
국 외 출 장 보 고 서

- TRB 93rd Annual Meeting -

2014. 1.

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김 준 기



국 토 연 구 원

I

출장개요

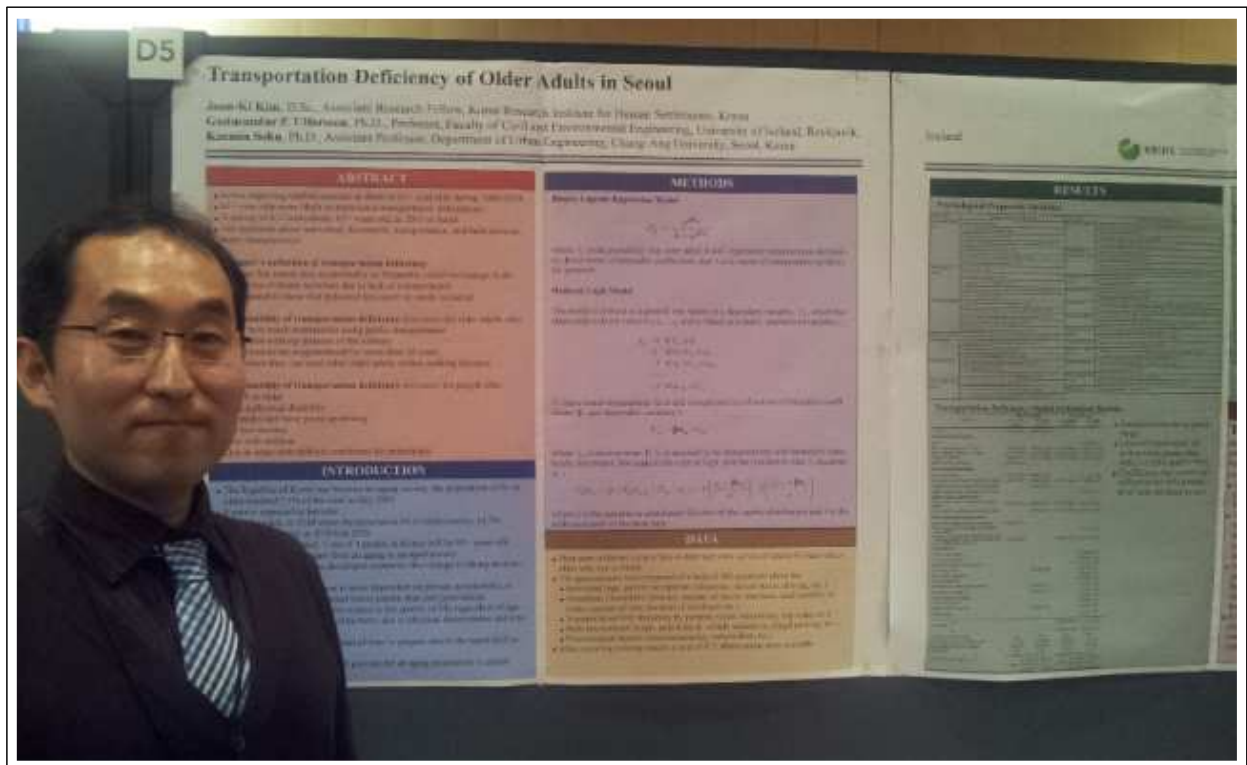
- 출 장 자 : 김준기 책임연구원 (국토연구원 국토인프라연구본부)
- 출장목적 : TRB 학술회의 참석 및 발표, 해외우수인력유치 노력
- 출장기간 : 2014. 1. 12(일) ~ 2014. 1. 17(금) (4박 6일, 기내1박)
- 출 장 지 : 미국 워싱턴 D.C.
- 기대효과
 - 국외 도로정책방향 및 도로교통 연구동향 파악
 - 사회학적 측면의 교통 가치 파악
 - 논문발표를 통한 위상제고 및 현지 연구자와의 교류를 통하여 인적 네트워크 구축
 - 국토연구원 홍보를 통한 해외우수인력 유치 기여
- 출 장 일 정

월 일 (요일)	출발지	도착지	업무수행내용
1/12(일)	인천	워싱턴 D.C	■ 출발(10:15) 및 도착(9:50) - 한양교통재미동문회 참석 및 연구원 홍보 (Marriot Hotel, 17:30)
1/13(월) ~ 16(수)	워싱턴 D.C.		■ TRB 학술회의 참석 및 발표 - KOTAA Technical Session 참석 및 연구원 홍보 (13일(월) 17:30) - 논문 포스터 발표 (14일(화) 10:45) - 논문 구도 발표 (14일(화) 13:30) - KOTAA 모임 참석 및 연구원 홍보 (14일(화) 18:00) - 해외유학생과의 미팅 (13일(월) ~ 15일(수))
1/16(목) ~17(금)	워싱턴 D.C.	인천	■ 출발(11:50) 및 도착(16:20) (기내1박)

1. 고령자 이동성 논문

□ 발표개요

- 논문제목: Transportation Deficiency of Older Adults in Seoul
- 저자 : 김준기(국토연구원 책임연구원), Gudmundur F. Ulfarsson (아이슬란드대 교수), 손기민(중앙대학교 교수)
- 발표 일시 및 장소 : 1월14일(화) 10:45-12:30, Marriott Hotel



<포스터 발표>

□ 주요 발표 내용 및 토의

【발표 내용】

- (연구개요) 한국의 고령자(65세 이상)는 급격하게 증가 예상가 예상되며, 고령자는 통행의 제약을 가장 크게 받는 그룹으로, 개인특성, 가족특성, 교통특성, 건조환경 특성 등이 고령자의 통행

의 제약에 미치는 영향을 분석

- 이동성 제약의 조작적 정의 : 교통수단의 부족으로 원하는 활동을 하지 못하는 것을 빈번히(occasionally) 또는 가끔(frequently) 경험할 때 이동성에 제약을 받는다고 정의함
- 이동성 제약을 감소시키는 환경 :
 - 대중교통 수단을 이용하여 목적지로 가는 방법을 알고 있을 때
 - 도보로 갈 수 있는 거리에 전철역이 있을 경우
 - 동네에 20년 이상 거주할 경우
 - 도보로 갈 수 있는 거리에 다른 고령자들을 만날 수 있는 장소가 있을 경우
- 이동성 제약을 증가시키는 환경 :
 - 75세 이상의 고령자
 - 신체적 장애가 있을 경우
 - 남성이면서 운전을 포기했을 경우
 - 저소득층일 경우
 - 아이들(children)과 같이 살 경우
 - 언덕 등으로 보행이 쉽지 않은 곳에 사는 경우
- (분석방법) 이항로지스틱회귀식(Binary Logistic Regression)과 순서형로짓(Ordered Logit)을 이용하여 이동성 제약 모형 구축

$P_n = \frac{e^{\beta x_n}}{1 + e^{\beta x_n}}$	$ \begin{aligned} y_n &= 0 \text{ if } U_n \leq 0, \\ &= 1 \text{ if } 0 < U_n \leq \mu_1, \\ &= 2 \text{ if } \mu_1 < U_n \leq \mu_2, \\ &= \dots \\ &= J \text{ if } \mu_{J-1} < U_n, \\ U_n &= \beta x_n + \varepsilon_n \end{aligned} $
<이항로지스틱회귀식>	<순서형로짓>

- (데이터) 서울에 거주하는 65세 이상의 노인을 대상으로 대면설문조사를 통하여 약 160개 항목에 대하여 조사
 - 개인특성 (연령, 성별, 직업, 교육수준, 결혼상태, 운전 유무 등)
 - 가정특성 (가족구성원 수, 월수입, 자동차수, 거주기간 등)
 - 통행특성 (통행목적별 통행 빈도, 통행시간, 통행비용 등)
 - 건조환경특성 (경사, 보차분리, 불법주차 등)
 - 잠재적 성향 (환경에 대한 관심, 독립성 등)
- (분석결과 및 결론) 대중교통수단에 대한 물리적 접근성 뿐만아니라, 인지적 접근성(대중교통수단 이용 정보)을 향상시켜야 하며, 고령자의 주요한 통행수단인 보행환경을 개선해야 함
 - 이동성 제약에 영향을 미치는 요인 (화살표는 확률의 증가 또는 감소를 의미)

Variables	Binary Logistic Regression	Ordered Logit Model		
		Frequently/ Occasionally	Rarely	Never
<i>Individual characteristics</i>				
Age ≥ 75		↑	↑	↑
Easy walking distance < 500m	↑	↑	↑	↓
≥ 1,000m	↓	↓	↓	↑
Physical disability	↑	↑	↑	↓
Male * Given up driving*	↑			
<i>Household characteristics</i>				
Live with spouse	↓	↓	↓	↑
Household income below \$2,000 per month	↑	↑	↑	↓
Child(ren) under 18 years old in household	↑			
Years lived in local community ≥ 20 years		↓	↓	↑
<i>Public transit characteristics</i>				
Know how to get to destination by public transit	↓	↓	↓	↑
Metro stations within easy walking distance		↓	↓	↑
<i>Built environment characteristics</i>				
Many hills/sloping roads in community	↑			
Strictly separated sidewalks from roads in community		↑	↑	↓
Places to meet other older adults within easy walking distance (e.g., senior citizens' center, community center, etc.)	↓	↓	↓	↑
<i>Latent factors</i>				
Community spirit	↓	↑	↑	↓
Dissatisfaction about public transit	↑	↑	↑	↓

【논의사항】

- 고령자들의 심리적 성향을 모형에 반영하여 이동성의 제약 요인을 분석함으로써 여러 변수의 영향요인을 통제할 수 있어 학술적으로 기존의 논문과 분명한 차별성을 가짐
- 물리적 개선 뿐만아니라 고령자들이 어떻게 대중교통시스템을 이용하는지 교육(홍보 등)이 필요함
- 고령자들의 주요한 통행모드는 도보이므로, 보행여건의 개선이 무엇보다도 시급하다고 할 수 있음

【시시점】

- 서울의 대중교통시스템은 세계 최고 수준으로, 물리적 대중교통시스템의 체계로만 고령자의 이동성 제약 문제를 극복할 수 있는 것은 아님
 - 물리적 서비스의 제공은 필수적이나 소프트적 서비스가 병행되어야 함
- ‘교통’ 단독만으로는 고령화 시대를 대비할 수 없으며, 반드시 토지이용을 고려해야 함
 - 도시 설계부터, 고령화를 대비하여 주요시설들을 도보로 이용할 수 있게 배치 하는 등의 노력이 필요

2. 고속도로 교통사고 영향 요인

□ 발표개요

- 논문제목: The Effect of Road Environment Factors on Freeway Traffic Crash Frequency during Daylight, Twilight, and Night Conditions
- 저자 : 홍성민 (홋카이도 대학교 박사과정), 김준기 (국토연구원 책임연구원), 오철 (한양대학교 교수), Gudmundur F. Ulfarsson (아이슬란드대 교수)
- 발표 일시 및 장소 : 1월14일(화) 13:30-15:15, Marriott Hotel



□ 주요 발표 내용 및 토의

【발표 내용】

- (연구개요) 한국은 지난 2007년부터 2010년까지 고속도로에서의 자동차 사고는 일출/일몰시간에는 8% 증가한 반면 그 외의 시간대에서는 감소한 것으로 나타나, 교통, 기하구조 등이 시간대별로 교통사고에 어떠한 영향을 미치는지를 분석
- (데이터) 서해안 고속도로, 중부 고속도로 및 중부내륙고속도로를 대상으로 10km로 도로구간을 구분(총 72 구간)하여 자료를 수집
 - 교통특성 : AADT, 소형/중형/대형 자동차비율
 - 환경특성 : 도시부/지방부, 빈번하게 안개가 발생하는 지역, 적설량, 강우량 등
 - 기하구조 : 차선수, IC/JC 수, IC 형태, 곡선반경, 경사, 터널수, 교량 수 등
- (방법론) 이질성을 극복하기 위하여 확률변수포아송/음이항 모형(Random Parameter Poisson/Negative Binomial Regressions Model) 적용
 - 모형식: $\beta_i = \beta + \phi_i$

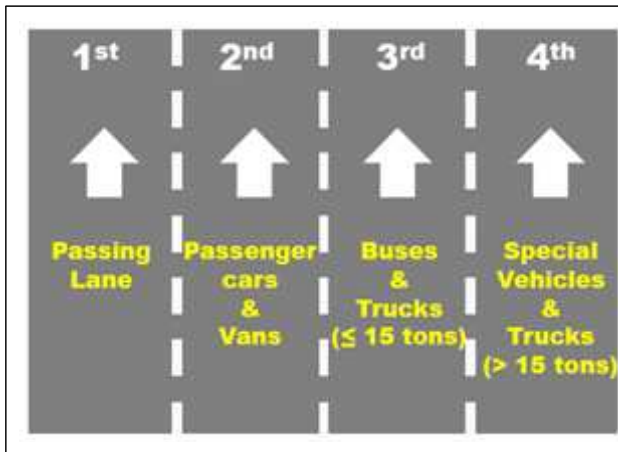
β : a vector of estimable parameters
 ϕ_i : a randomly distributed term

○ (결과) 모형분석 결과

- 교통특성 : 대형차량의 비율은 밤시간대의 교통사고를 증가시킴
- 기하구조특성 : 차선수와 IC/JC 수는 차량의 차선변경 및 이에 따른 통행속도의 차이에 영향을 미치므로 교통사고에 영향을 미치며, 교량은 교통사고 취약구간으로 나타남
- 환경특성 : 도시부의 경우 차선변경 및 차량간의 빈번한 마찰(conflict)이 발생함으로 교통사고를 증가시키는 것으로 나타났으며, 강설일수는 시야 및 노면의 마찰계수를 감소시키므로 교통사고에 부정적인 영향을 미치는 것으로 분석됨

○ (정책제언)

- 교통 운영 및 조정



<교통수단별 이용 차선 구분>



<차선 조정 시스템>

- 도로선형 및 운전자 정보



<도로선형 개선>



<차량내 경고 시스템>

- 교통안전시설



<교량-바람막이벽 설치>



<화물차 휴게소/쉼터 설치>

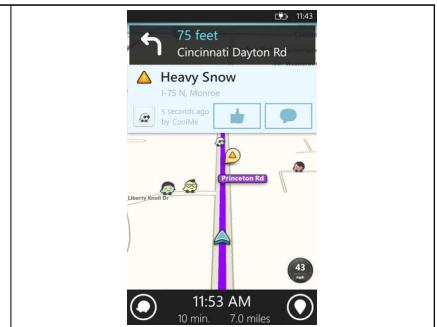
- 운전자 정보 시스템



<차량 감지>



<가변정보시스템>



<차량내 정보시스템>

【논의 사항】

- 고속도로 교통사고를 줄이기 위해서는 시급히 교육 등 인적요인의 개선이 필요함

- 교육의 중요성은 더할 나위 없으나, 안전한 인프라 제공 역시 필수적임

【시사점】

- 한국의 도로인프라(특히 고속도로)는 세계 최고수준으로 교통사고 저감을 위해서는 ITS를 적극 도입할 필요가 있음

□ 국토연구원 홍보 노력

○ KOTAA Annual Meeting과 Technical Session에서 국토연구원 홍보

※ KOTAA (Korean Transportation Association in America)는 한국과 재미교포의 교통 전문직 종사자 (학생, 교수, 산업 등)의 모임으로 매년 Transportation Research Board(TRB)에서 모임을 갖고 있으며, Technical Session은 주로 대학원생들을 대상으로 관심분야에 대한 발표를 통한 네트워크 형성 및 취업 활동에 도움을 주기 위한 목적으로 함

- KOTAA Technical Session: 2014. 1. 13(월) 5:30pm, Hilton Hotel

- KOTAA Annual Meeting: 2014. 1. 14(화) 6:00pm, Church Hotel

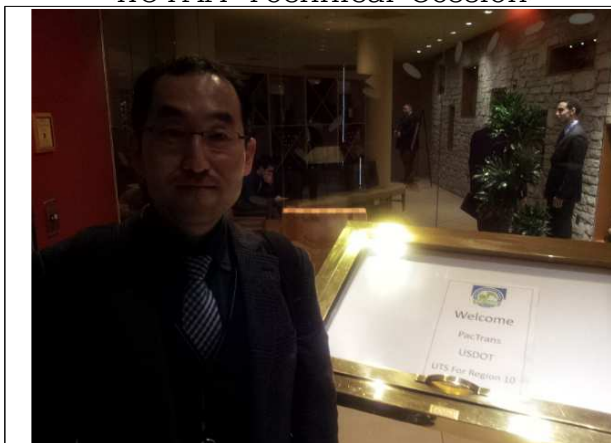
○ 대학교 리셉션 참석 및 유학생 개별 접촉을 통한 홍보활동



<KOTAA Technical Session>



<KOTAA Annual Meeting>



<워싱턴 대학교-PacTrans>



<플로리다 대학교>

□ 해외유학자 접촉 명단

연번	성명	연락처		학교	학과	전공	분야	박사졸업예정시기 (졸업년도)	비고 (국토연구원 관심 여부 등)
		이메일	전화번호						
1	송동윤	dsong81@gmail.com	+1-765-430-2209	Purdue University	Civil Engineering	Transportation Engineering	Travel Behavior, Stated-Preferece Modeling, ATIS, Transportation Psychology, Network Modeling	2014년 예정	관심 있음 (2006-2008 국토연구원 근무)
2	김기홍	kihong@pdx.edu	+1-213-284-2884	Portland state university	Urban Studies & Planning	Transportation Engineering	Activity-Based Travel Demand Modeling, Travel Behavior	2014년 6월 예정	관심 있음
3	김상기	ksangke@ncsu.edu	070-4064-7642	North Carolina State University	Civil Engineering	Transportation Engineering	Signal Optimization and ITS	2014년 5월 예정	
4	박준영	jypark121@gmail.com	US:4076836093 KOR:01088824156	University of Central Florida	Civil Engineering	Transportation Engineering	Traffic Safety, Crash Analysis, Data Mining, Statistic Analysis, ITS, Traffic Operation	2015년 7월 예정	관심 있음
5	소재현	ssojae82@gmail.com	+1-434-466-8902	University of Virginia	Civil & Environmental Engineering	Transportation Engineering	Traffic Operations & Management, Traffic Safety, Simulations, ITS, Evacuation Planning	2013년 8월 졸업	관심 있음 (Florida Atlantic University에서 포닥으로 연구 및 강의중)
6	윤태관	yoona0204@gmail.com	+1-865-382-0544	University of Tennessee	Civil Engineering	Transportation Engineering	Sustainable Transportation (Electric Vehicle Fleet Optimization, Car & Bike Sharing)	2014년 5월 예정	관심 있음 (지속가능한 교통관련 업무 희망)
7	이은수	eunsu.lee@ndsu.edu	+1-701-205-1525	North Dakota State University	Transportation & Logistics	Logistics & Supply Chain Systems	Spatial Analysis, Transportation Planning, Life-Cycle Cost Analysis	2011년 졸업	관심 있음 (Upper Great Plains Transportation Institute에서 Associate Research Fellow로 근무중)
8	이창주	cl8ax@virginia.edu mr.leechangju@gmail.com	+1-434-242-5513	University of Virginia	Civil & Environmental Engineering	Transportation Engineering	Transportation Planning & Economics (Public-Private Partnership, Value Capturing, ITS Evaluation, Transportation Substantiality, Traveler's Behavior Modelling)	2015년 5월 예정	관심 있음
9	최재성	jaesung.choi@my.ndsu.edu		North Dakota State University	Transportation & Logistics	Transportation Economics & Regulation	Transportation Economics, Econometrics, Operation Research, Spatial Analysis	2015년 12월 예정	관심 있음
10	김운	elly9911@gmail.com	+1-240-676-8735	University of Maryland	Civil & Environmental Engineering	Transportation Engineering	Traffic Safety, Operations, ITS	2014년 5월 예정	관심 있음
11	김현미	hmkim@umd.edu	+1-240-778-3945	University of Maryland	Civil & Environmental Engineering	Transportation Engineering	Traffic Safety, Traffic Operations	2016년 5월 예정	관심 있음
12	박성운	alza102@gmail.com	+1-301-523-1412	University of Maryland	Civil & Environmental Engineering	Transportation Engineering	Traffic Safety, Traffic Operations	2016년 5월 예정	관심 있음
13	김명섭	mkim27@gmail.com	+1-240-355-5023	University of Maryland	Civil & Environmental Engineering	Transportation Engineering	Public Transportation (Bus & Rail System) Planning & Analysis	2013년 8월 졸업	관심 있음
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□ 논문 2: 고령자 이동성 논문

No.14-2418 The Effect of Road Environment Factors on Freeway Traffic Crash Frequency during Daylight, Twilight, and Night Conditions Sungmin Hong / Hokkaido University, Japan Joonki Kim, D.Sc. / Korea Research Institute for Human Settlements Cheol Oh, Ph.D. / Hanyang University, Korea Gudmundur F. Ulfarsson, Ph.D. / University of Iceland, Iceland ACKNOWLEDGMENT This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIP) (NRF-2010-0029449). KTRB The 93rd Annual Meeting of the Transportation Research Board	Hong, Kim, Oh, and Ulfarsson Contents ■ Introduction ■ Data ■ Method ■ Analysis Results ■ Recommendations ■ Conclusions 2
Hong, Kim, Oh, and Ulfarsson Introduction  As of 2010, the following numbers are reported: • 32-Freeway lines • 3,859km-Length • 1,377,062,000-Vehicles • 3,924-Crashes • 389-Fatalities ■ Crash frequency (2007-2010) ○ 15% ↓ : daytime/ nighttime ○ 8% ↑ : twilight (http://www.krri.co.kr) 3	Hong, Kim, Oh, and Ulfarsson Introduction ■ Objectives ○ To investigate the effect of road environments on crash frequency under different light conditions ○ To derive recommendations for road design and traffic operations  • Traffic Characteristics • Geometric Characteristics • Environment Characteristics 4

[Data]

- A total of 6,158 crash cases during 2007-2010
- Vehicle malfunction excluded
- 10-km fixed section (72 sections)

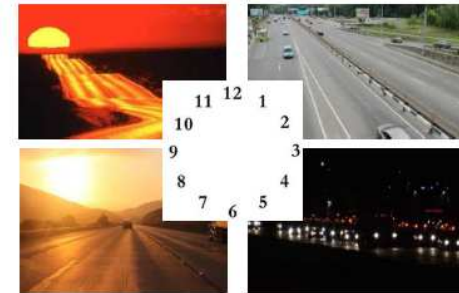


Seohaean freeway
Jungbu freeway
Jungbu-Naeryuk freeway

5

[Data]

Daytime/Nighttime/Twilight/Whole day



6

[Data]

- Independent Variables
 - Characteristics of Traffic, Environment, and Roadway Geometrics

Traffic Characteristics	AADT (AADT/1,000)
	Traffic share of light vehicles
	Traffic share of medium vehicles
	Traffic share of heavy vehicles
Environment Characteristics	Urban ($50,000 \leq \text{population}$) ($Y(1)/N(0)$)
	Frequent fog in area ($Y(1)/N(0)$)
	Snowfall (cm)
	Number of Days With snowfall
	Rainfall (mm)
	Number of Days With rainfall

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[Data]

- Independent Variables

Geometric Characteristics	Number of lanes	Long radius curves ($10,200 \text{ m} \leq R$)
	Number of interchanges/junctions	Transition curves
	Trumpet type interchanges	Number of Uninterrupted curves
	Interchange/junctions (except Trumpet type)	Crest vertical curves
	Short tangents ($L < 1,421 \text{ m}$)	Sag vertical curves
	Medium tangents ($1,421 \leq L < 4,000 \text{ m}$)	Horizontal & Crest vertical curves
	Long tangents ($4,000 \text{ m} \leq L$)	Horizontal & Sag vertical curves
	Short radius curves ($R < 4,000 \text{ m}$)	Number of tunnels
	Medium radius curves ($4,000 \leq R < 10,200 \text{ m}$)	Number of bridges

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Method

Analysis of Count Data

- Random Parameter Poisson/Negative binomial regressions: to capture heterogeneity (caused by long, fixed-length sections including varying geometrics and traffic)
- The estimable random parameter(β_i) is expressed

$$\beta_i = \beta + \phi_i$$

β : a vector of estimable parameters
 ϕ_i : a randomly distributed term

- Distributions for random parameters
 - Continuous variable: Normal distribution
 - Indicator variable: Uniform distribution

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Results

Traffic Characteristics

- Traffic share of light vehicles
 - Various drivers' characteristics and vehicle types
- Traffic share of heavy vehicles
 - Frequent travels by heavy vehicles (trucks) all night

<Average Marginal Effects>

	Daylight crash model	Night crash model	Twilight crash model	Total (whole 24h) crash model
	Negative binomial fixed parameter	Poisson random-parameter	Poisson random-parameter	Poisson random-parameter
Traffic share of light vehicles	50.6	64.07	17.28 ((+)100%, (-)0%)	136.51 ((+)100%, (-)0%)
Traffic share of heavy vehicles		69.10		163.19

* () : Random Parameter results with Positive and Negative parameter densities

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Results

Geometric Characteristics

- Number of lanes
 - Larger traffic, frequent lane changes
- Number of interchanges/junctions
 - Increased speed variation by merging and diverging

<Average Marginal Effects>

	Daylight crash model	Night crash model	Twilight crash model	Total (whole 24h) crash model
	Negative binomial fixed parameter	Poisson random-parameter	Poisson random-parameter	Poisson random-parameter
Number of lanes	3.13	2.26 ((+)100%, (-)0%)	1.48	5.51 ((+)100%, (-)0%)
Number of IC/JC	1.86		0.57	2.88

* () : Random Parameter results with Positive and Negative parameter densities

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Results

Geometric Characteristics

- Short tangents($L < 1,421$ m) between two or more curves
 - Limited sight distance, required more driving controls
- Combined horizontal and sag curves
 - Limited sight distance, driver workload for wheel adjustment, lateral deviation of vehicle positions

<Average Marginal Effects>

	Daylight crash model	Night crash model	Twilight crash model	Total (whole 24h) crash model
	Negative binomial fixed parameter	Poisson random-parameter	Poisson random-parameter	Poisson random-parameter
Short tangents ($L < 1,421$ m)			0.15	
Horizontal & Sag vertical curves	0.35			

* () : Random Parameter results with Positive and Negative parameter densities

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Results

Geometric Characteristics

- Number of bridges
 - Side-wind caused crashes
- Crest vertical curves
 - Further research is required

<Average Marginal Effects>

	Daylight crash model	Night crash model	Twilight crash model	Total (whole 24h) crash model
	Negative binomial fixed parameter	Poisson random-parameter	Poisson random-parameter	Poisson random-parameter
Number of bridges	0.57			
Crest vertical curves			-0.13	

* () : Random Parameter results with Positive and Negative parameter densities

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Results

Environment Characteristics

- Urban area
 - More traffic and greater conflicts between vehicles
 - Less traffic and fewer conflicts but drivers may drive more cautiously at night
- Number of days with snowfall
 - Slippery road conditions, poor visibility

<Average Marginal Effects>

	Daylight crash model	Night crash model	Twilight crash model	Total (whole 24h) crash model
	Negative binomial fixed parameter	Poisson random-parameter	Poisson random-parameter	Poisson random-parameter
Urban (Y(1)/N(0))	4.41	2.65 ((+78.9%, -)21.1%)	2.39 ((+100%, -)0%)	8.13 ((+84.5%, -)15.5%)
Number of Days With snowfall	0.12	0.05	0.04	0.2

* () : Random Parameter results with Positive and Negative parameter densities

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Results

Environment Characteristics

- Frequent fog in area
 - Limited sight distance (especially at night)
 - Distance headway depending on the level of fog density

<Average Marginal Effects>

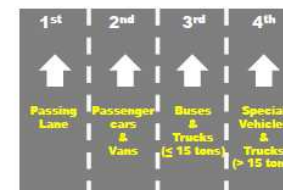
	Daylight crash model	Night crash model	Twilight crash model	Total (whole 24h) crash model
	Negative binomial fixed parameter	Poisson random-parameter	Poisson random-parameter	Poisson random-parameter
Frequent fog in area (Y(1)/N(0))	2.19	0.78 ((+59.8%, -)41.2%)	0.59	2.81 ((+74.1%, -)25.9%)

* () : Random Parameter results with Positive and Negative parameter densities

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Recommendations

Traffic operations and control



Lane Designation



LCS
(Lane Control System)

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Recommendations

Road Alignment and Driver Information



Combination of sag and horizontal curves



Warning signs

In-vehicle
warning
assistant

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Recommendations

Traffic Safety Measures

- Bridges – Windbreak fences
- Location and spacing of rest area for truck drivers



Windbreak fence



Rest Area

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Recommendations

Driver information for adverse weather conditions

- Fog/Snow: providing information by in-vehicle device and VMS



Vehicle sensors



VMS
(Variable Message Sign)



In-vehicle information
system

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Conclusions

- The influence of road environment factors on freeway traffic safety under different light conditions was investigated
 - Poisson and negative binomial models with fixed and random parameters were developed
- Traffic operations/control and geometric design considerations by different light conditions
- Differentiated/customized information for drivers by different light conditions to enhance situation awareness

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Q & A

Thank you
for your attention

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Appendix 1 - Method

- Goodness-of-fit (GOF)
 - Log-likelihood ratio(ρ^2) for evaluating GOF

$$\rho^2 = 1 - \frac{LL(\beta) - n}{LL(0)}$$

$LL(\beta)$: the log-likelihood at convergence for the full model

$LL(0)$: the value for the initial model with all parameters set to zero

n : the number of estimated parameters

- Marginal effects
 - To explain the size of the relationship between independent variables and the dependent variable

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Appendix 1 - Method

- Likelihood ratio χ^2 - test
 - To determine whether or not the fixed parameter model and random parameter model for the same light condition were statistically significantly different

- The likelihood ratio χ^2 value:

$$\chi^2 = -2[LL(\beta)_a - LL(\beta)_b]$$

$LL(\beta)_a$, $LL(\beta)_b$: the log-likelihood at convergence values for the two models being compared

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Appendix 2 – Modeling Results (Daylight)

	Daylight crash model			
	Poisson Random-parameter coefficient	p-value	Negative binomial Fixed-parameter Coefficient	p-value
Constant	-3.77	0	-4.13	0
Traffic Characteristics				
Traffic share of light vehicles	4.8	0	5.29	0
Standard deviation of parameter distribution (N)	0.4	0		
Traffic share of heavy vehicles				
Geometric Characteristics				
Number of lanes	0.31	0	0.33	0
Standard deviation of parameter distribution (N)	0.01	0.01		
Number of interchanges/junctions	0.2	0	0.19	0
Short tangents (L<1,421m)				
Crest vertical curves				
Horizontal & Sag vertical curves	0.04	0	0.04	0.05
Number of bridges	0.05	0	0.06	0.01
Standard deviation of parameter distribution (N)	0.05	0		
Environment Characteristics				
Urban(50,000 ≤ population) (Y(1)/N(0))	0.45	0	0.46	0
Standard deviation of parameter distribution (U)	0.19	0		
Frequent fog in area (Y(1)/N(0))	0.23	0	0.23	0
Standard deviation of parameter distribution (U)	0.09	0.01		
Number of Days With snowfall	0.01	0	0.01	0.01
Dispersion parameter for negative binomial distribution			0.15	0
Number of observations	281		281	
Log-likelihood at zero, $LL(0)_a$	-1155.414		-1155.414	
Log-likelihood at convergence, $LL(\beta)_a$	-803.659		-806.076	
ρ^2	0.292		0.294	
chi-square (critical)		2.706		
chi-square (random-fixed)		5.034		

Appendix 2 – Modeling Results (Night)

	Night crash model			
	Poisson Random-parameter coefficient	p-value	Negative binomial Fixed-parameter coefficient	p-value
Constant	-7.09	0	-6.73	0
Traffic Characteristics				
Traffic share of light vehicles	8.99	0	8.54	0
Standard deviation of parameter distribution (N)				
Traffic share of heavy vehicles	9.7	0	9.42	0.01
Geometric Characteristics				
Number of lanes	0.32	0	0.32	0
Standard deviation of parameter distribution (N)	0.09	0		
Number of interchanges/junctions				
Short tangents (L<1,421m)				
Crest vertical curves				
Horizontal & Sag vertical curves				
Number of bridges				
Standard deviation of parameter distribution (N)				
Environment Characteristics				
Urban(50,000 ≤ population) Y(1)/N(0)	0.37	0	0.43	0
Standard deviation of parameter distribution (U)	0.37	0		
Frequent fog in area Y(1)/N(0)	0.11	0	0.14	0.04
Standard deviation of parameter distribution (U)	0.36	0		
Number of Days With snowfall	0.01	0	0.01	0.08
Dispersion parameter for negative binomial distribution			0.14	0
Number of observations	281		281	
Log-likelihood at zero, $LL(0 0)$	-980.988		-980.988	
Log-likelihood at convergence, $LL(c \beta^c)$	-767.597		-771.241	
χ^2	0.207		0.206	
chi-square (critical)		2.706		
chi-square (random-fixed)		7.288		

Appendix 2 – Modeling Results (Twilight)

	Twilight crash model			
	Poisson Random-parameter coefficient	p-value	Negative binomial Fixed-parameter coefficient	p-value
Constant	-4.85	0	-5.05	0
Traffic Characteristics				
Traffic share of light vehicles	4.88	0	5.25	0
Standard deviation of parameter distribution (N)	0.46	0		
Traffic share of heavy vehicles				
Geometric Characteristics				
Number of lanes	0.42	0	0.42	0
Standard deviation of parameter distribution (N)				
Number of interchanges/junctions	0.16	0	0.15	0.01
Short tangents (L<1,421m)	0.04	0	0.04	0.07
Crest vertical curves	-0.04	0	-0.04	0.03
Horizontal & Sag vertical curves				
Number of bridges				
Standard deviation of parameter distribution (N)				
Environment Characteristics				
Urban(50,000 ≤ population) Y(1)/N(0)	0.68	0	0.69	0
Standard deviation of parameter distribution (U)	0.17	0		
Frequent fog in area Y(1)/N(0)	0.17	0	0.16	0.06
Standard deviation of parameter distribution (U)				
Number of Days With snowfall	0.01	0	0.01	0.05
Dispersion parameter for negative binomial distribution			0.16	0
Number of observations	281		281	
Log-likelihood at zero, $LL(0 0)$	-759.478		-759.478	
Log-likelihood at convergence, $LL(c \beta^c)$	-628.546		-629.755	
χ^2	0.158		0.158	
chi-square (critical)		2.706		
chi-square (random-fixed)		2.418		

Appendix 2 – Modeling Results (Whole day)

	Total crash model (whole 24 hour day)			
	Poisson Random-parameter coefficient	p-value	Negative binomial Fixed-parameter coefficient	p-value
Constant	-4.81	0	-4.91	0
Traffic Characteristics				
Traffic share of light vehicles	7.21	0	7.37	0
Standard deviation of parameter distribution (N)	0.33	0		
Traffic share of heavy vehicles	8.62	0	7.29	0.02
Geometric Characteristics				
Number of lanes	0.29	0	0.32	0
Standard deviation of parameter distribution (N)	0.03	0		
Number of interchanges/junctions	0.15	0	0.14	0
Short tangents (L<1,421m)				
Crest vertical curves				
Horizontal & Sag vertical curves				
Number of bridges				
Standard deviation of parameter distribution (N)				
Environment Characteristics				
Urban(50,000 ≤ population) Y(1)/N(0)	0.43	0	0.47	0
Standard deviation of parameter distribution (U)	0.36	0		
Frequent fog in area Y(1)/N(0)	0.15	0	0.15	0.01
Standard deviation of parameter distribution (U)	0.18	0		
Number of Days With snowfall	0.01	0	0.01	0.01
Dispersion parameter for negative binomial distribution			0.13	0
Number of observations	281		281	
Log-likelihood at zero, $LL(0 0)$	-1733.516		-1733.516	
Log-likelihood at convergence, $LL(c \beta^c)$	-986.907		-991.943	
χ^2	0.424		0.423	
chi-square (critical)		2.706		
chi-square (random-fixed)		10.071		

Appendix 3 -Summary of Random Parameter results with Positive and Negative parameter densities

Model	Variables	Distr.	Mean	S.D.	+ (%)	- (%)
Daylight	Traffic share of light vehicles	Normal	4.88	0.46	100.0%	0.0%
	Number of lanes	Normal	0.31	0.01	100.0%	0.0%
	Number of bridges	Normal	0.05	0.05	84.1%	15.9%
	Urban (50,000 ≤ population) Y(1)/N(0)	Uniform	0.45	0.19	100.0%	0.0%
Night	Frequent fog in area, Y(1)/N(0)	Uniform	0.23	0.09	100.0%	0.0%
	Number of lanes	Normal	0.32	0.09	100.0%	0.0%
	Urban (50,000 ≤ population) Y(1)/N(0)	Uniform	0.37	0.37	78.9%	21.1%
	Frequent fog in area Y(1)/N(0)	Uniform	0.11	0.36	59.8%	41.2%
Twilight	Traffic share of light vehicles	Normal	4.88	0.46	100.0%	0.0%
	Urban (50,000 ≤ population) Y(1)/N(0)	Uniform	0.68	0.17	100.0%	0.0%
Whole 24 h	Traffic share of light vehicles	Normal	7.21	0.33	100.0%	0.0%
	Number of lanes	Normal	0.29	0.03	100.0%	0.0%
	Urban (50,000 ≤ population) Y(1)/N(0)	Uniform	0.43	0.36	84.5%	15.5%
	Frequent fog in area, Y(1)/N(0)	Uniform	0.15	0.18	74.1%	25.9%

[부록 2] 논문

Transportation Deficiency of Older Adults in Seoul

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ABSTRACT

The Republic of Korea is expecting a near tenfold increase in the share of 65+ year old adults between the years 2000 and 2018. This population is more likely to experience transportation deficiencies as physical abilities deteriorate, necessitating new policies to provide mobility for older adults.

This study investigates transportation deficiency in a representative sample of 812 individuals, 65 years or older, surveyed in 2011 in Seoul. The survey contained 160 questions about individual, household, transportation, and built environment characteristics. Those responding that they either occasionally or frequently could not engage in desired out-of-home activities due to lack of transportation options were defined as transportation deficient, compared to those that indicated this never or rarely occurred.

The probability of transportation deficiency decreases for older adults who: know how reach destinations using public transportation, are within walking distance of the subway, have lived in the neighborhood for more than 20 years, live in areas with places where one can meet other older adults within walking distance. The probability of transportation deficiency increases for people who: are 75 or older, have a physical disability, are males and have given up driving, are low-income, live with children, live in areas with difficult conditions for pedestrians.

The policy recommendations highlight an improved pedestrian environment to facilitate walking, public transit improvements and information systems that make, especially bus transit, a more viable option for older adults. Policies need to take into account varying health and physical abilities of older adults.

Keywords: aging, transportation deficiency, transportation policy

1. INTRODUCTION

The population ratio of individuals who are 65 years old or older is increasing globally due to the extension of average lifespan and decrease in fertility. The Republic of Korea has become an aging society, as the population of individuals who are 65 or older reached 7.1% of the total population in July 2000 (1). Korea is expected to become an aged society when the population of individuals 65 or older reaches 14.3% in 2018 and a post-aged society at 20.8% in 2026 (1). It is forecasted that by 2042, one out of every three people in Korea will be 65 year old or older (1). This change is occurring fast. It will only take 18 years for Korea to change from an aging to an aged society. By comparison, in other developed countries, this same change in the population structure is taking an average of 62 years (2).

The current older population is more dependent on private automobiles, is more active, and has a different travel pattern than past generations (3–5). As health and economic conditions have improved for older adults in Korea, they have become more active than past generations. According to a 2010 household travel survey, the daily average trip frequency of those aged 65 or older increased by 50% between the year 2000 (0.9 trips/day) and 2010 (1.4 trips/day) (6). While the total number of driver's license holders increased by 3.2% annually from 2001 to 2011, the number of older driver's license holders has had an annual increase rate of 14.9% (7). As the number of older licensed drivers increases, the number of traffic crashes involving older drivers is also increasing. The total number of traffic crashes has decreased slightly from 2001 to 2011. However the number of crashes caused by older drivers increased 3.6 times between 2001 and 2011, the number of deaths from crashes caused by older drivers increased 2.6 times, and the number of injuries increased 3.9 times (7).

Mobility is a significant factor related to the quality of life regardless of age. Since older adults may have limited mobility due to physical deterioration and lower purchasing power, efforts must be made to motivate transportation policies that are safe and enhance the mobility of older adults (8–9). A slower rate of population aging in the developed countries means they have had relatively sufficient time (about 20–30 years) to prepare. However, Korea has an insufficient amount of time to prepare due to the rapid shift towards an older population, and, thus, the development of transportation policies for an aging population is urgent. In order to prevent or reduce problems due to older adults' travel limitations, it is necessary to prepare traffic policies that can assist in enhancing the mobility of older adults.

2. LITERATURE REVIEW

Older adults who drive a car tend to have better mobility than those who do not drive (10). If older drivers stop or reduce driving, their mobility decreases (11–14). Although older drivers self-regulate to a certain degree to avoid dangerous driving (15), they are more exposed to dangers that can cause traffic crashes because their physical capabilities have deteriorated compared to younger age groups (16–18). Additionally, this risk can perhaps also be linked to older adults' greater difficulty in comprehending some traffic signs (19). Therefore, driving cessation of older drivers has a positive effect in reducing crashes (17, 20). However, because driving cessation limits older adults' participation in social and leisure activities, it can bring social isolation (9, 21). If older drivers can no longer drive, it

affects not only themselves but also their families and friends. Therefore, transportation alternatives must be provided (22).

Other factors that influence the mobility of older adults are age, gender, education level, health, disability status, household characteristics, the built environment (23–30), traffic infrastructure and culture characteristics (31–32). Because such varied factors influence mobility and because in Korea cultural and individual characteristics, public transportation conditions and land usage are different from the United States and Europe, an investigation of the mobility of older adults in Korea can help further develop an understanding of the traffic characteristics of older adults. For example, the population (=35,473) within walking distance from a subway station in Seoul (approximately one-half mile) is, on average, much larger than the population (=1,490) within the same catchment area, as observed in 9 typical cities in the United States. This indicates the intensity of public transportation use in Seoul already exceeds the target level of cities in developed countries (33).

Most previous studies, aside from (34), overlook the individual's motivation and frustration that is connected to travel. Even if older adults do not make trips out of the home, it is not necessarily because they have no need or demand for trips, but possibly because they do not have the transportation means or their transportation environment is unfavorable. Therefore, in this study, the event when a desired activity is impossible because there is no means of transportation is used as a subjective index to understand the mobility environment of older adults, similar to (34). This work analyzes individual, household, and built environment characteristics, and also how individuals' psychological differences influence the mobility of older adults, as suggested by (35).

3. METHODS

This research employs the method used by Kim (34) to establish a model that analyzes factors that influence transportation deficiency defined as occasional or frequent instances of being unable to engage in desired out-of-home activities due to no means of transportation.

To investigate the relationship between the transportation deficiency of older adults and various influential factors data were collected using a face-to-face interview survey of adults 65 years old or older who live in Seoul. The survey interviews were taken in May and June 2011. A professional survey company was hired to perform the survey.

Participants were randomly sampled from a list of Seoul residents, 65 years or older in all 25 "Gu" administrative districts of Seoul but with the constraint that the sample shares for age, gender, and population within each "Gu" district matched the Seoul population census.

The company contacted sampled individuals with a phone call and asked for the person's participation. A face-to-face meeting took place where a surveyor interviewed the respondent, normally at the respondents home but interviews also took place at senior citizen centers, and in public places.

The questionnaire was composed of a total of 160 questions about individual characteristics (age, gender, occupation, education, marital status, driving capability, etc.), household characteristics (household form and number of family members, total monthly income, number of cars, duration of residence, etc.), transportation characteristics (trip

frequency by trip purpose, transportation means, travel time, trip costs, etc.), built environment characteristics (slope, separation of pedestrians and vehicles, illegal parking etc.), and psychological aspects (environmentalist, independency, etc.). After eliminating missing values, a total of 812 observations were available for analysis.

Responses on how often older adults could not engage in desired out-of-home activities because they had no means of transportation were collected using a four-point Likert scale (*never, rarely, occasionally, frequently*). Few respondents answered with ‘*frequently*’ and this category was grouped with the category of ‘*occasionally*’ for analysis. The resultant variable was titled “transportation deficiency” and is the dependent variable in the following analysis. Two analytical models were used to explore the influence of various factors on transportation deficiency: a binary logistic regression model and an ordered logit model.

Binary Logistic Regression Model

When the dependent variable has two types of values or a value between 0 and 1, the binary logistic regression model is appropriate (36). This is perhaps the most widely used model to estimate the relationship between a binary dependent and various independent variables. In this work the binary dependent variable is developed by grouping responses when the person experienced transportation deficiency (*frequently* or *occasionally*) and when the person didn’t (*never* or *rarely*). The model is defined with the following equation (36):

$$P_n = \frac{e^{\beta \mathbf{x}_n}}{1 + e^{\beta \mathbf{x}_n}}, \quad (1)$$

where P_n is the probability that older adult n will experience transportation deficiency, β is a vector of estimable coefficients, and $\mathbf{x}_n$ is a vector of independent variables for person n . To explain the impact of the independent variables the odds ratio is used:

$$\frac{P_n}{1 - P_n} = e^{\beta \mathbf{x}_n}, \quad (2)$$

which leads to the straightforward interpretation that, all else being equal, the probability that a person will indicate a transportation deficiency goes up with an increase in a variable if the variable’s coefficient is positive, and vice versa. An odds ratio greater than 1.0 indicates a higher probability of transportation deficiency than non-deficiency.

Ordered Logit Model

The ordered logit model is appropriate for use with dependent variables that have an order, such as a dependent variable surveyed with a Likert Scale (e.g. *never, rarely, occasionally* or *frequently*) (37). The model is defined in a general way based on a dependent variable, y_n , which has observable ordered values $0, 1, 2, \dots, J$, and is linked to a latent, unobserved variable, U_n (38):

$$\begin{aligned}
y_n &= 0 \text{ if } U_n \leq 0, \\
&= 1 \text{ if } 0 < U_n \leq \mu_1, \\
&= 2 \text{ if } \mu_1 < U_n \leq \mu_2, \\
&= \dots \\
&= J \text{ if } \mu_{J-1} < U_n,
\end{aligned} \tag{3}$$

where μ_j are estimable threshold parameters. U_n has a linear-in-parameter form and is expressed as a function of estimable coefficients, β , and observable variables, $\mathbf{x}_n$:

$$U_n = \beta \mathbf{x}_n + \varepsilon_n, \tag{4}$$

where ε_n is an error term. If ε_n is assumed to be independently and identically logistically distributed, this leads to the ordered logit, and the probability that y_n becomes j is (38–39):

$$P_n(y_n = j) = P_n(\mu_{j-1} < U_n < \mu_j) = F\left(\frac{\mu_j - \beta \mathbf{x}_n}{s}\right) - F\left(\frac{\mu_{j-1} - \beta \mathbf{x}_n}{s}\right), \tag{5}$$

where F is the cumulative distribution function of the logistic distribution and s is the scale parameter of the error term.

To aid interpretation of results, the average direct pseudo-elasticity which is the percentage change in probability when the indicator variables changes by unity (40), is calculated.

Principal Component Analysis

To develop an understanding of the psychological aspects and opinions of older adults, the survey contains several questions with responses on the four-point Likert scale (*‘Strongly Agree’*, *‘Agree’*, *‘Disagree’*, *‘Strongly Disagree’*). The survey avoided direct questions about psychological aspects because these would likely distort the results (41). For example, to understand the participants’ opinions regarding the environment, the survey did not directly ask “Do you feel that the environment is an important issue?”, and instead asked “I voluntarily participate in recycling trash outside of my house” in order to elicit opinion through actual behavior. Indirect questioning has several questions representing one idea. The related questions are combined into a single latent factor using Principal Component Analysis (PCA) (42). These latent factors were tested in both models.

4. DATA DESCRIPTION

Table 1 shows the descriptive statistics of all variables tested for the 812 participants. The variables are cross-classified by the dependent variable for transportation deficiency (the exact question is: ‘I cannot do the activities I desire because I don’t have the transportation means’) which was coded as one of three categories: *‘Never’*, *‘Rarely’*, and *‘Occasionally or Frequently’* as explained in the Methods. Before discussing the individual variables it is noted that the responses for the dependent variable were that 43.2% responded with *‘Never’*, 46.4% responded with *‘Rarely’*, and 10.3% responded with *‘Occasionally or Frequently’*.

The survey results indicate that transportation deficiency increases with age (age 65-79: 9.6%, age 70-79: 11.7%, age 80 and over 12.2%). Women report transportation deficiency more frequently (11.0%) than men (9.4%). Employed people report transportation deficiency less frequently (7.6%) than those unemployed (11.9%). Fewer people living with a spouse report transportation deficiency (8.6%) than widows/widowers (15.9%). Logically fewer people with a driver's license report a transportation deficiency (8.4%) than those without a license (11.4%). Similarly, people with a physical disability report transportation deficiency more frequently (28.6%) than those without disabilities (9.0%). The lower the household monthly income, the more people report experiencing transportation deficiency (under \$1,000: 15.8%; \$1,000-\$2,000: 11.0%; \$2,000-\$3,000: 13.9%; \$3,000-\$4,000: 5.7%; \$4,000 and over: 4.9%).

Regarding public transit, participants who do not know how to get to a desired destination using transit report transportation deficiency (18.1%) more often than those that know the system (8.0%) and similar trends are indicated when people are within a viable walking distance of subway stations or bus stop. Neighborhood services, such as a senior citizens' center, may also render transportation less needed and are thereby associated with lower frequency of transportation deficiency.

Table 2 shows a total of 18 factors that display the behavior and psychological aspects of the participants as developed by PCA. The factor score of older adults are estimated by using regression (43), and are used as psychological propensity variables in order to establish a model that can account for a transportation deficiency.

5. RESULTS

Table 3 shows the results for the models used to analyze the factors that influence transportation deficiency among older adults. The models with the latent factors were statistically superior to the models without the latent factors. Since the binary logistic regression and the ordered logit model are not hierarchical to each other their likelihoods cannot be directly compared with a likelihood ratio test. A chi-square test (χ^2) of the goodness-of-fit indicates the ordered logit model may be superior to the binary logistic regression model but the difference is not important as both models perform well. To increase the efficiency of the estimated coefficients, coefficients not found statistically significant at the 0.1 level were constrained to zero. No multicollinearity problems were present between the independent variables. The odds ratio of the binary logistic regression and the average direct pseudo-elasticity for the ordered logit model are presented in Table 4. Table 5 summarizes the factors that influence the probability that older adults experience transportation deficiency.

Individual Characteristics

Gender and age have relatively smaller influence on transportation deficiency experience compared to health and financial factors. The age of an older adult was statistically significant only in the ordered logit model with latent factors. According to the ordered logit model with latent factors, if an older adult's age is 75 or older, the probability of transportation deficiency is higher than for those who are younger (elasticity 44.8%), but this age effect is lower than the effect of physical disability (elasticity 98.2%) and financial

ability (household income below \$2,000 per month, elasticity 69.3%). This may be because the physical capabilities of older adults can differ greatly even among those at the same age. Therefore, it can be inferred that the factor that affects the probability of transportation deficiency is not age itself, but rather health status.

Because driving status has a close relationship with the traveling environment, the probability of experiencing transportation deficiency increases (odds ratio 2.005) for males who have given up driving. When asked why they gave up driving, 58% responded with 'voluntarily gave up due to safety' which is the majority of all participants. Other reasons included 'disease or disorder' (17%), 'advice from other people' (14%), and 'financial reasons' (11%).

Household Characteristics

Older adults who live with their spouse had a lower probability of transportation deficiency (odds ratio 0.613 and elasticity -24.2%). Older individuals in low-income households, whose total monthly income is \$2,000 or less, and in households with children, who are high school students or younger, are more likely to suffer transportation deficiency (odds ratio 2.33 and elasticity 69.3%). The reason may be because the older adults play a role in taking care of the children (34).

Older adults who have lived in the same community for 20 years or more had a decreased probability of experiencing transportation deficiency (elasticity -27.5%), which may be because they have established a social network over time in the community (34).

Public Transit Characteristics

Older adults who know how to use public transportation to go to destinations had a decreased probability of experiencing transportation deficiency (odds ratio 0.526 and elasticity -23.5%). Also when the subway was within easy walking distance, the probability of transportation deficiency was shown to decrease (elasticity -41.7%). This indicates that both physical accessibility as well as cognitive (information) accessibility is important. This implies that while expanding infrastructure is important for improving the travel conditions of older adults, publicizing/educating people about public transportation usage is also necessary.

Accessibility to subway stations had a statistically significant impact on older adults' transportation deficiency but accessibility to a bus stop was not statistically significant. This is because many facilities that make access more convenient, such as elevators, have been set up at subway stations but not at bus stops. Moreover, a passenger's step when getting on and off buses could be uncomfortably high until low-floor buses are generally in service. Another reason is that older adults can use the subway system for free in Korea but there is no discount benefit for buses. It was shown that the greater the discontent, or inconvenience, with public transportation, the greater the probability of transportation deficiency (odds ratio 1.575 and elasticity 1.6%). Therefore, the comfort and convenience of public transportation services must increase to satisfy the needs of older adults.

Built Environment Characteristics

Areas with many hills/sloping roads are linked with increased probability of transportation deficiency (odds ratio 2.625). In areas where sidewalks are strictly separated from the roads, the probability of experiencing transportation deficiency increased (elasticity 34.0%) This may reflect that the separation might be designed to streamline traffic flow by allotting more space for vehicular traffic rather than improving the pedestrian environment.

When located within walking distance from places where one can meet other older adults, such as senior citizen centers or district meeting halls, it was found that the probability of experiencing transportation deficiency decreased (odds ratio 0.609 and - 27.2%).

Psychological Aspects (Latent Factors)

Older adults who tend to be active and who drive automobiles had increased probability of experiencing transportation deficiency compared to those who are pliable (e.g., obey traffic regulation, respect others' opinion). Community spirit (e.g., participating in volunteer activities) decreased transportation deficiency in the binary logistic regression (odds ratio 0.414), but slightly increased it in the analysis made by the ordered logit model (elasticity 2.0%). This is the only case where the two models showed opposite results for an estimated effect. Since the ordered logit model is statistically favored by the chi-squared test, and as the ordered logit is more statistically efficient here than the binary model, the conclusion is to favor the ordered logit result. Older adults who tend to be pliable have a decreasing probability of transportation deficiency because they can balance the external environment and social context, and receive sufficient compensation for the utility loss that occurs due to not participating in out-of-home activities (8, 44–45).

6. DISCUSSION AND CONCLUSIONS

This study examines characteristics associated with older adults' transportation deficiency, here defined as occurring if the respondent frequently or occasionally cannot engage in desired out-of-home activity due to lacking the transportation means. The investigated characteristics describe the individual, household, public transport, built environment, and psychological aspects.

A binary logistic regression and an ordered logit model were used. A chi-squared test of goodness-of-fit slightly favored the ordered logit model. The results show that the size and direction of effects in both models are similar in most cases. However, a few variables were not statistically significant in one model while being significant in the other (e.g., age ≥ 70 and years, lived in local community ≥ 20 years). Also, in the case of community spirit, the results showed a small but opposing impact on transportation deficiency. The results are stronger when using the older adults' psychological descriptors, developed as latent factors with PCA.

The ordered logit model is favored here over the simpler binary logistic regression. If the number of observations is enough for an ordered logit model, it performs better and is more statistically efficient than the binary logistic model which combines categories. The ordered logit model therefore analyzes greater variance in the dependent variable and its resulting added efficiency leads to it being able to describe the effects better. However,

with smaller datasets, using the simplified binary analysis would be appropriate and by-and-large the results are quite comparable between models.

The probability of experiencing transportation deficiency decreases when the older adult knows how to go to a certain destination using public transportation, when a subway station is located within easy walking distance, when the person has lived in the same neighborhood for more than 20 years, or when places where one can meet other older adults, such as senior citizen centers or district meeting halls, are located within easy walking distance.

The probability of experiencing transportation deficiency increases for people who are older than 75, are males who have given up driving, for people who have a physical disability, have a total monthly household income of \$2,000 or less, live with children who are high school students or younger, or live in areas where there are many hills and slopes in the neighborhood.

Policies should be customized for each age group (e.g., 65–74, 75 or older) to recognize their differences (25). Also, policies need to take varying health and physical abilities into account and cannot simply be a one-size-fits-all for all who are 65 or older.

There was a large difference in mobility depending on the financial capability of older adults. Places where there are many low-income older adults must provide a public transportation system that enables the use of public transit for everyday activities like shopping and healthcare (46). It is also recommended that older adults receive lower cost or even free transportation in the bus system and not only in the subway system. This is important since the bus system serves the near neighborhood better but the subway system is designed to take people across the city and between neighborhoods.

A policy consideration that can enhance not only physical accessibility of public transportation but also cognitive accessibility (obtaining public transportation information) is required. While public transportation information systems are well established in the urban areas of Korea, it was found that older adults have difficulties accessing information on public transportation. Therefore, a policy review on enhancing the cognitive approach to fit the needs of older adults, e.g. with offline guidance and educational plans, is necessary (47–48). This is especially important for the bus system, which is more complex than the subway system.

A key mode of transport for older adults is walking, perhaps even more so than public transport. Walking carries with it no out-of-pocket costs, and brings health benefits that directly translate into daily life. Efforts that improve the pedestrian environment and access to parks, activity centers and services by walking will be beneficial, not only for older adults, but all residents in general.

According to the results, transportation deficiency increases especially for males who give up driving. This may in part be a psychological or expectation issue that must be dealt with for the general population during their lifetime, as this experience may be hard to overcome if it is only tackled at the point of no longer being able to drive. There must be available adequate mobility options for people who no longer drive. Buses were found to not have an impact on enhancing the mobility of older adults, which reflects that the current bus transit system is not satisfying the demands of older adults. If the bus transit system is to be a good option for older adults it needs to be improved, for example by

introducing low-floor buses (49), and organizing signs and sidewalks to facilitate access to bus stops (50), and through better information systems. In local areas where public transportation conditions are insufficient, a paratransit system with door-to-door service should be supplied (51).

It is recommended that a training program be provided so that capable, healthy older adults can safely drive (52), in conjunction with improvements in the driver's licensing system to ensure that older drivers at elevated risk for causing traffic crashes can be identified and their driving restricted appropriately (17).

Older adults suffer less from transportation deficiency in areas where there are senior citizen centers and parks within easy walking distance. This highlights the previous point that walking is a key mode of transport for older adults. In this context, community facilities should be planned and located considering older adults' walking distance. Furthermore, a safe and barrier-free walking environment must be provided (53). Generally, the pedestrian environment needs improvement especially in areas where older adults are concentrated.

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572 **TABLE 1 Descriptive Statistics**

Variables		Never	Rarely	Occasionally Frequently	Total
Transportation deficiency		351 (43.2%)	377 (46.4%)	84 (10.3%)	812 (100%)
Individual characteristics					
Age	65–69	228 (42.9%)	253 (47.6%)	51 (9.6%)	532 (65.5%)
	70–79	110 (46.0%)	101 (42.3%)	28 (11.7%)	239 (29.4%)
	80 ≤	13 (31.7%)	23 (56.1%)	5 (12.2%)	41 (5.0%)
	Average age*				69.2 (4.97)
Gender	Male	161 (48.8%)	138 (41.8%)	31 (9.4%)	330 (40.6%)
	Female	190 (39.4%)	239 (49.6%)	53 (11.0%)	482 (59.4%)
Employed (incl. self-employed)	Yes	122 (42.2%)	145 (50.2%)	22 (7.6%)	289 (35.6%)
	No	229 (43.8%)	232 (44.4%)	62 (11.9%)	523 (64.4%)
Retirement age	Average age*				60.0 (6.10)
Education level	Middle school (or less)	158 (39.8%)	192 (48.4%)	47 (11.8%)	397 (48.9%)
	High school graduate	153 (43.3%)	168 (47.6%)	32 (9.1%)	353 (43.5%)
	College graduate	38 (65.5%)	16 (27.6%)	4 (6.9%)	58 (7.1%)
	Graduate school graduate	2 (50.0%)	1 (25.0%)	1 (25.0%)	4 (0.5%)
Marital status	Married & living with spouse	280 (45.5%)	283 (45.9%)	53 (8.6%)	616 (75.9%)
	Widow/widower	71 (36.4%)	93 (47.7%)	31 (15.9%)	195 (24.0%)
	Unmarried	0 (0.0%)	1 (100.0%)	0 (0.0%)	1 (0.1%)
Driver's license	Yes	141 (49.5%)	120 (42.1%)	24 (8.4%)	285 (35.1%)
	No	210 (39.9%)	257 (48.8%)	60 (11.4%)	527 (64.9%)
	Average age of acquiring license*				36.4 (0.08)
Driving status of licensed drivers	Driving	108 (53.2%)	81 (39.9%)	14 (6.9%)	203 (71.2%)
	Given up driving	33 (40.2%)	39 (47.6%)	10 (12.2%)	82 (28.8%)
	Average age of giving up driving*				60.6 (0.09)
Assets	< \$10,000	4 (15.4%)	18 (69.2%)	4 (15.4%)	26 (3.2%)
	\$10,000–\$50,000	20 (35.1%)	26 (45.6%)	11 (19.3%)	57 (7.0%)
	\$50,000–\$100,000	33 (37.1%)	47 (52.8%)	9 (10.1%)	89 (11.0%)
	\$100,000–\$200,000	52 (41.9%)	56 (45.2%)	16 (12.9%)	124 (15.3%)
	\$200,000–\$300,000	56 (36.8%)	78 (51.3%)	18 (11.8%)	152 (18.7%)
	\$300,000–\$500,000	108 (52.4%)	88 (42.7%)	10 (4.9%)	206 (25.4%)
	\$500,000–\$1,000,000	51 (45.1%)	49 (43.4%)	13 (11.5%)	113 (13.9%)
	\$1,000,000 ≤	26 (59.1%)	15 (34.1%)	3 (6.8%)	44 (5.4%)
Regular monthly income	Allowance from spouse/sons/daughters	254 (43.8%)	266 (45.9%)	60 (10.3%)	580 (36.5%)
	Salary	121 (41.7%)	147 (50.7%)	22 (7.6%)	290 (18.2%)
	Lease, bank, fund, etc.	161 (48.8%)	141 (42.7%)	28 (8.5%)	330 (20.7%)
	National subsidy	165 (42.2%)	178 (45.5%)	48 (12.3%)	391 (24.6%)
Physical disability	Yes	11 (19.6%)	29 (51.8%)	16 (28.6%)	56 (6.9%)
	No	340 (45.0%)	348 (46.0%)	68 (9.0%)	756 (93.1%)
Use cane	Yes	12 (24.0%)	27 (54.0%)	11 (22.0%)	50 (6.2%)
	No	339 (44.5%)	350 (45.9%)	73 (9.6%)	762 (93.8%)
Take medication for chronic disease	Yes	172 (47.8%)	147 (40.8%)	41 (11.4%)	360 (44.3%)
	No	179 (39.6%)	230 (50.9%)	43 (9.5%)	452 (55.7%)

(Continued)

575 **TABLE 1 Descriptive Statistics (*Continued*)**

Variables		Never	Rarely	Occasionally Frequently	Total
Easy walking distance for respondent	< 500 m	18 (24.7%)	33 (45.2%)	22 (30.1%)	73 (9.0%)
	500 m–1,000 m	119 (34.9%)	181 (53.1%)	41 (12.0%)	341 (42.0%)
	10,000 m–2,000 m	146 (51.8%)	117 (41.5%)	19 (6.7%)	282 (34.7%)
	20,000 m ≤	68 (58.6%)	46 (39.7%)	2 (1.7%)	116 (14.3%)
Able to climb stairs	One floor	12 (24.0%)	29 (58.0%)	9 (18.0%)	50 (6.2%)
	Two floors	110 (37.9%)	146 (50.3%)	34 (11.7%)	290 (35.8%)
	Three floors	146 (43.6%)	154 (46.0%)	35 (10.5%)	335 (41.3%)
	Four floors	82 (60.3%)	48 (35.3%)	6 (4.4%)	136 (16.8%)
<i>Household characteristics</i>					
Number of adults in household	One	37 (30.8%)	60 (50.0%)	23 (19.2%)	120 (14.8%)
	Two	207 (42.5%)	229 (47.0%)	51 (10.5%)	487 (60.0%)
	Three or more	107 (52.2%)	88 (42.9%)	10 (4.9%)	205 (25.2%)
Preschooler in household	Yes	19 (79.2%)	5 (20.8%)	0 (0.0%)	24 (3.0%)
	No	332 (42.1%)	372 (47.2%)	84 (10.7%)	788 (97.0%)
Child(ren) under 18 years old in household	Yes	38 (55.9%)	24 (35.3%)	6 (8.8%)	68 (8.4%)
	No	313 (42.1%)	353 (47.5%)	78 (10.5%)	744 (91.6%)
Household monthly income	< \$1,000	46 (34.6%)	66 (49.6%)	21 (15.8%)	133 (16.4%)
	\$1,000–\$2,000	92 (38.8%)	119 (50.2%)	26 (11.0%)	237 (29.2%)
	\$2,000–\$3,000	54 (34.2%)	82 (51.9%)	22 (13.9%)	158 (19.5%)
	\$3,000–\$4,000	76 (53.9%)	57 (40.4%)	8 (5.7%)	141 (17.4%)
	\$4,000 ≤	83 (58.0%)	53 (37.1%)	7 (4.9%)	143 (17.6%)
Number of automobiles	Zero	168 (38.4%)	215 (49.2%)	54 (12.4%)	437 (53.8%)
	One	167 (48.4%)	149 (43.2%)	29 (8.4%)	345 (42.5%)
	Two or more	16 (53.3%)	13 (43.3%)	1 (3.3%)	30 (3.7%)
Available automobile whenever needed	Yes	167 (51.4%)	134 (41.2%)	24 (7.4%)	325 (40.0%)
	No	184 (37.8%)	243 (49.9%)	60 (12.3%)	487 (60.0%)
Housing type	Apartment	143 (48.3%)	117 (39.5%)	36 (12.2%)	296 (36.5%)
	Town house	68 (39.3%)	89 (51.4%)	16 (9.2%)	173 (21.3%)
	Luxury condo.	0 (0.0%)	1 (100.0%)	0 (0.0%)	1 (0.1%)
	Multiplex house	48 (37.8%)	62 (48.8%)	17 (13.4%)	127 (15.6%)
	Single family house	87 (42.2%)	104 (50.5%)	15 (7.3%)	206 (25.4%)
	Other	5 (55.6%)	4 (44.4%)	0 (0.0%)	9 (1.1%)
Home ownership	Own	290 (46.5%)	279 (44.8%)	54 (8.7%)	623 (76.7%)
	Rent	61 (32.3%)	98 (51.9%)	30 (15.9%)	189 (23.3%)
Years lived in local community	< 2 years	8 (57.1%)	6 (42.9%)	0 (0.0%)	14 (1.7%)
	2–5 years	32 (42.1%)	32 (42.1%)	12 (15.8%)	76 (9.4%)
	5–10 years	64 (37.0%)	89 (51.4%)	20 (11.6%)	173 (21.3%)
	10–20 years	133 (43.5%)	142 (46.4%)	31 (10.1%)	306 (37.7%)
	20–30 years	76 (46.6%)	73 (44.8%)	14 (8.6%)	163 (20.1%)
	30 years ≤	38 (47.5%)	35 (43.8%)	7 (8.8%)	80 (9.9%)
Previous housing type	Apartment	71 (44.9%)	72 (45.6%)	15 (9.5%)	158 (19.5%)
	Town house	71 (40.3%)	88 (50.0%)	17 (9.7%)	176 (21.7%)
	Luxury condo.	2 (100.0%)	0 (0.0%)	0 (0.0%)	2 (0.2%)
	Multiplex house	72 (44.4%)	69 (42.6%)	21 (13.0%)	162 (20.0%)
	Single family house	135 (43.8%)	144 (46.8%)	29 (9.4%)	308 (38.0%)
	Other.	0 (0.0%)	3 (75.0%)	1 (25.0%)	4 (0.5%)

(Continued)

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577

578 **TABLE 1 Descriptive Statistics (*Continued*)**

Variables		Never	Rarely	Occasionally Frequently	Total
Previous home ownership	Own	215 (45.7%)	213 (45.3%)	42 (8.9%)	470 (58.0%)
	Rent	136 (40.0%)	163 (47.9%)	41 (12.1%)	340 (42.0%)
Previous years lived in local community	< 2 years	1 (20.0%)	4 (80.0%)	0 (0.0%)	5 (0.6%)
	2–5 years	19 (32.2%)	30 (50.8%)	10 (16.9%)	59 (7.3%)
	5–10 years	68 (45.9%)	65 (43.9%)	15 (10.1%)	148 (18.2%)
	10–20 years	160 (40.0%)	196 (49.0%)	44 (11.0%)	400 (49.3%)
	20–30 years	78 (50.6%)	64 (41.6%)	12 (7.8%)	154 (19.0%)
	30 years ≤	25 (54.3%)	18 (39.1%)	3 (6.5%)	46 (5.7%)
<i>Public transit characteristics</i>					
Know how to get to destination by public transit	Yes	279 (44.7%)	295 (47.3%)	50 (8.0%)	624 (76.8%)
	No	72 (38.3%)	82 (43.6%)	34 (18.1%)	188 (23.2%)
Metro stations within easy walking distance	Yes	275 (51.3%)	215 (40.1%)	46 (8.6%)	536 (66.0%)
	No	76 (27.5%)	162 (58.7%)	38 (13.8%)	276 (34.0%)
Trunk/feeder bus stop within easy walking distance	Yes	330 (44.4%)	342 (46.0%)	72 (9.7%)	744 (91.6%)
	No	21 (30.9%)	35 (51.5%)	12 (17.6%)	68 (8.4%)
Shuttle bus stop within easy walking distance	Yes	296 (42.8%)	328 (47.4%)	68 (9.8%)	692 (85.2%)
	No	55 (45.8%)	49 (40.8%)	16 (13.3%)	120 (14.8%)
<i>Built environment characteristics</i>					
Many hills/sloping roads in community	Yes	51 (35.9%)	61 (43.0%)	30 (21.1%)	142 (17.5%)
	No	300 (44.8%)	316 (47.2%)	54 (8.1%)	670 (82.5%)
Strictly separated sidewalks from roads in community	Yes	249 (44.0%)	263 (46.5%)	54 (9.5%)	566 (69.7%)
	No	102 (41.5%)	114 (46.3%)	30 (12.2%)	246 (30.3%)
Furniture provided on sidewalks to take a rest	Yes	156 (41.1%)	184 (48.4%)	40 (10.5%)	380 (46.8%)
	No	195 (45.1%)	193 (44.7%)	44 (10.2%)	432 (53.2%)
Much illegal parking in community	Yes	113 (38.2%)	146 (49.3%)	37 (12.5%)	296 (36.5%)
	No	238 (46.1%)	231 (44.8%)	47 (9.1%)	516 (63.5%)
No dark spot in community due to lack of streetlights	Yes	269 (44.3%)	273 (45.0%)	65 (10.7%)	607 (74.8%)
	No	82 (40.0%)	104 (50.7%)	19 (9.3%)	205 (25.2%)
A park within walking distance	Yes	277 (45.8%)	272 (45.0%)	56 (9.3%)	605 (74.5%)
	No	74 (35.7%)	105 (50.7%)	28 (13.5%)	207 (25.5%)
Places to meet other older adults within easy walking distance (e.g., senior citizens' center, community center, etc.)	Yes	265 (45.9%)	262 (45.4%)	50 (8.7%)	577 (71.1%)
	No	86 (36.6%)	115 (48.9%)	34 (14.5%)	235 (28.9%)

Percentages are in parentheses. Percentages are calculated across categories (first three columns), and across categories of each variable (e.g. two rows for Yes–No variables) for the total frequency. Variables marked with * display mean (std. dev.) instead of frequency (percentage).

TABLE 2 Latent Factors Developed by Principal Component Analysis

Factor name	Questions (Factor loading value)
Automobile preference	I enjoy driving (0.861) I have an interest in driving (0.856) I make a hobby of driving (0.820) I think a car is more than just a means of transportation (0.775) I feel safe when I drive a car (0.753) I am protected by a car from bad weather (0.615) I believe a car guards my privacy (0.612)
Technology adopter	I use e-mail (0.801) I use internet banking (0.790) I frequently use the internet (0.754) I exchange a text message with family members and friends (0.624) I use a smartphone (0.622)
Activity propensity	I have many friends and acquaintances (0.745) Family members, relatives, and friends often visit me (0.719) I often contact family members, relatives, and friends (0.718) I often meet friends and acquaintances (0.700) I frequently have a dinner with other people (0.517)
Symbolic motive of automobile	I think car stands for its owner's social position and dignity (0.797) I envy those who drive a luxurious imported car (0.777) I judge people by his or her car (0.692) I think a car demonstrates who I am (0.616)
Community spirit	I have been joining a nonprofit organization (0.804) I do volunteer work (0.784) I used to be a leader of a nonprofit organization (0.608)
Obey traffic regulation	I do not understand why people speed (0.760) I do not understand why people drink and drive (0.696) I do not understand why people do not obey traffic rules (0.677)
Environmentalism	I try not to use a disposable product such as a disposable cup, wooden chopsticks, (0.756) I try to conserve water (0.713) I try to reduce unnecessary power use (0.701) I voluntarily separate trash even outside of my house (0.500)
Dissatisfaction about public transit	I feel a bus is uncomfortable (0.759) I think a bus fare is expensive (0.642) I feel a subway is inconvenient (0.635) I dislike paying transportation costs (e.g., fuel cost, parking cost, bus fare, etc.) (0.601)
Sensitivity to pollution	I hate exhaust gas (0.810) I hate air pollution (0.807)
Dangerous driving	I often drive while intoxicated (0.840) I often exceed the speed limit (0.802)
Passiveness	I prefer reading a book or watching TV alone to doing something with others (0.728) I feel more comfortable when doing nothing at home than doing something outside (0.698)
Healthy condition	I have good physical condition (0.669) I feel awkward when people offer their seats in a subway to me (0.523)
Parsimonious propensity	I dislike attending a meeting with a membership fee (0.665) I cannot understand the people who like eating out (0.580)
Competitive spirit	I get upset when other cars pass my car (0.665)
Respect others' opinion	I think the youth of nowadays are better than when we were young (0.741) I am easily receptive to someone's advice or opinion (0.575)
Healthy concerns	I am concerned about getting into a traffic accident (0.687) I am exercising regularly (0.519)
Public transit preference	I feel public transit is safer than a car (0.674) I keep public transit in mind for deciding a meeting place (0.592)
Independence	I dislike depending on others (0.714)

Factor analysis method: Principal Component Analysis rotated by Varimax with Kaiser Normalization. Only factor loading values which are more than 0.5 are showed. Factor loading value is ().

586 **TABLE 3 Transportation Deficiency Model Estimation Results**

Variables	Binary Logistic		Ordered Logit	
	w/o latent factors	w/ latent factors	w/o latent factors	w/ latent factors
Constant	-1.733(0.412)‡	-1.864(0.426)‡		
Individual characteristics				
Age ≥ 75				0.418(0.224)
Easy walking distance < 500m	1.064(0.332)‡	0.980(0.344)‡	0.729(0.261)‡	0.684(0.271)†
Easy walking distance $\geq 1,000$ m	-0.727(0.292)†	-0.705(0.299)†	-0.607(0.149)‡	-0.517(0.164)‡
Physical disability	0.989(0.357)‡	0.911(0.368)†	1.070(0.283)‡	0.782(0.299)‡
Male * Given up driving	0.695(0.415)			
Household characteristics				
Live with spouse	-0.552(0.268)†	-0.489(0.274)		-0.312(0.176)
Household income below \$2,000 per month	0.682(0.281)†	0.846(0.298)‡	0.697(0.144)‡	0.581(0.158)‡
Child(ren) under 18 years old in household		0.850(0.528)		
Years lived in local community ≥ 20 years				-0.358(0.170)†
Public Transit Characteristics				
Know how to get to destination by public transit	-0.684(0.261)‡	-0.642(0.265)†	-0.274(0.168)	-0.302(0.181)
Metro stations within easy walking distance		-0.496(0.266)	-0.774(0.148)‡	-0.607(0.164)‡
Built environment characteristics				
Many hills/sloping roads in community	0.965(0.276)‡			
Strictly separated sidewalks from roads in community				0.325(0.172)
Places to meet other older adults within easy walking distance (e.g., senior citizens' center, community center, etc.)	-0.454(0.263)		-0.448(0.154)‡	-0.357(0.168)†
Latent factors				
Technology adopter				0.128(0.075)
Activity propensity				0.209(0.078)‡
Symbolic motive of automobile				0.171(0.078)†
Community spirit		0.346(0.130)‡		0.342(0.077)‡
Obeys traffic regulation				-0.366(0.078)‡
Environmentalism				-0.198(0.077)‡
Dissatisfaction about public transit		0.454(0.137)‡		0.269(0.078)‡
Sensitivity to pollution		-0.412(0.131)‡		-0.350(0.076)‡
Parsimonious propensity				0.218(0.077)‡
Competitive spirit				0.284(0.077)‡
Respect others' opinion		-0.246(0.138)		-0.146(0.075)
Independence				-0.142(0.078)
Threshold, μ_1			-1.136(0.236)‡	-1.114(0.304)‡
μ_2			1.636(0.244)‡	1.956(0.312)‡
Number of observations	812	812	812	812
Log-likelihood for constants only	-270.066	-270.066	-774.213	-774.213
Log-likelihood at convergence	-226.706	-218.538	-706.350	-647.562
Adjusted ρ^2	0.127	0.146	0.079	0.134
Likelihood ratio statistics (χ^2)	w/o latent: 86.72 (d.f.=9)		w/o latent: 135.73 (d.f.=7)	
	(p-value ≤ 0.0001)		(p-value ≤ 0.0001)	
	w/ latent: 103.06 (d.f.=12)		w/ latent: 253.30 (d.f.=23)	
	(p-value ≤ 0.0001)		(p-value ≤ 0.0001)	

587 Standard errors are in parentheses. Level of significance: all with p-value greater than 90%, † > 95%, and ‡
588 > 99%. Coefficients that weren't significant at the 90% p-value level were restricted to zero and omitted from
589 the model.

590 **TABLE 4 Odds Ratio and Average Direct Pseudo-Elasticity of Variables**

Variables	Odds ratio of binary logistic regression	Elasticity of ordered logit model		
		Frequently/ Occasionally	Rarely	Never
<i>Individual characteristics</i>				
Age ≥ 75		44.8%	14.0%	-21.6%
Walkable distance < 500m	2.663	82.5%	22.1%	-33.8%
$\geq 1,000\text{m}$	0.494	-37.1%	-14.6%	35.1%
Physical disability	2.488	98.2%	24.6%	-38.0%
Male * Given up driving*	2.005			
<i>Household characteristics</i>				
Live with spouse	0.613	-24.2%	-8.7%	20.3%
Household income below \$2,000 per month	2.331	69.3%	24.1%	-27.1%
Child(ren) under 18 years old in household	2.340			
Years lived in local community ≥ 20 years		-27.5%	-11.1%	22.4%
<i>Public transit characteristics</i>				
Know how to get to destination by public transit	0.526	-23.5%	-8.4%	19.5%
Metro stations within easy walking distance		-41.7%	-15.3%	44.2%
<i>Built environment characteristics</i>				
Many hills/sloping roads in community	2.625			
Strictly separated sidewalks from roads in community		34.0%	12.6%	-16.2%
Places to meet other older adults within easy walking distance (e.g., senior citizens' center, community center, etc.)	0.609	-27.2%	-9.8%	23.5%
<i>Latent factors</i>				
Technology adopter		0.8%	2.3%	-3.1%
Activity propensity		1.2%	3.8%	-5.1%
Symbolic motive of passenger vehicle		1.0%	3.1%	-4.1%
Community spirit	0.414	2.0%	6.3%	-8.3%
Obey traffic regulation		-2.1%	-6.7%	8.9%
Environmentalism		-1.2%	-3.6%	4.8%
Dissatisfaction about public transit	1.575	1.6%	4.9%	-6.5%
Sensitivity to pollution	0.663	-2.1%	-6.4%	8.5%
Parsimonious propensity		1.3%	4.0%	-5.3%
Competitive spirit		1.7%	5.2%	-6.9%
Respect others' opinion	0.782	-0.9%	-2.7%	3.5%
Independence		-0.8%	-2.6%	3.4%

591 Odds ratio was calculated based on the binary logistic model w/ latent factors except the variable marked
592 with *, which was based on the binary logistic model w/o latent factors as it was not significant in the model
593 w/ latent factors. Elasticities were calculated based on the ordered logit model w/ latent factors. Direct
594 pseudo elasticities were applied except for latent variables, which were calculated as marginal effects.
595

596 **TABLE 5 Selected Variable Effects on the Probability of Transportation Deficiency**

Variables	Binary Logistic Regression	Ordered Logit Model		
		Frequently/ Occasionally	Rarely	Never
<i>Individual characteristics</i>				
Age ≥ 75		↑	↑	↑
Easy walking distance < 500m	↑	↑	↑	↓
≥ 1,000m	↓	↓	↓	↑
Physical disability	↑	↑	↑	↓
Male * Given up driving*	↑			
<i>Household characteristics</i>				
Live with spouse	↓	↓	↓	↑
Household income below \$2,000 per month	↑	↑	↑	↓
Child(ren) under 18 years old in household	↑			
Years lived in local community ≥ 20 years		↓	↓	↑
<i>Public transit characteristics</i>				
Know how to get to destination by public transit	↓	↓	↓	↑
Metro stations within easy walking distance		↓	↓	↑
<i>Built environment characteristics</i>				
Many hills/sloping roads in community	↑			
Strictly separated sidewalks from roads in community		↑	↑	↓
Places to meet other older adults within easy walking distance (e.g., senior citizens' center, community center, etc.)	↓	↓	↓	↑
<i>Latent factors</i>				
Community sprit	↓	↑	↑	↓
Dissatisfaction about public transit	↑	↑	↑	↓

597 Arrows show increase (up) or decrease (down) in elasticity and shading indicates change greater than 50%.
598 The variable marked with *, was based on the binary logistic regression w/o latent factors.

**The Effect of Road Environment Factors on Freeway Traffic Crash Frequency
during Daylight, Twilight, and Night Conditions**

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ABSTRACT

This research investigated the effect of road environment factors on freeway traffic crashes in Korea during the years 2007 through 2010 under the light conditions: daylight, twilight, night, and for comparison the whole 24 hour day. Both random and fixed parameter crash frequency models were estimated and applied in the analysis.

Several factors had statistically significant effects only during certain light conditions, notably, number of interchanges/junctions and number of bridges during daylight; traffic share of heavy vehicles during night and the whole 24 hour period; short tangent (<1,421 m) and number of crest vertical curves during twilight. Several factors were statistically significant regardless of light conditions, notably, traffic share of light vehicles, number of lanes, urban area, frequent fog in area, and number of days with snowfall. The random parameter model structure was found to be important because several factors had random effects: traffic share of light vehicles, number of lanes, urban area, and foggy area. Foggy areas were associated with increased crash frequencies in about 75% of sections and reduced crash frequencies in about 25%.

The results indicate that roadway design should avoid combining horizontal and sag vertical curves due to higher crash frequency. The varying effect of road environment factors on crash frequency by light condition should be used to improve driver information systems, for example, during daylight drivers need more information about upcoming interchanges/junctions.

Keywords: Light conditions; Accident frequency; Random parameter models; Traffic safety; Road geometrics

INTRODUCTION

Overall traffic crashes and freeway traffic crashes in Korea increased by approximately 7.2% during 2007 – 2010. Despite this increase, the fatalities of all traffic crashes in Korea decreased by 10.7% whereas the fatality of freeway traffic crashes decreased by 7.4%. Thus, countermeasures to improve traffic safety on freeways are still needed (1).

The Poisson regression model and negative binomial regression model have been commonly used as crash frequency models to investigate the number of traffic crashes occurring in roadway sections during a particular time period (2-7). Crash datasets for frequency analysis require a definition of the roadway sections. One way is to divide the road into homogeneous sections based on factors such as traffic volume and geometric design elements (8-9). The other major way is to divide the road into sections of a fixed length (2, 10).

The homogeneous section method has the merit that the properties within each section are identical. However, this method has several problems, including the crash locational error problem and unequal sample sizes (2, 11). The fixed length method has its own strengths, some of which can make up for the weaknesses of the homogeneous method to a certain extent. However, when the roadway section is long, many design attributes can have complicated interrelations and the statistical significance of geometry may be hard to measure. If the section is short, the number of crashes would be few—even zero—in many sections leading to its own branch of analytical problems (2); in part this occurs because the reported crash location may not be accurate since typically, crashes are reported to the nearest milepost.

Commonly the Poisson and the negative binomial regressions have been used with fixed parameters, meaning that each parameter has the same influence on the

occurrence of traffic crashes in all sections. Recently there have been safety applications using random parameter models in order to reflect reality better (12), but studies on crash frequency using random parameters are still rare. A random parameter frequency model has better interpretive power due to the ability to encompass heteroskedasticity (13, 14).

Previous studies have shown there is a relationship between traffic accident frequency, injury severity, and time of day (15-17). Also, driving behavior is different depending on time of day (18, 19). The objective of this research is to investigate the effect of road environment factors on freeway traffic crashes to find how or if the effect varies under different light conditions.

The next section describes the data available for study, followed by a description of the research method. This is followed by a presentation of the results and conclusions of this work.

DATA

The data contain information about traffic crash frequencies on several freeways in the Republic of Korea in the years 2007 through 2010. The freeways are the Seohaean Freeway, Jungbu Freeway (except the Jungbu Freeway connecting the cities of Daejeon and Tongyeong), and the Jungbu-naeryuk Freeway. These freeways have a uniform speed limit of 110 km/h. The section connecting Kimcheon and Hyunpoong junctions on the Jungbu-naeryuk Freeway of 2007 was excluded because this section was not open for operation until December of 2007.

Each crash is coded with a primary cause. The purpose of this paper is to investigate the effect of road environment on crash causation under different light conditions. For this reason the dataset included only crashes where neither driver nor vehicle was noted as the primary cause of the crash. This means that crashes noted as being caused by a vehicle malfunction were excluded and so were crashes caused by direct illegal or unsafe behavior (e.g. drunk driving). The total number of traffic crashes for analysis was 6,158. It should be noted that these are not the observations since several crashes can occur in the same roadway section, which is the unit of analysis.

The freeway system was divided into fixed length sections of 10 km in length in the available dataset and this somewhat large section length must be dealt with in the analysis. There were 281 roadway sections available for analysis.

A fixed section length has the benefits of minimizing crash location errors, sample size differences, and heteroskedasticity (2). This, coupled with the observation **time period of one year**, avoids an abundance of sections with zero crashes. The limitation of a long section is that roadway geometrics and traffic variables vary within the section. The data however contain information on the roadway geometrics within each section which helps capture the within-section variation.

The dependent variable was the number of traffic crashes that occurred in each road section **in each year over the period of 2007 through 2010**. The independent variables were characteristics of the traffic, roadway geometrics, and environment. Definitions and descriptive statistics of the variables are shown in Table 1.

146 **TABLE 1 Descriptive statistics of data for the 281 roadway sections**

	Mean	St.Dev.	Min.	Max.
Dependent Variable				
Number of crashes (daylight)	9.58	7.08	0	45
Number of crashes (night)	8.16	5.37	0	30
Number of crashes (twilight)	4.17	3.33	0	21
Number of crashes (24 hours)	21.91	14.10	2	92
Traffic Characteristics				
AADT (AADT/1,000)	39.59	26.47	8.69	140.36
Traffic share of light vehicles	0.81	0.06	0.63	0.95
Traffic share of medium vehicles	0.15	0.04	0.04	0.27
Traffic share of heavy vehicles	0.04	0.02	0.00	0.12
Geometric Characteristics				
Number of lanes	2.83	0.93	2	4
Number of interchanges/junctions	1.02	0.72	0	3
Trumpet type interchanges	0.78	0.56	0	3
Interchange/junctions (except Trumpet type)	0.23	0.52	0	2
Short tangents ($L < 1,421$ m)	3.25	1.96	0	8
Medium tangents ($1,421 \leq L < 4,000$ m)	1.30	0.92	0	3
Long tangents ($4,000 \text{ m} \leq L$)	0.12	0.37	0	2
Short radius curves ($R < 4,000$ m)	3.77	1.97	0	9
Medium radius curves ($4,000 \leq R < 10,200$ m)	0.79	0.85	0	3
Long radius curves ($10,200 \text{ m} \leq R$)	0.13	0.48	0	3
Transition curves	2.25	2.04	0	8
Number of Uninterrupted curves	0.63	1.12	0	5
Crest vertical curves	4.15	2.28	1	15
Sag vertical curves	4.23	2.17	1	11
Horizontal & Crest vertical curves	1.95	1.67	0	9
Horizontal & Sag vertical curves	1.95	1.68	0	10
Number of tunnels	0.67	1.11	0	5
Number of bridges	2.69	1.42	0	7
Environment Characteristics				
Urban ($50,000 \leq \text{population}$) (Y(1)/N(0))	0.90	0.30	0	1
Frequent fog in area (Y(1)/N(0))	0.38	0.49	0	1
Snowfall (cm)	16.92	13.40	0	50.1
Number of Days With snowfall	11.95	8.13	0	30
Rainfall (mm)	1,257.76	311.19	741.30	2,141.80
Number of Days With rainfall	101.23	13.83	76	144

Y(1)/N(0) means an indicator variable with values 1 or 0; L: length (m), R: radius (m)

The data were classified into four separate datasets by light conditions: daylight, night, twilight (sunrise or sunset), and the whole 24 hour day (the whole dataset), which were modeled separately as four models. The classification of the data by light conditions was developed based on the monthly time of sunrise, time of sunset, and the officially defined civil twilight which the Korea Astronomy and Space Science Institute provides. The civil twilight time was defined as the time when the sun has not risen (or has recently set) but the overall brightness still enables people to work outside and read the newspaper. There is a morning civil twilight just before sunrise, and an evening civil twilight just after sunset. The morning and evening

twilight periods are defined as the time between civil twilight and when the sun is at 25 degrees. The morning and evening twilight time periods were combined into one twilight period. Daylight was defined as the time period beginning at the time when the sun is at 25 degrees in the morning and ending when the sun is at 25 degrees in the evening. The selection of 25 degrees for the sun's angle above the horizon was based on previous research (20). During daylight, the driver is expected to feel no discomfort due to lack of light or low angle of the sun. Finally, the night was defined as the time from the evening civil twilight to morning civil twilight.

Annual Average Daily Traffic (AADT) was based on freeway traffic volume data obtained from an automated Traffic Monitoring System (TMS) (21) which provides the AADT based on interchange location. Since more than one AADT value could be measured for each section, they were weighted together to form one AADT value per roadway section per year.

The TMS classifies vehicles into light, medium, and heavy vehicles, and thereby provided the share of these vehicle types in the traffic stream. Light vehicles include passenger cars, medium vehicles include buses and lighter trucks, and heavy vehicles include tractor-trailers.

To consider the characteristics of land use, the freeways were divided into urban and rural freeways. An urban freeway, in general, passes through an area that has a population of more than 50,000 people (this is the standard of a city defined in Korea).

The tangent length is the straight distance between two horizontal curves within a roadway section. To test for non-linear effects, indicator variables were formed by classifying the tangent lengths in all sections into three groups using cluster analysis where the within-group variance is minimized and the between-group variance is maximized. This resulted in indicator variables representing the short, medium, and long tangents of the freeway sections. This allowed a flexible non-linear effect of tangent length on crash frequency instead of simply constraining a linear effect by using one length variable. The short tangent indicator variable was thereby defined if the length is less than 1,421 m. The medium tangent length is 1,421 m – 4,000 m, and the large tangent is longer than or equal to 4,000 m.

Similarly, horizontal curve radii within the sections were classified with cluster analysis and represented with indicator variables for short radius curves with a radius less than or equal to 4,000 m, medium radius curves had a radius between 4,000 m and 10,200 m, and the large radius curves had a radius over 10,200 m. An uninterrupted curve occurs where no tangent separates two horizontal curves.

The number of trumpet type interchanges was accounted for separately because that was the most common interchange type (79.7%) among the 296 interchanges/junctions in the analyzed sections. Other freeway geometric variables (e.g. tangent length, curve radii) were set as the count of the respective geometric feature within each of the sections.

Among the environment characteristics, the frequent fog in area indicator was defined as one for sections that have more than 30 foggy days per year according to the frequently foggy freeway standard of the Korea Expressway Corporation. In addition, snowfall and rainfall were represented by the amount of snow or rain the area received annually.

METHODS

The analysis of count data, like traffic crashes, has widely used the Poisson regression model. The Poisson probability of the number of crashes y_i occurring in section i of a freeway during a fixed time period—one year in this study—is given by:

$$\text{Prob}(y_i) = \frac{e^{-\lambda_i} \lambda_i^{y_i}}{y_i!}, \quad y_i = 0, 1, 2, \quad (1)$$

where $\lambda_i > 0$, the expected rate of crashes, is the Poisson parameter. The Poisson regression is developed by expressing the Poisson parameter as a log-linear-in-parameters function:

$$\ln \lambda_i = \beta x_i, \quad (2)$$

where x_i is a vector of observable explanatory variables and β is a vector of estimable parameters (22). The Poisson regression is based on the assumption that the variance and mean are equal. If the variance in y_i is greater than the mean, there may be problems of over-dispersion. In this case, the negative binomial model can be used. In the negative binomial model, an error term has been added to (2) (2):

$$\ln \lambda_i = \beta x_i + \varepsilon_i. \quad (3)$$

The exponentiated error term is assumed to be gamma-distributed with the mean of $\exp(\varepsilon_i)$ being 1 and the variance $\alpha > 0$. Then $\text{VAR}[y_i] = E[y_i][1 + \alpha E[y_i]] = E[y_i] + \alpha E[y_i]^2$. In other words, when α of the negative binomial model is not statistically significantly different from 0, the negative binomial model reduces to the Poisson regression model. Therefore, if α is statistically significantly larger than 0, the negative binomial model is appropriate.

Here the frequency data were based on long, fixed-length sections which include varying geometrics and traffic. In order to capture this heterogeneity, this research followed the work of (12) and (13) by developing random parameter Poisson and negative binomial regressions. The estimable random parameter is expressed:

$$\beta_i = \beta + \phi_i, \quad (4)$$

where ϕ_i is a randomly distributed term. An alternative specification allowing a correlation across random parameters (23), $\beta_i = \beta + \Gamma \phi_i$, using a lower triangular covariance matrix, Γ , is also tested. Recommendations for distributions of random parameters have been provided and were used in this research to develop the models (24-25). For continuous variables, the normal distribution was used; and the uniform distribution was used for indicator variables. The expected rate, λ_i , expressed conditioned on ϕ_i in the Poisson and negative binomial equations becomes:

$$\text{Poisson regression model: } \lambda_i | \phi_i = \exp(\beta x_i), \quad (5)$$

$$\text{Negative binomial model: } \lambda_i | \phi_i = \exp(\beta x_i + \varepsilon_i), \quad (6)$$

where $\lambda_i | \phi_i$ is the expected rate of crashes on freeway section i during a time period conditional on the random parameter ϕ_i . As a result, the log-likelihood (LL) of the model becomes:

$$LL = \sum_{\forall i} \ln \int_{\phi_i} g(\phi_i) P(y_i | \phi_i) d\phi_i, \quad (7)$$

where $g(\cdot)$ is the probability density function of ϕ_i . The simulated maximum likelihood method was used to estimate the random parameters Poisson and negative binomial models. Halton draws were used to simulate the integral in (7). This method has been commonly used because it samples a distribution more efficiently than equally distributed draws (24, 26, 27).

The goodness-of-fit (GOF) values for the models were calculated using the log-likelihood ratio, ρ^2 :

$$\rho^2 = 1 - \frac{LL(\beta) - n}{LL(0)}, \quad (8)$$

where $LL(\beta)$ is the log-likelihood at convergence for the full model, $LL(0)$ is the value for the initial model with all parameters set to zero, and n is the number of estimated parameters.

In order to determine whether or not the fixed parameter model and random parameter model for the same light condition were statistically significantly different, a likelihood ratio χ^2 -test was performed. The likelihood ratio χ^2 value is expressed:

$$\chi^2 = -2[LL(\beta)_a - LL(\beta)_b], \quad (9)$$

where $LL(\beta)_a$, $LL(\beta)_b$ are the log-likelihood at convergence values for the two models being compared, model a and b , with degrees of freedom equal to the difference in the number of parameters in the two models.

Marginal effects were used to explain the size of the relationship between independent variables and the dependent variable. In the case of a crash frequency model, the marginal effect measures changes in the expected number of crashes through the partial derivative $\partial \lambda_i / \partial x$ of some independent variable x . λ_i is defined through equations (2) and (3) for the Poisson and negative binomial respectively. The marginal effect is a point value, calculated for each section and must therefore be aggregated, here by taking the average for all sections (23).

ANALYSIS

The dependent variables of the four estimated models were the number of traffic crashes occurring in each section during 1) daylight, 2) night, 3) twilight (sunset or sunrise), and 4) the whole 24 hour day for comparison. The investigation was performed using the variables presented in Table 1. The random parameter models were estimated using 1000 Halton draws in the simulation, and parameters significant at the 0.1 level of significance were kept, less significant variables were constrained out of the models. This level of significance was chosen rather than the more stringent 0.05 level in order to provide better statistical power for the analysis, which was useful as the number of observations (roadway sections) is 281.

Poisson and negative binomial models were estimated using both fixed and random parameter models. The results show the over-dispersion parameters of the fixed parameter negative binomial models were always statistically significantly larger than zero. Hence the fixed parameter negative binomial models are presented in Table 2. For the random parameter negative binomial models, the over-dispersion was not statistically significantly larger than zero for any of the models. The random parameter Poisson models are therefore presented in Table 2. A test of the alternative specification of equation (4), allowing correlation across random parameters, showed that constraining this correlation out resulted in better fitting models. The marginal effects of the fixed parameter negative binomial and random parameter Poisson models are presented in Table 3.

At this point the question becomes which of these models is preferred, the fixed parameter negative binomial or the random parameter Poisson? The results of the χ^2 -test in (9) comparing the random parameter Poisson model and fixed parameter negative binomial model are presented at the end of Table 2. If the calculated χ^2 value exceeds the 90% critical value given the degrees of freedom, the fixed parameter model and random parameter model are statistically significantly different ($\chi^2_{\text{random-fixed}} > \chi^2_{\text{critical}}$).

The analysis found that for the models of daylight, night, and whole day, the fixed parameter negative binomial model and the random parameter Poisson model were statistically significantly different, while for the twilight models the fixed

parameter negative binomial model and the random parameter Poisson model were not statistically significantly different.

The results for random parameter estimates are summarized in Table 4, which also presents the type of distribution for each parameter along with the positive and negative parameter densities. This information aids the interpretation of results as this shows the percentage share of roadway sections where the random parameter takes a positive or negative value.

308 **TABLE 2 Estimation results for random and fixed parameter models of freeway crash frequency**

	Daylight crash model				Night crash model			
	Poisson		Negative binomial		Poisson		Negative binomial	
	Random-parameter		Fixed-parameter		Random-parameter		Fixed-parameter	
	coefficient	p-value	Coefficient	p-value	coefficient	p-value	coefficient	p-value
Constant	-3.77	0.00	-4.13	0.00	-7.09	0.00	-6.73	0.00
Traffic Characteristics								
Traffic share of light vehicles	4.80	0.00	5.29	0.00	8.99	0.00	8.54	0.00
Standard deviation of parameter distribution (N)	0.40	0.00						
Traffic share of heavy vehicles					9.70	0.00	9.42	0.01
Geometric Characteristics								
Number of lanes	0.31	0.00	0.33	0.00	0.32	0.00	0.32	0.00
Standard deviation of parameter distribution (N)	0.01	0.01			0.09	0.00		
Number of interchanges/junctions	0.20	0.00	0.19	0.00				
Short tangents (L<1,421m)								
Crest vertical curves								
Horizontal & Sag vertical curves	0.04	0.00	0.04	0.05				
Number of bridges	0.05	0.00	0.06	0.01				
Standard deviation of parameter distribution (N)	0.05	0.00						
Environment Characteristics								
Urban(50,000 ≤ population) (Y(1)/N(0))	0.45	0.00	0.46	0.00	0.37	0.00	0.43	0.00
Standard deviation of parameter distribution (U)	0.19	0.00			0.37	0.00		
Frequent fog in area (Y(1)/N(0))	0.23	0.00	0.23	0.00	0.11	0.00	0.14	0.04
Standard deviation of parameter distribution (U)	0.09	0.01			0.36	0.00		
Number of Days With snowfall	0.01	0.00	0.01	0.01	0.01	0.00	0.01	0.08
Dispersion parameter for negative binomial distribution			0.15	0.00			0.14	0.00
Number of observations	281		281		281		281	
Log-likelihood at zero, $LL(0)$	-1155.414		-1155.414		-980.988		-980.988	
Log-likelihood at convergence, $LL(\beta)$	-803.559		-806.076		-767.597		-771.241	
ρ^2	0.292		0.294		0.207		0.206	
chi-square (critical)		2.706				2.706		
chi-square (random-fixed)		5.034				7.288		

(Continued)

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TABLE 2 Estimation results for random and fixed parameter models of freeway crash frequency (Con

	Twilight crash model				Total Random coefficient
	Poisson Random-parameter		Negative binomial Fixed-parameter		
	coefficient	p-value	coefficient	p-value	
Constant	-4.85	0.00	-5.05	0.00	-4.81
Traffic Characteristics					
Traffic share of light vehicles	4.88	0.00	5.25	0.00	7.21
Standard deviation of parameter distribution (N)	0.46	0.00			0.33
Traffic share of heavy vehicles					8.62
Geometric Characteristics					
Number of lanes	0.42	0.00	0.42	0.00	0.29
Standard deviation of parameter distribution (N)					0.03
Number of interchanges/junctions	0.16	0.00	0.15	0.01	0.15
Short tangent (L<1,421m)	0.04	0.00	0.04	0.07	
Crest vertical curves	-0.04	0.00	-0.04	0.03	
Horizontal & Sag vertical curves					
Number of bridges					
Standard deviation of parameter distribution (N)					
Environment Characteristics					
Urban(50,000 ≤ population) (Y(1)/N(0))	0.68	0.00	0.69	0.00	0.43
Standard deviation of parameter distribution (U)	0.17	0.00			0.36
Frequent fog in area (Y(1)/N(0))	0.17	0.00	0.16	0.06	0.15
Standard deviation of parameter distribution (U)					0.18
Number of Days With snowfall	0.01	0.00	0.01	0.05	0.01
Dispersion parameter for negative binomial distribution			0.16	0.00	
Number of observations	281		281		
Log-likelihood at zero, <i>LL</i> (0)	-759.478		-759.478		-1
Log-likelihood at convergence, <i>LL</i> (β)	-628.546		-629.755		-9
ρ ²	0.158		0.158		
chi-square (critical)		2.706			
chi-square (random-fixed)		2.418			

311 The distribution of random parameters is identified in parentheses: normal distribution (N) and uniform distribution (U).

312 **TABLE 3 Average marginal effects for the random and fixed parameter models of freeway crash frequency**

	Daylight crash model		Night crash model		Twilight crash model
	Poisson Random- parameter	Negative binomial fixed parameter	Poisson Random- parameter	Negative binomial fixed parameter	Poisson Random- parameter
Traffic Characteristics					
Traffic share of light vehicles	39.06	50.60	64.07	69.61	17.28
Traffic share of heavy vehicles			69.10	76.83	
Geometric Characteristics					
Number of lanes	2.54	3.13	2.26	2.64	1.48
Number of interchanges/junctions	1.65	1.86			0.57
Short tangents ($L < 1,421$ m)					0.15
Crest vertical curves					-0.13
Horizontal & Sag vertical curves	0.33	0.35			
Number of bridges	0.41	0.57			
Environment Characteristics					
Urban($50,000 \leq \text{population}$)($Y(1)/N(0)$)	3.68	4.41	2.65	3.49	2.39
Frequent fog in area ($Y(1)/N(0)$)	1.89	2.19	0.78	1.16	0.59
Number of Days With snowfall	0.11	0.12	0.05	0.07	0.04

TABLE 4 Summary of random parameter results with positive (+) and negative (–) parameter densities

Model	Variables	Distr.	Mean	S.D.	+	–
Daylight	Traffic share of light vehicles	Normal	4.88	0.46	100.0%	0.0%
	Number of lanes	Normal	0.31	0.01	100.0%	0.0%
	Number of bridges	Normal	0.05	0.05	84.1%	15.9%
	Urban (50,000 ≤ population) Y(1)/N(0)	Uniform	0.45	0.19	100.0%	0.0%
	Frequent fog in area, Y(1)/N(0)	Uniform	0.23	0.09	100.0%	0.0%
Night	Number of lanes	Normal	0.32	0.09	100.0%	0.0%
	Urban (50,000 ≤ population) Y(1)/N(0)	Uniform	0.37	0.37	78.9%	21.1%
	Frequent fog in area (Y(1)/N(0))	Uniform	0.11	0.36	59.8%	41.2%
Twilight	Traffic share of light vehicles	Normal	4.88	0.46	100.0%	0.0%
	Urban (50,000 ≤ population) Y(1)/N(0)	Uniform	0.68	0.17	100.0%	0.0%
Whole 24 h	Traffic share of light vehicles	Normal	7.21	0.33	100.0%	0.0%
	Number of lanes	Normal	0.29	0.03	100.0%	0.0%
	Urban (50,000 ≤ population) Y(1)/N(0)	Uniform	0.43	0.36	84.5%	15.5%
	Frequent fog in area, Y(1)/N(0)	Uniform	0.15	0.18	74.1%	25.9%

RESULTS

Factors influencing traffic crashes for daylight, night, twilight, and the whole 24 hour day were found to be the traffic share of light vehicles, number of lanes, urban area, frequent fog areas, and number of days with snowfall. The traffic share of light vehicles had a random parameter for twilight and the whole day, but a fixed parameter for daylight and night. All had positive coefficients, showing that as the traffic share of light vehicles increases, the number of traffic crashes also increases. In the case of light vehicles, the large deviations in speed due to the diversity of types of drivers and vehicles, such as inexperienced drivers and experienced drivers, or compact cars and large sedans, compared to the heavier vehicle types may be the reason the number of crashes increases more for the light vehicle type.

It is noteworthy that AADT remained non-significant in the models. In a crash frequency model, AADT is usually one of the key variables. The reason for the performance of AADT here was caused by a combination of factors. The AADT was only **one value per section per year**, so it contained no seasonal or shorter temporal variation, but rather mainly geographic variation. Much of the geographic variation was captured by other included variables, notably number of lanes, traffic share of vehicle types, and environmental characteristics such as urban area. In testing the AADT variable in the models, it was also found that it conflicted with the constant in the daylight and whole day models, which is an indication of lack of variance and renders further support for the absence of this variable in the final models.

The traffic share of heavy vehicles had a fixed parameter for night and the whole day model. All had positive coefficients, showing that as the traffic share of heavy vehicles increases, the number of traffic crashes also increases. Drivers of heavy vehicles tend to drive all night to avoid traffic congestion during daytime, and it leads to drowsy driving, which may explain the elevated crash frequency of heavy vehicles at night. This lends support for regulations that ensure heavy vehicle drivers who drive at night receive appropriate rest.

Urban area had a random parameter in all models, and all had a positive sign indicating that urban freeways experience more crashes than rural freeways. The average marginal effects of this variable were higher in the fixed negative binomial models than in the random parameter Poisson models (Table 3). This may occur because urban areas have more traffic and greater conflicts between vehicles, which results in more traffic crashes (4). The effect of urban areas on freeway traffic crashes at night was the lowest in all the models, 0–0.74 with a mean of 0.37 and standard deviation of 0.37. Part of that effect may be the lesser traffic and fewer conflicts at night but drivers may also compensate for the reduced sight distance at night and drive more cautiously at night (28). In order to reduce traffic crashes in urban areas, it can be useful to support drivers with advanced technologies such as a Side Obstacle Warning System.

The number of lanes had a random parameter in the night and the whole 24 hour day models in Table 2. These had positive signs, indicating that as the number of lanes increases, the number of traffic crashes increases as well. Although the traffic volumes during nighttime are lower than during the day, roads with a greater number of lanes and thereby likely more traffic compared with roads with fewer lanes, and more lane changes are here linked with a greater number of crashes (4). The magnitudes of the marginal effects (Table 3) were different across light conditions. The average marginal effects during night were similar, 2.26 in the random parameters model and 2.64 in the fixed parameters model. However, for the whole 24 hour day the average marginal effect was 5.51 in the random parameters model and 7.04 in the fixed parameters model. The greater crash risk of multilane roads suggests that Lane Control Systems (LCS) may be able to improve traffic safety. LCS is one of the traffic management methods used on Changeable Message Signs (CMS). A CMS is a traffic control device that is capable of displaying one or more alternative messages (29). An LCS is used to manage traffic at the lane level, primarily to facilitate smooth lane changing (30).

Frequent fog in area had a random parameter in the night and whole 24 day models. In the case of night, the parameter had a mean of 0.11 and standard deviation of 0.36, yielding a 41.2% negative parameter density and a 59.8% positive parameter density (see Table 4). In the whole 24 hour day model, the parameter had a mean of 0.15, standard deviation 0.18, resulting in a negative density for 25.9% of the road sections and positive density for 74.1% (see Table 4). This suggests that frequent fog in areas increases the number of crashes in general but may decrease the amount of traffic crashes in some cases. This is because as fog increases, the distance headway of vehicles increases until a threshold of fog density is reached, above which distance headway decreases (31). Crash occurrence rates decrease as the fog density threshold is approached, while the crash rate increases as the threshold is exceeded. In terms of average marginal effects in Table 3, when the fog indicator goes from 0 (not a fog area) to 1 to indicate frequent fog area, the result was 2.19 for daylight, 1.16 for night, 0.68 for twilight, and 3.40 for the whole 24 hour day. Improved safety in fog areas could be achieved with smart roadsides which communicate with smart cars to let smart vehicles know the distance to the next vehicle is short. This also suggests proximity radar in vehicles that can detect vehicles ahead despite fog could provide safety benefits.

The number of days with snowfall had a fixed parameter of positive sign, which is in agreement with prior research (15, 32, 33). Snowfall makes it more likely for vehicles to skid, increasing the frequency of traffic crashes. Driver information

about the road ahead and possible frost conditions on either CMS or via in-vehicle information systems could help drivers compensate for the conditions.

The number of interchanges/junctions affects the flow of traffic and the variation of speed increases in such areas, which can contribute to more crashes (34). Combined horizontal and sag curves typically constrain sight distance more than separate horizontal and vertical curves. Such combined curves are suspected to be more dangerous (35, 36) and here the results associated them with a greater crash frequency in the daylight model. This suggests traffic safety might be improved by providing drivers with better information in advance about changing geometry, e.g. with warning signs.

Also, in this research, the most common types of crash on a bridge were a side-wind caused crash (37) and a guardrail-end crash (38). Therefore, the installation of windbreak fences on bridges is needed to reduce the probability of traffic crashes caused by side-wind along with safety guardrail-ends to improve visibility and reduce severity.

Traffic factors increasing crashes during twilight were shown to be the number of lanes, number of interchanges/junctions and short tangents. The number of interchanges/junctions had a positive fixed parameter, similar to the daylight crash model. Short tangents, between two or more curves, had a positive fixed parameter. Short tangents increase the risk of traffic crashes because of limited sight distance (39). On the other hand, crest vertical curves had a negative correlation with crash frequency, and more research is required regarding this factor.

The investigation was limited in the possible number of interactions between variables due to the number of observations and the length of roadway sections, which led to considerable within-section heterogeneity. Interesting expansions of this work would include an investigation of vertical and horizontal curves based on more detailed design parameters along with weather interactions with those parameters.

CONCLUSIONS

This research investigated the influence of road environment factors on freeway traffic safety under different light conditions using Poisson and negative binomial crash frequency models with fixed and random parameters. The analyzed regions were the Seohaean Freeway, Jungbu Freeway, and the Jungbu-naeryuk Freeway in Korea, with a speed limit of 110 km/h. Data collected in 2007 through 2010 was used.

The data were classified into crashes occurring during daylight, night, twilight, and models were developed for these light conditions and compared with a model for the whole 24 hour period. As a result of the analysis of the likelihood ratio, the fixed parameter negative binomial model was the most appropriate for the daylight traffic crashes but for the other time periods, the random parameter Poisson regression model was the most appropriate. In addition, the χ^2 -test showed that there was a significant difference in log-likelihood between the random parameters model and fixed parameters model in the daylight, night, and whole day, while there was not a significant difference between the fixed and random parameters models during twilight.

When comparing the models, it was evident that the factors have the least effect on traffic crash frequency during twilight. The marginal effects of all variables were lower there than in the other models. If this were merely an exposure artifact due to the twilight period being shorter than the other periods, then the tendency of the marginal effects would have been to be larger, since a small change to a low crash rate would be relatively larger. The significant difference between these models is

therefore evidence to suggest that driver behavior differs based on light condition. It appears from these results that drivers compensate for reduced light with more caution, in fact overcompensate when comparing the night and daylight models. The results for night indicated lower marginal effects on the variables than for the daylight model, in all cases except the share of light and heavy vehicles in the traffic stream. Greater number of both light vehicles and heavy vehicles, compared to medium vehicles, were associated with a greater increase in crash frequency at night than during daylight or twilight.

At night, fewer factors turned out to have significant effects, including geometric factors which were important during daylight and twilight. Only the number of lanes remained of the geometric characteristics. This could in part be a traffic volume effect. The lower volume at night renders the danger of curves and interchanges less serious, as the risk caused by these areas goes up with increasing chance of conflict with other vehicles. Night crash frequency is primarily affected by the distribution of vehicle types in the traffic stream and the environmental characteristics.

The road environment factors found to influence traffic crash frequency the most were the traffic share of light vehicles, urban area, number of lanes, frequent fog in area, and number of days with snowfall regardless of the light condition. All these variables increase the number of traffic crashes.

Among these variables there were some that did not influence traffic crashes during the night. In the case of the night crash model, the frequent fog in area received a random parameter with a mean coefficient value of 0.11 that had a positive correlation with traffic crashes, but the standard deviation value was 0.36 which led to some negative parameter density as well, indicating that fog was in some sections associated with a reduced crash frequency, although fog mostly tended to increase traffic crash frequency.

The influential factors of daylight traffic crashes were the number of interchanges/junctions, horizontal curves, the combined horizontal and sag vertical curves, and the number of bridges. Influential factors during twilight were the number of interchanges/junctions and crest vertical curves. All the variables, except the crest vertical curves during the twilight period, increase the frequency of traffic crashes.

The results indicate that the effects of observable traffic, environment, and especially roadway geometric characteristics on crash frequency differ by light condition. The results can be used when developing driver information systems as different information could be given to drivers about the road ahead based on light conditions. During daylight it is most important that drivers be aware of upcoming areas with multiple lanes and greater numbers of interchanges and junctions, and the greater caution required in such areas. The results indicate that roadway design should try to avoid combining horizontal and sag vertical curves. Warnings about fog ahead may improve safety. Even so, the limited sight distance during fog will remain a risk factor until vehicles can be equipped with proximity warning systems, which can provide drivers with information about obstacles beyond the visual sight distance in fog.

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