Using Rasch Modeling to Explore the Motorcyclist's Behavioral Intention in Red-light Running

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Abstract: An advisable 'evidence-based' strategy to reduce the red-light running should be built upon higher priorities of the driver's behavioral intention to run the red light under the common situations without the public controversies in the future. The purpose of this study is to use Rasch modeling with objective measurement to explore the priorities of the motorcyclist's behavioral intention in red-light running under the common situations. The results indicated that the participants reported higher levels of motorcyclist's behavioral intention in red-light running when there is nobody at night time, they are in a hurry, and they pass by not much heavy intersections; on the other hand, they reported lower levels of motorcyclist's behavioral intention in red-light running when there are passengers in the vehicle, and it is raining. In addition to red light cameras, this study provided traffic safety experts with objective evidence of other possible strategies to reduce the red-light running under the common situations from the behavioral science and Rasch modeling perspective.

Key Words: red-light running, Rasch modeling, motorcyclist's behavioral intention

1.INTRODUCTION

Running the red light is one of the most frequent and dangerous driving behaviors, which quite often result in fatal and injury crashes, especially for motorcyclists. The U.S. Department of Transportation (U.S. DOT) (2007) reported that there were 2,199 and 233,000 fatal and injury motor vehicle crashes occurred at signalized intersections respectively in the United States in 2006. In Taiwan, the numbers (percentages) of fatal and injury motor vehicle crashes caused by traffic signal violations were 265 (8.54%) and 27,135 (12.79%) respectively in 2006 (Taiwan National Police Administration, 2007). In a study of 4,526 police-reported crashes from four urban areas (Akron, Ohio; New Orleans, Louisiana; Yonkers, New York; and Arlington County, Virginia), Retting et al. (1995) found that running red light was the most common urban motor vehicle crash type, accounting for 22% of urban crashes and 27% of all injury crashes. In another study of 5,112 observations of drivers entering six signalized intersections in three cities (three Southeast Virginia cities),

Porter and England (2000) found that 35.2% of observed light cycles had at least one red-light runner prior to the onset of opposing traffic.

One of the major causes for the driver to run the red light is mostly explained by their driving situations, such as shorter yellow signal timing with higher red-light running (Bonneson and Son, 2003; Bonneson and Zimmerman, 2004). To prevent the driver from running the red light, we need thoroughly understand which situations will easily cause the driver to run the red light. In many studies, researchers have indicated that there are some situations which resulted in running the red light. Porter and England (2000) found that higher red-light running rates were observed in cities with larger intersections and higher traffic volumes. In a study of 880 licensed drivers participated in a telephone survey of red light running perceptions and behaviors, Porter and Berry (2001) found that the drivers reported being more likely to run the red light when driving alone (i.e., passengers reduced drivers' tendencies to run the red light), and speed up to beat the red lights when they were in a hurry, which was also found at the earlier Shinar's (1998) study. In addition to Porter and England (2000), Shinar (1998), Mohamedshah, Chen, and Council (2000), and Martinez and Porter (2006) all found that more red light running was associated with higher traffic volumes. Putranto and Sucipto (2007) observed an intersection approach in Jakarta, Indonesia, and found that the degree of saturations (Q/C) may influence motorcyclists' behaviors. Nevertheless, except Putranto and Sucipto's study, most of the studies were on the red light violation by car drivers instead of motorcyclists.

To reduce red light running and associated crashes, there have been numerous possible countermeasures to address up to now. Red light cameras (RLCs), which are expected to increase the driver's risk perception of being caught for violations, have been used extensively in a number of cities all over the world (Retting, Ferguson, and Hakkert, 2003; Retting, Ferguson, and Farmer, 2008) and shown consistently to reduce red light violations in US cities from about 40% (Retting et al., 1999a, 1999b) to 78% (Martinez and Porter, 2006). In British Columbia, Canada, there were 69% and 38% reduction in red light violations one and six months after the introduction of red light cameras, respectively (Chen et al., 2001). After reviewing international red light camera studies, Retting et al. (2003) concluded that red light cameras can reduce about 40-50 % red light violations. However, in addition to flaws in methodology (Office of the Majority Leader, 2001), the use of this approach may face with the public controversies such as collecting additional revenue and increasing crashes, in the international countries in the future (Pilkington, 2003; Delaney et al., 2005; Andreassen, 1995; Office of the Majority Leader, 2001; Burkey and Obeng, 2004; Garber et al. 2007; Langland-Orban, Pracht, and Large, 2008). Therefore, from the behavioral science perspective, an advisable 'evidence-based' strategy to reduce the red-light running should be built upon higher priorities of the driver's behavioral intention to run the red light under the common situations.

On the basis of classical test theory, total (or mean) item scores of the rating scale (e.g. the Likert scale) are often used to represent the priorities of the driver's behavioral intention to run the red light under which situations. However, the total (mean) item scores are calculated directly by treating the rating scale as interval-level measurements (i.e. arbitrarily assigned integers to responses). Doing so is not really justified since the data are ordinal but not interval in which equal differences represent equal intervals. Again, it is difficult to interpret the individual differences in the driver's behavioral intention when total item scores are equal but are allocated in not completely the same items. To integrate the information of items and latent construct (e.g. behavioral intention) into the measurement model, Rasch modeling , one

of advanced psychometric methods (Masters and Keeves, 1999), can be used to measure the driver's behavioral intention in red-light running under those potential situations, and further to exactly predict their future behavior in running the red light. In contrast to classical test theory, Rasch modeling can assess whether the content of the scale items covers the range of drivers' behavioral intention about the latent construct, the response options are appropriate for the respondents on the scale items, and the standard errors of the scale and the scale items are maintained across the reasonable range of scale scores.

To date, most countermeasures in red-light running literature have been developed from the reduction in red light violations instead of the motorcyclists themselves. Given the evidence (Shinar, 1998; Porter and England, 2000; Porter and Berry, 2001; Mohamedshah, Chen, and Council, 2000; Martinez and Porter, 2006) that suggests a relationship between red-light running and associated situations, creating a situation-specific behavioral intention scale may provide an opportunity to match the content of this scale to the content of a situation-matched strategy. Therefore, the purpose of this study is to use Rasch modeling to explore the priorities of the motorcyclist's behavioral intention in red-light running under those situations, and determine which situations will cause the motorcyclist being more likely or unlikely to run the red lights? The findings of this study will provide valuable information to develop road safety programs that are tailored to changing drivers who run the red lights.

2. RASCH MODELS

The Rasch model, developed by Rasch (1960) and advocated by Wright (Wright and Masters, 1982; Wright and Stone, 1979), is one of item response theory (IRT) models in which the total score across items characterizes a person totally. It is also the simplest of such models having the minimum of parameters for the person (just one), and just one parameter corresponding to each category of an item. This item parameter is generically referred to as a threshold (or step) parameter. When the item is dichotomous, there is only one threshold parameter for the item (called dichotomous Rasch model); when the item with more than two ordered categories, it is a polytomous item (called rating scale model or partial credit model). Most importantly, the family of Rasch models make objective measurement possible in the social and behavioral sciences.

2.1 Dichotomous Rasch Model
The simplest Rasch model is derived for the dichotomous form as follows,

$$\ln\left(\frac{P_{ni1}}{P_{ni0}}\right) = B_n - D_i, \text{ or equivalently, } P_{ni1} = \frac{\exp(B_n - D_i)}{1 + \exp(B_n - D_i)} \tag{1}$$

Here, P_{ni1} is the probability of person n will succeed on item i, P_{ni0} is the probability of failure $1 - P_{ni1}$, B_n is the ability of person n, where n= 1, …, N, and D_i is the difficulty of item i, where i= 1, …, L.

2.2 Rating Scale Model
Response categories in the questionnaire with Likert scale may include ordered rating such as "very unlikely/unlikely/neutral/likely/very likely" in this study, to represent the respondent increasing inclination towards the concept questioned (e.g. behavioral intention). The Rasch model can be extended for the polytomous form as follows (Andrich, 1978),

$$\ln\left(\frac{P_{nik}}{P_{ni(k-1)}}\right) = B_n - D_i - F_k \qquad (2)$$

Here, P_{nik} is the probability that person n, on encountering item i , would respond in category k, and P_{nik-1} is the probability that the response would be in category k-1. B_n is the ability of person n, D_i is the difficulty of item i, and F_k is the impediment to being observed in category k relative to category k-1, i.e., the kth step calibration.

2.3 Partial Credit Model

The partial credit model is similar to the rating scale model except that each item has its own threshold parameters (Wright and Masters, 1982), as follows,

$$\ln\left(\frac{P_{nik}}{P_{ni(k-1)}}\right) = B_n - D_i - F_{ik} \qquad (3)$$

Here, F_{ik} is the impediment to being observed in category k relative to category k-1 of item i.

2.4 Estimation Methods for Rasch Measures

The Rasch measures (parameters, i.e., the person ability and the item difficulty) must be inferred from data. Following Fisher (1922), the likelihood of the data set, L, is the product of the probabilities of the data points

$$L = \prod_{n,i} P_{nik}$$

Rasch estimates are non-linear transformations of data. Usually, estimation with non-linear functions requires an iterative approach until final estimates are obtained. Most estimation methods, e.g. joint maximum likelihood estimation (JMLE), marginal maximum likelihood estimation (MMLE), employ some form of the method of maximum likelihood. To implement one of the estimation methods (e.g., JMLE), we can use one of the current computer programs, e.g, Winsteps (Linacre, 2007). The JMLE estimates satisfy the optimal least squares criterion,

$$\left(R_n - \sum_{i=1|n}^{L} E_{ni}\right)^2 = 0, \text{ where } R_n = \sum_{n} X_{ni} \qquad (4)$$

Here, the marginal score (R_n) is the sum of all observations modeled to be generated by n persons, each data point (X_{ni}) has a value of one if person n succeeds on item i, and zero otherwise, and E_{ni} is the expected value of the data points. By using Newton-Raphson approach, better estimates are produced which minimize the discrepancies.

3. METHODS

3.1 Participants

The motorcycle is one of the most common traffic vehicles in Taiwan. Motorcycles experienced higher accident rate and resulted more severe injury than automobiles. Motorcyclists' red light running is therefore becoming to be an important traffic safety issue concerned by the authority. Therefore, participant motorcyclists in this study were recruited and gave informed consent on three different gas stations in Hsinchu City, Taiwan. Among the 441 participant motorcyclists, there were 206 female (46.7%) and 235 male (53.3%), and 335 married (76.0%) and 106 unmarried (24.0%). Their estimate mean age was 38.21 years (SD = 10.28). The average estimated driving year was 15.68 years (SD = 7.61). Most of the participants were college educated (49.9%), and high school graduates (35.6%) were the next.

Their estimate travel time in riding a motorcycle was 39.89 minutes per day (SD = 35.68). Among all the participant motorcyclists, 42.9% had run the red light equal or less than 5 times, 47.2% had run the red lights 6-10 times during the past one week respectively. About 10% of the participant motorcyclists committed more than 10 traffic violations in red-light running in one week.

3.2 Instrumentation

Participants were asked to make a response about their behavioral intention in red-light running under the following ten situations when they drove a motorcycle. The questions were " How likely will you run the red light at a signalized intersection under following situations? "
(1) when there is nobody around at night time.
(2) when there is nobody around at day time.
(3) when you are in a hurry.
(4) when you pass by a small signalized intersection.
(5) when the traffic is congested.
(6) when it is raining.
(7) when you see someone run the red lights.
(8) when you ride on a street that you are very familiar with.
(9) when you have stopped many times by traffic signals along the road.
(10) when you ride a motorcycle with a passenger

This intention scale was developed according to the methodology of the theory of planned behavior (Ajzen, 1991). Aside from those previous studies, these situations were elicited and pretested from 88 motorcyclists who were interviewed on two gas stations during the pilot phase of this study to ensure the content and construct validity. Responses were on a five-point Likert scale ranging from 'very unlikely' to 'very likely'. In the framework of classical test theory, the scale score was calculated by summing the responses to all items with a high score representing a strong behavioral intention in red-light running. All items were proved to have adequate discrimination since the discrimination indices were all greater than 0.40 (range=0.59 to 0.76), and the corrected item-total correlations were all greater than 0.3 (range= 0.49 to 0.68). The scale had higher internal consistency since its Cronbach's alpha value (0.88) was very well above the accepted 0.70 recommended cutoff (Nunnally and Bernstein, 1994).

3.3 Analyses

The major concept on which Rasch modeling is based is that there is a single underlying latent trait that is being measured. The unidimensionality is the most important assumption of Rasch modeling assumptions since the condition of unidimensionality must hold before the scale scores are estimated using Rasch modeling. In this study, the unidimensionality assumption will be examined by forcing a one-factor model in both an exploratory and a confirmatory factor analysis, respectively. In an exploratory approach, the unidimensionality will be confirmed if the scree plot of eigenvalues shows one dominant first factor, the solution explains at least 20% of the variance, and the factor loadings are greater than 0.30 (Reeve and Masse, 2004). In a confirmatory approach, the unidimensionality will be confirmed if the ratio value of chi-square and df (degrees of freedom) is less than 3, the Jöreskog-Sörbom GFI, the Bentler-Bonett NFI, and the Bentler CFI are greater than 0.90, the value of the SRMR (standardized root mean squared residual) is less than 0.10, and the factor loadings are all statistically significant (Kline, 1998). All statistical analyses above were performed using the SAS 9.1.3 in this study..

Rasch modeling was performed using the item response modeling program, Winsteps (Linacre, 2007). The first step of Rasch modeling was to determine the best-fitting Rasch model by comparing the fit of the rating scale and partial credit models. To compare the fit of the two models, a likelihood ratio test was performed by calculating the difference between the two models' deviance parameters. In addition, the number of items that fit the model was assessed. Fit was determined by calculating weighted fit mean square statistics and t statistics for each item. Items for which the weighted fit mean square statistics (MNSQ) was <0.75 or >1.33 and for which the weighted fit t statistics (t) was <-2.00 or >2.00 were considered to be fitting poorly. The model with the fewest poorly fitting items will be considered to be a better fit.

Later, we visually inspected the Wright's item-person map. This map not only provided the information of the items and thresholds, but it also provided the information of all the respondents on the same logit scale. Rasch modeling transformed the raw scores into log odds ratios on a common interval with zero being allocated to the mean. Usually, this map was used to determine whether those items are appropriate for the respondents, and whether those respondents are appropriate for the items. Theoretically, a scale, which has items by thresholds distributed uniformly along the Rasch scale continuum, will contain content appropriate for all the respondents.

4. RESULTS

4.1 Testing Unidimensionality Assumption
Whether in an exploratory approach or a confirmatory approach, the results of one-factor model showed that the unidimensional assumption was met for the scale of behavioral intention in red-light running under these situations. In an exploratory factor analysis, it was adequate for this scale that the one-factor solution explained 47.77% (much greater than 20%) of variance. The eigenvalue plot for this scale showed that the eigenvalue of only one factor was greater than one, and it was very dominant since the ratio of the first eigenvalue (4.78) and the second eigenvalue (0.85) was 5.62. In addition, factor loadings were all greater than 0.30, and their range was from 0.58 (minimum, item 6) to 0.76 (maximum, item 2) for this scale. In a confirmatory factor analysis, unidimensionality was also confirmed since the ratio (χ^2/df = 2.81) value was less than 3, the Jöreskog-Sörbom GFI, the Bentler-Bonett NFI, and the Bentler CFI were 0.96, 0.94, and 0.96, respectively, which were all greater than 0.90, the value of the SRMR (0.0368) was less than 0.10, and all of the factor loadings were statistically significant ($p < 0.05$).

4.2 Rasch Model Fitting and Comparisons
The magnitude of the deviance was lower for the partial credit model (deviance = 10138.879, df = 41) than for the rating scale model (deviance = 10219.528, df = 14). The difference between two models in the deviance, which was 80.649 (10219.528 - 10138.879) with 27 (41 - 14) degrees of freedom, was statistically significant at the level of alpha 0.05 under the chi-square distribution (the deviance equals twice the log-likelihood, and it is assumed to have a chi-square distribution). It suggested that the partial credit model fitted significantly better than the rating scale model for this scale.

Furthermore, we examined the weighted fit indices for the items, responses and items by response categories in the two models. For the rating scale model, all the parameter estimates

for the item by response category were outside the acceptable ranges. In contrast, for the partial credit model, they were all within the acceptable ranges (data not shown but available upon request). These results indicated that distances between response options were not the same across this scale items. Therefore, it suggested that the partial credit model fitted significantly better than the rating scale model for this scale.

4.3 Item and Person Estimate Analyses

Table 1 presents the item estimates, unweighted and weighted fit mean square statistics and t statistics for the items using the partial credit model. All of the item estimates not only had the weighted fit mean square statistics (MNSQ) between 0.75 and 1.33, but they also had the weighted fit t statistics (t) between -2.00 and 2.00. All of the items could measure the latent construct (i.e. behavioral intention to run the red light) sufficiently since the chi-square test of parameter equality was statistically significant, $\chi^2(9) = 1508.02$ ($p < 0.05$). Besides, the separation reliability was 0.99 for all of the items, and it was much better than the excellent 0.90 suggested criterion (Nunnally and Bernstein, 1994). It indicated that the partial credit model fitted the data better, and these items would be a better measure of motorcyclist's behavioral intention in red-light running under these situations.

In the Rasch modeling, the raw scores could be converted to a logit scale in the estimation process. Theoretically, the item estimates are most often located between -3 and +3 logits. Right now, all of the item estimates (D_i) are located within the reasonable ranges (see Table 1). To establish the association between the item estimates and motorcyclist's behavioral intention in red-light running under these situations, we need further to examine the direction and the magnitude of the item estimates on the Rasch behavioral intention scale continuum. Since the average item estimate is anchored at 0 logit, the item estimates located at zero (or near zero) on the behavioral intention scale continuum, e.g. item 9 (D_9=0.045) and item 2 (D_2=-0.036), will measure moderate-level motorcyclist's behavioral intention in red-light running under the situations of "when I have stopped many times by traffic signals along the road" and "when there is nobody around at day time".

The item estimates with positive logits (e.g. items 10 and 6) would measure lower levels of motorcyclist's behavioral intention in red-light running under these situations. That is to say, under the specific situations (e.g. there is a passenger on the motorcycle, it is raining, etc), they would have lower behavioral intention in red-light running. When the participant motorcyclists ride a motorcycle with passenger (D_{10}=1.341) or when it is raining (D_6=0.808), they would be more unlikely to run the red lights than those who ride a motorcycle in a congested traffic flow (D_5=0.268).

Table 1 Unweighted and Weighted Fits Statistics for the Items Using the Partial Credit Model

item	Estimate(D_i)	Error	Unweighted MNSQ	Fit t	Weighted MNSQ	Fit t	Raw Score
10	1.341	0.045	1.11	1.6	1.12	1.5	905
6	0.808	0.045	1.11	1.6	1.11	1.5	951
5	0.268	0.044	0.95	-0.8	0.95	-0.6	1118
7	0.204	0.043	0.92	-1.2	0.91	-1.4	1182
9	0.045	0.043	0.94	-0.9	0.95	-0.7	1182
2	-0.036	0.042	0.93	-1.0	0.92	-1.2	1266
8	-0.152	0.043	0.97	-0.4	0.98	-0.3	1247

4	-0.646	0.044	1.09	1.3	1.07	1.2	1433
3	-0.903	0.043	0.99	-0.1	0.99	-0.2	1522
1	-0.929	0.044	1.12	1.8	1.12	1.7	1565

MNSQ represents mean square fit statistics of the item parameters.

In contrast, the item estimates with negative logits (e.g. items 1, 3, and 4) would measure higher levels of motorcyclist's behavioral intention in red-light running under these situations (e.g. nobody around at night time, in a hurry, passing by a small signalized intersection). Furthermore, when there is nobody around at night time (D_1=-0.929) or when they are in a hurry (D_3=-0.903), the participant motorcyclists would be more likely to run the red lights than those motorcyclists who ride a motorcycle passing by a small signalized intersection (D_4=-0.646).

4.4 Implication shown in Item-Person Map

Figure 1 shows the person and item map for the scale of motorcyclist's behavioral intention in red-light running under these situations. In this map, the participant motorcyclists and item estimates are placed on both sides of the same logit metric scale which centered at a mean of zero. On the left of this map, participant motorcyclists who have higher behavioral intention in red-light running under these situations were located at the top of behavioral intention scale continuum, but those who have lower behavioral intention in red-light running under these situations were located at the bottom of behavioral intention scale continuum. Theoretically, most of the participant motorcyclist estimates are also located between -3 and +3 logits. However, not all of the participant motorcyclist estimates were located within the reasonable range (see Figure 1). There were only few participants (approximately 2.7%) outside the above ranges. Among the participants, 2% of these participants who were less than -3 logits were most unlikely to run the red lights under these situations, and 0.7% of those who were greater than +3 logits were most likely to run the red lights under these situations. Approximately 90% and 66% of the participants were distributed between -2 and +2 logits, and between -1 and +1 logits, respectively. In addition, the separation reliability was 0.86 for all participants above the accepted 0.70 recommended cutoff (Nunnally and Bernstein, 1994). Therefore, most of the participants were distributed widely on the low-moderate-high range of motorcyclist's behavioral intention in red-light running under these situations.

Figure 2 presents the person and item by threshold map for the scale of motorcyclist's behavioral intention in red-light running under these situations. In this map, there are four thresholds (which select one response option over the other lower response options) on the five-point behavioral intention scale. For this Likert-type scale, the location of item by threshold increases on the Rasch scale continuum when one threshold is moved to the other higher threshold. For the low level of behavioral intention, about seven participants with the person estimates less than -3 logits had much lower behavioral intention to run the red lights (data not shown but available upon request), but the first thresholds (unlikely over very unlikely) of items 4, 3, and 1 were targeting these participants. The results suggested that the 'very unlikely' response option was not chosen by those who had low behavioral intention in red-light running under the following three situations: when there is nobody around at night time, when I am hurry, and when I pass by a small signalized intersection.

On the other hand, for the high level of behavioral intention, fifteen participants with the person estimates greater than +3 logits had much higher behavioral intention to run the red lights (data not shown but available upon request), but the fourth thresholds (very likely over

likely) of items 10, 6, and 7 were targeting these participants. The results suggested that the 'very likely' response option was not chosen by those who had high behavioral intention in red-light running under the following three situations: riding motorcycle with a passenger, riding in the rain, and seeing someone run the red lights. However, most of the items could evaluate high, moderate, and low motorcyclist's behavioral intention in red-light running under these situations by their thresholds (see Figure 2). Therefore, the distribution of items by thresholds indicated that the behavioral intention scale had covered appropriately content representation of the latent construct for most of the participants.

```
                    Persons --- Map --- Items
                Logits
                        <more>+<rare>
                  4           |
                              |
                              |
                              |
                              |
                  3           |
                              |
                            X|
                              |
                            X|
                  2           |
                            X|
                           XX|
                            X|
                            X|
                           XX|10
                          XXX|
                  1       XXXX|
                         XXXX|6
                        XXXXXX|
                        XXXXXX|
                        XXXXXX|
                       XXXXXXX|5 7
                       XXXXXXX|
                  0     XXXXXXX|2 9
                    XXXXXXXXXX|8
                      XXXXXXXXX|
                      XXXXXXXX|
                      XXXXXXXX|4
                      XXXXXXXX|
                     XXXXXXXXX|1 3
                 -1    XXXXXXX|
                       XXXXXXX|
                        XXXXXX|
                          XXX|
                          XXXX|
                          XXXX|
                 -2       XXX|
                           XX|
                           XX|
                           XX|
                            X|
                            X|
                            X|
                 -3         X|
                              |
                            X|
                              |
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                 -4           |
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                              |
                        <less>+<frequ>
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Figure 1 Item-and-person map

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            Persons --- Map --- Items By Thresholds
          Logits
                  <more>+
            4                 |                                    10.4
                              |
                              |
                              |
                              |
            3                 |                            6.4 7.4
                              |                            5.4
                              |                            2.4
                             X|                            9.4
                              |
                              |                            4.4 8.4
                             X|
            2                 |
                             X|
                            XX|                            1.4
                             X|                            3.4
                             X|
                            XX|                   10.3
                           XXX|
            1            XXXX|                     6.3
                         XXXX|
                       XXXXX|           6.2 10.2
                       XXXXX|                     5.3
                       XXXXX|
                     XXXXXXX|                     7.3 9.3
                     XXXXXXX|           5.2        8.3
            0        XXXXXXX|
                  XXXXXXXXX|           9.2        2.3
                  XXXXXXXX|            7.2 8.2
                   XXXXXXX|            2.2
                   XXXXXXX|                       4.3
                   XXXXXXX|
                  XXXXXXXX|                       3.3
           -1      XXXXXXX|            4.2
                   XXXXXXX|            3.2        1.3
                    XXXXXX|10.1        1.2
                        XXX|
                      XXXX|6.1
                      XXXX|
           -2          XXX|
                        XX|
                        XX|2.1
                        XX|7.1
                         X|5.1
                         X|8.1 9.1
                         X|1.1
           -3            X|
                          |3.1
                         X|
                          |4.1
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           -4            |
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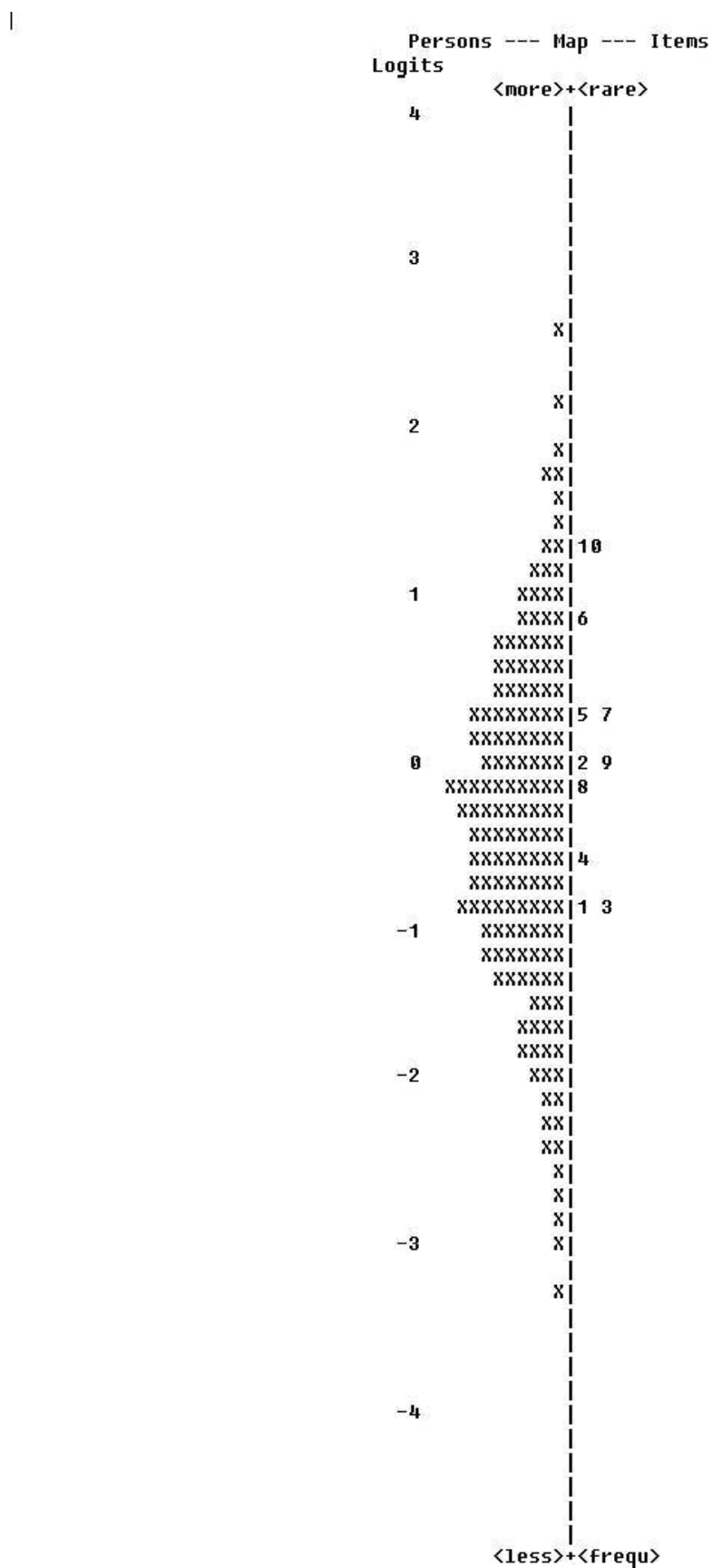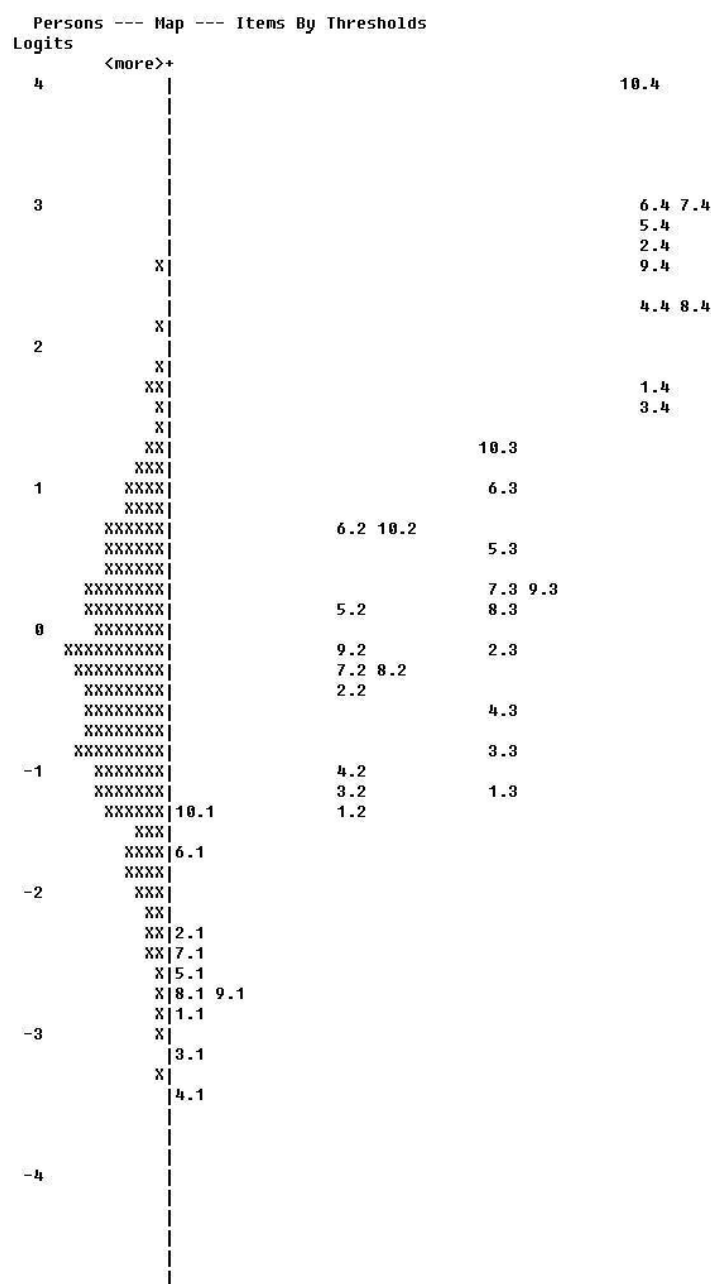
Figure 2 Item by threshold-and-person map

5. DISCUSSION

The purpose of this study was to evaluate the psychometric properties of the scale of motorcyclist's behavioral intention in red-light running using Rasch modeling, and further establish the ranking of the specific situations for the motorcyclist in red-light running. First of all, the results of testing unidimensionality assumption indicated that the unidimensional structure of the scale was confirmed for the scale of motorcyclist's behavioral intention in red-light running, and it was acceptable and available for using Rasch modeling to fit the scale of motorcyclist's behavioral intention in red-light running. In addition, the results of comparing the difference of two models in the deviance and fit statistics (item estimates and

thresholds of item) showed that the partial credit model was better than the rating scale model for the data in the scale of motorcyclist's behavioral intention in red-light running. Both results gave this scale a strong psychometric foundation for using Rasch modeling to analyze the data from all participants.

Second, the results of Rasch item analysis totally showed that this behavioral intention scale had strong construct validity and high internal reliability. In this analysis, the results indicated that the items could measure the same latent construct (i.e. motorcyclist's behavioral intention in red-light running) since the item estimates were allocated between -2 and +2 logits (see Table 1), the fit statistics (MNSQ or t) were not statistically significant, and the test of parameter equality were rejected. Furthermore, the results also indicated that the items had high internal reliability since the items all were distributed uniformly on the Rasch behavioral intention scale (see Figure 1), and the item estimates might be categorized into three clusters according to the direction and the magnitude of these item estimates, high (e.g. items 1, 3, and 4), moderate (e.g. items 5, 7, 9, 2, and 8), and low (e.g. items 10 and 6) motorcyclist's behavioral intention in red-light running. Therefore, the Rasch item analysis indicated that this behavioral intention scale had sound psychometric properties, validity and reliability, and the scale items were appropriate for the participants.

Next, the results of Rasch person analysis showed that most of the participants (about 90%) were distributed widely from high, moderate, to low behavioral intention interval continuum, except few participants at the top or the bottom with much higher or lower behavioral intention (i.e. so-called extremes). Again, the results of Rasch person analysis also showed that most of the participants in red-light running behavioral intention were distributed as a "bell-shaped" curve like a normal distribution (see Figure 1). It suggested that most of the participants could respond sufficiently their motorcyclist's behavioral intention in red-light running on the Rasch modeling scale continuum. Hence, most of the participants were appropriate for the scale items, and the scale items were appropriate for most of the participants, too.

From Rasch modeling viewpoint, there were three situations which most often caused the participants to run the red lights, when there is nobody around at night time (item 1), when the riders are in a hurry (item 3), and when the riders pass by a small signalized intersection (item 4), respectively. For the first situation above, the results showed that about 73% participants will be likely to run the red lights when there is nobody around at night time in this study (see Figure 1). In this situation, the participants might think that nobody including the policeman would see them to run the red lights at that time. So, this situation often caused the drivers intentionally to run the red lights. It is no doubt that red light cameras might be considered an advisable 'evidence-based' strategy to reduce red light violations and associated crashes under this situation.

All the same, the results showed that about 73% participants will be likely to run the red lights when they are in a hurry in this study. This finding was very similar to those of Shinar (1998), and Porter and Berry (2001). In Porter and Berry's (2001) telephone survey, the drivers who reported being more likely to run the red light were in a hurry when speeding up to beat red lights. Usually this situation forced the drivers to run the red light because of shorter yellow signal timing. Although red light cameras or longer yellow signal timing suggested Retting et al. (2008) might be considered as an alternative strategy to reduce red light violations, it had better provide the riders with more information about the potential accident risk of riding motorcycle in a hurry and running the red light.

Besides, approximately 60% participants will be likely to run the red lights when they pass by small signalized intersections. This finding was different from those of Porter and England (2000), Shinar (1998), Mohamedshah et al. (2000), and Martinez and Porter (2006). They all found that higher red light running was associated with higher traffic volumes in the urban areas. However, the policeman usually serves in the cities with larger intersections and higher traffic volumes In Taiwan. The drivers dare not run the red lights in the larger and heavy traffic intersections until the policeman is off duty. The policeman prevents the motorcyclists from running the red light in the higher traffic volumes. On the contrary, the participant motorcyclists are more likely to run the red lights at small signalized intersections in Taiwan since there is not any policeman over there. Whether the motorcyclists run the red light unintentionally or intentionally, one of the major possible reasons why they run the red lights under this situation is that it makes them to stop and wait for the next green light. Therefore, the coordination of traffic signals to provide a progressive signal time is suggested to prevent the motorcyclists from running the red lights.

On the other hand, riding with a passenger (item 10) was found to reduce the likelihood of running the red lights (see Table 1). This finding is the same as that of Porter and Berry (2001). They found that drivers reported being more likely to run the red light when driving alone. It might be the case that the riders might have more safety concern when carrying another person on their motorcycles. However, it still had 4.76% participant motorcyclists to run the red light even they rode their motorcycles with a passenger (shown in Figure 1). Finally, riding in the rain (item 6) was another situation to reduce the likelihood of running the red lights (see Table 1). However, the study results still showed that about 12.70% participant motorcyclists were still likely to run the red lights when riding in the rain (also see Figure 1). Some education, warning, enforcing, and penalty programs should be imposed on those motorcyclists who committed such dangerous riding behavior of running the red lights when carrying a passenger or riding in the rain.

6. CONCLUSION

Running the red light is one dangerous driving behavior and very frequent for the motorcyclists in Taiwan. One of the major causes for the driver to run the red light is mostly explained by their driving situations. The results indicated that the participants reported higher levels of motorcyclist's behavioral intention in red-light running when there is nobody at night time, they are in a hurry, and they pass by not much heavy intersections; on the other hand, they reported lower levels of motorcyclist's behavioral intention in red-light running when there are passengers in the vehicle, and it is raining. Furthermore, past and present studies showed that the motorcyclist's and the car driver's behaviors were different in some specific situations; the weather may influence the motorcyclist's behaviors, such as the motorcyclist may feel more dangerous than the car driver when doing a red light running in the rain; riding a motorcycle with a passenger may decrease the motorcyclist's behavioral intention since it is very difficult to make a motorcycle stop.

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