

# How Imperfect Practice Leads to Imperfection: A Hierarchical Linear Modeling Approach to Frustration during an Iterative Decision

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## ABSTRACT

This paper proposes the concept of law of diminishing returns and decisional commitment, by studying the way in which subjects hone in on a set of choices to make a decision over several decision occasions. We conducted an experiment with seventy-nine subjects who had to choose a computer they would buy, given monetary constraints, from a large choice set. Our goal in this research was to study how elapsed time and number of decision occasions affect choice quality.

We utilized hierarchical linear modeling in order to study the individuals' choice quality growth over time along with several individual-level covariates. Specifically, we posited that there may be conditions under which the law of diminishing returns may not always prevail to explain choice decisions. Our findings show significant results for two different models. The first model shows that choice quality and elapsed time are related in a quadratic fashion with confidence as a significant level 2 predictor. The second model shows that choice quality and number of decision occasions are linearly related with frustration as a significant level 2 covariate. Overall, the results show that the choice quality decreases over time, especially for those with high confidence level; choice quality increases with the number of decision occasions, especially for those with high frustration level.

## BACKGROUND LITERATURE

In order to understand how consumers arrive iterate to a choice gradually, we must first introduce and explain the literature surrounding the models we will formulate.

*Amount of information presented.* Previous research on choice set construction has shown that when the amount of information

displayed is structurally varied, information overload, resulting from less information acquisition, can result in lowered decision quality (Keller & Staelin; 1987; Lurie, 2004). Many researchers have shown that the two primary causes of the overchoice effect are cognitive load and anticipation of regret (Gourville & Soman, 2005). Cognitive load has been shown to be induced by increasing the set size (Iyengar & Lepper, 2000) whereas anticipation of regret can be reduced by offering warranties or returns on products. When consumers perceive a higher level of complexity with information than they were expecting, whether this is on a website or in a choice set, they tend to experience lower satisfaction and higher frustration (Krishen & Kamra, 2008). This research aims to explore an interesting question in regards to the ultimate choice quality, amount of time required, and the subjective state of the person.

The law of diminishing returns, stated as "When increasing amounts of one factor of production are employed in production along with a fixed amount of some other production factor, after some point, the resulting increases in output of product become smaller and smaller" (Johnson, 2005). Although this law was originally proposed to explain productivity in farming situations, it has continued to be applied to consumer choice models to explain, for example, attribute valuation (Johnson & Meyer, 1995). Economics literature has introduced cost-benefit analysis, which has been applied to consumer decision making strategy (Payne, Bettman, & Johnson, 1993) in terms of the trade-off between effort (cognitive load) and accuracy (choice quality). This framework suggests that compensatory decision making strategies are often bypassed in order to save effort and use noncompensatory heuristic ones, leading to a possible decrease in decision accuracy (Luce, Bettman & Payne, 2001).

*Decisional commitment.* Wood (2001) studied decision commitment in the context of return policies and signaling theory in e-commerce purchasing decisions. The commitment she discussed centered on a situation in which a consumer makes an initial decision, is presented further information, and then either chooses to commit to the initial decision or explore other alternatives. Other researchers have discussed decision commitment in terms of post-rationalization of a choice or judgment, discussing factors such as accountability (Tetlock, 1991; Luce, Bettman & Payne, 2001).

In the current research, subjects are presented with a set of choices which they can choose to iterate through as many times as they wish, until they reach a suitable decision. The aim is to investigate the relationship between the subjective outcomes of confidence and frustration as they relate to the objective outcomes of choice quality and elapsed time. Commitment, defined as, "...the state of being bound emotionally or intellectually to a course of action..." can be applied to a decision making context when subjects actually have the ability to freely choose until they reach their final decision (Houghton Mifflin, 2000). Thus we introduce the concept of decisional commitment in order to allow subjects to actively decide when they want to commit to a choice.

*Frustration, Satisfaction, and Confidence.* Fitzsimons, Greenleaf, and Lehmann (1997) discuss consumption satisfaction and decision satisfaction, noting that the latter is a more specific case of the former. In an empirical setting, Zhang and Fitzsimons (1999) suggest that the key delineator in this particular outcome variable is the word "process." Whereas most satisfaction research focuses on a consumers' post-choice satisfaction with the choice itself (Houston, Sherman, & Baker, 1991), choice process satisfaction as a variable was created in order to separate the *process* of making a choice with the choice itself. Krishen, Nakamoto and Herr (2008) conduct several studies which delineate between a choice process and a choice outcome (or choice process satisfaction or frustration versus decision satisfaction). They find that frustration and

satisfaction are consistently significantly negatively correlated across several experiments.

Botti and Iyengar (2004) highlight the difference between choosers and non-choosers by finding that the simple act of choosing is not a sufficient condition for outcome satisfaction. At a glance, this is something often taken for granted – that when an individual is presented with an array of goods and provided with one gratis, he/she will experience some level of satisfaction *above* that of someone who is merely presented with the same array of choices and not allowed to pick one. Yet Botti and Iyengar (2004) showed that it is not the simple act of choosing which produces increased satisfaction; individual goals and desires interact with the situation to determine final satisfaction. Iyengar and Lepper (2000) found similar angularities in subjective response to their extensive choice participants. In their sample, extensive choice participants reported enjoying the choice process more while still finding it to be more frustrating and difficult. Iyengar and Lepper (2000) conclude that the overchoice condition may have been more enjoyable but it was still overwhelming. Whereas frustration seems to be tied more to the *process*, satisfaction (even though it is measured as *choice process* satisfaction) appears to be linked more to the *outcome*. Research shows that higher knowledge normally translates to higher confidence (Krishen, Nakamoto, & Herr, 2008). Wood and Lynch (2002) reason that high knowledge consumers may have more confidence than they should about a new stimulus and therefore may process it less extensively.

## HYPOTHESES

A combination of the law of diminishing returns with this effort-accuracy framework would lead to the notion that choice quality, at some point, would be lessened by the addition of effort (computed as elapsed time), after passing the optimal choice in the optimal elapsed time. If the amount of information presented to the subjects is varied either systematically or randomly, the above hypothesis still holds true. Thus, the shape of the relationship between quality and elapsed time will hold constant even when the amount of

information presented varied. Thus we posit the hypothesis:

**H1:** *The shape of the relationship between choice quality and elapsed time will be quadratic, as in the law of diminishing returns; thus as the elapsed time increases, the choice quality will increase to a point past which the relationship will curve downwards.*

The second hypothesis of this study entails how measurement occasions, which, in some sense measures decisional commitment, relates to choice quality across subjects. Specifically, consumers with more experience are presented with more information regarding the alternatives, and would learn from the iterations of decision. The consumer then can choose to commit to his/her own initial decision, or switch to a better choice; as a result, the decision quality would increase as the latter iterations of decision occasions. We thus hypothesize that:

**H2:** *As the number of decision occasions increases, the choice quality per choice set will also increase.*

## THE MODELS

### *Model 1: Quality Over Time*

This research utilizes hierarchical linear modeling (HLM) to study how subjects change as they move towards their final choice decision. HLM allows the creation of two levels, the first which utilizes within-person data as separate decision occasions, and the second which allows single person-level outcome measurements to be integrated into the overall model (Raudenbush & Bryk, 2002). Given that our H1 hypothesis calls for a diminishing returns model, we formulate our level one equation as follows:

$$Y_{it} = \pi_{0i} + \pi_{1i}(\text{Elapsed Time})_{it} + \pi_{2i}(\text{Elapsed Time})_{it}^2 + e_{it} \quad (1.1.1)$$

The level one model is specified such that the dependent variable,  $Y_{ij}$  represents the choice quality per choice decision at time  $t$  for subject  $i$ . The first term on the right-hand side of equation

1.1.1, the intercept parameter, is the base ability of the person  $i$  at time 0. The independent variable in the equation is elapsed time. The first coefficient  $\pi_{1i}$  is the growth rate (i.e. improvement or decline) for subject  $i$  over the multiple subsequent occasions; thus it is the expected change during a fixed period of time. Finally, as this is formulated as a quadratic model, we also include  $\pi_{2i}$  as the acceleration of the growth rate for subject  $i$  over multiple subsequent occasions.

At the aggregate level, we also consider confidence as a critical individual characteristic that affects how the choice decision changes over time for a consumer. For a consumer with a higher level of confidence, his/her choice quality may decrease dramatically when he/she spent more time on making the decision. Therefore, at level 2 we have these equations:

$$\pi_{0i} = \beta_{00} + \beta_{01}(\text{Confidence}) + r_{0i} \quad (1.2.1)$$

$$\pi_{1i} = \beta_{10} + \beta_{11}(\text{Confidence}) + r_{1i} \quad (1.2.2)$$

$$\pi_{2i} = \beta_{20} + \beta_{21}(\text{Confidence}) + r_{2i} \quad (1.2.3)$$

The level two model, represented by equations 1.2.1, 1.2.2, and 1.2.3, allows for the specification of several person-level covariates, measured as independent variables.

### *Model 2: Quality Over Occasions*

Our second model will be used to test the second hypothesis which centers on the individual learning which occurs during the choice process. Again, hierarchical linear modeling will allow for measurement from the individual growth perspective. Thus, our level one equation will be as follows:

$$Y_{it} = \pi_{0i} + \pi_{1i}(\text{Decision Occasions})_{it} + e_{it} \quad (2.1.1)$$

At the aggregate level, we also take an individual difference into account to model the cross-individual differences. Level of frustration while making the decision may have an influence on how consumers' choice quality improves through the learning process. Thus, we posit frustration as a predictor as the personal level. At level 2, we have these equations:

$$\pi_{0i} = \beta_{00} + \beta_{01}(\text{Frustration}) + r_{0i} \quad (2.2.1)$$

$$\pi_{1i} = \beta_{10} + \beta_{11}(\text{Frustration}) + r_{1i} \quad (2.2.2)$$

Unlike model 1, this model is formulated such that occasions should be linearly related to choice quality. The variable specifications are identical to those given above, with the exception of the independent variable, decision occasions, which represents the number of times each person traverses through the decision process. The important note model 2 is that decision occasions are user-determined, i.e. the subjects are free to stay or leave the decision making process at will.

## THE EXPERIMENT

In this research, each subject was given the task of selecting the best possible computer from the choice set given to them per iteration, at or under \$3000. The initial set of choices they were presented was randomly constructed from the database of over 4000 computers. Regardless of the number of computers presented to the subject, we wish to study the within-subject behavior which unfolds as the person progresses through subsequent decision occasions. The present research question, then, centers on the relationship between the concept of decisional commitment, the time-quality tradeoff, and several post-choice subjective measures. The process used to make a decision is not specifically measured or relevant in this study, making it different than studies of, for example, emotional reaction to information/time constraints (as in Luce, Bettman & Payne, 2001) or effort-accuracy with regards to information overload (as in Lurie, 2004).

A software program was created in order to allow subjects to traverse through a choice process gradually (or abruptly, if they chose to do so). In order to simultaneously assess the quality and efficiency of the choice experience for each subject, we used both subjective measures (frustration and confidence) and objective measures (total elapsed time, total number of computers viewed, and final choice quality). The subjective measures were measured one time during the choice experiment per person, thus they are present as level 2 variables in our HLM model. The objective

variables were measured each time the subjects made a choice, and since the number of choices each subject made varied, these are present as level 1 variables in our HLM model.

## Experimental Procedure

*Design and Task.* After conducting two pretests, we determined attributes along with corresponding information to form a valid set of data for our choice paradigm. For our main experiment, 79 marketing undergraduates, enrolled in an introductory level marketing course participated in this study.

*Information Acquisition System.* A computer program (as shown in Figure 1) was designed in order to create the choice paradigm for the subjects; it contains a dataset of over 4000 choices. Subjects were presented with the following attributes per choice:

1. Make (brand) – Gateway, Dell, IBM, HP (4 options)
2. Model (fictitious combination of letters and numbers)
3. Processor speed – 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0 (7 options)
4. Hard drive size – 20, 40, 60, 80 (4 options)
5. RAM – 256 MB, 512 MB, 1024 MB (3 options)
6. Drive type – none, CD-ROM, CD-RW, DVD/CD-RW (4 options)
7. Internet connectivity – none, modem, ethernet, ethernet/wireless (4 options)
8. Price - ranges from \$499.99 to \$5044.99

Our pretests allowed for brand ranges in the dataset so as to reduce the impact of brand preference (Krishen and Nakamoto, 2009). Also, we assessed brand preferences for the brands represented in our dataset, and did not find any significant brand preferences for the participants. In the experiment, each subject was presented with the following task:

After hitting continue, you will be presented with a set of computers on the right hand side of your screen. Given a budget of at or under \$3000,

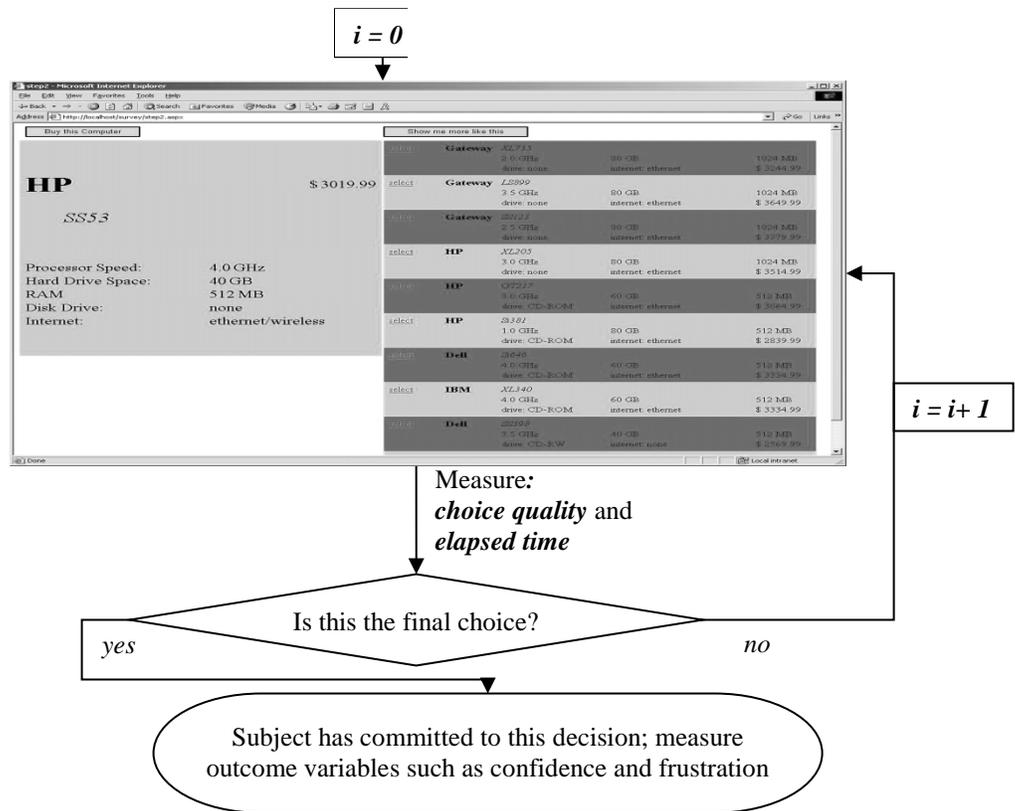
select the computer that best fits your needs for each set you see. Each time you pick one from the group presented to you, you will be presented with another set to choose from. Continue selecting computers until you think you've found the best selection for you. At that point, click the "Buy" button.

The set of initial choices presented to each subject was randomly generated. Determining which computers to display in the software program, following the initial random set, was accomplished through an "adaptive windowing" process using what we term the p-q choice algorithm. The P-Q metric is calculated for each occasion of the choice set experienced by the subject. To make this decision, we use a square window, centered on the previous choice on the p-q plane. We choose 80% of the next set of

computers to be displayed from inside this window. The remaining 20% are uniformly randomly selected. If the user clicks a choice again inside this window, the window size is adaptively reduced. Further, if the user clicks outside of this window, the window size is adaptively increased.

It is important to note that although this adaptive windowing should create higher quality choices over time; that is not guaranteed programmatically. This is due to the fact that subjects may make a less optimal choice which will then be adapted to in their next decision occasion. Figure 1 shows the decision process and the interplay between the variables of our model.

**Figure 1**  
**Decision Making Process**



### Experimental Variables

Choice quality was collected as the dependent variable in this study, measured by comparing the chosen computer per choice set with the best and worst ones in that set; this method of determining choice quality was also used by Luce (2004). The dependent variable, elapsed time was measured in seconds per choice set; Covariates, such as frustration and confidence, are also included in the level 2 model; the measurements of the covariates are listed in Appendix A.

Table 1 shows the descriptive statistics for the model variables. Elapsed time and choice quality are measured per choice occasion (which are collected per subject multiple times) and thus have  $n=699$ . On the other hand, the level 2 variables of interest are collected per person following the completion of the choice task, therefore there are only  $n=75$ . It is also interesting to make note that confidence and frustration have the high variances.

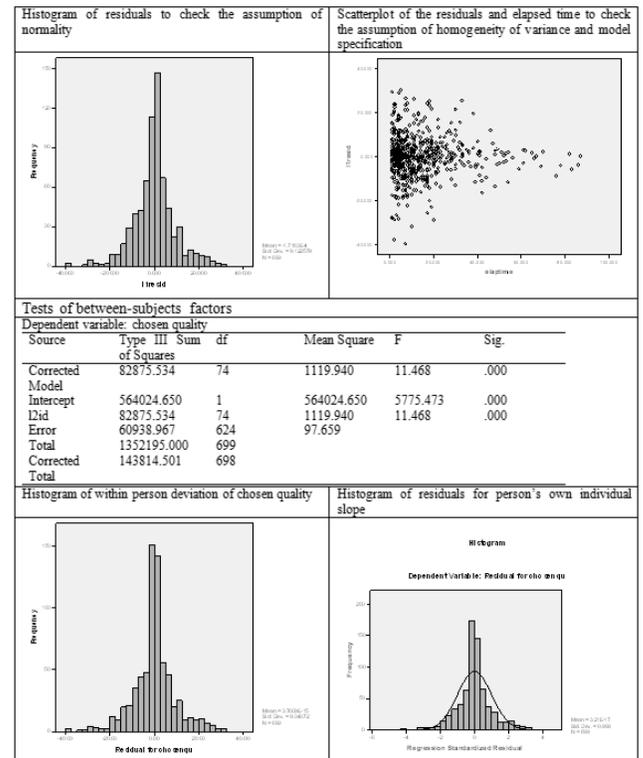
**Table 1**  
**Model 1 And 2 Variables**

| Variables      | N   | Mean  | Standard Deviation | Minimum | Maximum |
|----------------|-----|-------|--------------------|---------|---------|
| Occasion       | 699 | 10.84 | 12.62              | 1       | 71      |
| Elapsed time   | 699 | 12.95 | 14.21              | 1       | 87      |
| Chosen quality | 699 | 41.58 | 14.35              | 6       | 77      |
| Confidence     | 75  | 4.98  | 1.41               | 1.67    | 7       |
| Frustration    | 75  | 2.71  | 1.34               | 1       | 6       |

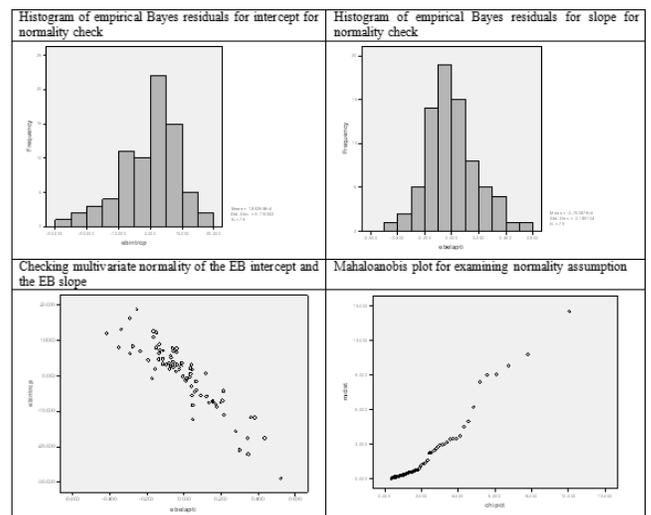
### Assumption Checks

Tables 2 and 3 illustrate the process used to check the required assumptions for formulation of models 1 and 2. As shown in the tables, the assumptions seem to be close to met. The one possible problem can be seen in Table 2, in the scatterplot of residuals and elapsed time for the assumption of homogeneity of variance; this plot does not necessarily appear to be homogeneous. There is more of a fan pattern in this graph. The other assumption checks for both Table 2 and 3 show that the assumptions are otherwise met.

**Table 2**  
**Level 1 Assumptions**



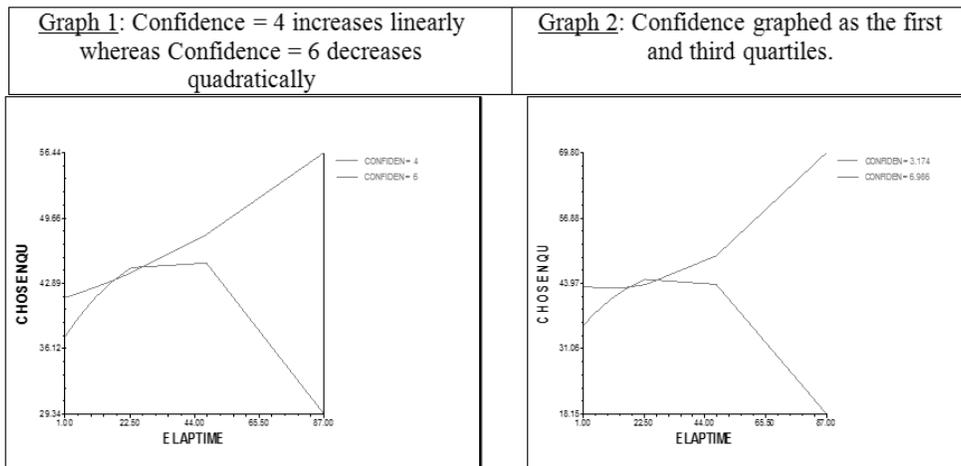
**Table 3**  
**Level 2 Assumptions**



**Table 4**  
**Model 1 Results**

|                      |                                     |     |                           |                           |           |                   |                |
|----------------------|-------------------------------------|-----|---------------------------|---------------------------|-----------|-------------------|----------------|
| <i>Fixed effect</i>  |                                     |     |                           |                           |           |                   |                |
|                      | <i>Fixed effect</i>                 |     | 27.870548                 | 6.477309                  | 4.303     | 73                | 0              |
|                      | CONFIDEN,                           | B01 | 2.243724                  | 1.246581                  | 1.8       | 73                | 0.076          |
|                      | For ELAPTIME SLOPE,<br>P1, INTRCPT2 | B10 | 1.266048                  | 0.397114                  | 3.188     | 73                | 0.003          |
|                      | CONFIDEN                            | B11 | -0.195301                 | 0.07838                   | -2.492    | 73                | 0.015          |
|                      | For ELAPSQUA SLOPE,<br>P2, INTRCPT2 | B20 | -0.021517                 | 0.005013                  | -4.292    | 73                | 0              |
|                      | CONFIDEN                            | B21 | 0.003738                  | 0.001014                  | 3.686     | 73                | 0.001          |
| <i>Random effect</i> |                                     |     | <i>Standard deviation</i> | <i>Variance component</i> | <i>df</i> | <i>Chi-square</i> | <i>P-value</i> |
|                      | INTRCPT1                            | R0  | 11.10442                  | 123.30812                 | 22        | 160.67007         | 0              |
|                      | ELAPTIME SLOPE                      | R1  | 0.55287                   | 0.30567                   | 22        | 47.03835          | 0.002          |
|                      | ELAPSQUA SLOPE                      | R2  | 0.0064                    | 0.00004                   | 22        | 34.67878          | 0.042          |
|                      | level-1                             | E   | 9.44786                   | 89.26204                  |           |                   |                |

**Figure 2**  
**Confidence as a Covariate**



## RESULTS

### Model 1: Quality Over Time

Tests of H1 began by checking the linear model for choice quality and elapsed time. Table 4 shows model 1 results.

In the final analysis of the relationship between chosen quality and elapsed time, the results show that the decision quality decreases quadratically with elapsed time. In addition, the effects of the squared elapsed time differ by a consumers' level of confidence regarding the decision. The results suggests that with a high level of confidence, a consumer's decision quality will more prominently decrease with squared elapsed time, as compared to one with lower level of confidence.

The results can be illustrated by Figure 2. For a consumer with low level of confidence, his/her choice decision would increase if he/she spends more time on the decision; however for a highly confident consumer, the decision quality decreases with time elapses.

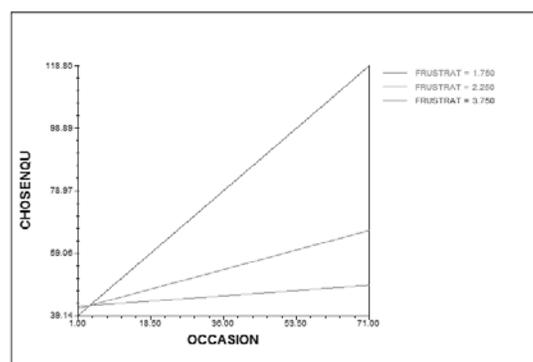
### Model 2: Quality Over Occasions

Tests of H2 began again by the same unconditional model as is given above. Table 5 shows the results for the analysis of this model.

**Table 5**  
**Model 2 Results**

|                      |                      |     |           |          |           |           |       |
|----------------------|----------------------|-----|-----------|----------|-----------|-----------|-------|
| <i>Fixed effect</i>  |                      |     |           |          |           |           |       |
|                      | <i>Fixed effect</i>  |     | 45.426866 | 3.802149 | 11.948    | 73        | 0     |
|                      | FRUSTRAT             | B01 | -1.98008  | 1.257234 | -1.575    | 73        | 0     |
|                      | <i>Random effect</i> |     | -0.815277 | 0.604708 | <i>df</i> | 73        | 0.182 |
|                      | FRUSTRAT             | R0  | 9.54047   | 0.201328 | 74        | 73        | 0     |
| <i>Random effect</i> |                      |     | 9.89393   | 97.88991 |           |           |       |
|                      |                      |     |           |          |           |           |       |
|                      | OCCASION SLOPE       | R1  | 1.47999   | 2.19037  | 69        | 414.88208 | 0     |
|                      | level-1              | E   | 8.69812   | 75.65721 |           |           |       |

**Figure 3**  
**Frustration as a Covariate**



The result shows that the decision quality increases linearly with choice occasions, indicating the learning effect in the decision process. This relationship between decision quality and choice occasion is more prominent when the level of frustration is high for the consumer. The results can be illustrated by Figure 3. When the data is plotted in quartiles, it shows the positive association between decision quality and the number of choice occasions; the association increases and the choice quality increases. For a consumer with high level of frustration, the increase rate of decision quality with decision occasions is higher than those with low level of frustration.

### CONCLUSIONS AND IMPLICATIONS

The results of this study show several interesting characteristics of choice decisions which hold even when the amount of information presented to a subject varies between choices. Using hierarchical linear modeling to analyze the data provides interesting insight into the way in which subjects traverse through their decision process at their own pace, with their own level of perfection, to meet their final decision. In the present research, respondents iterated through a choice process, and eventually reported their frustration and confidence, both of which serve as indicators of future satisfaction with the final decision. The connection between frustration with a shopping process and dissatisfaction with the decision itself has been studied and verified by several researchers (Yan & Lotz, 2009); this includes a study by Lee (2003) which suggests that frustrated customers are more likely to complain about their dissatisfaction with vending machines.

There are several important aspects of this research. First, our findings show that even though spending too much time often yields diminishing returns with regards to quality, there are exceptions to this phenomenon. As model 1 shows, when subjects spend too much time on making choice decisions, a consumer with high level of confidence is in fact suffer from lower choice quality. That is, highly confident consumers should not spend too much time on making choice decision. This finding is significant given that Lichtenstein et al. (1982)

have previously noted a highly researched finding in decision and judgment theory, overconfidence bias, which essentially shows that people often mis-calibrate their knowledge level. Second, we study the within-subject outcomes per decision iteration (occasion) using hierarchical linear modeling, which allows for rich formulation of the model and accounts for how subjects undergo a growth process as they make their decision.

Third, the second model was introduced to further expand on the relationships between occasions and quality. This model, as could be expected, showed how the quality of a subject's decision improves as he/she continues to iterate through occasions. Further, we found that frustration was a significant covariate in the model, and though not always the desired result, we showed that when subjects iterate through occasions and increase the quality of their decision more significantly; this relationship is stronger for consumers with higher level of frustration. This result could have direct impact, for example, on the way choice scenarios are constructed in the e-commerce domain and the process by which businesses can provide decision satisfaction. Essentially, consumers need to be provided with ample information so as to make decisions with as few iterations (i.e. clicks) as possible to improve their outcome satisfaction.

In summary, this research could be further extended such that we test the model with a different choice scenario, for example, by providing a website shopping experience. In a further study, we could take the confidence scale and research whether the phenomenon observed in terms of confidence level is more of an individual difference or if it is domain and task specific. Another avenue for future research would involve an extension of a choice process to eventually determine how the consumer would react to the decision made in terms of word of mouth. By providing an experiment in which the consumer could eventually choose to voice a complaint, the level of dissatisfaction or frustration with their choice could be determined (Koprowski & Aron, 2013). Finally, overconfidence and risk propensity are large research areas and may be an interesting set of scales to add in.

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## APPENDIX: Variable scales

### 1. *Confidence*

To measure the subject's confidence in her completion of the given task, we used a three-item seven-point semantic differential (Bruner, et al, 2001). The items consist of: uncertain/certain, not sure/sure, and not confident/confident (*Cronbach's*  $\alpha = .97$ ).

### 2. *Frustration*

We adapted a four-item Likert-type scale (not at all – very) to measure the degree of frustration the subject's experience during their interaction with the program (Taylor, 1994). The items in this scale consist of: uneasy, frustrated, angry, and uncertain. We used the following question: "The choice task made me feel..." for each of the items; the results were reliable (*Cronbach's*  $\alpha = .85$ ).