GENERATING NON-NORMAL DISTRIBUTIONS FOR INTERVAL SCHEDULES: EFFECTS ON INSTRUMENTAL BEHAVIOR

by

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B.A., in Psychology, Boğazici University, 2019

Submitted to the Institute of Biomedical Engineering
in partial fulfillment of the requirements
for the degree of
Master of Science
in
Biomedical Engineering

Boğaziçi University
2022

ACKNOWLEDGMENTS

First, I would like to thank my wife Eda Biricik and our beloved friend Kamran for their emotional and motivational support through this study.

This study was part of a bigger project that took lots of planning and data collection. I would like to thank my coworker for years Betül Tamer and all members of the Behavioral Biology Laboratory for their works. This study would not be practical without their studies.

I would like to thank my supervisor Dr. Daniela Schulz for her guidance through the project. She developed an inspiring novel method of DBS which pave the way for this thesis. I would also like to thank Dr. Burak Güçlü for his help and guidance on the hardware for stimulation and instrumental conditioning.

I would like to thank Ulaş Can Çakan for proofreading the thesis and his help on writing.

I would also like to thank Turkish Educational Society (TED) for funding and supporting my education and academic work and thank Turkish Scientific and Technological Research Association (TÜBİTAK) for funding my masters studies.

This project was funded by Boğaziçi University Scientific Research Projects (BAP) under Grant Number 15981 to Daniela Schulz

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ABSTRACT

GENERATING NON-NORMAL DISTRIBUTIONS FOR INTERVAL SCHEDULES: EFFECTS ON INSTRUMENTAL BEHAVIOR

VI schedules are used in instrumental conditioning to obtain a relatively constant response rate. In VI schedules, a reward is delivered following an operant response, that is emitted after a variable time interval has passed. A peculiarity of VI schedules is that responding increases as time spent in an interval increases, producing output which is less uniform. To reduce this effect, positively skewed distributions have been implemented. However, non-normal distributions cannot be generated with current number generators. Here, we have established a procedure in Microsoft Excel that generates non-normal distributions. We further ran instrumental conditioning protocols utilizing the distributions we generated to see the effects on instrumental behavior. We hypothesized that our distributions will lead to a time independent behavior after discrimination training, in which animals learned to discriminate between existence of the stimulus and a no-stimulus context. First, we analyzed discrimination training by comparing lever press rates and lever press latencies across days of training and time within session. Then, to see how our distributions affected the time-dependency, we analyzed the relationship between time after stimulus onset and lever press rates during discrimination training performing correlation analyses. We found that the animals pressed the lever less in the 21^{st} day of discrimination training in EXT state compared to the 1^{st} day. We also found that, although there was a significant moderate correlation between time after stimulus and the lever press rate in the 1^{st} day of discrimination training, the correlation was not significant for the 21^{st} day. However, a curvilinear function explained over 70% of the variance in the data. Here we showed an easy-to-use method to generate non-normal distributions with Microsoft Excel. Our findings suggest that distributions generated by the given formula led to learning in rats in 21 days, but the lever press responses were not time independent contrary to our expectations.

Keywords: Instrumental Conditioning, Variable Interval Schedules, Discrimination Training, Non-normal Distributions.

ÖZET

ARALIKLI PROGRAMLAR İÇİN NORMAL OLMAYAN DAĞILIMLAR OLUŞTURMA: EDİMSEL DAVRANIŞA ETKİLERİ

Aralıklı programlar, edimsel koşullamada görece düzenli bir tepki oranına ulaşmak için kullanılır. Aralıklı programlarda, değişken bir zaman aralığı geçtikten sonra verilen bir edimsel yanıtın ardından bir ödül verilir. Aralıklı programların ilginç bir özelliği, bir aralıkta harcanan zaman arttıkça tepki oranının artmasına ve daha az tekdüze bir tepki oranına yol açmasıdır. Bu etkiyi azaltmak için pozitif eğimli dağılımlar uygulanmıştır. Ancak güncel rastgele dağılım modelleri normal olmayan dağılımlar üretmekte yetersizdir. Bu çalışmada normal olmayan dağılımlar üretmek için Microsoft Excel'de bir prosedür geliştirdik. Sonrasında, ürettiğimiz normal olmayan dağılımların edimsel davranış üzerindeki etkisini incelemek için bu dağılımları kullanarak edimsel koşullama deneyleri yürüttük. Hipotezimiz, ürettiğimiz dağılımların sıçanlarda edimsel koşullamada zamandan bağımsız ve düzenli bir tepki oranına yol açacağıydı. Öncelikle, manivela tepki oranlarını ve tepki sürelerini tekrarlı ölçümler ANOVA testi ile analiz ettik. Daha sonra, ayırdetme öğreniminden önceki ve sonraki zaman ve tepki oranı ilişkilerini Pearson korelasyon testi ile analiz ettik. Ayırdetme öğreniminin 21. gününde 1. gününe kıyasla hayvanların EXT evresindeki manivela tepki oranlarının daha az olduğunu bulduk. Ayrıca, ayırdetme öğreniminin ilk gününde manivela tepki oranlarıyla zaman arasında kayda değer bir korelasyon bulduk, ancak bu fark ayırdetme öğreniminin 21. gününde kayda değer değildi. Bu çalışmada, normal olmayan dağılımlar üretmek için Microsoft Excel'de kullanımı kolay bir prosedür geliştirdik ve bu dağılımların edimsel davranışa etkilerini gösterdik. Bulgularımız, geliştirdiğimiz prosedür ile üretilen dağılımların 21 günde sıçanlarda öğrenmeye ve zamandan bağımsız edimsel davranışa yol açtığını gösteriyor.

Anahtar Sözcükler: Edimsel Koşullama, Aralıklı Zaman Programları, Ayırdetme Öğrenimi, Normal Olmayan Dağılımlar.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS

p	Probability Statistic
t	Time
N	Sample Size
S*	Reward
R	Response
S1	Stimulus
X	Mean
S_1	Sample size
F	F Statistic
χ^2	Chi-Square Statistic
η^2	Effect Size Statistic for ANOVA
r	Correlation Coefficient
R^2	Coefficient of Determination

LIST OF ABBREVIATIONS

FR	Fixed Ratio
FI	Fixed Interval
VR	Variable Ratio
VI	Variable Interval
EXT	Extinction
LP	Lever Press
ECB	Environmental Connection Board
VT	Variable Time
ITI	Inter Trial Interval
SPSS	Statistical Package for the Social Sciences
rft	Reinforcement
ANOVA	Analysis of Variance
GS4	Graphic State 4
Lft	Leftover
SD	Standard Deviation

1. INTRODUCTION

1.1 Law of Effect

In his work ”Descent of Man and Selection in Relation to Sex”, Charles Darwin argued about the evolution of not only the physical or mechanical traits of animals but also the evolution of psychological and mental capabilities [5]. He argued that as the mind goes through an evolutionary process, non-human animals also have mental capabilities such as curiosity, cognition, and reason [6].

In the light of Charles Darwin’s work, Edward Thorndike tried to assess the mental capabilities of non-human animals and quantify mental capability through empirical studies [7]. He argued that we could explain the behavior of the animals by studying associative processes in controlled experimental studies. In order to study the associative processes, he designed different kinds of escape boxes [1]. He put hungry cats into the boxes and left a portion of food outside the box to further motivate the animal to get out of the box. These escape boxes contained, for example, a lever that opens the gate when pressed or a string that could be pulled. He observed the animals and tracked their response behaviors, actions, and escape times. He repeated these experiments over and over again and observed the changes in animals’ responses.

Thorndike observed that when he put young cats in the puzzle boxes, at first, animals acted naturally. He described their behavior as:

> When put into the box the cat would show evident signs of discomfort and of an impulse to escape from confinement. It tries to squeeze through any opening; it claws and bites at the bars or wire; it thrusts its paws out through any opening and claws at everything it reaches; it continues its efforts when it strikes anything loose and shaky; it may claw at things within the box. It does not pay very much attention to the food outside, but seems simply to strive instinctively to escape from confinement. The vigor with which it struggles is extraordinary. For eight or ten minutes it will claw and bite and squeeze incessantly (p. 13) [1].

He observed that initially, animals responded randomly without an order. However, with repeated exposure to the puzzles, the animals started to act more orderly and efficiently. For example, cats put in Box A started to be more interested in the string that opens the cage door, and over repeated exposure, they began to act on the string immediately. The performance of some cats in Box A can be seen in Figure 1.1. As seen in Figure 1.1, animals started to get out of the box more efficiently over time. In other words, they learned how to escape the box.

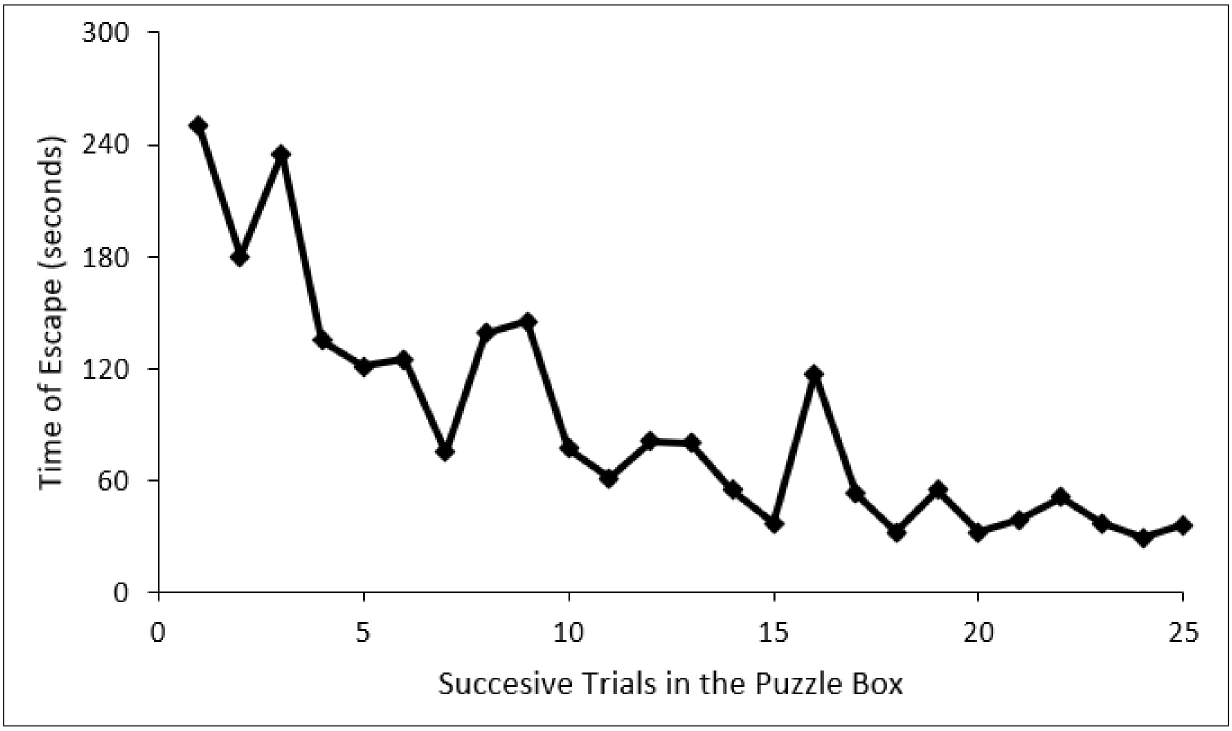

Figure 1.1 Escape performances of the animals in successive trials in Thorndike's Escape Box, adapted from [1]

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Thorndike argued that his studies were different from his time as he focused on the general psychology of animals rather than a simple eulogy [1, 8]. He asserted that his studies investigated not only the intelligence of the animals but also the "stupidity". He accepted that in later trials, an observer might get impressed by the intelligence of the animals. However, an observer present in the former trials would also see the "stupidity" of the animals. He did not explain his results by attributing a mean reason to the animals. On the contrary, he said that the animals learned to get out of the box faster in time not because they saw the working mechanism of the box and associated the string with an escape but because they experienced that pulling the string led to the escape from the box and achievement of the food. He explained the learning in terms of a simple trial and error process. He invented the term ”Law of Effect” based on his experiments with cats [7, 9]. Law of effect implies that responses that lead to satisfying results have a higher chance of occurrence, and responses that lead to undesirable outcomes have a lower chance of occurrence.

1.2 Instrumental Conditioning

B.F. Skinner criticized the behaviorists of the era for taking the easy way out by explaining the learning process with reference to non-observable mental states [10]. He argued that in order to study learning, one must strictly focus on the observable behaviors and results of these behaviors. He defined behavior as a continuous paradigm in which one behavior causes another continuously and thought that one needs to segment behavior to study it. Thus, he coined the term ”Operant Behavior” as an activity that has a measurable effect on the environment and treated it as the smallest measurable unit of behavior [2, 11].

Skinner also criticized the Law of Effect and argued that it lacked continuity and does not represent natural behaviors [10, 11]. In Thorndike’s puzzle boxes, animals must solve the paradigm by escaping the box to reach the reward. After an individual trial is complete, the animal needs to be put in the box again for a second trial. Similarly, he criticized the runway boxes and T mazes, which aim to measure learning. Runway boxes measure the latency of escape while T mazes measure choice behavior, but both lack continuity.

To overcome these problems, Skinner designed an experimental apparatus he termed the ”Operant Chamber” [2]. The Operant chamber contains a response unit such as a lever or a pecking disk and a reward unit that gives a food pellet or a drop of water. An illustration of the operant chamber can be seen in Figure 1.2. The most significant advantage of the operant chamber is that it provides continuous observation of the behavior. The animal can respond via the lever and get rewarded throughout the experimental trial. Unlike Thorndike's puzzle boxes, you do not need to restart the trial after every successful response.

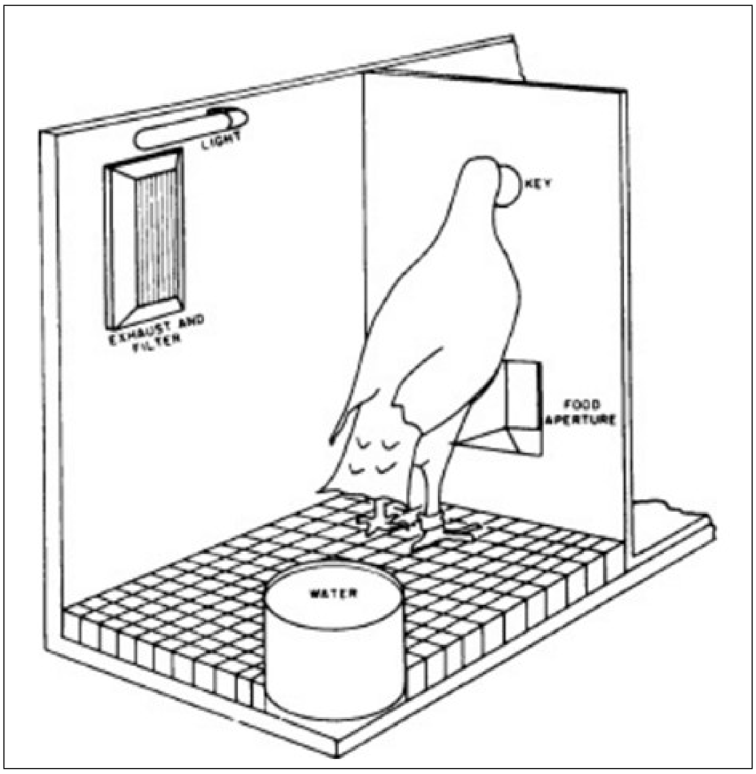


Figure 1.2 An Illustration of a Pidgeon performing in a Skinner Box [2]

Skinner also designed an apparatus called" Cumulative Recorder" to track the animals' behavior while inside the chamber [2]. The cumulative recorder is connected to the response unit inside the chamber and every time the animal responds the pen in the cumulative recorder moves one unit. An illustration of the cumulative recorder can be seen in Figure 1.3. The cumulative recorder is regularly spinning. Thus, it tracks the time and frequency of the responses throughout the experimental trial. The slope of the graphs created by the cumulative recorder reflects the response rate of the animals. If the slope is steeper, the animal's response rate is greater in that time period.

To study the operant behaviors and learning, B.F. Skinner created the instrumental conditioning procedures with Charles Ferster [2, 11]. In instrumental condi-

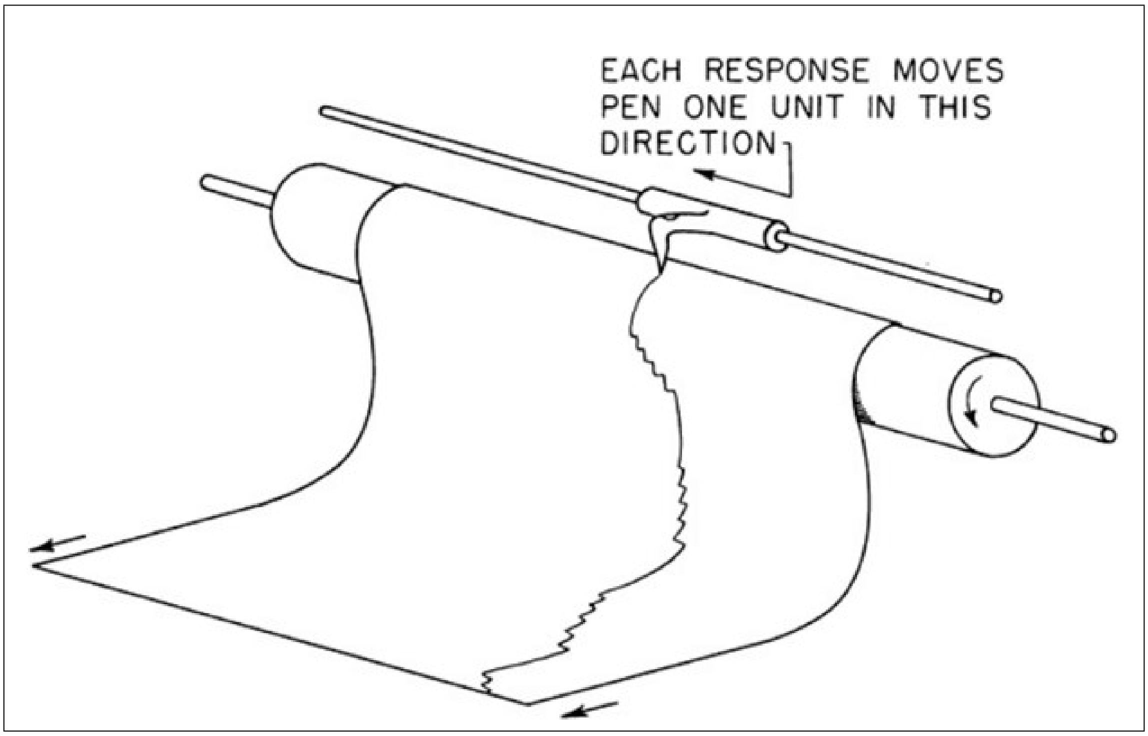


Figure 1.3 An Illustration of the Cumulative Recorder [2]

tioning procedures, an initially neutral stimulus is presented to the animals, and in the presence of that stimulus, the animals' responses would get either rewarded or punished [12, 13]. They categorized instrumental conditioning procedures according to their effects on the animal's behavior (reinforcement or punishment) and whether the response leads to a presentation or an omission of a biologically meaningful stimulus (positive or negative). If the initially neutral stimulus increases the animal's response, it is a reinforcement, and if it leads to a decrease, it is a punishment training. Also, if the response leads to a presentation of a stimulus, it is positive, and if the response leads to an omission of a stimulus, it is negative. Because of the ease of application and measurement, positive reinforcement trainings are the most used style of training [13]. To study learning with operant procedures, they created the ratio and interval schedules of instrumental conditioning.

1.3 Ratio Schedules

Schedules of reinforcement organize the relationship between the stimulus and reinforcement in instrumental conditioning [2]. In ratio schedules, reinforcement is delivered after a certain number of responses occur. In fixed ratio schedules, the number of responses necessary for reinforcement is constant, while in variable ratio schedules, it is selected from a predetermined set of possible numbers after each reinforcement. Generally, fixed ratio schedules are utilized for the initial learning process as the demands for these schedules are relatively low and animals learn these schedules relatively quickly [14, 15].

1.4 Interval Schedules

In interval schedules, the reward is contingent on the first response emitted after a certain time interval has passed since the last reinforcement [2]. In fixed interval schedules, the interval is constant throughout the experiment, while in variable interval schedules, the interval is selected from a predetermined set of possible time intervals after each reinforcement [14, 15]. Random interval schedules are a particular case of interval schedules. In random interval schedules, the probability of a reinforcement being arranged is constant. For example, in a random interval 10 schedule, there is a 0.1 chance of reinforcement being arranged at each second after the stimulus. However, random interval schedules are problematic as they do not give a finite range of possible intervals which may lead to extremely long intervals [3, 16]. In FI schedules, animals generally pause initially after the stimulus, as they are conditioned to wait for a fixed interval before reinforcement, but VI schedules generally lead to a constant response rate after the stimulus [3, 17].

However, the set of possible time intervals used for VI schedules drastically change the effects of VI schedules on the animal's behavior [2, 17]. For example, if an uniform distribution was used for VI schedules, animals would press the lever more frequently in longer time intervals as the probability of reinforcement increases with time. On the contrary, if an exponential distribution was used, animals would respond more steadily with no temporal contingencies, because of the skewed distribution and extremely long intervals. The main purpose of the VI schedules is to lead to a reliable steady response of the animals which is resistant to extinction [2]. In order to lead to a steady response rate, the distributions that are used for VI schedules need to be independent from time [3, 18]. In other words, the probability of reinforcement needs to be constant while the time after stimulus increases. There is a debate on what kind of distributions should be used for VI schedules to ensure that the VI schedules would lead to a time independent steady response rate [17, 18, 19].

1.5 Distributions That are Used for Interval Schedules

One of the first types of distributions Skinner used for VI schedules is the uniform distribution [2]. Uniform distributions are characterized by the minimum and maximum values of the distribution and every integer between those values have the same probability of being in the distribution. For example, if we consider an uniform distribution with a range from 0 to 20, the mean of this distribution would be 10.

Skinner discussed the effects of the range and the distribution profiles of the time intervals on the animal's behavior. Two different distributions of time intervals with the same mean and range can lead to different behavioral results. For example, if two distributions of time intervals have the same mean of 60 and the range from 0 to 120, but one distribution of time intervals increases by increments of 1 and the other by increments of 30, the first one would lead to a more steady and scattered response. Two distributions with the same mean and range can differ in their shape too. For example, the same distributions of time intervals discussed above can differ as one would be a uniform distribution while the other would be a normal distribution. In this example, both distributions of time intervals would have the same mean of 60 and range from 0 to 120, but the shape of the distributions would be different; thus, the behavior would be different.

Uniform distributions are easy to generate and apply to VI schedules, but as the probability of reinforcement increases with passing time, uniform distributions are time dependent and will lead to increased response rates with passing time. For a VI schedule that is created by using a uniform distribution of time intervals with a mean of T, where t stands for the time since the stimulus onset, the probability function would be

$$p(t) = \frac{1}{(2T - t)} \tag{1.1}$$

Thus, as the time since the stimulus onset increases, animals' probability of reinforcement also increases. As the probability of being reinforced increases, animals press the lever more with increases in the duration of the time interval used in the VI schedule, which leads to a time dependent behavior. Figure 1.4 compares the probability functions of a VI schedule with a uniform distribution and a random interval 10s schedule [2].

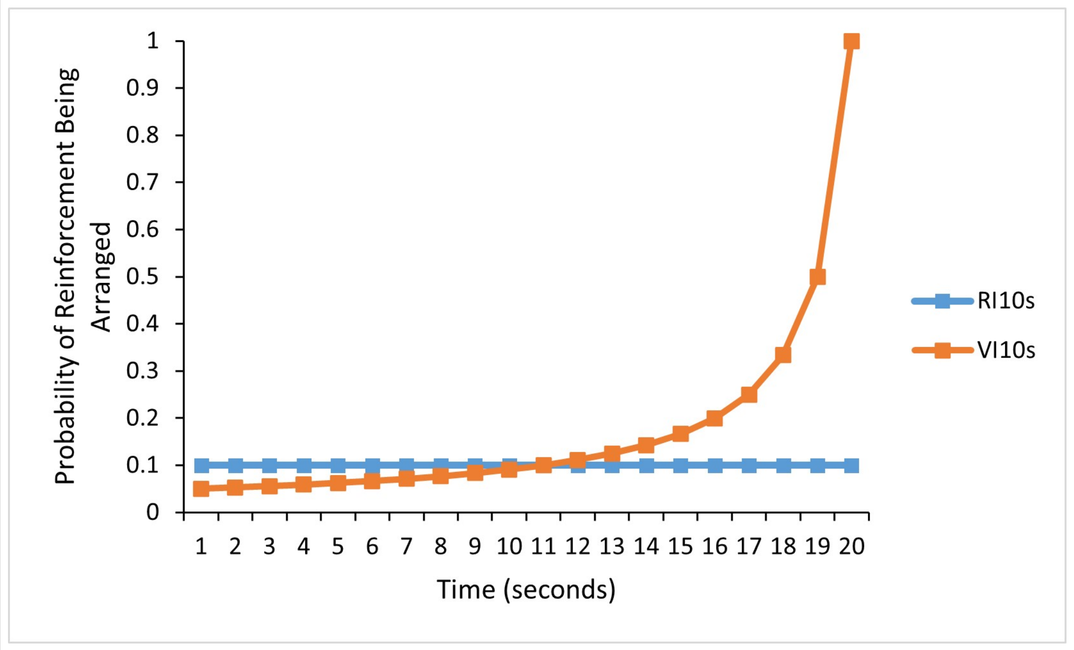


Figure 1.4 Probability of reinforcement curves of a VI 10 schedule with a uniform distribution of time intervals and a random interval 10 schedule, adapted from [3].

In order to deal with the time dependency problem of the uniform distributions of time intervals, exponential distributions of time intervals can be used to generate the VI schedules [17]. Unlike the uniform distributions of time intervals, the probability function of the exponential distributions of time intervals is not dependent on the time passed since the stimulus onset. The probability function of a VI schedule created by using an exponential distribution of time intervals with mean T would be as

$$p(t) = \frac{1}{T} \tag{1.2}$$

Thus, when the time since the stimulus onset increases, the probability of reinforcement remains constant as it is not dependent on time. However, even though exponential distributions of time intervals eliminate the time dependency problem, they lead to another problem. Exponential distributions of time intervals do not have a finite range, thus they may lead to some extremely long time intervals in VI schedules. If the time interval is extremely long, it may lead to an extinction in the animals and would not be practical to use in VI schedules[3, 20].

Fleshler and Hoffman created an algorithm to develop a new distribution of time intervals to solve the time dependency and extremely long range problems [18]. They created a set of equations to generate a distribution of time intervals that resembles the exponential distribution but at the same time has a finite range. However, as Bugallo discusses, even though the Fleshler and Hoffman algorithm solves the problems mentioned above, it creates new ones [17]. As the algorithm relies on a predetermined sample size N, the probability function is not constant, and if the sample size is not large enough, it may lead to a time dependency. As a response to the Fleshler and Hoffman algorithm, Bugallo came up with a novel proposition to solve the time dependency and infinite range problems [17]. They created a method that contradicts a fundamental characteristic of the classic instrumental conditioning procedures. In their new proposed method, not every interval results in reinforcement, similar to the peak procedure [21, 22] and discrimination training procedure [15, 23]. Briefly, they used an uniform distribution of time intervals for the VI schedules but they also made the procedure in a way that not every time interval resulted in reinforcement. For example, normally if the time interval is 85 seconds, after 85 seconds if the animal presses the lever it would get reinforced, but in Bugallo's procedure there is a chance that the animal might not get reinforced. Thus, it solves the time dependence problem as the probability of reinforcement does not increase with time. However, the method is problematic as every stimulus does not lead to a reinforcement even if the animal responds successfully, leading to extinction.

Lombas implemented the non-normal distributions of time intervals to minimize the time dependency problem [23]. For VI schedules, they used distributions of time intervals that ranged from 0 to 120 with a mean of 30. With these parameters, they created a distribution that resembles the exponential distribution of time intervals but does not have extremely long intervals. Using positively skewed non-normal distributions of time intervals does not eliminate the time dependency problem but minimizes it, and by doing so, it does not lead to other problems like extremely long intervals.

1.6 Present Study

Despite their importance, non-normal distributions cannot be generated with current number generators. There are some old generators for this purpose but modern random number generators are lacking [20]. Therefore, here we established an easy-to-use random number generator in Microsoft Excel that generates non-normal distributions. Then after establishing the random number generator, we generated non-normal distributions in line with Lombas et al. (2008) and descriptively analyzed these distributions in terms of mean, median, mode, skewness, and kurtosis and then plotted these distributions as histograms [23].

Further, we conducted instrumental conditioning experiments with VI schedules using the non-normal distributions of time intervals generated by our random number generator. We applied the instrumental conditioning procedures according to a BAP project conducted in our laboratory [4], which implemented the instrumental conditioning procedure of Lombas [23]. In this BAP project, animals were trained on FR, VI, and discrimination training schedules. In the discrimination training, animals learn to discriminate between the presence and the absence of the stimuli, as there will be trials with and without stimuli. In this BAP project, a deep brain stimulation schedule is also implemented. The present study only focuses on the effects of skewed distributions on behavior during discrimination training.

We then analyzed the behavioral outcomes on the 1st and 21st days of the discrimination training to assess if the instrumental conditioning led to learning in the animals. As an indication of learning, we hypothesized that the animals would press the lever more in the VI state on the 21st day of the discrimination training than on the 1st day. Similarly, we hypothesized that animals press the lever more in the EXT state on the 1st day of the discrimination training than on the 21st day

To see if the positively skewed distribution of time intervals generated by our generator lead to a steady response rate and if there is a time dependency in the animals' responses, we also analyzed the relationship between the time after the stimulus onset and the lever press rates in the VI state in the 1st and the 21st days of the experiment. We hypothesized that there will not be a significant correlation between the time after the stimulus onset and the lever press rate in the VI state in the 21st day of the discrimination training.

2. MATERIALS AND METHODS

2.1 Subjects

We used 8 naïve adult male Wistar rats (180-210 gr.) for this study. Animals were housed two per cage in a temperature and humidity-controlled room under a 12/12 day/night cycle (lights on at 8:00 a.m.). Animals were provided with ad libitum access to water except for during the experiments. Animals were food restricted throughout the study. All experiments were approved by Boğaziçi University Institutional Local Ethics Committee for the Use of Animals in Experiments (BÜHADYEK).

After an initial two weeks habituation period we started the food restriction procedure in which the animals were fed 50% of their baseline food intake until 90% of the free-feeding weight was reached. Afterwards animals received 80% of their daily food intake. Daily food intake was adjusted from time to time to ensure that the animals were kept at 90% of their free-feeding weight. We fed the animals in the evening after all the experimental trials finished in the evening. Every day before the daily feeding session, we weighed and handled the animals to acclimate them to the human contact. After each trial we calculated the total food the animals gained as reward and subtracted that from their daily food intake in the evening.

2.2 Instrumental Conditioning

2.2.1 Experimental Apparatus

We used two Habitest Modular System Operant Chambers(Coulbourn Instruments) that were kept in a custom-made sound-attenuating cabinet for the operant conditioning procedures. Both chambers were 36 cm high, 31 cm wide and 26 cm long, and the sound-attenuating cabinets were 60 cm high, 83 cm wide and 50 cm long. The operant chamber had two metal (left-right) and two transparent plastic walls. One of the plastic walls was facing the cabinet wall while the other was used for putting the animal into the chamber and for observation. There was a house light (H11-01R, Coulbourn Instruments) at the upper middle part of the left metal wall that turned on when the training sessions began. There were two retractable levers (H23-17RC, Coulbourn Instruments) with triple cue lights (H11-02R, Coulbourn Instruments) on top of the levers in both chambers one on the left and one on the right side of the magazine feeder. Minimum actuating force of 25 g is required for the retractable levers to close the switch. There was a high-power tone module (H12-02R-4.5, Coulbourn Instruments) at the upper left corner of the right metal wall. There is a jumper on the high-power tone module that allows the selection of high or low amplitudes. We used the module on low amplitude for all the experiments. There was a clicker module (H12-05R, Coulbourn Instruments) at the lower left corner of the left metal wall. There was a pellet feeder (H14-23R, Coulbourn Instruments) that was connected to a pellet delivery trough (H14-01R-LED, Coulbourn Instruments) in the middle part of the right metal wall between the two retractable levers in both chambers . All modules in the chamber were connected to and powered by an environmental connection board (ECB) (H03-04, Coulbourn Instruments). Operant chambers were connected to a computer through the ECB and an Habitest Linc system (H02- 01, Coulbourn Instruments). A representative figure of the operant setup can be seen in Figure 2.1.

The summary of the experimental apparatus in Figure 2.1 also includes a constant current stimulator setup which was not relevant for this study. This study was part of a BAP project that also incorporates electrical stimulation with instrumental conditioning and the data for the present study are taken from the main project [4].

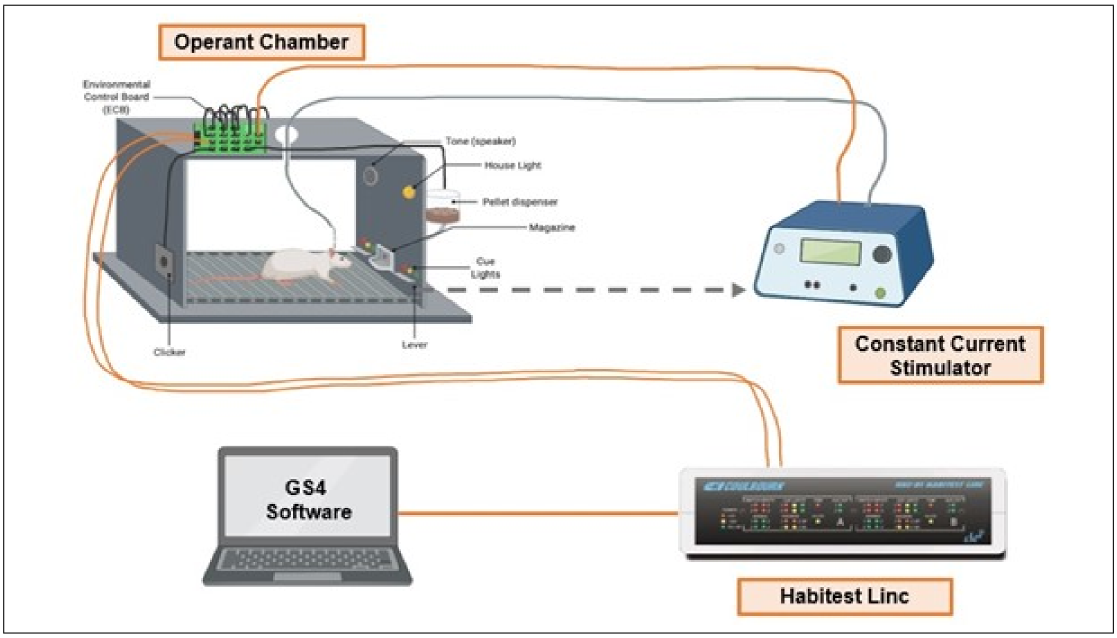


Figure 2.1 Summary of the Experimental Apparatus [4]

2.2.2 Instrumental Training

After 90% of the free-feeding weight is reached, we ran a magazine training protocol where a reward (S1*) (45 mg dustless precision pellets, Bio-Serv) was received under a variable time 20 seconds (VT20) schedule independent of a lever press (R) and stimulus (S1), for two days. In VT20 schedule, animals received a reward independent of their behavior every 20 seconds on average (range: 1-120). On day three, we ran magazine training and fixed ratio 1 (FR1) protocol in parallel where animals received S1* for every R when S1 was on but they also received 10 S1* in total while S1 was on, independent of R according to a VT20 schedule. We ran the FR1 protocol for 4 more days without the VT20 schedule in effect. We ran the experiments simultaneously in both chambers. The S1 was the illumination of the triple light cue in chamber 1 and the low amplitude sound from the high-power tone module in chamber 2. However, the inter trial intervals (ITI) were missing in the FR1 protocols at first, so we ran the FR1 protocols including the ITIs for 2 more days. The timetable of the experimental procedure is given in Table 2.1.

Table 2.1
Timetable of the Experimental Procedure.

	Habituation	Food Restriction	Magazine Training	FR1	FR2	FR5	FR10	VI30	VI45	Discrimination Training
Days	14	14	4 + 2	4 + 2	2	4	5	4	4	21

Next, the animals were shifted to a FR2 schedule where S1* was delivered for every 2 R while S1 was on. We ran the FR2 protocol for 2 days before we moved on to the FR5 protocol where S1* was delivered for every 5 R while S1 was on and after running the FR5 protocol for 4 days we moved on to the FR10 protocol where S1* was delivered for every 10 R while S1 was on. We ran the FR10 protocol for 5 days.

Thereafter, we started the Variable Interval 30 (VI30) schedule in which S1* was delivered for the first R emitted after a variable time interval has passed following the onset of S1. S1 was on during the entire interval, and after a variable time interval had passed, GS4 went on to the lever press (LP) state, in which animals had 15 seconds to press the lever and obtain a reward. When animals successfully press the lever in the LP state, S1* was delivered and GS4 went on to the ITI state for 15 seconds. If animals did not press the lever in the LP state in 15 seconds, GS4 starts the new trial. The time intervals were 30 seconds on average and ranged between 1-80 seconds. We used Microsoft Excel to generate the distributions for VI30. Detailed information and instructions about how to generate such distributions are given later in the methods section. We ran the VI30 protocol for 4 days.

Animal number 12 had a problem with pressing the lever at first. We utilized an AutoShaping procedure to train him to press the lever. Whenever the animal touched the correct lever, we gave S1* through the GS4 software to reinforce the behavior related to the correct lever. Number 12 caught up with the other animals during the VI45 training. All animals started the VI45 training at the same time.

During the VI45 training, S1* was delivered for the first R emitted after a variable time interval has passed after the onset of S1. S1 was on during the entire interval, and after a variable time interval had passed, GS4 went on to the LP state, in which animals had 15 seconds to press the lever and obtain a reward. When animals successfully press the lever in the LP state, S1* was delivered and GS4 went on to the ITI state for 15 seconds. If animals did not press the lever in the LP state, GS4 went on to ITI, and after 15 seconds of ITI, the new trial started. The time intervals were 45 seconds on average and ranged between 30-120 seconds. We used Microsoft Excel to generate the distributions for VI45. Detailed information and instructions about how to generate such distributions are given later in methods section. We ran the VI45 protocol for 4 days.

2.2.3 Discrimination Training

After the VI protocols, we started the VI45-EXT protocol, where we ran the VI45 protocol in parallel with the EXT protocol. After every ITI, GS4 generates a random number between 0 and 1. If that number was bigger than 0.5, GS4 went on to the VI45 state. If it was smaller, GS4 went on to the EXT state. The VI45 state was similar to the previous VI states, in which S1* was delivered for the first R emitted after a variable time interval passed after the onset of S1. In the LP state animals had 15 seconds to successfully press the lever and obtain a reward, if they press the lever in 15 seconds GS4 went on to the ITI. If the animals did not press the lever, GS4 went on to the ITI after 15 seconds of LP state. After 15 seconds of ITI GS4 generated a random number between 0 and 1 to determine the next trial. Time intervals were 45 seconds on average and ranged between 30-120 seconds for VI45 states. In the EXT state, S1 was off, and R did not lead to an S1*. After a variable time interval had passed after the start of the EXT state, GS4 went on to ITI. EXT protocols lasted for 60 seconds on average and ranged between 30-120 seconds. We used Microsoft Excel to generate the distributions for both VI45 and EXT. Detailed information and instructions about how to generate such distributions are given later in methods section.

2.3 Behavioral Parameters and Statistical Analysis

We used GS4 RunTime software to track the behavior of the animals while they were in training sessions. We analyzed performance on the 1^{st} and the 21^{st} days of VI45-EXT training. We also divided the individual training sessions into four equal quarters. In the VI45-EXT schedule, we tracked the behavioral parameters relevant to our study, such as Total Number of Lever Presses in VI State, Total Number of Lever Presses in EXT State, Lever Press Latency in VI State, Lever Press Latency in EXT State, Lever Press Latency in Lever Press State, Lever Press Rate (number of lever presses per minute) in VI State, Lever Press Rate in EXT State.

To see if the distributions of time intervals generated by our formula led to a steady response rate after the onset of S1, we randomly chose 6 trials in VI45 state for each animal from both the 1^{st} and the 21^{st} days of the experiment. Then we segregated the VI45 state into 5 second bins and calculated response rates of the animals in these time bins for both the 1^{st} and the 21^{st} days of the experiment.

We qualitatively analyzed the specific distributions of time intervals we generated with Excel. We analyzed the mean, median, mode, standard deviation, skewness, kurtosis, and range parameters of the distributions of time intervals with SPSS. We also created frequency distributions for each distribution of time intervals with Microsoft Excel.

We then, calculated the probability of reinforcement function of time after the onset of S1 described by Catania and Reynolds for all the distributions of time intervals we generated with our procedure in the present study [19]. For each second after the onset of S1 we calculated the frequencies of that specific time interval in the specific distributions we were interested. Then for each second we also calculated the cumulative frequencies. Finally, we calculated the probability of reinforcement function as

$$prft(t) = \frac{Frequency\ of\ (t)}{Sample\ Size - Cumulative\ Frequency\ of\ (t-1)} \tag{2.1}$$

where t was equal to the duration of VI interval. For example if we had a distribution of 1, 1, 2, 3, 4, 5, the sample size of our distribution would be 6. For second 1, the frequency would be 2, and the cumulative frequency of t-1 which is 0, would be 0 as there was no value in the distribution smaller than 1. Then the prft(1) would be

$$prft(1) = \frac{2}{6-0} = 0.33 \tag{2.2}$$

For time interval 2, the frequency would be 1, and the cumulative frequency would be 2. Then the prft(2) would be

$$prft(2) = \frac{1}{6-2} = 0.25 \tag{2.3}$$

For second 5, the frequency would be 1 and the cumulative frequency would be 5, as there were 5 values in the distribution smaller than 5. Then the prft(5) would be

$$prft(5) = \frac{1}{6-5} = 1 \tag{2.4}$$

The prft(t) function calculates the probability of a reinforcement being arranged in that particular second. It is a measure of time dependence for the distributions that are used for VI schedules. If the prft(t) function changes in relation to time, then the distribution would be time dependant. For example, the distribution 1, 1, 2, 3, 4, 5, would be a time dependant distribution, because it starts with 0 probability for prft(0) and goes to an absolute probability with prft(5).

We calculated the prft(t) functions for all of the distributions of time intervals we generated in the present study. We used Microsoft Excel to calculate and plot the prft(t) functions.

We conducted two-way repeated measures ANOVA with DAY of the training and QUARTER of the training as withing-group factors and Total Number of Lever Press in VI State, Total Number of Lever Press in EXT State, Lever Press Latency in VI State, Lever Press Latency in EXT State, Lever Press Latency in Lever Press State, Lever Press Rate in VI State, Lever Press Rate in EXT State as dependent variables.

We also conducted a Pearson Correlation Analysis between time after the onset of S1 and lever press rates in the VI State in the 1^{st} and the 21^{st} days of the discrimination training. For the Pearson correlation analysis we segregated the time after stimulus into 5 second bins, to analyze the change in the lever press rate with time after stimulus increasing. We also conducted linear and polynomial regression analysis with time after the stimulus onset as the regressor and lever press rates as the response variable.

For ANOVA, we conducted Mauchly's test of sphericity to ensure the sphericity assumption was met, checked if there were any outliers, and analyzed the skewness and kurtosis values for all dependent variables to ensure the normality assumption was met. For Pearson correlation analyses, we checked if there were any outliers, analyzed the skewness and kurtosis values for all dependent variables to ensure the normality assumption was met, and analyzed the linearity between the variables to check if the linearity assumption was met. We conducted all tests using two-way repeated measures ANOVA and Pearson Correlation Analysis in SPSS.

2.4 Generating Non-Normal Series with Microsoft Excel

2.4.1 Generating Non-Normal Series with Arbitrary Parameters

In order to generate non-normal distributions of time intervals we first decided on the parameters of the series, namely desired mean (X), minimum (min), maximum (max), and the size of the series (S). To obtain a skewed distribution we combined two distinct series. The first distribution was a uniform distribution with size S_1 and mean X_1. X_1 was equal to half the desired range while S_1 was suggested to be about 2 times the desired mean minus the minimum value, formulated as

$$X_1 = \frac{Max - Min}{2} \tag{2.5}$$

$$S_1 = 2 * (X - Min) \tag{2.6}$$

We used the ”RANDBETWEEN” function in excel to generate the first distribution. This function returns one number taken randomly from a uniform distribution with the specified minimum and maximum values. We ran this function S_1 times to generate the first distribution. After we generate the first distribution, we calculated the leftover value (Lft) we need to obtain the second distribution. The leftover value was equal to the size of the total series times desired mean minus the size of the first distribution multiplied with the mean of the first distribution, formulated as

$$Lft = (S * X) - (S_1 * X_1) \tag{2.7}$$

Then we used the leftover value to calculate the mean of the second distribution (X_2) which is equal to the leftover value over the size of the second distribution as

$$X_2 = \frac{Lft}{S_2} \tag{2.8}$$

We generated the second distribution according to a desired mean and standard deviation. In order to avoid values below the minimum we set the standard deviation of the second distribution to the mean of the second distribution divided by 2 minus 3 formulated as

$$SD_2 = \frac{X_2}{2} - 3 \tag{2.9}$$

We used half of X_2 to generate the widest distribution we can in our specified range and added ”-3” to ensure that the distribution does not have any negative numbers. Then we used the ”NORMINV” function in excel to generate the second distribution. This function had 3 parameters, probability, mean and SD. We already calculated the mean and SD for our distribution. The probability value defines the distribution characteristics of the distribution and as we want the second distribution to be taken from a normal distribution, we used Microsoft Excels own normal distribution formula, "RAND". However, "NORMINV" function generates rational numbers, but we want to obtain integers to use as time intervals. Thus, we got rid of the fractional components with "INT" function in excel. In the end our formula looked as

$$= INT\ (NORMINV\ (RAND\ (\ ),\ X_2,\ SD_2)) \tag{2.10}$$

This formula generated one number with our desired parameters. We ran this formula S_2 times to generate our second distribution.

Then we combined both distributions to obtain the non-normal distribution. As the second distribution was generated in reference to a mean and SD instead of a range, there can be negative values at times. We omitted the distributions that had negative values if there were any. In the end we obtained a distribution with mean X, range max, min and sample size S

2.4.2 Variable Interval 30 Schedule

We have created a VI30 schedule that has a positively skewed non-normal distribution of time intervals, which was created by merging two distinct distributions. The intervals range between 1 and 80 and have a mean of 30, The sample size was 150. In order to generate VI30 we first generated a uniform distribution with a range of intervals between 1 and 80, and a sample size of 60, as described in section 2.4.1. We used the "RANDBETWEEN" function in excel to generate the first series. Then we generated another distribution with a sample size of 90 to reach a final sample size of 150. We generated the second distribution according to its mean and SD with the "NORMINV" function in excel. We calculated the mean and SD according to the eq. 2.4 and 2.5. Then we merged the first and the second distributions to obtain a distribution of intervals that range between 1 and 80, have a mean of 30 and a sample size of 150. We omitted the distributions that have negative values.

2.4.3 Variable Interval 45 Schedule

Next, we have created a VI45 schedule, that is a positively skewed non-normal distribution, created by merging two distinct distributions. It has a wider range than the distribution used for the VI30 schedule. The intervals range between 1 and 120 and have a mean of 45. Sample size was 150. In order to generate VI45 we first generated a uniform distribution with a range of intervals between 1 and 120, and a sample size of 80, as described in 2.4.1. We used the ”RANDBETWEEN” function in excel to generate the first series. Then we generated another distribution with a sample size of 70 to reach a final sample size of 150. We generated the second distribution according to its mean and SD with the ”NORMINV” function in excel. We calculated the mean and SD according to the eq. 2.4 and 2.5. Then we merged the first and the second distributions to obtain a distribution of intervals that range between 1 and 120, have a mean of 45 and a sample size of 150. We omitted the distributions that have negative values.

2.4.4 Variable Interval 45 - EXT Schedule

Thereafter, we have created a VI45-EXT schedule that has a positively skewed non-normal distribution of time intervals, that was created by merging two distinct distributions. The range was narrower than VI45 for VI45-EXT and its minimum was 30 instead of 0 because it was used later in the instrumental training, and it was run in parallel with an extinction protocol. The intervals range between 30 and 120 and have a mean of 45. The sample size was 150. In order to generate VI45-EXT, first we generated a uniform distribution with a range of intervals between 30 and 120, and a sample size of 20 as described in 2.4.1. We decided on the mean and sample size of the uniform distribution according to equations 2.5 and 2.6. We used the ”RANDBETWEEN” function in excel to generate the first series. Then we generated another distribution with a sample size of 130 to reach a final sample size of 150. We generated the second distribution according to its mean and SD with the ”NORMINV” function in excel. We calculated the mean and SD according to the eq. 2.4 and 2.5. Then we merged the first and the second distributions to obtain a distribution of intervals that range between 30 and 120, have a mean of 45 and a sample size of 150. We omitted the distributions that had negative values.

Additionally, we generated another distribution by adding 15 to every value in the VI45 distribution. Then, we transformed every value that exceeds 120 to 120 and obtained another distribution with a mean of 60 and a range between 45 and 120 for EXT schedule. The VI45-EXT schedule was used for discrimination training. In this schedule the animal underwent reinforcement training with stimuli on and extinction trials without the stimuli, administered in a random order. The purpose of the discrimination training was to teach the animal the conditions in which the reinforcement was available. Thus, we generated the EXT distribution by using the VI45 distribution to minimize the difference between two trials.

2.4.5 Uniform Distribution

A uniform or rectangular distribution is a distribution in which each number within a specified range has an equal probability of being arranged. In order to create such a distribution in excel we used the ”RANDBETWEEN” function. This function had two parameters, a minimum and a maximum. To be able to make a clearer comparison we used 1-120 as the range and 150 as the sample size.

2.4.6 Normal Distribution

A normal or Gaussian distribution is a distribution that has the highest number of scores near the mean and is symmetric to the left and right sides of the mean. In order to create such a distribution in excel we used the ”NORMINV” function. This function had 3 parameters, probability, mean and SD. We used 60 as the mean and 20 as SD to approximate the parameters of our non-normal distributions. The probability value defines the distribution characteristics. We used excels own normal distribution formula, ”RAND”. But, as the ”NORMINV” function generates rational numbers, we also used ”INT” in excel to get rid of the fractions and obtain integers. In the end our formula looked as

$$= INT\ (NORMINV\ (RAND\ (\ ),\ X_2,\ SD_2)) \tag{2.11}$$

We ran this formula 150 times to obtain our normal distribution.

2.4.7 Exponential Distribution

An exponential distribution is a positively skewed distribution that is characterized with lower scores being the most frequent and more scattered data points at the end. In order to create such a distribution in Microsoft Excel, we first used the ”RAND” function to create a normal distribution between 0 and 1. Then we calculated the mean of the first distribution as X_{rand}. Later we generated an exponential distribution with a mean of 0.5 by taking the natural logarithm of 1 minus the normal distribution we created and then multiplying it with X_{rand}. Finally, our formula looked as

$$X_{rand} * \ln(1 - X) \tag{2.12}$$

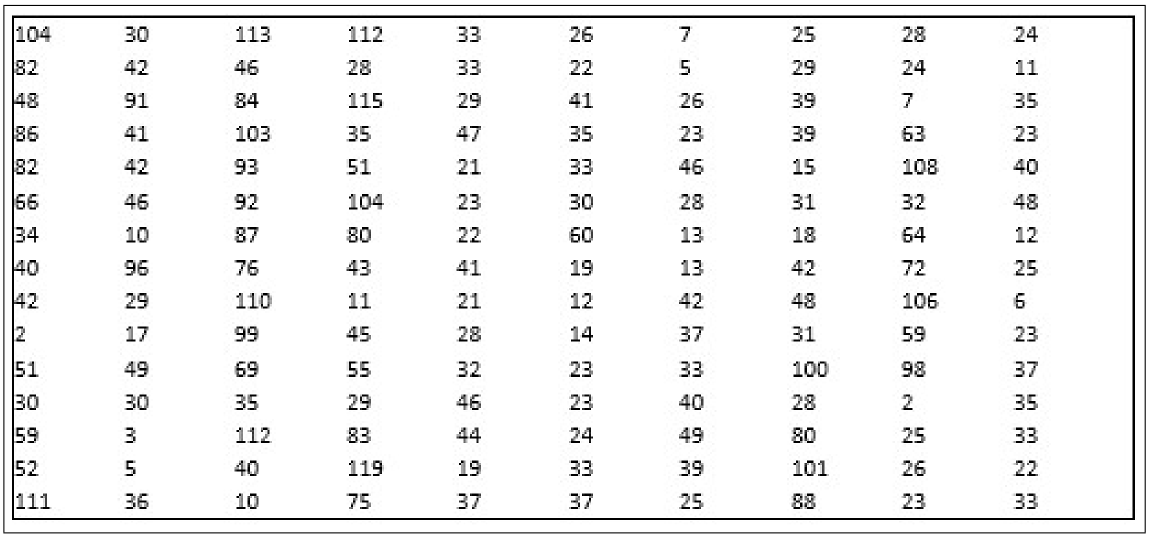
This formula generated an exponential distribution with a mean of 0.5. We multiplied the results of equation 2.8 with 120 to obtain an exponential distribution with a mean of 60. We ran equation 2.8 150 times to obtain the exponential distribution.

3. Results

3.1 Descriptive Analysis of the Generated Series

3.1.1 VI45 Distribution

The distribution of time intervals we have generated for our VI45 schedule is shown in Figure 3.1.



104	30	113	112	33	26	7	25	28	24
82	42	46	28	33	22	5	29	24	11
48	91	84	115	29	41	26	39	7	35
86	41	103	35	47	35	23	39	63	23
82	42	93	51	21	33	46	15	108	40
66	46	92	104	23	30	28	31	32	48
34	10	87	80	22	60	13	18	64	12
40	96	76	43	41	19	13	42	72	25
42	29	110	11	21	12	42	48	106	6
2	17	99	45	28	14	37	31	59	23
51	49	69	55	32	23	33	100	98	37
30	30	35	29	46	23	40	28	2	35
59	3	112	83	44	24	49	80	25	33
52	5	40	119	19	33	39	101	26	22
111	36	10	75	37	37	25	88	23	33

Figure 3.1 VI45 Distribution

The descriptive statistics for this distribution is shown in Table 3.1. Skewness value indicates that the VI45 distribution is positively skewed, as intended. Mode and median values confirm that smaller scores are more frequent.

Table 3.1
Descriptive Statistics for the VI45 Distribution.

	N	Mean	Median	Mode	SD	Skewness	Kurtosis	Minimum	Maximum
Statistic	150	45.35	36.5	23.33	29.945	0.922	-0.155	2	119

Figure 3.2 depicts this VI45 distribution as a frequency plot. The shape of this plot reflects a non-normal distribution, as intended, with a high number of scores around the mean (∼45) and fewer scores with increasing intervals.

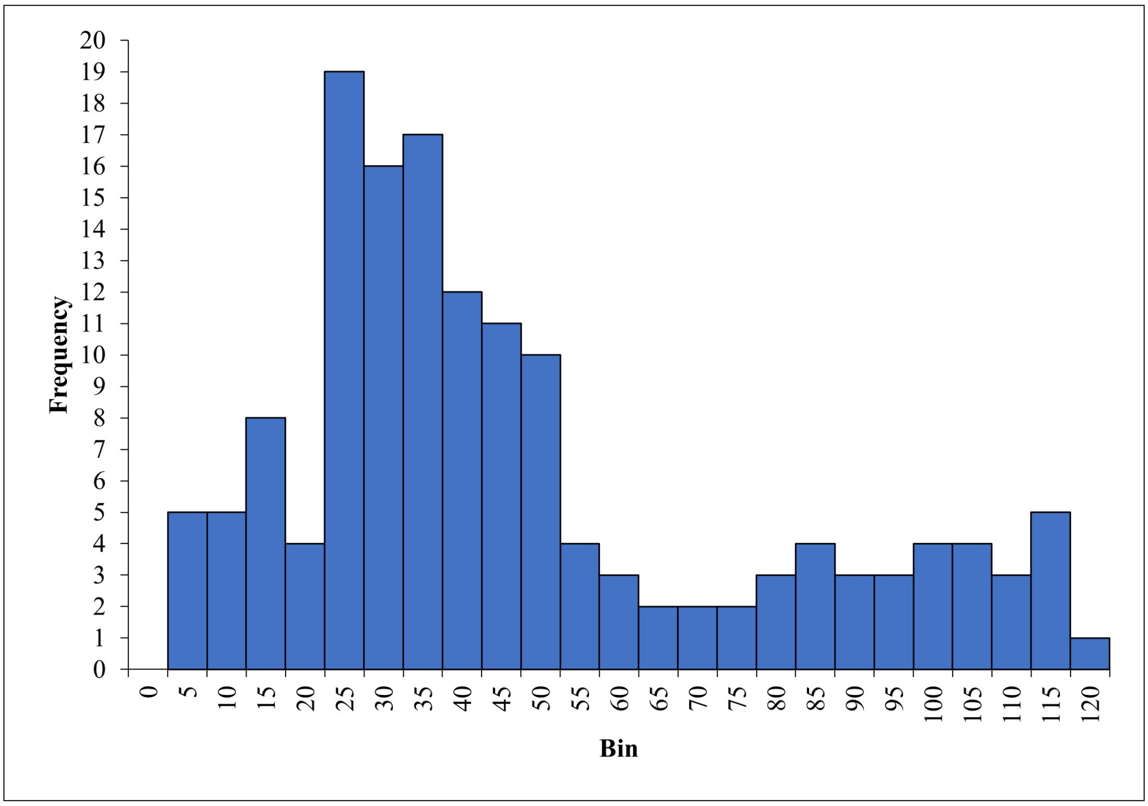


Figure 3.2 Frequency Distribution of the VI45 Distribution

Figure 3.3 shows the probability of reinforcement curve for the VI45 distribution we have generated for this study. On the x axis we have the time interval durations in seconds and on the y axis we have the probability of reinforcement. The slope of the curve indicates the time dependency of the distribution, as higher slope means increase in probability of reinforcement over time. Figure 3.3 shows that VI45 distribution maintained a steady probability of reinforcement rate for most intervals but with intervals longer than ∼100 seconds the probability of reinforcement increased in relation to time.

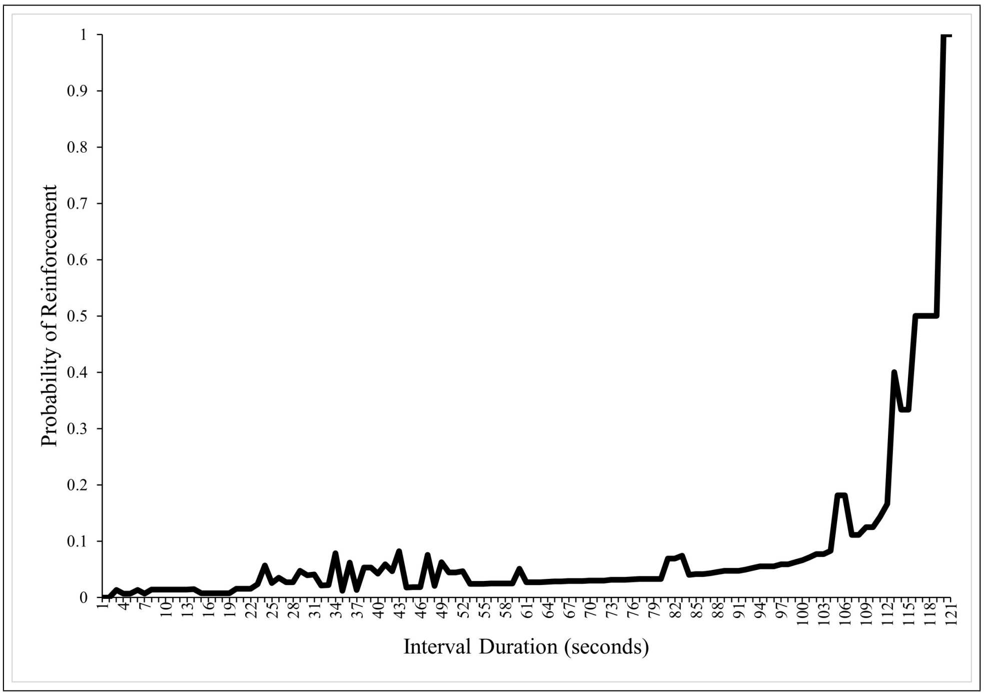
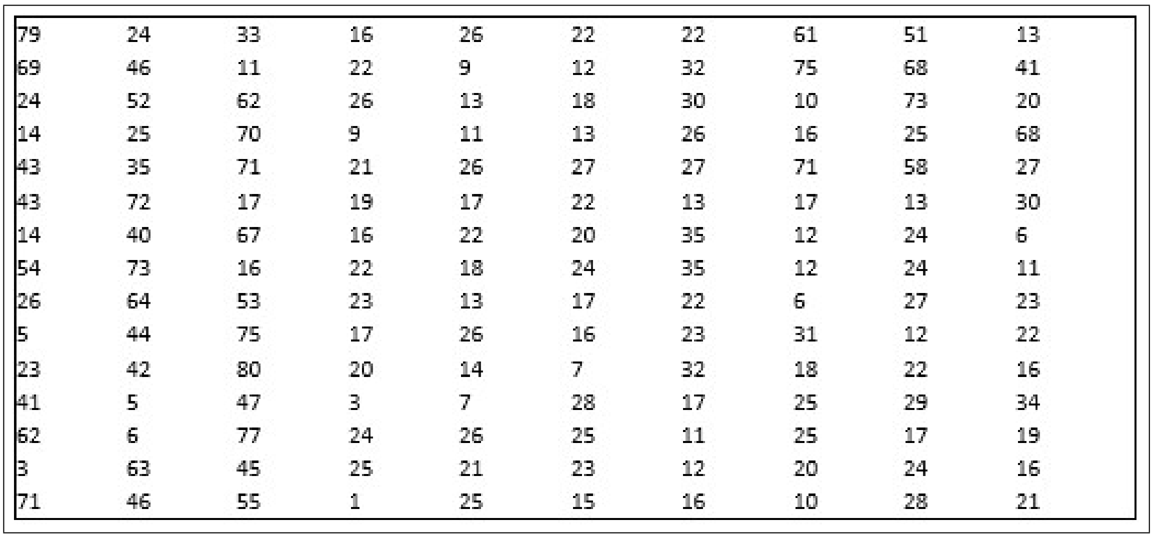


Figure 3.3 Probability of Reinforcement Curve for the VI45 Distribution.

3.1.2 VI30 Distribution

The distribution of time intervals we have generated for our VI30 schedule is shown in Figure 3.4.



79	24	33	16	26	22	22	61	51	13
69	46	11	22	9	12	32	75	68	41
24	52	62	26	13	18	30	10	73	20
14	25	70	9	11	13	26	16	25	68
43	35	71	21	26	27	27	71	58	27
43	72	17	19	17	22	13	17	13	30
14	40	67	16	22	20	35	12	24	6
54	73	16	22	18	24	35	12	24	11
26	64	53	23	13	17	22	6	27	23
5	44	75	17	26	16	23	31	12	22
23	42	80	20	14	7	32	18	22	16
41	5	47	3	7	28	17	25	29	34
62	6	77	24	26	25	11	25	17	19
3	63	45	25	21	23	12	20	24	16
71	46	55	1	25	15	16	10	28	21

Figure 3.4 VI30 Distribution

The descriptive statistics for this distribution is shown in Table 3.2. Skewness value indicates that the VI30 distribution is positively skewed, as intended. Mode and median values confirm that smaller scores are more frequent.

Table 3.2
Descriptive Statistics for the VI30 Distribution.

	N	Mean	Median	Mode	SD	Skewness	Kurtosis	Minimum	Maximum
Statistic	150	29.59	24	22	19.92	1.076	0.122	1	80

Figure 3.5 depicts this VI30 distribution as a frequency plot. The shape of this plot reflects a non-normal distribution, as intended, with a high number of scores around the mean (∼30) and fewer scores with increasing intervals.

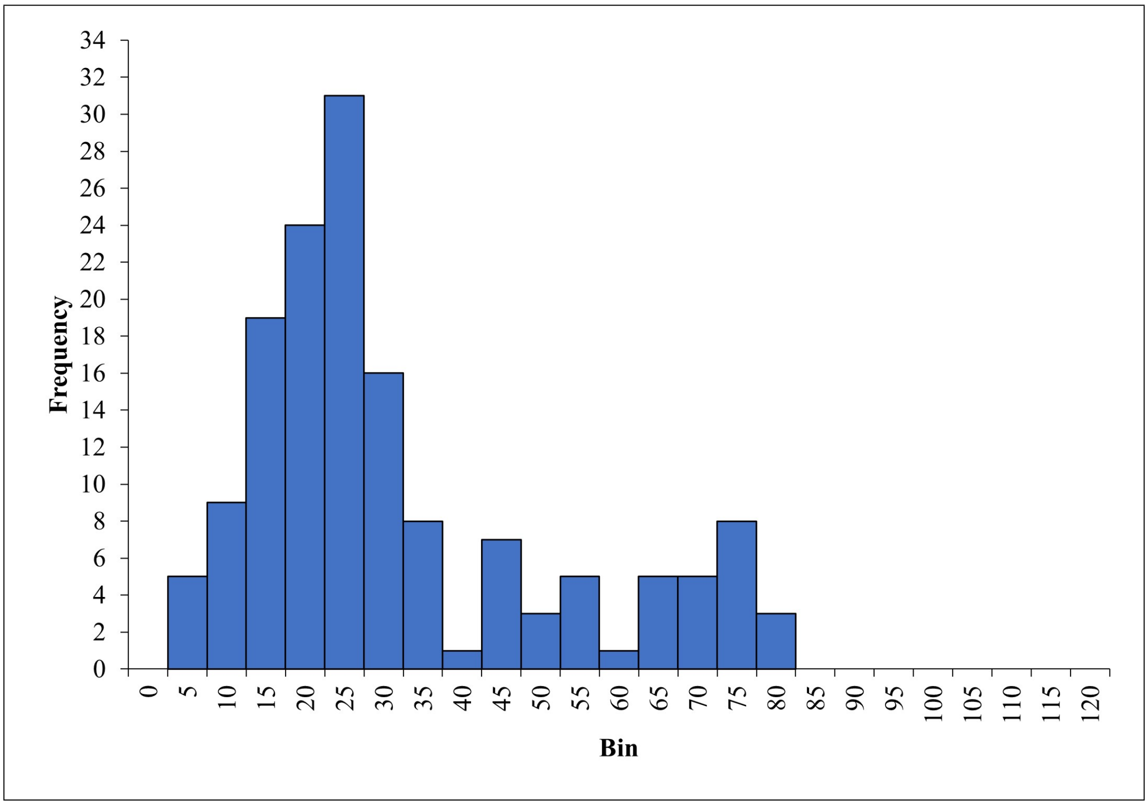


Figure 3.5 Frequency distribution of the VI30 Distribution

Figure 3.6 shows the probability of reinforcement curve for the VI30 distribution we have generated for this study. On the x axis we have the time interval durations in seconds and on the y axis we have the probability of reinforcement. The slope of the curve indicates the time dependency of the distribution, as higher slope means increase in probability of reinforcement over time. Figure 3.6 shows that VI30 distribution maintained a steady probability of reinforcement rate for most intervals but with intervals longer than ∼70 seconds the probability of reinforcement increased radically in relation to time.

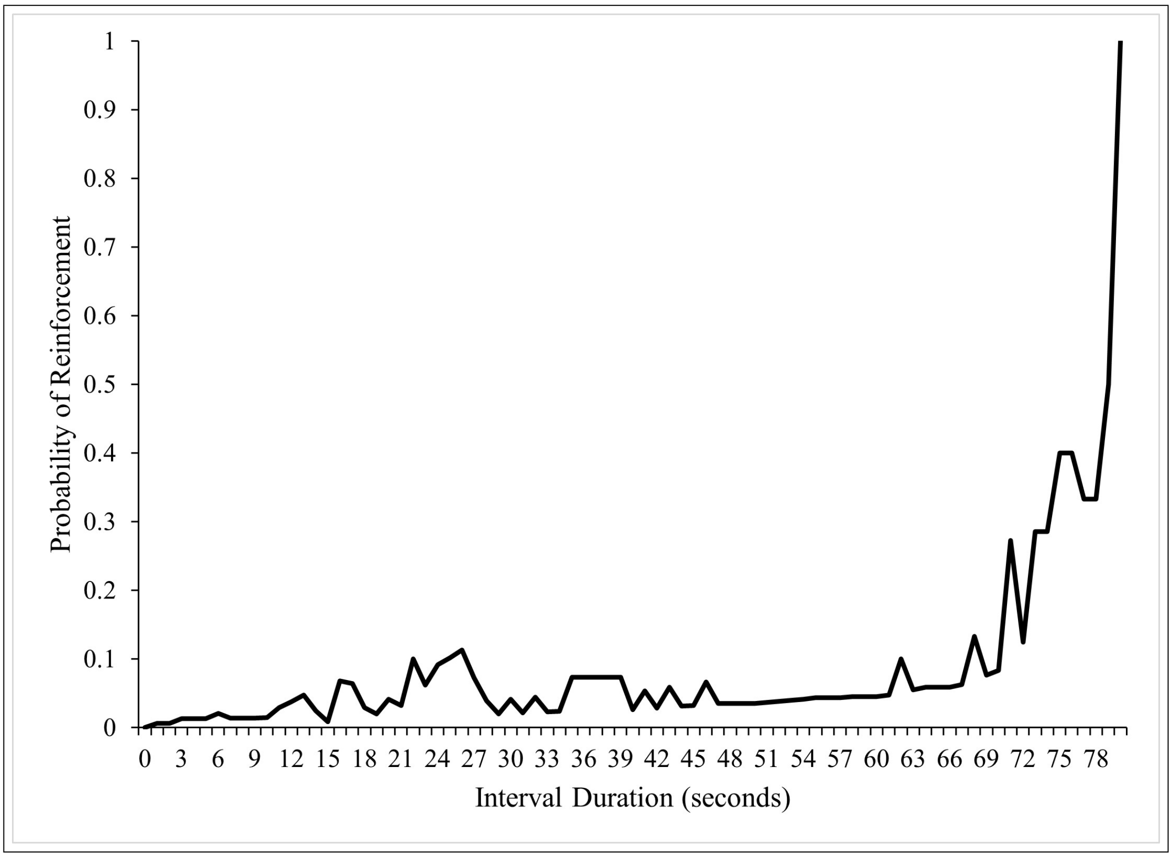
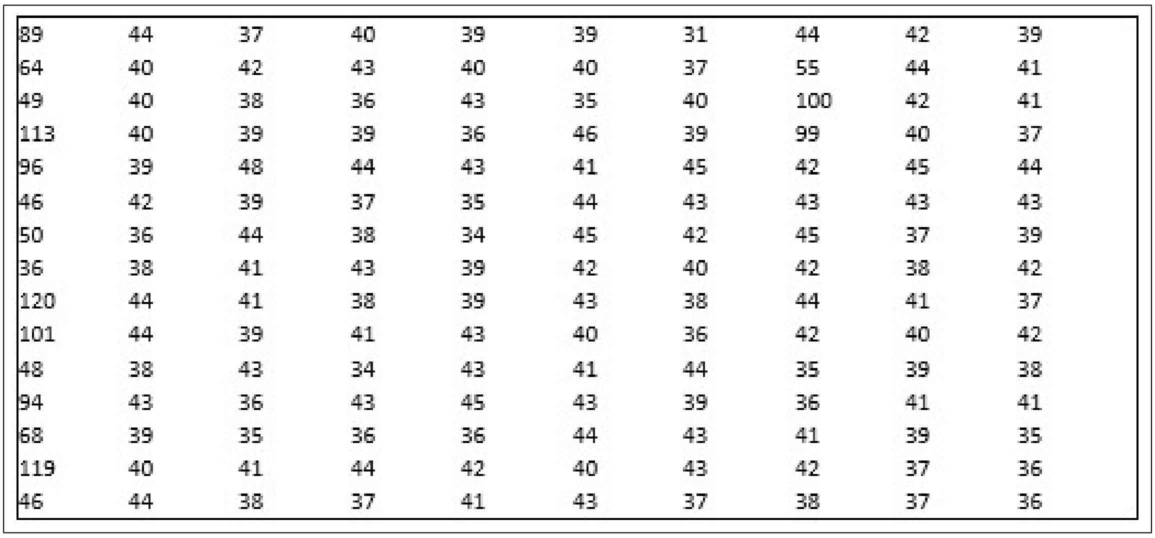


Figure 3.6 Probability of Reinforcement Curve for the VI30 Distribution.

3.1.3 VI45-EXT Distribution

The distribution of time intervals we have generated for our VI45-EXT schedule is shown in Figure 3.7.



89	44	37	40	39	39	31	44	42	39
64	40	42	43	40	40	37	55	44	41
49	40	38	36	43	35	40	100	42	41
113	40	39	39	36	46	39	99	40	37
96	39	48	44	43	41	45	42	45	44
46	42	39	37	35	44	43	43	43	43
50	36	44	38	34	45	42	45	37	39
36	38	41	43	39	42	40	42	38	42
120	44	41	38	39	43	38	44	41	37
101	44	39	41	43	40	36	42	40	42
48	38	43	34	43	41	44	35	39	38
94	43	36	43	45	43	39	36	41	41
68	39	35	36	36	44	43	41	39	35
119	40	41	44	42	40	43	42	37	36
46	44	38	37	41	43	37	38	37	36

Figure 3.7 VI45-EXT Distribution

The descriptive statistics for this distribution is shown in Table 3.3. Skewness value indicates that the VI45-EXT distribution is positively skewed, as intended.

Table 3.3
Descriptive Statistics for the VI45-EXT Distribution.

	N	Mean	Median	Mode	SD	Skewness	Kurtosis	Minimum	Maximum
Statistic	150	44.73	41	43	15.77	3.458	11.588	31	120

Figure 3.8 depicts this VI45-EXT distribution as a frequency plot. The shape of this plot reflects a non-normal distribution, as intended, with a high number of scores around the mean (∼45) and fewer scores with increasing intervals.

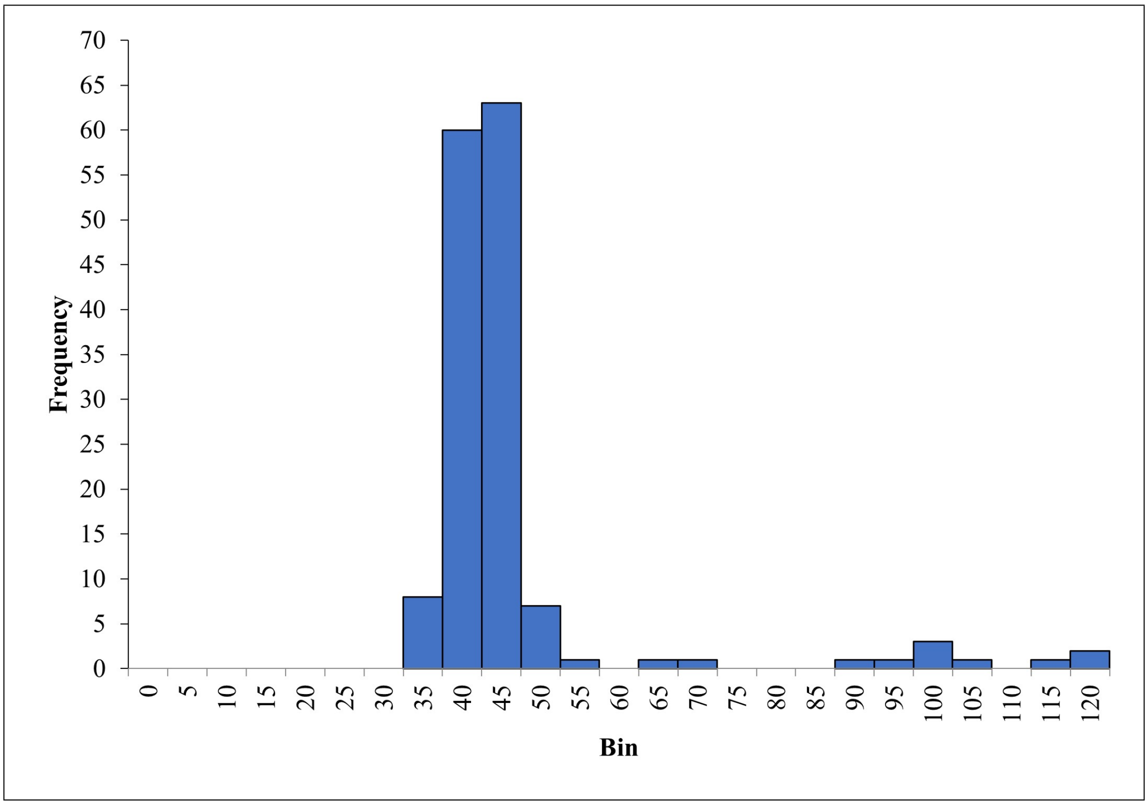


Figure 3.8 Histogram of the VI45-EXT Distribution

Figure 3.9 shows the probability of reinforcement curve for the VI45-EXT distribution we have generated for this study. On the x axis we have the time interval durations in seconds and on the y axis we have the probability of reinforcement. The slope of the curve indicates the time dependency of the distribution, as higher slope means increase in probability of reinforcement over time. Figure 3.9 shows that VI45-EXT distribution showed a peak at the mean (∼45), and later maintained a steady probability of reinforcement rate until a radical increase with time intervals longer than ∼100 seconds.

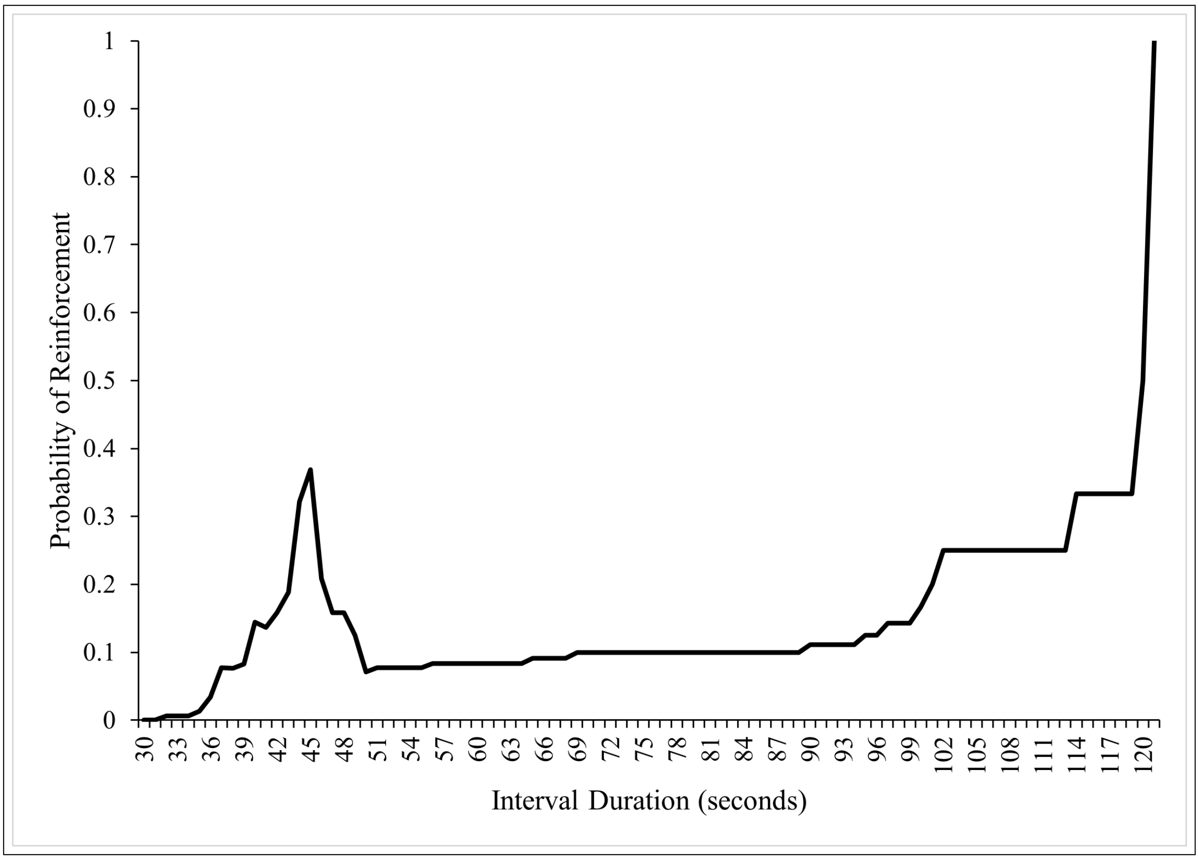
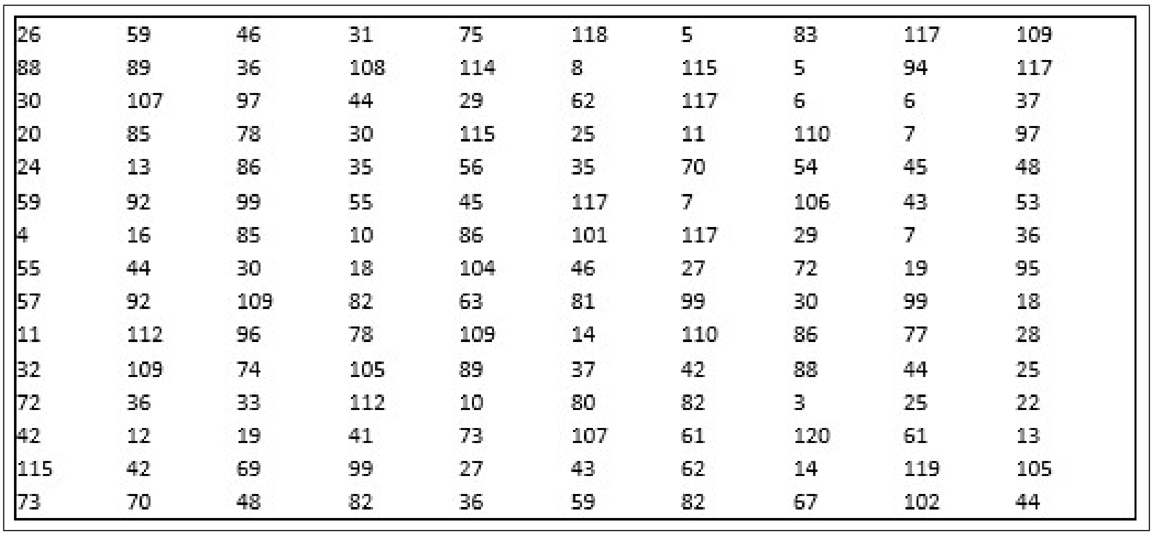


Figure 3.9 Probability of Reinforcement Curve for the VI45-EXT Distribution.

3.1.4 Uniform Distribution

The distribution of time intervals we have generated for our Uniform distribution is shown in Figure 3.10.



26	59	46	31	75	118	5	83	117	109
88	89	36	108	114	8	115	5	94	117
30	107	97	44	29	62	117	6	6	37
20	85	78	30	115	25	11	110	7	97
24	13	86	35	56	35	70	54	45	48
59	92	99	55	45	117	7	106	43	53
4	16	85	10	86	101	117	29	7	36
55	44	30	18	104	46	27	72	19	95
57	92	109	82	63	81	99	30	99	18
11	112	96	78	109	14	110	86	77	28
32	109	74	105	89	37	42	88	44	25
72	36	33	112	10	80	82	3	25	22
42	12	19	41	73	107	61	120	61	13
115	42	69	99	27	43	62	14	119	105
73	70	48	82	36	59	82	67	102	44

Figure 3.10 Uniform Distribution

The descriptive statistics for this distribution is shown in Table 3.4. Skewness value indicates that the Uniform distribution is not skewed, as intended. Median value confirms that this distribution is not skewed as it is close to the mean value.

Table 3.4
Descriptive Statistics for the Uniform Distribution.

	N	Mean	Median	Mode	SD	Skewness	Kurtosis	Minimum	Maximum
Statistic	150	61.18	59	117	35.854	0.052	-1.317	3	120

Figure 3.11 depicts this Uniform distribution as a frequency plot. The shape of this plot reflects a non-normal distribution, as intended, with similar frequency all over the range.

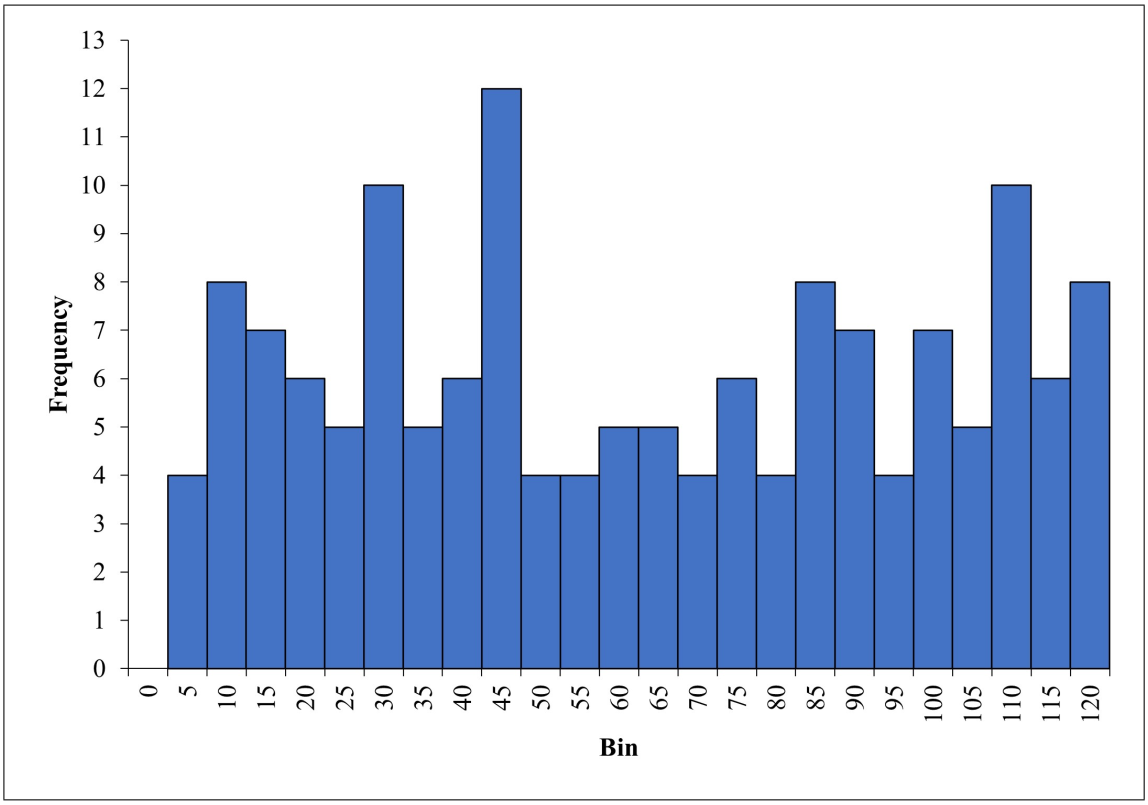


Figure 3.11 Histogram of the Uniform Distribution

Figure 3.12 shows the probability of reinforcement curve for the Uniform distribution we have generated for this study. On the x axis we have the time interval durations in seconds and on the y axis we have the probability of reinforcement. The slope of the curve indicates the time dependency of the distribution, as higher slope means increase in probability of reinforcement over time. Figure 3.12 shows that the Uniform distribution maintained a steady probability of reinforcement rate for most intervals but with intervals longer than ~100 seconds the probability of reinforcement increased radically in relation to time.

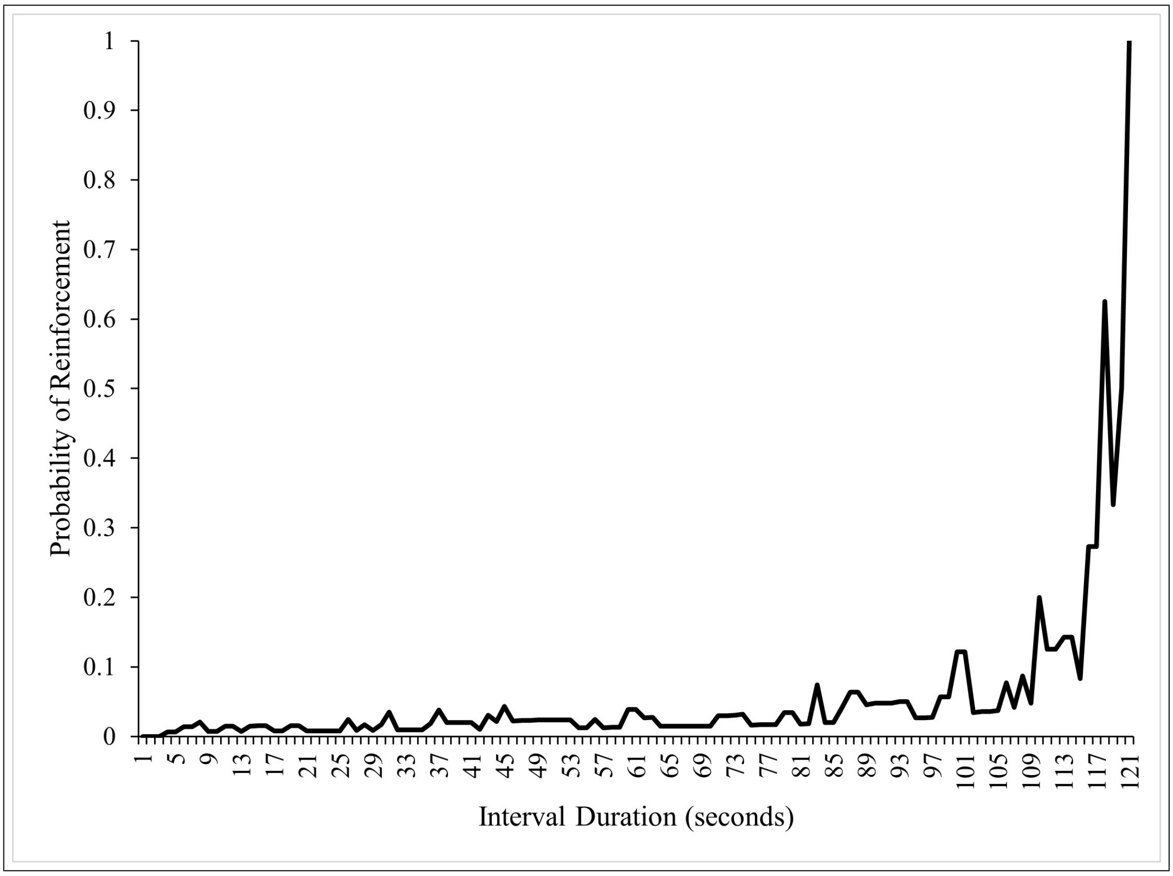
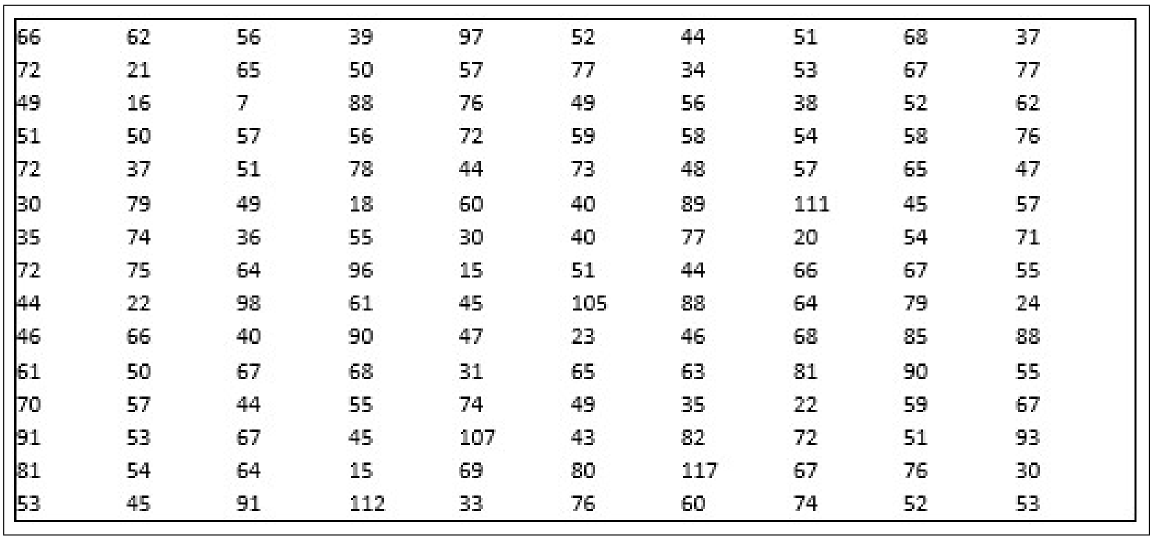


Figure 3.12 Probability of Reinforcement Curve for the Uniform Distribution.

3.1.5 Normal Distribution

The distribution of time intervals we have generated for our Normal distribution is shown in Figure 3.13.



66	62	56	39	97	52	44	51	68	37
72	21	65	50	57	77	34	53	67	77
49	16	7	88	76	49	56	38	52	62
51	50	57	56	72	59	58	54	58	76
72	37	51	78	44	73	48	57	65	47
30	79	49	18	60	40	89	111	45	57
35	74	36	55	30	40	77	20	54	71
72	75	64	96	15	51	44	66	67	55
44	22	98	61	45	105	88	64	79	24
46	66	40	90	47	23	46	68	85	88
61	50	67	68	31	65	63	81	90	55
70	57	44	55	74	49	35	22	59	67
91	53	67	45	107	43	82	72	51	93
81	54	64	15	69	80	117	67	76	30
53	45	91	112	33	76	60	74	52	53

Figure 3.13 Normal Distribution

The descriptive statistics for this distribution is shown in Table 3.5. Skewness value indicates that the Normal distribution is not skewed, as intended. Median value confirms that this distribution is not skewed as it is close to the mean value.

Table 3.5
Descriptive Statistics for the Normal Distribution.

	N	Mean	Median	Mode	SD	Skewness	Kurtosis	Minimum	Maximum
Statistic	150	59.16	57	67	21.25	0.145	0.107	7	117

Figure 3.14 depicts this Normal distribution as a frequency plot. The shape of this plot reflects a normal distribution, as intended, with higher number of scores around the mean (∼60) and decrease in frequency for scores away from the mean.

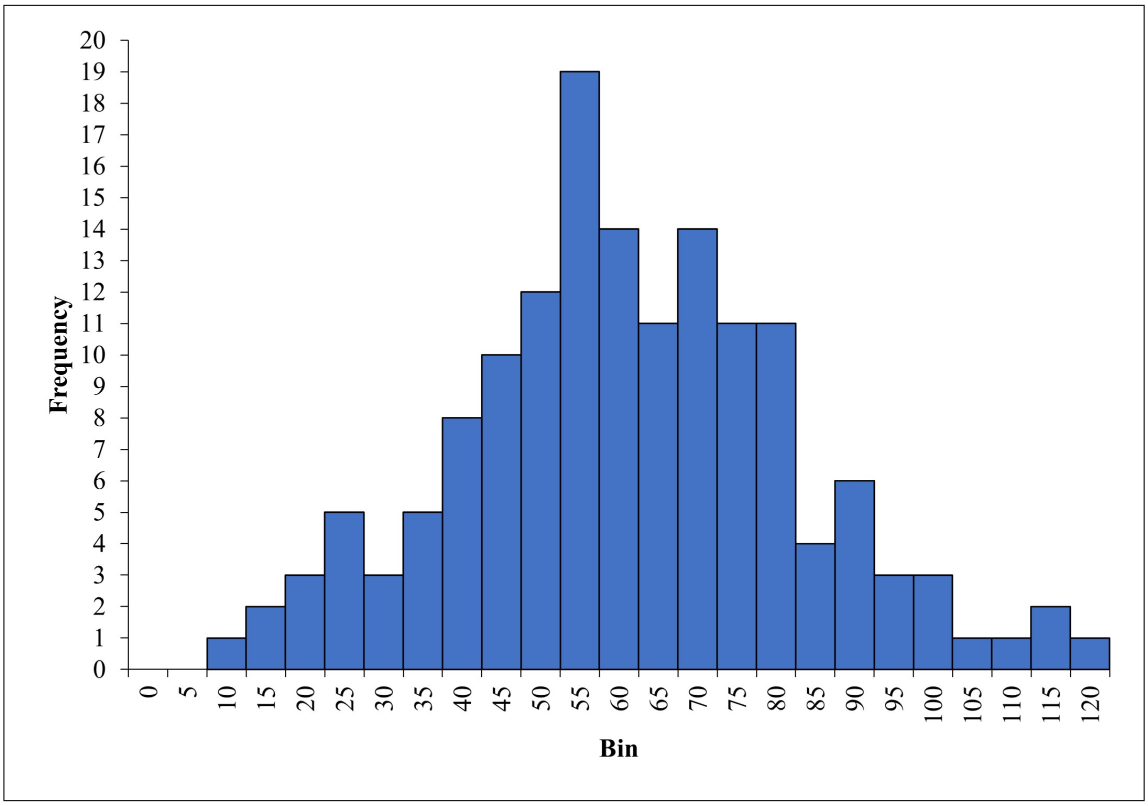


Figure 3.14 Histogram of the Normal Distribution

Figure 3.15 shows the probability of reinforcement curve for the Normal distribution we have generated for this study. On the x axis we have the time interval durations in seconds and on the y axis we have the probability of reinforcement. The slope of the curve indicates the time dependency of the distribution, as higher slope means increase in probability of reinforcement over time. Figure 3.15 shows that the Normal distribution maintained a steady probability of reinforcement rate for shorter time intervals. However, for time intervals longer than the mean (∼60), probability of reinforcement increased with time.

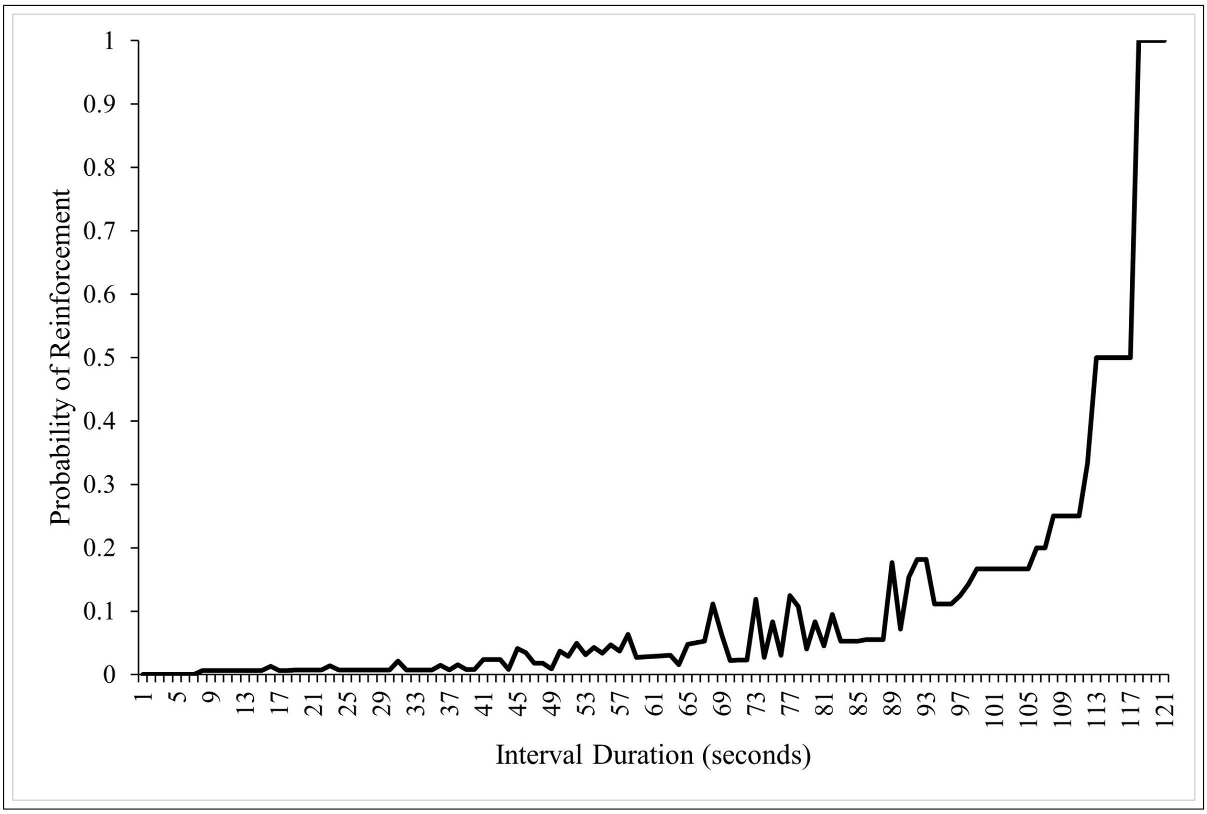
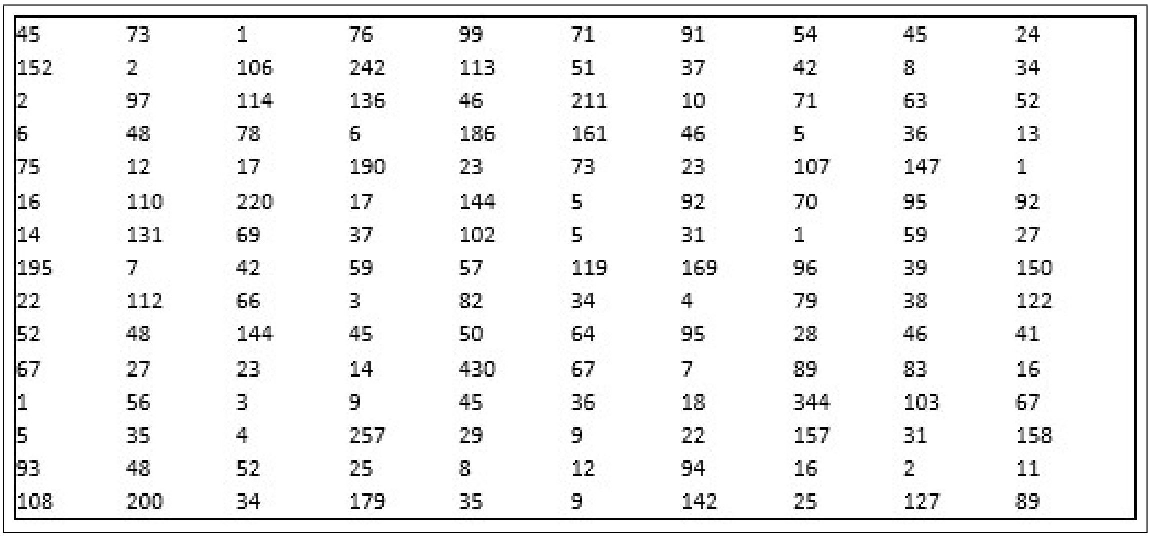


Figure 3.15 Probability of Reinforcement Curve for the Normal Distribution.

3.1.6 Exponential Distribution

The distribution of time intervals we have generated for our Exponential distribution is shown in Figure 3.16.



45	73	1	76	99	71	91	54	45	24
152	2	106	242	113	51	37	42	8	34
2	97	114	136	46	211	10	71	63	52
6	48	78	6	186	161	46	5	36	13
75	12	17	190	23	73	23	107	147	1
16	110	220	17	144	5	92	70	95	92
14	131	69	37	102	5	31	1	59	27
195	7	42	59	57	119	169	96	39	150
22	112	66	3	82	34	4	79	38	122
52	48	144	45	50	64	95	28	46	41
67	27	23	14	430	67	7	89	83	16
1	56	3	9	45	36	18	344	103	67
5	35	4	257	29	9	22	157	31	158
93	48	52	25	8	12	94	16	2	11
108	200	34	179	35	9	142	25	127	89

Figure 3.16 Exponential Distribution

The descriptive statistics for this distribution is shown in Table 3.6. Skewness value indicates that the Exponential distribution is positively skewed, as intended. Median value confirms that this distribution is positively skewed as it is smaller than the mean value. Range of the exponential distribution is extremely big compared to other distributions.

Table 3.6
Descriptive Statistics for the Exponential Distribution.

	N	Mean	Median	Mode	SD	Skewness	Kurtosis	Minimum	Maximum
Statistic	150	69.25	49	1,5,45	67.731	2.01	6.288	1	430

Figure 3.17 depicts this Exponential distribution as a frequency plot. The shape of this plot reflects a non-normal distribution, as intended, with higher number of scores around the lower range values and a decrease in frequency with increasing time intervals.

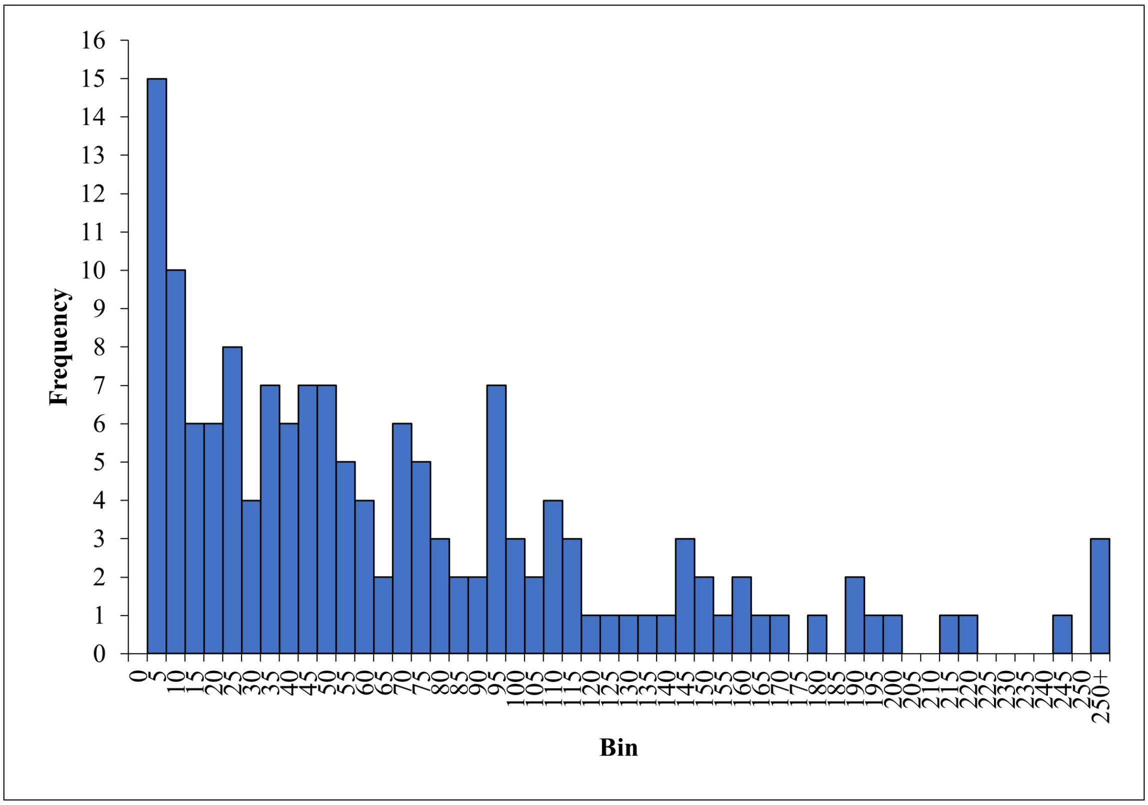


Figure 3.17 Histogram of the Exponential Distribution

Figure 3.18 shows the probability of reinforcement curve for the Uniform distribution we have generated for this study. On the x axis we have the time interval durations in seconds and on the y axis we have the probability of reinforcement. The slope of the curve indicates the time dependency of the distribution, as higher slope means increase in probability of reinforcement over time. Figure 3.18 shows that the Exponential distribution maintained a steady probability of reinforcement rate for time intervals smaller than ∼150 seconds, and showed an increase in probability of reinforcement with time for longer time intervals.

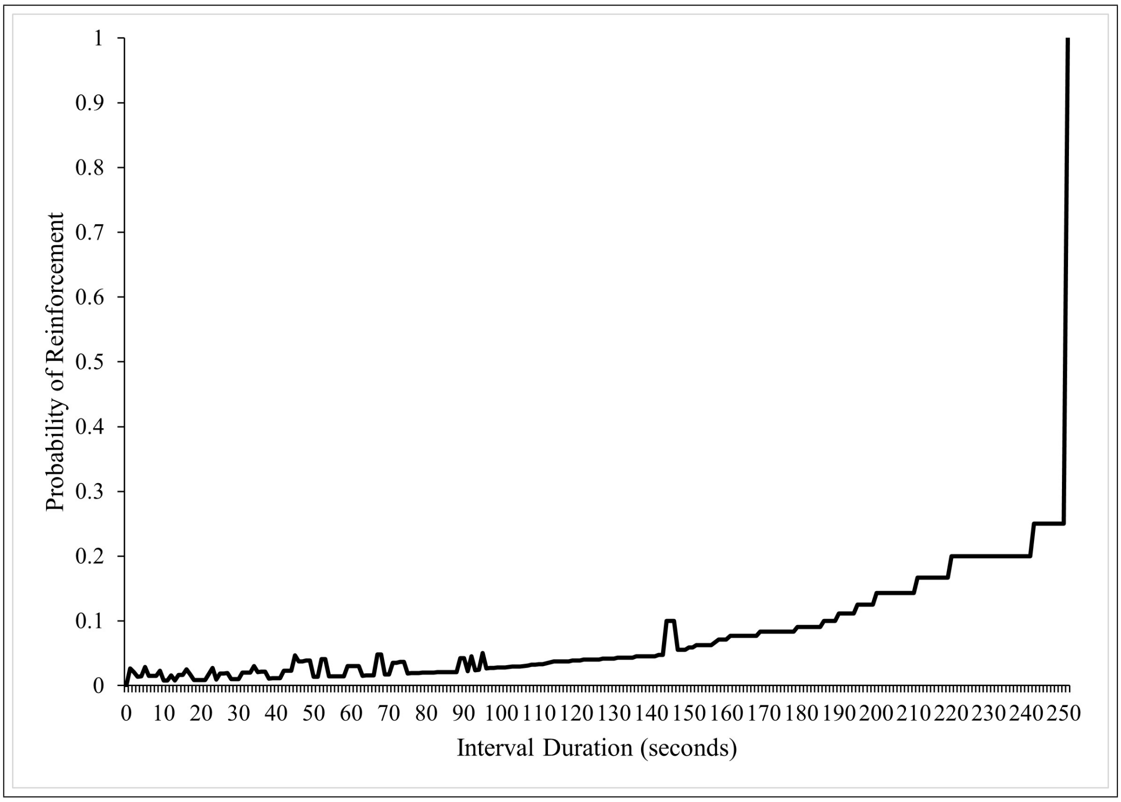


Figure 3.18 Probability of Reinforcement Curve for the Exponential Distribution.

3.2 Statistical Analysis

3.2.1 Operant Performance Across Training Sessions and Time Within Session

3.2.1.1 Total Number of Lever Presses in VI State.

We found that the distributions were normally distributed and there were no outliers. Mauchly's test indicated that the sphericity assumption was met for QUARTER ($\chi^2(5) = 11.128$, p = 0.052), DAY (because it only has two groups), and for DAY X QUARTER ($\chi^2(5) = .759$, p = 0.980). A repeated measures ANOVA with DAY and QUARTER as repeated measures factors revealed that, the main effects of DAY (F (1,7) = .311, p = .594, $\eta^2 = 0.043$) and QUARTER (F (3,21) = .365, p = .779, $\eta^2 = 0.050$) on the total number of lever presses in VI state were not significant. However, we found a statistically significant interaction effect between DAY and QUARTER (F (3,21) = 3.346, p = .039, $\eta^2 = 0.323$). Mean number of lever presses in VI State (±SEM) across training session and time within session are shown in Figure 3.19.

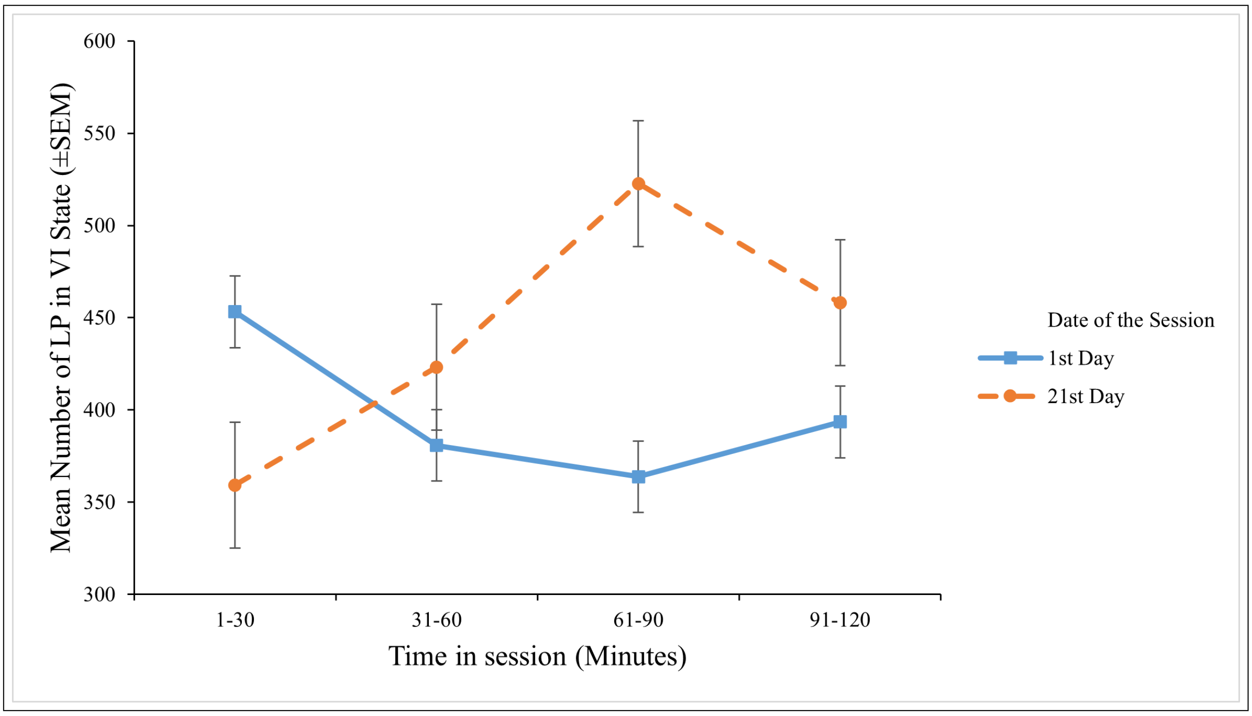


Figure 3.19 Total Number of Lever Presses in VI State Across DAY and QUARTER.

3.2.1.2 Total Number of Lever Presses in EXT State.

We found that the distributions were normally distributed and there were no outliers. Mauchly's test indicated that the sphericity assumption is met for QUARTER ($\chi^2(5) = 6.990$, p = 0.227), DAY (because it only has two groups), and for DAY X QUARTER ($\chi^2(5) = 2.631$, p = 0.760).

A repeated measures ANOVA with DAY and QUARTER as repeated measures factors revealed that, there were statistically significant main effects of QUARTER (F (3,21) = 4.3628, p = .016, $\eta^2 = 0.382$) and DAY (F (1,7) = 26.807, p = .001, $\eta^2 = 0.793$) on the total number of lever presses in the EXT state. Also, the interaction effect between QUARTER and DAY was found to be statistically significant (F (3,21) = 3.885, p = .024, $\eta^2 = 0.357$). Mean number of lever presses in EXT State (±SEM) across training session and time within session are shown in Figure 3.20.

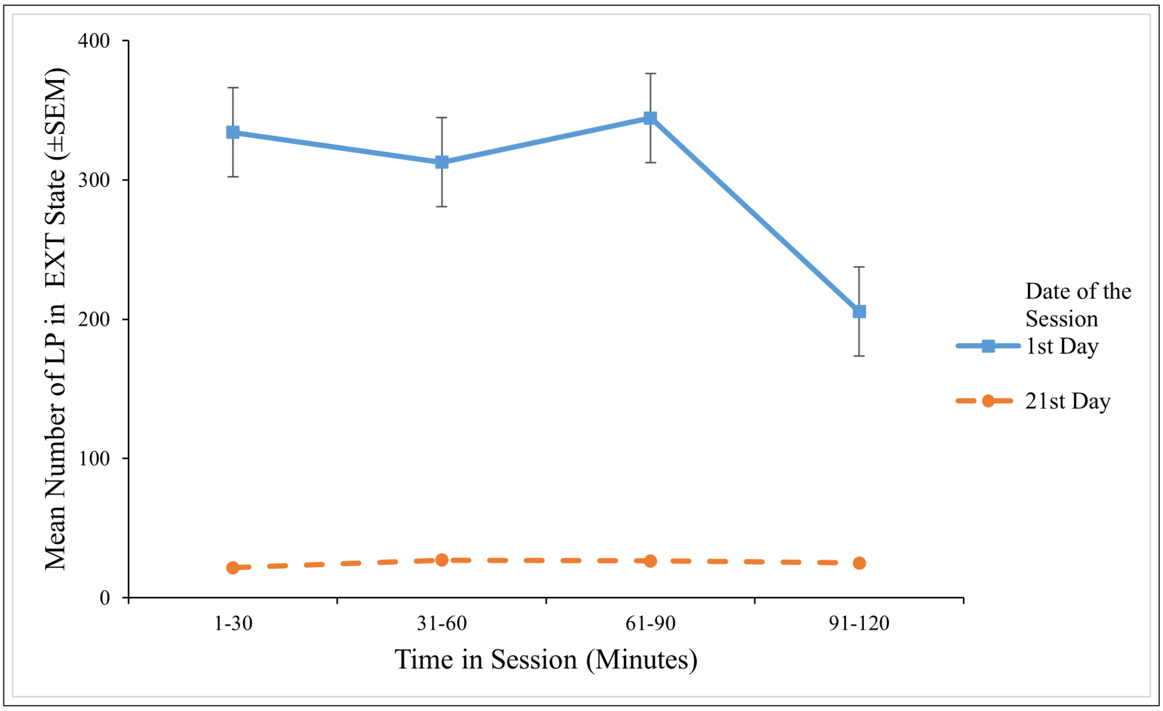


Figure 3.20 Total Number of Lever Presses in EXT State Across DAY and QUARTER.

3.2.1.3 Lever Press Latency in VI State.

We found that the distributions were normally distributed and there were no outliers. Mauchly's test indicated that the sphericity assumption was met for QUARTER ($\chi^2(5) = 3.983$, $p = 0.557$), and DAY (because it only has two groups), but was violated for the DAY X QUARTER ($\chi^2(5) = 13.333$, $p = 0.022$). Greenhouse-Geisser corrections were used for the analysis of the interaction effect.

A repeated measures ANOVA with DAY and QUARTER as repeated measures factors revealed that, there were no statistically significant main effects of DAY (F (1,7) = 4.064, $p = .084$, $\eta^2 = 0.367$), QUARTER (F (3,21) = 0.163, $p = 0.920$, $\eta^2 = 0.023$) or an interaction effect of QUARTER X DAY (F (3,21) = 1.989, $p = .185$, $\eta^2 = 0.221$) on lever press latency in VI state. Mean lever press latencies in VI State (±SEM) across training session and time within session are shown in Figure 3.21.

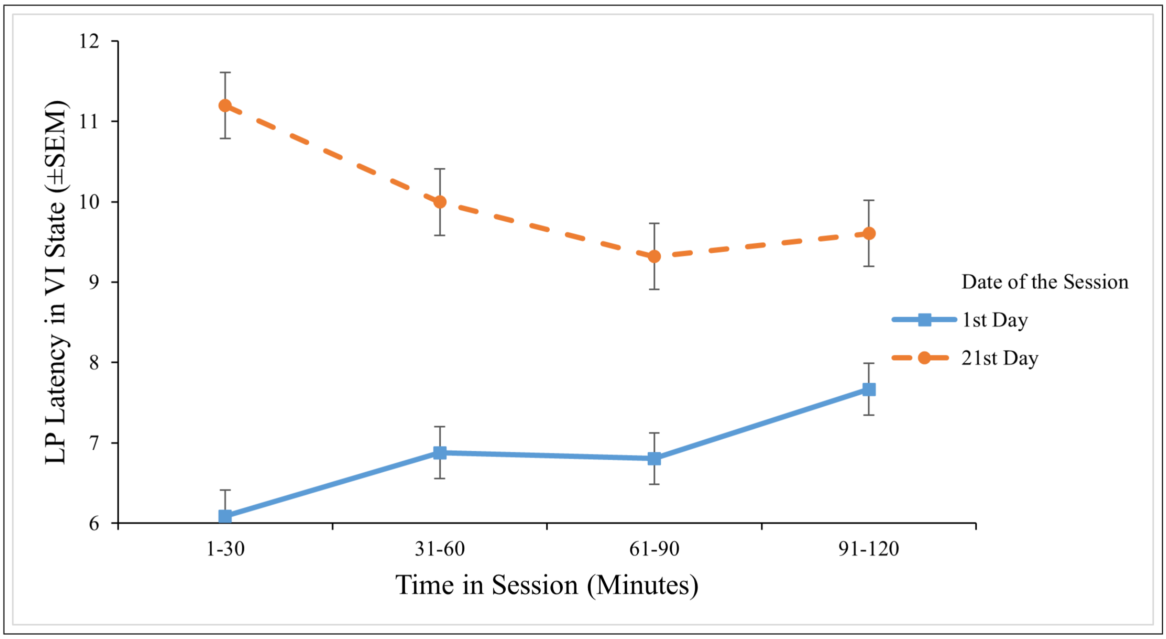


Figure 3.21 Lever Press Latency in VI State Across DAY and QUARTER.

3.2.1.4 Lever Press Latency in EXT State.

We found that the distributions were normally distributed and there were no outliers. Mauchly's test indicated that the sphericity assumption was met for DAY and QUARTER interaction effect ($\chi^2(5) = 8.594$, $p = 0.131$), and DAY (because it only has two groups), but was violated for QUARTER ($\chi^2(5) = 12.216$, $p = 0.034$). Greenhouse-Geisser corrections were used for the analysis of the main effect of QUARTER.

A repeated measures ANOVA with DAY and QUARTER as repeated measures factors revealed that, there were statistically significant main effects of DAY ($F\ (1,7) = 13.511$, $p = .008$, $\eta^2 = 0.659$), and QUARTER ($F\ (3,21) = 3.790$, $p = .026$, $\eta^2 = 0.351$) on lever press latency in EXT State. There was no statistically significant interaction effect of DAY X QUARTER ($F\ (3,21) = 2.651$, $p = .075$, $\eta^2 = 0.275$). Mean lever press latencies in EXT State (±SEM) across training session and time within session are shown in Figure 3.22.

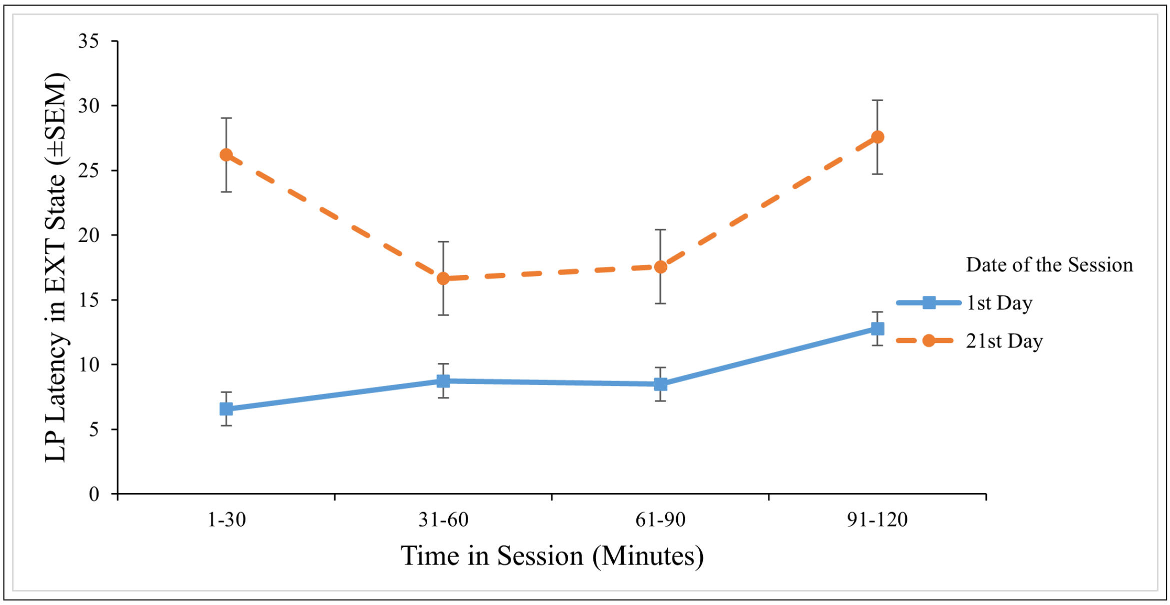


Figure 3.22 Lever Press Latency in EXT State Across DAY and QUARTER.

3.2.1.5 Lever Press Latency in Lever Press State.

We found that the distributions were normally distributed and there were no outliers. Mauchly's test indicated that the sphericity assumption was met for DAY X QUARTER ($\chi^2(5) = 1.730$, p = 0.887), and DAY (because it only has two groups), but was violated for QUARTER ($\chi^2(5) = 16.934$, p = 0.005). Greenhouse-Geisser corrections were used for the analysis of the main effect of QUARTER.

A repeated measures ANOVA with DAY and QUARTER as repeated measures factors revealed that, there was a statistically significant main effect of DAY (F (1,7) = 12.154, p = .010, $\eta^2 = 0.635$) on lever press latency in Lever Press state. The main effect of QUARTER (F (3,21) = 0.990, p = .369, $\eta^2 = 0.124$) and the interaction effect of DAY X QUARTER (F (3,21) = 0.973, p = .424, $\eta^2 = 0.122$) were not statistically significant. Mean lever press latencies in LP State (±SEM) across training session and time within session are shown in Figure 3.23.

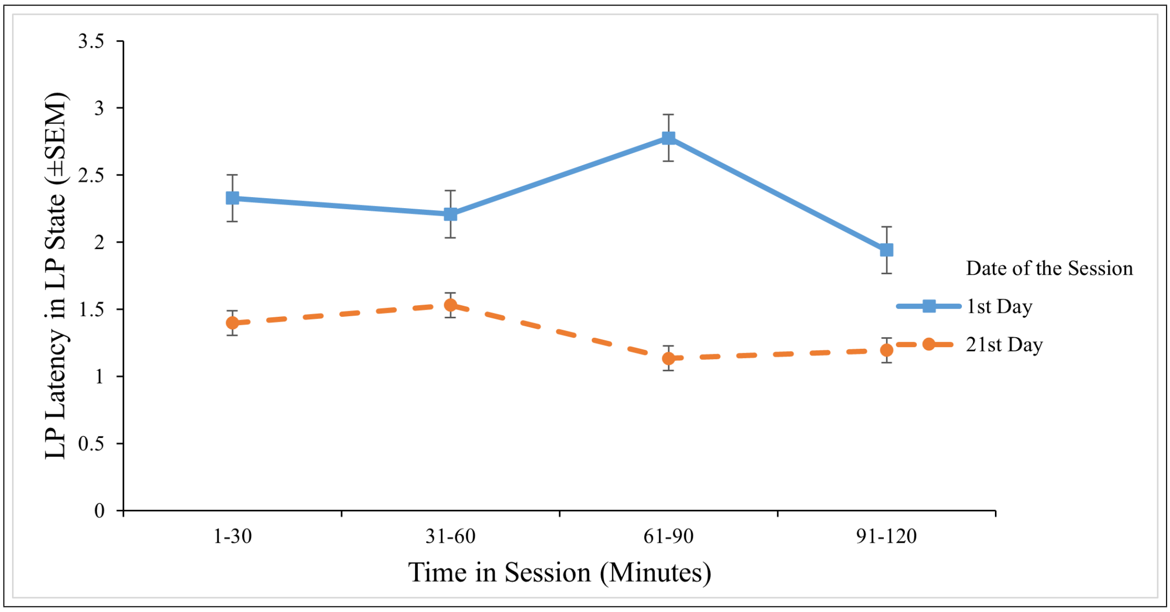


Figure 3.23 Lever Press Latency in LP State Across DAY and QUARTER.

3.2.1.6 Lever Press Rate in VI State.

We found that the distributions were normally distributed and there were no outliers. Mauchly's test indicated that the sphericity assumption were met for QUARTER ($\chi^2(5) = 8.328$, p = 0.144), DAY (because it only has two groups), and DAY X QUARTER ($\chi^2(5) = 3.275$, p = 0.662).

A repeated measures ANOVA with DAY and QUARTER as repeated measures factors revealed that, there were no statistically significant main effect of DAY (F (1,7) = .055, p = .821, $\eta^2 = 0.008$), and QUARTER (F (3,21) = 1.390, p = .273, $\eta^2 = 0.166$) on the lever press rate in VI State. Also, the interaction effect of DAY X QUARTER (F (3,21) = 1.711, p = 0.195, $\eta^2 = 0.196$) was not statistically significant. Mean lever press rates in VI State (±SEM) across training session and time within session are shown in Figure 3.24.

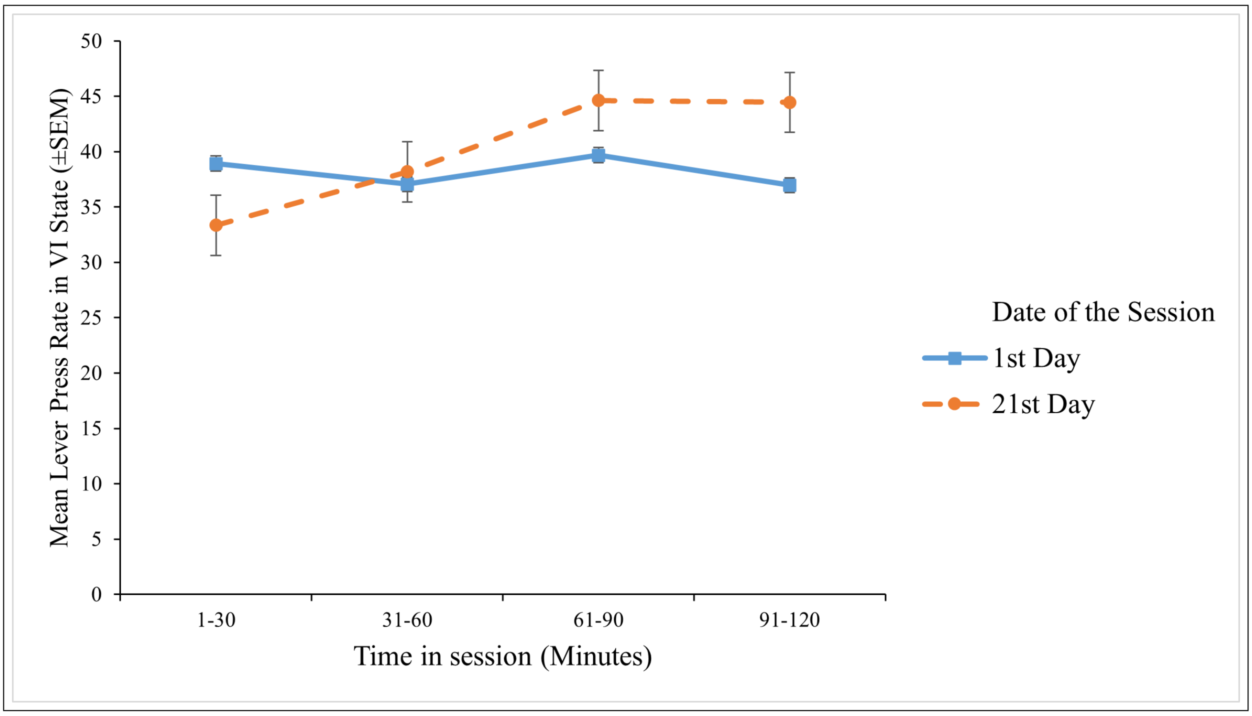


Figure 3.24 Mean Lever Press Rate in VI State Across DAY and QUARTER.

3.2.1.7 Lever Press Rate in EXT State.

We found that the distributions were normally distributed and there were no outliers. Mauchly's test indicated that sphericity assumption was violated for QUARTER ($\chi^2(5) = 22.086$, p = 0.001), and DAY X QUARTER ($\chi^2(5) = 12.161$, p = 0.035), but it was met for DAY (because it only has two groups). Greenhouse-Geisser corrections were used for the analysis of the main effect of QUARTER and the interaction effect of DAY X QUARTER.

A repeated measures ANOVA with DAY and QUARTER as repeated measures factors revealed that, there were statistically significant main effects of DAY (F (3,21) = 28.598, p = .001, $\eta^2 = 0.803$), and DAY X QUARTER (F (3,21) = 4.649, p = .047, $\eta^2 = 0.399$) on lever press rate in EXT state. The main effect of QUARTER (F (3,21) = 3.367, p = .088, $\eta^2 = 0.325$) was not statistically significant. Mean lever press rates in EXT State (±SEM) across training session and time within session are shown in

Figure 3.25.

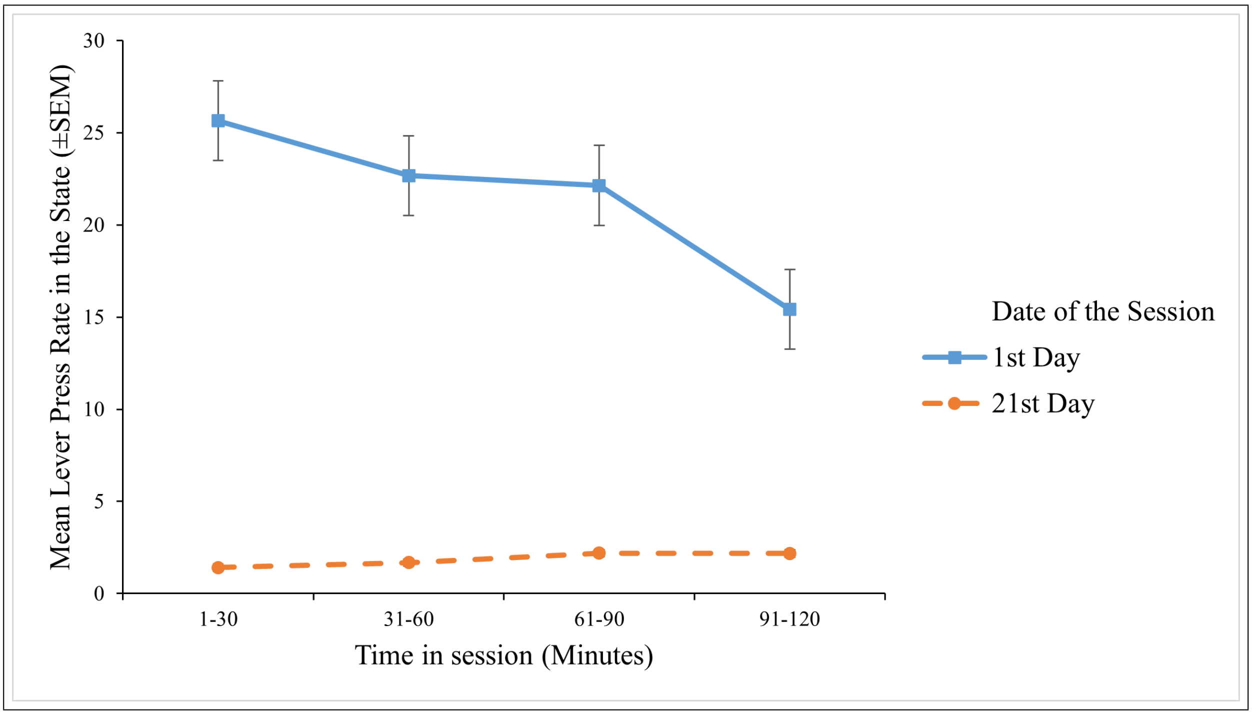


Figure 3.25 Mean Lever Press Rate in EXT State Across DAY and QUARTER.

3.2.2 Correlation Between Lever Press Rate and Time After Stimulus Onset in VI State

To test the hypothesis that, instrumental training with non-normal distributions lead to time independent response rate, we conducted a Pearson Correlation Analysis between time after stimulus onset and lever press rate in VI State on both the 1^{st} and the 21^{st} days of discrimination training. There were no outliers in any of the distributions, all distributions were normally distributed, and there was a linear relationship between the variables.

The results of the Pearson correlation analysis revealed that there was a significant moderate negative correlation between time after stimulus onset and lever press rate on the 1^{st} day of discrimination training (r (22) = -.493, p = .017), indicating that with increases in time after stimulus onset lever press rate decreased. However, the correlation between time after stimulus onset and lever press rate in the 21^{st} day of the discrimination training was not significant (r (22) = .284, p = .189), indicating that lever press rate was independent of time after stimulus onset. The scatter plots and linear regression analysis of time after stimulus onset and lever press rates on both the 1^{st} and the 21^{st} days of discrimination training are shown in Figure 3.26. We also found that there was a significant moderate correlation between the lever press rate on the 1^{st} day and the 21^{st} day of discrimination training (r (22) = .445, p = .033).

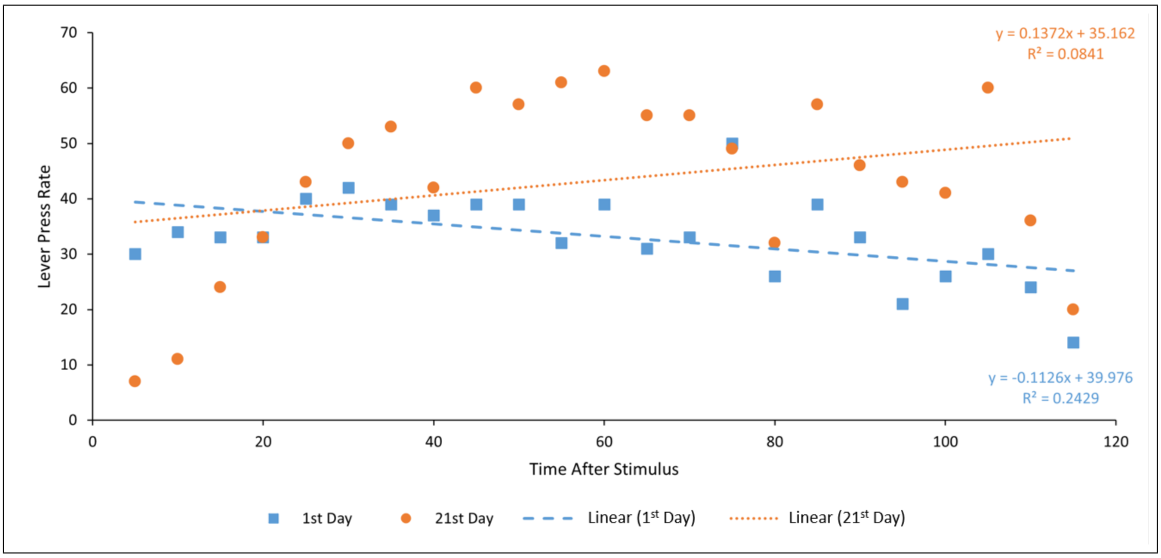


Figure 3.26 Scatter Plot and Linear Regression Analysis of Time and LP Rate Across DAYs.

Visual examination of the scatter plots indicated that a linear regression might not be the best fit to explain the relationship between time after stimulus onset and lever press rate. Thus, we also fitted a curvilinear function and found that the explained variance was higher with a 2^{nd} degree polynomial function. The scatter plots and 2^{nd} degree polynomial regression analysis of time after stimulus onset and lever press rates on both the 1^{st} and the 21^{st} days of discrimination training are shown in Figure 3.27. For VI intervals lasting 60 seconds or less, longer intervals correlated with a higher lever press rate and shorter intervals with a lower lever press rate. By contrast, for VI intervals between 60 and 120 seconds, longer intervals correlated with a lower lever press rate. Therefore the data predicted a time-dependency, but not a strictly linear one.

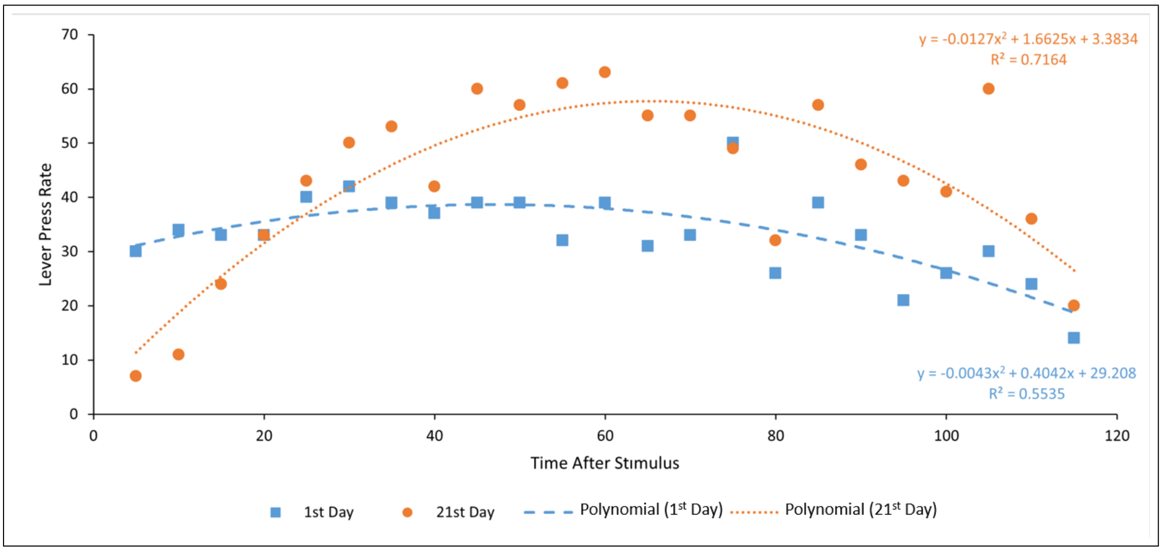


Figure 3.27 Scatter Plot and Polynomial Regression Analysis of Time and LP Rate Across DAYs.

4. Discussion

4.1 Present Study

The nature of the distributions of time intervals that are used for variable interval schedules is up to debate in the literature and some suggested utilizing positively skewed distributions [23]. However, in spite of their importance non-normal distributions can not be generated with current number generators. Therefore, our goal was to create a random number generator that is capable of generating non-normal distributions of time intervals and to analyse the effects of the generated distributions on instrumental behavior.

First, we established the procedure to generate the non-normal distributions of time intervals suggested by [23] in Microsoft Excel. Briefly, in order to attain a positively skewed distribution of time intervals we merged a normal distribution and an uniform distribution. Second, we studied the nature of the distributions of time intervals and the results generated by our procedure. Then, we descriptively analyzed these distributions of time intervals to analyze the nature of the distributions we generated. We also generated a probability of reinforcement curve for each distribution of time intervals according to [19] to have a measure of time dependency.

To study the effects of the non-normal distributions of time intervals on instrumental behavior, we trained 8 naïve wistar rats on FR and VI schedules according to Lombas et al. (2008)[23]. We used the positively skewed distributions of time intervals we generated for the variable interval schedules. We performed the instrumental conditioning using Graphic State 4 software and measured the number of lever presses, and latencies to lever press throughout the training. We specifically focused on the behavior in the 1^{st} and the 21^{st} day of the discrimination training to test whether our procedure led to learning and the positively skewed distributions of time intervals resulted in time independent behavior.

Finally, we conducted statistical analyses to investigate the nature of the generated distributions of time intervals and to analyze their effects on instrumental behavior. We descriptively analyzed the non-normal distributions of time intervals and plotted histogram charts. To measure learning, we conducted two-way repeated measures ANOVA on total number of lever presses, lever press rates and latencies to lever press as dependent variables with DAY and QUARTER as within group factors. We conducted a Pearson Correlation and linear regression analysis between time after stimulus onset and lever press rate to examine the time dependence of lever press rate. Further, we also conducted polynomial regression analysis between time after stimulus onset and lever press rates to find the line of best fit to explain the lever press rate in terms of time after stimulus onset.

4.2 Conclusions

We analysed the means, medians, modes, standard deviations, skewness, kurtosis, minimum and maximum values of the distributions of time intervals we generated. We also plotted the histogram charts of the distributions to have a broad understanding of the nature of the distributions. The objective of the descriptive analysis was to find out if our procedure was successful in generating distributions of time intervals with predefined parameters.

We found out that the procedure was successful in generating normal and non-normal distributions of time intervals with our chosen parameters. For example, the expected range for the VI45 distribution was between 1 and 120 while the mean was 45. The VI45 distribution we generated had a minimum value of 2 and a maximum value of 119 with a mean of 45.35. We also studied the skewness to confirm the shape of the distribution. The VI45 distribution was positively skewed at a skewness 0.922.

The probability of reinforcement function was suggested, to predict the effects of distributions of time intervals on instrumental behavior [19]. Probability of reinforcement curves show the probability that a reinforcement will be arranged at a particular time passed following the onset of the stimulus. Thus, it has a direct relationship with the response rate of the animal. Increase in the probability of reinforcement in a certain time period, leads to increase in response rate [19]. Thus, in order to lead to a time independent response rate, the probability of reinforcement curves need to be time independent as well. In other words, the probability of a reinforcement being arranged should stay relatively constant over time. Results of our study show that, p(rft) for VI30 and VI45 distributions were similar to that of a normal distribution. However, because of relatively more skewed distribution, VI45-EXT had a more desirable shape relative to other distributions we generated in our study.

Overall, the p(rft) data showed that the time dependency is not eliminated completely. But, this was expected, since the distributions of time intervals we used for this study were all finite distributions. For example, a VI45-EXT distribution with a minimum of 30 and a maximum of 120, has a probability of reinforcement of 1, 120 seconds after the stimulus. This automatically leads to time dependent behavior in the animals, because with a higher p(rft), the animals are expected to press the lever more. There are some studies that suggest using infinite distributions of time intervals or other probabilistic methods, but those cause other problems, such as extinction [17, 18].For this reason, Lombas et. al. utilized positively skewed distributions of time intervals to minimize the time dependency problem [23]. Here we showed that even though it does not eliminate the problem, extremely positively skewed distributions of time intervals, such as the VI45-EXT distribution used in the present study, might minimize the time dependency problem functionally.

We conducted two-way repeated measures ANOVA to analyze the performance of the animals that were trained with the distributions we have generated. The repeated measures factors were the DAY of the trial (1^{st} and 21^{st} day) and the QUARTER in the trial (1-4). The dependent variables were the Total Number of Lever Presses in VI State, Total Number of Lever Presses in EXT State, Lever Press Latency in VI State, Lever Press Latency in EXT State, Lever Press Latency in LP State, Lever Press Rate in VI State, and Lever Press Rate in EXT State.

We found that the Total Number of Lever Presses in VI State did not change significantly with DAY, contrary to our expectations, but that the Total Number of Lever Presses in EXT State dropped significantly by the 21^{st} day of the experiment as expected. Similarly, lever press rate did not change between days in VI state, whereas it dropped on the 21^{st} day of the experiment in EXT state. These results show that the experimental procedure we used, led to discrimination learning in the animals. Animals learned to discriminate between VI and EXT states through the 21 days of the experiment, and their behavior changed accordingly. However, contrary to our expectations, we did not see a change in lever press behavior in VI state in the 21 days of discrimination training. This might be due to the lengthy experimental procedure. Animals were introduced to the VI procedure before discrimination training. Thus, it might be possible that when we started discrimination training, animals were already saturated in terms of VI training and discrimination training led to no change in the behavior in VI state. However, EXT state was novel to the animals in discrimination training, so 21 days of discrimination training led to learning, as expected. Also, there are some physical limits for the lever press behavior. Animals learned to press the lever for a reward for more than three weeks before discrimination training. In these three weeks, they became pretty efficient at pressing the lever. Thus there might be no room left for improvement at the start of discrimination learning for the animals.

ANOVA analyses with QUARTER as the repeated measures factor shows that the lever press behavior was stable through the experimental trial. There were no significant differences across QUARTERS in the Total Number of Lever Presses in VI State, but the Total Number of Lever Presses in EXT State was smaller in the 4^{th} QUARTER compared to others. This might be due to learning within the trial. The reason behind that drop in the 4^{th} QUARTER might be that animals learn they would not get a reward even if they press the lever in EXT state, and they start pressing the lever less. However, this difference in the Total Number of Lever Presses in EXT State in the 4^{th} QUARTER might also be due to the randomness of the experimental procedure. In discrimination training, the occurrence of VI or EXT state is random, with an equal chance for both. Thus, in the 4^{th} QUARTER, there might be fewer EXT states, leading to a less lever press in EXT state in the 4^{th} QUARTER. This explanation is also supported by the lever press rate analysis, as there was no significant difference of lever press rate between the 4^{th} QUARTER and the others.Lever press rate is a better analysis of behavior for QUARTERS because it takes duration of the state into account.

We found that there was no significant difference in the lever press latency of the animals in VI state for both DAY and QUARTER, similar to the lever press rate behavior. As expected, the lever press latency in EXT state was higher in the 21^{st} day of the experiment compared to the 1^{st} day. As the animals pressed the lever less in EXT state as the experiment proceeded, they also pressed the lever later. We also showed that the lever press latency was higher in the 4^{th} QUARTER compared to the 3^{rd} QUARTER. This behavior change might be due to fatigue or within trial learning as we discussed for the changes in total number of lever presses in EXT state. As the experiment proceeded, animals learned the trial length and procedure and may have started to behave less motivated through the end of the trials. Further, we showed that the lever press latency in LP state was less in the 21^{st} day of the experiment compared to the 1^{st} day. This shows that even though the animals did not press the lever more in VI state, they learned to predict the reinforcement time. Animals were ready to press the lever when the experimental procedure went on to the LP state, thus the latency was less.

The main objective of the VI schedules is to lead to a steady instrumental behavior in the presence of the stimulus. But, finite distributions of time intervals are implemented, for practical reasons, which lead to an increase in lever press rates with increases in time after the stimulus onset [3, 17]. We conducted a Pearson correlation analysis, in order to see the changes in lever press rates of the animals with changes in time after the stimulus. The Pearson Correlation analysis showed a significant moderate negative correlation between time after the stimulus and lever press rates on the 1^{st} day of discrimination training. However, this correlation was not significant on the 21^{st} day of discrimination training. As expected, there was a linear relationship between time and lever press rates in the 1^{st} day of discrimination training. However, contrary to the expectations, the direction of the relationship was reversed, meaning the lever press rates decreased with time after the stimulus onset. This might be due to the FR training. In FR training the animals were trained to press the lever as soon as the stimulus was presented, thus it reinforced lever presses right after the stimulus. This decrease in lever press rate with time after stimulus increasing might be a residue effect of FR training, that gradually disappear in VI training. After 21 days of discrimination training, there was no linear relationship between lever press rate and time after the stimulus onset as expected.

However, with the visual examination of the scatter plots, we noticed that there might be a curvilinear relationship between the lever press rates and time after the stimulus onset. Thus, we conducted regression analyses with both linear and polynomial regression functions. We found that data from the 21^{st} day of discrimination training fit the second-degree polynomial regression function better than the linear function. The regression line resembled a reverse U shape meaning lever press rates were lower for shorter and longer time intervals but peaked for moderately long intervals. The decrease in lever press rates for shorter intervals might be due to the initial pause. Skinner observed that the interval schedules led to an initial pause after the reinforcement, but the lever press rates increased back to a steady average response rate quickly [2]. Similarly, we observed a decrease in lever press rates for the first 15 seconds of the VI state. We also observed a decrease in lever press rates for longer intervals. This decrease in lever press rates for longer intervals was also evident on the 1^{st} day of discrimination training as well. This decrease in lever press rates for longer intervals might be due to fatigue or a decrease in motivation with longer intervals. In other words, we observed a positive linear correlation between time after stimulus onset and lever press rate for VI intervals with a duration of 60 seconds or less and a negative linear correlation between time after stimulus onset and lever press rate for VI intervals with a duration between 60 and 120 seconds. Therefore, the data predicted a time-dependency, but not a strictly linear one.

4.3 Limitations and Future Directions

In this study, we created a novel procedure to generate non-normal distributions of time intervals for use in VI schedules [23]. The non-normal distribution generator works as intended. However, as we can see in the probability of reinforcement functions of the distributions we generated, none of the distributions were perfectly time independent [19]. As Catania and Reynolds argue, if the probability of reinforcement function changes with time, then that distribution of time intervals will lead to time-dependent behavior. In order to create time-independent behavior, distributions with infinite time intervals should be implemented.

We created a procedure that generates non-normal distributions that are generally used in VI schedules. However, as this project was part of a bigger BAP project, we only worked on the behavioral effects of the non-normal distributions. Even though there are many studies on the behavioral effects of uniform and exponential distributions of time intervals, a comprehensive controlled comparison of the behavioral implications of non-normal, uniform, and exponential distributions is necessary to confirm the findings of our study. The next goal for this study would be to publish the generator for use by others, as it provides an easy to use method to generate and implement non-normal distributions for instrumental conditioning.

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