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Perceptions and Preferences of University Students for Use of Pedestrian Bridge: A Gender Based Study

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Abstract

This research highlights a very important aspect of road safety which is related to the use of pedestrian facilities by young adults, with special focus on the differences related to gender. Pedestrians are considered as the most vulnerable road user group. Moreover, involvement of young people in road crashes is among the most alarming aspects for most of the countries in the world. This research employs a survey questionnaire to determine the preferences related to use of pedestrian bridge, before and after its rehabilitation. The analysis of the questionnaire included statistical tests, logistic regression and CART model. It was found that the physical condition of the bridge has the most profound effect on the hazard perception of young pedestrians, in spite of the presence of other factors related to safety and security. Most of the pedestrians preferred using the pedestrian bridge during the afternoon, irrespective of the condition of the bridge. It was also found that the before data had a higher impact of gender, with more female respondents showing safety concerns and using the pedestrian bridge. The after data showed a more uniform distribution among genders. Although, the CART model showed significant impact of gender on the perception related to beggars, being the most important risk hazard. It is recommended for future studies to be performed on a larger dataset, include more variables and employ CART technique for modeling.

Keywords: Pedestrian bridge, Students, Perception, Hazard factors, Traffic Safety

1. Introduction

Traffic crashes are an important cause of concern for researchers, academics and practitioners all around the world. Their effects are not limited to loss of property, instead, they often extend to life-long disabilities and loss of life (James et al., 2020). Pedestrians are often reported to be

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involved in severe crashes, so much so that they have been termed under the category of vulnerable road users (Sun et al., 2022).

Another important factor, associated with road crashes, is the involvement of young adults in them (Cox and Cicchino, 2021). These young people are expected to build the future of a nation. Thus, their involvement in road crashes is considered an issue of immense concern. As stated above, there are higher chances of having severe crashes when these young people are using the road space as pedestrians.

Therefore, it is extremely important that their safety should be ensured by providing them with appropriate facilities and encouraging them to use these facilities. In this context, many studies have been conducted to study the issues associated with the use of pedestrian facilities such as Landa-Blanco and Avila (2020). However, conditions in developing countries, such as Pakistan, have unique issues related to law and order, mismanagement, security and, most important of all, gender disparity (Kalim and Afridi, 2020). It becomes critical that pedestrian behavior in such be studied in the context of such issues and appropriate measures are taken which address these issues.

The city of Karachi possesses a particular road infrastructure trait which is unique to itself, which is the ‘Signal-Free-Corridors’. The concept of urban expressways came in the 1960s when such high mobility corridors were built in New York City. These expressways were mostly grade separated and possessed an exclusive right-of-way, thus, preventing the movement of other traffic and pedestrians over them (Waqar, 2016). A similar approach was coined in the mid and late 2000s in Karachi where such urban expressways were built but these corridors were mostly at grade and did not possess an exclusive right-of-way. Therefore, the movements of pedestrians were not restricted on these highly vehicular centric roads. They promoted high speed continuous flow of traffic over large lengths. This continuous flow of non-lane-based mixed-traffic provided little to no refuge for pedestrians to cross them. Zubair et al. (2015) found that pedestrians were amongst the road users most vulnerable to accidents on signal-free-corridors. Since the widths of these roads were more than 30ft on most locations, it was difficult for women, children and elderly to cross them. The number of pedestrian bridges built on these roads is not sufficient (Raza, 2016) and are placed at great distances (Heera, 2013). As a result, the pedestrian related accidents increased two-folds on such corridors, shortly after their start of operation (Kumar et al., 2010). Apart from pedestrians, these signal-free-corridors were responsible for fatalities of other vulnerable road users such as motorcyclists (Jooma, 2016). Alternatively, these corridors contributed little to the problem of traffic jam (Matin et al., 2012).

Keeping this view in mind, this research aims to study the hazard perception of university students in Karachi in relation to use of pedestrian bridge from the perspective of different genders. Statistical analysis and models have been used to study their behavior. The results of this study are expected to highlight the key issues hindering the use of pedestrian facilities in the circumstances of developing countries. Consequently, authorities could use the findings of this research to promote the use of pedestrian facilities among young people, especially around educational institutions.

2. Study Area

The investigated pedestrian bridge is located on a major arterial in the city of Karachi, Pakistan, which is called University Road. It lies exactly in front of the gate meant specifically for the use

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of students at NED University of Engineering and Technology which is the second most populated university in the city. There are other major universities located on the same road. The bridge serves as the only means of crossing the road as there are iron grills placed along the median to prevent crossings at grade and the traffic volume is high with fast moving vehicles during working hours, that is, from 7 am till midnight. The deck of the bridge is located at 21 feet height above the finished road level. It is a steel structure with 8.5 feet width of aisle which is 122 feet long. Pedestrian volume is concurrent with the class timings of the university resulting in high frequencies from 8:30 to 9:30 in the morning and 3:45 to 4:45 in the evening. It was provided with steel guardrails on both sides for safety. Over the period of time the guardrails were stolen by addicts which resulted in a completely open deck from all sides. The pedestrians kept using the bridge despite the safety concerns because crossing the road at grade was not possible. Guardrails were installed along metal sheets as part of the bridge renovation.

3. Survey Instrument

The Pedestrian Based Questionnaire (PBQ) was used as the survey instrument (Mcllroy et al 2019). Pedestrians who used the bridge during the three peak periods of time (8:15-9:15 a.m., 1:00-2:00 p.m., 4:00-5:00 p.m.), were interviewed. The pre-renovation survey was conducted on 19th November 2021. The deck of the bridge was open from all sides as no guardrails were present during that time. The post renovation survey was conducted on 4th March 2022. The deck of the bridge was protected from the sides with the provision of guardrails and metal sheets during that time. Pedestrians were asked to rate the bridge as safe or not safe depending upon their perception and experience while crossing the bridge. All the pedestrians were interviewed on the same day by the same interviewer. Other questions or observations of the survey included;

- Gender
- Preferred time of crossing/using the bridge
- Most important hazard factor

100 samples were collected before as well as after the renovation of the bridge. The response data is given in appendix A and B.

4. Modeling Techniques

Several techniques have been used in this study to analyze the data. These include parametric techniques such as t-tests, correlation, Analysis of Variance (ANOVA) and logistic regression models. Moreover, non-parametric techniques were also employed in some cases to support or ascertain the results. These include Kolmogorov–Smirnov (KS) tests and classification tree (CART) models. A significance level of 5% was set for all parametric tests and logistic regression tests, as per common practice (Harrison et al., 2020). All comparative tests were conducted using MS Excel worksheets, while statistica (from StatSoft.inc) was used for model development and testing.

T-tests are employed to test the equality of means/proportions between two datasets. In each case, the t-statistic (or z-statistic) is compared with a standard normal t (or z) distribution (Laken, 2013). In this research, t-test for proportions was used test the safety ranking of pedestrian bridge by different genders in the before dataset. The test statistic was calculated using equations (1) and (2).

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$$\hat{p} = \frac{y_1+y_2}{n_1+n_2} \tag{1}$$

$$Z = (p_1 - p_2)/\left[\sqrt{\frac{\hat{p}(1-\hat{p})}{\frac{1}{n_1}+\frac{1}{n_2}}}\right] \tag{2}$$

Where y_1 is the proportion of responses which rated the bridge unsafe from male respondents, while y_2 is that for the female for respondents, n_1 and n_2 are the number of male and female respondents in the dataset, respectively (Cohen, 1992).

Paired t-test was used to compare the responses of pedestrians to Q2 and Q4 in the after dataset. T-statistic for this test is calculated as per equations (3) and (4).

$$S_{\bar{x}} = S_{diff}/\sqrt{n} \tag{3}$$

$$t = (\bar{x}_{diff} - 0)/S_{\bar{x}} \tag{4}$$

Where S_{diff} is the standard deviation of difference of individual pair of values between the datasets and n is the number of values in the datasets, which must be equal for the paired comparison (De Winter, 2019).

Pearson correlation coefficient was also used in the above case, to support the results of the paired t-test. The coefficient can be calculated as per equation (5).

$$r = \sum(x_i - \bar{x})(y_i - \bar{y}) / \sqrt{\sum(x_i - \bar{x})^2(y_i - \bar{y})^2} \tag{5}$$

Where x_i and y_i are the values in the two datasets and $\bar{x}$ and $\bar{y}$ are the means for each dataset (Cohen et al., 2009).

ANOVA was used in several cases including comparing time of crossing for each gender in each of the before and after datasets, comparing time of crossing in between the before and after datasets, comparing responses for Q2 and Q4 in the after dataset, and comparing hazard perception between the before and after datasets. ANOVA test is based upon the measuring and comparing the variation in the overall dataset with that between different groups of responses. The test employs Fisher's (F) statistic to test the significance of results which can be calculated using equation (6).

$$F = MSSgroup/MSStotal \tag{6}$$

Where *MSSgroup* refers to the mean sum of squares of deviation between the groups and *MSStotal* refers to the mean sum of squares of deviation in the overall dataset (Judd et al., 2017).

KS test was used as a non-parametric alternative to ANOVA, employed in conjunction with it, to reinforce or find the conflict in the results of ANOVA. It was done because of the statistical assumptions which are established for employing ANOVA (refer to Quene and Van den Bergh (2004). Hence, KS test was employed to avoid the reliance of a restricted test on the datasets of this study which had very few responses to test all the assumptions. KS test compares the difference in the cumulative frequency distribution of the two datasets which a critical statistic (termed as 'D'). D-statistic can be calculated as per equation (7).

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$$D = c_\alpha \sqrt{\frac{(n_1+n_2)}{n_1 n_2}} \tag{7}$$

Where c_α is the coefficient, fixed as 1.73 for 5% significance level, n_1 and n_2 are the number of observations in the two datasets being compared (Frey, 2016).

In addition to comparative analysis, classification models were also developed to predict the hazard perception of respondents in the before and after datasets. Similar to the tests, two different models were selected for this case to capture the relationships between variables from different aspects. These models included logistic regression, which is a statistical model. While CART models were also used which belong the category of machine learning techniques.

Logistic regression models can be used to calculate the utility function for each category of response (type of hazard in this case). These utility functions are, then, used in the logistic function (see equation (8) to calculate the probability of the response.

$$p(i = c) = \frac{e^{u_c}}{e^{\sum u_i}} \tag{8}$$

Where u_i is the utility function for any response i, and c is the response variable for which the probability is being calculated. The utility coefficients are calculated by maximizing the log-likelihood function for the model. This research employs multinomial logistic regression because the number of hazards were either three or four (El-Habil, 2012).

CART models were used as a non-parametric alternative to the regression models. These models work on finding the best split of data, based upon a primary variable, at different levels. Hence, it forms a tree-like structure which can be efficiently utilized to study multilevel non-linear relationships. At each level, the algorithm would determine the best variable and its split by minimizing the Gini Index (GI) for the available dataset. GI can be calculated as per equation (9).

$$GI = (1 - \sum p_i) \tag{9}$$

Where p_i is the probability or proportion of data belonging to each possible outcome (Daniya et al., 2020).

4. Results

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics of the data collected in the before and after datasets. It can be observed that datasets were slightly biased towards the female respondents as they were more frequently using the bridge as all times of survey. The safety perception changed drastically by the installation of the guardrail, which will be discussed further in the coming section. Afternoon was found to be the most preferred time of crossing in before and after datasets. The primary hazard factor was guardrail in the before dataset, while it was the addict in the after dataset.

Table 1. Descriptive Statistics of Data

Parameter	Values in Before Dataset	Values in After Dataset

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Number of Responses	100	100
Male	41	46
Female	59	54
Bridge is Safe	15	100
Bridge is Unsafe	85	00
Morning Crossing Time	24	37
Afternoon Crossing Time	70	46
Evening	6	17
Hazard Factor: Guardrail	62	N/A
Hazard Factor: Addict	17	44
Hazard Factor: Beggar	19	18
Hazard Factor: Dog	2	38

4.2 Statistical Analysis

A t-test was performed to check the significance in the difference of proportions of respondents from different genders, who ranked the bridge unsafe. The results of this t-test are shown in Table 2. P-value for the test statistic was less than 5% hence the significance of difference in the proportions is proved. Furthermore, Figure 1 shows that the proportion of female respondents was more than male respondents who ranked the bridge unsafe. Hence, it can be said that the female respondents were significantly more concerned about the safety of bridge compared to male respondents. This trend is also seen in some of the previous studies related to site safety, such as Saxena and Yadav (2023). Interestingly, it is not the case found in study done in Spain (Useche et al., 2021). Hence, is could be said that female pedestrians are more concerned about safety of pedestrian facilities in Eastern (or Indian Sub-continent to be specific) while it may not be the case in the western countries.

Table 2. T-test for Proportions for Safety Ranking in the Before Data

Parameter	**Value**
p1, male saying unsafe	0.73
p2, female saying unsafe	0.93
$\hat{p}$ (using equation 1)	0.85
Z (using equation 2)	-2.76
P ($z \leq Z$)	0.003

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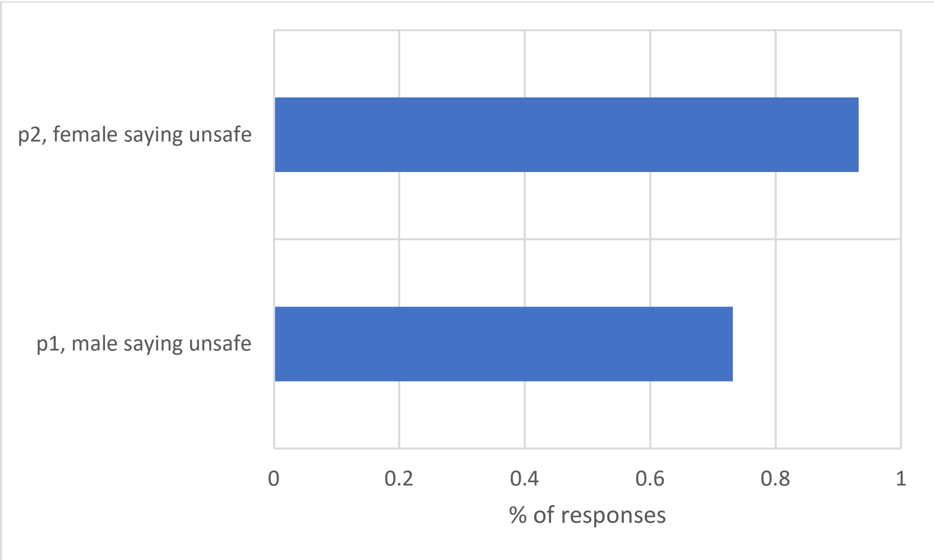

Figure 1. Comparison of Safety Perception of Respondents in Before Dataset

Interestingly, when the safety perception was asked in the after dataset, when the guardrail was installed, all the respondents ranked the bridge to be safe. Considering the fact that overall 85% of the respondents ranked the bridge unsafe before the guardrail installation, it is an extremely drastic improvement. Hence, it could be said that proper installation of the facilities plays a very important role in building the safety perception of road users. This is also confirmed by a previous study which highlighted the importance of design aspects on safety perception of road users (Maynard, 2013).

ANOVA and KS tests were performed to check the significance of difference in responses related to time of crossing by different genders. The results of these tests are shown in Tables 3 and 4. The ANOVA test shows that there is significant variation in the reported time of crossing in the respondents (p-value of 0.04), however, it did not show any significant variation for respondents from different genders. The later was established through KS test, wherein the maximum difference in cumulative frequency was 0.43 while the critical value was 0.35. Hence, it can be concluded that there is significant variation in responses opting for different times of the day for using bridge and gender has a significant impact on these responses.

Table 3. ANOVA for Time of Crossing in Before Dataset

Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Time of Crossing	1089	2	545	21.95	0.04	19
Gender	54	1	54	2.07	0.28	18.51
Error	52	2	26			
Total	1195	5				

Table 4. KS Test for Time of Crossing in Before Dataset

	Male	**Female**	**Cumulative frequency**	**Cumulative frequency**	**KS D**

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			before	after	value
Morning	8	16	0.19	0.39	0.19
Afternoo n	29	41	0.90	1.39	0.48
Evening	4	2	1	1.43	0.43
				D (Using equation (7)) =	0.35

Figure 2 shows that most of the respondents opted to cross in the afternoon time, which could be attributed to the class times which normally finish in the afternoon. As to the case of the morning time, the lower preference could be the fact that students may not opt to take the pedestrian bridge to save time and prefer to cross on the ground, while they are rushing to their classes. Saving time is found to be one of the most influential factors because of which people avoid pedestrian bridges, in the literature related to the use of pedestrian bridges (Hasan and Napiah, 2017). There were more female respondents which were using the bridge in the peak times (morning and afternoon). As per the results of the tests, this increase in female respondents is significantly higher than their male counterparts. The study by Ojo et al. (2022) also confirmed the trend of higher use of footbridge among female students.

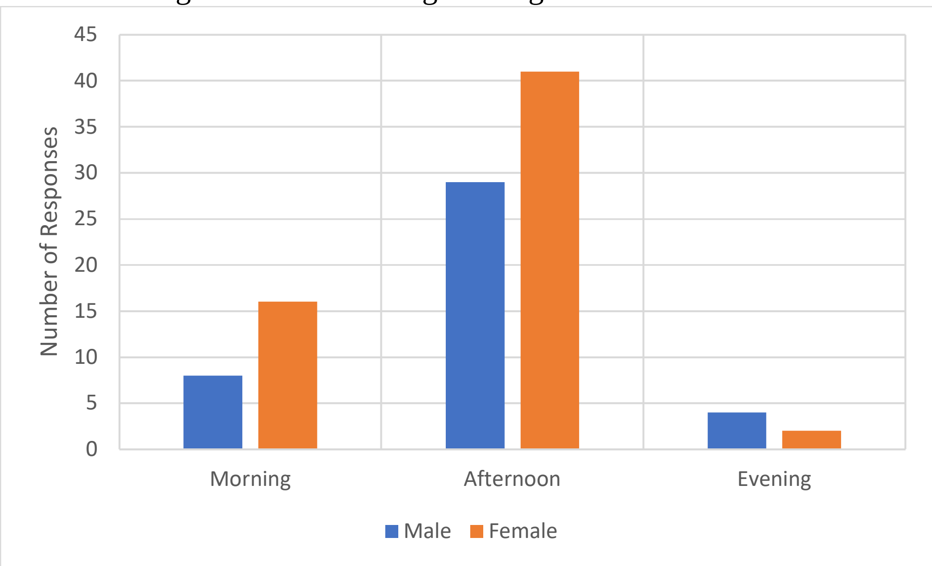

Figure 2. Comparison of Crossing Times by Different Genders in the Before Dataset

ANOVA and KS tests were also performed to check the difference in responses for time of crossing in the before and after datasets. Their results are shown in Tables 5 and 6. In both tests, there was no significant difference detected in the crossing times reporting. Hence, the reporting of crossing times was same in the before and after datasets, which could be taken as an indication of consistency among the respondents as no other factor changed (except installation of the guardrail) in the study settings.

Table 5. ANOVA for Time of Crossing Before and After

Source of	SS	df	MS	F	P-	F crit

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Variation					**value**	
Time of Crossing	2186	2	1093.167	5.04	0.16	19
Before and After	00	1	00	00	1	18.51
Error	433	2	216.5			
Total	2619	5				

Table 6. KS Test for Time of Crossing Before and After

	Before	**After**	**Cumulative frequency before**	**Cumulative frequency after**	**KS D value**
Morning	24	37	0.24	0.37	0.13
Afternoon	70	46	0.94	0.83	0.11
Evening	6	17	1	1	0
				D =	0.24

The consistency of preferred time of crossing was further reinforced by the ANOVA and KS tests (Table 7 and 8) performed on the after datasets. In this case, ANOVA showed a significant difference in the reporting times of crossing. Trends shown in Figure 3 are similar to Figure 2, with afternoon having the highest response rate and higher female reporting in all cases. However, there was no significant effect detected due to the gender in the times of crossing by ANOVA or KS test. This could be attributed to the higher willingness of male students to use bridge, when the guardrail was installed. It may have reduced the significance of difference of their responses with female respondents shown in the before dataset.

Table 7. ANOVA for Time of Crossing in After Dataset

Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Time of Crossing	220	2	110	21.32	0.04	19
Gender	11	1	10	2.06	0.28	18
Error	10	2	5			
Total	241	5				

Table 8. KS Test for Time of Crossing in After Dataset

	Male	**Female**	**Cumulative frequency male**	**Cumulative frequency female**	**KS D value**
Morning	19	18	0.41	0.33	0.08
Afternoon	21	25	0.87	0.80	0.07
Evening	6	11	1.00	1.00	0.00
				D =	0.35

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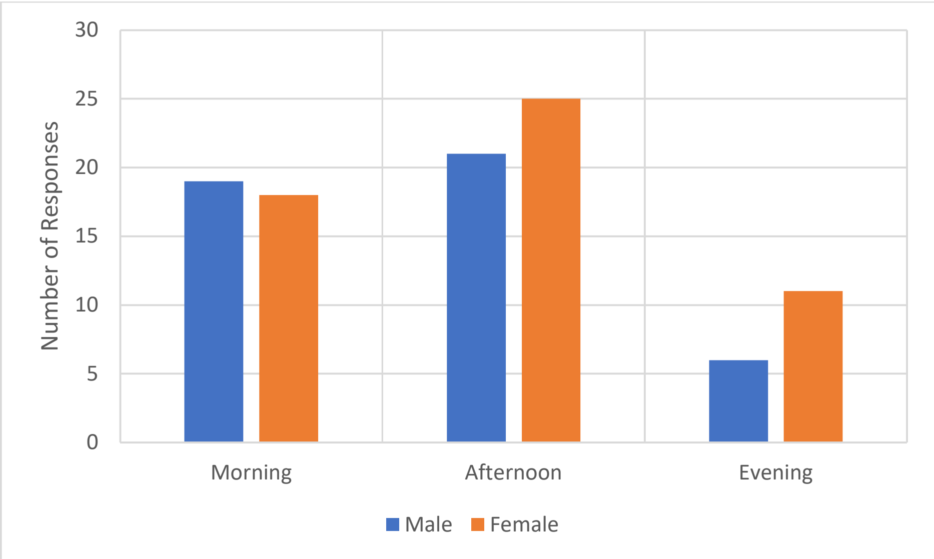

Figure 3. Comparison of Time of Crossing in the After Dataset

ANOVA and KS tests were also performed to check the difference between the hazard perceptions in the before and after samples. It should be noted that the before dataset contained guardrail as one of the possible hazards, while the after dataset did not have this after it was fixed. Hence, the respondents who opted for the other hazard factors (addict, beggar or dog), which were 38 from the available dataset of 100, were taken into consideration from the before dataset for the purpose of this comparison. The ANOVA test (shown in Table 9) did not show any significance difference in the perception. However, the KS test (shown in Table 10) showed a critical D-value which was approximately the same as maximum difference found in the cumulative frequencies. Hence, it was considered to be a significant difference according to the result of KS test.

Tables 9. ANOVA for Hazard Perception Before and After

Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Type of Hazard	530	2	265	0.50	0.66	19
Before and After	0	1	0	0	1	18.51
Error	1057	2	528			
Total	1587	5				

Table 10. KS Test Hazard Perception Before and After

	Before	After	Cumulative frequency before	Cumulative frequency after	KS D value
Addict	45	44	0.45	0.44	0.01
Beggar	50	18	0.95	0.62	0.33
Dog	5	38	1	1	0
				D =	0.33

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Figure 3 shows that the proportion of responses for Addict were same in the before and after datasets, in both cases it was more than 40%. Hence, the issue of security which rises in the presence of an addict is the primary concern for many of the respondents when the design of bridge is safe. The significant difference was shown in the rating of Beggar and Dog, with higher rating for Beggar in the before sample while this was the case for Dog in the after sample. This could be linked to the fact that beggars would be encroaching on part of the walking space as they sit there and then they approach every walking person for alms. Hence, the pedestrians would have felt a higher risk of falling over without the guardrail.

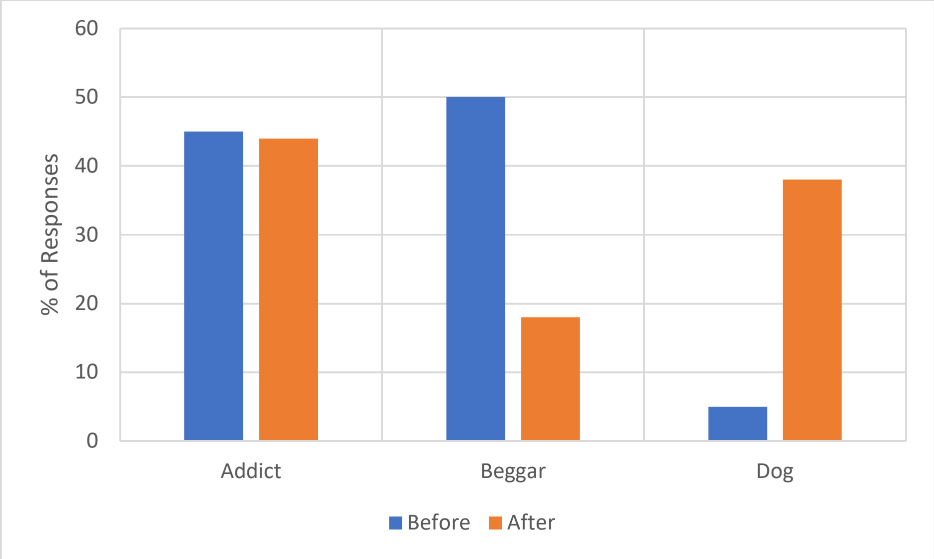

Figure 4. Comparison of Hazard Perceptions in Before and After Samples

4.3 Models

As mentioned earlier, logistic regression and CART models were developed for the before and after dataset. However, the data was imbalanced in terms of the number of responses for each hazard level, as shown in Table 1. If the models are developed with this raw data, then they will be biased towards predicting the majority class. Hence, samples for the hazard factors were duplicated to match with the hazard factor responses opted by the majority of respondents (Lee and Li, 2015). For example, the before dataset has 62 responses for Guardrail, hence, number of responses for Addict, Beggar and Dog were duplicated so that each one of them has 62 responses. This resulted in 248 samples (62x4) for the before dataset. Whereas 132 samples were used for the models of after dataset since 44 people chose Addict, and other two hazards were also duplicated to have the same value. In each case, 20% of the data was randomly selected and kept aside to validate the model.

Logistic regression models were developed for the before and after datasets. The utility function for the before dataset is shown in Equations (10), (11) and (12), while those for the after dataset are shown in Equations (13 and (14). In the case of the model of before dataset, the probability of choosing Guardrail, Addict or Beggar would be calculated using Equation (8), while that for choosing Dog will be calculated as ($1 - P_{Guardrail} - P_{Addict} - P_{Beggar}$). Same would be done for calculating probability for choosing Beggar in the after dataset.

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$U_{Guardrail}$ = 13.38 - 9.29(Female) + 1.17(Unsafe) - 5.40(Afternoon) + 12.25(Morning) (10)
U_{Addict} = 13.80 - 9.00(Female) + 0.63(Unsafe) - 5.49(Afternoon) + 12.00(Morning) (11)
U_{Beggar} = 7.70 - 8.61(Female) + 1.00(Unsafe) + 0.29(Afternoon) + 17.77(Morning) (12)

From the coefficients of utility functions in the before dataset (Equations (10) – (12)), it is clear that female respondents are less likely to choose Guardrail, Addict or Beggar, alternatively, they are more likely to select the Dog. It was also verified through the data in which the respondents who selected Dog were all females. These respondents have higher coefficient on the utility function of Guardrail, as compared to Addict or Beggar. Moreover, people who deem the bridge unsafe mainly do it due to the Guardrail issue which is shown by its higher coefficient in Equation (10) compared to Equations (11) or (12). People who want to cross during the afternoon or morning are more likely to be concerned with beggars. People who cross in the afternoon time are less likely to choose Guardrail or Addict. The morning crossing time has a positive impact on the selection of Guardrail and Addict; however, its impact is even higher on selection of Beggar.
Based upon these observations, it could be said that getting rid of beggars and dogs will benefit the female users and those who cross in the afternoon, who are the majority of students in the dataset. Moreover, getting rid of beggars may have a greater impact on the morning time users and may increase the utilization of the bridge.

U_{Addict} = 0.02 – 0.26(Morning) + 0.61(Afternoon) (13)
U_{Dog} = -0.07 – 0.79(Morning) + 0.87(Afternoon) (14)

Equations (13) and (14) show that gender has no impact on the choice of hazard factors. This was also seen in the case of its impact on time of crossing in the after dataset. As stated earlier, installation of guardrail may have prompted more male pedestrians to cross resulting in diminishing the impact of gender. The time of day has higher impact on choosing Dog as compared to Addict. Moreover, respondents crossing in the morning time are less likely to choose Addict or Dog, while those crossing in Afternoon time are more likely to select them. Hence, getting rid of dogs and addicts, in the presence of guardrail will be beneficial for the majority of the users who cross during afternoon time. On the other hand, morning users could be more concerned about beggars as their impact on Addicts and Dogs' utility function is negative.
Accuracy of the models was measured in terms of rates of accuracy which is calculated using the Equations (15).

$$Accuracy = (CP)/(TS) \qquad (15)$$

Where CP are the number of observations correctly predicted by the model, and TS are the total number of samples (Nemer, 2021).

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The parameters for the logistic regression models are shown in Table 11 for the before and the after cases. For each case, a sample of 20% observations was randomly selected for validation of the model which were not used for developing the model. The accuracy of these models in both cases is very low. This justifies the use of another technique in the form of CART models in this study. However, it should be noted that the accuracy for the after dataset was slightly better than before dataset model. This could be attributed to simplification in the prediction problem with less output classes in the after dataset (Bayen and Murnane, 1996).

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Table 11. Parameters for Logistic Regression Models

Parameter	**Before Model**		**After Model**	
	Training Data	**Test Data**	**Training Data**	**Test Data**
Initial Log-likelihood	-275.78		-116.39	
Final Log-likelihood	-220.16		-111.65	
Accuracy	0.45	0.41	0.50	0.43

The other type of model used in this study are CART models. Figures 5 and 6 show the structure of each of these models. Figure 5 shows that the time of crossing is the primary variable which affects the hazard choice, as it is at the top of the tree. Respondents who prefer to cross in the evenings either select Addict or Dog as the main hazard, based upon their overall perception of the bridge. It seems that these respondents consider the bridge unsafe at these times due to the presence of the Addict.

As for the other times of crossing, female respondents crossing during morning either select guardrail or beggar, former seems to be the cause of considering the bridge unsafe by them. Female respondents who cross during afternoon, select addict or beggar, among which beggar seems to be the cause of considering the bridge unsafe by female. Male respondents, whether crossing in morning or afternoon, choose guardrail when they consider to be unsafe, otherwise, they choose addict. Hence, these observations point to the fact that removal of addicts may increase the utilization of bridge in the morning and evening times for the male students, and in the afternoon times for the female students.

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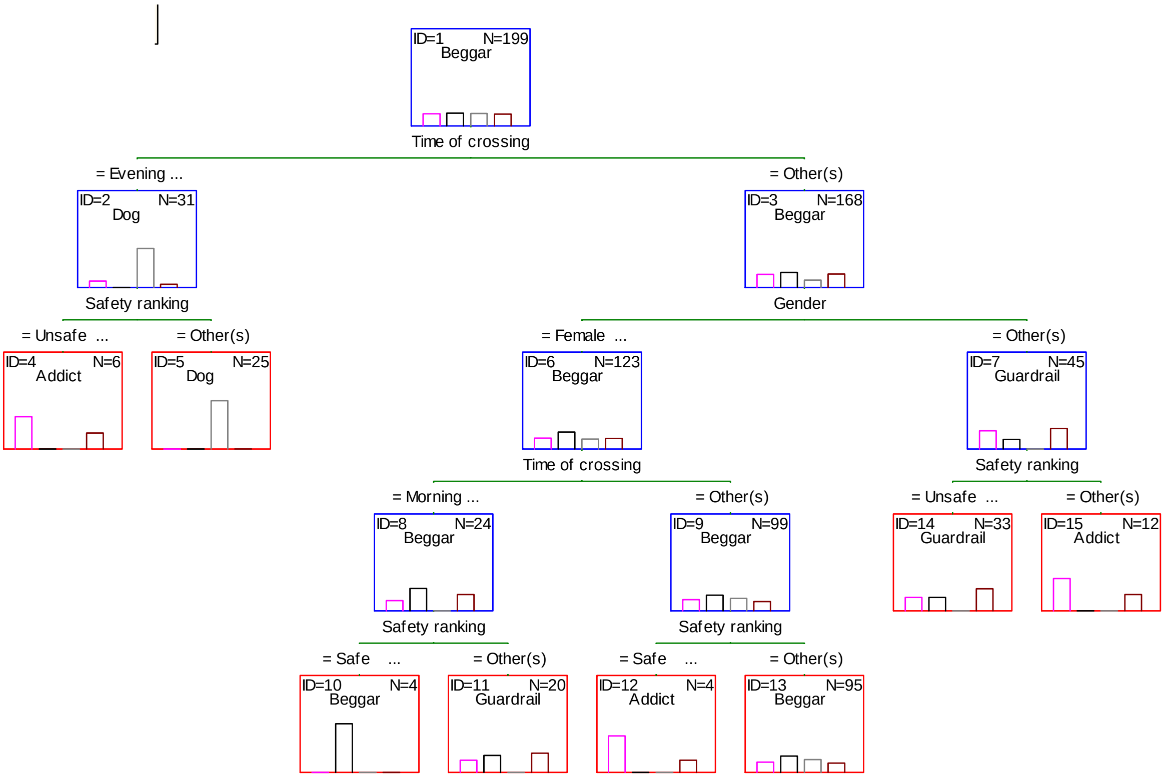

Figure 5. CART Model for Before Dataset

CART model in Figure 6, for the after dataset, has less variables as safety ranking is not considered in this case, for the reasons already stated earlier. Similar to the before dataset, time of crossing is still the top classifier for the tree. With the guardrail, people who cross during afternoon are more likely to consider Dog as the primary hazard, irrespective of their gender. For users who cross during morning or evening, beggar is the main concerns for females and addict is the main concern for male students.

Figure 7 shows the accuracies of CART models for each dataset, on the training and test samples. These accuracies are similar to those obtained from logistic regression models. Hence, use of other techniques or collection of extended data (including more variables) is highly recommended for future studies. It is also clear that observations from the CART models provide more insights, compared to logistic regression models, into the decision process in an efficient manner through its tree structure. Hence, its application to similar datasets is advised, which is also corroborated in the literature (Li et al., 2016).

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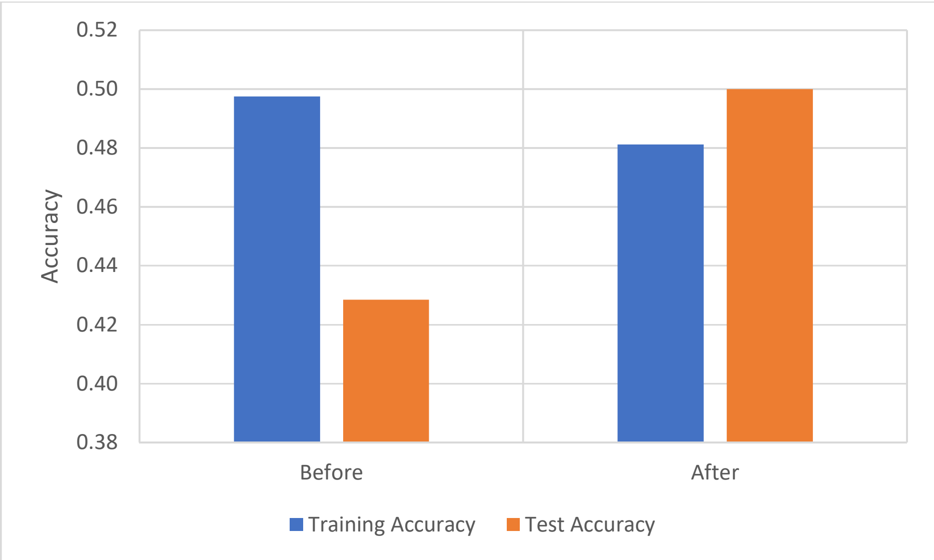

Figure 7. Accuracy of CART Models

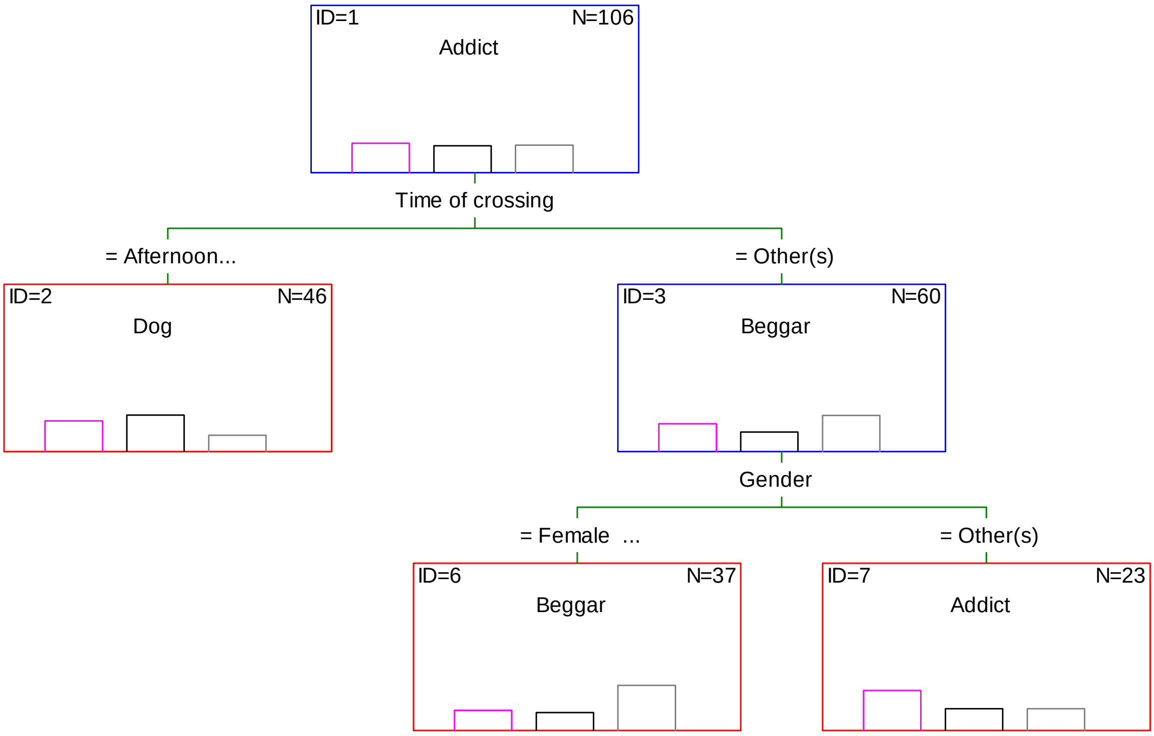

Figure 6. CART Model for After Dataset

Based upon the above observations, a t-test for proportion was conducted to determine if the proportions of genders are significantly different from each other. The test results in Table 12 show that the difference between these proportions of was not significant. Therefore, it can be

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said that the change in the effect of gender in the after-dataset parameters is not because of the change in dataset, instead, it was due to the change in settings.

Table 12. T-test for Proportions for Gender

Parameter	Value
p1, female in the before dataset	0.59
p2, female in the after dataset	0.54
$\hat{p}$ (using equation 1)	0.56
Z (using equation 2)	0.71
P ($z \leq Z$)	0.76

5. Conclusions

This study aimed to understand the hazard perception related to use of pedestrian bridge among university students in Karachi, Pakistan. Data of 100 students was taken before and after the improvement of a pedestrian bridge at University Road in Karachi. Statistical analysis, logistic regression and CART models were used to explore the perception for different genders of students.

It was found that rehabilitation (installation of guardrail) had a significant impact on changing the overall hazard perception of the young pedestrians, even when the other factors persisted. The most important time of crossing for these students was the afternoon, while evening was the least utilized time of the bridge. These findings are corroborated from another study, which was done in another city of Pakistan by Kamal et al. (2013). There were more female participants in the dataset, which could be due to their higher use of the pedestrian bridge. Female participants were found to be more concerned about the safety of the bridge in the before data. CART model revealed that in most cases, it was due to beggar or addict rather than the missing guardrail. Logistic regression model also showed that people crossing in morning and afternoon are more concerned about the presence of beggar when there was no guardrail. While in the after dataset, morning crossers were more concerned about dogs and addicts. This gives an indication that the changes on the bridge will not only change the overall perception about the facility, but it may alter the perception about other existing factors.

The use of logistic regression models revealed important findings. However, the model accuracies were found to be low with possible reasons being small sample size and lack of explanatory variables. Hence, it is recommended for future studies to attempt a much deeper analysis with larger sample size and number of variables. CART models were found to be very efficient in displaying the relationships between the variables at different levels.

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Appendix A: Before Data

Gender	Safe/Unsafe	Hazard Factor	Best Time of Crossing
Female	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Guard Rail	Afternoon
Male	Safe	Addict	Morning
Female	Unsafe	Addict	Afternoon
Male	Unsafe	Guard Rail	Afternoon
Male	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Beggar	Morning
Female	Unsafe	Beggar	Morning
Male	Safe	Addict	Afternoon
Male	Unsafe	Addict	Afternoon
Male	Unsafe	Guard Rail	Morning
Female	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Beggar	Afternoon
Female	Unsafe	Beggar	Afternoon
Male	Unsafe	Beggar	Afternoon
Female	Unsafe	Guard Rail	Morning
Male	Unsafe	Guard Rail	Afternoon
Male	Unsafe	Addict	Afternoon
Female	Unsafe	Beggar	Afternoon
Female	Unsafe	Addict	Afternoon
Male	Unsafe	Beggar	Afternoon
Female	Unsafe	Beggar	Afternoon
Female	Unsafe	Guard Rail	Afternoon
Female	Safe	Guard Rail	Afternoon
Male	Unsafe	Addict	Morning
Female	Unsafe	Guard Rail	Afternoon
Male	Unsafe	Guard Rail	Afternoon
Male	Unsafe	Beggar	Afternoon
Female	Unsafe	Beggar	Afternoon
Female	Unsafe	Addict	Morning
Female	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Guard Rail	Afternoon
Male	Unsafe	Beggar	Afternoon
Male	Unsafe	Guard Rail	Afternoon
Male	Safe	Guard Rail	Afternoon
Female	Unsafe	Addict	Afternoon
Female	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Guard Rail	Morning
Male	Unsafe	Addict	Afternoon

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Male	Unsafe	Guard Rail	Afternoon
Male	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Beggar	Afternoon
Female	Unsafe	Addict	Afternoon
Male	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Guard Rail	Morning
Male	Safe	Addict	Afternoon
Female	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Guard Rail	Afternoon
Male	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Beggar	Afternoon
Female	Unsafe	Guard Rail	Afternoon
Male	Safe	Guard Rail	Afternoon
Female	Unsafe	Beggar	Morning
Male	Safe	Guard Rail	Afternoon
Female	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Guard Rail	Morning
Female	Unsafe	Guard Rail	Afternoon
Male	Unsafe	Guard Rail	Afternoon
Male	Unsafe	Guard Rail	Afternoon
Male	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Guard Rail	Afternoon
Male	Safe	Guard Rail	Morning
Female	Unsafe	Addict	Afternoon
Female	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Guard Rail	Afternoon
Male	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Guard Rail	Morning
Female	Unsafe	Beggar	Afternoon
Male	Unsafe	Guard Rail	Evening
Female	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Guard Rail	Morning
Male	Safe	Guard Rail	Morning
Male	Safe	Guard Rail	Afternoon
Female	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Beggar	Afternoon
Female	Unsafe	Dog	Afternoon
Male	Unsafe	Guard Rail	Morning

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Male	Safe	Guard Rail	Afternoon
Female	Safe	Beggar	Morning
Male	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Addict	Evening
Female	Unsafe	Guard Rail	Morning
Male	Unsafe	Guard Rail	Morning
Female	Safe	Dog	Evening
Female	Safe	Addict	Afternoon
Male	Unsafe	Guard Rail	Morning
Male	Safe	Guard Rail	Evening
Female	Unsafe	Addict	Afternoon
Male	Unsafe	Guard Rail	Afternoon
Female	Unsafe	Beggar	Afternoon
Male	Unsafe	Guard Rail	Evening
Male	Unsafe	Guard Rail	Evening
Female	Unsafe	Guard Rail	Morning
Female	Unsafe	Addict	Morning
Female	Unsafe	Beggar	Afternoon
Female	Unsafe	Guard Rail	Morning
Female	Unsafe	Guard Rail	Morning

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Appendix B: After Data

Gender	Safe/Unsafe	Hazard Factor	Best Time of Crossing
Male	Safe	Addict	Morning
Female	Safe	Dog	Afternoon
Male	Safe	Addict	Morning
Male	Safe	Addict	Morning
Male	Safe	Dog	Afternoon
Female	Safe	Addict	Afternoon
Female	Safe	Dog	Afternoon
Male	Safe	Addict	Afternoon
Male	Safe	Addict	Morning
Male	Safe	Addict	Morning
Female	Safe	Dog	Evening
Female	Safe	Addict	Morning
Female	Safe	Beggar	Morning
Female	Safe	Dog	Afternoon
Male	Safe	Beggar	Evening
Male	Safe	Addict	Morning
Female	Safe	Addict	Morning
Female	Safe	Addict	Morning
Female	Safe	Dog	Afternoon
Male	Safe	Dog	Afternoon
Male	Safe	Dog	Evening
Male	Safe	Beggar	Afternoon
Male	Safe	Addict	Morning
Female	Safe	Addict	Evening
Female	Safe	Addict	Morning
Female	Safe	Dog	Evening
Male	Safe	Dog	Afternoon
Male	Safe	Dog	Afternoon
Female	Safe	Addict	Afternoon
Female	Safe	Addict	Evening
Female	Safe	Addict	Morning
Male	Safe	Addict	Morning
Male	Safe	Beggar	Morning
Male	Safe	Dog	Morning
Female	Safe	Addict	Afternoon
Female	Safe	Addict	Evening
Female	Safe	Dog	Afternoon
Female	Safe	Beggar	Morning
Male	Safe	Addict	Evening

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Male	Safe	Dog	Afternoon
Female	Safe	Dog	Afternoon
Female	Safe	Dog	Afternoon
Male	Safe	Addict	Afternoon
Female	Safe	Beggar	Morning
Male	Safe	Addict	Morning
Male	Safe	Dog	Evening
Female	Safe	Addict	Afternoon
Female	Safe	Addict	Evening
Female	Safe	Addict	Afternoon
Male	Safe	Beggar	Afternoon
Male	Safe	Dog	Morning
Male	Safe	Dog	Morning
Female	Safe	Dog	Morning
Female	Safe	Addict	Afternoon
Male	Safe	Dog	Evening
Female	Safe	Dog	Evening
Female	Safe	Addict	Afternoon
Male	Safe	Addict	Afternoon
Male	Safe	Dog	Afternoon
Female	Safe	Dog	Afternoon
Female	Safe	Beggar	Morning
Female	Safe	Addict	Afternoon
Male	Safe	Addict	Afternoon
Male	Safe	Addict	Evening
Male	Safe	Beggar	Afternoon
Female	Safe	Addict	Afternoon
Female	Safe	Dog	Morning
Female	Safe	Dog	Morning
Male	Safe	Dog	Afternoon
Male	Safe	Addict	Morning
Male	Safe	Beggar	Morning
Female	Safe	Beggar	Morning
Female	Safe	Addict	Morning
Female	Safe	Dog	Afternoon
Female	Safe	Dog	Evening
Female	Safe	Addict	Afternoon
Male	Safe	Beggar	Afternoon
Female	Safe	Addict	Afternoon
Female	Safe	Beggar	Afternoon
Male	Safe	Dog	Afternoon

https://doi.org/10.59879/A3EiA

Female	Safe	Addict	Morning
Female	Safe	Beggar	Morning
Male	Safe	Dog	Morning
Male	Safe	Dog	Afternoon
Female	Safe	Addict	Afternoon
Female	Safe	Beggar	Evening
Male	Safe	Addict	Afternoon
Male	Safe	Beggar	Morning
Male	Safe	Dog	Afternoon
Female	Safe	Dog	Afternoon
Female	Safe	Dog	Afternoon
Male	Safe	Addict	Afternoon
Male	Safe	Addict	Afternoon
Female	Safe	Beggar	Evening
Female	Safe	Beggar	Morning
Male	Safe	Addict	Morning
Male	Safe	Addict	Morning
Female	Safe	Dog	Morning
Female	Safe	Dog	Afternoon
Female	Safe	Dog	Evening

https://doi.org/10.59879/A3EiA