National Cheng Kung University

Department of Transportation and Communication

Management Science

Master Thesis

Aberrant Driving Behavior Analysis and Driving Risk Level Assessment for Inter-city Bus Fleet

客運車隊駕駛員偏差駕駛行為分析及駕駛風險等級評估之研究

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碩士論文

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Aberrant Driving Behavior Analysis and Driving Risk Level Assessment for Inter-city Bus Fleet

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中　華　民　國　108　年　7　月　13　日

ABSTRACT

Due to the growing trend of public transportation, inter-city bus (highway bus) as ground transport plays an essential role in Taiwan. However, the traffic accidents involving with bus usually accompany serious casualties and financial loss. The fatality rate of bus are 10 times higher than sedans in recent years, and it shows urgency of bus safety in Taiwan. Thus, driving behavior is gradually valued by inter-bus carriers. The bus driver is charged with serious responsibility, and his driving behavior is influenced to a significant degree by his own human factors.

This study will collect information of inter-city bus driver human factors and the status of aberrant driving behavior from the case study company. A relative risk level evaluation mechanism will be developed based on the frequency and distribution of aberrant driving behavior. The research aims to enhance efficiency of the fleet management system and highway safety in general through quantifying relative driving risk of each driver. We apply artificial neural network (ANN) models to predict the frequency of aberrant driving behavior and the risk level of each driver by individual human factors. The predictive models perform high accuracy in case. Spearman correlation coefficient was used to calculate the correlation between the human factors and driving risk. Driving fatigue, symptom, disease and high neuroticism would cause high driving risk; Enough sleep hours, high agreeableness and high annual household income lead to low driving risk. By establishing a systematic driving risk assessment mechanism, inter-city bus industry can reduce the occasion of traffic accidents and further raise corporate integrity and reputation.

Keywords: Bus drivers, Human factors, Aberrant driving behavior,

Artificial neural network, Driving risk level

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摘要

客運業近年來因為擁有逐漸提升的服務品質與便宜的價格而佔有一席之地。然而，與客運車輛有關之交通事故常會伴隨著嚴重的人員傷亡與未知的經濟損失，現已成為不可忽視的安全問題，且發生事故亦會降低消費者對客運公司的聲譽與信賴。客運業者近年除了關注於車輛操作影響經濟油耗的問題外，亦逐漸重視駕駛人的駕駛行為對交通安全所造成的影響。超過九成的交通事故是由人為因素所引起，且駕駛行為亦會受到人因特性所影響，理應探討人因特性對駕駛行為之影響，進而降低發生交通事故的潛在因素。

本研究配合個案客運公司調查客運業職業駕駛員的人因特性資料，並透過智慧行車紀錄器取得偏差駕駛行為資料。首先藉由偏差駕駛行為資料建立駕駛風險分級評估機制，將駕駛員依據潛在危險程度區分為高低等級，而後探討人因特性可能導致的偏差駕駛行為及駕駛風險分級結果，透過量化駕駛員的駕駛風險以進行有效的車隊管理。本研究應用人工神經網路(Artificial neural network, ANN)模型建構人因特性與個別偏差駕駛行為和整體駕駛風險分級結果之間的關聯性模型，模型表現出良好的預測準確度，接著透過斯皮爾曼相關得出駕駛疲勞、症狀疾病及高神經質是造成駕駛風險的主要因素，充足的睡眠、高和善性及高年家戶所得則是減少駕駛風險的主要因素。針對研究結果提出管理建議，期望能在事故前端的角度來防範交通事故的發生，進一步提升企業的安全誠信與聲譽。

關鍵詞：客運駕駛員、人因特性、偏差駕駛行為、類神經網路、駕駛風險分級

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誌謝

兩年時間匆匆，研究所的尾聲緩緩響起，還記得自己為什麼要進入研究所，還記得自己第一次見到魏老師的青澀表現，還記得那些過往的歡笑與愁顏。這一路上的跌跌撞撞，遇見了太多的人事物，我很幸運能有這段緣分，旅途上的美好將留存成回憶，旅途上的遺憾將銘記於心，花謝，一定有結果。

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懷念與502研究室成員們一同奮鬥的日子，在論文生活裡相互扶持的佳瑄跟佑霖，細心照護我生活大小事的嘉真、佩憶、佩珊跟佳弦，還有一同學習的學長宥諭、俊杰、柏淵、美茜，感謝能遇到活潑的大家。還有交管、電管所認識的好朋友們，五樓、四樓、二樓跟地下室，很幸運能遇見你們，期待未來能再次見面!

最後，感謝父母支持我所做的任何選擇，我愛我的家庭，永遠。我也將褪去學生這身保護色，可能去國軍on-line，可能去私人企業闖闖，但無論如何，路途顛頗我會走完，路途順遂我會感恩，屬於我的書本已翻到下一個篇章。

賴家偉 謹誌

於成大交管502研究室

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CHAPTER 1 INTRODUCTION

1.1 Research background and motivation

In recent years, the government has been actively promoting the development of public transportation. Transit stations are being built in major cities, which not only serve as a transportation hub but enhance the inter-city mobility by soliciting the service to inter-city (highway) bus operator. The service volume of inter-bus industry in Taiwan for the past ten year is shown in Figure 1.1. According to statistics, the passengers have slowdown gradually from 2009 to 2018. The trend is mainly attributed to the impact of the rise of other inter-city transport services. However, inter-city bus service still has owned fixed and continuous customers since the service has cheaper fair and higher accessibility than most long-distance travel options.

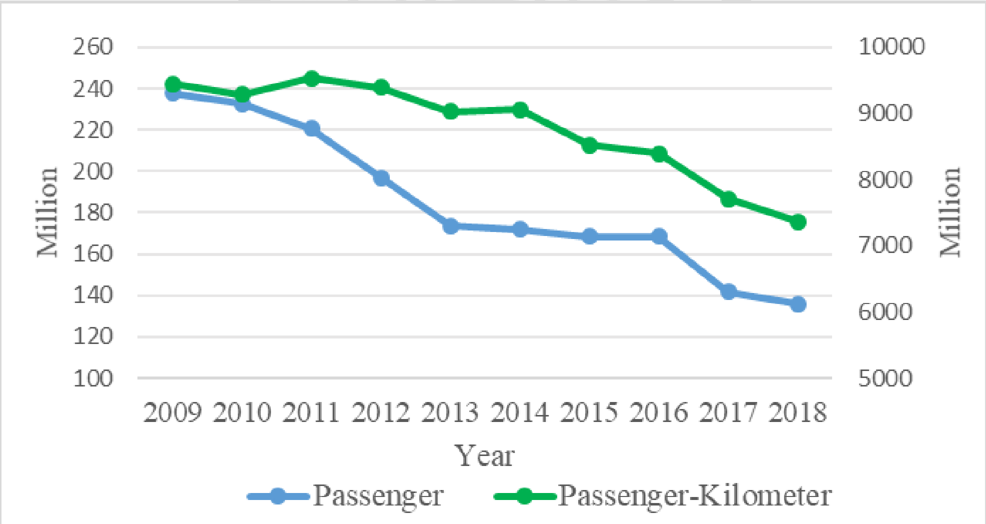

Figure 1.1 Annual service volume of inter-city bus industry

Source: Monthly Statistics of Transportation and Communications Republic of China, 2018

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However, as we assume that the difference of mobility between transport services is ruled out, the safety still seems to be relatively insufficient among other inter-city transport services. Inter-city bus does not have exclusive lanes, which means that driving with multiple traffic flows might dramatically increase accident frequency. In addition, bus is the typical commercial vehicle which defined as the vehicle designed to carry at least 10 people. High capacity vehicles could increase the chance of there being serious casualties and financial loss in an accident. Table 1 shows the annual report of traffic accidents in Taiwan (2018). Although the number of accidents, fatalities and injuries caused by sedan are relatively high, the accident rate, fatality rate of bus all are 10 times higher than that of sedan. It shows that the bus safety has been an urgent topic in Taiwan. Although the issues of route planning and fuel consumption greatly affect the company's economy and shipping efficiency, the problem of driving safety not only disturb goods in transit but directly affect human safety.

Table 1.1 Statistics on road traffic accident in Taiwan, 2018

Types of First Party	Sedan	Bus	Truck
Registered Vehicles (x10,000)	684.6	3.4	109
# Accidents	373	22	256
# Injuries	241	1	113
# Fatalities	395	22	275
Accident Rate Per 10,000 Vehicles	0.54	6.49	2.35
Injured Rate Per 10,000 Vehicles	0.35	0.3	1.04
Fatality Rate Per 10,000 Vehicles	0.58	6.49	2.52

Source: Monthly Statistics of Transportation and Communications Republic of China, 2018

Traffic accidents involve interaction among human factors, vehicle factors and environmental factors. Human factors are pointed as primary accident causes that

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more than 90% traffic accident resulted by human behaviors (Treat et al., 1979). Driving behaviors is considered highly relevant to driving safety. In Taiwan, 98% of the A1 type and A2 type road traffic accidents are caused by human error (Yearly Statistics of Police Administration Republic of China, 2018). The driving behavior is influenced by drivers' human factors, which leads to the possibility of having aberrant driving behavior and thus affects driving safety.

This study acquires human factors from case study company, including dimensions of socioeconomic factors, physiological factors, working factors and personality. Then integrated with the aberrant driving behaviors recorded on board, including lane shifting, not keeping a safe distance, exorbitant revolutions per minute, exceeding the speed limit, hard acceleration and overusing the electromagnetic brake. To enhance road safety, its necessary to construct a reasonable mechanism to supervise driving behavior for bus drivers. In addition to assisting bus operator in assessing job performance, the mechanism can also be used as prediction of risk level to assess driver's eligibility. Drivers classified as higher risk level should be admonished while those classified as lower risk level should be encouraged.

1.2 Research objectives

The inter-city bus service still has been necessary nowadays. However, the bus service accompanies high incidence of accidents and often causes serious casualties, and negligent management may result in more accidents. Although traffic accident may also involve vehicle and road environment factors, the main cause of accident is attributed to the human factors. That is to say bus drivers play a crucial role in road safety during driving.

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The purpose of this study is to link different orientation of human factors with aberrant driving behaviors that affects driving safety, i.e., identifying the degree of influence that individual human factors induce specific aberrant driving behavior induced. We construct a risk grading system to assess driving performance. The evaluation mechanism can assist the operator to preferentially hire drivers with low driving risk during recruiting, so that it can prevent accidents from happening.

The research objectives are summarized as follows:

1. To establish an evaluation mechanism based on overall driving risk converted from several aberrant driving behaviors. By discriminating the relative severity of overall driving risk in a group of people, we would obtain driving risk level from classifying the overall risk of aberrant driving behavior.
2. To figure out the influence of individual human factors on driving behaviors. We establish a prediction structure based on human factors and driving behaviors. Confirming the degree of importance of each human factor, it would be used to assess the potentially risk of single aberrant driving behavior.

After assessing the overall driving risk through constructing the driving risk level, it is expected that the driver's possible driving risk level could be predicted by the human factors in advance. We explore the human factors that may lead to higher driving risk and aim to reduce the incidence of human error in road accidents.

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1.3 Research flow chart

Figure 1.2 illustrates the research flowchart. The contents of this study are briefly described as below.

1. Research background and motivation

   The study first introduces the background and motivation. It is necessity and urgency to enhance driving safety of bus drives. Then we determine the research objective and scope.

2. Literature review

   There are increased literatures discussing the driving behavior. The journal paper and master's thesis about human factor, driving behavior, driving performance, and grading system are reviewed.

3. Construct research structure

   According to the literature review and operator interview, emphasis is placed on the construct that can link human factors to aberrant driving behavior. And based on previous studies, this study then constructs a research framework and the respective hypotheses.

4. Questionnaire investigation

   After interviewing the operator, this study designs the questionnaire and survey for case study company.

5. Data collection and analysis

   The driver’s human factors are collected from questionnaire investigation, and driving behavior were detected by digital tachograph. We integrated human factors with driving behavior, and transform each aberrant driving behavior into single risk value. Then we construct a grading system to classify drivers.

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6. Result and discussion

   Result and discussion carry out applying artificial neuron network to make predicting the aberrant driving behaviors and driving risk level. For each human factor, we discuss with the empirical study result.

7. Conclusion and suggestion

   First, we draw conclusions and feasible suggestions based on the research results. Second, we point out the research restrictions and provide future research direction.

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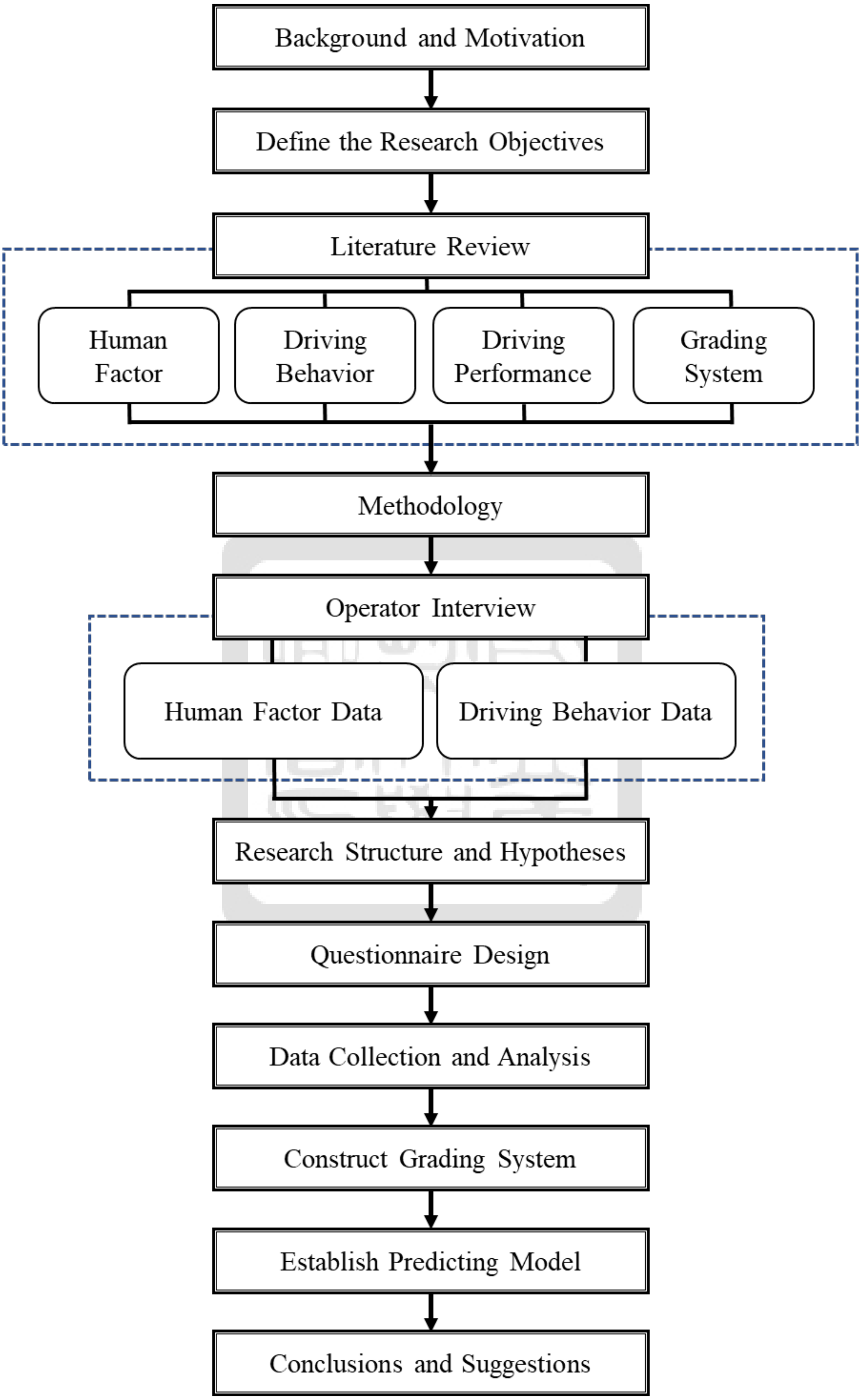

Figure 1.2 Research flow chart

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CHAPTER 2 LITERATURE REVIEW

The problem of driving safety has been continuously discussed and previous studies usually focus on the relationship between various factors and driving behavior. Driving risk of driver is an extensive problem without doubt because of the different factors are existing to influence human beings. In this chapter, related researches of human factors, driving behavior, performance and driver grading system are reviewed.

In the following, Section 2.1 reviews the definition of ergonomics and human factors which have been measured in previous studies. Section 2.2 reviews the categories and influence of aberrant driving behavior. Section 2.3 reviews the recent studies of evaluating driving performance. Section 2.4 shows the grading rule used to classify driving performance or other indicators. 2.5 summarizes Chapter 2 by providing the key point from each section.

2.1 Human Factors

Ergonomics focus on the investigation of human factors and applied to design anything that involves people. Human factors are biased towards the discussion of "human characteristic", and involves the domain of psychology, physiology, medicine, anthropology, biology, etc. The emphasis of human factors is placed on reducing personnel errors to reduce accidents, preventing operational fatigue and excessive load to enhance human performance, increasing system safety, and ensuring environment to stabilize operation, maintenance and control of the system. This study discusses the definition of ergonomics and personality in Section 2.1.1 and Section 2.1.2, then review the literature on human factors in Section 2.1.3.

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2.1.1 Ergonomics

The Oxford Dictionary defines ergonomics as “the scientific study of people and their working conditions, especially done in order to improve effectiveness”. The founding father of the word “Ergonomic” should be date back to the 1857s. A Polish scholar, Wojciech Jastrzebowski coined the word "ergonomics" from the roots “ergon” and “nomos” in Greek. “Ergon” means work and “nomos” means principle or law, therefore, the "ergonomics" can be directly translated into the working principle.

There are several organizations and scholar had ever defined ergonomics. Murrell (1949) defined ergonomics as the scientific study of the relationship between human and working environment. Pheasant (2014) defined that ergonomics is the science of work related to various human working activities. The Board of Certification in Professional Ergonomics (BCPE, 1996) has defined ergonomics as a body of knowledge about human abilities, human limitations, and other human characteristics that are relevant to design.

The widely accepted definition is from International Ergonomics Association (IEA, 2000), the organization defines ergonomics as a “Scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data, and other methods to design in order to optimize human well-being and overall system performance.” Figure 2.1. shows the purpose of ergonomics. Ergonomics contributes to enhancing design of products, jobs, environments, organizations and tasks to make them interactive with the needs, abilities and limitations of people.

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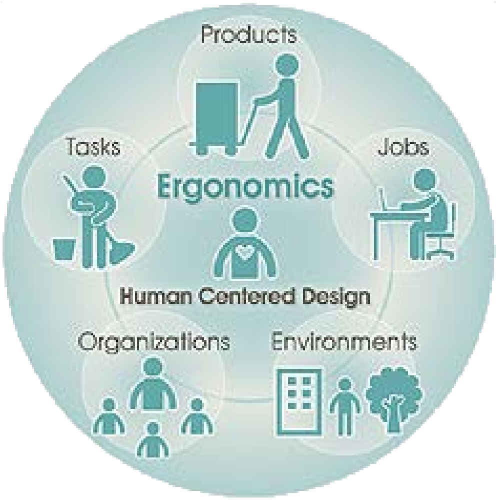

Figure 2.1 The purpose of ergonomics

Source: IEA, 2000

According to the above definition, ergonomics can be summarized as a compatible scientific criterion between the human, the machine (facilities) and the environment (Zhu, 1994). In traffic safety management, the occurrence of traffic accident is probably the imbalance between the driver, the vehicle and the road system (Dong, 2007). This study focuses on analyzing the human factors of driver and hope to understand the relationship between human factors and human behavior to enhance traffic safety. The following section review the human factors of driver.

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2.1.2 Personality

This study classified personality traits as part of the human factors in the study so as to describe the mental state of drivers. Personality are influenced by innate and acquired environments. It distinguishes the individual differences in human behavior and thought, and also produces different responses in facing environmental changes. If these features are persistent and have frequent performance, they can be called personality traits.

Individual responses will be associated with various personality traits at the same time. However, due to different research directions and topics concerned by domestic and foreign scholars, the classification of personality traits may be partially different. Costa & McCrae (1989) expanded into five factor model (FFM) based on the NEO model (Neuroticism-Extraversion-Openness inventory) in their previous study. The Big-five model is currently the most widely accepted and widely used personality theory which generally refers to “Extraversion”, “Agreeableness”, “Conscientiousness”, “Neuroticism” and “Openness to Experience”. Each personality trait is described below (Costa & McCrae,1989; McCrae & John, 1992; Roccas, Sagiv, Schwartz, & Knafo, 2002; Chapman & Goldberg, 2017):

1. Extraversion

Extraversion dimension includes the sub traits such as friendliness, gregariousness, assertiveness, activity level, excitement Seeking, cheerfulness. It indicates how a person tend to attract from social interactions. People who are high in extraversion perform outgoing and enthusiastic while those who are low in extraversion is introverted and comfortable working by self.

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2. Agreeableness

Agreeableness dimension includes the sub traits such as agreeableness dimension are: trust, morality, altruism, cooperation, modesty, sympathy. It shows the degree of compliance with regulations and desiring things run smoothly. People who are high in agreeableness are willing to cooperate with others instead of competition.

3. Conscientiousness

Conscientiousness dimension includes the sub traits such as self-efficacy, orderliness, dutifulness, achievement-striving, self-discipline, cautiousness. Those who are high in conscientiousness tend to be more detail-oriented and self-disciplined. They always show consistent attitude and mindful of details in pursuing target. Conversely, people with low conscientiousness are more casual and unreliable.

4. Neuroticism

Neuroticism is also known as “emotional stability” which more tend to express negative emotions. Neuroticism dimension includes the sub traits such as anxiety, anger, depression, self-consciousness, immoderation, vulnerability. It describes the tendency to experience negative feelings. People who are high in neuroticism (low in emotional stability) tend to be emotionally reactive, and people who are low in neuroticism (high in emotional stability) tend to be emotionally stable and calm.

5. Openness to Experience

Openness, or openness to experience dimension, includes the sub traits such as imagination, artistic interests, emotionality, adventurousness, intellect, liberalism. It refers to having sense of curiosity about the world or thing around. People who are high in openness are tend to be more creative and think widely. On the contrary, people who are low in openness are tend to be close-minded and may struggle with abstract thinking.

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2.1.3 Human factors affecting driving performance

Applying a variety of scale measurement can simultaneously link human factors with other behavioral dimensions. Lajunen and Summala (1995) applied skill scale and safety-motive scale to investigate the influence of driving experience on driving skills and safety-motive. The result shows that driver with more driving experience, the fluency of operating the vehicle is higher than driver with less driving experience. And the operation of the vehicle is more fluent to men than women. However, the man and women with less driving experience have higher safety-motive.

The potential relationship between drivers' lifestyle and the traffic accident risk was be clarified. Chliaoutakis, Darviri and Demakakos (1999) generalized ten lifestyle traits from 74 lifestyle variables by principal component analysis (PCA), including culture, sport activity, elegance, car addiction, alcohol and drugs, etc. The logistic regression analysis showed that those who performed high participation in culture or religion lifestyle would face low accident risk, and those who performed high participation in alcohol consumption or drive without destination would face high accident risk.

Human factors will influence the driving performance of drivers in specific circumstances. Yagil (2001) used three scenarios to test the driver's aggressive reactions when the driver response to frustration. The driver who have frustration experience may have more aggressive reactions, and negative impressions are accumulated and remembered by the driver. When face to similar negative situations, there will be higher chance of causing aggressive driving. The study also pointed out that personality traits, emotions and situations also affect the intention of violation.

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Institute of Occupational Safety and Health (IOSH) from Council of Labor Affairs (CLA) (2008) published the “Prevention Manual of Professional Driving Health Hazard”. It is a government agency and aims to enhance labor safety and work environment in Taiwan. To enhance driving safety, the manual teaches drivers to understand driving risk and health issues, then propose different factors to improve human performance. Working hours, dietary condition, alcohol and drug use, BMI, etc. are introduced to improve driving status.

Poor sleep quality may lead to driving fatigue, further reducing the ability to drive and control the vehicle. Sun (2012) analyzed the relationship between the sleep problems of professional bus driver and the experience of traffic accidents. The quality of sleep is significantly related to the driver's experience in traffic accidents. The factors affecting the quality of sleep may also affect driving behavior and lead to traffic accidents especially in long-distance driving.

Previous studies collected human factors with personnel database from company or questionnaire. Chen (2014) applied structural equation modeling (SEM) to analyzed driver human factors and organization human factors that affect driving behavior. The human factors were collected from designed questionnaire. The study divided driver’s human factors into physiological factors, socioeconomic status, occupational aptitude, psychological factors four dimensions. Drinking habits, sleep hours, personality, illness and other human factors would lead to poor driving performance. The feedback and review of human factors could be used to develop suggested direction of improving driving performance.

In addition to affecting driving performance, human factors are also related to different accident characteristics. Feng, Li, Ci and Zhang (2016) classified 1380 drivers who involved in fatal traffic accidents into three clusters by taking multiple

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human factors into consideration. The differences among three clusters are the age of bus driver and history of traffic violation (crashes and convictions). Then application of the ordered logistic model could assess the impact of each risk factors (the crash level, the vehicle level and the bus driver level) among different types of bus drivers. The study found that the records of violation behavior would cause different degrees of impact on three types of drivers. Gender and age factors would also affect the severity of fatal accidents.

Li (2017) continued Chen's (2014) research to forecast aberrant driving behavior with Big Five personality traits, which include extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience (Costa and McCrae, 1989; McCrae & John, 1992). The study construct driving risk level through transferring aberrant driving behavior into driving risk. Five personalities were used to predict driving level by ordered logit regression. The result showed that driver with higher neuroticism or conscientiousness trait world be classified into higher risk level, and driver with higher agreeableness world be classified into lower risk level.

2.2 Driving Behavior

This study collected bus driver's driving behavior data through digital tachograph to review driving performance. Aberrant driving behavior directly affect road safety, so it is identified as the main research object. Section 2.2.1 reviews the definition of the aberrant driving behavior and Section 2.2.2 reviews the driving behavior.

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2.2.1 Aberrant driving behavior

Reason, Manstead, Stradling, Baxter and Campbell (1990) considered aberrant behavior as a straying from the path, and committed aberrant driving behavior is various “bad” and “silly” behavior on the road. Three fairly robust factors of human factors were identified in the study: slips, mistakes and violations, respectively. Slips were defined as “the unwitting deviation of action from intention”; Errors were defined as “the failure of planned actions to achieve their intended consequences”; Violations were defined as “deliberate (though not necessarily reprehensible) deviations from those practices believed necessary to maintain the safe operation of a potentially hazardous system” Aberrant driving behavior varies with different driving cultures, most of which are mainly composed of slips, errors and violations. The detailed definition is as shown in Table 2.1.

The study distinguishes the three aberrant behaviors according to the degree of danger. Slip behaviors may only bring out danger to the driver self, and the risk to other road users is lower. Mistake behavior may take influence on other road users, and violation behavior would cause danger to other road users. Thus, the three types of aberrant driving behaviors affect the degree of danger from high to low is violation, error and slip.

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The types of aberrant driving behavior might be not exactly the same in previous studies. However, the aberrant driving behaviors applied were mainly extended from slips, errors and violations. For example, the error could be subdivided into hazardous errors and non-hazardous errors according to the degree of risk; The violations could be subdivided into intentional violations and non-intentional violations according to driver’s intention. Yin (2004) summarized the applied aberrant driving behaviors in previous studies as shown in Figure 2.2.

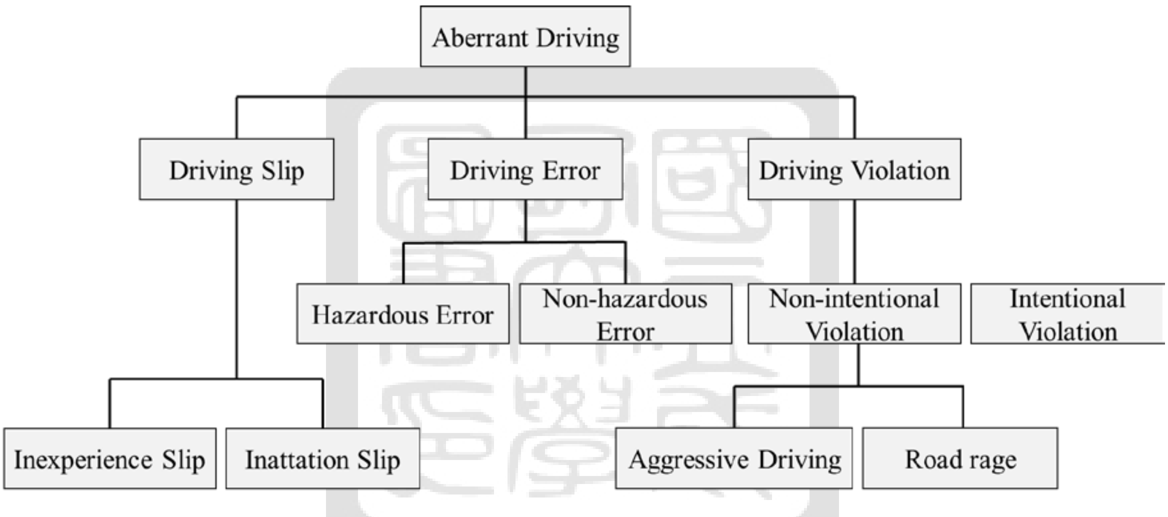

Figure 2.2 Aberrant driving behavior classification

Source: Yin (2004)

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Table 2.1 Definition of aberrant driving behavior

Aberrant driving behavior	**Fairly robust factors**	**Definition in Merriam-Webster Dictionary**	**Reason et al. (1990)**	**Example**
Error	Relatively harmless slip (Lapse)	Slip: To fall into error or fault	Error of action	1. Switch on wrong vehicle equipment (wiper, headlight, turn signal, etc.). 2. Misread the signs or roadside facilities.
		Lapse: A slight error typically due to forgetfulness or inattention		
	Dangerous error (Mistake)	Error: An act or condition of ignorant or imprudent deviation from a code of behavior	Departure of planned actions	1. Underestimate the speed or undetected the appearance of an oncoming vehicle when overtaking. 2. Steer without paying attention to pedestrians or outside vehicles
		Mistake: To make a wrong judgment of the character or ability		
Violation	Violation	Violation: An act of irreverence or desecration	Deliberate deviations	1. Drive after drunk or excessive blood alcohol. 2. Run the red light when the vehicle is scarce late at night.

Source: Reason et al. (1990)

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2.2.2 Driving risk

Risk is explained as the situation involving exposure to danger (the Oxford Dictionary). Driving risk can be defined as a potential threat that may lead to vehicle crashes or other accidents (Wang et al., 2015). People often make risky subjective judgments on the severity and probability of risk. To enhance driving safety, the safety applications can be divided into two areas: active safety and passive safety (Jarašūniene & Jakubauskas, 2007). Active safety aims to help drivers avoid accidents, which is more similar to the purpose of our research to reduce the probability of accident; Passive safety tends to help people save life and reduce injuries.

In previous study, quantitative and qualitative method are widely used to assess risk. The abstract driving risk may be quantified as actual values to compare the proportion of risk. Actual driving data may collect from diverse vehicular on-board units (Chen, 2014; Wang et al., 2015), self-reported driving behaviors (Reason et al.,1990; Mallia et al., 2015; Vahedi, Shariat Mohaymany, Tabibi & Mehdizadeh, 2018) or even traffic ticket (Vahedi et al., 2018). Vehicular on-board units include on-board diagnostic Ⅱ (OBD Ⅱ), tachograph, GPS, accelerometer, and radar, etc., which alert drivers with historical driving records. Self-reported driving behaviors are usually measured through the driver behavior questionnaire (DBQ) to review undesirable driving habits. Traffic ticket reflects the traffic law enforcement.

The management strategies usually use past accumulated records to guard against opportunities that may occur in driving in the future. The naturalistic driving data may be further classified or cluster drivers into different level to set as driving risk indicator. Therefore, the driving risk assessments for fleet management are often

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based on the concept of relative comparison, and there is no absolute standard to determine the level of risk.

2.2.3 Studies of driving behavior

The influence of human factors on traffic safety cannot be expressed by single or few variables. Reason et al. (1990) considered that there are many human factors in causing traffic accidents, and it was necessary to classify these human factors in a structured way. Therefore, the Driver Behavior Questionnaire (DBQ) was proposed to complete the survey through 520 British drivers. The questionnaire contains four aberrant driving behaviors, including slip, mistake, unintended violation and deliberate violation. After investigation and factor analysis, the results indicated that the aberrant driving behavior was divided into violations, dangerous errors, and relatively harmless lapses.

To explore the relationship between sensation seeking, aberrant driving behavior and traffic accidents, Rimmö and Åberg (1999) utilized Driver Behavior Questionnaire (DBQ) and Sensation Seeking Scales (SSS) to collect 705 questionnaires from young driver. Four types of aberrant driving behavior include violations, mistakes, inattention and inexperience errors (the slips factor was subdivided into inattention errors and inexperience errors because of the difference in age and gender). Figure 2.3 shows model of relations between each latent variable (thrill and adventure seeking, TAS; disinhibition, Dis). The study pointed out that there is significant correlation between sensation seeking and aberrant driving behavior, especially for driving violations. Driving violations and driving errors have proven to be stable predictor of traffic accidents and offences.

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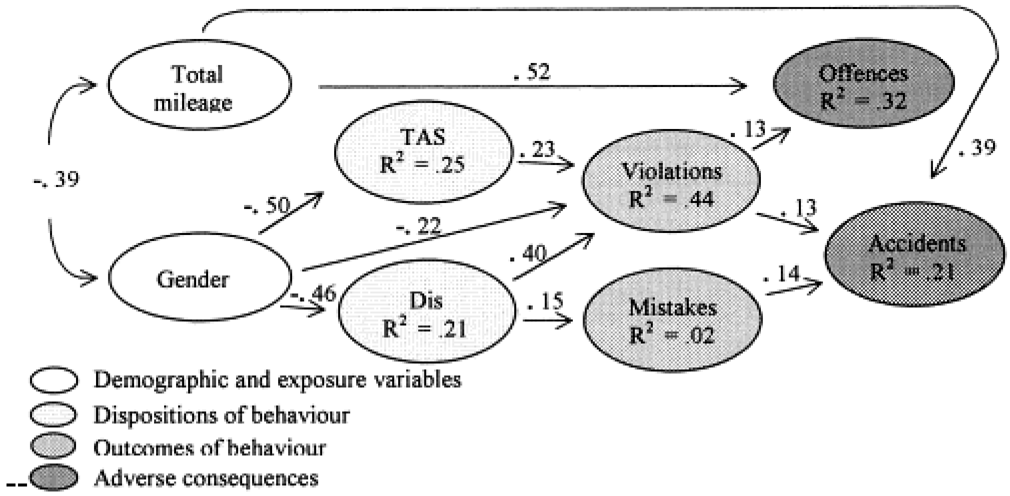

Figure 2.3 Model of relations between sensation seeking, aberrant driving behavior and traffic accidents

Source: Rimmö and Åberg (1999)

Aberrant driving behaviors are easily caused by an abnormal mental state of the driver. Westerman and Haigney (2000) developed the Driving Behavior Inventory (DBI) through the Driver Behavior Questionnaire (DBQ) developed by Reason et al. (1990) and a study on driving pressure (Gulian et al., 1989). The study discussed the influence of driving pressure on aberrant driving behavior. Those who are lack of awareness or easy to get nervous are prone to have more errors and violations, and the greater the pressure, the higher the possibility of causing errors and violations. Therefore, the probability of traffic accident is positive related to the frequency of violations and operational errors.

The potential impact of violations on traffic accidents does not be different depending on the country or sample is needed to be identified. Sullman, Meadows and Pajo (2002) investigated the factor structure of the Driver Behavior Questionnaire (DBQ) and the relationship between aberrant driving behavior and crash involvement for 378 truck drivers. Aberrant driving behaviors can be categorized into: errors,

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lapses and violations and aggressive violations. The items of aberrant driving behaviors depend on the version of the DBQ used in the study. The results of the study indicated that even in different countries or research subjects, violation behavior also has significant relationship with traffic accidents.

Lajunen, Parker, and Summala (2004) utilized the Driver Behavior Questionnaire (DBQ) which originally designed for the British drivers to explore whether driving behavior in the UK, the Netherlands and Finland differed from culture to culture. The driving behaviors was divided into slips, errors, general violations and aggressive violations. The research confirmed that DBQ is also applicable in Finland and the Netherlands.

The management of the driving safety in the organization do affect the driver's performance. Öz, Özkan and Lajunen (2014) applied Trip-focused Organizational Safety Climate Scale (TOSCS) to obtain reliable two-factor solution, scilicet Trip Safety Monitoring and Control (TSMC) and Tacit Agreement to Trip Safety (TATS). Errors, violations and positive driver behaviors was taken to score driver's behavior. The trip-focused organization with strong safety culture / climate is found to own safer employees and professional drivers with less frequencies of error and violation in particular.

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2.3 Performance

The Oxford Dictionary define performance as “how well or badly you do something; how well or badly something works”, which is used to measure the work accomplishment of organization. The job performance of professional driver can also be regarded as driving performance. Section 2.3.1. review the definition of the job performance, Section 2.3.2 review the definition of the driving performance and Section 2.3.3 review the driving performance.

2.3.1 Job performance

Campbell (1990) defined job performance as the behavior of an individual who is an organization member, fulfilling organization expectations and regulating target needs. Motowidlo and Stephan (2003) defined as “the total expected value to the organization of the discrete behavioral episodes that an individual carries out over a standard period of time.” The variance in performance represent the difference in the expected or organizational value of human behavior.

The emphasis on safety would improve the job performance of employees in the organization. Ronen and Zuroff (2017) proposed a structural equation modeling (SEM) model in which secure attachment, job performance and job promotion mediated by two social rank behaviors about dominant-leadership and coalition-building. The research proved that higher secure attachment may lead to more dominant-leadership and coalition-building behaviors which further bring in higher job performance and job promotion. Training employees to adopt more positive social rank behaviors is efficient than enhancing attachment security among employees.

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The perception of work safety from supervisor would determine the performance of the employee. Huang et. al. (2018) examined the relationship between supervisory safety communication and safety climate to predict safety performance and safety outcomes. The data collected from 4600 professional truck drivers from a U.S trucking company within six months. The study shows that supervisory safety communication had both main and moderating effects on safety behavior and able to predict truck drivers' injury rates. If supervisor prefer higher quality of safety communication, the organization will show up higher safety performance and less lost time injuries.

2.3.2 Driving performance

The concept of job performance added to the identity of the driver in transportation industry can be defined as driving performance. "Driving performance" can be broadly defined as: the performance of driving behavior during driving. In terms of driving performance appraisal, driving behaviors can be roughly divided into "driving attitude" and "driving habits" two orientation (Chang, 2001). "Driving attitude" means the degree of attention and courtesy performance when driving on the road, and "driving habits" means the degree of influence of the conventional operation on the machine and the ride comfort.

Improving driving safety by managing drivers is an important issue in transportation service nowadays. The past literatures mostly evaluate driving performance on the dimension of "Driving habits", because "Driving attitude" are difficult to quantify. "Driving habits" are the actual behaviors of driving, it can be detected by tachograph or various vehicular on-board units and can also be quantified.

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The study uses driving behavior to explore driving performance as a part of "Driving habits". Specific driving behaviors are used to assess the performance of driving based on research design and different cultural backgrounds. Evaluation indicators for driving performance have been proposed in previous studies, showed in Table 2.2.

Table 2.2 Indicators review of driving performance

Literature resource	Indicators of driving performance
Lerner et al. (1999)	The study proposed seven indicators, including: Head selection; Speed selection; Intersection negotiation; Maneuver avoidance; Gap acceptance; Crash avoidance; Lane placement.
Uang and Hwang (2003)	The study proposed the criteria of driving performance, including: Trip duration; Driving speed; Number of navigation errors.
Harrison (2004)	The study applied following behaviors to detect impact of driving experience on learner drivers, including: Number of driving trips; Distance and time of each driving trip; Level of confidence; Number of crashes and near misses; Unpleasant emotional interactions.
Chen (2005)	The study took three behavior as the best model for performance evaluation, including: Speeding times; Emergency times;

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Literature resource	Indicators of driving performance
	Rapid acceleration times.
Mullen et al. (2010)	The study collected five indicators by driving simulator, including: Starting, stopping, and backing; Signal violation, right-of-way, and inattention; Moving in the roadway; Passing and speed; Turning.
Chen (2014)	The study applied nine driving behaviors as behavior indicators, including: Shift to right; Shift to left; Abnormal stays; Not Keeping a Safe Distance; Severely not keeping a safe distance; Exorbitant Revolutions Per Minute; Exceeding the Speed Limit; Hard Acceleration; Overusing the Electromagnetic Brake.
Li (2017)	The study integrated nine driving behaviors in Chen (2014) into six indicators, including: Lane Shifting; Not Keeping a Safe Distance; Exorbitant Revolutions Per Minute; Exceeding the Speed Limit; Hard Acceleration; Overusing the Electromagnetic Brake.

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2.3.3 Studies of driving performance

Driving behaviors are not only related to driving performance, but also to the impact on fuel consumption. Pan (2006) applied digital driving recorder and driver's information to explore driver performance, and divided variables into car index, driver index, time consumption index, speed index, fuel consumption index and driving performance six dimensions based on influence of variables. The study link dimensions through structural equation modeling (SEM) to discuss the factors that affect driving performance and fuel consumption. Driving performance included emergency braking time / frequency, acceleration time / frequency and speeding time / frequency six recorded driving behavior. The results show that the fuel consumption index significantly impacted by car index, time consumption index and speed index. Speed index also has significant impact on driving performance, which evaluated by maximum acceleration, maximum deceleration and maximum travel speed.

Miyajima, Ukai, Naito, Amata, Kitaoka. and Takeda (2011) proposed a driver risk evaluation method based on driving behaviors captured with drive recorders, three indicators of driver's acceleration, deceleration, and steering behavior included. Acceleration behavior is evaluated using maximum longitudinal vehicle acceleration per minute and vehicle velocity. Deceleration Behavior was categorized the into four categories based on different traffic situations, including sudden braking, intensive and long braking, situation-aware braking, moderate braking. Steering behavior is evaluated based on the relationship between the minimum radius of road curvature and road design speed.

To solve problem of limited ecological validity (predetermined routes and time) in driving test, Vetter et al. (2018) select three different driving exercises including

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on-road driving test, obstacle course and maneuvering course. A test battery of psychometric was used to detect reaction time, concentration, ability to gain an overview, reactive stress tolerance, logical reasoning, and safety-related personality traits from truck driver. However, the required skills and abilities for each exercise was not connected. To enhance driving performance, more comprehensive improvement of skills and abilities are needed to cope with various situations.

2.4 Driver Grading System

Grading system is commonly applied in our daily life, such as movie rating system, fare basis, disaster level, etc. These systems usually grade products according to age, price, severity, etc., and these grading rules mostly from the legal regulation. The existing grading systems about transportation are discussed in Section 2.4.1, and driver grading system is reviewed in Section 2.4.2.

2.4.1 Grading system in transportation

There are many grading systems in the existing transportation industries, in which the driving license is a fairly ordinary example. According to art. 53 of Traffic Regulation (2017), the driving license can be divided into 15 categories based on the purpose of usage, car type, carrying capacity or other conditions, which is driving license for general/professional light passenger vehicle, general/professional truck, general/professional container truck, etc. It is a grading concept that limits the driving qualification of the vehicle.

Traffic Accident Processing Specification (2015) classify the severity of the accident into three degrees, including A1 (a traffic accident causing death of personnal on the spot or within 24 hours), A2 (a traffic accident causing injury to

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personnal or death of more than 24 hours) and A3 (a traffic accident with only property loss). In highway system, the transportation of dangerous goods is also subject to three levels of access control, including no entry, vehicle escort requirement and free passage.

Although bus driver has passed the threshold of the license of professional bus, there is no advanced classification of the bus driver’s performance. Driving behavior of the driver is the key factor affecting road safety, and we can also regard it as the indicator of driving performance. Therefore, we review the driver grading system reflected by the driving behavior in next section. It is excepted to further enhance road safety and manage driver more efficiently.

2.4.2 Studies of driver grading system

Naito et al. (2009) applied clustering algorithm to divide the braking behavior into A-D four patterns as risk high to low (A: Emergent braking, B: Intensive and long braking, C: Situation braking, D: Moderate braking). In addition, the risk of danger, uniqueness and unsteadiness were evaluated based on the braking distance and the change situation from four braking patterns. The study normalized three risk items and overall judgement value for each driver within intervals of scale 10%, 20%,40%, 20%, and 10% from the most risk-free were evaluated as A, B, C, D and E. Drivers with rating A are the safest, and drivers with rating E are the most dangerous.

Reasonable grading results can be used as the basis for strategy implementation. Miyajima et al. (2011) continued Naito’s et al. (2009) research results, applying three indicators of driver's acceleration, deceleration, and steering behavior as the

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benchmark to assess driving risk. Three indicators were individually classified according to the degree of risk, and compare the analysis results with the information provided by the risk consultant. The risk consultant rated driver's evaluation score from A to E level and compare with each proportion of behaviors. The study found that the indicator of driver's acceleration and steering behavior were related to the information provided by the risk consultant. The attended driver was given feedback to reduce risky driving behavior.

Feng et al. (2016) applied the ordered logistic model to assess the impact of each risk factors on the fatality severity of traffic accidents among different types of bus drivers. The study transfers the severity of the accident into equivalent fatalities based on the code of the maximum Abbreviated Injury Scale (MAIS) in 1969, and divided equivalent fatalities from level 1 to 3 in order of accident severity. The bus drivers are classified into three clusters by the K-means cluster analysis, including "Middle-aged drivers with history of driving violations", "Young and elderly drivers with history of driving violations", "Drivers without history of driving violations." Three clusters also show differences in severity of fatal accident.

Li (2017) utilized min-max normalization to transfer the frequencies of six aberrant driving behavior into single driving risk, and summed up the single risk into overall driving risk. Two grading rules were used to classify 62 professional bus drivers in five risk levels, fixed interval and fixed percentage (Naito, 2009) included. The (overall) risk level shows relative driving risk in purposed group, and the higher the risk level represent the higher potential probability of traffic accident on the road.

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2.5 Summary

Through literature review, we derive the association between driving behavior and traffic accidents. Poor driving behavior would be judged as poor driving performance, which lead to high driving risk and further increase the potential opportunity that face traffic accident. The study tends to avoid consecutive traffic accident by managing the driving behavior of the frontend. Most previous studies used the questionnaire to obtain the behavioral characteristics from the professional or tested driver, and the answering result were regarded as the main evaluation item. The study intends to utilize quantified driving behavior which collected by digital tachograph. The historical records reflect the frequency of actual driving behavior of a driver during the unit time. However, the indicators of driving performance in each research may be quite different. Table 2.3 lists the indicators that also detect by driving recorder in previous study. The selection of driving performance indicators is based on the influence level to road safety. The more driving performance indicators mean the driver could be evaluated more multifaceted, but it may be limited by the difference in the instrument and the detection capability.

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Table 2.3 Review of driving performance indicator

Indicators of Driving Performance	Literature review*				
	Chen (2005)	Pan (2006)	Lin (2009)	Chen (2014)	Li (2017)
Driving speed		○			
Hard acceleration	○	○	○	○	○
Hard deceleration			○		
Hard braking	○	○			
Exceeding the speed limit	○	○	○	○	○
Not keeping a safe distance			○	○	○
Exorbitant revolutions per minute			○	○	○
Lane shifting			○	○	○
Overusing the electromagnetic brake			○	○	○
Idling too long		○	○	○	

* "○" means the indicator was used in the study

Source: This study

In the human factor literature, individual differences determine driver's driving behavior, which in turn affects road safety. Most human factors rely on the questionnaire to measure or existing personnal file. Driver's human factors show significant impact on partial aberrant driving behavior through previous research results. Human factors can be separated into driver factors, organization factors, vehicle factors and environment factors. This study focuses on the driver's human factors, and organizes the previous studies as Table 2.4.

There is minority of research at present to further classify the frequency of aberrant driving behavior into overall indicators. The grading rule of driving risk for professional driver is also needed to be established. Therefore, this study presents a driver risk grading system through driving behavioral data from case company, and explore the correlation between human factors, aberrant driving behaviors and driving risk level.

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Table 2.4 Review of human factors

Human Factors	Literature Review*													
	Reason	Lajunen et al.	Chliaoutakis et al	Yin	Wang	IOSH	Kao	Tsao	Sun	Tseng	Di Milia et al.	Chen	Lin	Feng et al.
	1990	1995	1999	2004	2006	2008	2008	2011	2012	2012	2013	2014	2016	2016
Gender	◎	◎	◎	◎	○		○	◎	○	○	○			◎
Age	◎		○	○	◎		○	◎	○	○	○	○	◎	◎
Education level			○	◎	◎		○	◎		○		○		
BMI						○			◎			○		
Marriage status			○	○			○					○	◎	
Annual household income								○				○	○	
Driving experience		◎	○		○		○			◎				
Driving seniority				○			◎	○	○			○	○	
History of crashes				○					◎	○		○		◎
Commute time	○						○				◎	○		
Driving hours						○	○		◎			○		
Sleep hours							○		◎		◎	○	◎	
Driving fatigue							◎				◎	◎		
Alcohol drinking patterns			◎			○	◎					○	◎	
Disease						○			◎			◎		
Personality				◎	◎		◎	◎			◎	○	◎	

* "○" means the human factor used in the study; "◎" means the human factor proved to affect driving behavior.

Source: This study

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CHAPTER 3 RESEARCH METHODOLOGY

As describe in Chapter 1, the purpose of this study is to design a relational model of driving behaviors and driving risk level. We apply artificial neural network models to predict driving behaviors and hypothetical driving risk level to obtain predictive models. Chapter 3 introduces the research structure and variable acquisition. Section 3.1 present the research framework and describes the assumptions of this research. Section 3.2 shows arrangement of variables and variables in use. Section 3.3 introduce the artificial neural network.

3.1 Research Structure

The driving behaviors considered in this study focus on improper driving behaviors, so we define driving behaviors as “aberrant driving behavior”. This study is to explore the relational model between human factors and aberrant driving behavior. We follow the framework constructed by Li et al. (2017) to predict aberrant driving behavior and driving risk level. The conceptual framework is presented in Figure 3.1. (grading driving risk) and Figure 3.2. (steps for predicting). We plan to construct a risk level evaluation mechanism to assess driving performance, and comprehend that the aberrant driving behavior and driving risk level may be induced by specific human factors. The conceptual framework includes four main parts: Data collection, grading driving risk level, predicting aberrant driving behavior, predicting driving risk level, and the details of research steps are specified as follows:

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1. Data collection: Data collection affects the result directly. We have two dimensions at the beginning of the study. According to the human factors reviewed in Section 2.1, we acquired human factors through personnel database, physical examination report and questionnaire survey assisted by case study company. On the other hand, the aberrant driving behaviors are detected by digital tachograph. The number of aberrant driving behaviors is accumulated within three months (a season). All the next steps are extended from these two dimensions.
2. Grading driving risk level: Since the recorded number of aberrant driving behavior among each driver may be widely distributed, this study has to normalize aberrant driving behavior into single driving risk. In other words, the driving risk associated with a driver's aberrant driving behavior is counted by the relative danger of each driver's frequency of aberrant driving behavior. After transferring the number into single driving risk, we sum up all single driving risk into overall driving risk. It means to assess driving performance more comprehensively. Afterwards, we apply grading rules to classify personal overall driving risk into personal driving risk level. The third dimension is confirmed and represents the comparison result about each driver's overall risk within the driving behaviors that we can detect.
3. Predicting aberrant driving behavior: After collecting data, we can first construct the relational model between human factors and each aberrant driving behavior. Therefore, not only one model is set in this step. It is based on the purposed aberrant driving behaviors filtered in Section 3.3.2.
4. Predicting driving risk level: Similar to Step 3, the target of the predictive model is driving risk level instead of aberrant driving behavior. That is, we construct the relational model between human factors and hypothetical driving risk level. Since

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the driving risk level is categorical variable, we can obtain classification accuracy of the predictive model. Each human factor may have different influence on overall driving risk level, and we aim to confirm the influence between each human factor and driving risk level.

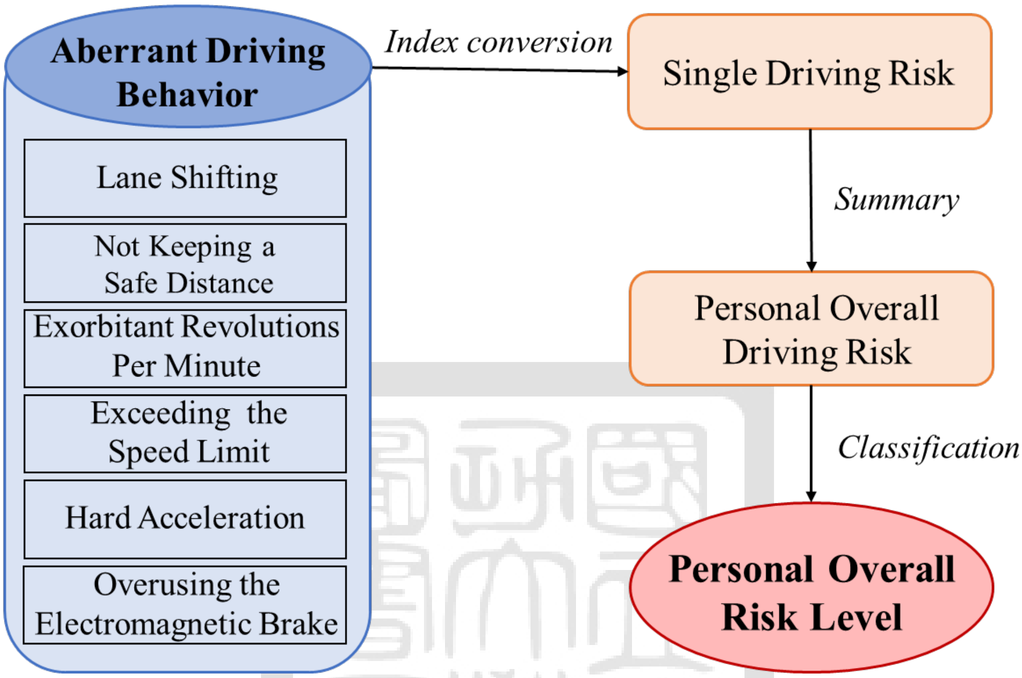

Figure 3.1 Research framework- grading driving risk level

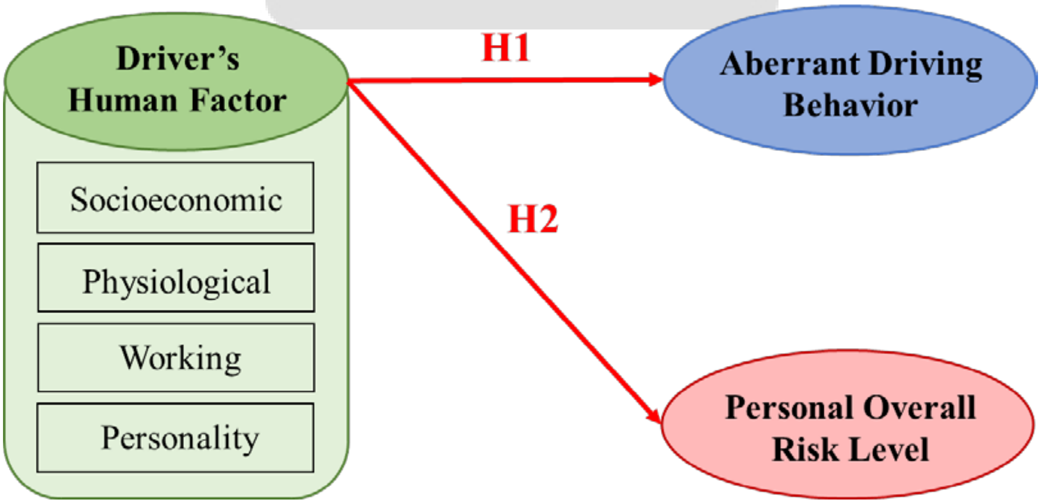

Figure 3.2 Research framework- steps for predicting

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Difference in human factors may be reflected on the reaction of driving behavior (Rimmö, 1999; Chliaoutakis, 1999; Chen, 2014) which in turn affects the driving performance and overall road safety. We define the driving behaviors which may cause negative impact on traffic as “aberrant driving behavior”. The purposeful assessment and management on drivers are the emphasis in this study, expecting to reduce the possibility of traffic accidents. Thus, this study establishes the relationships in three dimensions, human factors, aberrant driving behaviors and driving risk level. We put forward two hypotheses about three dimensions (Figure 3.2.), and the detailed hypotheses are as follows:

H 1: The human factors have significant impact on “Aberrant driving behaviors;”

- H 1-1: The human factors have significant impact on “Lane shifting;”
- H 1-2: The human factors have significant impact on “Not keeping a safe distance;”
- H 1-3: The human factors have significant impact on “Exorbitant revolutions per minute;”
- H 1-4: The human factors have significant impact on “Exceeding the speed limit;”
- H 1-5: The human factors have significant impact on “Hard acceleration;”
- H 1-6: The human factors have significant impact on “Overusing the electromagnetic brake;”

H 2: The human factors have significant impact on “Driving risk level.”

3.2 Research Variable and Questionnaire Design

This study explores the two aspect of driver’s human factors and aberrant driving behavior. The variable about various human factors and aberrant driving behavior are explained respectively in Section 3.2.1 and Section 3.2.2.

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3.2.1 Driver's human factors

Among the human factors, section 2.1 reviews the human factors considered in previous studies. In addition to the common socioeconomic factors, it is known that distinct of human factors would lead to difference in driving behavior. From the traffic accident point of view, the "Haddon Matrix" is the widely used accident analysis architecture (Haddon, 1980). In Haddon matrix, the traffic accident can be divided into pre-event, event and post-event based on the occurrence time of the accident. Then three main dimensions including human factors, vehicle factors and environment factors (psychical environment and socioeconomical environment) are used to explore factors to be improved. However, vehicle factors and environment factors are usually subject to technical and cultural interference. The driver sample in this study belongs to the same case company, that is to say that the vehicle equipment and driving environment may will be assumed quite similar.

Therefore, under the limited scope of the research, the two major dimensions about vehicle factors and environment factors were deleted. This study aims to collect driver's human factors to predict driving behaviors and prevent potential accident through personnel management.

Drivers are unconsciously affected by the individual human factors while driving, further affecting driving behavior and driving performance. This study generalizes human factor variables, then subdivide these human factor variables into four dimensions, including socioeconomic factors, physiological factors, working factors and personality. The classification structure is as shown in the Table 3.1.

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Table 3.1 The classification structure of human factors

Dimensions	Human factors
Socioeconomic Factors	Education level
	Marriage status
	Annual household income
Physiological factors	Gender
	Age
	BMI
	Disease
	Alcohol drinking patterns
Working factors	Driving seniority
	History of crashes
	Driving hours
	Commute time
	Sleep hours
	Driving fatigue
Personalities	Extraversion
	Agreeableness
	Conscientiousness
	Neuroticism
	Openness to Experience

Since the study involved in large number of human factors, there were different resource used to establish dataset. The study cites the human factors collected from the “personnel database”, “physical examination report” and “questionnaire survey” of case company in the study of Chen (2014) as the main axis of subsequent research analysis. Personnel database and physical examination report were the most basic and accurate data resource, and questionnaire survey should be applied to collect the remaining human factors which requested in research design. Details (contains variable name, type of variable, variable value and resource) of each human factor considered are shown in Table 3.2 to Table 3.5. We further differentiated the variables into qualitative (categorical) variables and quantitative (discrete and continuous)

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variables so as to understand the type of data. Some questions involve personal privacy, so the answers are asked in discrete intervals. Each factor and reasons for inclusion in the study are described below:

1. Socioeconomic factors

This dimension mainly covers the background information of the driver, which is also considered as basic demographic data in the past studies. We can measure economic and social status to individual through understanding factors such as income, education, career, etc.

(1) Education level:

In the trend of continuous innovation of vehicle equipment, drivers with different education background may have different familiarities and operational capabilities for technology products. The response to road conditions may also be vary.

(2) Marriage status

Lin (2016) found that married drivers with children had better emergency response ability, which can reduce the occurrence of aberrant driving behavior.

(3) Annual household income:

The annual income of households represents the economic ability of family. Economic pressure may affect the driver's emphasis on work and the tendency to drive safely (avoid violation of rules).

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Table 3.2 Socioeconomic factors

Human factor	Type of variable	Value	Source
Education level	Categorical	Junior degree or below Senior degree Bachelor degree Master degree or above	Questionnaire survey
Marriage status	Categorical	Unmarried Married	Personnel database
Annual household income	Categorical	< 350,000 (NTD$) 350,000 – 499,999 (NTD$) 500,000 – 699,999 (NTD$) 700,000 – 999,999 (NTD$) > 1,000,000 (NTD$)	Questionnaire survey

2. Physiological factors

The dimension displays personal physical condition and part of self-image, which may be defined based on medical science. Disease factor was further divided into disease index, symptom index and amblyopia to distinguish the type of illness.

(1) Gender:

In past many studies and cases, gender differences are significantly different in driving performance, driving attitudes and risk perception. Therefore, it is often regarded as an important variable.

(2) Age:

In the fields of medical and scientific, there are often differences between different age groups. Body functions (responsiveness, health) may decline with age. For example, young drivers are considered to have higher driving risks than elder drivers.

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(3) Body Mass Index (BMI):

Since the health condition of driver is hard to measure, the BMI value is used to measure the driver's health and is also representative of the driver's self-discipline. It calculated as the weight (kilogram) divided by height (meter) squared.

(4) Disease index

Dong (2007) point out that the driver who lost due physiological function needs to have diagnosis, and is positively related to work injury and dangerous behavior. This study summarized the diseases in physical examination report from case company, including hypertension, diabetes, chronic bronchitis, pulmonary emphysema, heartburn reflux, peptic ulcer, gastritis, thyroid disease, heart disease, liver disease, asthma, tuberculosis, kidney disease, epilepsy, anemia, otitis media, stroke, cataract, hearing disorders, cancer, totally as 19 diseases..

(5) Symptom index

Symptoms that occur after taking the drug or getting sick may reduce the responsiveness and mental state of driver (Dong, 2007) and will pose a potential threat to driving safety. This study applied and summarized the symptoms in physical examination report from case company, including cough, phlegmy, headache, palpitations, fatigue, tired, constipation, upper back pain, lower back pain, numb limbs, joint pain, polyuria, frequent urination, hematuria, tinnitus, difficulty breathing, nausea, abdominal pain, diarrhea, muscle weakness of limbs, chest pain, bloody stools and dysuria, totally as 24 symptoms.

(6) Amblyopia

Drivers may experience traffic accidents due to incomplete vision (e.g. blind side and driving in the rain) or deterioration of vision. Therefore, well visual is the basis of safe driving on the road. People with Amblyopia may not be able to conclude

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potential risk and have no reasonable response time, so the study included driver amblyopia in consideration.

(7) Alcohol drinking patterns

Previous studies have pointed out that alcohol has negative impact on mental status of driver. Drinking habits may affect mental state of driver and may further contribute to driving fatigue and aberrant driving behavior (Kao, 2008).

Table 3.3 Physiological factors

Human factor	**Type of variable**	**Value**	**Source**
Gender	Categorical	Male Female	Personnel database
Age	Discrete	Years	Personnel database
BMI	Continuous	Weight (kg) / Height(m)^2	Physical examination report
Disease index	Discrete	Number of diseases	Physical examination report
Symptom index	Discrete	Number of symptoms	Physical examination report
Amblyopia	Categorical	No Yes	Physical examination report
Alcohol drinking patterns	Categorical	Never drink Stop drinking Occasionally drink Drink every day	Physical examination report

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3. Working factors

This dimension describes the driver's working condition and related factors. Some may be according to driver’s lifestyle, for example, sleep hours and driving fatigue. These factors represent the relationship of interaction between job and aberrant driving behavior.

(1) Driving seniority:

Driving seniority can be viewed as driving experience. The higher seniority shows the higher salary and more skilled in vehicle. Therefore, the study takes this variable into consideration. Previous study also points out that seniority may also affect driving fatigue (Kao, 2008)

(2) History of crashes:

Crash experience may have alert or educational significance for elder drivers, and pay more attention to their own driving behavior (Feng et al., 2016; Pérez-Marín, 2019), so historical of crashes was listed into the scope of consideration.

(3) Driving hours:

Excessive driving hours lead to poor mental state and less control over driving behavior (Sun, 2012). In addition, since each driver may have different work time and dispatch instruction and driving hours is positively related to the recorded time of digital tachograph, it is necessary to understand the working time.

(4) Commute time:

Excessive commuting time will increase the overall length of time outside the driver and reduce the amount of sleep hours, indirectly causing dangerous behavior during commuting or work (Di Milia et al., 2013).

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(5) Sleep hours:

Previous studies have shown that insufficient sleep hours cause the driver to have fatigue (Di Milia et al., 2011). To explore the correlation between sleep hours and driving behavior, it is considered.

(6) Driving fatigue:

Driving fatigue has been an important occupational safety issue. The study applied Alanine aminotransferase (ALT) index to quantify the degree of fatigue. Chen (2014) prove that ALT index is highly related to driving fatigue and working performance. If ALT index is higher than 45, the function of liver may be abnormal.

Table 3.4 Working factors

Human factor	**Type of variable**	**Value**	**Source**
Driving seniority	Discrete	Year	Personnel database
History of crashes	Discrete	Frequency (within a season)	Personnel database
Driving hours	Discrete	Hours (within a season)	Personnel database
Commute time	Discrete	Minute (back and forth)	Questionnaire survey
Sleep hours	Discrete	Hours (within a day)	Questionnaire survey
Driving fatigue	Discrete	Alanine aminotransferase (ALT)	Physical examination report

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4. Personality

Personality traits involve the psychological state of drivers, which is an essential link to understand the drivers. Previous studies have proved that personality perform a considerable impact on driving behaviors or driving risks (Mallia et al., 2015; Li, 2017). Although there are differences in the classification and definition of personality, most of the research results attribute that personality are related to driving operations.

The interpretation of Big-five personality has been discussed in Section 2.1.2., and it will not be repeated here. This section explores the composition of the questionnaire on personality. The measuring dimension and questions in personality questionnaire was based on Big-five personality proposed by Costa and McCare (1992). The research referenced questions organized by Chiang (2004), Wang (2006), and Chen (2014) as the following questionnaire in Table 3.5. and measured by 5-point Likert scale.

Table 3.5 Personality questions

Human factor	Dimensions and Question	Scale
Big-five personality	**Extraversion**	5-point Likert scale
	1. I am a person with leadership.	
	2. I like to stay in a lively place.	
	3. Others are easy to accept my opinion.	
	4. I am an active person.	
	5. I am an energetic person.	
	6. Most people that I know like me.	
	Agreeableness	
	7. Most people that I know like me.	
	8. I enjoy working with others.	
	9. I am a person who always tries my best to help	

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Human factor	Dimensions and Question	Scale
	others	
	10. I am not a person who respects others. *	
	11. I get on well with my family or colleagues.	
	12. I consider other people's positions.	
	13. I consider other people's positions.	
	14. I am a considerate person.	
	Conscientiousness	
	15. I am a stickler for routine.	
	16. I am a conscientious person.	
	17. I am a person who constantly pursues growth.	
	18. I often complete things on time.	
	19. I strive to be the best in everything I participate.	
	20. I am a person who lacks planning to do things. *	
	Neuroticism	
	21. I am a person who is easy to get upset.	
	22. I am a person with stress tolerance. *	
	23. I often get angry at how others treat me.	
	24. I seldom feel lonely or depressed. *	
	25. I often feel nervous and jumpy.	
	26. I am a person who likes to be alone.	
	27. I am a person with emotional control. *	
	Openness to Experience	
	28. I am a person who always comes up with new methods.	
	29. I am a curious person.	
	30. I am a person who can think overall.	
	31. I am not a creative person. *	
	32. I am interested in thinking about the nature of the universe or the human environment.	
	* tables negative question.	

Source: Costa and McCare (1992), Chiang (2004), Wang (2006), Chen (2014)

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3.2.2 Aberrant driving behavior

In view of the driving behavior variables, each driving behavior can be defined as an “event” happen on the road. The event of each aberrant driving behavior was detected by digital tachograph from cooperative bus operator. The recording period pass through three months (one season) in 2012. The judgment criteria of each aberrant driving behavior are as follow:

1. Shift to right

The vehicle shifts to the right side without flashing the turn signal while the driving speed is higher than 70 km/h.

2. Shift to left

The vehicle shifts to the right side without flashing the turn signal while the driving speed is higher than 70 km/h.

3. Not keeping a safe distance

The distance from the car ahead is between driving speed subtract 30 meters and driving speed subtract 60 meters lasts for more than 3 seconds while the driving speed is higher than 70 km/h.

4. Severely not keeping a safe distance

The distance from the car ahead is less than driving speed subtract 60 meters lasts for more than 3 seconds while the driving speed is higher than 70 km/h.

5. Exorbitant revolutions per minute

Rotation speed exceed 2000 rpm lasts for more than 2 seconds and do not recorded at specific section in highway.

6. Exceeding the speed limit

The driving speed exceed 120 km/hr lasts for more than 3 seconds.

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7. Hard acceleration

The acceleration greater or equal to 3 km/h while the driving speed is higher than 70 km/h.

8. Overusing the electromagnetic brake

The driver pulls down the electromagnetic brake for more than 8 seconds.

9. Idling for too long

Rotation speed is between 0 and 800 and the driving speed is less than 2 km/h lasts for more than 20 minutes.

This study drawn the number of violations which judged conforming the threshold. If the threshold of any driving behavior is matched, one event would be recorded. However, the severity of the event (ex: slightly exceeding the speed limit and seriously exceeding the speed limit) cannot be distinguished, which can only be quantified as once occurring. As far as dealing with practical research, the data recoded in form of the number of aberrant driving behavior is practical and convenient enough. By taking into account the effectiveness of the driving risk assessment, the meaningless behavior variables would be deleted and similar behavior variables would be combined. The detailed process will be explained in Chapter 4.

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3.3 Research Methodology

This section introduces the data preprocessing methods and the theory of predictive model that will be used in subsequent studies.

3.3.1 Literature review and organization

Through literature review, we can learn the field of development and progress of recent studies. After establishing the direction of research, we can clearly understand which aspect of the research needs to be strengthened or improved. This study integrates the human factor variables used in previous literature that may be related to driving safety. Then the definition and comparison of driving behavior and driving performance are carried out. In addition, the relevant research on the grading assessment of driving behavior was also reviewed. The above literatures have been collated and organized to become the basis of this research.

3.3.2 Data collection

The classification of driving behavior and the evaluation of human factors were the two major targets in this study. With the development of technology, vehicular on-board units (ex: tachograph, accelerometer) gradually replaces behavior questionnaire (ex: DBQ) as the main tool to measure driving behavior. This study used the driving behavioral database detected by digital tachograph, which simultaneously improved accuracy and authenticity of driving behavior assessment. In the aspect of human factors, we quote the data result surveyed by Chen (2014), including personnel database, physical examination report and questionnaire survey.

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3.3.3 Descriptive statistical analysis

After having the research data, the basic narrative statistical analysis can obtain the distribution state of the sample, such as spread, variation, tendency, etc. The data presented in tabular and visual format allow us to view the accuracy of the data, or even to delete meaningless or redundant variables.

3.3.4 Correlation analysis

Correlation analysis is applied to display the direction and the strength of the relationship between two variables. Pearson correlation and Spearman's rank order correlation (Spearman correlation) are two commonly used evaluation method. Pearson correlation usually present the linear correlation between continuous variables, especially satisfying the assumption that the variable conforms to the normal distribution; Spearman correlation is based on the rank to calculate the nonlinear correlation, which the requirement is that the data should be ordinal (Hauke & Kossowski, 2011).

The positive or negative signs of the coefficient value represent the direction of correlation; The magnitude of the coefficient value represents the strength of the correlation and fall between -1 and 1. The closer the coefficient value is to 1, the higher the correlation; the closer to 0, the lower the correlation. If the coefficient value is higher than 0.7, it shows that there is great collinearity between the variables and should be adjusted.

3.3.5 Box-and-whisker plot

Box-and-whisker plot is abbreviated as boxplot, which is a kind of statistical

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graph that can effectively display the dispersion of data (Tukey, 1977). It is also often applied in various domain, common in quality management, but the practice is relatively cumbersome. The box consists of the mean, median, first quartile (Q1) and third quartile (Q3) of the data. In addition, there will be lines extending outward from the first and third quartiles to form the “fence”. Observations that are outside the fence are judged to be the outliers. Figure 3.3 presents the Box-and-whisker plot. The fence is defined as equation (3-1) and equation (3-2), where interquartile range (IQR) means the distance between Q3 and Q1.

$$\text{Fence}_{Min} = Q_1 - 1.5 * IQR \tag{3-1}$$

$$\text{Fence}_{Max} = Q_3 + 1.5 * IQR \tag{3-2}$$

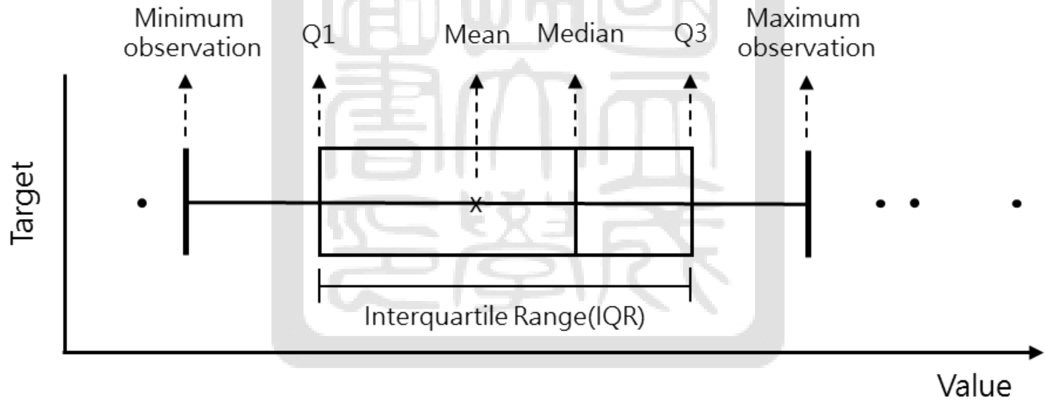

Figure 3.3 Box-and-whisker plot

Source: Tukey, 1977

3.3.6 Jenks natural breaks optimization

Jenks natural breaks optimization, also called Jenks optimization method, which is a clustering method applied to find out the best arrangement of observations into multiple group. And it is selected as the default classification method in the ArcGIS software package. Different from the commonly used clustering method (k-means,

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hierarchical clustering, etc.), the method is especially targeted at grouping one-dimensional data and good for data that are not evenly distributed. One-dimensional data usually has sorting feature, and the data complexity is relatively simple. After classifying observations, the grading result has the smallest inter-class deviation and maximize the between-class deviation. The Jenks natural breaks optimization determining the best grouping result with following iterative process (Jenks, 1967):

Step 1. Calculate the “sum of squared deviations between classes (SDBC).”

Step 2. Calculate the “sum of squared deviations from the array mean (SDAM).”

Step 3. Subtract the SDBC from the SDAM, which equals to the “sum of squared deviations from the class means (SDCM).”

Step 4. After inspecting each of the SDBC, we should move one unit from the class with the largest SDBC toward the class with the lowest SDBC.

Step 5. Repeat step 1 to 4 until the sum of the within class deviations reaches a minimal value.

Step 6. Calculated the goodness of variance fit (GVF) by equation (3-3), which ranges from 0 (worst fit) to 1 (perfect fit).

$$GVF = \frac{\mathrm{SDAM} - \mathrm{SDCM}}{\mathrm{SDAM}} = 1 - \frac{SDCM}{SDAM} \qquad (3\text{-}3)$$

K-means has the same meanings as Jenks in grouping purposes, which is the smallest inter-class deviation and the highest between-class deviation. Since one-dimensional data is relatively simple than multi-dimensional data, what really needs to be done is to is to optimize the “interval”. K-means discusses whether each object should move to another cluster. Jenks checks the setting of the boundary value. In comparison, Jenks owns clearer meaning in one-dimensional data and the calculation is more time-saving.

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3.3.7 Elbow method

Elbow method is a method used to help deciding the appropriate number of clusters (most people call it “k”) before doing cluster analysis. The method looks at the percentage of variance explained and the marginal gain for the change in the number of k. We should select a k of clusters so that adding another cluster would not able to give much better modelling of the dataset (Bholowalia & Kumar, 2014). Thorndike (1953) pointed out that a sudden marked changing of the curve at any point should identify a distinctively right cluster target.

3.3.8 Artificial Neural Network (ANN) Model

The artificial neural network is a computational model that imitates the structure and features of a biological neural network. “A neural network is a massively parallel distributed processor made up of simple processing units, which have a natural propensity for storing experimental knowledge and making it available for use” (Haykin, 2001). Artificial neural network is the initial architecture in artificial intelligence (AI), and new advances motivate it to solve more intricate problems. (LeCun et al., 2015)

The architecture of the ANN model can be defined and divided into three levels which from basic to complete are sorted into processing element, layer and network. The simple processing elements (called artificial neurons) is the basic unit to implement model calculation based on the neurons in animal species. Several processing elements with the same function are combined to form “layers”, then several layers with different functions are combined to form an integral “networks”. Figure 3.4 displays the function of the neuron (Moghaddam, Afandizadeh & Ziyadi,

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2011). The input value x_i will go through summation function and activation function to transform into output value. The summation function is formulated as equation (3-4), which is used to calculate the aggregate input from previous layer. Bias node θ_j is a constant term that may help the ANN model fit best for the training data and give freedom to model perform. The input values are multiplied by the weight coefficients, and the products are summed as a phased value Net_j. The activation functions are mathematical functions used to transform the phased value Net_j into an output value γ. The output value will be transformed within a certain range (in between 0 to 1 or -1 to 1 etc.) depended upon the activation function. Table 3.6 lists the popular types of activation functions. The neuron network with non-linear activation functions which is different from linear function may be able to learn and model more complicated data (Specht,1990；Glorot & Bengio, 2010；Karlik & Olgac, 2011).

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$$Net_j = \sum_i w_{i,j} x_i + \theta_j \tag{3-4}$$

where,

Net_j is the aggregate input to the jth neuron.

x_i is the input value of the ith neuron.

$w_{i,j}$ is the weight of the connection between the ith and jth neuron.

θ_j is the weighted value from a bias node.

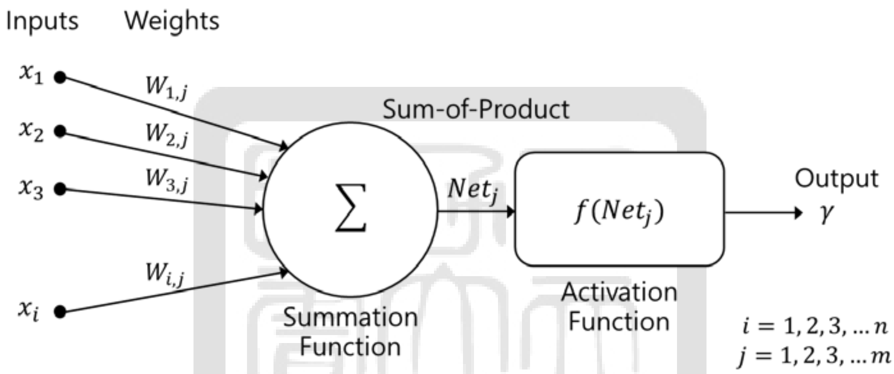

Figure 3.3 Function of neuron

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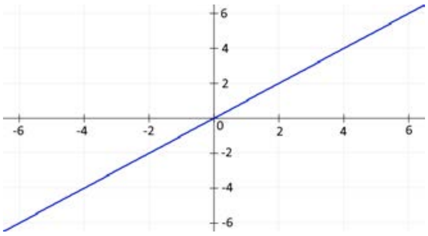
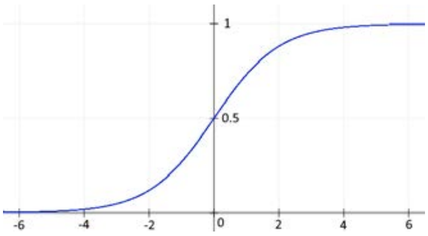
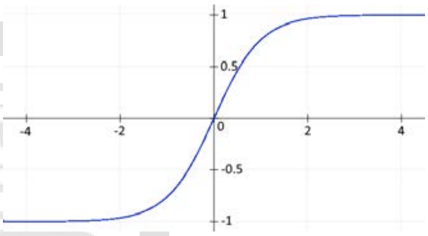
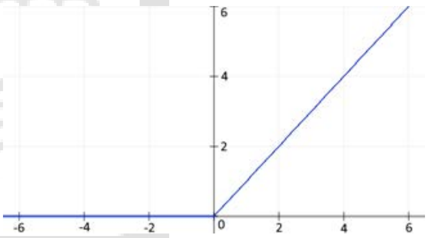
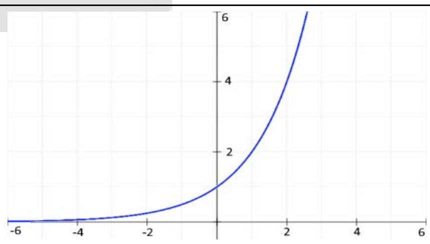
Table 3.6 Activation function

Function	**Equation**	**Figure**
Identity (Linear)	$f(x) = x$	
Logistic sigmoid	$f(x) = \dfrac{1}{1+e^{-x}}$	
Hyperbolic tangent (Tach)	$f(x) = \dfrac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$	
Rectified Linear Unit (ReLU)	$f(x) = \max(0, x)$	
Exponential	$f(x) = e^{x}$	
Softmax	$\sigma(x_i) = \dfrac{e^{x_i}}{\sum_{k=1} e^{x_k}}$	Softmax function is a K-dimensional vector $\sigma(x_i)$ mapped from random real values z.

Source: Specht (1990), Glorot & Bengio (2010), Karlik & Olgac (2011), Nasrabadi (2007)

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The neural network model applied in this study is multilayer perceptron (MLP) which is one of the frequently used network structures. The multilayer perceptron is composed of a parallel distributed processing (PDP) system which operated though interrelated artificial neurons to implement human thought (Feldman & Ballard, 1982). Illustrated in Figure 3.3, it is a classical learning structure for training networks with one hidden layer. The operational links between two layers are the weight coefficients. By training samples, the weight coefficients can be optimized. The feedforward network is widely and frequently used for classification, prediction, and optimization (Golden, Wasil, Coy, & Dagli, 1997). However, the relationship among variables in real life is mostly non-linear. Multilayer perceptron can model linear and especially non-linear functions without concerning the data distribution as different as contrasting to statistical approaches.

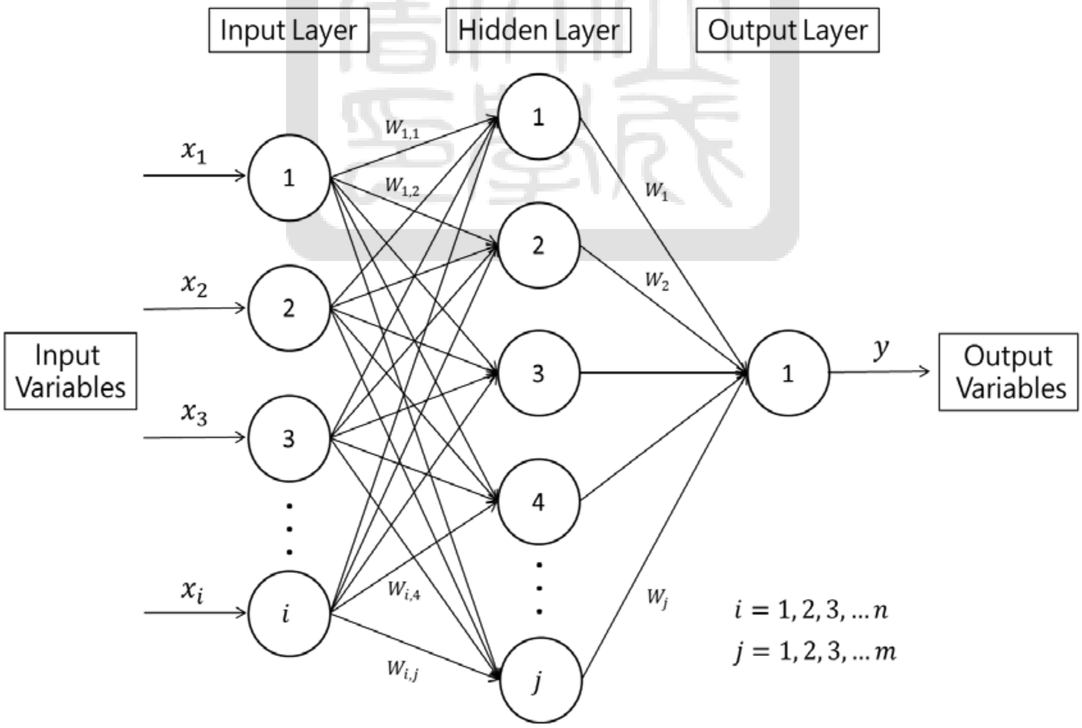

Figure 3.4 Multilayer perceptron

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In addition to reviewing the operation of neurons and the basic architecture of the ANN model, the second half of this Section will be divided into three parts: 1. Advantages and weaknesses, 2. Back Propagation and 3. Topology to examine the way in which neural networks update weight coefficients and the limitations on model operation.

1. Advantages and weaknesses

The application of Artificial neural networks is a very popular topic in recent years. The purpose of the model is most biased towards predicting unknown samples or states, and ANN model has been applied to diverse academic sectors, including transportation, industry, medicine, etc. The ANN model has high prediction accuracy and high variable adaptability so that it performs strong ability to construct predictive model. Conversely, the ANN model needs relatively high construction cost and more cumbersome construction process. The advantages and weaknesses of ANN approach are summarized as follows:

Advantages-

(1) Artificial neural network model is a nonlinear model yielding high prediction accuracy.

(2) ANN model can express interactions between input variables.

(3) ANN model can deal with various types of input variables, including qualitative variables, quantitative variables and logic variables.

(4) ANN model has been widely utilized in solving the problem about function mapping, series prediction, sample classification, etc.

Weaknesses-

(1) Since ANN model is non-linear, there may be infinite sets of solution. And it is difficult to prove which set of solutions is the best solution.

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(2) In the process of ANN model training, it is necessary to go through a lengthy process of trial and error to obtain the appropriate number of hidden layers and neurons. In addition, the learning rate parameter needs to be set by self. The overall network optimization work is quite time-consuming.

(3) ANN model applies iterative method (stochastic gradient descent) to approximate the optimal link weight and threshold. Because of the large amount of calculation, it consumes certain computer resources.

(4) ANN model encompasses large number of adjustable parameters for linking weights and thresholds, which is prone to overlearning. That is to say that the network may has less error in training samples, but has higher error in test samples.

2. Back Propagation

The error Backpropagation (BP) algorithm is usually applied to calculate the error contribution of each neuron after a batch of data is processed (Rumelhart, Hinton, & Williams, 1986). During training, the error between the actual output and the target output is calculated, and the corrected algorithm is sent back to the previous layer. Weight coefficients are corrected, and the training periods restart until the error reaches the minimum and before the error starts to increase again. The final weight coefficients should provide relatively accurate output (Werbos, 1975). Bishop (1995) summarized training steps for backpropagation algorithm, as below:

Step 1. randomly generate initial weight coefficients,

Step 2. import training data and forward propagate through the network to obtain an output,

Step 3. calculate the error between actual output and the target output,

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Step 4. propagate error back through the multilayer perceptron,

Step 5. adjust weight coefficients to decrease the output error,

Step 6. repeat steps 2–6 for each sample pattern until overall error is relatively low.

The number of times that a batch of data pass through the network called "iteration." The backpropagation algorithm applied iterative method- Stochastic gradient descent (SGD) to make weight coefficients efficient updated (Bottou, 2012). The SGD achieves the minimum error (cost function) through optimizing the weight alone the direction of gradient. However, since the activation function and cost function are non-linear functions, the network may not converge to the correct. The mentioned problem illtreated in Figure 3.4. If the random initial weight is located at the blue point 1, the algorithm will adjust the weights by follow the error slope until arrive the lowest point (red point), called "Local cost minimum"; On the contrary, if the random initial weight is located at the blue point 2, the lowest point (green point) is relatively the best solution of all cost minimum, called "Global cost minimum." Therefore, the "Local cost minimum" do not necessarily equal the "Global cost minimum." We have to try training the network multiple times with different initial weights to capture "Global cost minimum."

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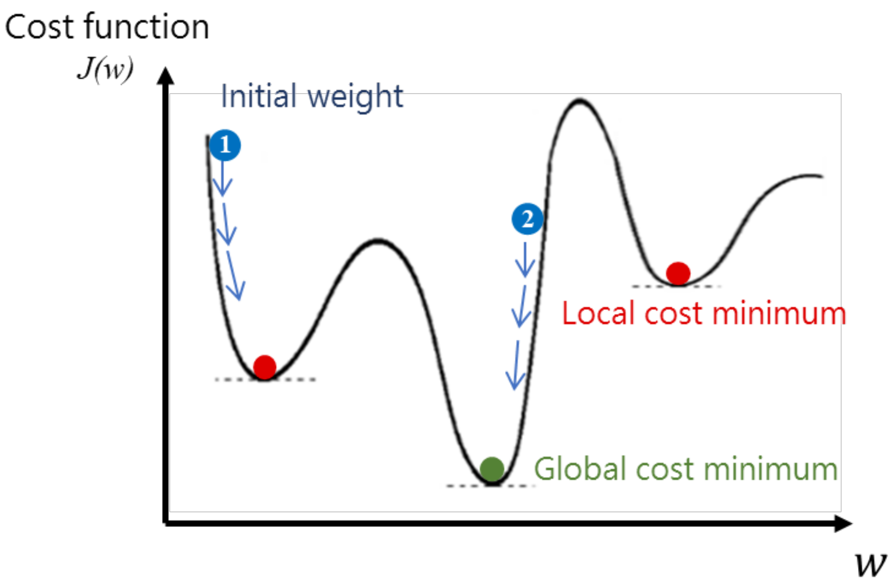

Figure 3.5 Stochastic gradient descent

3. Topology

The ANN topology plays a fundamental role in its functionality and performance. Fiesler and Beale (1996) defined the neural network topology as consisting of a neural framework and interconnection structure. To determine the final architecture of the ANN model, a (lengthy) process of trial and error is used to select the best performance from different networks.

Although neural networks have lots of weights so that it performs well to capture the characteristics of the training set. However, over complicated structures are more likely to contribute to overfitting problem. If the model does much better on the training set than test set, then we're likely face overfitting problem (Figure 3.5)(Tetko, Livingstone & Luik, 1995). In other word, the model cannot properly generalize to predict new data. To avoid facing overfitting problem, there are several ways to enhance the ability of generalization: training with more data, simplifying the model, early termination, etc.

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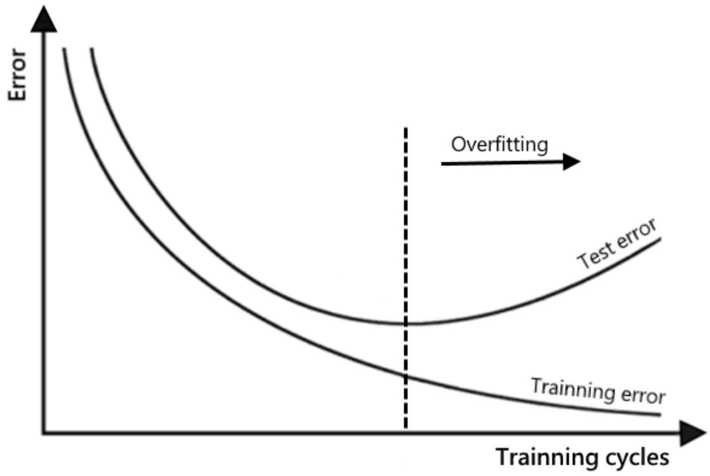

Figure 3.6 Overfitting problem

Neural networks are widely used mathematical models with strong learning ability in deep learning area. However, many research refuses to apply ANN model because of the most criticized feature: doubting with "black box." Different from other statistical methods, there is no satisfactory interpretation of their working process (due to the hidden layers) (Benítez, Castro, & Requena, 1997). We can obtain the output with high approximation to actual value, but no definitive answer of how the network calculate and learning method. Although there are doubts about using ANN model, such constraints are acceptable in most practical situations because its practicability is far more important than understanding how it works. In addition, this method is more able to calculate complex data and better learning ability.

3.3.9 Performance assessment

After the predictive model is constructed, the test data is entered and the output value is calculated. We can confirm the predictive ability of the model rely on performance indicators to assess. The study applied the accuracy (correct rate) and the mean absolute percentage error (MAPE) to understand the performance of ANN

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model. The advantage is that it is not affected by the sample size and can more accurately estimate the difference between the actual value and the estimated value (Lewis, 1982). The higher accuracy and smaller MAPE represent the learning ability and effect of model is better. Equation (3-5) and equation (3-6) show the calculation formula, and the additional criteria for MAPE are shown in Table 3.7.

$$\text{Accuracy} = \frac{the\ number\ \ of\ sample\ predicted\ correctly}{the\ \ number\ of\ total\ sample} \times 100\% \qquad (3\text{-}5)$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{observed_i - predicted_i}{observed_i}\right| \times 100\% \qquad (3\text{-}6)$$

Table 3.7 Interpretation of typical MAPE values

Mean Absolute Percentage Error (MAPE)	
MAPE	**Interpretation**
< 10 %	High accurate forecasting
10% ~ 20 %	Good forecasting
20% ~ 50 %	Reasonable forecasting
> 50 %	Inaccurate forecasting

Source: Lewis (1982)

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CHAPTER 4 EMPIRICAL EXPERIMENT

The framework of this study is as shown in Section 3.1 and the purpose be mainly divided into two parts: constructing the driving risk level and predicting driving risk by human factors. The study cites the data collected by Chen (2014) to analyze driving behaviors and construct the predictive model. The dataset of human factors was collected from personnel database and physical examination report in March 2012 and issuing questionnaire to professional bus drivers by case company in January 2014. The dataset of driving behavior was recorded by digital tachograph from April to June 2012. The study connected human factors with aberrant driving behavior of each driver to carry out the subsequent analysis.

This chapter first overview similar research of research team in Section 4.1. and then describes the status of data collection and basic analysis of samples in Section 4.2. Section 4.3 and Section 4.4 then propose a method for constructing driving risk level based on the complete dataset obtained. Section 4.5 construct a predictive model of human factors.

4.1 Team Research Overview

The study continues the research direction of research team which has accumulated four different research topics since 2014. These researches tended to explain the relationship between drivers and driving behaviors. The human factor or personality are applied to measure differences between drivers, and driving behaviors are usually applied to evaluate driving performance. Internal service (Lin, 2016) or job situation (Liang, 2015) were also considered in previous team studies.

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Table 4.1 Summary of team researches

Research	Related dimension					Driving performance	Methodology
	Human factor	Personality	Internal service	Job situation*	Driving behavior		
Chen (2014)	✓	✓			✓	Work quality	Structural Equation Modeling
Liang (2015)	✓			✓	✓	Driving behavior	Structural Equation Modeling
Lin (2016)	✓		✓		✓	Driving behavior	Structural Equation Modeling
Li (2017)		✓			✓	Driving behavior	Cluster analysis; Fixed interval rule; Fixed percentage rule; Poisson Regression; Multiple Regression; Logistic Regression.
The study	✓	✓			✓	Driving behavior	Box-and-whisker plot; Jenks Optimization Method; Artificial Neural Network.

* Job situation included the job satisfaction, organizational climate, job stress and retention.

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The study integrated related dimensions, driving performance and methodology in Table 4.1. Chen (2014), Liang (2015) and Lin (2016) applied structural equation modeling (SEM) to reflect the relationship between dimensions. Li (2017) applied fixed interval and fixed percentage rules to classify drivers, and diverse regression model to construct predictive model, including poisson regression, multiple regression, logistic regression. This study applied Box-and-whisker plot and Jenks natural breaks optimization to classify drivers, and artificial neural network model to construct predictive model.

4.2 Data Description

Under the constraints of the research framework and limited resources, the study focuses on the bus drivers who assigned to drive the bus that equipped with digital tachograph in the case company. The research target has been limited to a specific group with similar working environment. The bus drivers most service the go trip or back trip between Tainan and Taipei (routing on national highway) during our research period from April to June 2012. After confirming the driver, the human factors were obtained through personnel database, physical examination report and questionnaire survey. The event records of the aberrant driving behavior were extracted out from digital tachograph in the case company.

This section is devoted to the basic statistical analysis of human factor variables in Section 4.1.1 and driving behavior variables in Section 4.1.2. Adjustments to driving behavior are explained in section 4.1.3.

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4.2.1 Description of human factor

The human factors in the study are composed of socioeconomic factor, physiological factor, working factor and personality. A total of 62 driver's data were valid data, which service in the same route and time period. Each record should contain three sources of dataset, including personnel database, physical examination report and questionnaire survey.

When constructing a neural network model, we can apply both qualitative variables and quantitative variables. To preserve the information and feature of the data, this study did not discretize continuous variables or discrete variables into different categories. Therefore, the human factor variables would be divided into two parts for description.

Table 4.2 display the frequency distribution of qualitative factors. It contains each factor in socioeconomic dimension, and gender, amblyopia and alcohol drinking patterns in physiological dimension. As for the education level, most of the drivers have senior degree, which are 47 (75.8%) drivers. And the second is junior degree for 9 (14.5) drivers or below. Bachelor and junior degree each contain 4 (6.5%) and 2 (3.2%) drivers; For the distribution if marriage status, 21 (33.9%) drivers are unmarried and 41 (66.1%) drivers are married. To annual household income, drivers are the most in five hundred thousand to seven hundred thousand dollars income (42, 67.7), and following is three hundred and fifty thousand to five hundred thousand dollars (11, 17.7%), and the least is less than three hundred and fifty thousand (0, 0%).

The bus drivers surveyed in the study are 62 (100%) male drivers and without female drivers (0%), so the factor should be deleted since there is no difference among

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drivers; 7 (11.3%) drivers had the problem of amblyopia and 55 (88.7%) drivers did not have the problem; In alcohol drinking patterns, 22 (35.5%) drivers never drink alcohol before and 8 (12.9%) drivers already stop drinking. Most of drivers used to drink occasionally (25, 40.3%) and less driver drink every day (7, 11.3%).

Table 4.2 Frequency distribution of qualitative factors

<table>
<tr><th>Dimension</th><th>Human factor</th><th>Response</th><th>Number</th><th>Percentage</th></tr>
<tr><td rowspan="11">Socioeconomic</td><td rowspan="4">Educational level</td><td>Junior degree or below</td><td>9</td><td>14.5%</td></tr>
<tr><td>Senior degree</td><td>47</td><td>75.8%</td></tr>
<tr><td>Bachelor degree</td><td>4</td><td>6.5%</td></tr>
<tr><td>Master degree or above</td><td>2</td><td>3.2%</td></tr>
<tr><td rowspan="2">Marriage status</td><td>Unmarried</td><td>21</td><td>33.9%</td></tr>
<tr><td>Married</td><td>41</td><td>66.1%</td></tr>
<tr><td rowspan="5">Annual household income (NTD$)</td><td>< 350,000</td><td>0</td><td>0.0%</td></tr>
<tr><td>350,000 – 499,999</td><td>11</td><td>17.7%</td></tr>
<tr><td>500,000 – 699,999</td><td>42</td><td>67.7%</td></tr>
<tr><td>700,000 – 999,999</td><td>7</td><td>11.3%</td></tr>
<tr><td>> 1,000,000</td><td>2</td><td>3.2%</td></tr>
<tr><td rowspan="8">Physiological</td><td rowspan="2">Gender</td><td>Male</td><td>62</td><td>100.0%</td></tr>
<tr><td>Female</td><td>0</td><td>0.0%</td></tr>
<tr><td rowspan="2">Amblyopia</td><td>No</td><td>55</td><td>88.7%</td></tr>
<tr><td>Yes</td><td>7</td><td>11.3%</td></tr>
<tr><td rowspan="4">Alcohol drinking patterns</td><td>Never drink</td><td>22</td><td>35.5%</td></tr>
<tr><td>Stop drinking</td><td>8</td><td>12.9%</td></tr>
<tr><td>Occasionally drink</td><td>25</td><td>40.3%</td></tr>
<tr><td>Drink every day</td><td>7</td><td>11.3%</td></tr>
</table>

Source: Case company, 2012; Chen (2014); The study

Table 4.3 and Table 4.4 display the descriptive statistics of quantitative factors. Minima (Min) shows the lowest value in data; Maxima (Max) shows the highest value in data; Mean shows the average value of the overall data; Standard deviation (SD) measures the degree of dispersion of a set of data. In addition, the study illustrates

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continuous and discrete variables in histogram in Appendix A, which make readers more aware of sample distribution. For example, the age of the issued bus drivers ranges from 24 to 56 years old. The mean age of total sample is 41 years old. The interval of 45-50 years old are the majority of total sample.

Due to descriptive statistics and histograms, we may learn that there is difference among each driver in most of human factor. In factor of history of crashes, only 3 (5%) drivers have experience of one time. The lack of history of crashes could be attributed to the fact that the recording time was too short so that only a few drivers had an accident during the period, and the study remove it from input variables. In personality dimension, Chen (2014) has already proved that the questionnaire result passed the reliability analysis (Cronbach alpha > 0.7) to satisfy internal consistency. The distribution of conscientiousness and neuroticism was concentrated in narrow interval (both are within value 1.5). It shows that the driver may be conservative to fill out the questionnaire so that there is not much difference in answering.

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Table 4.3 Descriptive statistics of quantitative factors

Dimension	Human factor	Value	Min.	Max.	Mean	SD
Physiological	Age	Years	24	56	41.27	7.76
	BMI	Index	18	33	25.04	3.37
	Disease index	Index	0	2	0.39	0.64
	Symptom index	Index	0	7	0.84	1.35
Working	Driving seniority	Years	0	11	4.50	3.42
	History of crashes	Frequency	0	1	0.05	0.22
	Driving hours	Hours	435	711	622.86	58.92
	Commute time	Minutes	2	120	38.71	28.83
	Sleep hours	Hours	6	11	7.89	1.39
	Driving fatigue	ALT	10	96	29.29	20.01

Source: Case company, 2012; Chen, 2014; The study

Table 4.4 Descriptive statistics of personality factors

Dimension	Human factor	Value	Min.	Max.	Mean	SD
Personality	Extraversion	Point	2.00	4.67	3.39	0.51
	Agreeableness	Point	2.38	4.50	3.48	0.48
	Conscientiousness	Point	3.00	4.33	3.58	0.35
	Neuroticism	Point	2.71	3.86	2.98	0.23
	Openness to Experience	Point	2.60	4.20	3.19	0.31

Source: Case company, 2012; Li, 2017; The study

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4.2.2 Description of driving behavior

According to the event record provided by the case company, 62 professional drivers have driven bus which equipped with the digital tachograph from April to June 2012. The descriptive statistics of driving behaviors are shown in Table 4.5. We can learn the difference in driving behavior from the broad data scope (the range between maximum and minimum). We can also estimate that the degree of dispersion of the number of driving behaviors is quite high from the standard deviations.

Table 4.5 Descriptive statistics of driving behaviors within one season

Driving behavior	Value	Min.	Max.	Mean	SD
Shift to right	Frequency	0	3368	482.98	700.00
Shift to left	Frequency	0	3478	466.60	652.11
Not keeping a safe distance	Frequency	0	1774	143.71	328.65
Severely not keeping a safe distance	Frequency	0	1045	157.34	193.84
Exorbitant revolutions per minute	Frequency	0	66	2.52	8.76
Exceeding the speed limit	Frequency	0	188	5.11	24.57
Hard acceleration	Frequency	0	226	16.24	36.15
Overusing the electromagnetic brake	Frequency	0	28	2.79	5.01
Idling for too long	Frequency	0	553	12.73	70.00

Source: Case company, 2012; Chen, 2014; The study

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4.2.3 Correlation analysis

The backpropagation algorithm in artificial neural model is to learn the sample through modifying the weight. The algorithm itself does not have the ability to filter variables. In other words, after the model is generated, each input variable will have an influential weight. Therefore, invalid variables are easy to make the model learning poor. Similar to the linear regression model, the collinearity between variables may lead to infinite number of solutions. We have to test the correlation between each factor to achieve model convergence.

Table 4.6 and Table 4.7 show the result of correlation analysis. We can learn that the correlation coefficients between the variables is quite low, and only few (extraversion-conscientiousness) are close to 0.7. Since the correlation coefficient do not exceed the threshold for high correlation, it will not be deleted. Remaining human factors will set as the input variables for subsequent predictions.

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Table 4.6 Correlation coefficient of human factor variables (1)

Human factor	Age	BMI	Disease index	Symptom index	Driving seniority	Driving hours	Commute time	Sleep hours	Driving fatigue
Age	1	0.031	0.151	0.168	.349**	0.009	-0.009	-0.047	-0.028
BMI	0.031	1	0.181	-0.035	0.110	0.068	-0.227	0.092	.324*
Disease index	0.151	0.181	1	.304*	0.030	0.000	-0.113	-.320*	0.223
Symptom index	0.168	-0.035	.304*	1	0.121	-0.087	0.035	-0.150	-0.039
Driving seniority	.349**	0.110	0.030	0.121	1	0.053	0.130	0.022	-0.101
Driving hours	0.009	0.068	0.000	-0.087	0.053	1	0.121	0.245	-0.131
Commute time	-0.009	-0.227	-0.113	0.035	0.130	0.121	1	-0.044	-0.056
Sleep hours	-0.047	0.092	-.320*	-0.150	0.022	0.245	-0.044	1	-0.246
Driving fatigue	-0.028	.324*	0.223	-0.039	-0.101	-0.131	-0.056	-0.246	1
Extraversion	-0.114	-0.055	-0.078	-0.129	-0.125	.273*	-0.002	0.212	-0.220
Agreeableness	0.050	0.028	-.254*	-0.039	0.041	0.230	-0.042	.299*	-.438**
Conscientiousness	-0.095	-0.121	-0.111	-0.116	-0.161	0.151	-0.118	0.078	-0.106
Neuroticism	0.078	0.208	.314*	-0.009	0.098	-0.176	-0.072	-.323*	.304*
Openness to Experience	0.071	-0.052	0.029	-0.065	-0.089	0.120	-0.054	0.225	-0.082

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

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Table 4.7 Correlation coefficient of human factor variables (2)

	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness to Experience
Age	-0.114	0.050	-0.095	0.078	0.071
BMI	-0.055	0.028	-0.121	0.208	-0.052
Disease index	-0.078	-.254*	-0.111	.314*	0.029
Symptom index	-0.129	-0.039	-0.116	-0.009	-0.065
Driving seniority	-0.125	0.041	-0.161	0.098	-0.089
Driving hours	.273*	0.230	0.151	-0.176	0.120
Commute time	-0.002	-0.042	-0.118	-0.072	-0.054
Sleep hours	0.212	.299*	0.078	-.323*	0.225
Driving fatigue	-0.220	-.438**	-0.106	.304*	-0.082
Extraversion	1	0.128	.678**	-0.147	.411**
Agreeableness	0.128	1	.280*	-.460**	0.190
Conscientiousness	.678**	.280*	1	-0.159	.306*
Neuroticism	-0.147	-.460**	-0.159	1	-0.105
Openness to Experience	.411**	0.190	.306*	-0.105	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

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4.2.4 Adjustment

The definition and threshold of aberrant driving behavior provided by the case passenger company has been discussed in section 3.2.2. There are total nine aberrant driving behaviors collected. However, in order to assess the driving risk more effectively, this study needs to adjust the adopted driving behavior. We tend to measure driving risk with more critical driving behavior.

Through the advice of the case company on the experience of driving safety management, we made the following adjustments: The original consideration of "abnormal stays" was one of the deviating driving practices that may lead to safety, but this behavior was mainly affected by the environment or dispatch instructions. Fuel consumption and exhaust emissions at idle have a greater impact on the efficiency of travel and environmental impacts. It is not the main cause of the increase in the risk of traffic accidents. Li (2017) analyzed the correlation coefficient between each driving behavior and integrated behaviors with strong acceleration. "Shift to right" and "shift to left" were merged into "land shifting" (correlation coefficient: 0.679), and "severely not keeping a safe distance" was incorporated into "not keeping a safe distance" (correlation coefficient: 0.721). Appropriate utilization of driving behavior into the assessment can lead to more reasonable evaluation criteria.

The driving behaviors in this study is taken as the length of season. Although the record period seems to be similar, the actual driving hours is inconsistent since the bus industry exists the characteristics of different dispatch instructions and unfixed period of driving. In the study, relative concepts are used to assess and grade the risk of drivers, so the event data must be converted into fair standards. The study applied "driving hours" in one of the human factors to convert aberrant driving behavior into

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equal standard, which is similar to the definition of "exposure." The converting method is formulated as equation (4-1). After deletion and adjustment of exposure conversion, the descriptive statistics of adjusted driving behavior are reorganized in Table 4.8.

$$B_i^j = b_i^j \times \frac{e_{Max}^j}{e_i^j} \tag{4-1}$$

where,

B_i^j is the converted number of driving behavior j for driver i,

b_i^j is the number of driving behavior j for driver i recorded within one season,

e_{Max} is the maximum exposure within one season, and

e_i is the exposure for driver i within one season.

Table 4.8 Descriptive statistics of adjusted driving behavior

Driving behavior	**Number**	**Min.**	**Max.**	**Mean**	**SD**
Land shifting	62	0	5090.6	1115.89	1426.66
Not keeping a safe distance	62	0	3142.1	352.8	589.4
Exorbitant revolutions per minute	62	0	90.9	3.1	11.8
Exceeding the speed limit	62	0	307.5	7.4	39.6
Hard acceleration	62	0	238.7	18.6	40.4
Overusing the electromagnetic brake	62	0	30.1	3.3	6.0

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4.3 Driving Risk Conversion

After converting driving behavior into driving behavior within equal time units, the study tends to establish a risk assessment mechanism. Each driving behavior selected in Section 4.1.3 is the basis of driving risk and is regarded as an indicator of driving risk. The study hoped that the behavioral data recorded by the case company can be appropriately classified through data science to express the driving risk of the driver. Section 4.2.1 discusses the characteristics of the behavioral data. Section4.2.2 and 4.2.3 describe the methods and processes of transforming single driving risk.

4.3.1 Features of driving behavior

To understand the distribution feature of driving behavior, the study presents the data from low to high in the line chart as Figure 4-1 to Figure 4-3. It can be seen that the distribution of exorbitant revolutions per minute is similar to that of exceeding the speed limit (Figure 4.2). The number of behaviors of nearly half or more drivers is 0, indicating that the majority of driving performed well in this behavior during the recording period. It can be preliminarily inferred that most drivers are relatively safe in the performance of these two aberrant driving behaviors. However, it can also be seen that there are serious discrete problems in every behavior, and it is necessary to strengthen the reminder and education for the driver.

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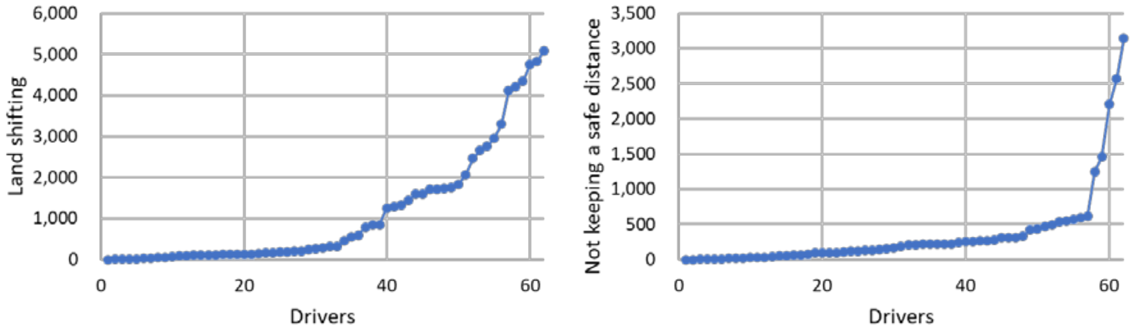

Figure 4.1 Incremental sequence of land shifting (left) and not keeping a safe distance (right)

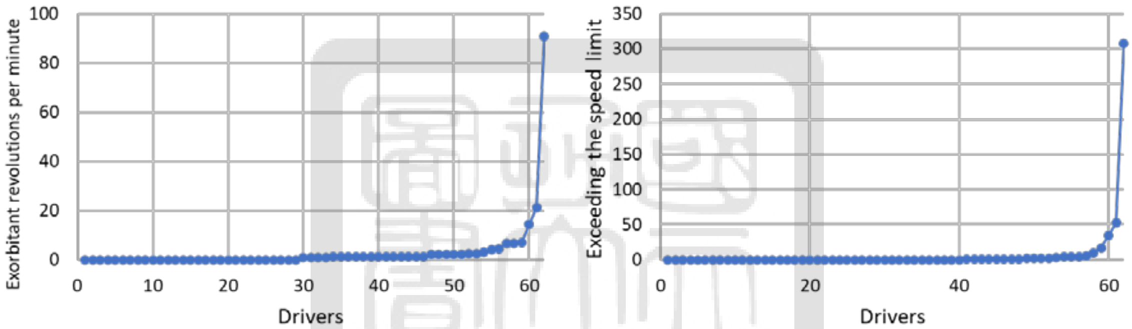

Figure 4.2 Incremental sequence of exorbitant revolutions per minute (left) and exceeding the speed limit (right)

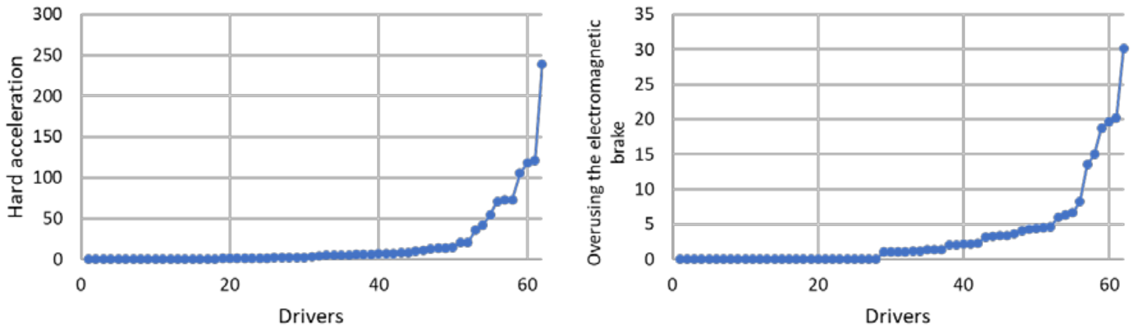

Figure 4.3 Incremental sequence of Hard acceleration (left) and Overusing the electromagnetic brake (right)

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4.3.2 Single driving risk

This study applied six aberrant driving behaviors as the evaluation targets of driving risk. Continuing the research concept of Li (2017), driving risk value for each behavior will be established, which will be further summarized to form the overall driving risk. However, each driver may often be involved in specific aberrant driving behaviors, rather than evenly distributed among all aberrant driving behaviors. In other words, different drivers may behave quite differently towards the same driving behavior. Due to the quite difference in the frequency of aberrant behavior among individuals, it is difficult to establish a fair and reasonable threshold to manage drivers. We can only use the relative risk approach to judge the degree of individual risk.

In practice, it is less significance to know the definitely number of driving behavior (event data). The main purpose of risk assessment is to distinguish and judge the degree of risk of driving and can be directly applied to risk management. The study tends to group each driving behavior into single driving risk index, which value from one to higher number. A higher value means higher chance to have aberrant driving behavior. The detailed process to establish risk index is organized in the next section.

4.3.3 Converting process

Based on the above analysis and discussion, we can understand that the aberrant driving behavior data taken in this study is positive skew (right skew) distributions with outliers. However, outliers may easily distort the prediction results. In addition, it is possible that single outlier forms a group by selves in cluster analysis, especially

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in the case of insufficient samples. Therefore, how to deal with outliers is a focus of this study. It is necessary to separate the outliers first before making further evaluation.

After obtaining driving behavior within equal time units, we applied Box-and-whisker plot to determine the outlier among data. The number of aberrant driving behavior has extreme positive skew, and the outliers are mainly concentrated in areas larger than the maximum (Q3+1.5*IQR). Figure 4.4 shows Box-and-whisker plot of each single driving behavior. Table 4.8 shows the values (Min, Q1, Q2, Q3, Mean, Max and Interquartile range) on the graph. It can be seen from the figure that the points beyond the maximum value (red line) are judged as outliers, which are temporarily removed before the next stage of clustering. The number of outliers which should be removed for each driving behavior is: 5 for land shifting; 5 for not keeping a safe distance;7 for exorbitant revolutions per minute; 10 for exceeding the speed limit; 10 for hard acceleration; 6 for overusing the electromagnetic brake. Table 4.9 present the descriptive statistics of adjusted driving behavior that the outliers have been removed. To compared Table 4.10 with Table 4.8, the max number and the mean of each behavior decline and the standard deviation dropped sharply, which represent the dataset tended to be more stable but still keep the distribution of positive skew.

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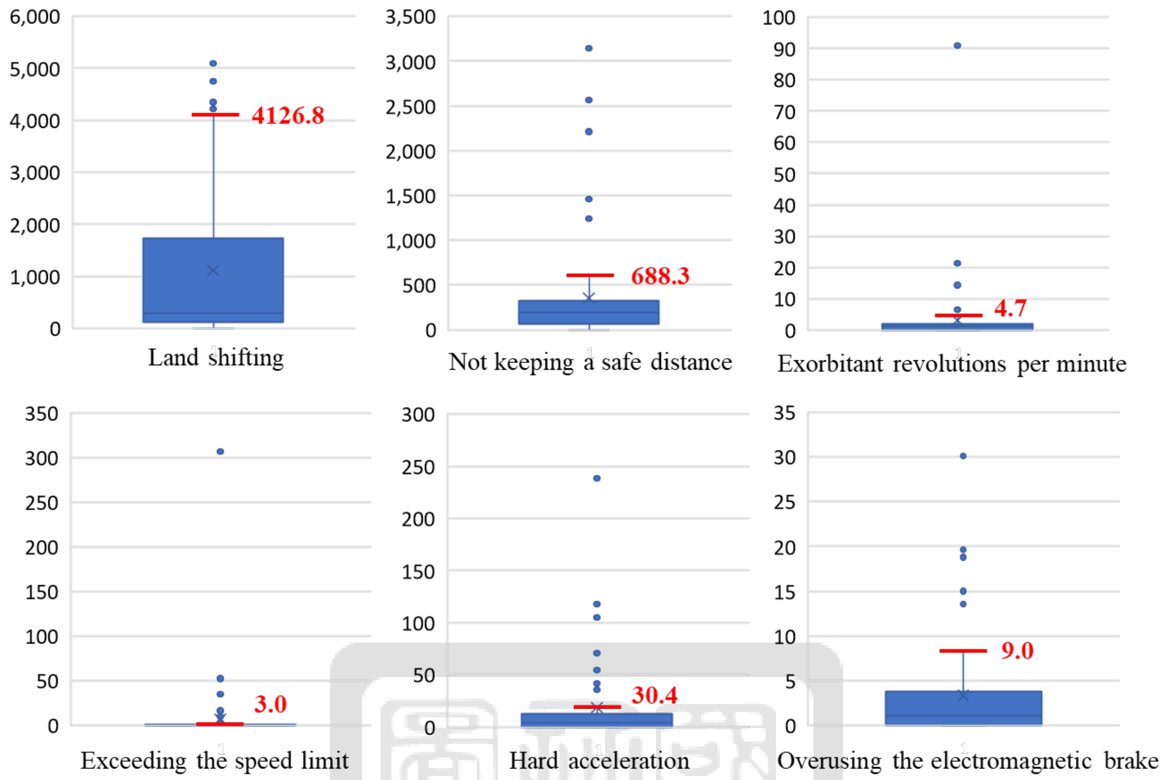

Figure 4.4 Box-and-whisker plot result for each driving behavior

Table 4.9 Values in Box-and-whisker plot

Driving behavior	Min. Fence	Q1	Q3	Mean	Max. Fence	ΔQ
Land shifting	0	118.3	1721.7	1115.9	4126.8	1603.4
Not keeping a safe distance	0	64.7	314.1	352.8	688.3	249.4
Exorbitant revolutions per minute	0	0	1.9	3.1	4.7	1.9
Exceeding the speed limit	0	0	1.2	7.4	3.0	1.2
Hard acceleration	0	0	12.2	18.6	30.4	12.2
Overusing the electromagnetic brake	0	0	3.6	3.3	9.0	3.6

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Table 4.10 Descriptive statistics of driving behavior without outliers

Driving behavior	Number	Min.	Max.	Mean	SD
Land shifting	57	0	4108.3	806.00	997.89
Not keeping a safe distance	57	0	613.9	197.4	172.4
Exorbitant revolutions per minute	55	0	4.2	0.8	1.0
Exceeding the speed limit	52	0	2.4	0.3	0.7
Hard acceleration	52	0	20.6	4.2	5.3
Overusing the electromagnetic brake	56	0	8.3	1.6	2.1

Separating outliers allows us to group data more efficiently. At this section, the study only group single aberrant driving behavior, which can be regarded as the one-dimensional clustering. Common one-dimensional clustering methods in previous studies were standard deviation, equal intervals, quartile, etc. In this study, we applied Jenks natural breaks optimization method to grade the remaining number of aberrant driving behavior. Differ from traditional clustering method, the method may consider statistical features of data distribution but should customize the number of target class (k). It also improves the disadvantage of usually impractical and inaccurate for setting range by hand.

The study used The Real Statistics Resource Pack in Microsoft Excel to complete the calculations of Jenks natural breaks optimization. An inappropriate selection of k may lead to worse result. We applied “Elbow method” to determine the number of groups (k). We test the goodness of variance fit (GVF) of k for 2, 3, 4 and 5, which illustrated in Figure 4.5. When the k value is increased from two groups to three groups, there is a significant increase in GVF. When increasing to four groups from three groups and increasing to five groups from four groups, GVF has limited improvement and cannot improve the performance of modelling data. Thus, we set k for 3 to carried out Jenks natural breaks optimization, which proved to have better

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consequence.

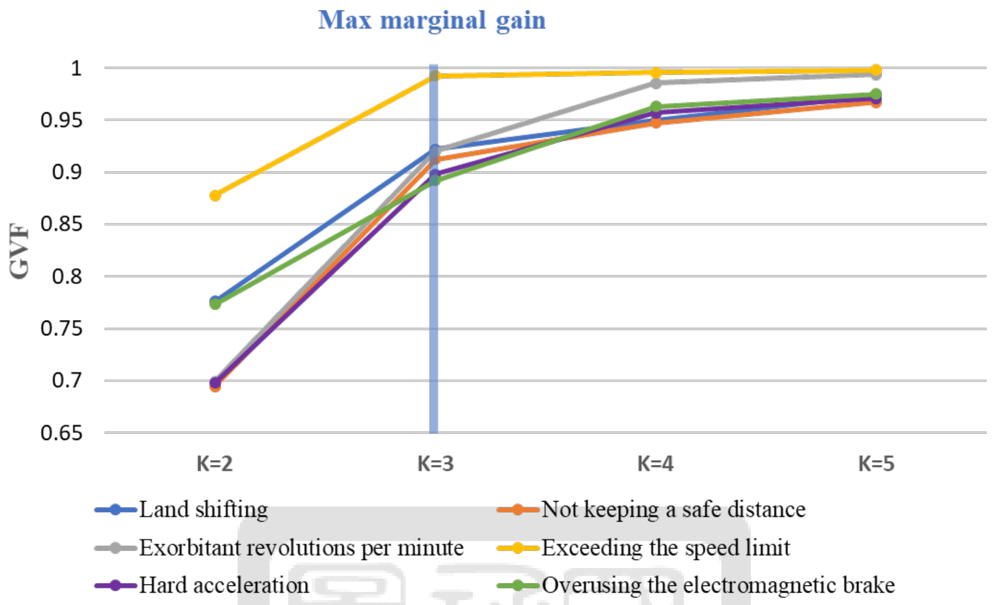

Figure 4.5 Elbow method for remaining number of aberrant driving behavior

. We form 3 classes (groups) within the given range through applying Jenks natural breaks optimization, which realized that the members within same class has similar frequency of aberrant driving behavior. The judgment boundary and GVF of each aberrant driving behavior are shown in Table 4.11. The GVF in each driving behavior is higher than 0.7 and close to 1 (perfect fit). The lower the class in each driving behavior, the higher the safety of the driver; The higher the class in each driving behavior, the higher the risk of the driver. We remove the outliers at the beginning of data processing to avoid unsatisfactory clustering results. However, the removed outliers indeed represent the highest risk (more than the previous three classes) among all drivers. Thus, the study defines outliers as class 4 in establishing single driving risk index. In summary, the class from 1 to 4 simultaneously represents the index value from 1 to 4 which is convenient for calculations in subsequent research.

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Table 4-11 The boundary of each class

Driving behavior	Class 1		Class 2		Class 3		GVF
	Lower	*Upper*	*Lower*	*Upper*	*Lower*	*Upper*	
Land shifting	0	848.88	1256.34	2068.67	2464.27	4108.28	0.92
Not keeping a safe distance	0	139.66	156.99	336.43	420.90	613.92	0.91
Exorbitant revolutions per minute	0	0.00	1.01	1.37	2.03	4.22	0.92
Exceeding the speed limit	0	0.00	1.03	1.43	2.00	2.39	0.99
Hard acceleration	0	2.33	3.69	10.77	12.64	20.61	0.90
Overusing the electromagnetic brake	0	1.40	2.03	4.68	6.01	8.33	0.89

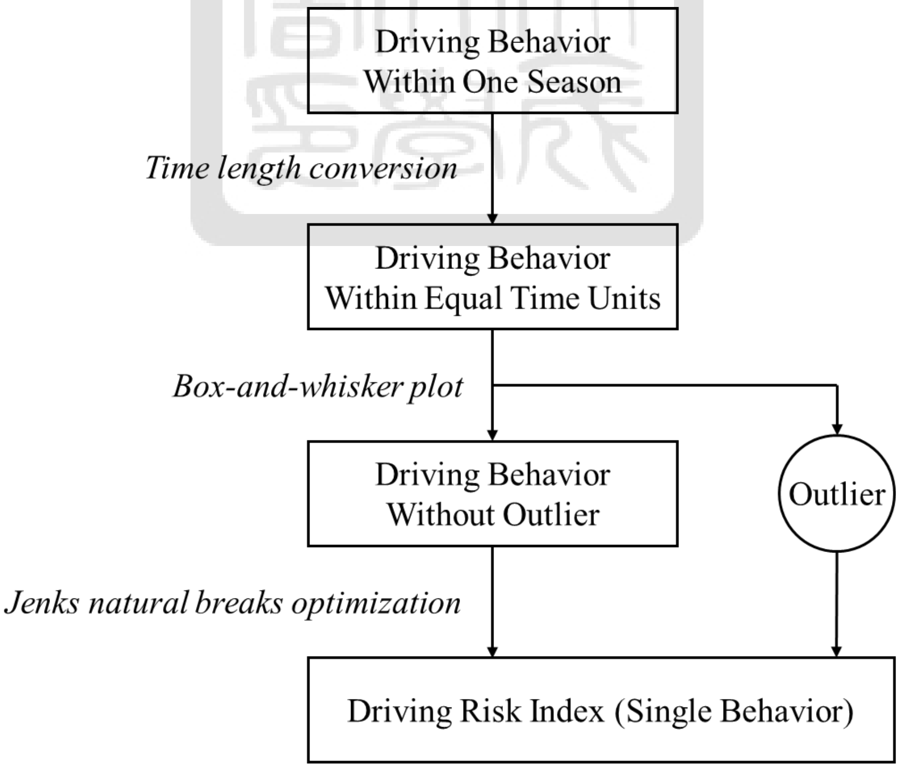

Figure 4.6 The framework of risk conversion

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The above data processing process are illustrated in Figure 4.6. Through the Box-and-whisker plot and Jenks natural breaks optimization, each single driving behavior in four classes was obtained. The mean in each class (cluster) are calculated in Table 4.12, which show that the mean indeed increases as the class increases. However, since each driving behavior must be set to the same standard without assigning weight, we define class 1 to 4 as value of risks index 1 to 4. The final grading result of driving risk index is consolidated in Table 4.13. Driving risk index in value 1 and value 2 represent that the driver's overall performance of driving safety is relatively well, and meanwhile risk index in value 3 and value 4 represent that the driver's overall performance of driving safety is relatively poor.

Table 4.12 Mean in each class

Driving behavior	**Class**			
	Class 1	***Class 2***	***Class 3***	***Class 4***
Land shifting	214.09	1612.94	3039.49	4648.62
Not keeping a safe distance	60.09	243.49	521.9	2124.38
Exorbitant revolutions per minute	0	1.16	2.59	21.59
Exceeding the speed limit	0	1.17	2.19	44.33
Hard acceleration	0.63	6.59	15.92	93.31
Overusing the electromagnetic brake	0.29	3.32	6.84	19.54

Table 4.13 Frequency of risk index in each driving behavior

Driving behavior	**Value of Risk Index**			
	Value 1	***Value 2***	***Value 3***	***Value 4***
Land shifting	39	12	6	5
Not keeping a safe distance	28	20	9	5
Exorbitant revolutions per minute	29	17	9	7
Exceeding the speed limit	40	8	4	10
Hard acceleration	30	16	6	10
Overusing the electromagnetic brake	37	15	4	6

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4.4 Constructing the Overall Driving Risk Level

The single driving risk index symbolizes the ranking and assessment of the single behavior of individual among the fleet. A driver may be exposed to different kinds of aberrant driving behaviors, so this section tends to discuss driving risk in an overall way. Section 4.3.1 describes the overall driving risk and Section 4.3.2 further classify overall driving risk.

4.4.1 Overall driving risk

Contrary to single driving risks, the overall driving risk are viewed from multiple perspectives. The overall scope set in this study covers six aberrant driving behaviors, and the previous section has described the method of data preprocessing. Equation (4-2) display that single driving risk index is transformed through Box-and whisker to identify outliers and Jenks natural breaks optimization to grade relatively risk. Equation (4-3) shows that summarizing the scores of all independent driving behavior index may be possible to get an overall aberrant driving risk index between 6 and 24. We further applied cumulative percentage graph in Figure 4.7 to understand the distribution of overall driving risk index. 50 % of the drivers may involve low frequency of aberrant driving behavior, so they result in a lower overall driving risk index (under index value 10). The distribution is a typical type in fleet since most drivers may take self-security as a consideration

$$B_i^j \xrightarrow[\text{Jenks natural breaks optimization}]{\text{Box-and whisker,}} r_i^j \tag{4-2}$$

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$$R_i = \sum_{j=1}^{n} r_i^j \tag{4-3}$$

where,

B_i^j is the number of driving behavior j for driver i (has converted by driving time),

r_i^j is the single driving risk index of driving behavior j for driver i, and

R_i is the overall driving risk index for driver i.

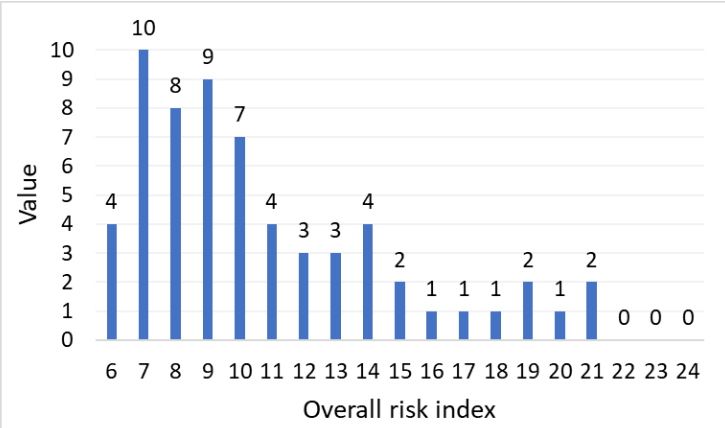

Figure 4.7 Distribution of overall driving risk index

4.4.2 Driving risk level

After aggregating single driving risk index into overall driving risk index, we hope to further assess the overall risk level of bus drivers through clustering. Different from the classification process used in Section 4.2.3 above, there is no problem with outlier since we have already discretized the outliers. And the number of groups (k) will be directly specified as 5. In terms of management, the 4 groups represent no intermediate value, which means that in the single driving risk index, we hope to identify the high risk and low risk directions for future analysis; While the 5 groups represent a median value, which is less like the 4 groups forcing a clear distinction

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between high and low risks. It is an appropriate number of groups. In previous studies, the target groups were often be odd number (Naito et al., 2009; Miyajima et al., 2011; Li, 2017), while the three groups are too monotonous to be used as a management basis.

In this section, we tend to group overall driving risk index by a regular way. The output range of overall driving risk index is between 6 (high risk in every driving behaviors) and 24 (high risk in every driving behaviors), which is fixed that based on the number of adopted driving behavior and can be known in advance. The method is to bin the predictable output range in to five interval (k), and then define the level according to the output of the overall driving risk index. The higher the level, the higher the overall driving risk. In this study, 19 index values should be divided into five groups. However, 19 index values cannot be equally divided into five groups. We should follow the rule of leniently filling up to confirm the composition of each level. That is to say only three performances of risk index will be classified as level five which have the highest driving risk. Table 4.14 shows the rules of binning and the final result of classifying drivers. There are most of drivers classified as level 1 (31, 50 %), 17 (27.4 %) drivers are in level 2, 8 (12.9 %) drivers are in level 3, 6 (9.7 %) drivers are in level 4 and no driver is in level 5.

Table 4.14 Result of binning

Level	**Threshold**		**Range**	**Count**	**Pct.**
	Lower	***Upper***			
1	6	9	4	31	50.0%
2	10	13	4	17	27.4%
3	14	17	4	8	12.9%
4	18	21	4	6	9.7%
5	22	24	3	0	0%

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4.5 Network Model for Predicting Driving Risk

After converting the driving risk index and constructing the driving risk level, the study applied artificial neural network model to evaluate the impact of different human factors on driving risk and try to e stablish a predictive model. Software - STATISTICA 13 was used to complete the operation of ANN model. Section 4.4.1 explain the model established for the single driving risk index; Section 4.4.2 is the model result for the overall risk level; Section 4.4.3 discuss the sensitivity analysis of the variables and models.

4.5.1 Pre-processing and clarification of Model

The study applied the Automated Network Search (ANS) in STATISTICA 13 to construct network. Before constructing the models, several coefficients need to be clarified and preset:

1. Segmentation of dataset

   The study set 70% samples (about 44 drivers) as the training set and 30% samples (about 18 drivers) as the testing set. Seed for sampling is the rule to determine which sample is set as training dataset or testing dataset. After testing a model, we should reset the seed for sampling in random to capture better solution in probable. The seed for sampling is set as 1000, 1500, 2000, 2500, 3000, 3500, 4000, 4500, 5000 and 5500 in this study.

2. Topology

   The number of hidden layers was fixed to one layer. ANS may automatically search for the best solution of model. However, since ANN is a non-linear model, it may encounter the problem of local cost minimum. The

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neural network algorithms first set the random initial weight, and then uses the method of stochastic gradient descent to find the best value. To solve the problem of local cost and global cost minimum, we set 300 random initial weight to find the best network in each seed for sampling, but it is still unable to determine if it is the global cost minimum. We take average from 10 best model based on 10 random seed for sampling, and would also show the best performance of ANN model. Hidden neurons would be randomly set in the range between half of number of input variables and twice as number of input variables.

3. Activation function

Since the activation function is not the main object of discussion, the study fixed the activation function and so as to simplify the complexity of the study. Hyperbolic tangent function (Tach.) was set for hidden neurons, which usually be recommended and perform well because of its symmetry. Softmax function was set for output neurons, which is dedicated to data grouping.

4. Error function

Sum-of-squares error and cross-entropy error are select as the error function which are used to evaluate the performance of network during training. The cross-entropy error is applied in classification problems and the sum-of-squares error is applied in regress problems.

5. Weight decay

To avoid the problem of overfitting, we set weight decay as 0.0001 for minimum and 0.001 for maximum in both hidden layer and output layer. Weight decay regularization modify the error function to be compromises between performance and weight size.

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6. Data normalization

Among all factors, continuous, discrete or categorical variables in nominal scale (marriage status and amblyopia) can be directly used as input values for the model. However, the categorical variables in ordinal scale (educational level, annual household income and alcohol drinking patterns) should first be mapped to the range -1 to 1 to avoid saturation effect. The normalization method is in equation (4-4).

$$x_{scaled} = 2 \times \frac{x - x_{Min}}{x_{Max} - x_{Min}} - 1 \tag{4-4}$$

7. Model performance

We can learn the predictive ability from the testing result. Section 3.3.9 has already introduced the method to assess performance. The accuracy is applied in classification problems and the MAPE is applied in regress problems.

The study applied the human factor to construct predictive model of aberrant driving behavior and driving risk. The human factor as the input variable contains 19 variables in 4 dimensions; Eight targets are sequentially inserted as the output variable according to the purpose of the study, including six single driving risk indexes, the overall driving risk index and the overall driving risk level. The above is consolidated in Table 4.15. Finally, sensitivity analysis is used to find out the importance (sensitivity) of each input variable.

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Table 4.15 Constructing process of ANN models

Input layer			
Input	**Human factor**	**Input**	**Human factor**
X1	Education level	X11	Driving hours
X2	Marriage status	X12	Commute time
X3	Annual household income	X13	Sleep hours
X4	Age	X14	Driving fatigue
X5	BMI	X15	Extraversion
X6	Disease index	X16	Agreeableness
X7	Symptom index	X17	Conscientiousness
X8	Amblyopia	X18	Neuroticism
X9	Alcohol drinking patterns	X19	Openness to Experience
X10	Driving seniority		

Output layer		
Predictive model	**Analysis**	**Output value**
Model 1_ Land shifting	Classification	Index 1, Index 2, Index 3, Index 4
Model 2_ Not keeping a safe distance	Classification	
Model 3_ Exorbitant revolutions per minute	Classification	
Model 4_ Exceeding the speed limit	Classification	
Model 5_ Hard acceleration	Classification	
Model 6_ Overusing the electromagnetic brake	Classification	
Model 7_ Overall risk index	Regression	Risk index: 6 to 24
Model 8_ Overall driving risk level	Classification	Level 1, Level 2, Level 3, Level 4, Level 5

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4.5.2 Single behavior

The study tends to construct artificial neural network models for each aberrant driving behavior. There are six aberrant driving behavior in the study so that six models would be constructed. Since we face the problem of shortage of samples, accuracy is calculated by the average value of 10 random networks to complete multiple verifications. The study calculated average accuracy and highest accuracy from 10 random predictions. Standard deviation (SD) of accuracy represent stability of predictive model. The complete results for 10 random networks are recorded as Table B.1 and Table B.2 in Appendix B. The accuracy of predicting single driving risk index through human factor is summarized in Table 4.16.

Land shifting and overusing the electromagnetic brake performed well forecast result in both average and highest accuracy. Each driving behavior owned at least 60 percent accuracy in average performance and 70 percent accuracy in highest performance. It shows that neural networks can establish the correlation between the human factors and most aberrant driving behaviors It indicated that hypotheses 1 (H 1) is accepted, which the human factors have significant impact on “aberrant driving behaviors.”

Table 4.16 Predictive accuracy in single driving risk index

Model	**Driving behavior**	**Accuracy***		**SD**
		Average	***Highest***	
Model 1	Land shifting	79.44 %	88.89 %	6.95
Model 2	Not keeping a safe distance	64.44 %	72.22 %	3.88
Model 3	Exorbitant revolutions per minute	66.11 %	77.78 %	8.47
Model 4	Exceeding the speed limit	73.33 %	83.33 %	6.31
Model 5	Hard acceleration	70.00 %	77.78 %	4.68
Model 6	Overusing the electromagnetic brake	79.44 %	88.89 %	6.44
*Accuracy are calculated by the average value of 10 random networks				

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4.5.3 Overall driving risk

The study further construct model for predicting overall driving risk index (Model 7) and overall driving risk level (model 8) classified from overall index. In Model 7, the study defined the overall driving risk index as discrete value and sets it as the output value of the model. Moreover, the model is not a classification problem which cannot be expressed as accuracy. The study calculated the correlation coefficient (R) between actual and predicted values and the mean absolute percentage error (MAPE) as the evaluation standard of model performance.

Table 4.17 shows the summarized model performance and Table B.3 contains ten detailed results in Appendix B. The average and highest correlation coefficients are more than 0.7, which shows that there is great collinearity between the target value (actual value) and output value (predictive value). In addition, the average and highest MAPE are in the range of 10% ~20%, and means the models perform good forecasting (Lewis, 1982). Figure 4.8 illustrates the correlation between the actual target and the predictive output in seed 1000 for example. The fitness line (sequential line) represents the accurate prediction. The value above the fitness line is called overestimated, meanwhile, the value below the fitness line is called underestimated.

Table 4.17 Predictive performance in overall driving risk index

Model 7	**Testing performance***					
	R			**MAPE**		
	Average	***Highest***	***SD***	***Average***	***Highest***	***SD***
Overall risk index	0.830	0.882	0.04	18.36 %	13.2 %	2.86
*Performance are calculated by the average value of 10 random networks						

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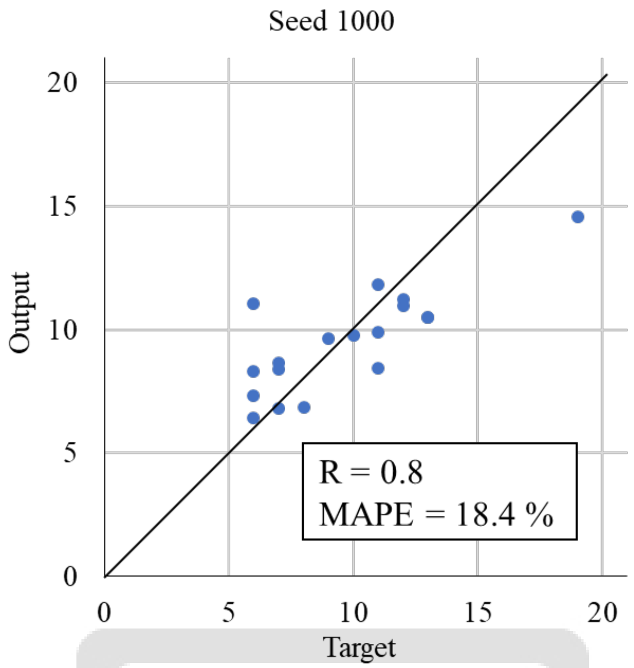

Figure 4.8 Scatter diagram of predicted results - Seed 1000

In Model 8, the following steps are similar to Section 4.4.2. The study tends to predict the final result of overall driving risk level. We calculated average and highest accuracy and further established confusion matrix of each target level. Table 4.18 shows the summarized model performance and Table B.4 contains ten detailed results in Appendix B. Since the number of test sample is different in each level, it is unnecessary to list highest accuracy and standard deviation of each level. The model has 79.44 percent accuracy in average and may up to 88.89 percent accuracy, and it performs well in predicting level 1 and level 4. Thus, Model 7 and Model 8 show that hypotheses 2 (H 2) is accepted, which the human factors have significant impact on "driving risk level."

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Table 4.18 Predictive accuracy in overall driving risk level

Model 8	**Accuracy***		
	Average	***Highest***	***SD***
Overall driving risk level	79.44 %	88.89%	6.4
Level 1	88.64 %	-	-
Level 2	69.09 %	-	-
Level 3	55.56 %	-	-
Level 4	84.21 %	-	-

*Accuracy are calculated by the average value of 10 random networks

4.5.4 Sensitivity analysis

Sensitivity analysis can calculate the relative importance of the variables through changing the value of the input variable or removing the input variable. The study applied sensitivity analysis to understand the effect of human factors on aberrant driving behavior. Sensitivity analysis in STATISTICA 13 is defined as that the value of each input variable is in turn replaced with the mean of training sample, and then summitted to the neural network repeatedly. The resulting network error is recorded and would be compared to original error.

The study took sensitivity analysis on Model 7 since the error in regression problem change more obvious than classification problem. Table 4.19 shows the summary of sensitivity analysis and detailed result for each selected model is in Table B.5 in Appendix B. The ratio is the network error with given input divided by the network error with original input. If the ratio is 1 or less, the input variable has no effect on model construction. In addition, sensitivity analysis can only rate the importance of input variables, so the study further applied Spearman correlation to learn the direction of correlation based on rank (nonlinear) correlation.

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Through Table 4.19, we can learn the degree of relationship between each human factor and overall driving risk. The study arranged the sensitivity ratio from high to low. Since the study used more diverse variables for analysis, the sensitivity ratio of each variable is relatively low. Nevertheless, we knew that most human factors have influence on the predictive ability of the model. Although the result of Spearman correlation may reflect part of nonlinear correlations based on rank of value, it still exists nonlinear features that cannot be measured or the direction of correlation is unknown.

Among all the human factors, seven human factors not only owned higher sensitivity, but also perform significantly related to the overall driving risk index in spearman correlation. In socioeconomic dimension, only annual household income (-.288*) has negative correlation to driving risk. In phycological dimension, disease index (.330**) and symptom index (0.263*) both has positive correlation to driving risk. In working dimension, sleep hours (-.432**) has negative correlation to driving risk and driving fatigue (.367**) has positive correlation to driving risk. In personality, agreeableness (-.306*) has negative correlation to driving risk and driving fatigue neuroticism (.320*) has positive correlation to driving risk. In other words, the driver who has higher driving fatigue, symptom index, neuroticism and disease index tend to perform higher driving risk; The driver who has higher sleep hours, agreeableness and annual household income tend to perform less driving risk. However, it is not definitely to say that the remaining variables that are not significantly related in Spearman correlation have no effect on the driving risk. The remaining variables still perform a certain degree of importance in constructing a neural network.

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Table 4.19 Comparison of sensitivity

Dimension	Human factor	Average ratio	Spearman correlation
Working	Driving fatigue	1.327	.367**
Physiological	Symptom index	1.148	.263*
Personality	Neuroticism	1.147	.320*
Working	Sleep hours	1.107	-.432**
Personality	Agreeableness	1.086	-.306*
Physiological	Disease index	1.065	.330**
Socioeconomic	Annual household income	1.061	-.288*
Physiological	Age	1.057	-0.171
Personality	Conscientiousness	1.056	0.195
Working	Driving hours	1.054	-0.171
Working	Driving seniority	1.051	-0.117
Physiological	Amblyopia	1.050	-
Physiological	Alcohol drinking patterns	1.050	0.147
Socioeconomic	Education level	1.041	0.072
Socioeconomic	Marriage status	1.029	-
Working	Commute time	1.029	-0.075
Personality	Extraversion	1.024	0.151
Physiological	BMI	1.011	-0.061
Personality	Openness to Experience	0.997	-0.044

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is signific ant at the 0.05 level (2-tailed).

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4.6 Summary

In the chapter, the historical records of six aberrant driving behavior (land shifting, not keeping a safe distance, exorbitant revolutions per minute, exceeding the speed limit, hard acceleration and overusing the electromagnetic brake) are converted into single driving risk index by multi-stage defining data and grouping. The study first applied Box-and-whisker plot to identify outliers, and then clustered single behavior by Jenks natural breaks optimization. It is then aggregated and graded into overall driving risk index and overall driving risk level which hoping to alert drivers in a more comprehensive approach. There were four indexes in single driving risk and four levels in overall driving risk level (other fleet may have five levels).

In addition, 19 human factors were used to construct predictive model. Through collecting human factors from personnel database, physical examination report and questionnaire survey, we have multi-dimensioned data to construct predictive model. The accuracy in predicting single driving behavior is 79.4 percent in land shifting, 64.4 percent in lot keeping a safe distance, 66.1 percent in exorbitant revolutions per minute, 73.3 percent in exceeding the speed limit, 70 percent in hard acceleration and 79.4 percent in overusing the electromagnetic brake. For overall driving risk, the neural model performed 18.4 percent (good forecasting) MAPE in overall index and 79.4 percent accuracy in overall level. The above results indicate that neural networks have a certain ability to construct predictive models in this study.

The study applied sensitivity analysis to understand how important each human factor is to the model. However, since the operation of the neural network has been regarded as a black box, it is difficult to confirm the direction of influence for each factor. The study further applied Spearman correlation to obtain the direction of

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influence. Seven human factors perform higher sensitivity and also be significant in Spearman correlation. Driving fatigue, symptom index, neuroticism and disease index are “positive” related to overall driving risk. Sleep hours, agreeableness and annual household income are “negative” related to overall driving risk. Although the remaining factors are not significantly related to overall driving risk in Spearman correlation, they also contribute to the construction of neural networks in a nonlinear form.

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CHAPTER 5 CONCLUSIONS AND SUGGESTIONS

The purpose of this study is to establish a driving risk assessment mechanism based on aberrant driving behavior through risk index conversion, and further explore the correlation among human factors, each driving behavior and risk classification. We collected driver's human factor by questionnaire survey and driving behaviors recorded by digital tachograph. A multi-stage method was proposed to convert driving behavior into risk index, and then establish risk predictive models through applying artificial neural network model. This section discussed the results of the study and put forward specific conclusions and recommendations to provide inter-city bus operator for fleet safety management and risk assessment.

5.1 Conclusions

Based on the results and process of data analysis in chapter 4, the study explains the results of the various stages as follows:

1. Driving behavior data

Through the advancement of technology, we have ability to manage the fleet in a scientific way. The study obtained the data of aberrant driving behavior by digital tachograph and is the result of historical statistics. We followed Li (2017) to remove driving behavior which has less effect on driving safety and merge similar driving behaviors. Since the operator does not want to have similar driving behaviors as an evaluation indicator when managing the fleet, the study defines it as a necessary step to carry out risk management. In addition, it is much fairer that we calculate the accumulated driving hours and then convert each single driving behavior data into equal exposure.

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2. Grading rule

The behavior data in this study has a significant feature, which is the frequency of each driving behavior is quite different among the fleet. The two-step grouping method which purposed in the study not only identify the highest risk (outliers) of drivers effectively, but also satisfy the highest similarity within the group after data grouping. It does not harm anyone's rights, and differ from the general binning that may result in a harder grouping result.

Although the sample scale of this study is only 62 professional drivers, the proposed method can be applied to a larger fleet in the future. Each driver may often be involved in specific aberrant driving behaviors, rather than evenly distributed among all aberrant driving behaviors. The method of grouping is not specifically designed for the fleet in this study, but for how we deal with the inevitable feature of grading behavior data.

3. Predictive model

Another purpose of this study is to predict the aberrant driving behavior by collecting human factors of bus driver. Since the frequency of driving behavior has already been broken into risk index from value 1 to value 4, we apply the ability of classification in neural network to construct the model instead of predicting actual frequency of driving behaviors. The neural network model shows good predictive ability by input human factors from drivers, which can predict the single risk index in average 70 percent accuracy or overall risk index in almost 80 percent accuracy. However, fleet safety management not only affects the company's reputation, but also brings benefits to traffic safety. Therefore, we still have to pursue higher predictive accuracy as much as possible so that it can be widely applied to fleets in different scales.

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4. Fleet management

The classification results of single driving behaviors and overall driving risk can be used to manage a fleet or a group of drivers. For drivers on duty, which have the historical driving record, individual performance of each driver can be translated directly from the process proposed in the study. The bus operator is able to remind drivers for relatively bad performance in specific driving behavior, and could combine reward or punishment mechanism with the overall driving risk level. For example, most of the grading results in overall driving risk levels are concentrated at level 1 (50%) and level 2 (27.4%), which is suitable for management in the form of increasing rewards or increasing supervisions as risk levels increase; For the appointment of new drivers, they do not have the historical driving record. The use of predictive models can obtain possible driving performance, which can be taken into account for appointments.

Besides the above management recommendations for driving risk level, the study further propose the management of human factors to the driver through sensitivity analysis and Spearman correlation analysis in order to reduce the frequency of aberrant driving behavior (driving risk). The study divided this part into positive influence, negative influence and non-significant influence for discussion:

(1) Human factors with positive influence on driving risk:

I. Driving fatigue

Driving fatigue (ALT index) has significant positive correlation on driving risk, and the sensitivity ratio is the highest among all human factors. The more fatigue the driver has, the higher the chance to have aberrant driving behavior. The causes of fatigue are quite diverse, including long hours of driving, lack of

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sleep, etc. In order to prevent driving fatigue and reduce accidents, it is effective that passenger drivers have adequate sleep and a short break in the shift interval (Li, 2010). When a driver’s mental condition is poor or high ALT index is measured, he should be prohibited from scheduling and driving vehicles.

II. Symptom index & Disease index

Symptom index and disease index are both positively related to the driving risk. Physical examination report can reflect the real physical condition, so that we could determine rationality of the driver's shift. The bus operator should encourage drivers to treat disease or symptom to reduce the risk of potential accidents.

III. Neuroticism

Neuroticism in personality traits has significant positive correlation with driving risk. Past studies have also pointed out that hostility and anxiety traits directly predicted the aberrant driving behaviors (Yagil, 2001; Mallia et al, 2015). The performance of Neuroticism can be applied to the evaluation criteria for appointments.

(2) Human factors with negative influence on driving risk:

I. Sleep hours

There is a significant negative correlation between sleep hours and driving risk, meaning that lack of sleep leads to an increase in aberrant driving behavior. In addition, sleep hours are also a negative factor of driving fatigue (Li, 2010). Insufficient sleep may also cause drowsy driving, which affect driver’s control ability to the vehicle (Stutts et al., 2003). Arranging the appropriate driving hours and requiring the driver to manage his or her sleep hours can improve driving

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safety and reduce driving fatigue, or further improve sleep quality.

II. Agreeableness

Agreeableness in personality traits has significant negative correlation with driving risk, which shows that drivers with high Agreeableness have better driving performance. The operator could improve driving performance through staff education (Tsao, 2011). The performance of Agreeableness can be applied to the evaluation criteria for appointments.

III. Annual household income

Annual household income is negatively correlated with driving risk, which means the drivers with higher annual household incomes may pay more attention to their driving behavior and own safety. Although substantial control over personal income is not possible, it also indicates that income may affect the safety performance of driving. The bus operator can motivate drivers to demand better driving performance through bonuses or rewards.

(3) Human factors with non-significant influence on driving risk:

Education level, marriage status, age, BMI, amblyopia, alcohol drinking patterns, driving seniority, driving hours, commute time, extraversion, conscientiousness and openness to experience did not have significant correlation to overall driving risk in Spearman correlation, so we cannot propose management advice by direction of correlation. However, we can learn that each factor still has some influence in constructing the model based on sensitivity analysis. So, when we ask for a model with high predictive accuracy, we can first insert the variables with high sensitivity.

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5.2 Suggestions

This section provides suggestions on the safety risk management of drivers based on the content and results of each stage in the research. The study also suggests for the future studies on the research process and results as follows:

1. The study proposes a new process to deal with discrete data and examine the distribution of the number of driving behaviors through data science. Although other clustering methods are available (e.g. standard deviation, equal intervals), the methods of the study represent the most commonly and widely used. Each clustering method may present the data in different ways and pushed out different aspects of centralization trend. Actually, the clustering method and target k used may result in different interpretations of the dataset. As a manager, it is the responsibility to choose the method that best suits the research needs and presents the data in a meaningful and transparent manner whenever possible.
2. The occurrence of traffic accidents is generally attributed to the interaction between human, vehicle and environment. However, this study is limited by the complexity of road environment composition and vehicle conditions, so we only discuss the impact of human factors. Future research may explore the possibility of incorporating road environment composition and vehicle conditions into the study, and further establish the impact of road environment and vehicle condition on aberrant driving behaviors.
3. All driving behaviors are considered equally important in this study. Although aberrant driving behavior would increase the potential chance of traffic accident, each driving behavior may cause different degree of influence on traffic flow. Some behavior (land shifting, not keeping a safe distance, etc.) directly affect the

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traffic flow, and some behavior (exorbitant revolutions per minute) would decrease driving stability. It is suggested that future studies may consider the "weight" of behavioral severity to achieve more comprehensive risk assessment.

4. The part of human factor variables in this study depend on the answers provided by professional driver, which may be slightly different from the actual situation. Safety management is considered as additional control for drivers, so that drivers may be reluctant to participate the survey or tend to choose more conservative options when filling in the questionnaire. In addition, some questions (personality, annual household income, etc.) only rely on the subjective judgment to answer, which have probability to be fail to reflect the driving condition. It is recommended to combine scientific instruments to receive accurate information or observe subject in long-term to collect more effective information; Another possibility is that this study is limited by the size of the sample, which makes it difficult for some problems to distinguish the state of the driver. Therefore, future should consider expanding the sample size of the test driver to improve data differentiation and analysis accuracy.

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Appendix A Sample Distribution of Quantitative Human Factors

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This section illustrates the human factors in Section 4.1.1. Since some human factor is in type of discrete, the sample value may be exactly equal to the critical value. The study considers the critical value as a larger interval, for example, driver in 30 years old would be divided into group 30 to 35 (Figure A.1), and so on.

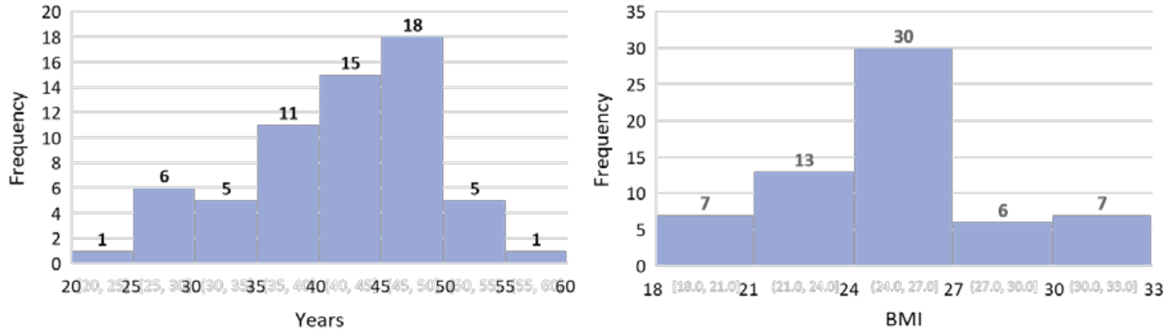

Figure A.1 Distribution of age (left) and BMI (right)

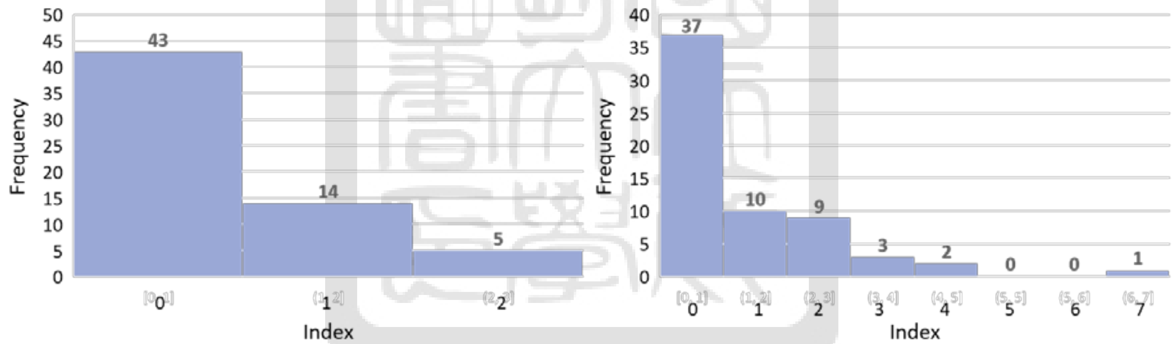

Figure A.2 Distribution of disease index (left) and symptom index (right)

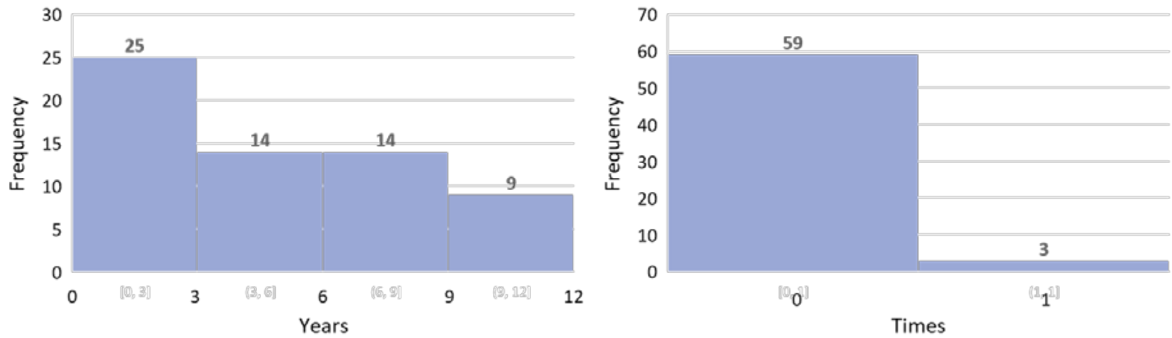

Figure A.3 Distribution of driving seniority (left) and history of crashes (right)

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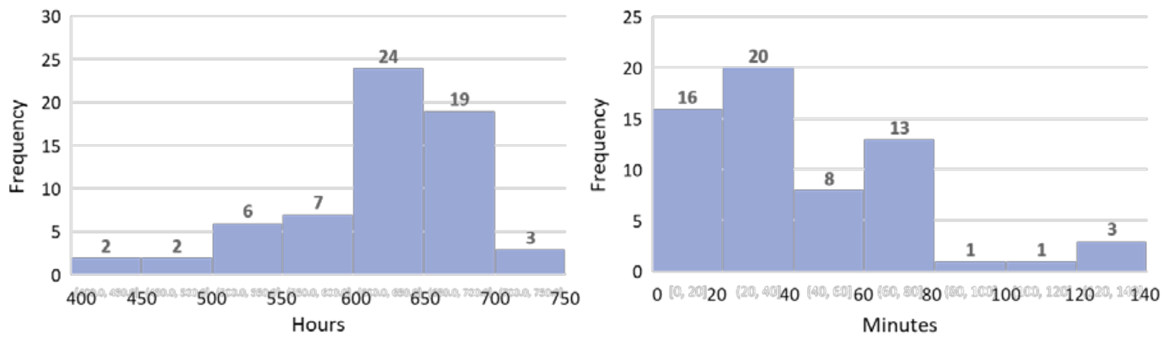

Figure A.4 Distribution of driving hours (left) and commute time (right)

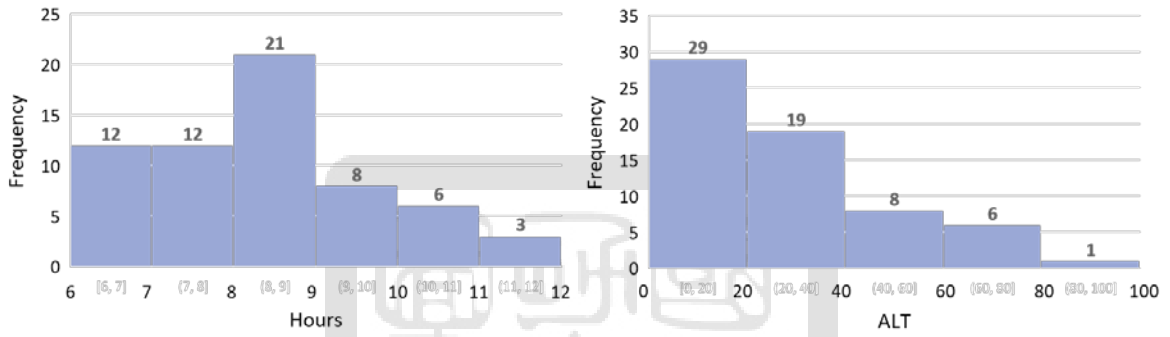

Figure A.5 Distribution of sleep hours (left) and driving fatigue (right)

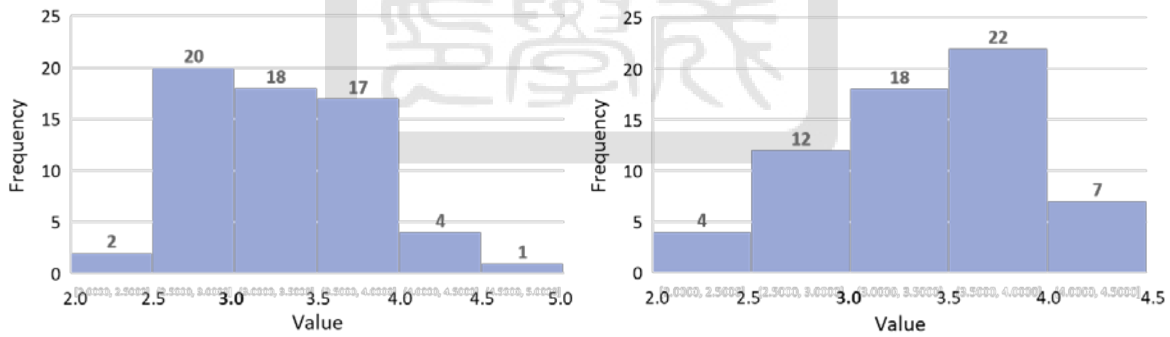

Figure A.6 Distribution of Extraversion (left) and Agreeableness (right)

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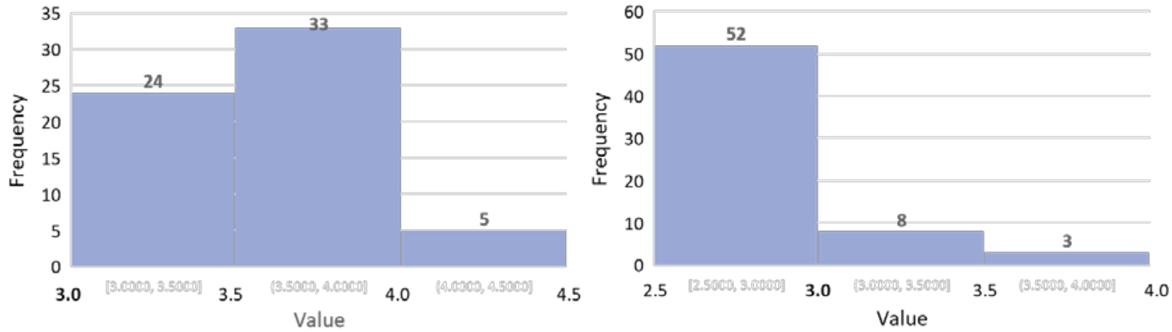

Figure A.7 Distribution of Conscientiousness (left) and Neuroticism (right)

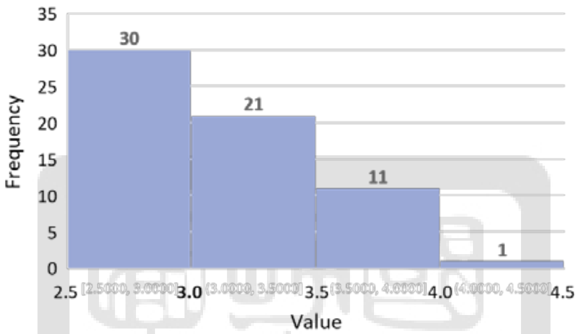

Figure A.8 Distribution of Openness to Experience

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Appendix B Result of Random ANN Models

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B.1 Predictive model performance in single driving risk index (1)

Seed for samples	Land shifting		Not keeping a safe distance		Exorbitant revolutions per minute	
	Network name	**Testing performance**	**Network name**	**Testing performance**	**Network name**	**Testing performance**
Seed 1000	21 - 16 - 4	83.33 %	21 - 17 - 4	66.67 %	21 - 18 - 4	61.11 %
Seed 1500	21 - 21 - 4	88.89 %	21 - 34 - 4	61.11 %	21 - 21 - 4	77.78 %
Seed 2000	21 - 27 - 4	77.78 %	21 - 34 - 4	66.67 %	21 - 16 - 4	55.56 %
Seed 2500	21 - 11 - 4	72.22 %	21 - 26 - 4	66.67 %	21 - 11 - 4	55.56 %
Seed 3000	21 - 13 - 4	88.89 %	21 - 34 - 4	61.11 %	21 - 20 - 4	72.22 %
Seed 3500	21 - 19 - 4	66.67 %	21 - 14 - 4	66.67 %	21 - 35 - 4	61.11 %
Seed 4000	21 - 25 - 4	77.78 %	21 - 16 - 4	66.67 %	21 - 11 - 4	72.22 %
Seed 4500	21 - 26 - 4	77.78 %	21 - 18 - 4	61.11 %	21 - 16 - 4	77.78 %
Seed 5000	21 - 10 - 4	83.33 %	21 - 11 - 4	61.11 %	21 - 24 - 4	66.67 %
Seed 5500	21 - 30 - 4	77.78 %	21 - 11 - 4	61.11 %	21 - 28 - 4	61.11 %
Average	-	**79.44 %**	-	**63.89 %**	-	**66.11 %**
SD	-	6.95	-	2.93	-	8.47

The activation functions in artificial neural networks were set as hyperbolic tangent function in hidden layer and softmax function in output layer. The hidden neuron was set in the range between half of number of input variables (10) and twice as number of input variables (38).

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B.2 Predictive model performance in single driving risk index (2)

Seed for samples	Exceeding the speed limit		Hard acceleration		Overusing the electromagnetic brake	
	Network name	**Testing performance**	**Network name**	**Testing performance**	**Network name**	**Testing performance**
Seed 1000	21 - 22 - 4	72.22 %	21 - 13 - 4	77.78 %	21 - 37 - 4	88.89 %
Seed 1500	21 - 30 - 4	66.67 %	21 - 29 - 4	72.22 %	21 - 10 - 4	72.22 %
Seed 2000	21 - 13 - 4	77.78 %	21 - 10 - 4	61.11 %	21 - 11 - 4	72.22 %
Seed 2500	21 - 30 - 4	72.22 %	21 - 11 - 4	72.22 %	21 - 14 - 4	83.33 %
Seed 3000	21 - 16 - 4	66.67 %	21 - 24 - 4	66.67 %	21 - 22 - 4	72.22 %
Seed 3500	21 - 14 - 4	72.22 %	21 - 15 - 4	66.67 %	21 - 13 - 4	88.89 %
Seed 4000	21 - 14 - 4	66.67 %	21 - 12 - 4	72.22 %	21 - 11 - 4	77.78 %
Seed 4500	21 - 28 - 4	72.22 %	21 - 38 - 4	66.67 %	21 - 11 - 4	77.78 %
Seed 5000	21 - 13 - 4	83.33 %	21 - 10 - 4	72.22 %	21 - 13 - 4	77.78 %
Seed 5500	21 - 10 - 4	83.33 %	21 - 16 - 4	72.22 %	21 - 12 - 4	83.33 %
Average	-	**73.33 %**	-	**70.00 %**	-	**79.44 %**
SD	-	6.31	-	4.68	-	6.44

The activation functions in artificial neural networks were set as hyperbolic tangent function in hidden layer and softmax function in output layer. The hidden neuron was set in the range between half of number of input variables (10) and twice as number of input variables (38).

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B.3 Predictive model performance in overall driving risk index

Seed for samples	Network name	Training performance	Testing performance	MAPE	Error function	Hidden activation	Output activation
Seed 1000	21 - 35 - 1	0.699	0.800	18.9%	Sum of squired	Tach.	Tach.
Seed 1500	21 - 14 - 1	0.791	0.735	18.8%	Sum of squired	Tach.	Tach.
Seed 2000	21 - 24 - 1	0.961	0.824	17.8%	Sum of squired	Tach.	Tach.
Seed 2500	21 - 17 - 1	0.969	0.817	16.7%	Sum of squired	Tach.	Tach.
Seed 3000	21 - 14 - 1	0.978	0.843	13.2%	Sum of squired	Tach.	Tach.
Seed 3500	21 - 18 - 1	0.736	0.869	18.2%	Sum of squired	Tach.	Tach.
Seed 4000	21 - 33 - 1	0.754	0.805	22.9%	Sum of squired	Tach.	Tach.
Seed 4500	21 - 22 - 1	0.996	0.862	21.5%	Sum of squired	Tach.	Tach.
Seed 5000	21 - 36 - 1	0.937	0.870	20.3%	Sum of squired	Tach.	Tach.
Seed 5500	21 - 35 - 1	0.995	0.871	15.3%	Sum of squired	Tach.	Tach.
Average	-	**0.88**	**0.83**	**18.36%**	-	-	-
SD	-	0.121	0.043		-	-	-

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B.4 Predictive model performance in overall driving risk level

Seed for samples	Network name	Training performance	Testing performance	Error function	Hidden activation	Output activation	Level 1	Level 2	Level 3	Level 4
Seed 1000	21 - 12 - 4	65.90%	83.33%	Cross entropy	Tach.	Softmax	89%	75%	-	100%
Seed 1500	21 - 10 - 4	100%	88.89%	Cross entropy	Tach.	Softmax	77%	100%	100%	100%
Seed 2000	21 - 13 - 4	100%	66.67%	Cross entropy	Tach.	Softmax	86%	75%	40%	50%
Seed 2500	21 - 13 - 4	100%	83.33%	Cross entropy	Tach.	Softmax	100%	60%	67%	100%
Seed 3000	21 - 11 - 4	100%	72.22%	Cross entropy	Tach.	Softmax	100%	33%	50%	100%
Seed 3500	21 - 20 - 4	100%	77.78%	Cross entropy	Tach.	Softmax	88%	67%	50%	100%
Seed 4000	21 - 15 - 4	70.45%	77.78%	Cross entropy	Tach.	Softmax	82%	100%	0%	67%
Seed 4500	21 - 21 - 4	100%	77.78%	Cross entropy	Tach.	Softmax	100%	71%	50%	67%
Seed 5000	21 - 13 - 4	100%	83.33%	Cross entropy	Tach.	Softmax	88%	60%	100%	100%
Seed 5500	21 - 12 - 4	84.09%	83.33%	Cross entropy	Tach.	Softmax	89%	75%	-	100%
Average	-	**92.04%**	**79.44%**	-	-	-	**88.64%**	**69.09%**	**55.56%**	**84.21%**
SD	-	13.6	6.4	-	-	-	-	-	-	-

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B.5 Result of sensitivity analysis

Dimension	**Human factors**	**Seed for samples (ratio)**										**Average ratio**	**Rank**
		1000	***1500***	***2000***	***2500***	***3000***	***3500***	***4000***	***4500***	***5000***	***5500***		
Socioeconomic	Education level	1.00	1.01	1.07	1.00	1.04	1.02	1.03	1.14	1.10	1.00	1.041	14
	Marriage status	1.02	1.09	1.35	0.94	0.99	0.99	0.99	1.00	0.94	0.98	1.029	15
	Annual household income	1.03	1.11	1.08	1.04	1.01	1.03	1.04	1.07	1.16	1.04	1.061	7
Physiological	Age	1.00	1.06	1.23	1.03	1.03	1.03	1.02	1.02	1.13	1.02	1.057	8
	BMI	1.00	1.01	1.00	1.00	1.02	1.00	1.00	1.04	1.04	1.00	1.011	18
	Disease	1.01	1.25	1.06	1.02	1.06	1.02	1.04	1.08	1.06	1.05	1.065	6
	Symptom index	1.06	1.27	1.34	1.12	1.18	1.07	1.02	1.13	1.25	1.04	1.148	2
	Amblyopia	0.94	1.09	1.29	1.22	1.04	1.05	0.94	1.00	0.94	0.99	1.050	12
	Alcohol drinking patterns	0.98	1.07	1.04	1.02	1.05	1.05	0.99	1.13	1.14	1.03	1.050	13
Working	Driving seniority	1.05	1.04	1.11	0.97	1.09	0.99	1.00	1.12	1.12	1.02	1.051	11
	Driving hours	1.03	1.06	1.03	1.04	1.05	1.02	1.03	1.07	1.17	1.04	1.054	10
	Commute time	1.00	1.06	1.03	1.00	1.02	1.00	1.00	1.11	1.07	1.00	1.029	16
	Sleep hours	1.04	1.13	1.14	1.06	1.11	1.08	1.08	1.16	1.17	1.10	1.107	4
	Driving fatigue	1.11	1.45	1.44	1.27	1.43	1.25	1.15	1.60	1.35	1.22	1.327	1
Personality	Extraversion	1.00	1.09	0.98	1.00	0.98	1.00	1.00	1.12	1.07	1.00	1.024	17
	Agreeableness	1.02	1.04	1.10	1.03	1.09	1.08	1.07	1.12	1.21	1.10	1.086	5
	Conscientiousness	1.04	1.02	1.14	1.05	1.03	1.08	1.07	1.07	1.01	1.05	1.056	9
	Neuroticism	1.06	1.13	1.31	1.13	1.17	1.15	1.09	1.13	1.20	1.10	1.147	3
	Openness to Experience	1.00	0.99	1.00	1.00	0.95	1.00	0.99	0.98	1.06	1.00	0.997	19

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Appendix C Human Factor Questionnaire in Chinese

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國立成功大學

國道客運公司駕駛員人因特性調查問卷

親愛的駕駛長，您好:

感謝運將在百忙之中抽空填寫本問卷，本研究為探討『**國道客運公司駕駛員之人因特姓、車輛駕駛行為與駕駛績效之研究**』，主要目的為瞭解客運公司運匠們生活狀況與人格特質以及駕駛績效的關聯性。此研究問卷是採記名方式，但收集的資料僅供學術整體性分析之用，決不會洩漏個人資料給公司或者其他用途。由衷感謝運將們的協助和幫忙。

敬祝

身體健康 行車平安!

國立成功大學交通管理科學系研究所

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生活狀況問卷

此處為調查您的生活狀況，請依照現在與過去的實際情況填寫。

姓名:________________　　　　　　　　員工編號:_______________

1.請問您的最高學歷為?

□中學以下　□高中(職)　□專科　□大學　□研究所以上

2.請問您 101 年的婚姻狀態為?

□未婚　□已婚(有______個孩子)

3A.請問您目前的家庭年所得約為?

□35 萬元以下　□35 萬(含)-50 萬元　□50 萬(含)-70 萬元

□70 萬(含)-100 萬元　□100 萬元以上

3B.承上題，請回想 101 年度狀況是否相同?

□約相同　□約高_________萬元　□約低_________萬元

4A.請問您平均每天睡眠時數約為_____小時?

4B.承上題，請回想 101 年度狀況是否相同?

□約相同　□約高_________小時　□約低_________小時

5A.請問您平均每天工作上下班通勤時間總共約為______分鐘?

5B.承上題，請回想 101 年度狀況是否相同?

□約相同　□約高_________分鐘　□約低_________分鐘

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人格特性問卷

此問卷沒有對錯，請問最直覺的想法回答以下問題。

問卷題目	同意程度				
	非常同意	同意	無意見	不同意	非常不同意
1. 我是具領導力的人	□	□	□	□	□
2. 我喜歡待在熱鬧的地方	□	□	□	□	□
3. 別人容易接受我的意見	□	□	□	□	□
4. 我是具主動性的人	□	□	□	□	□
5. 我是精力充沛的人	□	□	□	□	□
6. 我很喜歡與人交談	□	□	□	□	□
7. 我認識的人大部分都喜歡我	□	□	□	□	□
8. 我與他人合作愉快	□	□	□	□	□
9. 我是個總會盡所能幫助他人的人	□	□	□	□	□
10. 我不是個尊重他人的人	□	□	□	□	□
11. 我與家人或同事相處融洽	□	□	□	□	□
12. 我會考慮他人的立場	□	□	□	□	□
13. 我是能接受不同觀念的人	□	□	□	□	□
14. 我是體貼的人	□	□	□	□	□
15. 我是遵守常規的人	□	□	□	□	□
16. 我是做事負責盡心的人	□	□	□	□	□
17. 我是不斷追求成長的人	□	□	□	□	□
18. 我經常如期完成事情	□	□	□	□	□
19. 我對於所做每件事都努力成為最優秀的	□	□	□	□	□

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問卷題目	同意程度				
	非常同意	同意	無意見	不同意	非常不同意
20. 我是個做事缺乏計畫的人	☐	☐	☐	☐	☐
21. 我容易東操煩西操煩	☐	☐	☐	☐	☐
22. 我是具壓力容忍能力的人	☐	☐	☐	☐	☐
23. 我常因別人對待我的方式而感到生氣	☐	☐	☐	☐	☐
24. 我很少覺得孤單或憂鬱	☐	☐	☐	☐	☐
25. 我常常覺得緊張與神經過敏	☐	☐	☐	☐	☐
26. 我是個喜歡獨處的人	☐	☐	☐	☐	☐
27. 我是具情緒控制力的人	☐	☐	☐	☐	☐
28. 我是常提出新方法的人	☐	☐	☐	☐	☐
29. 我是好奇心很重的人	☐	☐	☐	☐	☐
30. 我是能整體思考的人	☐	☐	☐	☐	☐
31. 我是不具創新能力的人	☐	☐	☐	☐	☐
32. 我對思索宇宙或人類環境的本質很有興趣	☐	☐	☐	☐	☐

本問卷到此結束，再次感謝您的參與和協助！

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