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The Age Limit for Motorcyclists to Stop Riding in an Effort to Improve Rider Safety

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ABSTRACT

The purpose of this study is to develop a model that can predict when motorcyclists should stop riding due to a decline in alertness, which occurs as the rider ages, resulting in a decreased ability to ride safely. In Indonesia, the number of accidents in 2020 was notably high among individuals aged 10-29 years. This accident rate then decreases until the age of 49, but increases again for those aged 50 years and above. The number of motorcycles in Indonesia continues to grow each year, contributing to the increasing number of accident cases annually. This study was conducted in Riau province, Indonesia, with a total of 860 respondents. Data collection was carried out through interviews. Since the data in this study is probabilistic, it is suitable for analysis using a Bayesian network. The results show that elderly motorcyclists are likely to have a high level of alertness at 57%, adult motorcyclists at 68%, and adolescent motorcyclists at 75%. In scenario 1, elderly motorcyclists whose vision is obstructed while riding are likely to have a high level of alertness at 47%. In scenario 2, elderly motorcyclists riding on roads with roadside variability are likely to have a high level of alertness at 57%. In scenario 3, elderly motorcyclists riding in a fatigued condition are likely to have a high level of alertness at 56%. In scenario 4, elderly motorcyclists riding on pothole-ridden roads are likely to have a high level of alertness at 57%. The findings of this study indicate that riders aged 46-65 years are highly vulnerable to accidents due to having the lowest level of alertness compared to other age groups. It is recommended that motorcyclists aged 46–65 years stop riding motorcycles.

Keywords: Accidents, Adolescents, Adults, Bayesian, Elderly, Motorcycle.

INTRODUCTION

Statistical data from Indonesia shows that the number of motorcycle accidents is quite high, with age being one of the key factors contributing to this high accident rate (Bucsuházy et al., 2019; Skyving et al., 2021; Lumba et al., 2024b). The impact of these accidents, such as the significant number of victims suffering severe injuries, is also noteworthy (Lumba et al., 2024a). Motorcycles are particularly popular among young riders (Lumba et al., 2022b) in Indonesia. However, young riders tend to have less stable emotional and mental states, which greatly increases their potential for accidents (Megías-Robles et al., 2022; Maghelal et al., 2023). Moreover, young riders often lack driving experience (Kerruish et al., 2022), leading many to engage in risky behaviors that contribute to accidents. These behaviors include exceeding speed limits (Jannusch et al., 2021), using mobile phones while riding (Lyon et al., 2020; Ali & Haque, 2023; Katrakazas et al., 2020; Brands et al., 2022), and participating in illegal street racing. Their inexperience also increases the likelihood of committing traffic violations, either intentionally or unintentionally (Jannusch et al., 2021; Muley et al., 2022; Lyon et al., 2020; Ali & Haque, 2023; Katrakazas et al., 2020; Brands et al., 2022; Rahman et al., 2021). In addition, young riders are often more exposed to online content compared to middle-aged and older riders. This exposure can motivate them to engage in disorderly behavior in traffic (Nicolls et al., 2024), further increasing the risk of accidents (Moller et al., 2021) compared to more experienced riders (Tselentis et al., 2020). Although the number of accident victims decreases as riders age, this trend reverses and begins to rise again among riders aged 60–69 years (Zhu et al., 2022).

Middle-aged drivers are generally more experienced than young drivers (Patten et al., 2006; Kerruish et al., 2022). Young adult novice drivers are more prone to physical and mental fatigue during driving compared to middle-aged drivers (Tong et al., 2024). Moreover, as drivers age, sensory accuracy tends to decrease, and memory capacity may decline, especially in older drivers, which can impair decision-making while driving (Park et al., 2021). Many factors contribute to the occurrence of accidents, one of which is maneuvering while driving. Maneuvers performed by older adult drivers are among the biggest factors causing fatal accidents (Skyving et al., 2023). In addition to these issues, the behavior of using mobile phones while driving is not limited to young drivers, but is also observed among middle-aged drivers. The use of mobile phones by middle-aged drivers can reduce the headway, increasing the risk of accidents (Gazder & Assi, 2022). However, social media also presents an opportunity to convey traffic safety messages effectively to middle-aged, young, and older drivers (Nicolls et al., 2025).

Older riders face several limitations while riding, including impaired vision, lack of focus, longer reaction times (Yeung & Wong, 2015), quick onset of fatigue (Chu, 2020), frequent health issues during rides (Skyving et al., 2021), and insufficient understanding of modern vehicle technology (Wada et al., 2020; Classen et al., 2021; Stamatiadis & Kirk, 2020; Nguyen et al., 2023). Another factor contributing to decreased rider alertness is fatigue, which can result from prolonged trips (Elvik, 2023), insufficient sleep (Lumba et al., 2022b), and extended driving durations. These conditions undoubtedly reduce rider performance (Wijayanto et al., 2021; Takeyama et al., 2023), significantly increasing the potential for accidents (Lumba, 2022c). Older drivers in unhealthy conditions are more likely to experience declines in driving performance (Toepper et al., 2024). Additionally, cognitive decline in older drivers can result in reduced safe driving abilities, such as an increased likelihood of engaging in wrong-way driving behavior (Nihei et al., 2022). Regarding the emotional state of older drivers, the emotional levels of older male drivers, especially under conditions of increased cognitive workload, contribute to longer reaction times (Oztürk et al., 2023; Biernacki & Lewkowicz, 2020) and a higher number of errors (Biernacki & Lewkowicz, 2020). Single-vehicle accidents are often experienced by male drivers over 80 years old and female drivers over 70 years old (Kim et al., 2023), with older male drivers having a higher probability of fatal single-vehicle crashes (Dzinyela et al., 2023). Generally, male drivers are involved in more accidents than female drivers (Naghawi & Bannoura, 2019). Regarding road geometry, older drivers at intersections significantly reduce intersection capacity due to higher lost time and lower saturation flow rates (Lu & Pernía, 2000).

Several studies have explored ways to improve the safety of elderly drivers. In terms of road geometry, there is a need for planning that accommodates the conditions of elderly drivers, such as designing safer intersections (Zhao et al., 2020) and providing safe routes by limiting or eliminating the need for left turns (Stamatiadis & Kirk, 2020). Enhancing safety for elderly drivers can also be achieved by reviewing driving licenses (Chu, 2020). For example, drivers who take driving courses before the age of 75 have a lower risk of accidents (Ulleberg et al., 2022). Currently, Indonesia does not have a law regulating a maximum age limit for motorcycle riders. While some researchers do not propose a specific maximum age for riders, they recommend that older riders use assistive devices or tools to improve their safety. Additionally, other road users should adapt their behavior to accommodate older riders to improve overall safety (Haan et al., 2022; Veerhuis et al., 2025; Attuquayefio et al., 2023; Wood et al., 2024).

Several previous studies have also explored the impact of driver alertness. Drivers who are on the road for extended periods, particularly in monotonous conditions or while being sleep-deprived, experience a decrease in alertness, which affects their ability to process visual information around them (Ma et al., 2003; Roge et al., 2004). Furthermore, driving for long periods during the day in monotonous conditions can lead to a continuous decline in alertness (Schmidt et al., 2009). Driver alertness tends to increase when driving on winding roads, whereas driving on straight roads does not significantly affect alertness levels (Larue et al., 2011). The level of alertness of road users plays a significant role in shaping the probability distribution of accident severity when an accident occurs (Lapparent, 2005).

Statistical data in Indonesia indicates that the number of accident victims over the last three years has been quite high. The number of motorcycles in Indonesia in 2020, 2021, and 2022 was 136,137,451, 141,992,573, and 148,261,817, respectively. During the same period, the number of accidents also showed an upward trend, with 100,028 accident victims in 2020, 106,172 in 2021, and 139,258 in 2022 (BPS-Statistic Indonesia, 2023). In 2020, there were 100,028 accident victims, and in 2021 this number increased by 6.14% to 106,172. Then, in 2022, the number of accident victims rose again by 31.16% to 139,258. This data indicates that the increase in the number of motorcycles each year correlates with the rising number of accidents in Indonesia. Approximately 70.93% of accidents nationwide involved motorcyclists, and 25% of these victims were minors. Among the victims, 26,906 were aged 10-19 years, 29,281 were aged 20-29 years, 18,553 were aged 30-39 years, and 17,980 were aged 40-49 years. Notably, the number of accidents increased drastically among riders aged 50 years and above, with 31,740 victims (Ministry of Transportation, 2020). The significant increase in accident rates among older age groups highlights the need to determine a maximum age limit for riding motorcycles as part of the efforts to improve motorcyclist safety. Addressing these issues requires research focused on enhancing motorcyclist safety. The aim of this study is to develop a model that can estimate when motorcycle riders should stop riding due to a decline in alertness as they age, which results in a reduced ability to ride safely. This study will be valuable for the Ministry of Transportation of the Republic of Indonesia and local governments in formulating regulations and programs aimed at improving motorcyclist safety in Indonesia.

To achieve the objectives of this study, it is vital to find a solution to reduce the risk of accidents by creating a model that predicts when motorcyclists should stop using motorcycles. This model is based on three factors: human factors, road conditions, and the environment, with all three factors being considered simultaneously. The study is conducted in Riau province, Indonesia. Data was collected through interviews with motorcyclists who had experienced accidents. Since the data is probabilistic, the most suitable analysis for developing this model is the Bayesian network analysis. The model obtained will be validated to assess its accuracy using independent data. If the model proves accurate, it will help identify the dominant variables. This model will also determine the maximum age limit for motorcyclists. Based on this, strategies and measures to improve traffic safety for motorcyclists will be formulated.

METHODS

The research was conducted in Riau province, Indonesia, with data collected from two cities: Pekanbaru and Pasir Pengaraian. Pekanbaru, the capital of Riau province, represents larger cities in Indonesia, which tend to share similar characteristics, particularly in terms of road infrastructure. In contrast, Pasir Pengaraian, the capital of Rokan Hulu Regency, represents smaller cities in Indonesia that exhibit comparable characteristics, including road infrastructure. The reason for selecting these locations is the high number of motorcycles in Riau province, with a total of 3,485,246 units. Riau is also among the top 10 provinces in Indonesia with the highest number of motorcycles. Statistical data from the Riau police in 2023 shows that the severity of accidents was quite high, with 651 fatalities, 357 serious injuries, and 1,742 minor injuries. Furthermore, the number of traffic violations throughout 2023 was 158,854 cases, reflecting an increase of 2.64% compared to the previous year (Polda Provinsi Riau, 2022). Additionally, data from 2023 reveals that roads under the authority of Riau province are in poor conditions, with 881.20 km of roads severely damaged and 526.96 km of road surfaces unpaved (Provinsi Riau Dalam Angka, 2024). These road conditions certainly pose a significant risk to drivers, especially when sections lack lighting. Drivers unfamiliar with the road also face an increased risk, leading to a higher potential for accidents. The sampling technique used in this study was purposive sampling, a method where respondents are selected based on specific criteria. The criterion for the inclusion of respondents in this study was motorcyclists who had experienced accidents, both single and non-single accidents. Respondents who met this criterion were selected randomly, and verbal consent was obtained for their participation. The respondents included adolescent, adult, and elderly riders who had been involved in motorcycle accidents in Riau province.

Data collection was conducted through interviews, where the respondents were approached and interviewed. Some of the questions asked include:

1. What is your name?
2. What is your gender?
3. How old were you when the accident occurred?
4. How much sleep did you get the night before the accident?
5. Did you feel tired before the accident?
6. How long did you drive before the accident occurred?
7. What time did the accident happen?
8. What was the geometry of the road just before the accident?
9. How was the variation in views on the left and right sides of the road just before the accident?
10. How was your visibility when the accident occurred?
11. What was the condition of the road surface at the location of the accident?

Additionally, the number of accident victims reaches 2,750. The research sample size was calculated using Slovin's formula:

$$\mathrm{n} = \frac{\mathrm{N}}{1 + \mathrm{Ne}^2}$$

where, n=sample size, N=population=2,750, e=margin of error=5%. The calculation results in a sample size of 349.21 respondents:

$$349.21 \text{ responden} = \frac{2{,}750}{1+2{,}750 \times 0.05^2}.$$

The survey collected data from 1,447 respondents, with 860 experiencing accidents under low-alertness conditions and 587 respondents under high-alertness conditions. For this study, the sample focused on drivers involved in accidents in low-alertness conditions, totaling 860 participants. This group included 355 elderly drivers (aged 46-65), 270 adult drivers (aged 26-45), and 235 teenage drivers (aged 12-25). Out of the 860 respondents, 634 respondents were used for data analysis, while the remaining 226 respondents were used to validate the model.

The justification for the variables used in the Bayesian network structure, as shown in Table 1, is as follows: When a driver's view is obstructed or blocked by something, he/she may have difficulty identifying the movement of traffic in front of or around him/her (Lumba et al., 2016). Failure to identify this will lead the driver to make incorrect decisions, such as whether to stop, avoid, or continue (Yeung & Wong, 2015). The wrong decision made will impact the driver's level of alertness. Additionally, road factors influence the level of driver alertness, such as road geometry and roadside variability (Larue et al., 2011; Lumba et al., 2018; Thiffault & Bergeron, 2001). Road geometry is related to curves and straight roads. Driver alertness tends to increase when driving on curves compared to driving on straight roads. On straight roads, the activities performed by drivers are fewer and tend to be repetitive, which can lead to drowsiness and reduce alertness, increasing the risk of accidents. Driving on flat roads may help drivers stay more focused on the traffic flow around them, while when driving on roads with potholes, the driver's attention tends to focus more on the road conditions, causing him/her to miss the movement of nearby vehicles. This leads to a lower level of driver alertness. Furthermore, variables, such as the duration of driving, driving time, and the amount of sleep the driver had the night before the accident, all affect the driver's level of fatigue, which in turn influences his/her alertness. This can be explained by the fact that the longer a driver is on the road, the greater is the likelihood that he/she will experience fatigue (Ma et al., 2003; Hensher et al., 1992). Similarly, drivers whose sleep is disrupted or who lack sufficient sleep the night before driving are more likely to become fatigued sooner on the road (Lumba et al., 2022b; Ma et al., 2003). Additionally, driving under hot conditions can contribute to driver fatigue (Horberry et al., 2008; Roudsari et al., 2003; Vorko-Jovic et al., 2005; Crankson, 2006; Clarke et al., 2009). This fatigue impairs the driver's ability to operate the vehicle effectively (Dingus et al., 2006), leading to a decrease in alertness while driving.

The data obtained was analyzed using a Bayesian network with GeNie 2.0 software (BayesFusion, Software GeNie, 2023). Bayesian network analysis is a probabilistic method used to model dependencies among random variables in a system. Bayesian networks are represented as graphs consisting of nodes, each representing a random variable, while the arrows indicate the probabilistic dependencies among variables. Each node has a probability distribution that describes the dependencies among the variables. The hypotheses in Bayesian network analysis include: 1) There are causal relationships among variables; 2) The variables in the model can be treated as independent under specific conditions; 3) The variables follow a defined probabilistic distribution; 4) The structure is a directed acyclic graph that illustrates the relationships among variables; 5) Distribution parameters are determined based on data or domain knowledge. Bayesian networks are particularly suitable for modeling uncertainty. The steps involved in Bayesian network analysis include: 1) identifying the appropriate variables in the system to be analyzed; 2) determining the relationships among variables based on data; 3) defining the conditional probability distribution for each variable; 4) Making inferences to calculate the probability of unknown variables based on existing evidence.

The formula for the Bayesian network is:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B|A)P(A) + P(B|-A)P(-A)}$$

where, A = Event A, B = Event B, P(A|B) is the probability of Event A happening if Event B has occurred. Figures (1) and (2) show examples of Bayesian network structures. The analysis of the Bayesian network in Figure (1) (with 3 variables) can be calculated using this formula:

P(Y) = P(Y|A2, B2) x P(A2) P(B2) + P(Y|A2,-B2) x P(A2) P(-B2) + P(Y|-A2,B2) x P(-A2) P(B2) + P(Y|-A2,-B2) x P(-A2) P(-B2)

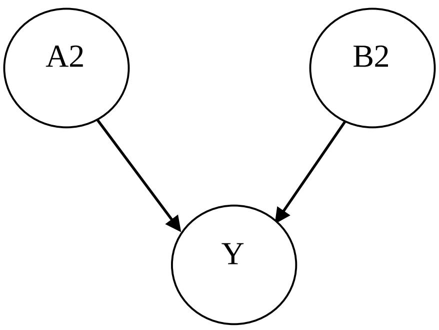

Figure (1): Example of Bayesian network analysis with 3 variables, where P = probability

Figure (1) illustrates that the structure of a Bayesian network consists of three variables: A2, B2, and Y. This means that the probability distribution or value of Y is influenced by the variables A2 and B2. For example, in a garden equipped with a sprinkler (a tool for plant watering), the probability distribution of the soil being wet or not wet is influenced by the rain variable and the sprinkler variable. Denoted as: Y = soil condition, A2 = weather, B2 = sprinkler, variable Y has two values (wet and not wet), variable A2 has two values (rain/A2 and no rain/-A2), and variable B2 has two values (on/B2 and off/-B2). This means that the probability distribution of variable Y consists of 2 values of variable A2 × 2 values of variable B2 × 2 values of variable Y, resulting in 8 possible combinations of soil conditions (wet or not wet). This implies that the probability distribution of Y has 8 possibilities, with 4 distributions where the soil will be wet and 4 distributions where the soil will not be wet.

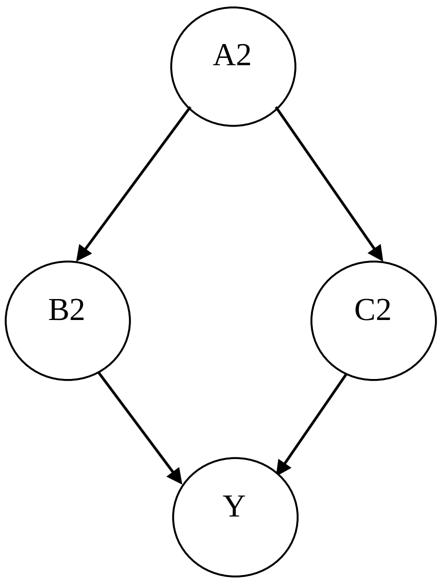

Figure (2): Example of analysis of Bayessian network with 4 variables

Analysis of Bayesian network in Figure (2) (with 4 variables) can be calculated with the following formula:

P(Y) = P(Y|B2,C2,A2) P(B2|A2) x P(C2|A2) + P(Y|B2,-C2,A2) x P(-B2|A2) x P(-C2|A2) + P(Y|-B2,-C2,A2) x P(-B2|A2) x P(C2|A2) + P(Y|-B2,-C2,A2) x P(-B2|A2) x P(-C2|A2).

Bayesian networks are more suitable for predicting accident severity than regression models (Zong et al., 2013). Additionally, the data obtained in this study is probabilistic, making it ideal for analysis using Bayesian networks to model uncertainty (Pearl, 1988; Jensen & Nielsen, 2007). There are fundamental differences between Bayesian network analysis and regression analysis. In regression analysis, population parameters are treated as unknown quantities, whereas in Bayesian network analysis, population parameters are considered variables with prior distributions. Moreover, regression analysis does not allow for the inclusion of two independent variables with strong correlations, which is not a limitation in Bayesian networks. Linear regression methods are typically simpler, with fewer variables, and they handle linear relationships among variables, while Bayesian networks can model non-linear relationships. Finally, model validation is conducted by calculating the Mean Absolute Deviation (MAD), which is the average difference between the model results and the field conditions. This is calculated using the following formula.

$$\mathrm{MAD} = 1/\mathrm{n}\sum|\mathrm{Actual} - \mathrm{Forecast}|.$$

RESULTS AND DISCUSSION

The following section provides a detailed description of data regarding accidents involving motorcyclists with low levels of alertness just before the incident. According to the survey, male motorcyclists are more likely to be involved in accidents, making up 55.84% of cases compared to 44.16% for females. Additionally, 63.25% of motorcyclists involved in accidents did not have a valid driver's license (SIM). The data also shows that 66.26% of the accidents were single-vehicle incidents. Furthermore, motorcyclists traveling at speeds between 50-60 km/h experienced the highest number of accidents, representing 35.02% of the total incidents, when compared to other speed ranges. The majority of accidents occurred between 12:00 and 18:00, accounting for 44.64% of the cases. The survey also found that 65.62% of accidents took place on straight roads, while 34.38% occurred on roads with minimal roadside variability. Additionally, 30.13% of respondents involved in accidents reported experiencing vision impairments, such as blocked views due to objects. About 40.69% of accidents took place on monotonous road sections, and 35.08% occurred on roads with potholes. Lastly, around 24.14% of accidents occurred during rainy weather conditions.

Several variables directly influence the probability of motorcycle riders' alertness levels, including obstructed views before the accident, road geometry, roadside variability, fatigue, and road smoothness. The fatigue factor, in particular, is influenced by variables, such as the duration of riding (Elvik, 2023), riding time, and the amount of sleep the rider gets the night before the accident (Lumba et al., 2022b). Data analysis using GeNie 2.0 software shows that elderly motorcycle riders are likely to have a low alertness level (43%), adult riders 32%, and adolescent riders 25%, as shown in Figure (3). This means that the analysis results indicate that elderly motorcycle riders are likely to have a high alertness level of 57% (100% - 43%), adult riders 68% (100% - 32%), and adolescent riders 75% (100% - 25%). Adolescent riders exhibit a higher level of alertness compared to adult and elderly riders. Several reasons contribute to this higher level of alertness in young riders. Adolescent riders tend to have better physical and cognitive functions compared to other age groups. Their physical functions include sharp vision, acute hearing, and good stamina. Meanwhile, their cognitive functions are also relatively strong, such as better attention or focus, quicker problem identification and processing, and faster responses to potential issues.

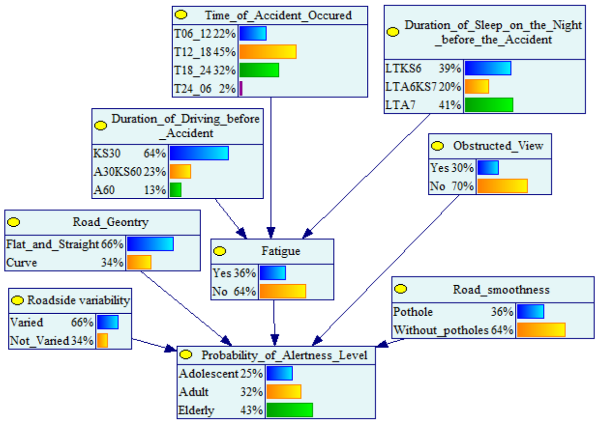

Figure (3): A probability model for low motorcyclist alertness levels

where, KS30: 30 minutes or less of driving, A30KS60: Above 30 minutes up to 60 minutes of driving, A60: Above 60 minutes of driving, T: Accident time, LTKS6: 6 hours or less of sleep on the night before the accident, LTA6KS7: Above 6 hours up to 7 hours of sleep on the night before the accident, LTA7: Above 7 hours of sleep on the night before the accident.

On the other hand, as individuals age, both physical and cognitive functions decline, resulting in a decrease in the level of alertness among elderly riders when faced with sudden or unexpected obstacles. The results of this study regarding elderly riders are consistent with previous research (Yeung & Wong, 2015; Chu, 2020; Skyving et al., 2021; Wada et al., 2020; Classen et al., 2021; Stamatiadis & Kirk, 2020; Nguyen et al., 2023).

The model equation for the probability of the level of driver alertness is:

P(AL) = P(AL)1 + P(AL)2 + P(AL)3 + P(AL)4 + P(AL)5 + P(AL)6 + P(AL)7 + P(AL)8 + P(AL)9 + P(AL)10 + P(AL)11 + P(AL)12 + P(AL)13 + P(AL)14 + P(AL)15 + P(AL)16 + P(AL)17 + P(AL)18 + P(AL)19 + P(AL)20 + P(AL)21 + P(AL)22 + P(AL)23 + P(AL)24 + P(AL)25 + P(AL)26 + P(AL)27 + P(AL)28 + P(AL)29 + P(AL)30 + P(AL)31 + P(AL)32.

Example of calculation of probability of the level of driver alertness 1 or P(AL)1:

P(AL)1= P(AL| BR, Y, TH, DL, BV, DD, TAO, DS) P(Y| DD, TAO, DS);

where, P=Probability, AL=alertness, RS= Road smoothness, F=Fatigue, OV= Obstructed view, RG= Road geometry, RV=Roadside variability, BR=Potholes, TBR=Without potholes, Y=Yes, T=No, TH=Obstructed view, TTH=Unobstructed view, DL=Flat and straight, BT=Curve, BV=Varied, TBV=Not varied, DD=Duration of driving before accident, TAO=Time of accident occurrence, DS=Duration os sleep at night before the accident.

Furthermore, the probability model of riders' alertness levels was validated by calculating the Mean Absolute Deviation (MAD), which measures the average difference between the model results and field conditions. The MAD value obtained indicates the accuracy of the model or the degree of closeness between the model and field conditions. The calculation results show that the MAD value is 23%, meaning that the model accuracy is 77%. In addition to validation through the calculation of the Mean Absolute Deviation, validation is also conducted using the following formula for comparison:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

For alertness probability levels ≥ 50%, a value of 1 is assumed, while for levels < 50%, a value of 0 is assumed. The definitions of TP, TN, FP, and FN are as follows:

1. TP (True Positive): The number of correct predictions of 1 (the model predicts 1 and the actual value is 1).
2. TN (True Negative): The number of correct predictions of 0 (the model predicts 0 and the actual value is 0).
3. FP (False Positive): The number of incorrect predictions of 1 (the model predicts 1 and the actual value is 0).
4. FN (False Negative): The number of incorrect predictions of 0 (the model predicts 0 and the actual value is 1).

From Table 1, the following values were obtained: TP = 0, TN = 21, FP = 1, FN = 8. Thus, the accuracy of the model is 70%.

$$70\% = \frac{0 + 21}{0 + 21 + 1 + 8}.$$

Table 1. Validation of the model

P	Road smoothness	Fatigue	Obstructed view	Road geometry	Roadside variability	Probability of alertness level	
						Actual	Model
1	BR	Y	TH	DL	BV	0	0
2	BR	Y	TH	DL	TBV	0	0
3	BR	Y	TH	BT	BV	0	0
4	BR	Y	TH	BT	TBV	0	0
5	BR	Y	TTH	DL	BV	1	0
6	BR	Y	TTH	DL	TBV	1	0

7	BR	Y	TTH	BT	BV	0	0
9	BR	T	TH	DL	BV	0	0
10	BR	T	TH	DL	TBV	0	0
11	BR	T	TH	BT	BV	0	0
12	BR	T	TH	BT	TBV	0	0
13	BR	T	TTH	DL	BV	1	0
14	BR	T	TTH	DL	TBV	0	0
15	BR	T	TTH	BT	BV	1	0
16	BR	T	TTH	BT	TBV	0	0
17	TBR	Y	TH	DL	BV	0	0
19	TBR	Y	TH	BT	BV	0	0
20	TBR	Y	TH	BT	TBV	0	0
21	TBR	Y	TTH	DL	BV	0	0
22	TBR	Y	TTH	DL	TBV	0	0
23	TBR	Y	TTH	BT	BV	0	0
24	TBR	Y	TTH	BT	TBV	1	0
25	TBR	T	TH	DL	BV	0	0
26	TBR	T	TH	DL	TBV	0	0
27	TBR	T	TH	BT	BV	0	0
28	TBR	T	TH	BT	TBV	1	0
29	TBR	T	TTH	DL	BV	1	0
30	TBR	T	TTH	DL	TBV	0	1
31	TBR	T	TTH	BT	BV	1	0
32	TBR	T	TTH	BT	TBV	0	0

Scenario 1 shows that when a motorcycle rider's view is obstructed, there is a probability of low alertness of 19% for adolescent riders, 28% for adult riders, and 53% for elderly riders, as shown in Figure (4). It also shows that when a motorcycle rider's view is obstructed, adolescent riders are likely to have a high alertness level of 81% (100%-19%), adult riders 72% (100%-28%), and elderly riders 47% (100%-53%). This means that young riders have a higher level of alertness even when their view is blocked by an object in front of them, compared to adult and elderly riders. Meanwhile, elderly riders have the lowest level of alertness when their view is obstructed, compared to riders in other age groups. Adolescent riders tend to have faster responses than older riders, which results in a higher level of alertness, even when obstacles or barriers affect their view while driving. Furthermore, adolescent riders are more capable of identifying, processing, and responding to obstacles more quickly than older riders, who tend to have limitations in these areas. This study aligns with the findings of Li et al. (2015), which emphasized the need for caution on road sections blocked by certain objects, as failure to detect sudden dangers can potentially lead to accidents (Yeung & Wong, 2015) and increase the severity of the accident (Lumba et al., 2016).

Scenario 2 shows that when motorcycle riders pass a road with varying roadside variability, the probability of low alertness is 19% for adolescent riders, 39% for adult riders, and 43% for elderly riders, as shown in Figure (5). It also shows that when motorcycle riders pass a road with roadside variability, the probability of high alertness is 81% (100% - 19%) for adolescent riders, 61% (100% - 39%) for adult riders, and 57% (100%-43%) for elderly riders. This means that young riders have a higher level of alertness when crossing road sections with varying roadside variability, compared to adult and elderly riders. Meanwhile, elderly riders have the lowest level of alertness when crossing these road sections, compared to other age groups. Adolescent riders process and respond more quickly when roadside variability conditions change, compared to older riders, who tend to be slower at processing and responding to changes in their surroundings. This study aligns with findings from Larue et al. (2011) and Lumba et al. (2018), which indicated that road sections with varying roadside variability can reduce the level of monotony while driving, but this condition can also lead to earlier fatigue in drivers (Thiffault & Bergeron, 2001; Ma et al., 2003), thereby decreasing their ability to drive safely (Dingus et al., 2006).

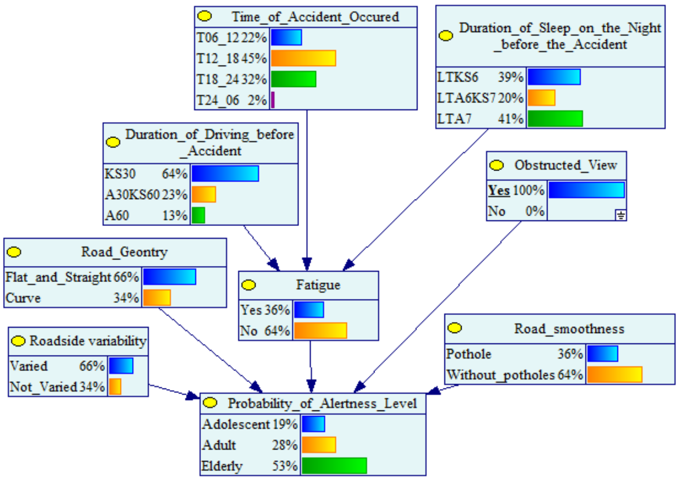

Figure (4): Scenario 1: Level of alertness when visibility is obstructed

Scenario 3 shows that when motorcycle riders drive in a fatigued condition, the probability of low alertness is 23% for adolescent riders, 33% for adult riders, and 44% for elderly riders, as shown in Figure (6). It also shows that when motorcycle riders are driving in a fatigued condition, the probability of high alertness is 77% (100%-23%) for adolescent riders, 67% (100%-33%) for adult riders, and 56% (100%-44%) for elderly riders. This means that young riders have a higher level of alertness when fatigued compared to adult and elderly riders. Meanwhile, elderly riders have the lowest level of alertness when fatigued, compared to other age groups. Adolescent riders tend to have better stamina, so when they feel fatigued, recovery does not take long. In contrast, elderly riders experience physical limitations, meaning that when they feel fatigued, their bodies need more time to recover. This condition results in adolescent riders maintaining a higher level of alertness, even when fatigued. This study is in line with research conducted by Chu (2020), which stated that elderly riders experience fatigue more quickly. In contrast, younger middle-aged riders tend to experience less fatigue while driving compared to late middle-aged riders (Tong et al., 2024). Survey data from the study showed that the percentage of motorcyclists who had low levels of alertness and experienced fatigue before an accident tended to fluctuate. Specifically, 36.3% of elderly riders experienced fatigue before an accident, 38.14% of adult riders experienced fatigue before an accident, and 35.85% of adolescent riders experienced fatigue before an accident. This indicates that the difference in the percentage of elderly riders compared to adult and adolescent riders tends to fluctuate, with only minor differences. However, due to the decline in physical and cognitive functions, elderly riders tend to have a lower level of alertness (Yeung & Wong, 2015) compared to adult and adolescent riders.

Scenario 4 shows that when motorcycle riders are driving on a pothole-ridden road, the probability of low alertness is 22% for adolescent riders, 35% for adult riders, and 43% for elderly riders, as shown in Figure (7). It also shows that when motorcycle riders are driving on a pothole-ridden road, the probability of high alertness is 78% (100%-22%) for adolescent riders, 65% (100%-35%) for adult riders, and 57% (100%-43%) for elderly riders. This means that young riders have a higher level of alertness when crossing potholes, compared to adult and elderly riders. Meanwhile, elderly riders have the lowest level of alertness when crossing potholes, compared to other age groups. Adolescent riders tend to have better visual perception, allowing them to see objects in front of them more clearly. This ability makes young riders more prepared to face potential dangers in front of them, whether they need to stop or avoid an obstacle. However, this ability to respond quickly is not typically possessed by elderly riders, as increasing age leads to a decline in physical and cognitive functions. In such conditions, elderly riders may focus more on the potholes in the road rather than on the surrounding traffic. This focus can cause elderly riders to fail to detect dangers from the front or from their surroundings, hindering their decision-making process regarding whether to stop or avoid obstacles (Yeung & Wong, 2015).

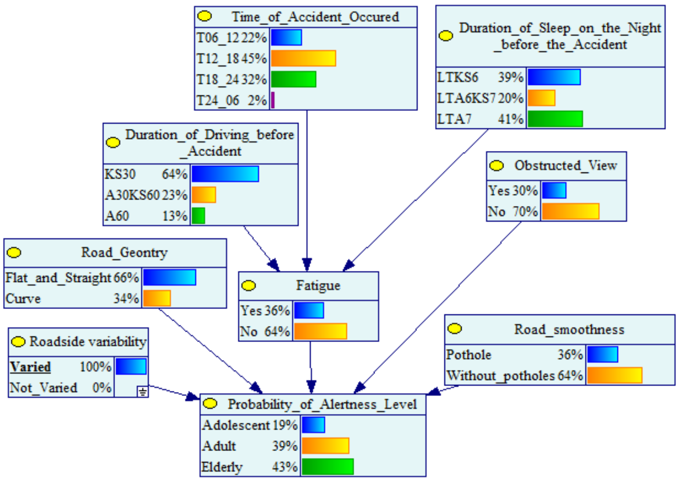

Figure (5): Scenario 2: Level of alertness to varying roadside variability

The results of the baseline model, Scenario 1, Scenario 2, Scenario 3, and Scenario 4, indicate that adolescent and adult riders have a relatively high level of alertness compared to elderly riders. The low level of alertness among elderly riders will undoubtedly increase the risk of accidents, both single-vehicle and multi-vehicle accidents. These findings are consistent with research conducted by Zhu et al. (2022) and the Ministry of Transportation (2020), which stated that accident rates tend to increase among elderly drivers. The causes of accidents among elderly drivers include reduced vision, slower reaction times (Yeung & Wong, 2015), decreased concentration, fatigue (Chu, 2020), difficulties in understanding vehicle technology (Wada et al., 2020; Classen et al., 2021), and medical conditions while driving (Skyving et al., 2021). Based on the results of the above analysis, elderly riders (45-65 years) are advised not to ride motorcycles or to consider switching to other modes of transportation, such as cars.

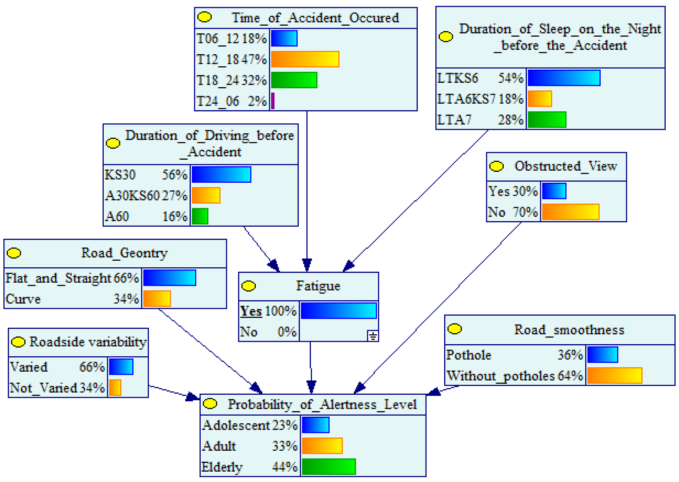

Figure (6): Scenario 3: Level of alertness when driving in a fatigued condition

If the rider wishes to continue riding the motorcycle, several strategies can be implemented to improve the safety of elderly riders, including:

1. Elderly riders should be accompanied by other

riders, especially to help them overcome their visual limitations. For example, when an elderly rider's view is unobstructed, the probability of high alertness is 61% (100% - 39%).

2. Avoiding roads that lack roadside variability, as such roads can reduce elderly riders' alertness by 1%, from 57% to 56%.
3. It is recommended that elderly riders avoid riding when fatigued, as riding in a non-fatigued state can increase their alertness level by 2%, from 56% to 58% (100% - 42%).
4. Driving licenses should be reviewed when the motorcyclist reaches 46 years of age.
5. Elderly motorcyclists need to undergo regular health checks.
6. Elderly motorcyclists should avoid driving at night, as their vision tends to be limited.
7. Elderly drivers should take training aimed at restoring their ability to drive safely.

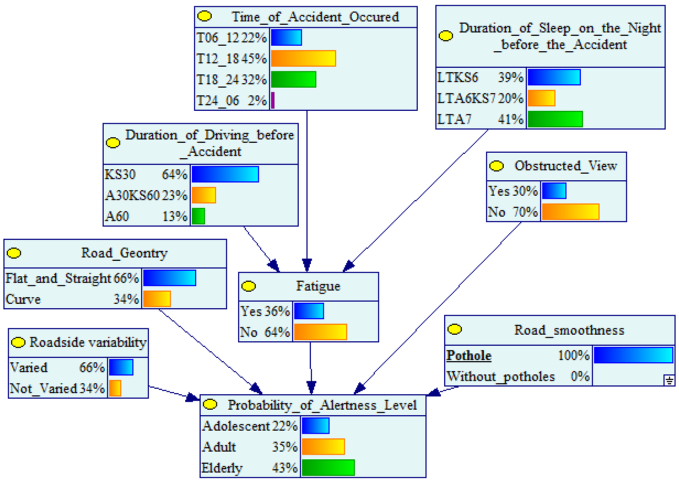

Figure (7): Scenario 4: Level of alertness when driving on pothole-ridden roads

In addition, policymakers should implement policies aimed at improving the safety of elderly drivers, including regular health checks, driving age restrictions, special road infrastructure planning, and strict law enforcement. Specific recommendations for policy changes include: 1) A law should be created to limit the maximum age for riding a motorbike; 2) Road planning and facilities should be designed with elderly riders in mind; 3) There should be periodic reviews of elderly riders' driving licenses; 4) Special vehicle designs should be developed for elderly riders. A limitation of this study is that the age groups are spaced quite far apart. It is recommended that future research considers smaller age group intervals to obtain a more accurate model. Referring to the Department of Health of the Republic of Indonesia, the following age groupings are suggested: 1) Early adolescence: 12-16 years; 2) Late adolescence: 17-25 years; 3) Early adulthood: 26-35 years; 4) Late adulthood: 36-45 years; 5) Early elderly: 46-55 years; 6) Late elderly: 56-65 years.

CONCLUSIONS

Elderly motorcycle riders are likely to have a high level of alertness of 57%, adult riders 68%, and adolescent riders 75%. Scenario 1 shows that elderly motorcycle riders whose view is obstructed are likely to have a high alertness level of 47%, the lowest compared to other age groups. Scenario 2 shows that elderly riders passing roads with varying roadside variability are likely to have a high alertness level of 57%, the lowest compared to other age groups. Scenario 3 shows that when elderly motorcycle riders are driving in a fatigued state, their probability of maintaining a high alertness level is 56%, the lowest compared to other age groups. Scenario 4 shows that elderly motorcycle riders driving on pothole-ridden roads are likely to have a high alertness level of 57%, the lowest compared to other age groups. The results of the baseline model and several scenarios indicated that adolescent and adult riders have a relatively high level of alertness compared to elderly riders. This means that elderly drivers are undoubtedly at a high risk of accidents, whether single-vehicle or multiple-vehicle accidents. The findings of this study suggest that elderly riders (46-65 years old) are advised not to ride motorcycles or to switch to other modes of transportation, such as cars, due to their low level of alertness while driving. Several strategies should be followed to improve the safety of elderly riders, including: 1) Elderly riders should be accompanied by other riders when driving; 2) Elderly riders should avoid roads that lack roadside variability; 3) Elderly riders should avoid riding when fatigued; 4) Driving licenses of elderly riders should be reviewed; 5) Elderly riders should undergo regular health checks; 6) Elderly riders should avoid driving at night; 7) Elderly riders should take training to drive safely. The social implications of this study include that its results can encourage governmental policies to introduce regulations related to the maximum age limit for motorcycle riders, which would improve road safety for all users. For further research, it is recommended to: 1) Develop a model that predicts a safe distance between vehicles; 2) Create a model that predicts when a driver will fall asleep due to fatigue; 3) Collaborate with other disciplines to develop warning sensors for maintaining safe distances from other vehicles and detecting when drivers are at risk of falling asleep while driving. In addition, policymakers at both the central and local government levels should implement policies aimed at improving the safety of elderly drivers, including regular health checks, driving age restrictions, special road infrastructure planning, and strict law enforcement.

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