of human-integrated robot system in four time-varying circumstances - Subject 1

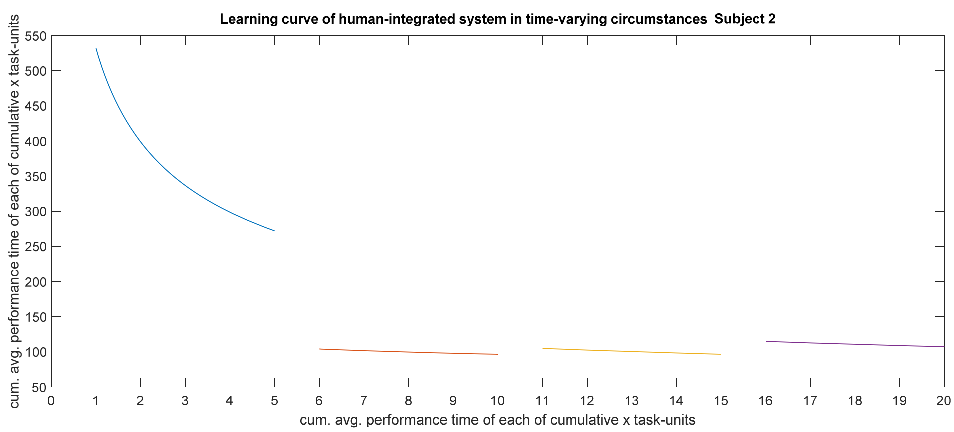


Figure Appx 9. Learning curve of human-integrated robot system in four time-varying circumstances - Subject 2

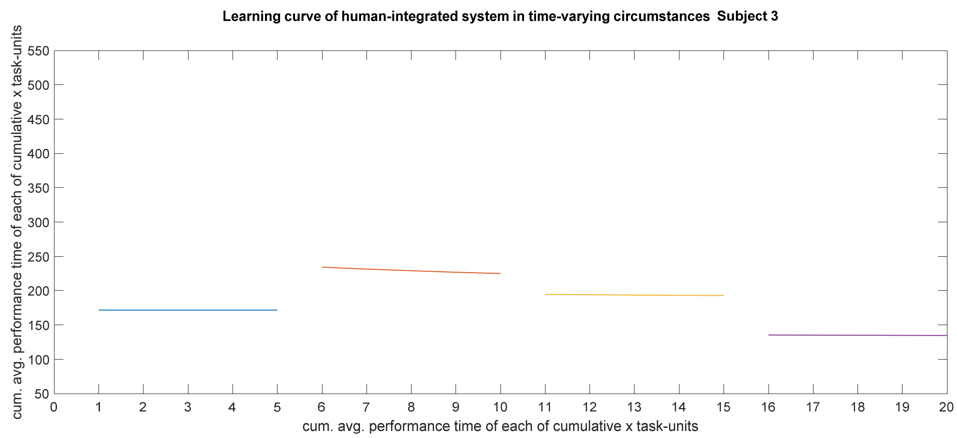


Figure Appx 10. Learning curve of human-integrated robot system in four time-varying circumstances - Subject 3

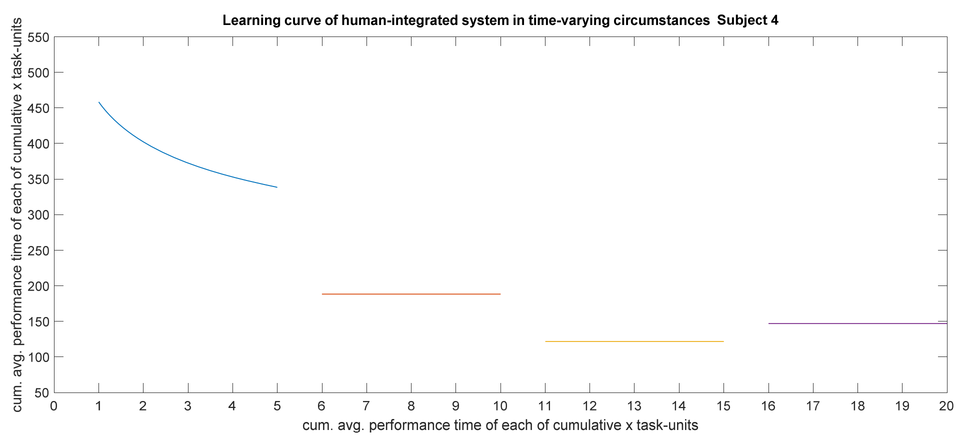


Figure Appx 11. Learning curve of human-integrated robot system in four time-varying circumstances - Subject 4

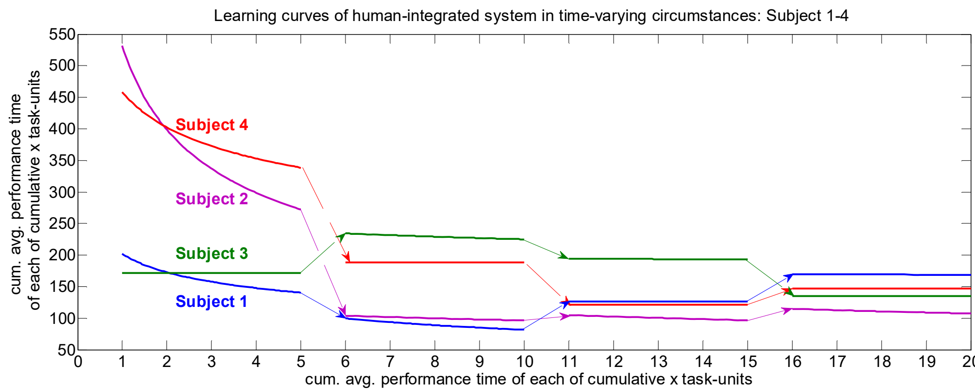


Figure Appx 12. Learning curves of human-integrated robot system in four time-varying circumstances - Subject 1-4

Table Appx 11. Summary of fitted learning slope parameters

	CIR1	CIR2	CIR3	CIR4
Subject 1	-0.2253	-0.3913	0.00373	-0.01404
Subject 2	-0.4162	-0.1485	-0.2665	-0.3066
Subject 3	0.149	-0.07965	-0.02768	-0.0242
Subject 4	-0.1886	0.1312	0.08527	0.1397

Because $-1 < bi < 0$ by defaults, the values of b_i are screened by the formula: $b_i = \min(bi, 0)$. This means, if $b_i = 0$, there was no learning gain in the tested circumstance. The screened values are listed in the table below.

	CIR1	CIR2	CIR3	CIR4
Subject 1	-0.2253	-0.3913	0	-0.01404
Subject 2	-0.4162	-0.1485	-0.2665	-0.3066
Subject 3	0	-0.07965	-0.02768	-0.0242
Subject 4	-0.1886	0	0	0

Calculating sets of adaptability index and learning index

The learning index is actually the average of learning slopes across varying circumstances. LI_k shows the average of learning 'speed' of an operator k in a range of circumstances. The closer to -1, the faster learning speed of the operator.

Table Appx 12. Learning slopes and Learning indexes

	b_1	b_2	b_3	b_4	**LI_k**
Subject 1	-0.2253	-0.3913	0	-0.014	**-0.158**
Subject 2	-0.4162	-0.1485	-0.2665	-0.3066	**-0.284**
Subject 3	0	-0.0797	-0.0277	-0.0242	**-0.033**
Subject 4	-0.1886	0	0	0	**-0.047**

Table Appx 13. Descriptive Statistics of the learning slopes

Variable	**N**	**Mean**	**SE Mean**	**StDev**	**Variance**	**Sum of Squares**	**Minimum**	**Maximum**
Subject 1	4	-0.1577	0.0934	0.1868	0.0349	0.2041	-0.3913	0
Subject 2	4	-0.2844	0.0553	0.1105	0.0122	0.3603	-0.4162	-0.1485
Subject 3	4	-0.0329	0.0168	0.0335	0.0011	0.0077	-0.0796	0
Subject 4	4	-0.0471	0.0471	0.0943	0.0089	0.0356	-0.1886	0

Table Appx 14. Adaptability coefficients and adaptability indexes

	$\boldsymbol{\gamma_{1,2}}$	$\boldsymbol{\gamma_{2,3}}$	$\boldsymbol{\gamma_{3,4}}$	**AI_k**
Subject 1	0.765	0.866	0.706	**0.779**
Subject 2	1.851	0.588	0.482	**0.974**
Subject 3	0.742	1.013	1.347	**1.034**
Subject 4	1.621	1.538	0.884	**1.348**

Table Appx 15. Descriptive Statistics of adaptability indexes

Variable	**N**	**Mean**	**SE Mean**	**StDev**	**Variance**	**Sum of Squares**	**Minimum**	**Maximum**
Subject 1	3	0.7792	0.0467	0.0809	0.0065	1.8344	0.7065	0.8663
Subject 2	3	0.974	0.44	0.762	0.58	4.004	0.482	1.851
Subject 3	3	1.034	0.175	0.303	0.092	3.391	0.742	1.347
Subject 4	3	1.348	0.233	0.404	0.163	5.776	0.884	1.621

The adaptability coefficient of a Subject of an operator from CIR_i to CIR_{i+1} is calculated by the formula $\gamma_{i,i+1} = \frac{A_i\left(U_{i+1} - U_i\right)}{A_{i+1}\left(L_{i+1} - U_i\right)}$, where $A_i(U_{i+1}-U_i)$ and $A_{i+1}(L_{i+1}-U_i)$ are cumulative average performance times of each of x units in two consecutive circumstances. In Figure Appx 13, γ_1 of

Subject 1 is a ratio of $A_1(U_1\text{-}U_0)|U_{0=0}$ = 153.522 to $A_2(L_2\text{-}U_1)$ = 200.75, thus $\gamma_1 = \frac{153.522}{200.75} = 0.7647$. The other values of adaptability coefficients in the model is calculated in a similar way (See Table Appx 14).

Figure Appx 13. Value of $A_i(x)$ at x = $L_{i+1}\text{-}U_i$, $U_{i+1}\text{-}U_i$

CIR$_i$	x	x = L_{i+1}-U_i, U_{i+1}-U_i	$A_i(x)$			
		L_i, U_i	**Subject 1**	**Subject 2**	**Subject 3**	**Subject 4**
i=1	1	**L_1=1**	201.83	531.76	171.74	458.37
	5	**U_1 =5**	153.522	251.376	200.454	305.316
i=2	6	**L_2=6**	200.75	135.81	270.32	188.31
	10	**U_2 =10**	109.156	117.006	210.706	187.074
i=3	11	**L_3=1**	126	198.94	207.9	121.65
	15	**U_3=15**	124.464	129.578	195.04	129.9
i=4	16	**L_4=16**	176.18	268.79	144.83	146.88
	20	**$U_{4=}$20**	164.054	176.408	136.374	223.25

The adaptability index of Subject 1 (AI_1) is the average of adaptability coefficients of this subject across four circumstances. In Table Appx 14, AI_1 is the average of γ_1 , γ_2 and γ_3.

4. 5. Calculating Performance Score (PS)/System Effectiveness

Table Appx 16. Table of T_i

CIR$_i$	x	x = L_{i+1}-U_i, U_{i+1}-U_i	T_i=$A_i(L_i)$			
		L_i, U_i	**Subject 1**	**Subject 2**	**Subject 3**	**Subject 4**
i=1	1	**L_1=1**	201.83	531.76	171.74	458.37
i=2	6	**L_6=6**	200.75	135.81	270.32	188.31
i=3	11	**L_{11}=1**	126	198.94	207.9	121.65
i=4	16	**L_{16}=16**	176.18	268.79	144.83	146.88

Table Appx 17. Table of $T_i(U_i\text{-}U_{i\text{-}1})$

			$T_i(U_i\text{-}U_{i\text{-}1})$			
CIR$_i$	**Ui, i=1…4**	**U_i-$U_{i\text{-}1}$**	**Subject 1**	**Subject 2**	**Subject 3**	**Subject 4**
1	U_0=0, U_1=5	U_1-U_0=5	1009.15	2658.8	858.7	2291.85

2	U_2=10	U_2-U_1=5	1003.75	679.05	1351.6	941.55
3	U_3=15	U_3-U_2=5	630	994.7	1039.5	608.25
4	U_4=20	U_4-U_3=5	880.9	1343.95	724.15	734.4

In the table above, the second column is about U_i, the upper bound of circumstance *i*. The third column is the number of task repetitions in each circumstance. The last column $T_i(U_i-U_{i-1})$ is calculated by multiplying T_i to the value of U_i-U_{i-1} with respect to subject k in circumstance i. Table Appx 17 explains the values in formula of E_{Du} from right to left.

Table Appx 18. Learning slopes b_i

	CIR1	**CIR2**	**CIR3**	**CIR4**
Subject 1	-0.2253	-0.3913	0	-0.014
Subject 2	-0.4162	-0.1485	-0.2665	-0.3066
Subject 3	0	-0.0797	-0.0277	-0.0242
Subject 4	-0.1886	0	0	0

Table Appx 19. AI_{Du}, LI_{Du}, E_{Du}

Variable	*N*	*Mean*	*SE Mean*	*StDev*	*Variance*	*Sum of Squares*	*Minimum*	*Maximum*
AI_{Du}	4	1.034	0.118	0.236	0.056	4.441	0.779	1.348
LI_{Du}	4	-0.1305	0.0584	0.1168	0.0136	0.1091	-0.2844	-0.0329

Table Appx 20. The calculation of AI_{Du}

	Gamma 1	**Gamma 2**	**Gamma 3**	**AI_k**	
Subject 1	0.765	0.866	0.706	0.779	**AI_{Du}**
Subject 2	1.851	0.588	0.482	0.974	**1.034**
Subject 3	0.742	1.013	1.347	1.034	
Subject 4	1.621	1.538	0.884	1.348	

Table Appx 21.

Table Appx 22. The calculation of LI_{Du}

	CIR1	CIR2	CIR3	CIR4	LI_k	
Subject 1	-0.2253	-0.3913	0	-0.014	-0.158	**LI_{Du}**
Subject 2	-0.4162	-0.1485	-0.2665	-0.3066	-0.284	**-0.1305**
Subject 3	0	-0.0797	-0.0277	-0.0242	-0.033	
Subject 4	-0.1886	0	0	0	-0.047	

Table Appx 23. The calculation of E_{Du}

				$[U_i-U_{i-1}][T_i(U_i-U_{i-1})]^{bi}$			
CIR_i	Ui, i=1..4	**U_i-U_{i-1}**	**U_i-U_{i-2}**	**Subject 1**	**Subject 2**	**Subject 3**	**Subject 4**
1	$U_0=0$, $U_1=5$	$U_1-U_0=5$	5	702.227	1416.376	858.700	2240.643
2	$U_2=10$	$U_2-U_1=5$	5	513.706	534.693	880.182	574.830
3	$U_3=15$	$U_3-U_2=5$	5	630.000	875.022	994.207	585.015
4	$U_4=20$	$U_4-U_3=5$	5	650.281	1343.950	724.150	734.400
						p_u	**4**
						E_{Du}	**3564.596**

APPENDIX H. RESEARCH PARTICIPANT CONSENT FORM

Purdue IRB Protocol #: 1801020097 - Expires on: 20-FEB-2019

RESEARCH PARTICIPANT CONSENT FORM

A Measure of Human-Integrated System Performance under Time-Varying Circumstances

Dr. Steven J Landry, Nguyen Nguyen V P
School of Industrial Engineering
Purdue University

What is the purpose of this study?

This research is about developing a way to measure the performance of human working with a system ('human integrated system') such as a computer or a machine under time-varying situations ('circumstances'). Workers who operate continuously a forklift handle loads from indoors to outdoors and vice versa is an example of human working under time-varying circumstances.

Most systems operate under time-varying circumstances and scientists do not know how to evaluate the best system design when the operator in that system moves between time varying circumstances.

We aim to evaluate the measure of human integrated system performance in time-varying circumstances through the human-system experiments, in which you will perform a task using an electrical device in a series of time varying circumstances. You must be at least 18 years old to participate in the study.

What will I do if I choose to be in this study?

You must be over the age of 18, a student enrolled at Purdue University and cannot be color-blind. You will participate in a study of human working with an electrical device. You will be given an electrical device such as a smartphone or a tablet.

In this study, you will carry out an abstract task of fruit visual inspection. Instead of working with real fruit, you will participate in a visual checking procedure with colored balls. There are a number of containers which contain identical colored balls.

To start out, you will be given an instruction document where you can learn the purpose of the experiment, read the task description and follow the task guidelines to perform the mission. You will repeat the task 5 times in three circumstances. Then, lastly you will answer the questionnaire on the given device.

How long will I be in the study?

You will participate in three continuous circumstances, each including 5 repetitions and lasting about 20 minutes. When a rest break ('delay between circumstances') is applied, you are free to leave and come back to complete the experiment. The study will last maximum one hour without including rest breaks and last maximum two and half hours including rest breaks.

APPENDIX I. TASK INSTRUCTION

You will participate in a study of humans using an electronic device in **three settings.**

1. In each setting, you will:

1. Carry out the task of visual inspection with colored balls by following a visual checking procedure.
2. Repeat the task 5 times and we will collect the completion time of the task each time.

2. Between the settings, you will take a short break.

3. Please do the following steps in each setting in order:

1. You will be given: task instructions, an electronic device, gloves, a color checking chart, a questionnaire, and one case of colored balls.
2. You will be provided a *recorded instruction* when you're ready.
3. For each repetition, open the *inspection procedure webform* in the given device, follow its procedure, and use the *standard color chart* to perform the task.
4. Notify the experimenter when you complete each repetition.

APPENDIX J. INSPECTION PROCEDURE

SUBTASKS:

1. Count the number of colored ball cases. These cases are randomly taken out for inspections.
2. Identify the color of the balls and then select the correct colored balls from a dropdown list or input its name into the name box in the web form.
3. Check the origin of the produce and then select the correct answer from a dropdown list or input the information into an empty box in the web form
4. Inspect the minimum quality requirements of each container/case by checking a rating scale for the specific following characteristics with reference to a given color chart.

Rating scale of [a specific characteristic]:

__1_not at all

__2_slightly (observe 1-2 defective units/balls)

__3_somewhat (observe 3-5 defective units/balls)

__4_quite much (observe 6-10 defective units/balls per case)

__5_very much (observe > 10 defective balls/units per case)

a) Intact
   i. The balls ('fruit') should not have any damage or injury spoiling the integrity of the produce. Unhealed cracks are not allowed.
   ii. Check Photo_1 in the color chart for examples.
   iii. Rate the intact condition

1	2	3	4	5
no damages at all	**slightly** 1-2 damaged units	**somewhat** 3-5 damaged units	**quite much** 6-10 damaged units	**very much** > 10 damaged units

   i. Save the result

b) Sound
   i. The balls ('fruit') should not be affected by rotting or deterioration: (1) Fresh dents due to rough handling, (2) Spots
   ii. Check Photo_2 in the color chart for examples
   iii. Rate the sound condition

1	2	3	4	5
no fresh cracks or spots at all	**slightly** 1-2 units having fresh cracks or spots	**somewhat** 3-5 units having fresh cracks or spots	**quite much** 6-10 units having fresh cracks or spots	**very much** > 10 units having fresh cracks or spots

iv. Save the result

c) Clean

i. The balls ('fruit') should not have any sooty mold and should be free of visual soil, dust or residue of foreign matter.

ii. Check Photo_3 in the color chart for examples

iii. Rate the clean condition

1	2	3	4	5
Free of visual soils	**slightly** 1-2 units with sooty mold, visual soil, dust or residue of foreign matter	**somewhat** 3-5 units with sooty mold, visual soil, dust or residue of foreign matter	**quite much** 6-10 units with sooty mold, visual soil, dust or residue of foreign matter	**very much** > 10 units with sooty mold, visual soil, dust or residue of foreign matter

iv. Save the result

d) Fresh in appearance

i. The balls ('fruit') should not have any sign of withering or loss of firmness.

ii. Check Photo_4 in the color chart for examples

iii. Rate the fresh in appearance condition

1	2	3	4	5
No sign of withering	**slightly** 1-2 units with withering or loss of firmness	**somewhat** 3-5 units with withering or loss of firmness	**quite much** 6-10 units with withering or loss of firmness	**very much** > 10 units with withering or loss of firmness

iv. Save the result

e) Alien items
   i. Alien items are the items with a different color or a different shape or a different pattern from the surrounding and identified items you are working with.
   ii. For example, the case/container of red balls should not have white balls or any different colored balls, or smaller size balls.

5. For each fruit container, take a photo by using the given device. Select the photo icon on the webform, and find the link to the photo the subject took in from the gallery and attach it.
6. Hit the review button in the webform and then submit it.

APPENDIX K. INSPECTION WEB-FORM

Online Inspection web-form

3/17/2018 Online Survey Software | Qualtrics Survey Solutions

PURDUE
UNIVERSITY

INTRO.
The inspection task is based on physical attributes of fruit. When working on specific types of fruit, the inspectors should follow exhaustive guidelines on fruit inspection.

For inspecting fruit, the inspectors need to check the following: **color and physical characteristics** (size of the fruit). The subject opens the inspection web form and follows the instructions and inspection procedure in the web form.

The inspection procedure includes the following subtasks:

Q1. Count the number of colored ball in the given case.

10 17 24 31 38 45 52 59 66 73 80

Number of colored balls

Q2. Identify the color of the balls in the given case and then input its color name into the name box accordingly in the web form.

	Select the correct answers from dropdown lists
Color of the balls in the given case	▼

Q3. Check the origin of the produce and then select the correct answer from dropdown lists

	Select the correct answers from dropdown lists
The origin of the product	▼

INTRO. **Inspect the minimum quality requirements of each container/case** by checking a rating scale for the specific following characteristics with reference to a

https://purdue.ca1.qualtrics.com/jfe/form/SV_5hGPbX699RAehXD 1/5 given color chart.

What do you need? **A given color chart**

Rating scale of [a specific characteristic]:

1 = excellent not at all
2 = good slightly (observe 1-2 defective units/balls)
3 = average somewhat (observe 3-5 defective units/balls)
4 = poor quite much (observe 6-10 defective units/balls per case)
5 = terrible very much (observe > 10 defective balls/units per case)

Q4.a.
[a specific characteristic] = **Intact**
i. The balls ('fruit') should not have any damage or injury spoiling the integrity of the produce. Unhealed cracks are not allowed.
ii. Check **Photo_1** in the color chart for examples.
iii. Rate the intact condition

1 no damages at all
2 slightly, 1-2 damaged units
3 somewhat, 3-5 damaged units
4 quite much, 6-10 damaged units
5 very much, > 10 damaged units

	no damages at all Excellent	slightly (1-2 damaged units) Good	somewhat (3-5 damaged units) Average	quite much (6-10 damaged units) Poor	very much (> 10 damaged units) Terrible
Case i	○	○	○	○	○

Q4.b.
[a specific characteristic] = **Sound**
i. The balls ('fruit') should not be affected by rotting or deterioration: (1) Fresh dents due to rough handling, (2) Spots
ii. Check **Photo_2** in the color chart for examples

iii. Rate the sound condition

1 no fresh cracks or spots at all
2 slightly, 1-2 units having fresh cracks or spots
3 somewhat, 3-5 units having fresh cracks or spots
4 quite much, 6-10 units having fresh cracks or spots
5 very much, > 10 units having fresh cracks or spots

	no fresh cracks or spots at all Excellent	**slightly** 1-2 units having fresh cracks or spots Good	**somewhat** 3-5 units having fresh cracks or spots Average	**quite much** 6-10 units having fresh cracks or spots Poor	**very much** > 10 units having fresh cracks or spots Terrible
Case i	○	○	○	○	○

Q4.c.

[a specific characteristic] = **Fresh in appearance**

i. The balls ('fruit') should not have any sign of withering or loss of firmness.

ii. **Check Photo_3** in the color chart for examples

iii. Rate the fresh in appearance condition

1 Free of visual soils
2 slightly, 1-2 units with sooty mold, visual soil, dust or residue of foreign matter
3 somewhat, 3-5 units with sooty mold, visual soil, dust or residue of foreign matter
4 quite much, 6-10 units with sooty mold, visual soil, dust or residue of foreign matter
5 very much, > 10 units with sooty mold, visual soil, dust or residue of foreign matter

	No sign of withering Excellent	**slightly** 1-2 units with withering or loss of firmness Good	**somewhat** 3-5 units with withering or loss of firmness Average	**quite much** 6-10 units with withering or loss of firmness Poor	**very much** > 10 units with withering or loss of firmness Terrible
Case i	○	○	○	○	○

Q4.d.

[a specific characteristic] = **Free from damage caused by pests**

i. The balls ('fruit') should not have any sign of deep holes or double circles on the surface.

ii. Check **Photo_4** in the color chart for examples

iii. Rate the free from damage caused by pests condition

1 No sign of withering

2 slightly, 1-2 units with withering or loss of firmness

3 somewhat, 3-5 units with withering or loss of firmness

4 quite much, 6-10 units with withering or loss of firmness

5 very much, > 10 units with withering or loss of firmness

	No sign of deep holes or double circles	**slightly** 1-2 units with deep holes or double circles	**somewhat** 3-5 units with deep holes or double circles	**quite much** 6-10 units with deep holes or double circles	**very much** > 10 units with deep holes or double circles
	Excellent	Good	Average	Poor	Terrible
Case i	○	○	○	○	○

Q4.e.

Alien items

i. Alien items are the items with a different color or a different shape or a different pattern from the surrounding and identified items you are working with.

ii. For example, the case/container of red balls should not have white balls or any different colored balls, or smaller size balls.

Select the answer YES (Alien items exist) or NO (No alien items found)

	Yes (Alien items exist)	No (No alien items found)
Case i	○	○

Q5.

Take and save a photo of fruit containers

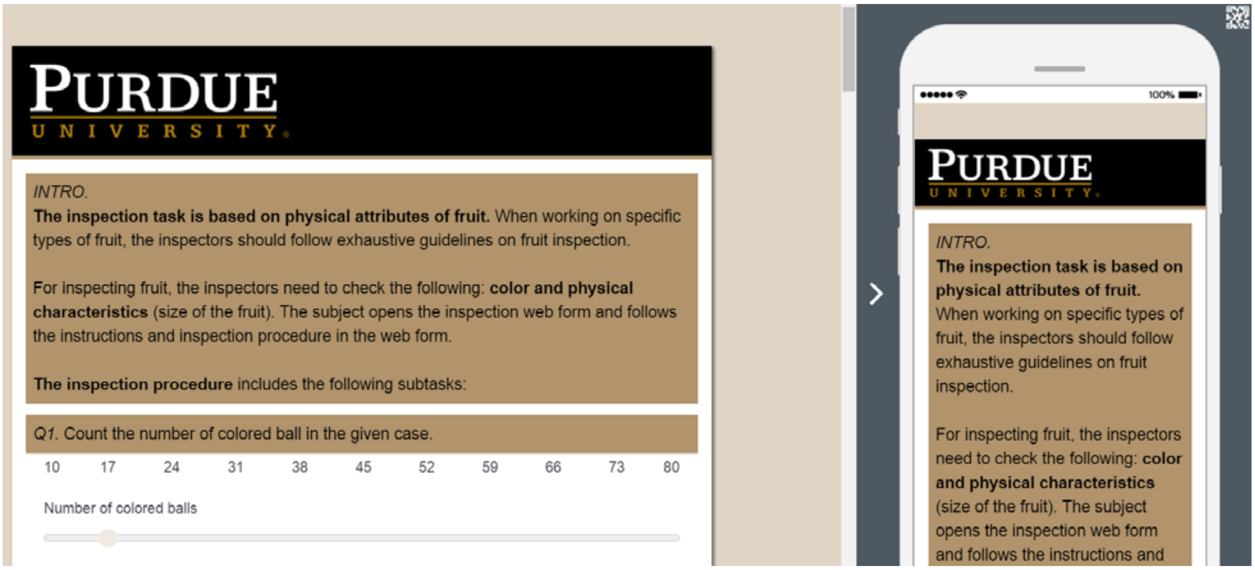
For given fruit containers, take a photo by using the given device. Select the photo icon on the webform, and find the link to the photo the subject took in from the gallery and attach it.

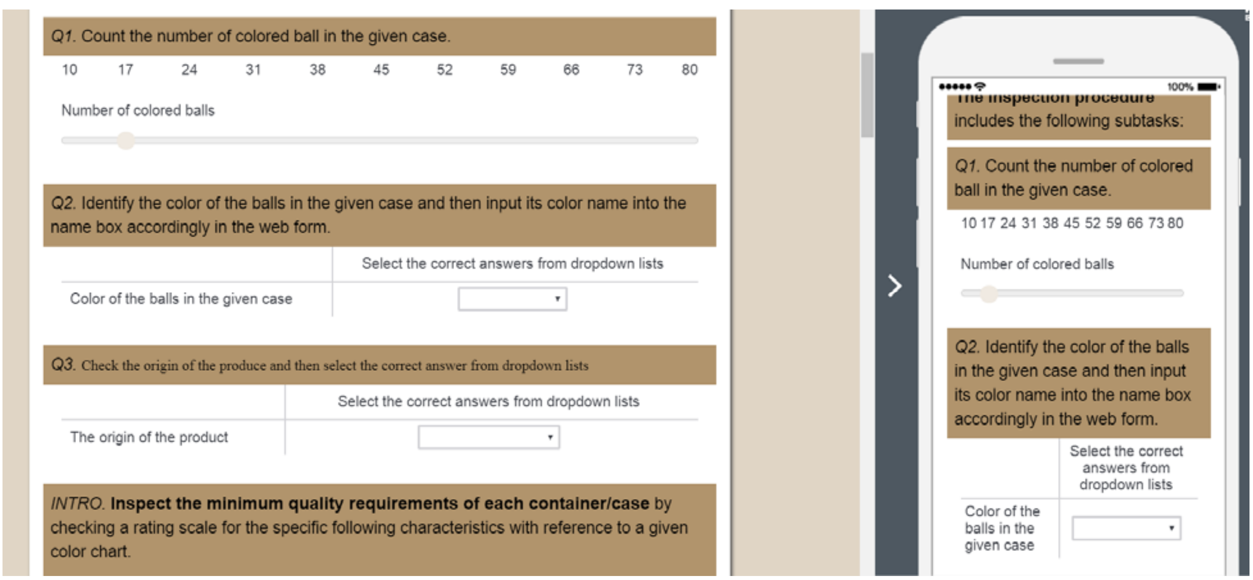
Drop files or click here to upload

Final. Thank you! Please review your answers and hit the arrow button to submit the result!

→

The web-form views on Tablet and iPhone





INTRO. **Inspect the minimum quality requirements of each container/case** by checking a rating scale for the specific following characteristics with reference to a given color chart.

What do you need? **A given color chart**

Rating scale of [a specific characteristic]:

1 = excellent not at all
2 = good slightly (observe 1-2 defective units/balls)
3 = average somewhat (observe 3-5 defective units/balls)
4 = poor quite much (observe 6-10 defective units/balls per case)
5 = terrible very much (observe > 10 defective balls/units per case)

Q4.a.
[a specific characteristic] = **Intact**
i. The balls ('fruit') should not have any damage or injury spoiling the integrity of the produce. Unhealed cracks are not allowed.
ii. Check **Photo_1** in the color chart for examples.
iii. Rate the intact condition

1 no damages at all
2 slightly, 1-2 damaged units
3 somewhat, 3-5 damaged units

INTRO. **Inspect the minimum quality requirements of each container/case** by checking a rating scale for the specific following characteristics with reference to a given color chart.

What do you need? **A given color chart**

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Q4.a.
[a specific characteristic] = **Intact**
i. The balls ('fruit') should not have any damage or injury spoiling the integrity of the produce. Unhealed cracks are not allowed.
ii. Check **Photo_1** in the color chart for examples.
iii. Rate the intact condition

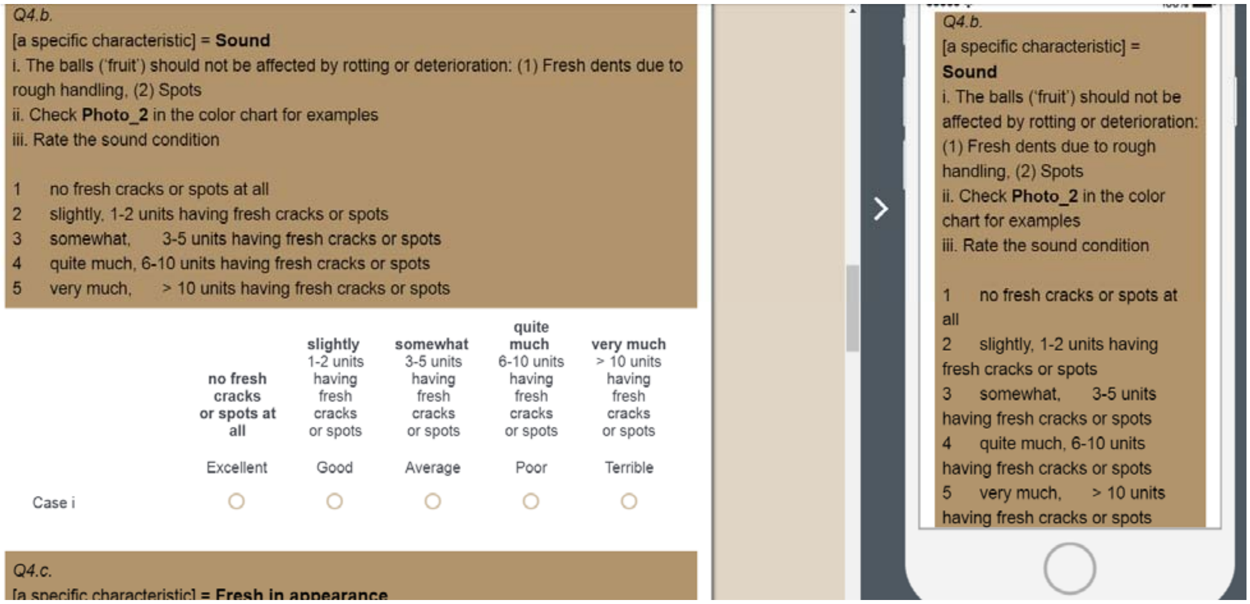
1 no damages at all
2 slightly, 1-2 damaged units
3 somewhat, 3-5 damaged units
4 quite much, 6-10 damaged units
5 very much, > 10 damaged units

	no damages at all	slightly (1-2 damaged units)	somewhat (3-5 damaged units)	quite much (6-10 damaged units)	very much (> 10 damaged units)
	Excellent	Good	Average	Poor	Terrible
Case i	○	○	○	○	○

Q4.b.
[a specific characteristic] = **Sound**
i. The balls ('fruit') should not be affected by rotting or deterioration: (1) Fresh dents due to rough handling, (2) Spots

Q4.a.
[a specific characteristic] = **Intact**
i. The balls ('fruit') should not have any damage or injury spoiling the integrity of the produce. Unhealed cracks are not allowed.
ii. Check **Photo_1** in the color chart for examples.
iii. Rate the intact condition

1 no damages at all
2 slightly, 1-2 damaged units
3 somewhat, 3-5 damaged units
4 quite much, 6-10 damaged units
5 very much, > 10 damaged units



Q4.b.

[a specific characteristic] = **Sound**

i. The balls ('fruit') should not be affected by rotting or deterioration: (1) Fresh dents due to rough handling, (2) Spots

ii. Check **Photo_2** in the color chart for examples

iii. Rate the sound condition

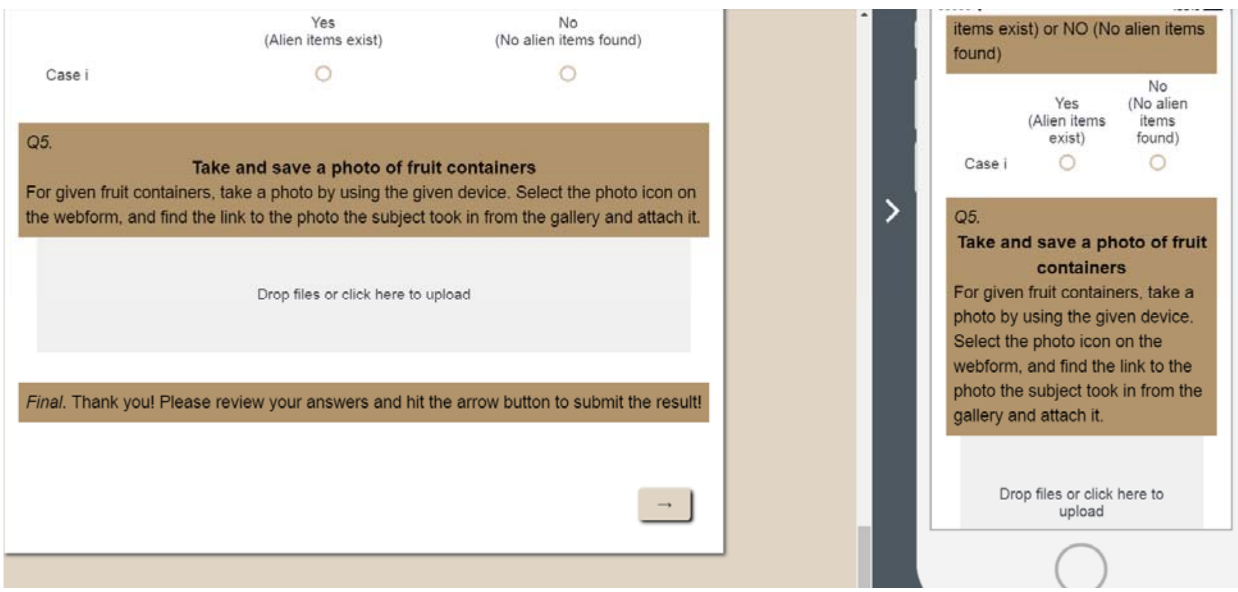
1 no fresh cracks or spots at all
2 slightly, 1-2 units having fresh cracks or spots
3 somewhat, 3-5 units having fresh cracks or spots
4 quite much, 6-10 units having fresh cracks or spots
5 very much, > 10 units having fresh cracks or spots

	no fresh cracks or spots at all	**slightly** 1-2 units having fresh cracks or spots	**somewhat** 3-5 units having fresh cracks or spots	**quite much** 6-10 units having fresh cracks or spots	**very much** > 10 units having fresh cracks or spots
	Excellent	Good	Average	Poor	Terrible
Case i	○	○	○	○	○

Q4.c.

[a specific characteristic] = **Fresh in appearance**

Q4.b.
[a specific characteristic] = **Sound**
i. The balls ('fruit') should not be affected by rotting or deterioration: (1) Fresh dents due to rough handling, (2) Spots
ii. Check **Photo_2** in the color chart for examples
iii. Rate the sound condition
1 no fresh cracks or spots at all
2 slightly, 1-2 units having fresh cracks or spots
3 somewhat, 3-5 units having fresh cracks or spots
4 quite much, 6-10 units having fresh cracks or spots
5 very much, > 10 units having fresh cracks or spots



	Yes (Alien items exist)	No (No alien items found)
Case i	○	○

Q5.

Take and save a photo of fruit containers

For given fruit containers, take a photo by using the given device. Select the photo icon on the webform, and find the link to the photo the subject took in from the gallery and attach it.

Drop files or click here to upload

Final. Thank you! Please review your answers and hit the arrow button to submit the result!

→

items exist) or NO (No alien items found)
Yes (Alien items exist) No (No alien items found)
Case i
Q5.
Take and save a photo of fruit containers
For given fruit containers, take a photo by using the given device. Select the photo icon on the webform, and find the link to the photo the subject took in from the gallery and attach it.
Drop files or click here to upload

Submission results of the web-form

Default Report

PHD. Inspection procedure - VERSION 3.1

March 17th 2018, 4:32 am EDT

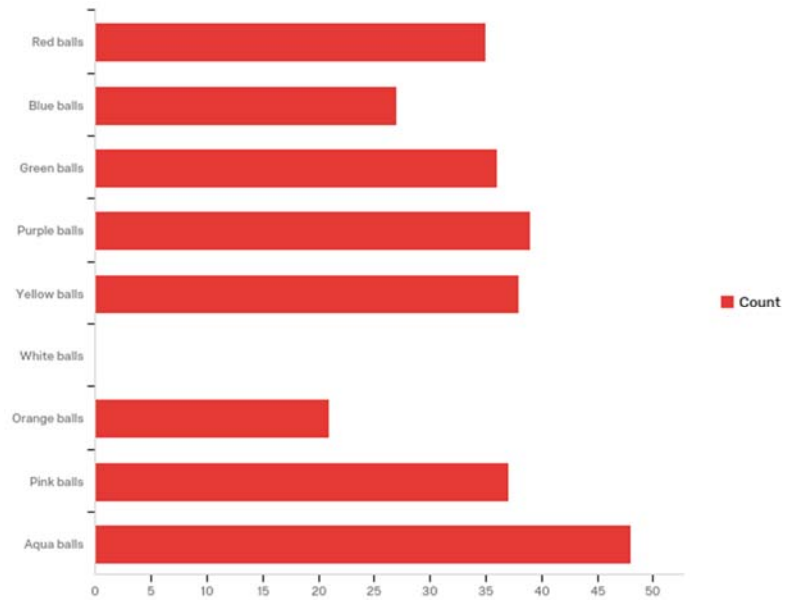
Q1 - Count the number of colored ball in given cases.

#	Field	Minimum	Mean	Count
1	Number of colored balls	26.00	50.87	281

#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
1	Number of colored balls	26.00	75.00	50.87	7.53	56.72	281

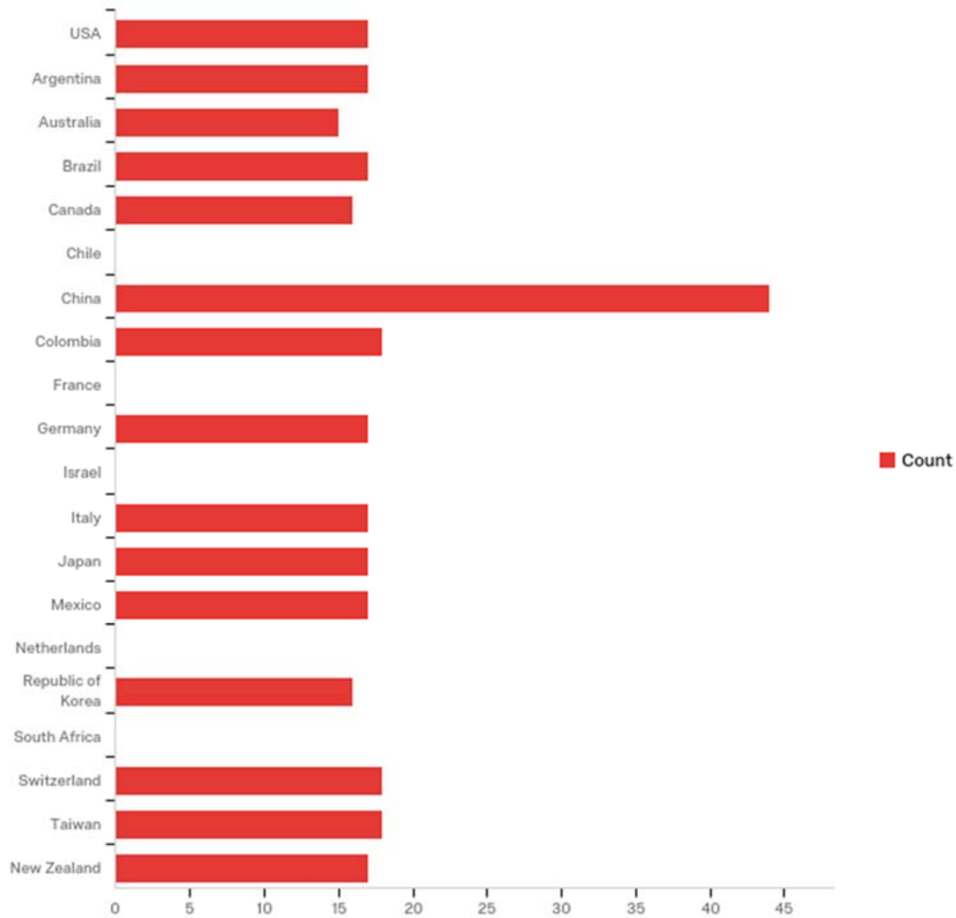
#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
1	Number of colored balls	26.00	75.00	50.87	7.53	56.72	281

Q2#1 - Identify the color of the balls in the given case and then input its color name into the name box... - Select the correct answers from dropdown lists



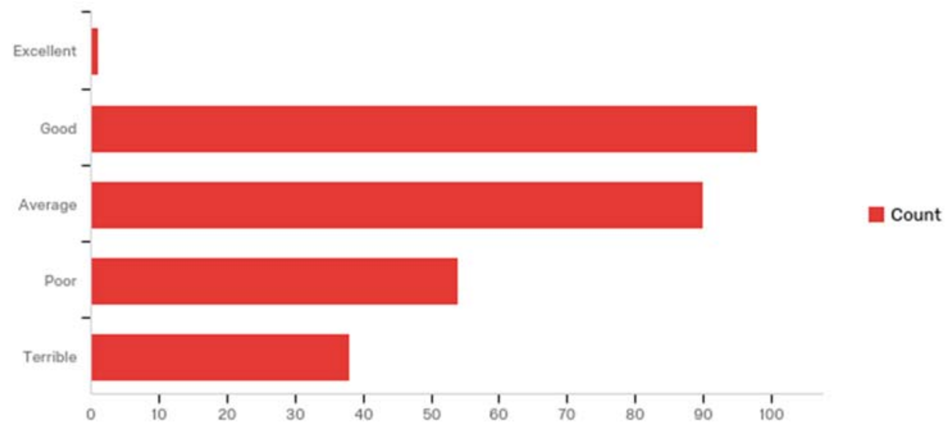
#	Answer	%	Count
1	Red balls	12.46%	35
2	Blue balls	9.61%	27
3	Green balls	12.81%	36
4	Purple balls	13.88%	39
5	Yellow balls	13.52%	38
6	White balls	0.00%	0
7	Orange balls	7.47%	21
8	Pink balls	13.17%	37
9	Aqua balls	17.08%	48
	Total	100%	281

Q3#1 - Check the origin of the produce and then select the correct answer from dropdown lists - Select the correct answers from dropdown lists

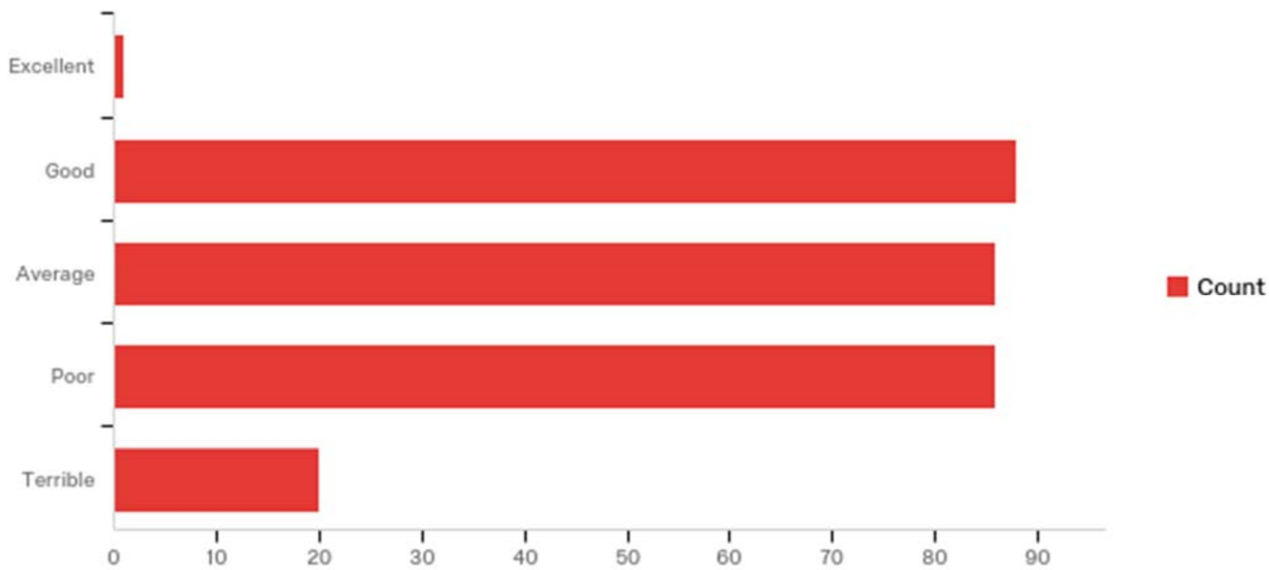


#	Answer	%	Count
1	USA	6.05%	17
2	Argentina	6.05%	17
3	Australia	5.34%	15
4	Brazil	6.05%	17
5	Canada	5.69%	16
6	Chile	0.00%	0
7	China	15.66%	44
8	Colombia	6.41%	18
9	France	0.00%	0
10	Germany	6.05%	17
11	Israel	0.00%	0
12	Italy	6.05%	17
13	Japan	6.05%	17
14	Mexico	6.05%	17
15	Netherlands	0.00%	0
16	Republic of Korea	5.69%	16
17	South Africa	0.00%	0
18	Switzerland	6.41%	18
19	Taiwan	6.41%	18
20	New Zealand	6.05%	17
	Total	100%	281

Q19 - Intact. The balls ('fruit') should not have any damage or injury spoiling the integrity of the produce. Unhealed cracks are not allowed. ii. Check Photo_1 in the color chart for examples.iii. Rate the intact condition

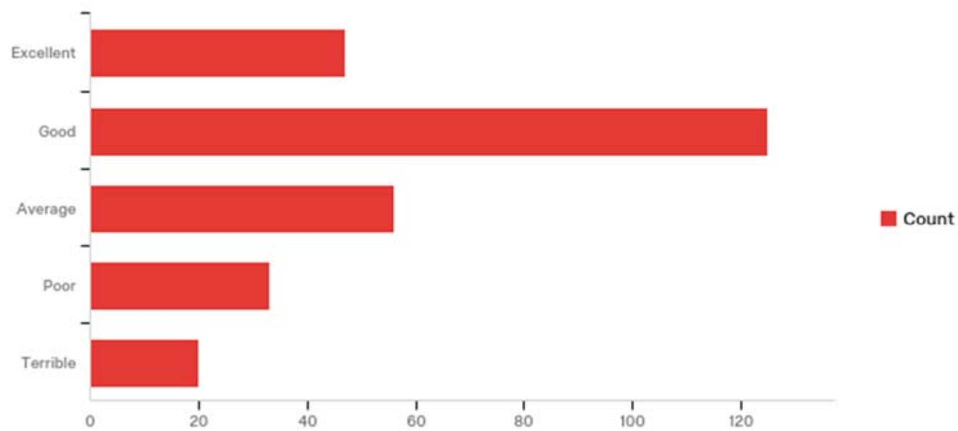


Q4.b - [a specific characteristic] = Sound i. The balls ('fruit') should not be affected by rotting or deterioration: (1) Fresh dents due to rough handling, (2) Spots ii. Check Photo_2 in the color chart for examples iii. Rate the sound condition 1 no fresh cracks or spots at all 2 slightly, 1-2 units having fresh cracks or spots3 somewhat, 3-5 units having fresh cracks or spots4 quite much, 6-10 units having fresh cracks or spots5 very much, > 10 units having fresh cracks or spots



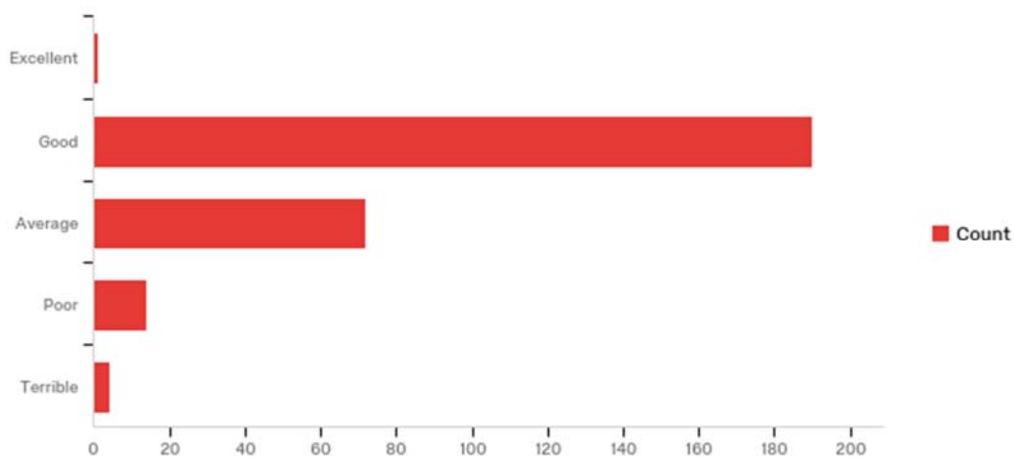
#	Answer	%	Count
148	Excellent	0.36%	1
149	Good	31.32%	88
150	Average	30.60%	86
151	Poor	30.60%	86
152	Terrible	7.12%	20
	Total	100%	281

Q4.c - [a specific characteristic] = Fresh in appearance i. The balls ('fruit') should not have any sign of withering or loss of firmness. ii. Check Photo_3 in the color chart for examples iii. Rate the fresh in appearance condition 1 Free of visual soils 2 slightly, 1-2 units with sooty mold, visual soil, dust or residue of foreign matter3 somewhat, 3-5 units with sooty mold, visual soil, dust or residue of foreign matter4 quite much, 6-10 units with sooty mold, visual soil, dust or residue of foreign matter5 very much, > 10 units with sooty mold, visual soil, dust or residue of foreign matter



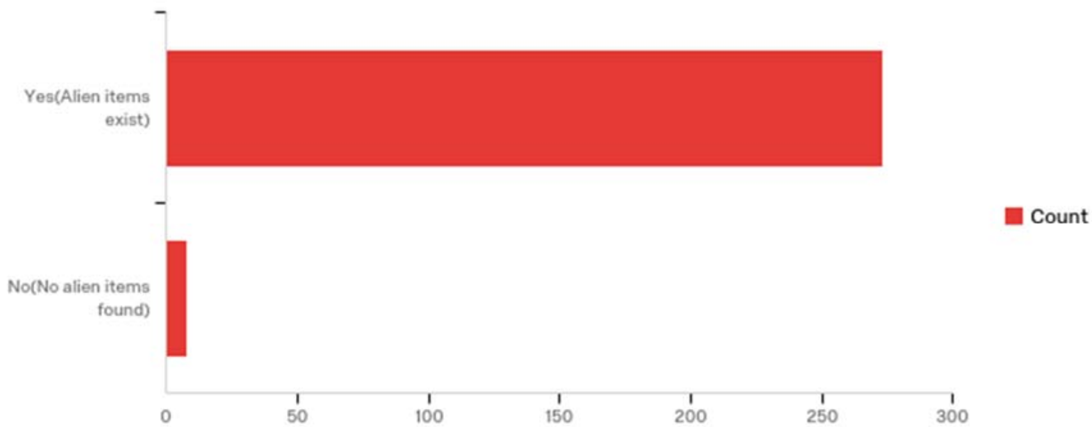
#	Answer	%	Count
32	Excellent	16.73%	47
33	Good	44.48%	125
34	Average	19.93%	56
35	Poor	11.74%	33
36	Terrible	7.12%	20
	Total	100%	281

Q4.d - [a specific characteristic] = Free from damage caused by pests i. The balls ('fruit') should not have any sign of deep holes or double circles on the surface. ii. Check Photo_4 in the color chart for examples iii. Rate the free from damage caused by pests condition 1 No sign of withering 2 slightly, 1-2 units with withering or loss of firmness3 somewhat, 3-5 units with withering or loss of firmness4 quite much, 6-10 units with withering or loss of firmness5 very much, > 10 units with withering or loss of firmness



#	Answer	%	Count
13	Excellent	0.36%	1
14	Good	67.62%	190
15	Average	25.62%	72
16	Poor	4.98%	14
17	Terrible	1.42%	4
	Total	100%	281

Q4.e - Alien items i. Alien items are the items with a different color or a different shape or a different pattern from the surrounding and identified items you are working with. ii. For example, the case/container of red balls should not have white balls or any different colored balls, or smaller size balls. Select the answer YES (Alien items exist) or NO (No alien items found)

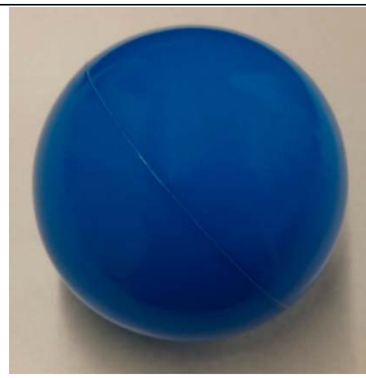
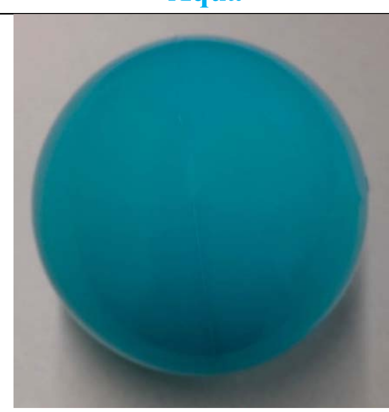


#	Answer	%	Count
37	Yes (Alien items exist)	97.15%	273
38	No (No alien items found)	2.85%	8
	Total	100%	281

Q5 - Take and save a photo of fruit containers For given fruit containers, take a photo by using the given device. Select the photo icon on the webform, and find the link to the photo the subject took in from the gallery and attach it.

For each fruit container, take a photo by using the given device.

APPENDIX L. STANDARD COLOR CHART

Red balls	Blue balls	Green balls
		
Purple	**Yellow**	**White**
		
Orange	**Pink**	**Aqua**
		

Photo#	**Defective characteristic**	**Examples of defective items on red balls**	
This part is used for Q4a. **Photo 1**	**Count # of balls that have marks of thin wavy lines or triangular shapes.** For damaged items, the balls might have thin wavy lines or triangular shapes.		
This part is used for Q4b. **Photo 2**	**Count # of balls that have rubber bands around the balls** For rotting or deteriorating items, the balls might have thick lines or apparent spots		
This part is used for Q4c. **Photo 3**	**Count # of balls that have dents on the surface or distortion in shape.** For unfresh items, the balls should not show any sign of distortion in shape.		
This part is used for Q4d. **Photo 4**	**Count # of balls that have double circles on a piece of tape on the surface** For items damaged by pests, the balls should not have any sign of double circles.		
This part is used for Q4e. **Alien items**	Alien items are the **items with a different color** or **a different shape from the surrounding and identified items** you are working with.	For example, the case of red balls should not have white balls or any different colored balls, or smaller size balls. 	

APPENDIX M. QUESTIONNAIRE FORM

Project Title: A measure of human-integrated system performance under time-varying circumstances

Instructions

This questionnaire aims to collect your experience on the performing the inspection task on a given system under varying circumstances. Your responses will help us to understand the characteristics of human performance under continuous circumstances as well as to evaluate the proposed measure. Please read each question and indicate HOW STRONGLY YOU AGREE (1) OR DISAGREE (7) with the question by selecting an according number on the scale. If you <u>do not know the answer</u>, select N/A.

1. Part A. The Post-Study System Usability Questionnaire (PSSUQ) for evaluating the system

PSSUQ Items: Answer all of the following questions, using the following scale:

i. 1 = Strongly agree, 2 = Mostly agree, 3 = Agree, 4 = Neither agree nor disagree, 5 = Disagree, 6 = Mostly disagree, 7 = Strongly disagree
ii. If you don't have an opinion or think the question is not applicable to you, select 4.

1. Overall, I am satisfied with how easy it is to use this system

Strongly agree	Mostly agree	Agree	Uncertain	Disagree	Mostly disagree	Strongly disagree	Undecided
1	2	3	4	5	6	7	N/A

2. It was simple to use this system

Strongly agree	Mostly agree	Agree	Uncertain	Disagree	Mostly disagree	Strongly disagree	Undecided
1	2	3	4	5	6	7	N/A

3. I was able to complete the tasks and scenarios quickly using this system

Strongly agree	Mostly agree	Agree	Uncertain	Disagree	Mostly disagree	Strongly disagree	Undecided
1	2	3	4	5	6	7	N/A

4. I felt comfortable using this system

Strongly agree	Mostly agree	Agree	Uncertain	Disagree	Mostly disagree	Strongly disagree	Undecided
1	2	3	4	5	6	7	N/A

5. It was easy to learn to use this system

Strongly agree	Mostly agree	Agree	Uncertain	Disagree	Mostly disagree	Strongly disagree	Undecided
1	2	3	4	5	6	7	N/A

6. I believe I could become productive quickly using this system

Strongly agree	Mostly agree	Agree	Uncertain	Disagree	Mostly disagree	Strongly disagree	Undecided
1	2	3	4	5	6	7	N/A

8. The system gave error messages that clearly told me how to fix problems

Strongly agree	Mostly agree	Agree	Uncertain	Disagree	Mostly disagree	Strongly disagree	Undecided
1	2	3	4	5	6	7	N/A

9. Whenever I made a mistake using the system, I could recover easily and quickly

Strongly agree	Mostly agree	Agree	Uncertain	Disagree	Mostly disagree	Strongly disagree	Undecided
1	2	3	4	5	6	7	N/A

10. The information (such as on-line help, on-screen messages, and other documentation) provided with this system was clear

Strongly agree	Mostly agree	Agree	Uncertain	Disagree	Mostly disagree	Strongly disagree	Undecided
1	2	3	4	5	6	7	N/A

11. It was easy to find the information I needed

Strongly agree	Mostly agree	Agree	Uncertain	Disagree	Mostly disagree	Strongly disagree	Undecided
1	2	3	4	5	6	7	N/A

12. The information was effective in helping me complete the tasks and scenarios

Strongly agree	Mostly agree	Agree	Uncertain	Disagree	Mostly disagree	Strongly disagree	Undecided
1	2	3	4	5	6	7	N/A

13. The organization of information on the system screens was clear

Strongly agree	Mostly agree	Agree	Uncertain	Disagree	Mostly disagree	Strongly disagree	Undecided
1	2	3	4	5	6	7	N/A

14. The interface of this system was pleasant

Strongly agree	Mostly agree	Agree	Uncertain	Disagree	Mostly disagree	Strongly disagree	Undecided
1	2	3	4	5	6	7	N/A

15. I liked using the interface of this system

Strongly agree	Mostly agree	Agree	Uncertain	Disagree	Mostly disagree	Strongly disagree	Undecided
1	2	3	4	5	6	7	N/A

16. This system has all the functions and capabilities I expect it to have

Strongly agree	Mostly agree	Agree	Uncertain	Disagree	Mostly disagree	Strongly disagree	Undecided
1	2	3	4	5	6	7	N/A

17. Overall, I am satisfied with this system

Strongly agree	Mostly agree	Agree	Uncertain	Disagree	Mostly disagree	Strongly disagree	Undecided
1	2	3	4	5	6	7	N/A

2. Part B. The Post-Study Questionnaire for evaluating circumstances

PSSUQ Items: Answer all of the following questions, using the following scale:

i. 1 = Extremely influential, 2 = Very influential, 3 = Somewhat influential, 4 = Slightly influential, 5 = Not at all influential

ii. We encourage you to leave your comments to elaborate your answers.

1. In circumstance 1 (CIR1), please circle = IN, OG or ON. How did this circumstance and its conditions influence your performance of completing the task?

		Extremely influential	Very influential	Somewhat influential	Slightly influential	Not at all influential	Undecided
	CIR1	1	2	3	4	5	N/A
Conditions	Indoor (I)	1	2	3	4	5	N/A
	Outdoor (O)	1	2	3	4	5	N/A
	No gloves (N)	1	2	3	4	5	N/A
	Gloves (G)	1	2	3	4	5	N/A

Comment: ____

2. In circumstance 2 (CIR2), please circle = IN, OG or ON. How did this circumstance and its conditions influence your performance of completing the task?

		Extremely influential	Very influential	Somewhat influential	Slightly influential	Not at all influential	Undecided
	CIR2	1	2	3	4	5	N/A
Conditions	Indoor (I)	1	2	3	4	5	N/A
	Outdoor (O)	1	2	3	4	5	N/A
	No gloves (N)	1	2	3	4	5	N/A
	Gloves (G)	1	2	3	4	5	N/A

Comment: ____

3. In circumstance 3 (CIR3), please circle = IN, OG or ON. How did this circumstance and its conditions influence your performance of completing the task?

		Extremely influential	Very influential	Somewhat influential	Slightly influential	Not at all influential	Undecided
	CIR3	1	2	3	4	5	N/A
Conditions	Indoor (I)	1	2	3	4	5	N/A
	Outdoor (O)	1	2	3	4	5	N/A
	No gloves (N)	1	2	3	4	5	N/A
	Gloves (G)	1	2	3	4	5	N/A

Comment: ____

APPENDIX N. RAW DATA COLLECTION

Subject	**System**	**Order**	**Delay (m)**		
1	Tablet	O2	5		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
CIR 1	1	6	43	48	403.48
	2	1	59	89	119.89
	3	1	33	81	93.81
	4	1	26	89	86.89
	5	0	55	86	55.86
CIR 2	1	1	36	83	96.83
	2	1	3	24	63.24
	3	1	4	9	64.09
	4	1	19	18	79.18
	5	1	5	38	65.38
CIR 3	1	1	31	95	91.95
	2	1	12	9	72.09
	3	1	12	29	72.29
	4	1	17	21	77.21
	5	1	7	88	67.88

Subject	**System**	**Order**	**Delay (m)**		
2	iPhone 5	O2	5		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
CIR 1	1	6	17	82	377.82
	2	3	7	81	187.81
	3	3	9	68	189.68
	4	2	58	66	178.66
	5	2	45	26	165.26
CIR 2	1	2	38	98	158.98
	2	2	3	83	123.83
	3	2	2	69	122.69
	4	1	37	50	97.5
	5	1	33	53	93.53
CIR 3	1	2	21	95	141.95
	2	2	13	44	133.44
	3	2	6	10	126.1
	4	2	0	59	120.59
	5	1	50	29	110.29

Subject	System	Order	Delay (m)		
3	iPhone 5	O5	1		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
CIR 1	1	16	6	65	966.65
	2	7	11	64	431.64
	3	7	12	0	432
	4	6	19	92	379.92
	5	5	1	87	301.87
CIR 2	1	4	37	87	277.87
	2	4	25	48	265.48
	3	4	13	8	253.08
	4	2	57	73	177.73
	5	2	58	18	178.18
CIR 3	1	4	41	28	281.28
	2	3	33	4	213.04
	3	4	0	41	240.41
	4	2	55	50	175.5
	5	2	53	2	173.02

Subject	System	Order	Delay (m)		
4	iPhone 5	O2	10		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
CIR 1	1	6	45	87	405.87
	2	2	51	69	171.69
	3	2	24	61	144.61
	4	2	14	89	134.89
	5	1	45	53	105.53
CIR 2	1	2	11	43	131.43
	2	2	10	60	130.6
	3	2	19	46	139.46
	4	2	6	70	126.7
	5	1	37	27	97.27
CIR 3	1	3	16	10	196.1
	2	3	2	70	182.7
	3	2	33	37	153.37
	4	1	57	50	117.5
	5	2	4	94	124.94

Subject	System	Order	Delay (m)		
5	Tablet	O5	1		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
	(1)	*(2)*	*(3)*	*(4)*	*(5)+(3)+(4)/100*
CIR 1	1	6	51	5	411.05
	2	2	54	32	174.32
	3	2	42	27	162.27
	4	2	37	74	157.74
	5	2	5	7	125.07
CIR 2	1	2	44	23	164.23
	2	2	8	31	128.31
	3	2	18	46	138.46
	4	2	1	12	121.12
	5	2	9	55	129.55
CIR 3	1	3	8	89	188.89
	2	2	14	70	134.7
	3	2	28	79	148.79
	4	2	21	57	141.57
	5	2	2	62	122.62

Subject	**System**	**Order**	**Delay (m)**		
6	iPhone 5	O3	10		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
CIR 1	1	12	48	99	768.99
	2	5	14	57	314.57
	3	3	16	59	196.59
	4	3	59	13	239.13
	5	3	11	90	191.9
CIR 2	1	3	24	5	204.05
	2	3	28	8	208.08
	3	3	7	53	187.53
	4	2	48	38	168.38
	5	3	51	15	231.15
CIR 3	1	2	47	37	167.37
	2	3	5	57	185.57
	3	3	0	36	180.36
	4	3	21	61	201.61
	5	2	21	90	141.9

Subject	System	Order	Delay (m)		
7	Tablet	O5	5		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
CIR 1	1	7	34	70	454.7
	2	3	24	63	204.63
	3	3	9	89	189.89
	4	3	35	81	215.81
	5	3	9	9	189.09
CIR 2	1	3	38	51	218.51
	2	2	24	63	144.63
	3	2	59	84	179.84
	4	2	46	47	166.47
	5	2	47	95	167.95
CIR 3	1	4	40	40	280.4
	2	4	30	30	270.3
	3	4	37	50	277.5
	4	2	44	86	164.86
	5	2	31	81	151.81

Subject	System	Order	Delay (m)		
8	iPhone 5	O3	1		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
CIR 1	1	12	26	83	746.83
	2	7	33	35	453.35
	3	5	43	18	343.18
	4	5	31	37	331.37
	5	5	31	79	331.79
CIR 2	1	8	1	70	481.7
	2	8	5	43	485.43
	3	5	27	35	327.35
	4	5	44	82	344.82
	5	5	8	7	308.07
CIR 3	1	5	15	22	315.22
	2	4	35	18	275.18
	3	6	3	73	363.73
	4	5	22	1	322.01
	5	4	11	69	251.69

Subject	System	Order	Delay (m)		
9	Tablet	O5	10		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
CIR 1	1	10	23	93	623.93
	2	3	26	35	206.35
	3	2	56	18	176.18
	4	2	46	18	166.18
	5	1	59	7	119.07
CIR 2	1	3	18	38	198.38
	2	3	5	39	185.39
	3	3	27	99	207.99
	4	3	38	91	218.91
	5	4	8	11	248.11
CIR 3	1	3	30	74	210.74
	2	2	32	61	152.61
	3	3	20	0	200
	4	3	20	5	200.05
	5	2	59	15	179.15

Subject	System	Order	Delay (m)		
10	Tablet	O3	1		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
CIR 1	1	16	39	66	999.66
	2	7	13	65	433.65
	3	6	4	3	364.03
	4	4	33	35	273.35
	5	4	11	49	251.49
CIR 2	1	4	45	18	285.18
	2	4	33	80	273.8
	3	4	2	20	242.2
	4	3	38	9	218.09
	5	4	30	81	270.81
CIR 3	1	3	23	5	203.05
	2	4	15	37	255.37
	3	4	53	14	293.14
	4	3	29	77	209.77
	5	3	18	90	198.9

Subject	System	Order	Delay (m)		
11	iPhone 5	O5	10		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
CIR 1	1	5	37	9	337.09
	2	4	36	71	276.71
	3	3	10	35	190.35
	4	3	38	94	218.94
	5	3	11	79	191.79
CIR 2	1	3	2	81	182.81
	2	2	58	10	178.1
	3	2	40	56	160.56
	4	2	20	3	140.03
	5	2	32	94	152.94
CIR 3	1	4	18	76	258.76
	2	3	23	25	203.25
	3	3	57	96	237.96
	4	3	7	87	187.87
	5	3	23	17	203.17

Subject	System	Order	Delay (m)		
12	Tablet	O3	5		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
CIR 1	1	13	37	72	817.72
	2	5	53	32	353.32
	3	5	48	39	348.39
	4	3	28	90	208.9
	5	2	40	46	160.46
CIR 2	1	4	42	96	282.96
	2	3	52	30	232.3
	3	4	53	57	293.57
	4	3	16	38	196.38
	5	3	25	71	205.71
CIR 3	1	3	46	87	226.87
	2	3	24	57	204.57
	3	4	47	58	287.58
	4	3	53	89	233.89
	5	3	37	84	217.84

Subject	System	Order	Delay (m)		
13	iPhone 5	O2	1		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
CIR 1	1	7	47	84	467.84
	2	3	57	86	237.86
	3	4	21	73	261.73
	4	3	31	86	211.86
	5	3	31	26	211.26
CIR 2	1	3	44	63	224.63
	2	3	40	48	220.48
	3	3	17	19	197.19
	4	2	38	78	158.78
	5	2	53	61	173.61
CIR 3	1	3	34	46	214.46
	2	3	10	15	190.15
	3	3	1	30	181.3
	4	3	11	30	191.3
	5	3	29	15	209.15

Subject	**System**	**Order**	**Delay (m)**		
14	Tablet	O2	10		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
CIR 1	1	12	33	45	753.45
	2	3	56	20	236.2
	3	6	30	63	390.63
	4	6	28	61	388.61
	5	2	31	51	151.51
CIR 2	1	3	36	78	216.78
	2	3	32	17	212.17
	3	3	25	30	205.3
	4	2	52	85	172.85
	5	2	44	80	164.8
CIR 3	1	2	47	45	167.45
	2	2	52	19	172.19
	3	2	47	46	167.46
	4	2	26	68	146.68
	5	2	31	90	151.9

Subject	**System**	**Order**	**Delay (m)**		
15	Tablet	O3	10		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
	(1)	*(2)*	*(3)*	*(4)*	*(5)+(3)+(4)/100*
CIR 1	1	9	27	49	567.49
	2	5	20	38	320.38
	3	3	20	36	200.36
	4	3	57	69	237.69
	5	3	48	56	228.56
CIR 2	1	3	8	68	188.68
	2	3	5	20	185.2
	3	3	46	7	226.07
	4	2	47	85	167.85
	5	2	41	30	161.3
CIR 3	1	3	21	56	201.56
	2	2	41	56	161.56
	3	3	15	12	195.12
	4	3	1	83	181.83
	5	3	1	35	181.35

Subject	System	Order	Delay (m)		
16	iPhone 5	O5	5		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
	(1)	*(2)*	*(3)*	*(4)*	*(5)+(3)+(4)/100*
CIR 1	1	5	25	1	325.01
	2	2	43	4	163.04
	3	2	42	79	162.79
	4	2	28	0	148
	5	2	24	12	144.12
CIR 2	1	2	46	25	166.25
	2	2	35	70	155.7
	3	2	37	97	157.97
	4	2	18	5	138.05
	5	2	37	20	157.2
CIR 3	1	2	45	20	165.2
	2	2	31	6	151.06
	3	2	33	56	153.56
	4	2	28	40	148.4
	5	2	35	94	155.94

Subject	**System**	**Order**	**Delay (m)**		
17	iPhone 5	O3	5		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
CIR 1	1	9	51	89	591.89
	2	7	7	79	427.79
	3	4	14	35	254.35
	4	4	37	83	277.83
	5	3	37	51	217.51
CIR 2	1	5	34	71	334.71
	2	4	47	87	287.87
	3	4	54	43	294.43
	4	5	7	10	307.1
	5	5	27	50	327.5
CIR 3	1	4	44	29	284.29
	2	4	43	2	283.02
	3	4	31	45	271.45
	4	3	21	29	201.29
	5	3	23	51	203.51

Subject	System	Order	Delay (m)		
18	Tablet	O2	1		
Circumstance	**Repetition**	**Minutes**	**Seconds**	**1/100 Seconds**	**Completion time (s)**
	(1)	*(2)*	*(3)*	*(4)*	*(5)+(3)+(4)/100*
CIR 1	1	7	50	66	470.66
	2	5	48	5	348.05
	3	4	13	83	253.83
	4	4	30	37	270.37
	5	3	34	82	214.82
CIR 2	1	3	26	40	206.4
	2	4	25	37	265.37
	3	4	4	2	244.02
	4	2	46	42	166.42
	5	3	53	1	233.01
CIR 3	1	4	6	28	246.28
	2	3	44	0	224
	3	4	22	93	262.93
	4	3	28	61	208.61
	5	3	25	13	205.13

APPENDIX O. CALCULATIONS OF LEARNING CURVES

Table Appx 24. Calculations of Learning Curves for iPhone

	1	2	3	4	5	6	7	8	9
	Subject 2	**Subject 3**	**Subject 4**	**Subject 6**	**Subject 8**	**Subject 11**	**Subject 13**	**Subject 16**	**Subject 17**
Delay	5	1	10	10	1	10	1	5	5
Order	Order 2: IN -> ON -> OG	Order 5: ON -> IN -> OG	Order 2: IN -> ON -> OG	Order 3: OG -> IN -> ON	Order 3: OG -> IN -> ON	Order 5: ON -> IN -> OG	Order 2: IN -> ON -> OG	Order 5: ON -> IN -> OG	Order 3: OG -> IN -> ON
1	377.82	966.65	405.87	768.99	746.83	337.09	467.84	325.01	591.89
2	282.82	699.15	288.78	541.78	600.09	306.90	352.85	244.03	509.84
3	251.77	610.10	240.72	426.72	514.45	268.05	322.48	216.95	424.68
4	233.49	552.55	214.27	379.82	468.68	255.77	294.82	199.71	387.97
5	219.85	502.42	192.52	342.24	441.30	242.98	278.11	188.59	353.87
1	158.98	277.87	131.43	204.05	481.70	182.81	224.63	166.25	334.71
2	141.41	271.68	131.02	206.07	483.57	180.46	222.56	160.98	311.29
3	135.17	265.48	133.83	199.89	431.49	173.82	214.10	159.97	305.67
4	125.75	243.54	132.05	192.01	409.83	165.38	200.27	154.49	306.03
5	119.31	230.47	125.09	199.84	389.47	162.89	194.94	155.03	310.32
1	141.95	281.28	196.10	167.37	315.22	258.76	214.46	165.20	284.29
2	137.70	247.16	189.40	176.47	295.20	231.01	202.31	158.13	283.66
3	133.83	244.91	177.39	177.77	318.04	233.32	195.30	169.61	279.59
4	130.52	227.56	162.42	183.73	319.04	221.96	194.30	164.31	260.01
5	126.47	216.65	154.92	175.36	305.57	218.20	197.27	162.63	248.71

Table Appx 25. Calculations of Learning Curves for Tablet

	1	2	3	4	5	6	7	8	9
	Subject 1	**Subject 5**	**Subject 7**	**Subject 9**	**Subject 10**	**Subject 12**	**Subject 14**	**Subject 15**	**Subject 18**
Delay	5	1	5	10	1	5	10	10	1
Order	Order 2: IN -> ON -> OG	Order 5: ON -> IN -> OG	Order 5: ON -> IN -> OG	Order 5: ON -> IN -> OG	Order 3: OG -> IN -> ON	Order 3: OG -> IN -> ON	Order 2: IN -> ON -> OG	Order 3: OG -> IN -> ON	Order 2: IN -> ON -> OG
1	403.48	411.05	454.70	623.93	999.66	817.72	753.45	567.49	470.66
2	261.69	292.69	329.67	415.14	716.66	585.52	494.83	443.94	409.36
3	205.73	249.21	283.07	335.49	599.11	506.48	460.09	362.74	357.51
4	176.02	226.35	266.26	293.16	517.67	432.08	442.22	331.48	335.73
5	151.99	206.09	250.82	258.34	464.44	377.76	384.08	310.90	311.55
1	96.83	164.23	218.51	198.38	285.18	282.96	216.78	188.68	206.40
2	80.04	146.27	181.57	191.89	279.49	257.63	214.48	186.94	235.89
3	74.72	143.67	180.99	197.25	267.06	269.61	211.42	199.98	238.60
4	75.84	138.03	177.36	202.67	254.82	251.30	201.78	191.95	220.55
5	73.74	136.33	175.48	211.76	258.02	242.18	194.38	185.82	223.04
1	91.95	188.89	280.40	210.74	203.05	226.87	167.45	201.56	246.28
2	82.02	161.80	275.35	181.68	229.21	215.72	169.82	181.56	235.14
3	78.78	157.46	276.07	187.78	250.52	239.67	169.03	186.08	244.40
4	78.39	153.49	248.27	190.85	240.33	238.23	163.45	185.02	235.46
5	76.28	147.31	228.97	188.51	232.05	234.15	161.14	184.28	229.39

APPENDIX P. CALCULATIONS ON ADAPTABILITY PARAMETERS

Table Appx 26. Calculations on adaptability for iPhone

	Delay	Order	Gamma 1,2	Gamma 2,3	AI_k	$AI_{(iPhone)}$
Subject 2	5	Order 2: IN -> ON -> OG	1.38	0.84	**1.383**	1.334215784
Subject 3	1	Order 5: ON -> IN -> OG	1.81	0.82	**1.808**	
Subject 4	10	Order 2: IN -> ON -> OG	1.46	0.64	**1.465**	
Subject 6	10	Order 3: OG -> IN -> ON	1.68	1.19	**1.677**	
Subject 8	1	Order 3: OG -> IN -> ON	0.92	1.24	**0.916**	
Subject 11	10	Order 5: ON -> IN -> OG	1.33	0.63	**1.329**	
Subject 13	1	Order 2: IN -> ON -> OG	1.24	0.91	**1.238**	
Subject 16	5	Order 5: ON -> IN -> OG	1.13	0.94	**1.134**	
Subject 17	5	Order 3: OG -> IN -> ON	1.06	1.09	**1.057**	

	Delay	Order	CIR1	CIR2	CIR3	LI_k
Subject 2	5	Order 2: IN -> ON -> OG	-1	-0.4957	-0.4072	**-0.634**
Subject 3	1	Order 5: ON -> IN -> OG	-1	-0.9997	-1	**-1.000**
Subject 4	10	Order 2: IN -> ON -> OG	-1	-0.3469	-0.6814	**-0.676**
Subject 6	10	Order 3: OG -> IN -> ON	-1	-0.7171	-0.5422	**-0.753**
Subject 8	1	Order 3: OG -> IN -> ON	-1	-1	-1	**-1.000**
Subject 11	10	Order 5: ON -> IN -> OG	-1	-0.6197	-0.9324	**-0.851**
Subject 13	1	Order 2: IN -> ON -> OG	-1	-0.8039	-0.763	**-0.856**
Subject 16	5	Order 5: ON -> IN -> OG	-1	-0.5362	-0.5306	**-0.689**
Subject 17	5	Order 3: OG -> IN -> ON	-1	-1	-1	**-1.000**
						$LI_{(iPhone)}$ = - 0.8287

Table Appx 27. Calculations on adaptability parameters for Tablet

	Delay	Order	Gamma 1,2	Gamma 2,3	AIk	AI(Tablet)
Subject 1	5	Order 2: IN -> ON -> OG	1.57	0.80	**1.570**	1.463
Subject 5	1	Order 5: ON -> IN -> OG	1.25	0.72	**1.255**	
Subject 7	5	Order 5: ON -> IN -> OG	1.15	0.63	**1.148**	
Subject 9	10	Order 5: ON -> IN -> OG	1.30	1.00	**1.302**	
Subject 10	1	Order 3: OG -> IN -> ON	1.63	1.27	**1.629**	
Subject 12	5	Order 3: OG -> IN -> ON	1.34	1.07	**1.335**	
Subject 14	10	Order 2: IN -> ON -> OG	1.77	1.16	**1.772**	
Subject 15	10	Order 3: OG -> IN -> ON	1.65	0.92	**1.648**	
Subject 18	1	Order 2: IN -> ON -> OG	1.51	0.91	**1.509**	

	Delay	Order	CIR1	CIR2	CIR3	Lik
Subject 1	5	Order 2: IN -> ON -> OG	-1	-0.1141	-0.0757	**-0.397**
Subject 5	1	Order 5: ON -> IN -> OG	-1	-0.5253	-0.6484	**-0.725**
Subject 7	5	Order 2: IN -> ON -> OG	-1	-0.7799	-1	**-0.927**
Subject 9	10	Order 3: OG -> IN -> ON	-1	-0.6917	-0.7466	**-0.813**
Subject 10	1	Order 3: OG -> IN -> ON	-1	-1	-0.7126	**-0.904**
Subject 12	5	Order 5: ON -> IN -> OG	-1	-1	-0.8126	**-0.938**
Subject 14	10	Order 2: IN -> ON -> OG	-1	-0.7731	-0.5426	**-0.772**
Subject 15	10	Order 5: ON -> IN -> OG	-1	-0.6474	-0.706	**-0.784**
Subject 18	1	Order 3: OG -> IN -> ON	-1	-0.7275	-0.8866	**-0.871**
						LI(tablet)
						-0.792

APPENDIX Q. CALCULATIONS OF PS

Table Appx 28. Calculations of PS_{iphone}

		Subject 2	Subject 3	Subject 4	Subject 6	Subject 8	Subject 11	Subject 13	Subject 16	Subject 17
	Delay	5	1	10	10	1	10	1	5	5
	Order	Order 2: IN -> ON -> OG	Order 5: ON -> IN -> OG	Order 2: IN -> ON -> OG	Order 3: OG -> IN -> ON	Order 3: OG -> IN -> ON	Order 5: ON -> IN -> OG	Order 2: IN -> ON -> OG	Order 5: ON -> IN -> OG	Order 3: OG -> IN -> ON
CIR1	T1	377.82	966.65	405.87	768.99	746.83	337.09	467.84	325.01	591.89
CIR2	T1	158.98	277.87	131.43	204.05	481.70	182.81	224.63	166.25	334.71
CIR3	T1	141.95	281.28	196.10	167.37	315.22	258.76	214.46	165.20	284.29

CIR1	b1	-1	-1	-1	-1	-1	-1	-1	-1	-1
CIR2	b2	-0.4957	-0.9997	-0.3469	-0.7171	-1	-0.6197	-0.8039	-0.5362	-1
CIR3	b3	-0.4072	-1	-0.6814	-0.5422	-1	-0.9324	-0.763	-0.5306	-1

		Es1	Es2	Es3	Es4	Es5	Es6	Es7	Es8	Es9
CIR1		377.82	966.65	405.87	768.99	746.83	337.09	467.84	325.01	591.89
CIR2		357.96	278.00	376.00	321.72	481.70	337.15	307.99	350.71	334.71
CIR3		368.54	281.28	327.47	349.68	315.22	288.50	314.05	351.65	284.29
	SUM/ CIR	1104.32	1525.93	1109.34	1440.38	1543.75	962.74	1089.88	1027.36	1210.89
	$E_{(iphone)}$	**1223.845**								

Table Appx 29. Calculations of PS_{iphone}

		Subject 1	Subject 5	Subject 7	Subject 9	Subject 10	Subject 12	Subject 14	Subject 15	Subject 18
	Delay	5	1	5	10	1	5	10	10	1
	Order	Order 2: IN -> ON -> OG	Order 5: ON -> IN -> OG	Order 5: ON -> IN -> OG	Order 5: ON -> IN -> OG	Order 3: OG -> IN -> ON	Order 3: OG -> IN -> ON	Order 2: IN -> ON -> OG	Order 3: OG -> IN -> ON	Order 2: IN -> ON -> OG
CIR 1	T1	403.48	411.05	454.70	623.93	999.66	817.72	753.45	567.49	470.66
CIR 2	T1	96.83	164.23	218.51	198.38	285.18	282.96	216.78	188.68	206.40
CIR 3	T1	91.95	188.89	280.40	210.74	203.05	226.87	167.45	201.56	246.28

CIR 1	b1	-1	-1	-1	-1	-1	-1	-1	-1	-1
CIR 2	b2	-0.1141	-0.5253	-0.7799	-0.6917	-1	-1	-0.7731	-0.6474	-0.7275
CIR 3	b3	-0.0757	-0.6484	-1	-0.7466	-0.7126	-0.8126	-0.5426	-0.706	-0.8866

		Es1	Es2	Es3	Es4	Es5	Es6	Es7	Es8	Es9
CIR 1		403.48	411.05	454.70	623.93	999.66	817.72	753.45	567.49	470.66
CIR 2		402.93	352.58	311.40	325.83	285.18	282.96	312.33	332.80	320.02
CIR 3		407.01	332.63	280.40	316.86	322.47	306.74	349.62	323.52	295.59
	SUM/ CIR	1213.42	1096.26	1046.50	1266.62	1607.31	1407.42	1415.40	1223.81	1086.27
	$E_{(iphone)}$	**1262.556**								

APPENDIX R. CALCULATIONS OF SS

Table Appx 30. Calculations of SSIPHONE

Question	S2*	S3	S4	S6	S8	S11	S13	S16	S17	Lower limit	Mean	Upper limit
1	1	5	2	5	2	3	3	3	3	2.3	3.0	3.7
2	1	3	1	5	2	3	3	2	3	1.9	2.6	3.2
3	2	5	1	4	2	3	2	2	1	1.7	2.4	3.2
4	1	3	1	4	2	3	2	2	2	1.7	2.2	2.8
5	2	2	2	2	1	3	3	1	2	1.6	2.0	2.4
6	2	5	1	2	1	3	5	3	2	1.8	2.7	3.5
7	0	0	0	0	1	3	4	0	0	0.0	0.9	1.7
8	3	0	2	0	1	3	4	5	3	1.4	2.3	3.3
9	3	5	0	3	1	3	3	2	1	1.5	2.3	3.2
10	1	3	1	1	1	3	4	1	1	1.1	1.8	2.4
11	1	3	1	2	1	3	3	1	1	1.2	1.8	2.3
12	2	5	2	3	2	3	3	1	2	1.9	2.6	3.2
13	2	5	2	5	3	3	3	4	3	2.7	3.3	3.9
14	2	5	1	5	4	2	5	3	4	2.6	3.4	4.3
15	2	5	1	5	2	2	4	2	3	2.1	2.9	3.7
16	1	5	1	4	2	2	3	3	3	1.9	2.7	3.4
** S: Subject*										Overall scores		
SysUse	1.500	3.833	1.333	3.667	1.667	3.000	3.000	2.167	2.167	2.2	2.556	2.9
InfoQual	1.667	2.667	1.000	1.500	1.167	3.000	3.500	1.667	1.333	1.7	2.000	2.3
IntQual	2.000	5.000	1.333	5.000	3.000	2.333	4.000	3.000	3.333	1.7	2.167	2.6
Overall	1.625	3.688	1.188	3.125	1.750	2.813	3.375	2.188	2.125	2.2	2.431	2.6

Table Appx 31. Calculations of SSTABLET

Question	S1*	S5	S7	S9	S10	S12	S14	S15	S18	Lower limit	Mean	Upper limit
1	1	2	1	3	1	1	2	2	2	1.3	1.7	2.1
2	1	2	1	3	1	1	2	1	1	1.0	1.4	1.8
3	1	3	1	3	1	2	2	1	2	1.3	1.8	2.2
4	2	2	1	4	1	1	2	2	1	1.2	1.8	2.3
5	1	1	1	2	1	1	1	1	1	0.9	1.1	1.3
6	1	2	1	2	3	2	2	2	2	1.6	1.9	2.2
7	4	0	1	2	5	1	3	1	0	0.9	1.9	2.9
8	3	5	1	2	1	1	4	1	2	1.4	2.2	3.0
9	3	2	1	3	2	1	4	1	1	1.4	2.0	2.6
10	3	5	1	3	1	1	3	1	1	1.3	2.1	2.9
11	3	2	1	3	1	1	3	1	1	1.2	1.8	2.3
12	2	1	1	3	1	1	3	1	1	1.1	1.6	2.0
13	3	3	1	4	2	1	2	1	1	1.4	2.0	2.6
14	3	2	1	4	3	1	3	1	2	1.6	2.2	2.8
15	3	3	1	5	1	1	3	2	5	1.8	2.7	3.5
16	2	2	1	2	2	1	3	1	3	1.5	1.9	2.3
** S: Subject*										Overall scores		
SysUse	1.167	2.000	1.000	2.833	1.333	1.333	1.833	1.500	1.500	1.4	1.667	1.9
InfoQual	3.000	2.500	1.000	2.667	1.833	1.000	3.333	1.000	1.000	1.6	1.870	2.1
IntQual	3.000	2.667	1.000	4.333	2.000	1.000	2.667	1.333	2.667	1.3	1.667	2.0
Overall	2.250	2.313	1.000	3.000	1.688	1.125	2.625	1.250	1.625	1.7	1.875	2.0

Table Appx 32. Circumstance scores (I-iPhone)

	S2*	S3	S4	S6	S8	S11	S13	S16	S17	Score
IN	4	4	2	2	2	1	5	2	2	2.667
Indoor (I)	4	2	1	1	3	2	5	3	1	2.444
No gloves (N)	2	1	1	3	1	5	5	2	3	2.556
ON	4	4	1	3	1	2	4	3	2	2.667
Outdoor (O)	3	2	2	3	2	2	3	4	2	2.556
No gloves (N)	2	1	2	3	3	4	5	2	2	2.667
OG	3	2	1	3	1	2	3	3	4	2.444
Outdoor (O)	3	2	2	3	1	2	3	4	3	2.556
Gloves (G)	1	2	1	3	1	3	2	2	3	2.000

** S: Subject*

Table Appx 33. Circumstance scores (II-Tablet)

	S1*	S5	S7	S9	S10	S12	S14	S15	S18	Score
IN	2	5	3	4	5	4	3	1	4	3.444
Indoor (I)	2	4	3	5	5	3	2	1	3	3.111
No gloves (N)	2	5	5	3	5	4	2	1	5	3.556
ON	2	4	3	3	3	2	3	1	3	2.667
Outdoor (O)	2	4	3	1	2	2	2	2	2	2.222
No gloves (N)	3	5	5	3	5	2	2	1	5	3.444
OG	3	3	3	1	2	3	2	2	2	2.333
Outdoor (O)	3	4	3	1	1	3	2	3	2	2.444
Gloves (G)	3	3	3	1	3	2	2	2	2	2.333

** S: Subject*

APPENDIX S. FITTING DISTRIBUTION

Distribution ID Plot for Gamma-bar

Descriptive Statistics

N	N*	Mean	StDev	Median	Minimum	Maximum	Skewness	Kurtosis
18	0	1.39862	0.253470	1.35894	0.91614	1.8081	-0.0747359	-0.789563

Box-Cox transformation: λ = 1

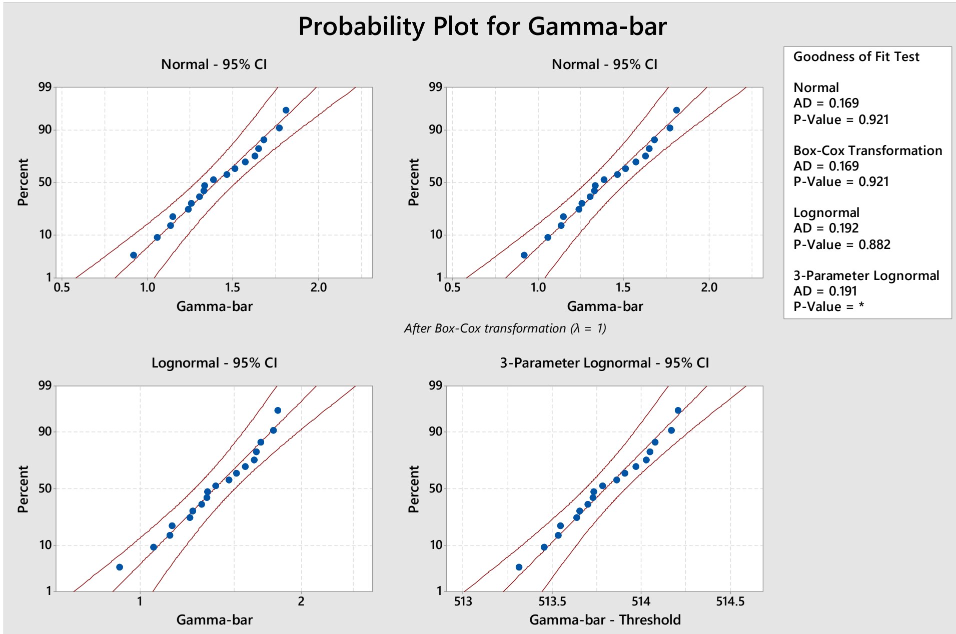
Goodness of Fit Test

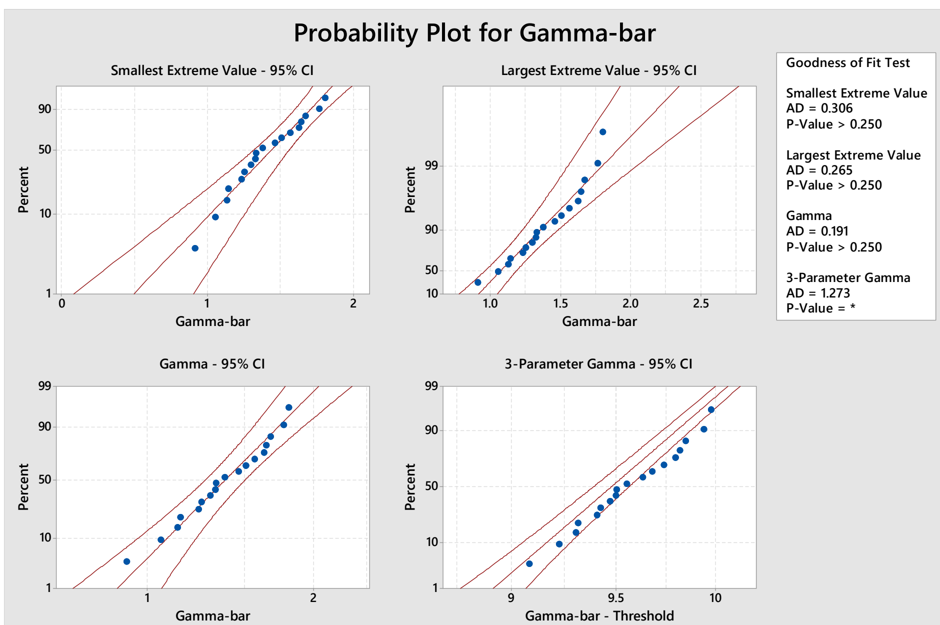
Distribution	AD	P	LRT P
Normal	0.169	0.921	
Box-Cox Transformation	0.169	0.921	
Lognormal	0.192	0.882	
3-Parameter Lognormal	0.191	*	0.417
Exponential	5.612	<0.003	
2-Parameter Exponential	1.948	<0.010	0.000
Weibull	0.219	>0.250	
3-Parameter Weibull	0.184	>0.500	0.514
Smallest Extreme Value	0.306	>0.250	
Largest Extreme Value	0.265	>0.250	
Gamma	0.191	>0.250	
3-Parameter Gamma	1.273	*	1.000
Logistic	0.216	>0.250	
Loglogistic	0.214	>0.250	
3-Parameter Loglogistic	0.216	*	0.583

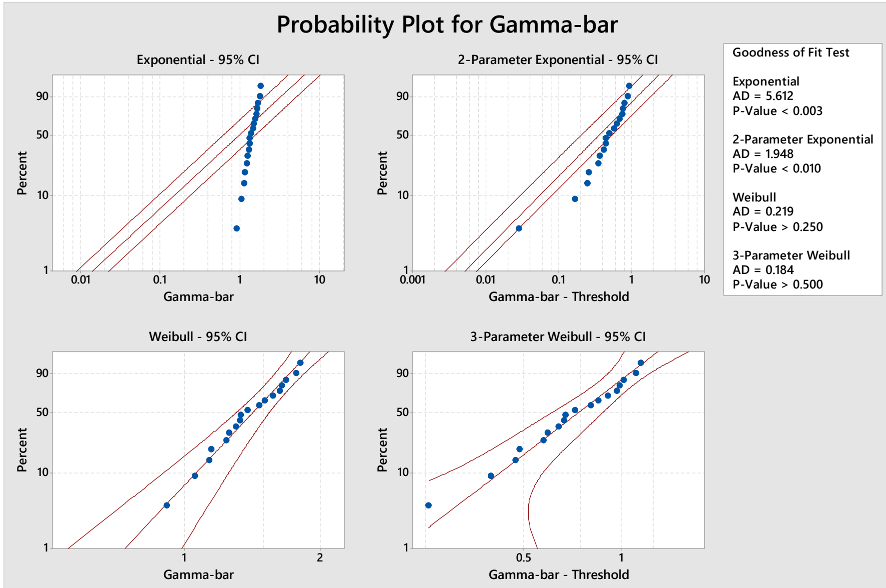
ML Estimates of Distribution Parameters

Distribution	Location	Shape	Scale	Threshold
Normal*	1.39862		0.25347	
Box-Cox Transformation*	1.39862		0.25347	
Lognormal*	0.31929		0.18759	
3-Parameter Lognormal	6.24183		0.00048	-512.39771
Exponential			1.39862	
2-Parameter Exponential			0.51086	0.88776
Weibull		6.48772	1.50200	
3-Parameter Weibull		3.37701	0.82269	0.66134
Smallest Extreme Value	1.52069		0.22321	
Largest Extreme Value	1.27511		0.23384	
Gamma		31.03852	0.04506	
3-Parameter Gamma		1479.77325	0.00641	-8.17215
Logistic	1.39866		0.14712	
Loglogistic	0.32654		0.10712	
3-Parameter Loglogistic	6.23962		0.00029	-511.26252

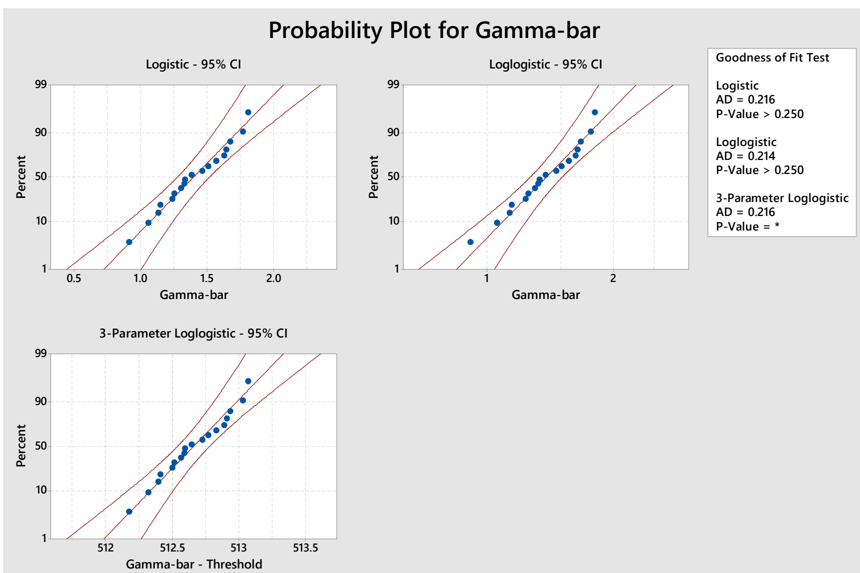
* Scale: Adjusted ML estimate


Probability Plot for Gamma-bar
Normal - 95% CI
Normal - 95% CI
Lognormal - 95% CI
3-Parameter Lognormal - 95% CI
Percent
Gamma-bar
Gamma-bar - Threshold
After Box-Cox transformation (λ = 1)
Goodness of Fit Test
Normal
AD = 0.169
P-Value = 0.921
Box-Cox Transformation
AD = 0.169
P-Value = 0.921
Lognormal
AD = 0.192
P-Value = 0.882
3-Parameter Lognormal
AD = 0.191
P-Value = *


Probability Plot for Gamma-bar
Smallest Extreme Value - 95% CI
Largest Extreme Value - 95% CI
Gamma - 95% CI
3-Parameter Gamma - 95% CI
Percent
Gamma-bar
Gamma-bar - Threshold
Goodness of Fit Test
Smallest Extreme Value
AD = 0.306
P-Value > 0.250
Largest Extreme Value
AD = 0.265
P-Value > 0.250
Gamma
AD = 0.191
P-Value > 0.250
3-Parameter Gamma
AD = 1.273
P-Value = *



Probability Plot for Gamma-bar
Exponential - 95% CI
2-Parameter Exponential - 95% CI
Weibull - 95% CI
3-Parameter Weibull - 95% CI
Percent
Gamma-bar
Gamma-bar - Threshold
Goodness of Fit Test
Exponential
AD = 5.612
P-Value < 0.003
2-Parameter Exponential
AD = 1.948
P-Value < 0.010
Weibull
AD = 0.219
P-Value > 0.250
3-Parameter Weibull
AD = 0.184
P-Value > 0.500



Probability Plot for Gamma-bar
Logistic - 95% CI
Loglogistic - 95% CI
3-Parameter Loglogistic - 95% CI
Percent
Gamma-bar
Gamma-bar - Threshold
Goodness of Fit Test
Logistic
AD = 0.216
P-Value > 0.250
Loglogistic
AD = 0.214
P-Value > 0.250
3-Parameter Loglogistic
AD = 0.216
P-Value = *

Distribution ID Plot for Beta-bar

```
Descriptive Statistics

 N  N*       Mean     StDev     Median  Minimum  Maximum  Skewness  Kurtosis
18   0  -0.810483  0.153682  -0.831735       -1  -0.3966   1.02564   1.69614
```

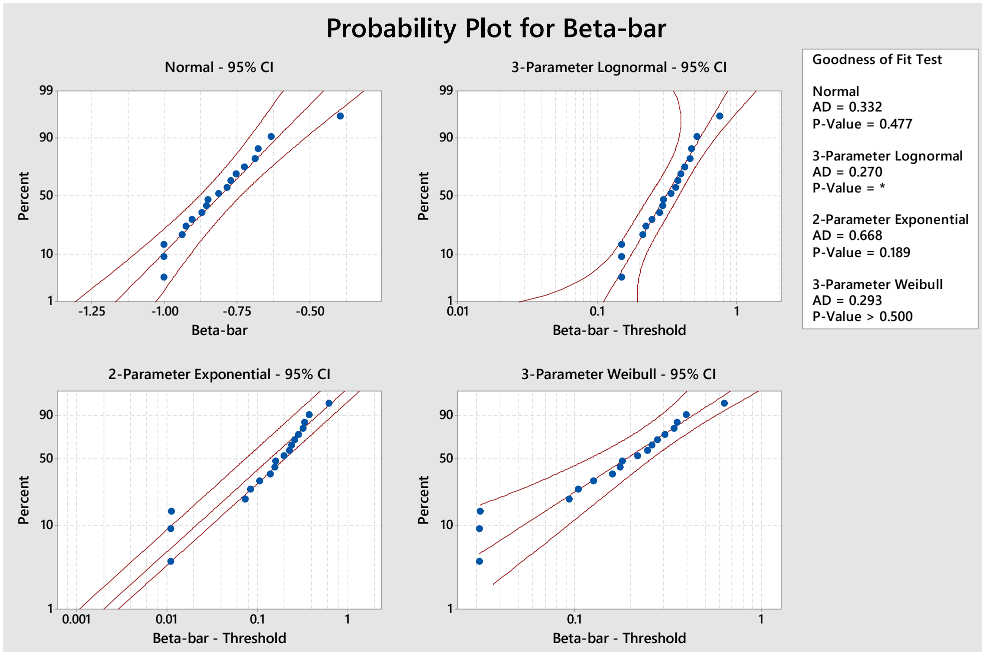

```
Descriptive Statistics

 N  N*       Mean     StDev     Median  Minimum  Maximum  Skewness  Kurtosis
18   0  -0.810483  0.153682  -0.831735       -1  -0.3966   1.02564   1.69614
```

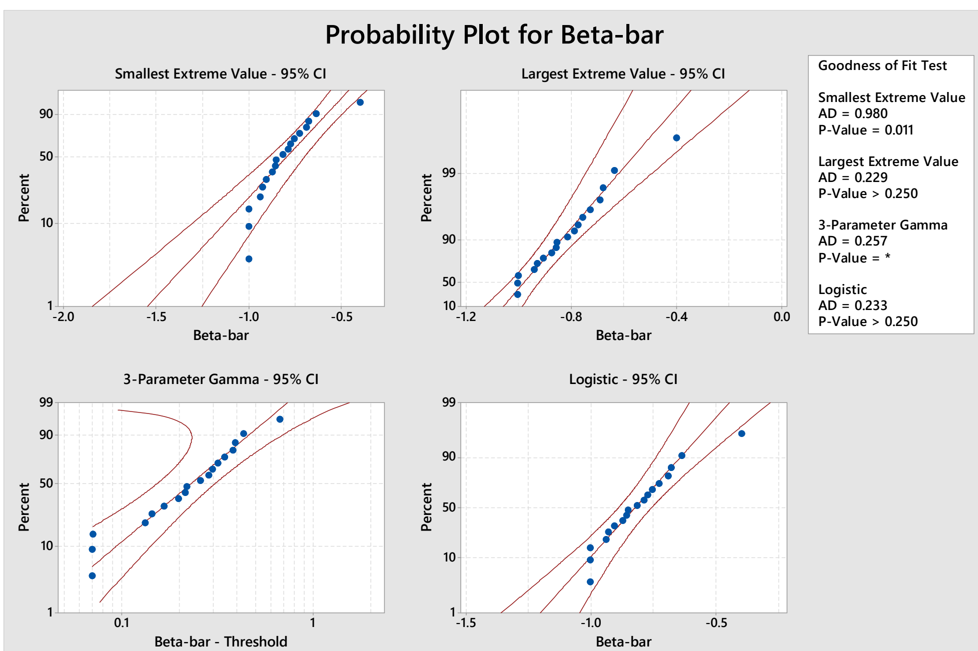

```
Goodness of Fit Test

Distribution                AD       P
Normal                   0.332   0.477
3-Parameter Lognormal    0.270       *
2-Parameter Exponential  0.668   0.189
3-Parameter Weibull      0.293  >0.500
Smallest Extreme Value   0.980   0.011
Largest Extreme Value    0.229  >0.250
3-Parameter Gamma        0.257       *
Logistic                 0.233  >0.250
3-Parameter Loglogistic  0.254       *
```

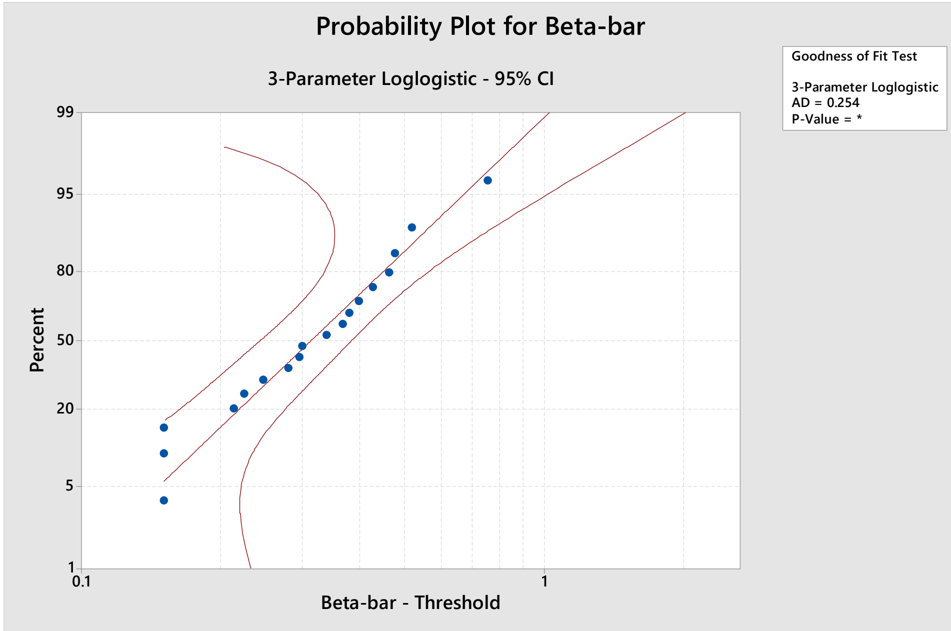

```
Descriptive Statistics

 N  N*       Mean     StDev     Median  Minimum  Maximum  Skewness  Kurtosis
18   0  -0.810483  0.153682  -0.831735       -1  -0.3966   1.02564   1.69614


Goodness of Fit Test

Distribution                AD       P
Normal                   0.332   0.477
3-Parameter Lognormal    0.270       *
2-Parameter Exponential  0.668   0.189
3-Parameter Weibull      0.293  >0.500
Smallest Extreme Value   0.980   0.011
Largest Extreme Value    0.229  >0.250
3-Parameter Gamma        0.257       *
Logistic                 0.233  >0.250
3-Parameter Loglogistic  0.254       *
```


```
ML Estimates of Distribution Parameters

Distribution             Location    Shape    Scale  Threshold
Normal*                  -0.81048           0.15368
3-Parameter Lognormal    -1.17416           0.44155   -1.15039
2-Parameter Exponential                     0.20066   -1.01115
3-Parameter Weibull                1.47911  0.24379   -1.03124
Smallest Extreme Value   -0.72973           0.17801
Largest Extreme Value    -0.87859           0.11648
3-Parameter Gamma                  2.89819  0.08959   -1.07013
```

```
Logistic                    -0.82187          0.08245
3-Parameter Loglogistic     -1.15921          0.25758    -1.15084

* Scale: Adjusted ML estimate
```






Probability Plot for Beta-bar
3-Parameter Loglogistic - 95% CI
Goodness of Fit Test
3-Parameter Loglogistic
AD = 0.254
P-Value = *
Percent
99
95
80
50
20
5
1
0.1
1
Beta-bar - Threshold

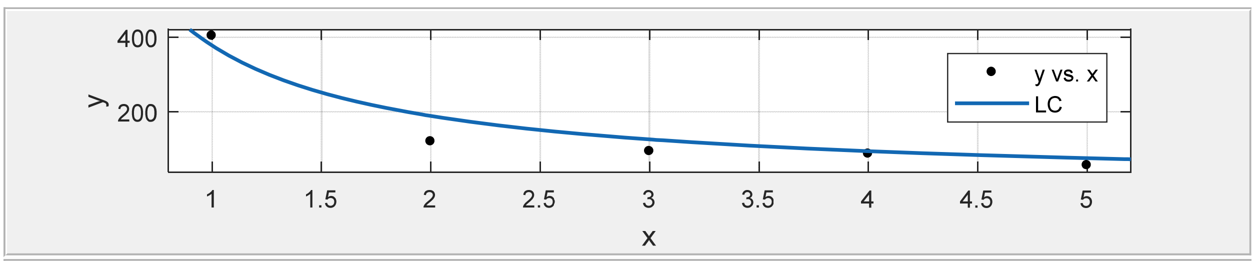
APPENDIX T. FITTING LEARNING SLOPES

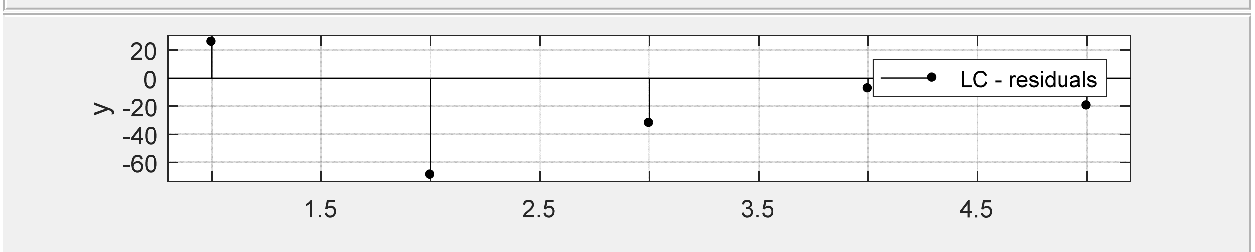
Table 7.1 Fitted learning slopes for iPhone

	System	Order	Delay (m)
	iPhone 5	O2	5

Circumstance 1

y=[377.82 282.82 251.77 233.49 219.85] General model: f(x) = 377.82*x^(b) Coefficients (with 95% confidence bounds): b = -1 (fixed at bound)	Goodness of fit: SSE: 9162 R-square: 0.8871 Adjusted R-square: 0.9097 RMSE: 42.81





Circumstance 2

y=[158.98 141.41 135.17 125.75 119.31]	Goodness of fit:
General model:	SSE: 1.067e+04
f(x) = 158.9800*x^(b)	R-square: 0.8685
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.8685
b = -0.4957 (-1.196, 0.2044)	RMSE: 51.64

Circumstance 3

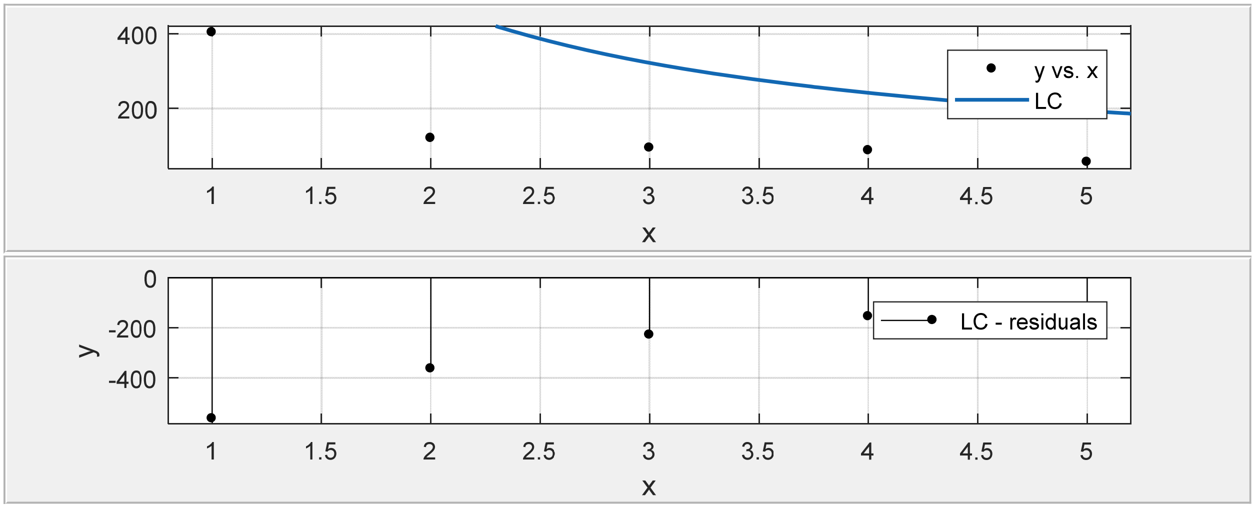
y=[141.95 137.70 133.83 130.52 126.47]	Goodness of fit:
General model:	SSE: 1.238e+04
f(x) = 141.9500*x^(b)	R-square: 0.8474
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.8474
b = -0.4072 (-1.161, 0.3461)	RMSE: 55.63

Subject	System	Order	Delay (m)
3	iPhone 5	O5	1

Circumstance 1

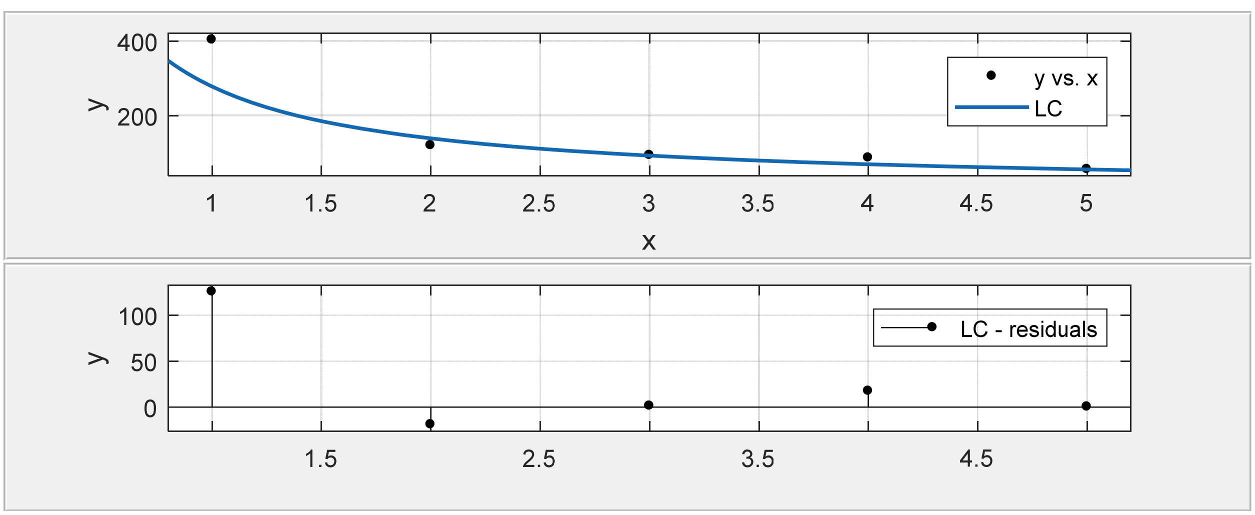
y=[966.65 699.15 610.10 552.55 502.42]	Goodness of fit:
General model:	SSE: 7.173e+05
f(x) = 966.6500*x^(b)	R-square: -7.84
Coefficients (with 95% confidence bounds):	Adjusted R-square: -6.072
b = -1 (fixed at bound)	RMSE: 378.8

Warning: A negative R-square is possible if the model does not contain a constant term and the fit is poor (worse than just fitting the mean). Try changing the model or using a different StartPoint.



Circumstance 2

y=[277.87 271.68 265.48 243.54 230.47]	Goodness of fit:
General model:	SSE: 4390
f(x) = 277.8700 *x^(b)	R-square: 0.9459
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.9459
b = -0.9997 (-1.478, -0.521)	RMSE: 33.13



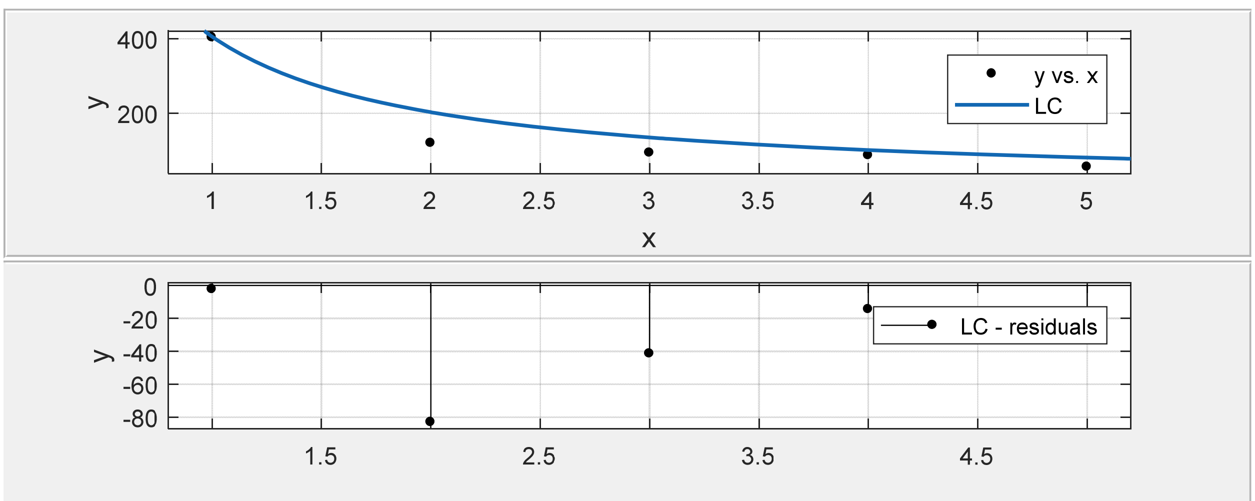
Circumstance 3

y=[281.28 247.16 244.91 227.56 216.65]	Goodness of fit:
General model:	SSE: 4233
f(x) = 281.2800 *x^(b)	R-square: 0.9478
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.9583
b = -1 (fixed at bound)	RMSE: 29.1

	System	Order	Delay (m)
	iPhone 5	O2	10

Circumstance 1

y=[405.87 288.78 240.72 214.27 192.52]	Goodness of fit:
General model:	SSE: 1.206e+04
f(x) = 405.8700*x^(b)	R-square: 0.8514
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.8811
b = -1 (fixed at bound)	RMSE: 49.11

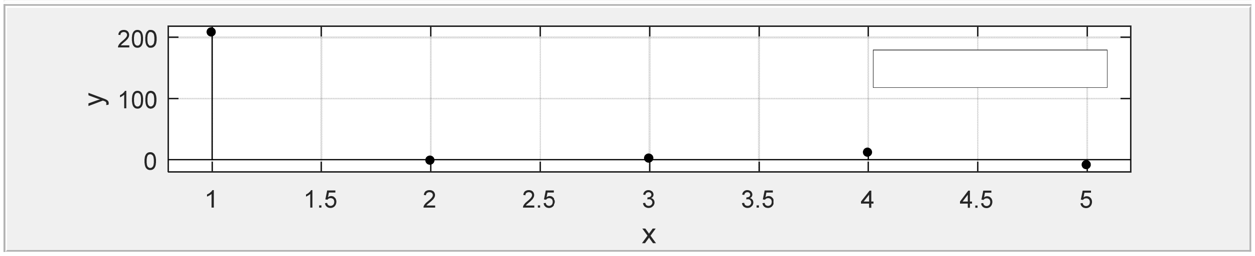


Circumstance 2

y=[131.43 131.02 133.83 132.05 125.09] General model: f(x) = 131.4300*x^(b) Coefficients (with 95% confidence bounds): b = -0.3469 (-1.135, 0.4408)	Goodness of fit: SSE: 1.358e+04 R-square: 0.8326 Adjusted R-square: 0.8326 RMSE: 58.28

Circumstance 3

y=[196.10 189.40 177.39 162.42 154.92] General model: f(x) = 196.1000*x^(b) Coefficients (with 95% confidence bounds): b = -0.6814 (-1.285, -0.07769)	Goodness of fit: SSE: 7537 R-square: 0.9071 Adjusted R-square: 0.9071 RMSE: 43.41

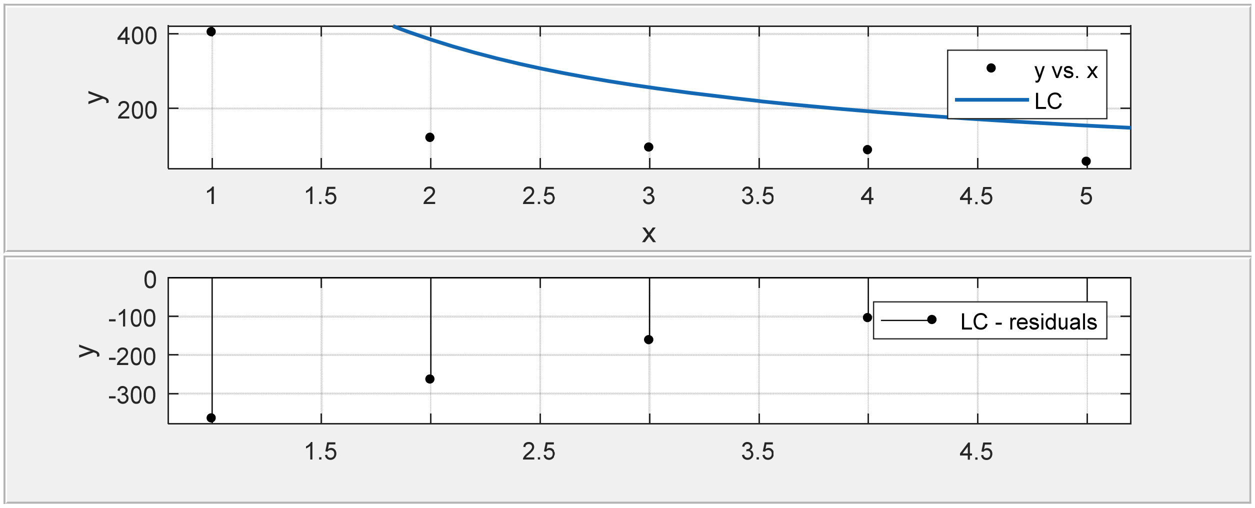


Subject	System	Order	Delay (m)
6	iPhone 5	O3	10

<u>Circumstance 1</u>

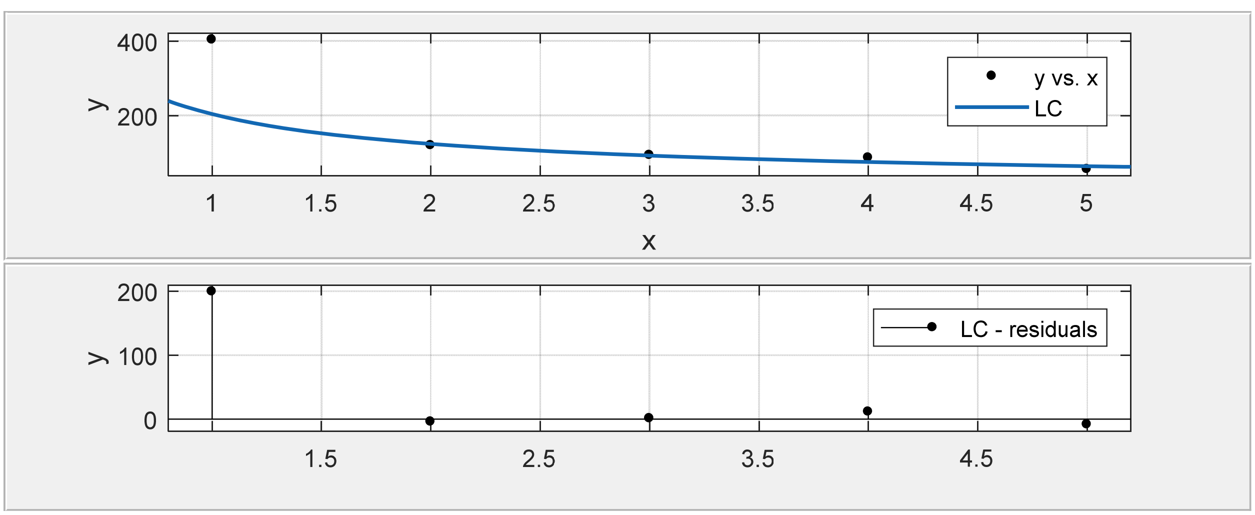
y=[768.99 541.78 426.72 379.82 342.24]	Goodness of fit:
General model:	SSE: 3.294e+05
f(x) = 768.9900*x^(b)	R-square: -3.059
Coefficients (with 95% confidence bounds):	Adjusted R-square: -2.247
b = -1 (fixed at bound)	RMSE: 256.7

Warning: A negative R-square is possible if the model does not contain a constant term and the fit is poor (worse than just fitting the mean). Try changing the model or using a different StartPoint.



Circumstance 2

y=[204.05 206.07 199.89 192.01 199.84] General model: f(x) = 204.0500*x^(b) Coefficients (with 95% confidence bounds): b = -0.7171 (-1.303, -0.1316)	Goodness of fit: SSE: 7024 R-square: 0.9134 Adjusted R-square: 0.9134 RMSE: 41.9



Circumstance 3

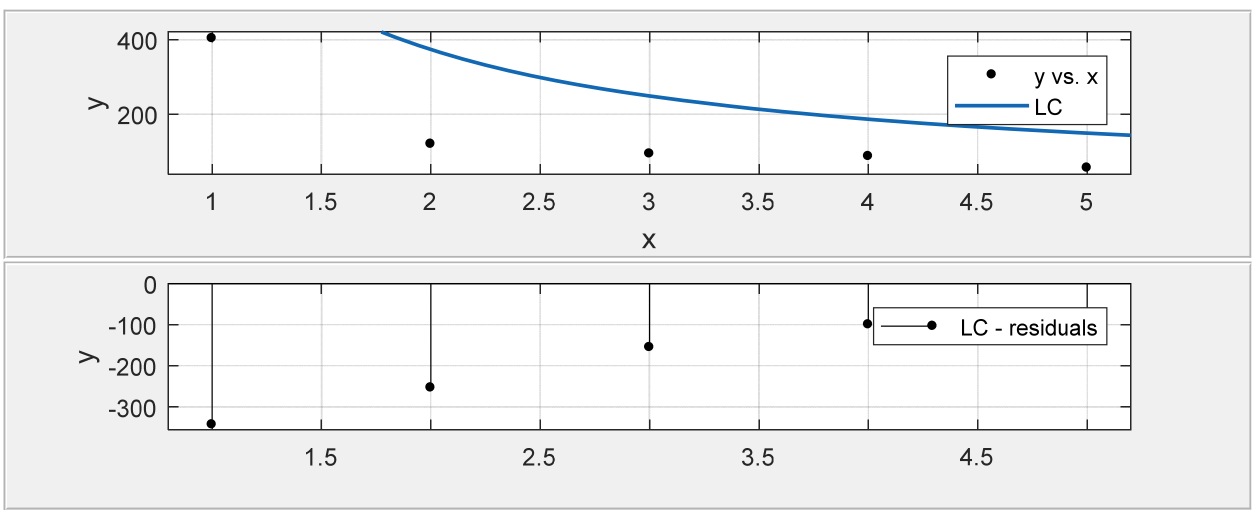
y=[167.37 176.47 177.77 183.73 175.36]	Goodness of fit:
General model:	SSE: 9826
f(x) = 167.3700*x^(b)	R-square: 0.8789
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.8789
b = -0.5422 (-1.22, 0.1352)	RMSE: 49.56

Subject	System	Order	Delay (m)
8	iPhone 5	O3	1

Circumstance 1

y=[746.83 600.09 514.45 468.68 441.30]	Goodness of fit:
General model:	SSE: 2.952e+05
f(x) = 746.8300 *x^(b)	R-square: -2.638
Coefficients (with 95% confidence bounds):	Adjusted R-square: -1.911
b = -1 (fixed at bound)	RMSE: 243

Warning: A negative R-square is possible if the model does not contain a constant term and the fit is poor (worse than just fitting the mean). Try changing the model or using a different StartPoint.

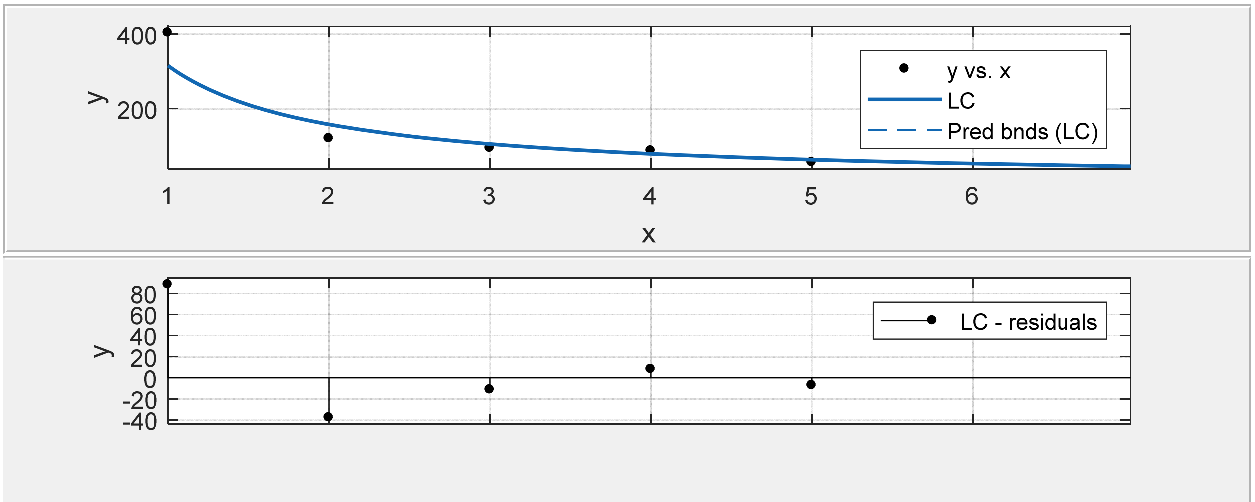


Circumstance 2

y=[481.70 483.57 431.49 409.83 389.47]	Goodness of fit:
General model:	SSE: 3.382e+04
f(x) = 481.7000 *x^(b)	R-square: 0.5832
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.6666
b = -1 (fixed at bound)	RMSE: 82.24

Circumstance 3

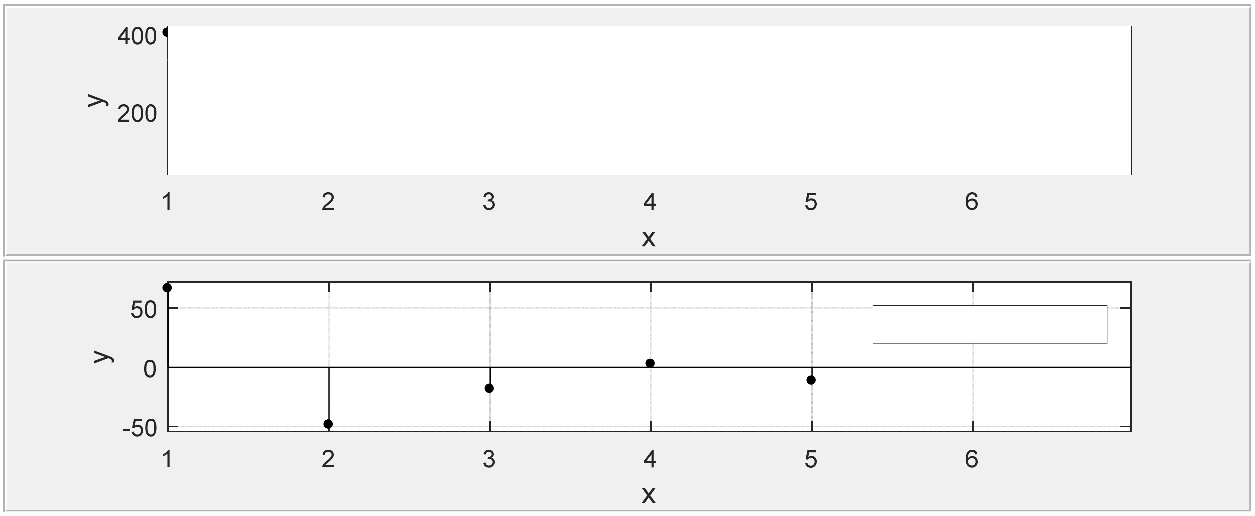
y=[315.22 295.20 318.04 319.04 305.57]	Goodness of fit:
General model:	SSE: 5679
f(x) = 315.2200 *x^(b)	R-square: 0.93
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.944
b = -1 (fixed at bound)	RMSE: 33.7



Subject	System	Order	Delay (m)
11	iPhone 5	O5	10

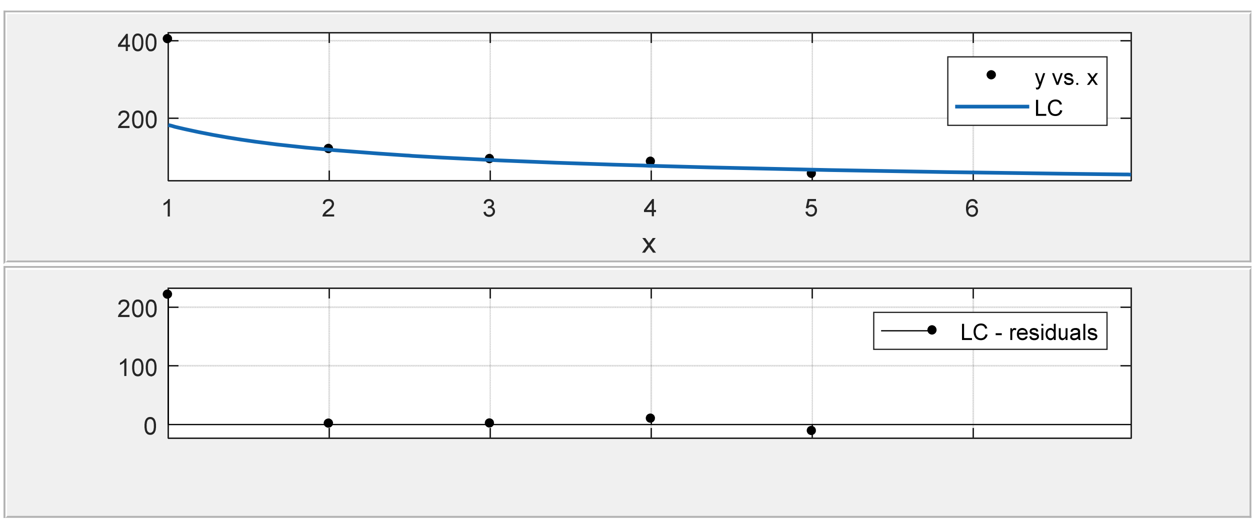
Circumstance 1

y=[337.09 306.90 268.05 255.77 242.98] General model: f(x) = 337.0900 *x^(b) Coefficients (with 95% confidence bounds): b = -1 (fixed at bound)	Goodness of fit: SSE: 1.159e+04 R-square: 0.8571 Adjusted R-square: 0.8857 RMSE: 48.15



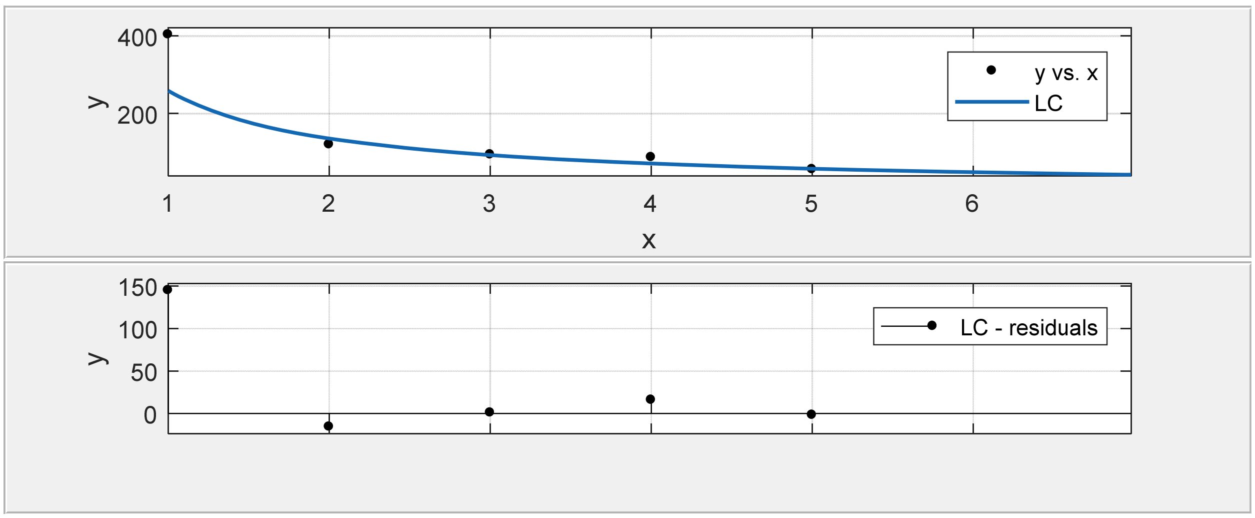
Circumstance 2

y=[182.81 180.46 173.82 165.38 162.89]	Goodness of fit:
General model:	SSE: 8509
f(x) = 182.8100 *x^(b)	R-square: 0.8951
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.8951
b = -0.6197 (-1.256, 0.01711)	RMSE: 46.12



Circumstance 3

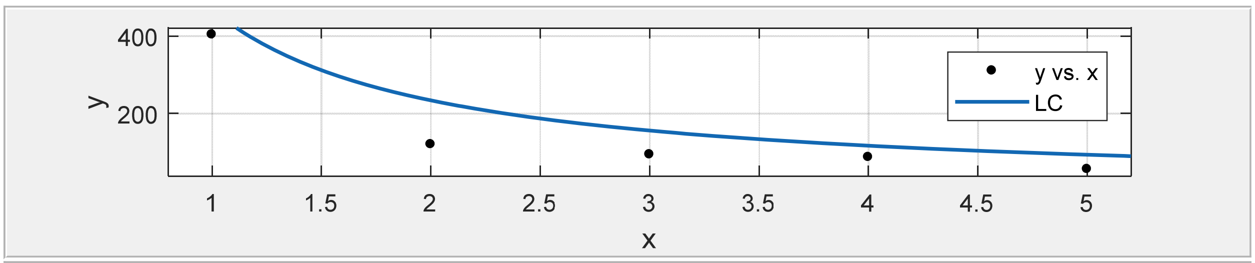
y=[258.76 231.01 233.32 221.96 218.20]	Goodness of fit:
General model:	SSE: 4352
f(x) = 258.7600 *x^(b)	R-square: 0.9464
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.9464
b = -0.9324 (-1.405, -0.4599)	RMSE: 32.99

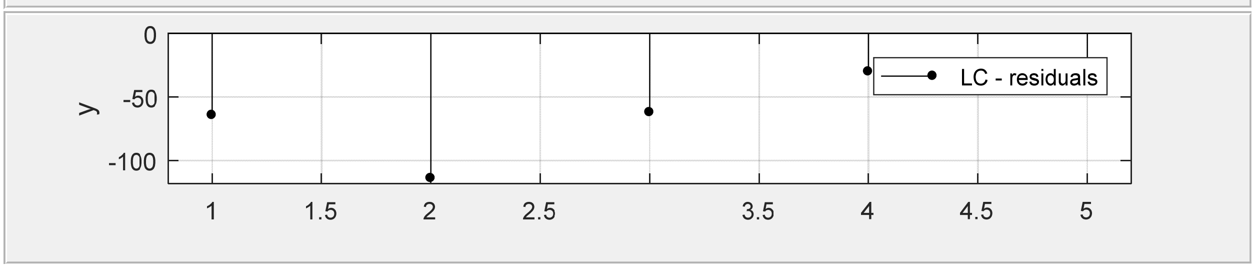


Subject	**System**	**Order**	**Delay (m)**
13	iPhone 5	O2	1

Circumstance 1

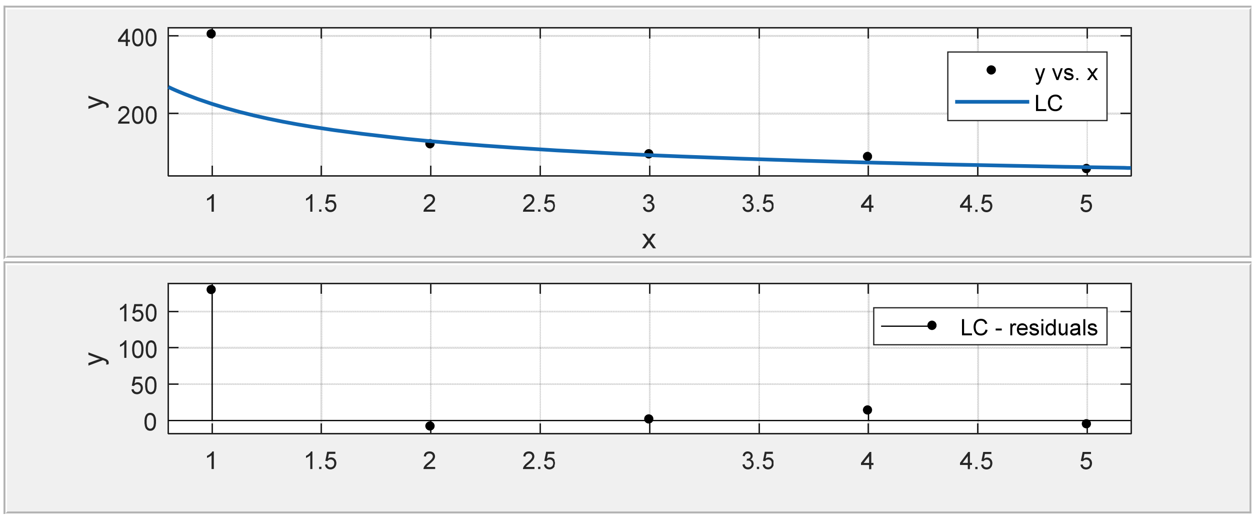
y=[467.84 352.85 322.48 294.82 278.11]	Goodness of fit:
General model:	SSE: 2.926e+04
f(x) = 467.8400 *x^(b)	R-square: 0.6394
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.7115
b = -1 (fixed at bound)	RMSE: 76.5





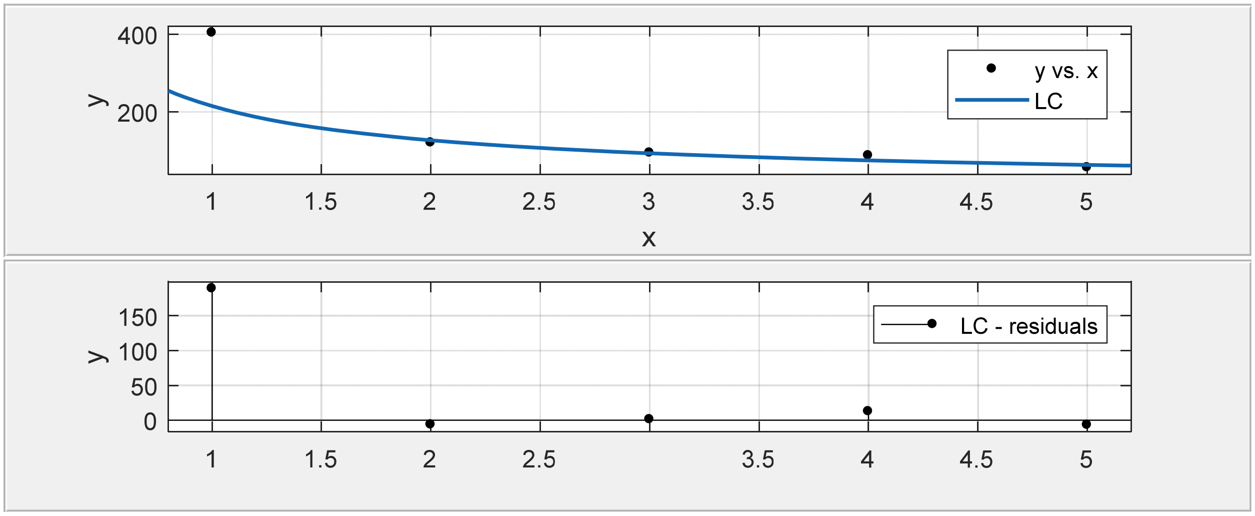
Circumstance 2

y=[224.63 222.56 214.10 200.27 194.94] General model: f(x) = 224.6300 *x^(b) Coefficients (with 95% confidence bounds): b = -0.8039 (-1.345, -0.2633)	Goodness of fit: SSE: 5859 R-square: 0.9278 Adjusted R-square: 0.9278 RMSE: 38.27



Circumstance 3

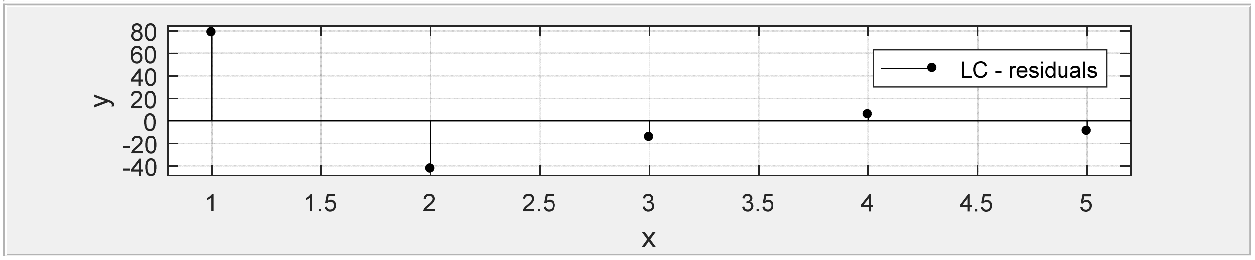
y=[214.46 202.31 195.30 194.30 197.27] General model: f(x) = 214.4600 *x^(b) Coefficients (with 95% confidence bounds): b = -0.763 (-1.327, -0.1987)	Goodness of fit: SSE: 6432 R-square: 0.9207 Adjusted R-square: 0.9207 RMSE: 40.1



Subject	System	Order	Delay (m)
16	iPhone 5	O5	5

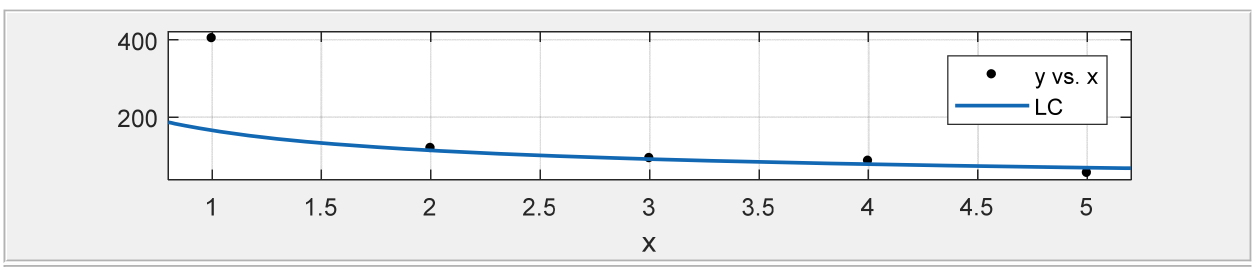
Circumstance 1

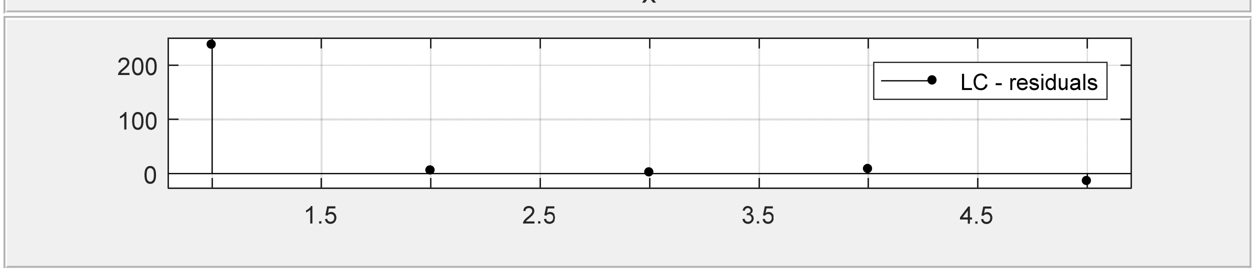
y=[325.01 244.03 216.95 199.71 188.59] General model: f(x) = 325.0100 *x^(b) Coefficients (with 95% confidence bounds): b = -1 (fixed at bound)	Goodness of fit: SSE: 1.337e+04 R-square: 0.8352 Adjusted R-square: 0.8682 RMSE: 51.72



Circumstance 2

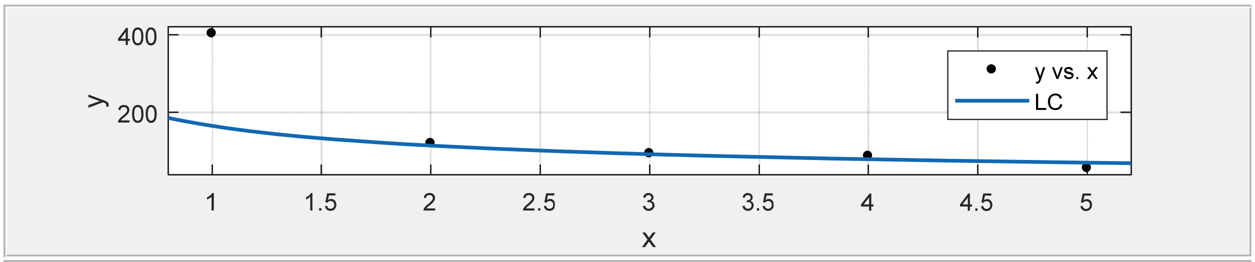
y=[166.25 160.98 159.97 154.49 155.03] General model: f(x) = 166.2500 *x^(b) Coefficients (with 95% confidence bounds): b = -0.5362 (-1.217, 0.1442)	Goodness of fit: SSE: 9931 R-square: 0.8776 Adjusted R-square: 0.8776 RMSE: 49.83

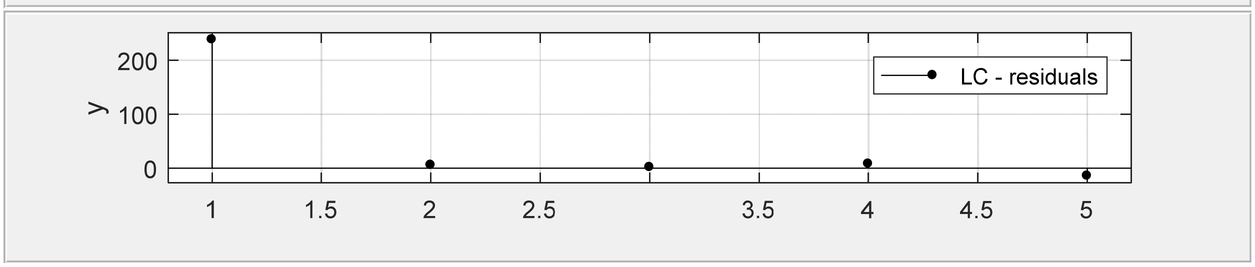




Circumstance 3

y=[165.20 158.13 169.61 164.31 162.63]	Goodness of fit:
General model:	SSE: 1.003e+04
f(x) = 165.2000 *x^(b)	R-square: 0.8764
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.8764
b = -0.5306 (-1.214, 0.1527)	RMSE: 50.08



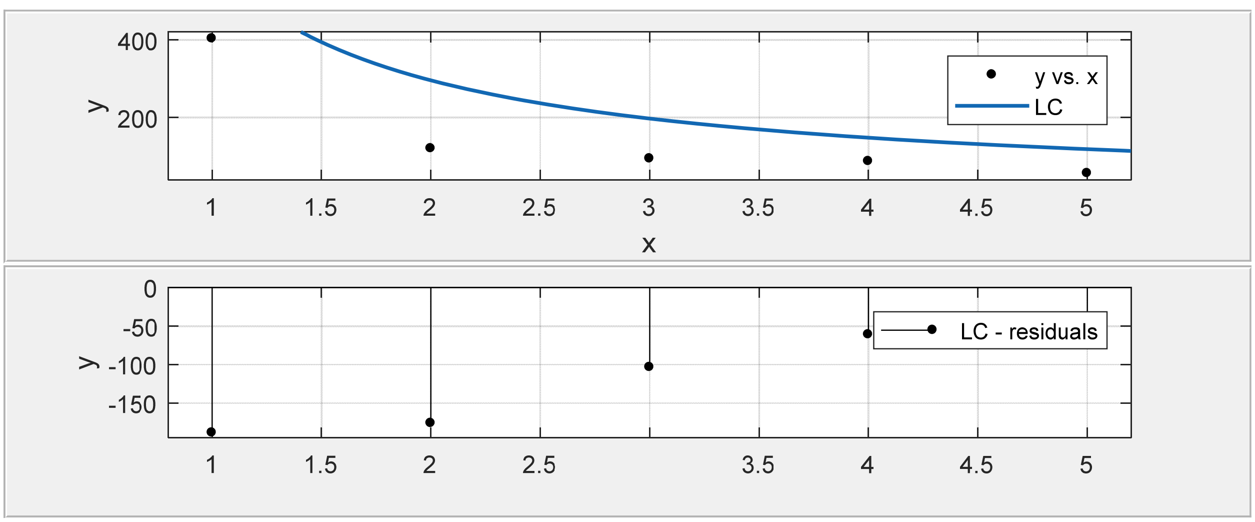


Subject	System	Order	Delay (m)
17	iPhone 5	O3	5

Circumstance 1

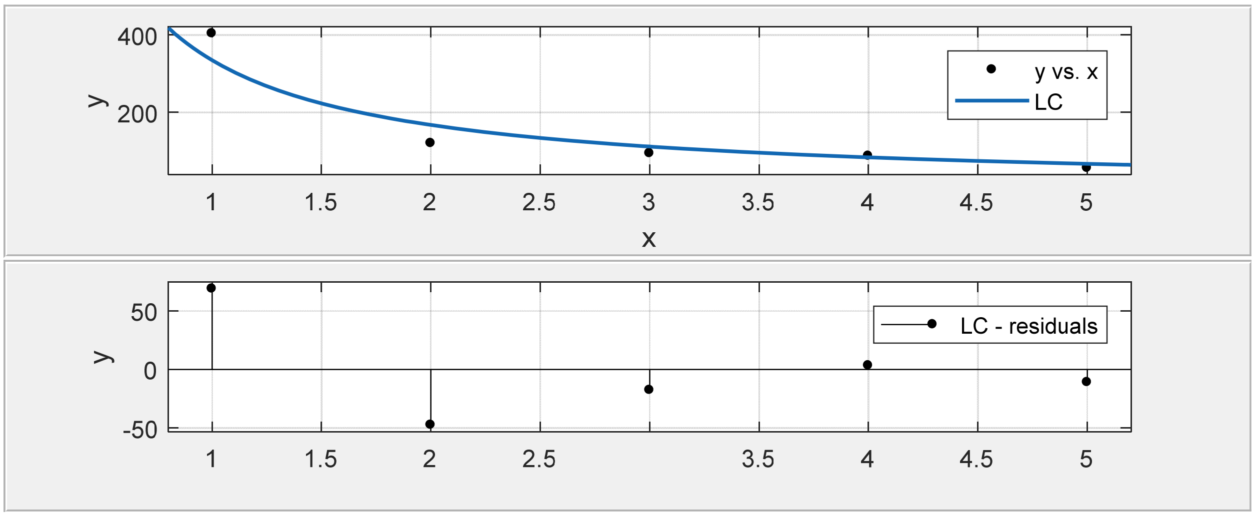
y=[591.89 509.84 424.68 387.97 353.87] General model: f(x) = 591.8900 *x^(b) Coefficients (with 95% confidence bounds): b = -1 (fixed at bound)	Goodness of fit: SSE: 1.092e+05 R-square: -0.3455 Adjusted R-square: -0.07638 RMSE: 147.8

Warning: A negative R-square is possible if the model does not contain a constant term and the fit is poor (worse than just fitting the mean). Try changing the model or using a different StartPoint.



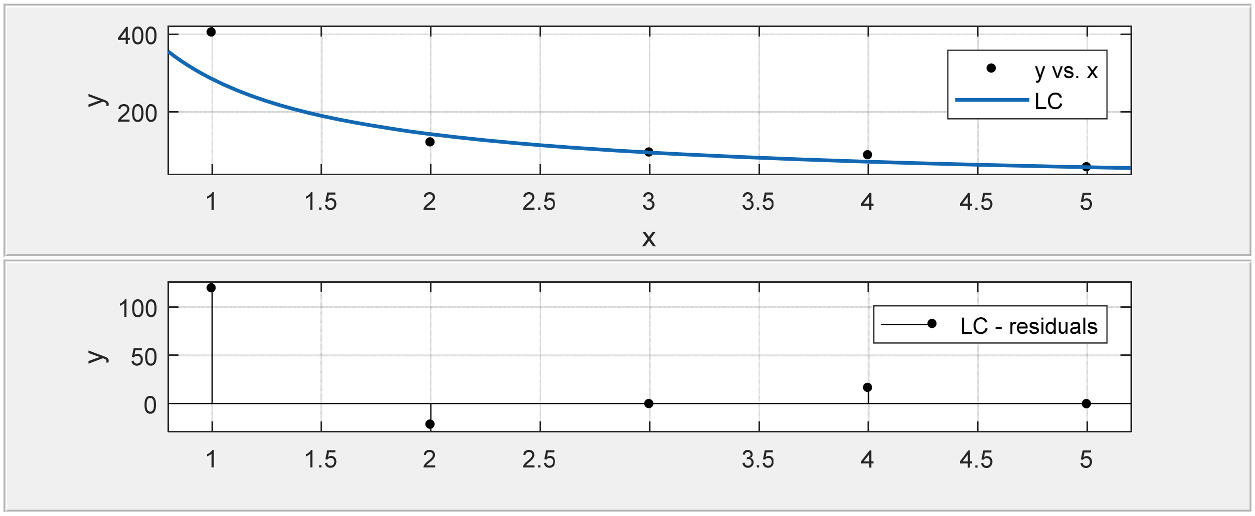
Circumstance 2

y=[334.71 311.29 305.67 306.03 310.32]	Goodness of fit:
General model:	SSE: 1.213e+04
f(x) = 334.7100 *x^(b)	R-square: 0.8505
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.8804
b = -1 (fixed at bound)	RMSE: 49.25



Circumstance 3

y=[284.29 283.66 279.59 260.01 248.71]	Goodness of fit:
General model:	SSE: 4094
f(x) = 284.2900 *x^(b)	R-square: 0.9495
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.9596
b = -1 (fixed at bound)	RMSE: 28.61



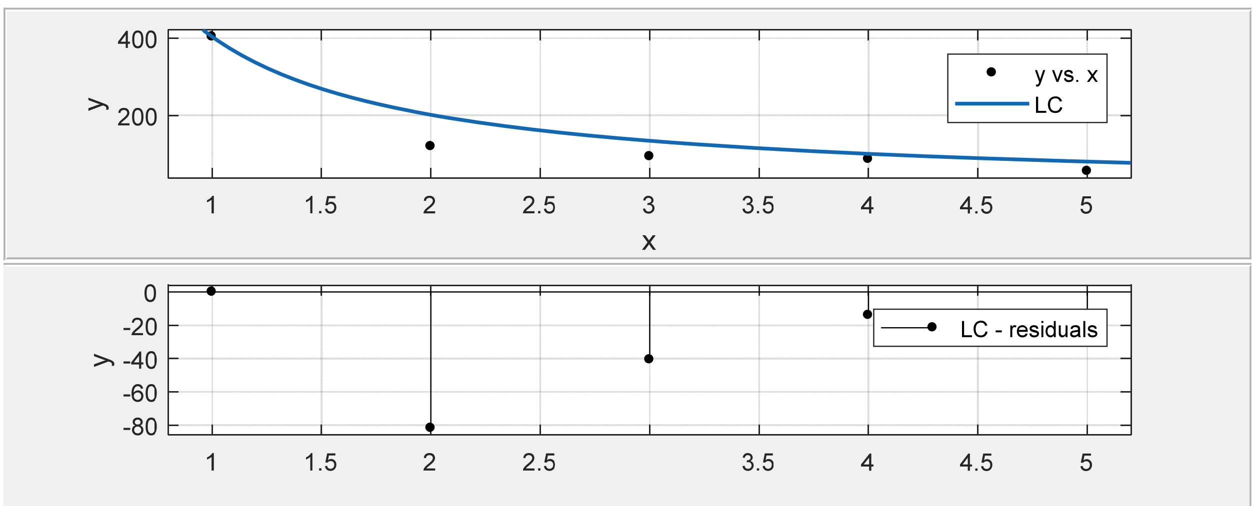
400
200
y
1
1.5
2
2.5
3
3.5
4
4.5
5
x
y vs. x
LC
100
50
0
y
LC - residuals

Table 7.2 Fitted learning slopes for Tablet

	System	Order	Delay (m)
	Tablet	O2	5

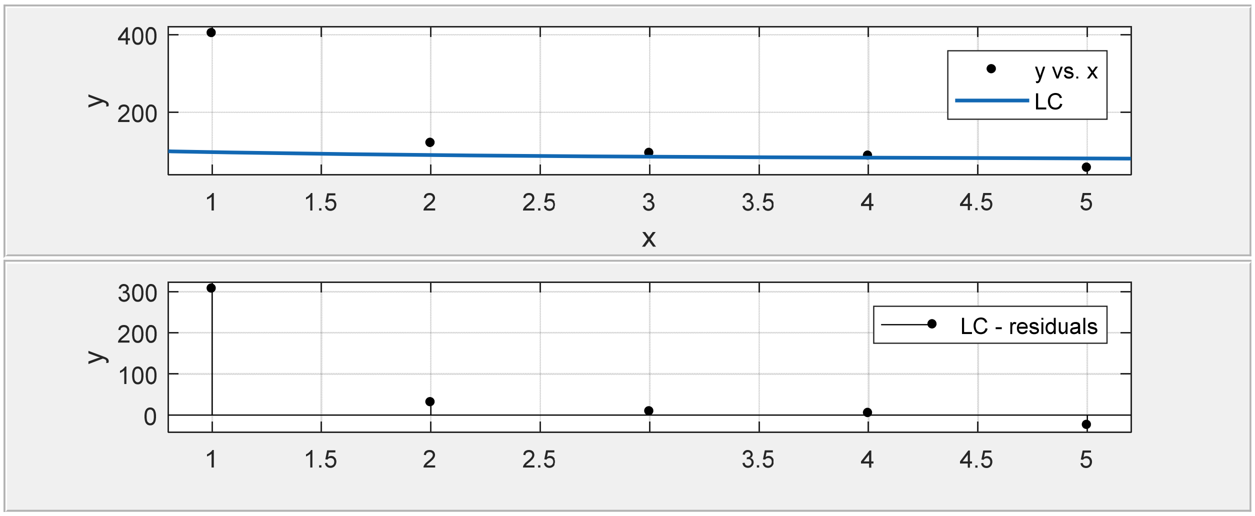
Circumstance 1

y=[403.48 261.69 205.73 176.02 151.99] General model: f(x) = 403.4800 *x^(b) Coefficients (with 95% confidence bounds): b = -1 (fixed at bound)	Goodness of fit: SSE: 1.16e+04 R-square: 0.857 Adjusted R-square: 0.8856 RMSE: 48.17



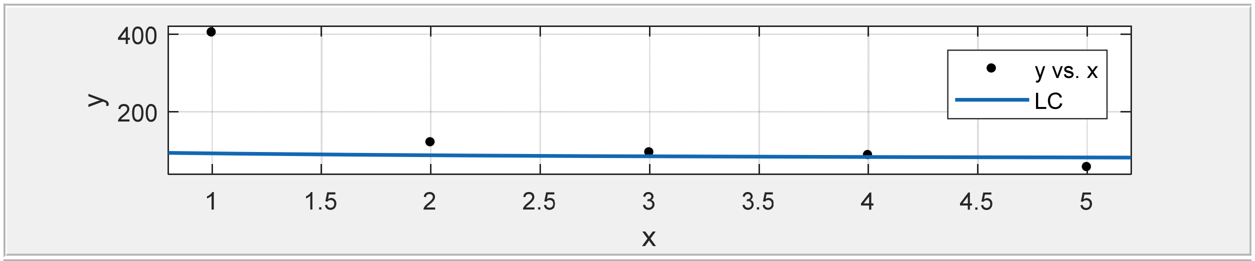
Circumstance 2

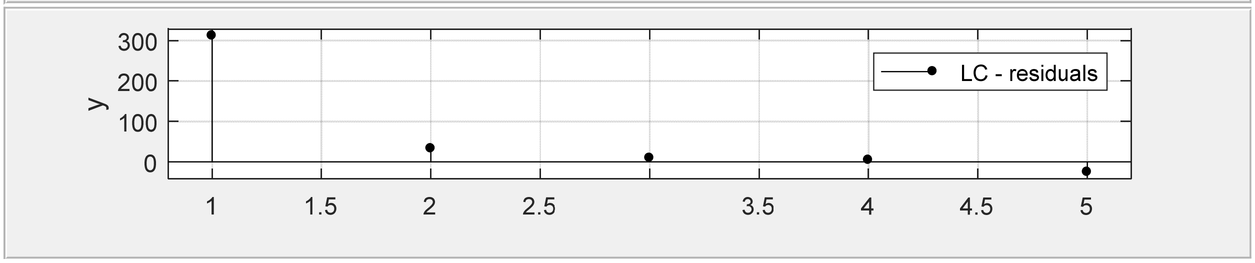
y=[96.83 80.04 74.72 75.84 73.74] General model: f(x) = 96.8300 *x^(b) Coefficients (with 95% confidence bounds): b = -0.1141 (-1.028, 0.8004)	Goodness of fit: SSE: 1.849e+04 R-square: 0.7721 Adjusted R-square: 0.7721 RMSE: 67.99



Circumstance 3

y=[91.95 82.02 78.78 78.39 76.28] General model: f(x) = 91.9500 *x^(b) Coefficients (with 95% confidence bounds): b = -0.0757 (-1.011, 0.8592)	Goodness of fit: SSE: 1.933e+04 R-square: 0.7617 Adjusted R-square: 0.7617 RMSE: 69.52

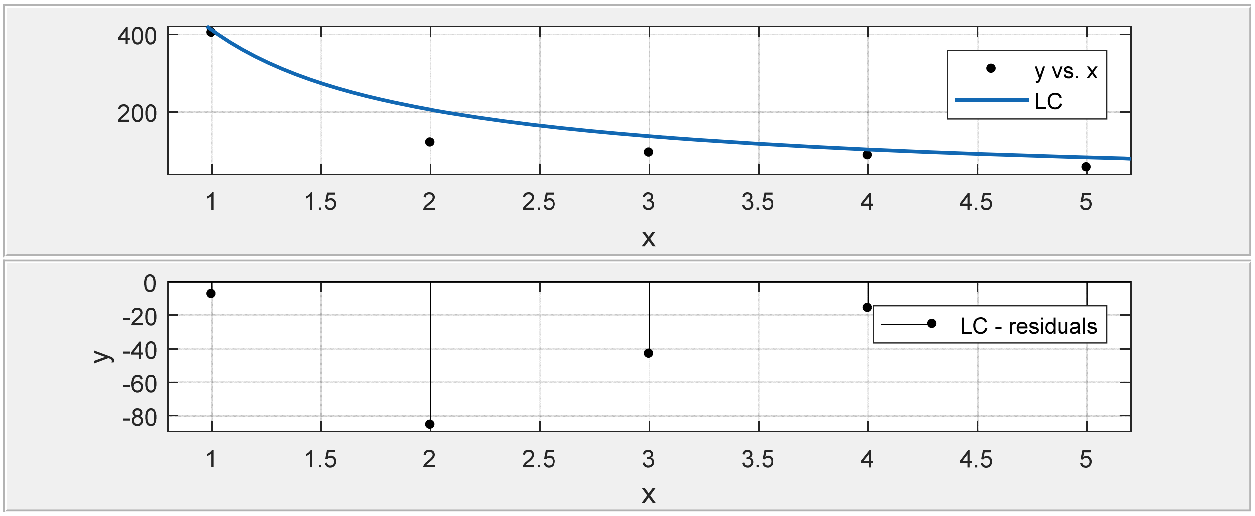




Subject	**System**	**Order**	**Delay (m)**
5	Tablet	O5	1

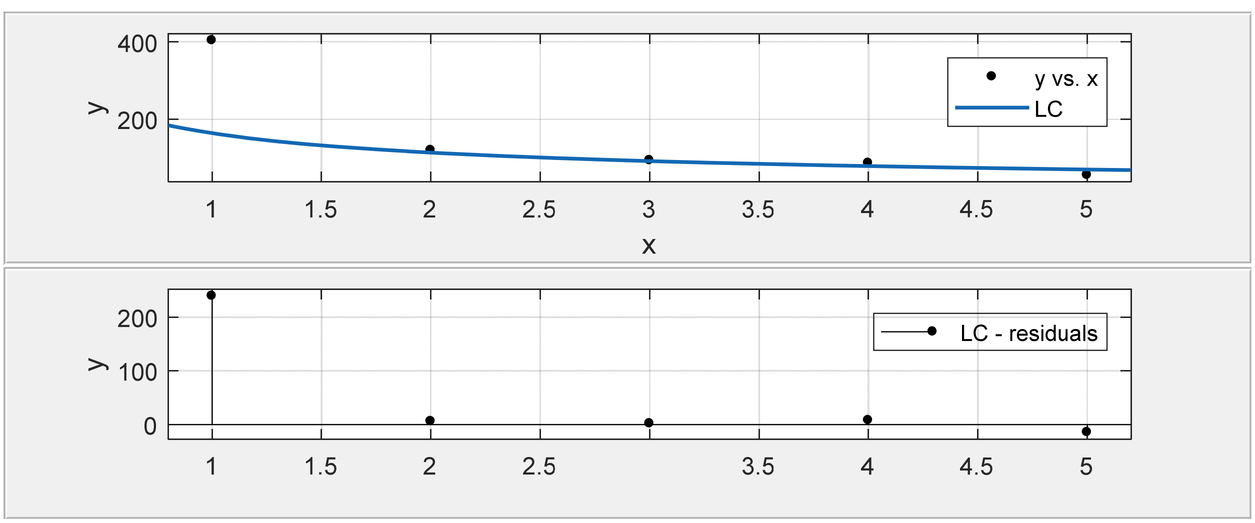
Circumstance 1

y=[411.05 292.69 249.21 226.35 206.09] General model: f(x) = 411.0500 *x^(b) Coefficients (with 95% confidence bounds): b = -1 (fixed at bound)	Goodness of fit: SSE: 1.324e+04 R-square: 0.8368 Adjusted R-square: 0.8694 RMSE: 51.46



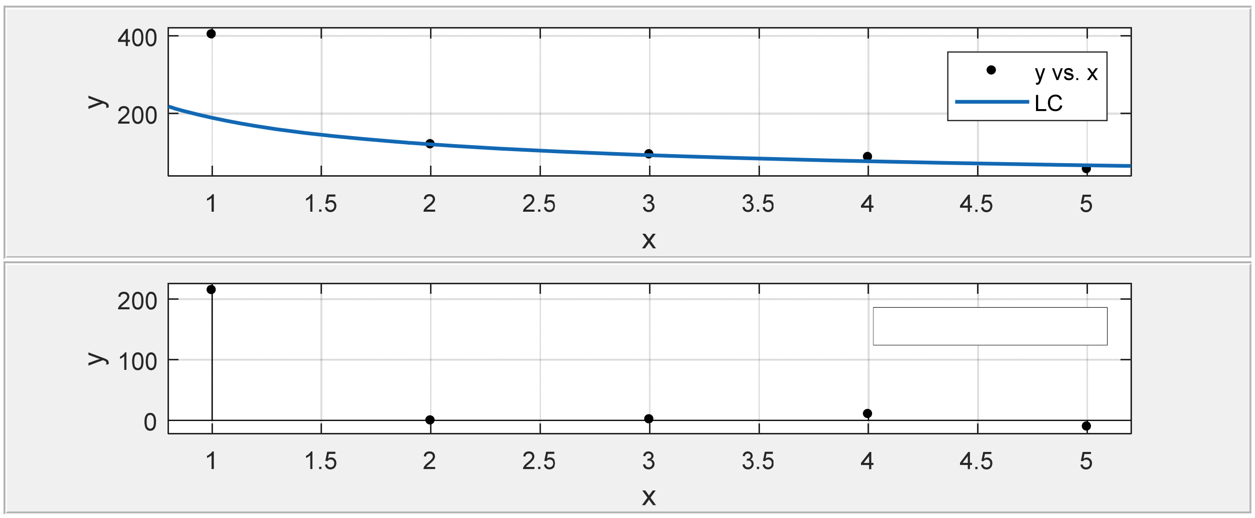
Circumstance 2

y=[164.23 146.27 143.67 138.03 136.33]	Goodness of fit:
General model:	SSE: 1.013e+04
f(x) = 164.2300 *x^(b)	R-square: 0.8752
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.8752
b = -0.5253 (-1.211, 0.1606)	RMSE: 50.31



Circumstance 3

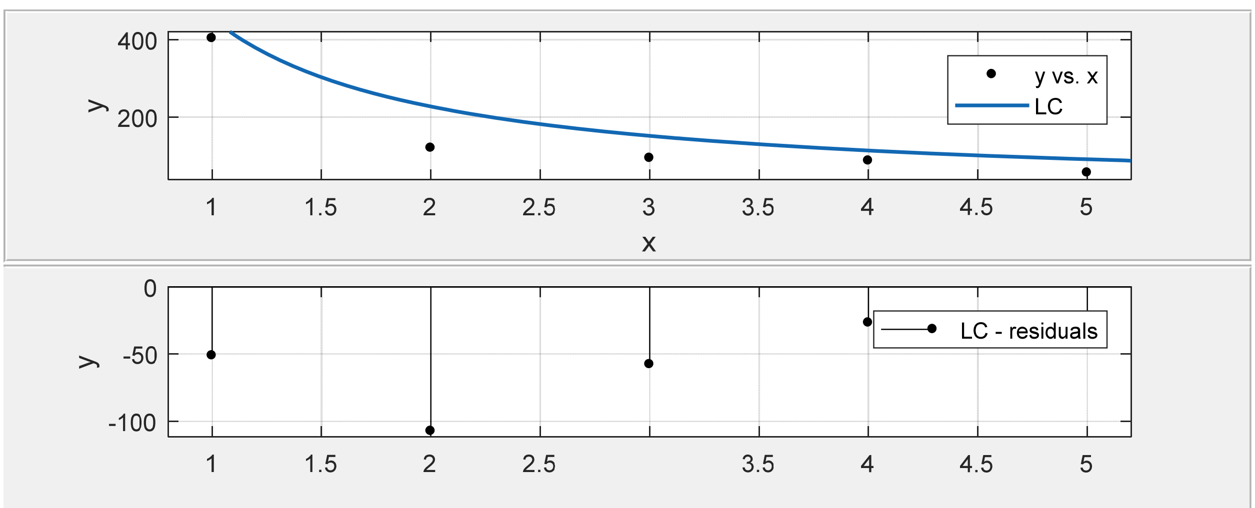
y=[188.89 161.80 157.46 153.49 147.31]	Goodness of fit:
General model:	SSE: 8046
f(x) = 188.8900 *x^(b)	R-square: 0.9008
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.9008
b = -0.6484 (-1.27, -0.02703)	RMSE: 44.85



	System	Order	Delay (m)
	Tablet	O5	5

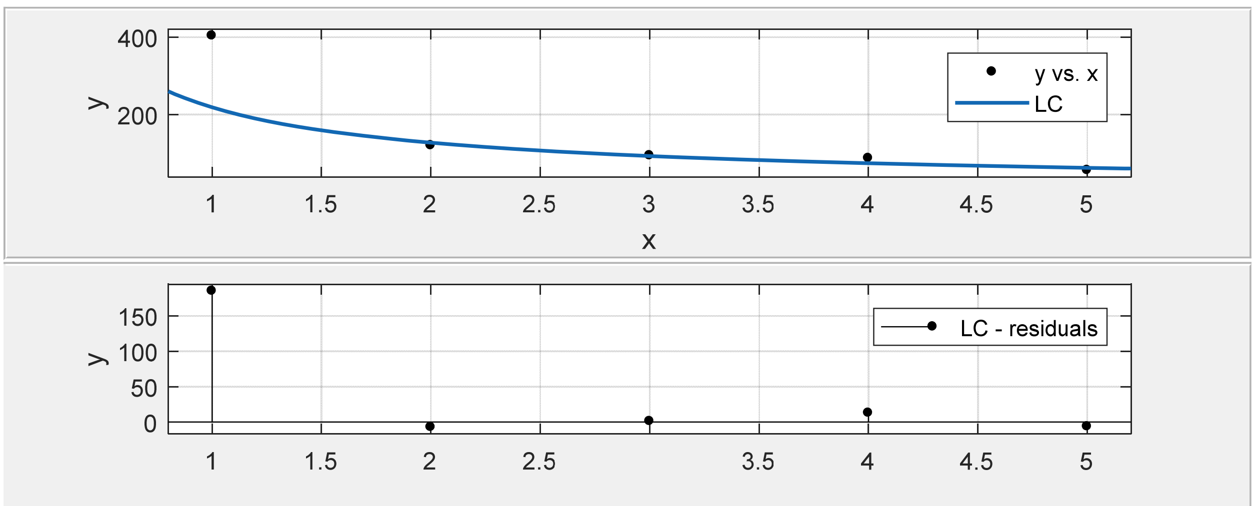
Circumstance 1

y=[454.70 329.67 283.07 266.26 250.82]	Goodness of fit:
General model:	SSE: 2.59e+04
f(x) = 454.7000 *x^(b)	R-square: 0.6808
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.7447
b = -1 (fixed at bound)	RMSE: 71.97



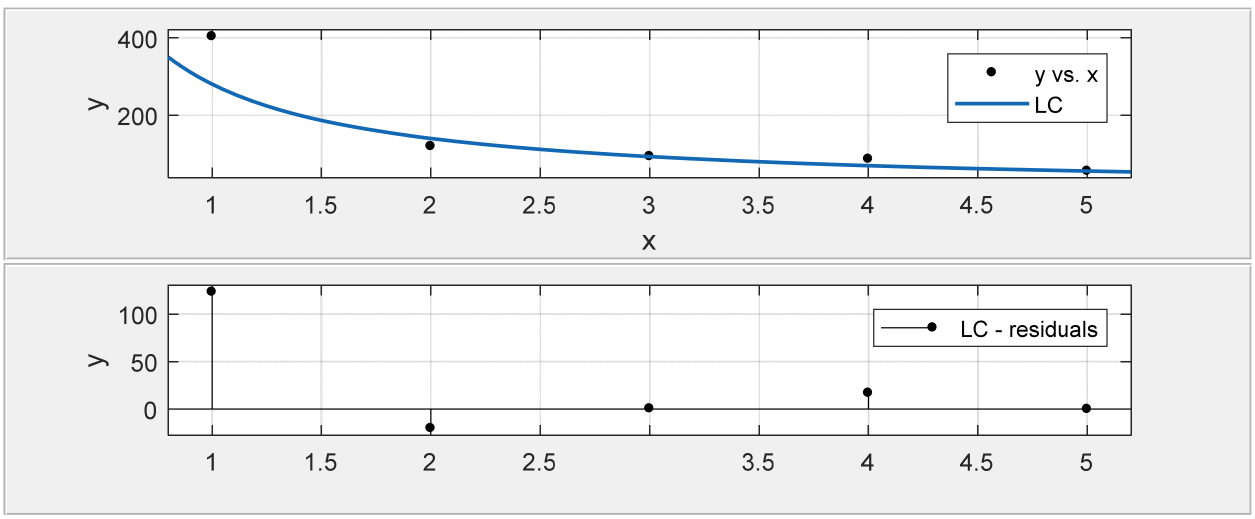
Circumstance 2

y=[218.51 181.57 180.99 177.36 175.48]	Goodness of fit:
General model:	SSE: 6208
f(x) = 218.5100 *x^(b)	R-square: 0.9235
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.9235
b = -0.7799 (-1.335, -0.2244)	RMSE: 39.4



<u>Circumstance 3</u>

y=[280.40 275.35 276.07 248.27 228.97] General model: f(x) = 280.4000 *x^(b) Coefficients (with 95% confidence bounds): b = -1 (fixed at bound)	Goodness of fit: SSE: 4275 R-square: 0.9473 Adjusted R-square: 0.9579 RMSE: 29.24

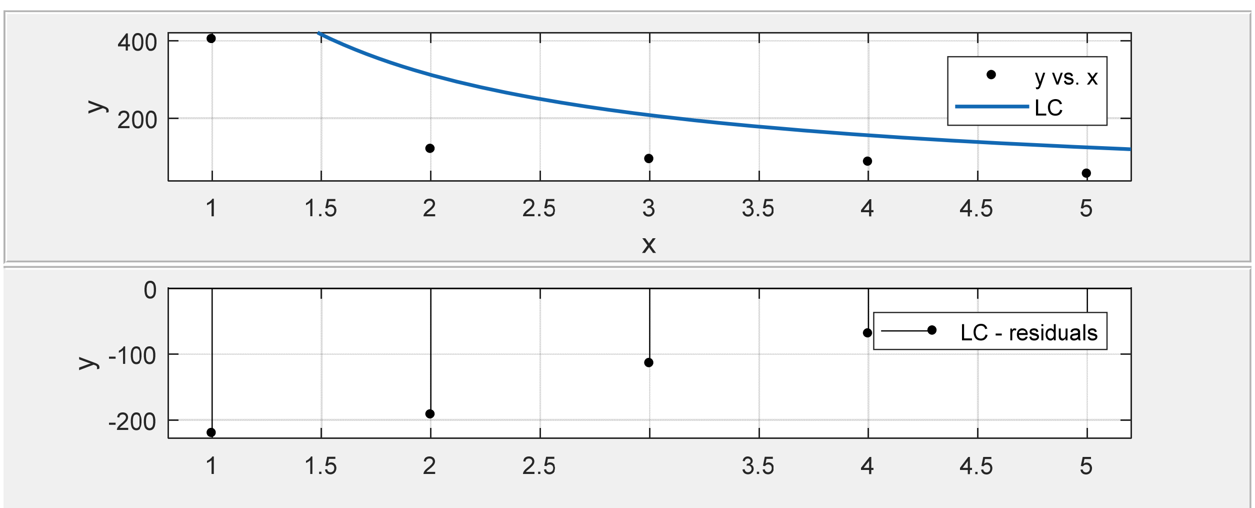


	System	Order	Delay (m)
	Tablet	O5	10

Circumstance 1

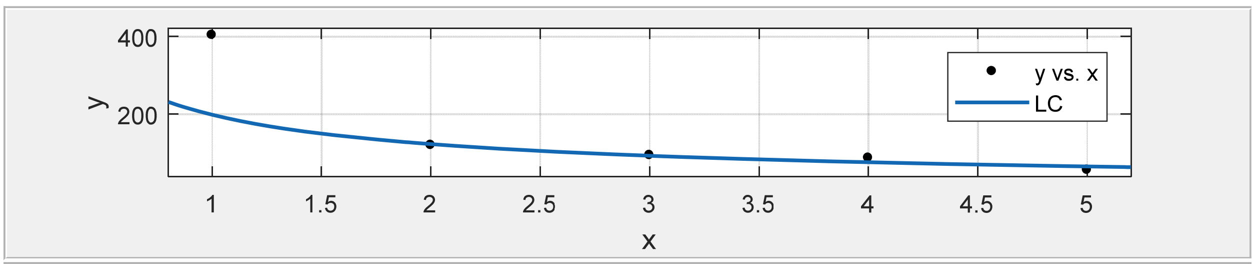
y=[623.93 415.14 335.49 293.16 258.34]	Goodness of fit:
General model:	SSE: 1.4e+05
f(x) = 623.9300 *x^(b)	R-square: -0.7258
Coefficients (with 95% confidence bounds):	Adjusted R-square: -0.3806
b = -1 (fixed at bound)	RMSE: 167.4

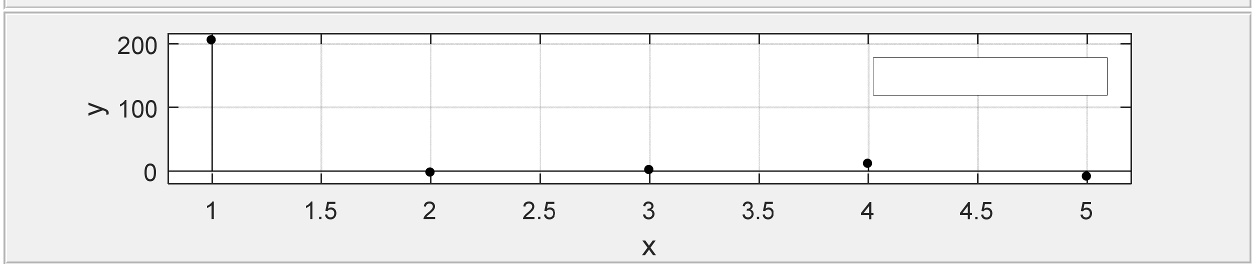
Warning: A negative R-square is possible if the model does not contain a constant term and the fit is poor (worse than just fitting the mean). Try changing the model or using a different StartPoint.



Circumstance 2

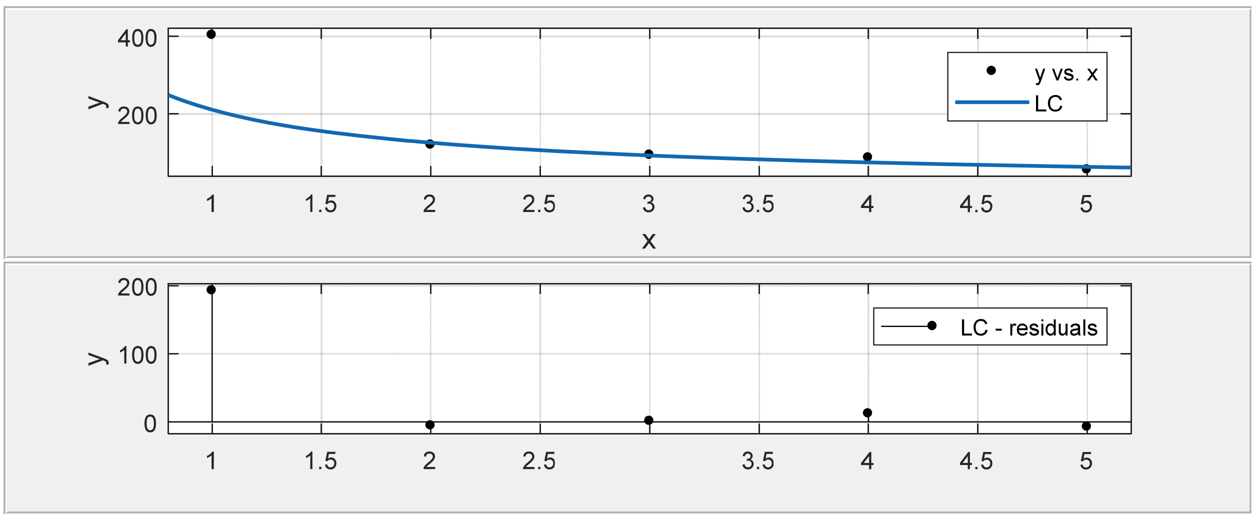
y=[198.38 191.89 197.25 202.67 211.76]	Goodness of fit:
General model:	SSE: 7385
f(x) = 198.3800 *x^(b)	R-square: 0.909
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.909
b = -0.6917 (-1.29, -0.09334)	RMSE: 42.97





Circumstance 3

y=[210.74 181.68 187.78 190.85 188.51]	Goodness of fit:
General model:	SSE: 6631
f(x) = 210.7400 *x^(b)	R-square: 0.9183
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.9183
b = -0.7466 (-1.318, -0.1752)	RMSE: 40.72

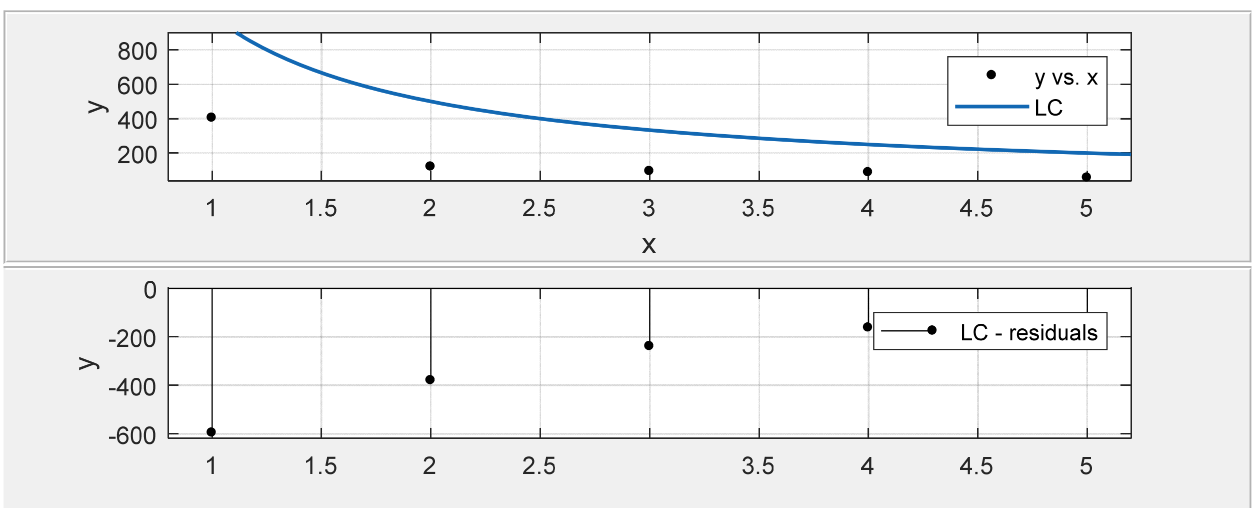


	System	Order	Delay (m)
	Tablet	O3	1

Circumstance 1

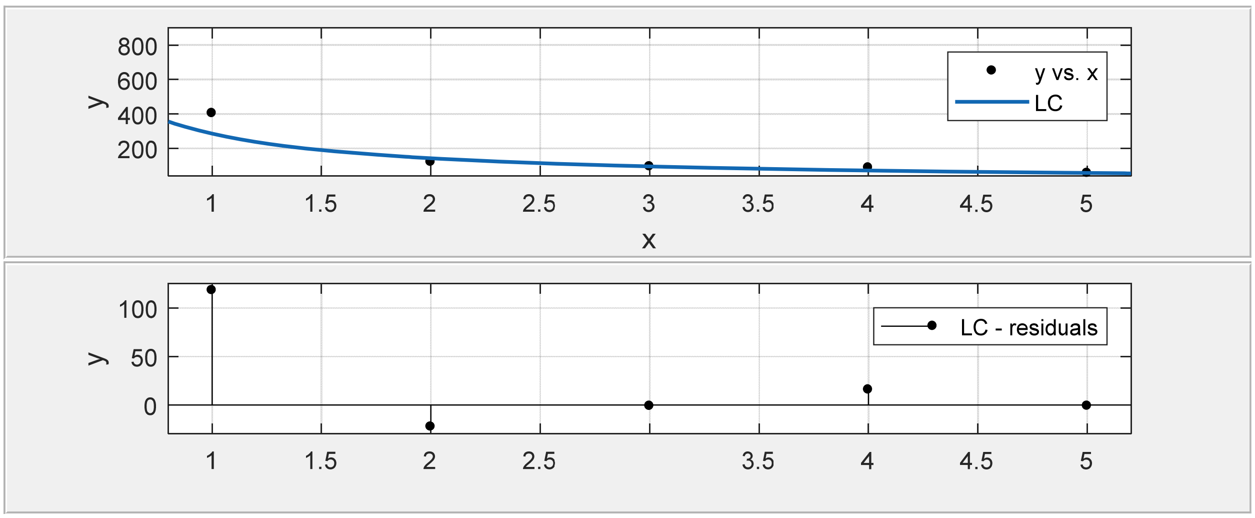
y=[999.66 716.66 599.11 517.67 464.44]	Goodness of fit:
General model:	SSE: 7.967e+05
f(x) = 999.6600 *x^(b)	R-square: -8.818
Coefficients (with 95% confidence bounds):	Adjusted R-square: -6.855
b = -1 (fixed at bound)	RMSE: 399.2

Warning: A negative R-square is possible if the model does not contain a constant term and the fit is poor (worse than just fitting the mean). Try changing the model or using a different StartPoint.



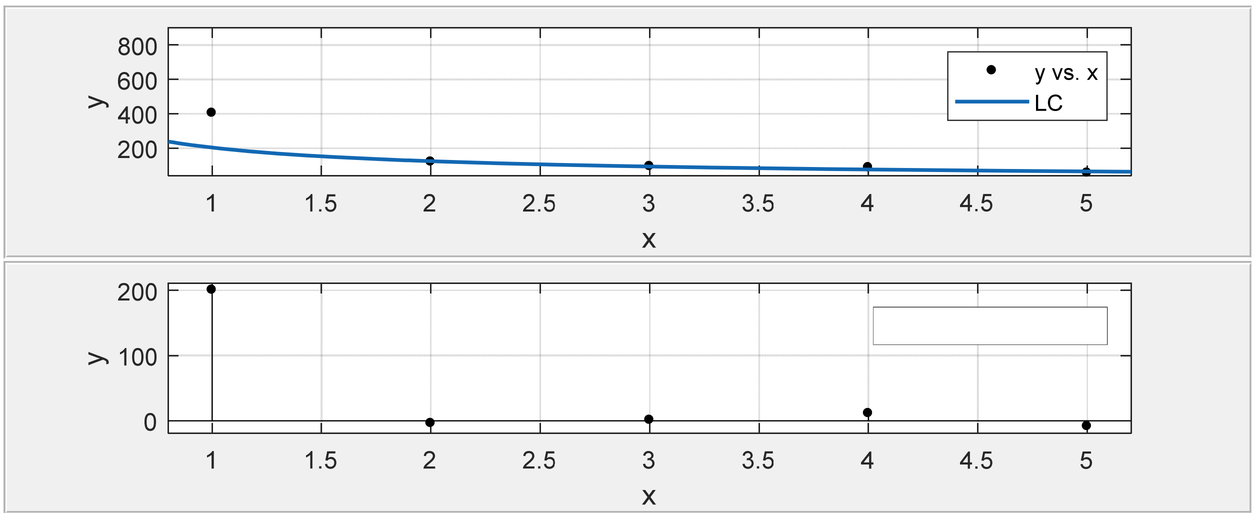
Circumstance 2

y=[285.18 279.49 267.06 254.82 258.02]	Goodness of fit:
General model:	SSE: 4052
f(x) = 285.1800 *x^(b)	R-square: 0.9501
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.96
b = -1 (fixed at bound)	RMSE: 28.47



<u>Circumstance 3</u>

y=[203.05 229.21 250.52 240.33 232.05] General model: f(x) = 203.0500 *x^(b) Coefficients (with 95% confidence bounds): b = -0.7126 (-1.3, -0.1249)	Goodness of fit: SSE: 7086 R-square: 0.9127 Adjusted R-square: 0.9127 RMSE: 42.09

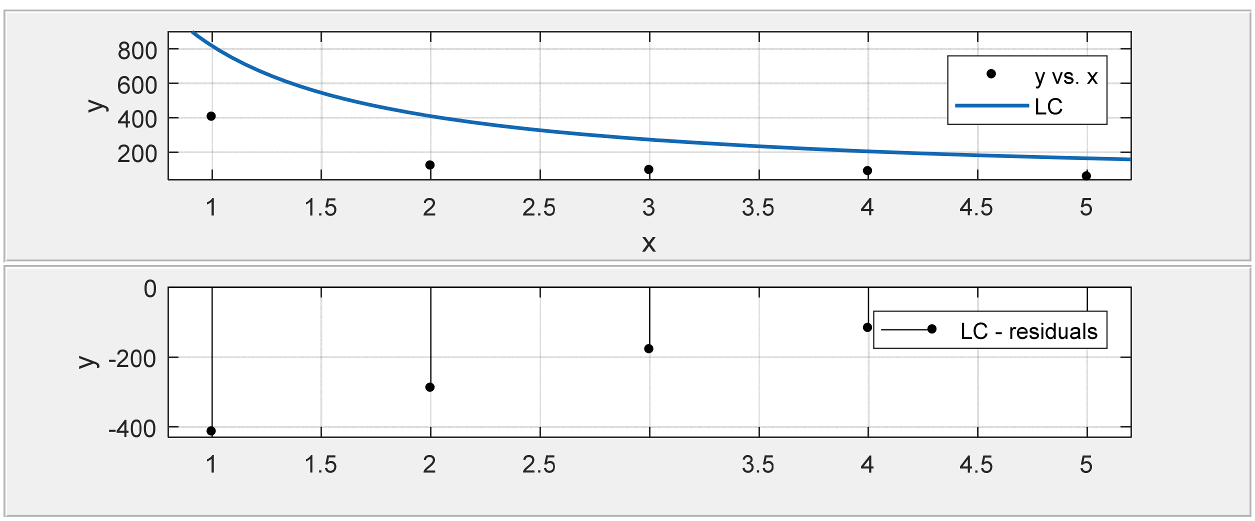


Subject	System	Order	Delay (m)
12	Tablet	O3	5

Circumstance 1

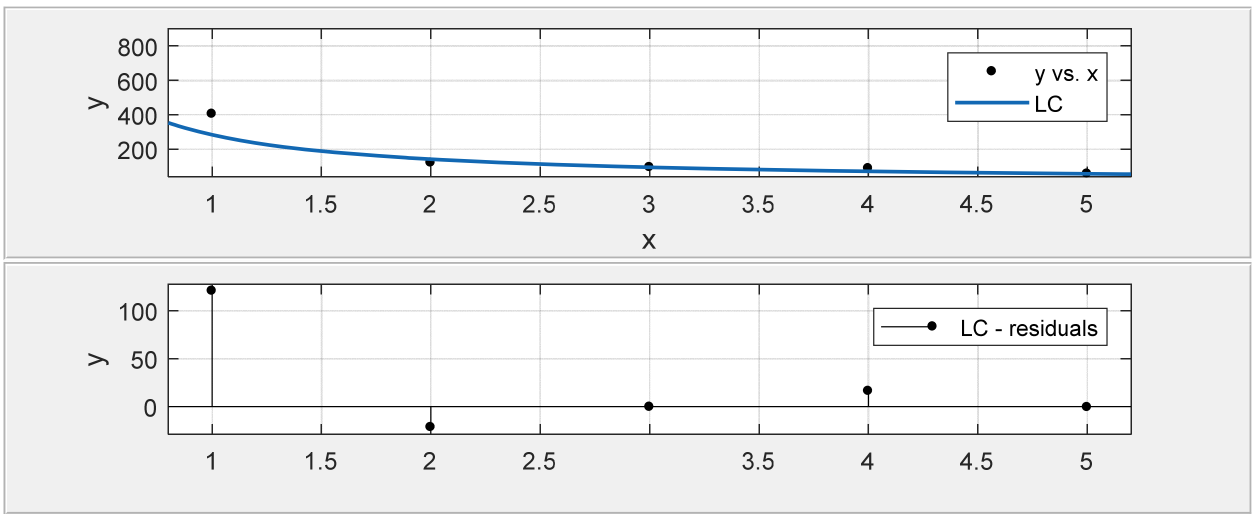
y=[817.72 585.52 506.48 432.08 377.76]	Goodness of fit:
General model:	SSE: 4.111e+05
f(x) = 817.7200 *x^(b)	R-square: -4.067
Coefficients (with 95% confidence bounds):	Adjusted R-square: -3.053
b = -1 (fixed at bound)	RMSE: 286.7

Warning: A negative R-square is possible if the model does not contain a constant term and the fit is poor (worse than just fitting the mean). Try changing the model or using a different StartPoint.



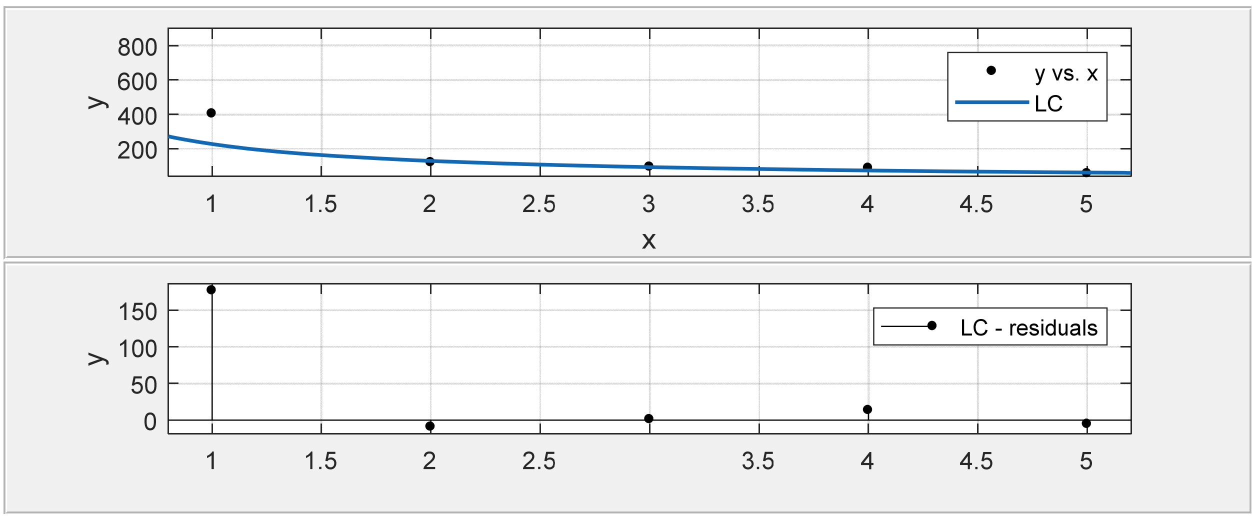
<u>Circumstance 2</u>

y=[282.96 257.63 269.61 251.30 242.18] General model: f(x) = 282.9600 *x^(b) Coefficients (with 95% confidence bounds): b = -1 (fixed at bound)	Goodness of fit: SSE: 4155 R-square: 0.9488 Adjusted R-square: 0.959 RMSE: 28.83



<u>Circumstance 3</u>

y=[226.87 215.72 239.67 238.23 234.15]	Goodness of fit:
General model:	SSE: 5739
f(x) = 226.8700 *x^(b)	R-square: 0.9293
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.9293
b = -0.8126 (-1.348, -0.2772)	RMSE: 37.88

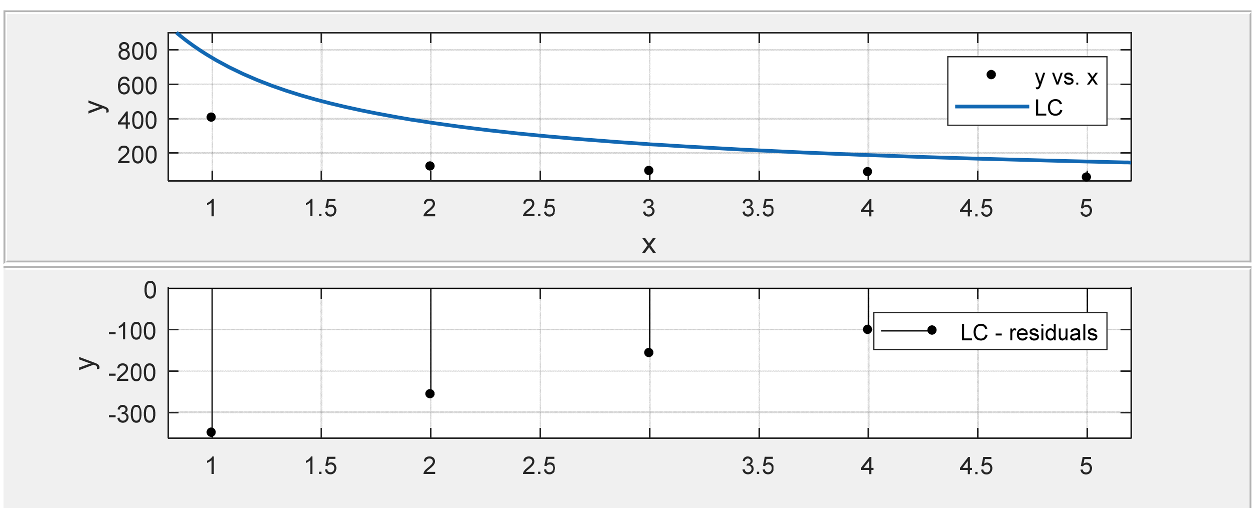


	System	Order	Delay (m)
	Tablet	O2	10

Circumstance 1

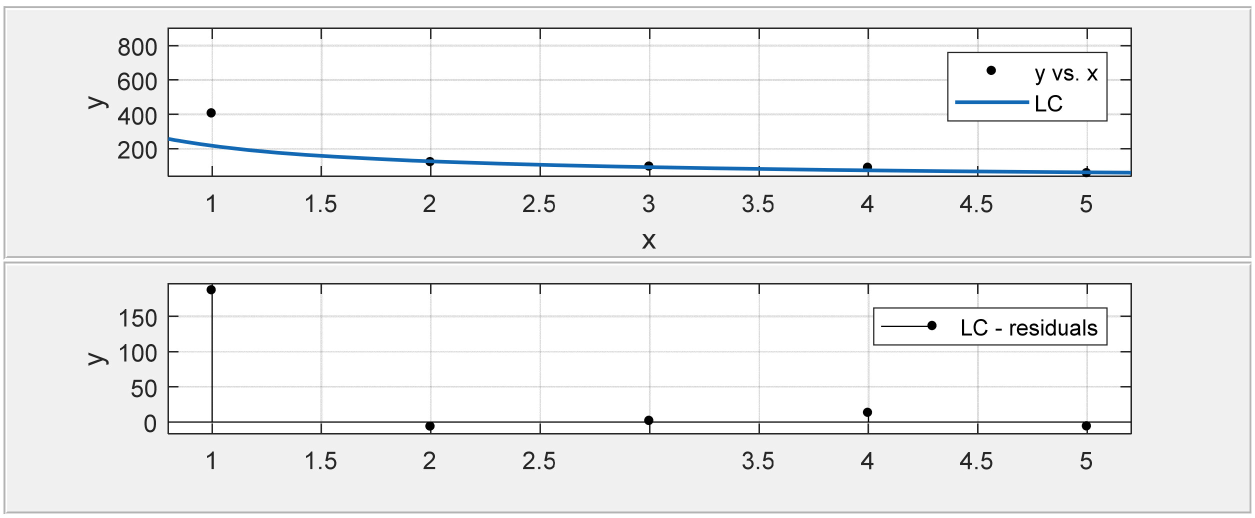
y=[753.45 494.83 460.09 442.22 384.08]	Goodness of fit:
General model:	SSE: 3.052e+05
f(x) = 753.4500 *x^(b)	R-square: -2.762
Coefficients (with 95% confidence bounds):	Adjusted R-square: -2.009
b = -1 (fixed at bound)	RMSE: 247.1

Warning: A negative R-square is possible if the model does not contain a constant term and the fit is poor (worse than just fitting the mean). Try changing the model or using a different StartPoint.



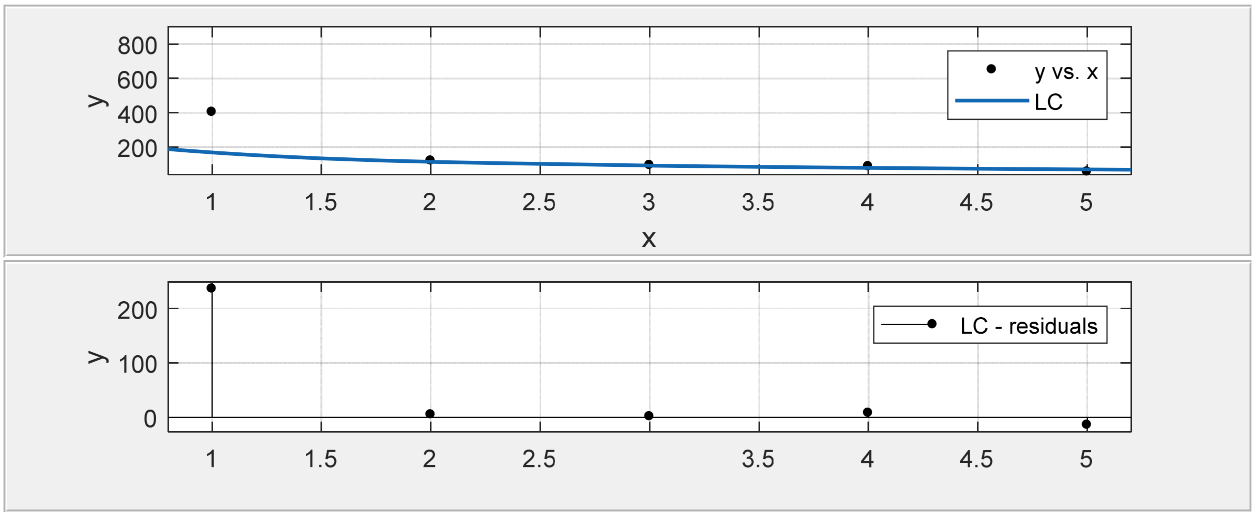
Circumstance 2

y=[216.78 214.48 211.42 201.78 194.38] General model: f(x) = 216.7800 *x^(b) Coefficients (with 95% confidence bounds): b = -0.7731 (-1.333, -0.2131)	Goodness of fit: SSE: 6314 R-square: 0.9222 Adjusted R-square: 0.9222 RMSE: 39.73



Circumstance 3

y=[167.45 169.82 169.03 163.45 161.14]	Goodness of fit:
General model:	SSE: 9818
f(x) = 167.4500 *x^(b)	R-square: 0.879
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.879
b = -0.5426 (-1.22, 0.1346)	RMSE: 49.54

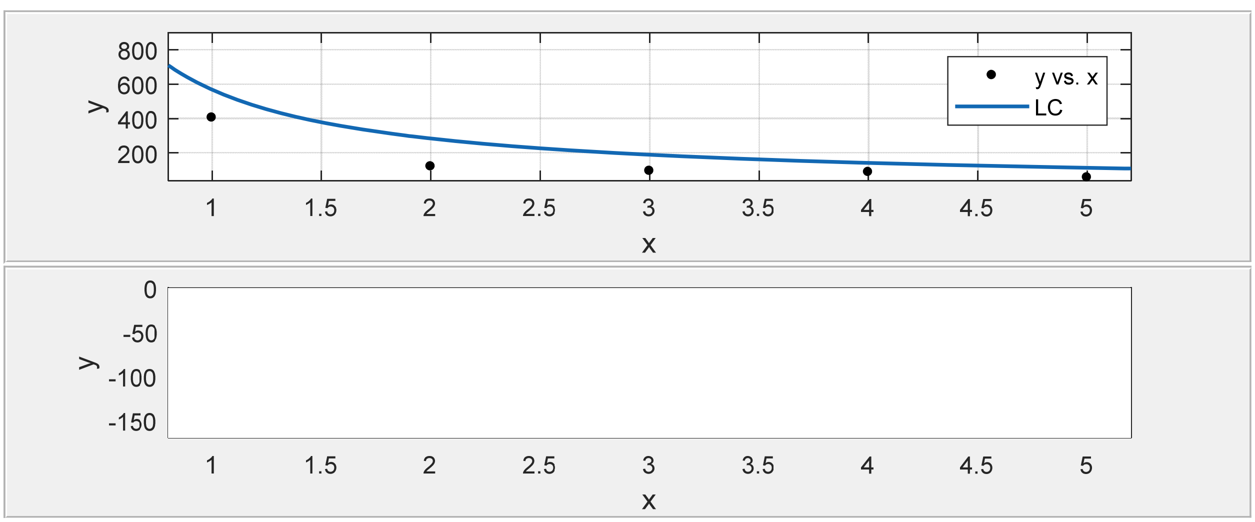


	System	Order	Delay (m)
	Tablet	O3	10

<u>Circumstance 1</u>

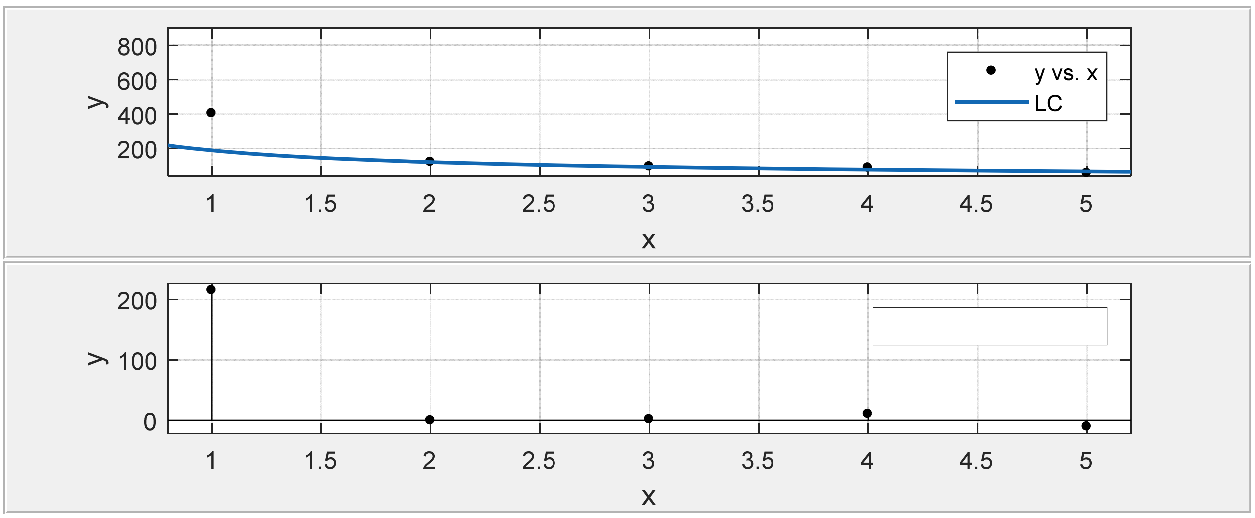
y=[567.49 443.94 362.74 331.48 310.90]	Goodness of fit:
General model:	SSE: 8.835e+04
f(x) = 567.4900 *x^(b)	R-square: -0.08888
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.1289
b = -1 (fixed at bound)	RMSE: 132.9

Warning: A negative R-square is possible if the model does not contain a constant term and the fit is poor (worse than just fitting the mean). Try changing the model or using a different StartPoint.



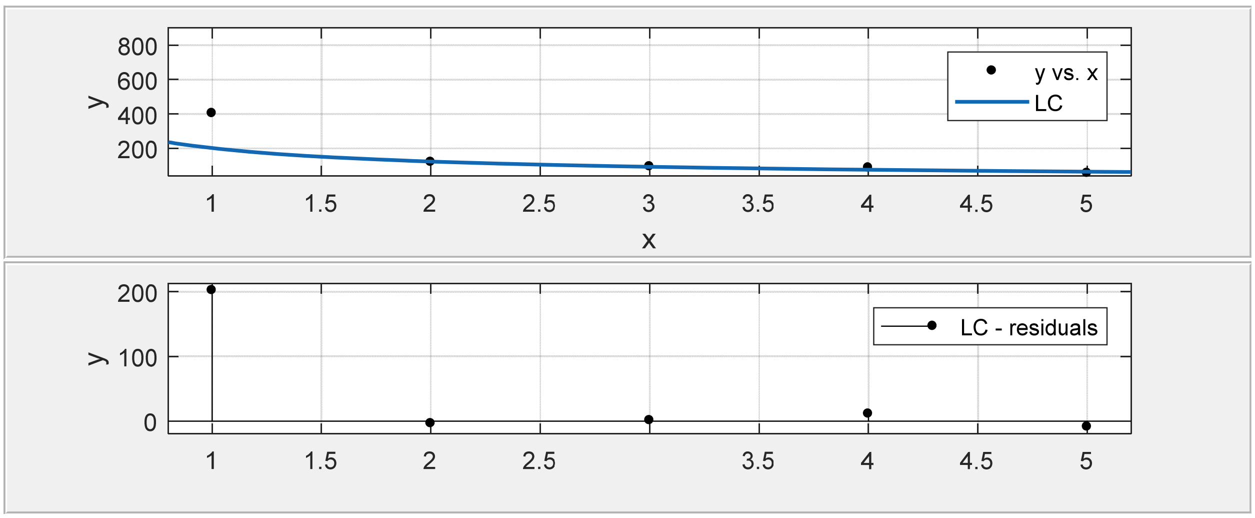
Circumstance 2

y=[188.68 186.94 199.98 191.95 185.82]	Goodness of fit:
General model:	SSE: 8062
f(x) = 188.6800 *x^(b)	R-square: 0.9006
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.9006
b = -0.6474 (-1.269, -0.02553)	RMSE: 44.89



Circumstance 3

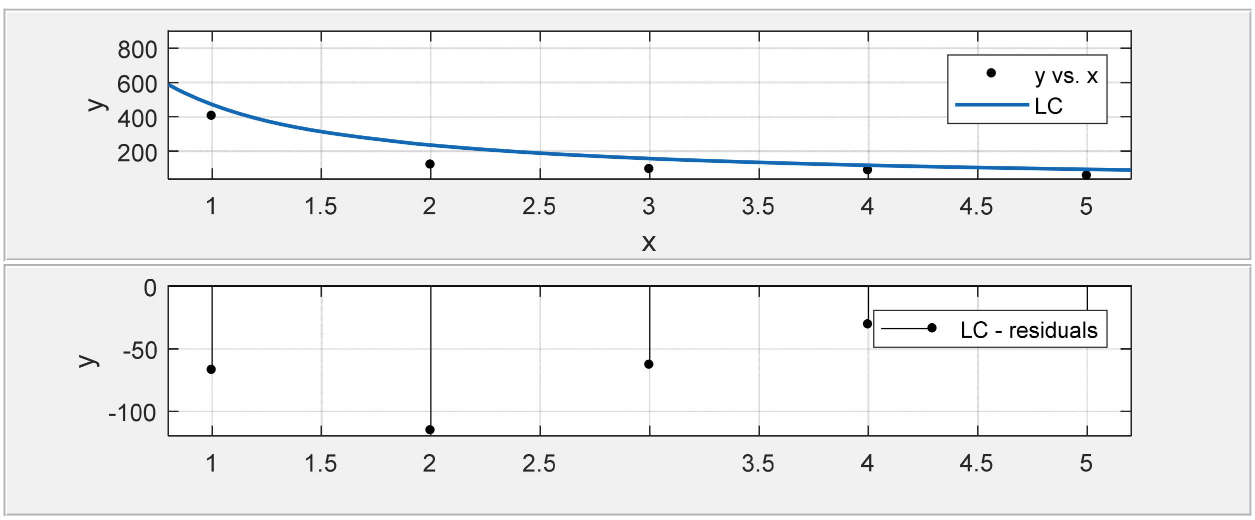
y=[201.56 181.56 186.08 185.02 184.28]	Goodness of fit:
General model:	SSE: 7179
f(x) = 201.5600 *x^(b)	R-square: 0.9115
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.9115
b = -0.706 (-1.297, -0.1149)	RMSE: 42.37



Subject	System	Order	Delay (m)
18	Tablet	O2	1

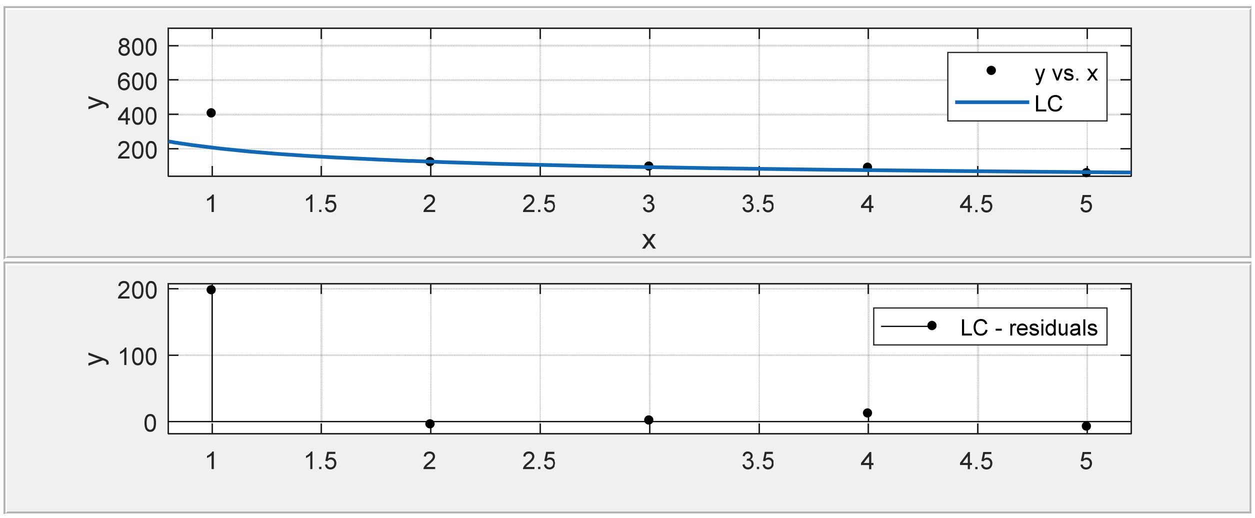
Circumstance 1

y=[470.66 409.36 357.51 335.73 311.55]	Goodness of fit:
General model:	SSE: 3.012e+04
f(x) = 470.6600 *x^(b)	R-square: 0.6288
Coefficients (with 95% confidence bounds):	Adjusted R-square: 0.7031
b = -1 (fixed at bound)	RMSE: 77.61



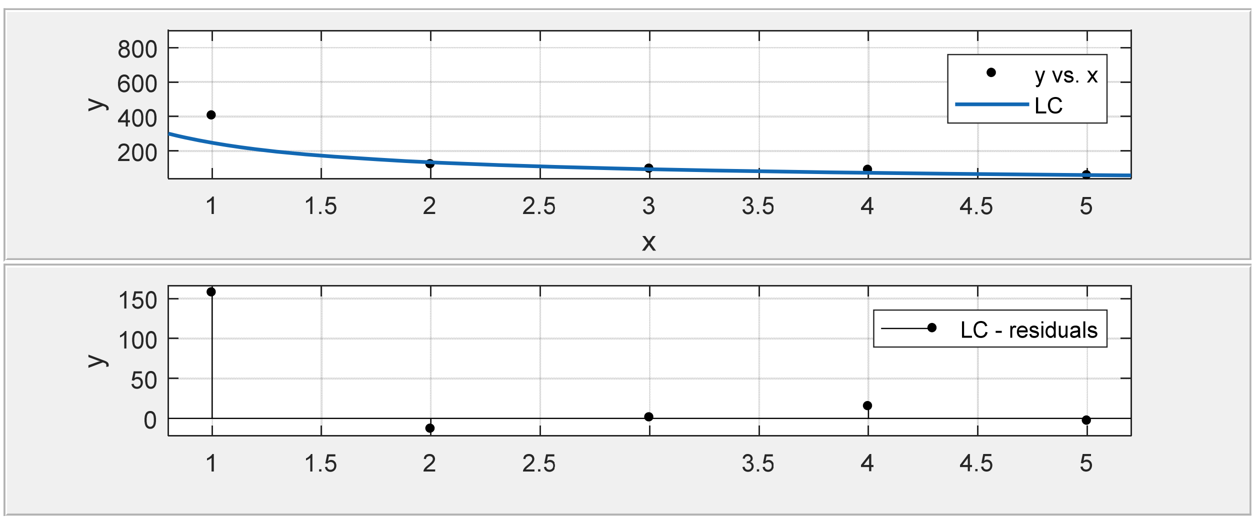
<u>Circumstance 2</u>

y=[206.40 235.89 238.60 220.55 223.04] General model: f(x) = 206.4000 *x^(b) Coefficients (with 95% confidence bounds): b = -0.7275 (-1.308, -0.1471)	Goodness of fit: SSE: 6881 R-square: 0.9152 Adjusted R-square: 0.9152 RMSE: 41.48



<u>Circumstance 3</u>

y=[246.28 235.14 244.40 235.46 229.39] General model: f(x) = 246.2800 *x^(b) Coefficients (with 95% confidence bounds): b = -0.8866 (-1.382, -0.3916)	Goodness of fit: SSE: 4830 R-square: 0.9405 Adjusted R-square: 0.9405 RMSE: 34.75



APPENDIX U. GENERAL LINEAR MODEL OF GAMMA-BAR AND BETA-BAR VERSUS SYSTEM, ORDER, DELAY

General Linear Model: Gamma-bar versus System, Order, Delay

Method

Factor coding (-1, 0, +1)

Factor Information

Factor	Type	Levels	Values
System	Fixed	2	System I, System II
Order	Fixed	3	O2, O3, O5
Delay	Fixed	3	1, 5, 10

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
System	1	0.07465	0.074654	1.25	0.325
Order	2	0.08099	0.040495	0.68	0.557
Delay	2	0.20466	0.102330	1.72	0.289
System*Order	2	0.23023	0.115117	1.94	0.258
System*Delay	2	0.00480	0.002398	0.04	0.961
Order*Delay	4	0.25892	0.064729	1.09	0.468
Error	4	0.23795	0.059486		
Total	17	1.09220			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.243898	78.21%	7.41%	0.00%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	1.3986	0.0575	24.33	0.000	
System					
System I	-0.0644	0.0575	-1.12	0.325	1.00
Order					
O2	0.0908	0.0813	1.12	0.327	1.33
O3	-0.0216	0.0813	-0.27	0.803	1.33
Delay					
1	-0.0061	0.0813	-0.07	0.944	1.33
5	-0.1274	0.0813	-1.57	0.192	1.33
System*Order					
System I O2	-0.0631	0.0813	-0.78	0.481	1.33
System I O3	-0.0957	0.0813	-1.18	0.304	1.33
System*Delay					
System I 1	-0.0074	0.0813	-0.09	0.932	1.33
System I 5	-0.0153	0.0813	-0.19	0.860	1.33
Order*Delay					
O2 1	-0.110	0.115	-0.95	0.395	1.78
O2 5	0.114	0.115	0.99	0.377	1.78
O3 1	-0.099	0.115	-0.86	0.440	1.78

```
  O3 5          -0.053    0.115    -0.46    0.666  1.78
```

```
Regression Equation

Gamma-bar = 1.3986 - 0.0644 System_System I + 0.0644 System_System II
+ 0.0908 Order_O2
            - 0.0216 Order_O3 - 0.0692 Order_O5 - 0.0061 Delay_1 - 0.1274 Delay_5
            + 0.1335 Delay_10 - 0.0631 System*Order_System I O2
- 0.0957 System*Order_System
            I O3 + 0.1588 System*Order_System I O5 + 0.0631 System*Order_System II O2
            + 0.0957 System*Order_System II O3 - 0.1588 System*Order_System II O5
            - 0.0074 System*Delay_System I 1 - 0.0153 System*Delay_System I 5
            + 0.0226 System*Delay_System I 10 + 0.0074 System*Delay_System II 1
            + 0.0153 System*Delay_System II 5 - 0.0226 System*Delay_System II 10
            - 0.110 Order*Delay_O2 1 + 0.114 Order*Delay_O2 5 - 0.005 Order*Delay_O2
10
            - 0.099 Order*Delay_O3 1 - 0.053 Order*Delay_O3 5 + 0.152 Order*Delay_O3
10
            + 0.208 Order*Delay_O5 1 - 0.061 Order*Delay_O5 5 - 0.147 Order*Delay_O5
10
```

General Linear Model: Beta-bar versus System, Order, Delay

Method

Factor coding (-1, 0, +1)

Factor Information

Factor	Type	Levels	Values
System	Fixed	2	System I, System II
Order	Fixed	3	O2, O3, O5
Delay	Fixed	3	1, 5, 10

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
System	1	0.006000	0.006000	0.29	0.620
Order	2	0.119681	0.059841	2.86	0.169
Delay	2	0.061058	0.030529	1.46	0.334
System*Order	2	0.000289	0.000144	0.01	0.993
System*Delay	2	0.017029	0.008514	0.41	0.690
Order*Delay	4	0.113899	0.028475	1.36	0.386
Error	4	0.083552	0.020888		
Total	17	0.401507			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.144527	79.19%	11.56%	0.00%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	-0.8105	0.0341	-23.79	0.000	
System					
System I	-0.0183	0.0341	-0.54	0.620	1.00

Order					
O2	0.1095	0.0482	2.27	0.085	1.33
O3	-0.0861	0.0482	-1.79	0.149	1.33
Delay					
1	-0.0821	0.0482	-1.70	0.163	1.33
5	0.0465	0.0482	0.96	0.389	1.33
System*Order					
System I O2	-0.0028	0.0482	-0.06	0.957	1.33
System I O3	-0.0029	0.0482	-0.06	0.955	1.33
System*Delay					
System I 1	-0.0410	0.0482	-0.85	0.443	1.33
System I 5	0.0078	0.0482	0.16	0.879	1.33
Order*Delay					
O2 1	-0.0804	0.0681	-1.18	0.303	1.78
O2 5	0.1390	0.0681	2.04	0.111	1.78
O3 1	0.0266	0.0681	0.39	0.716	1.78
O3 5	-0.1187	0.0681	-1.74	0.156	1.78

Regression Equation

```
Beta-bar = -0.8105 - 0.0183 System_System I + 0.0183 System_System II
+ 0.1095 Order_O2
           - 0.0861 Order_O3 - 0.0234 Order_O5 - 0.0821 Delay_1 + 0.0465 Delay_5
           + 0.0356 Delay_10 - 0.0028 System*Order_System I O2
- 0.0029 System*Order_System I
           O3 + 0.0057 System*Order_System I O5 + 0.0028 System*Order_System II O2
           + 0.0029 System*Order_System II O3 - 0.0057 System*Order_System II O5
           - 0.0410 System*Delay_System I 1 + 0.0078 System*Delay_System I 5
           + 0.0331 System*Delay_System I 10 + 0.0410 System*Delay_System II 1
           - 0.0078 System*Delay_System II 5 - 0.0331 System*Delay_System II 10
           - 0.0804 Order*Delay_O2 1 + 0.1390 Order*Delay_O2 5 - 0.0587 Order*Delay_O2
10
           + 0.0266 Order*Delay_O3 1 - 0.1187 Order*Delay_O3 5 + 0.0921 Order*Delay_O3
10
           + 0.0538 Order*Delay_O5 1 - 0.0203 Order*Delay_O5 5 - 0.0335 Order*Delay_O5
10
```