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Risk perception, protective behavior, and transit ridership during COVID-19: Longitudinal insights from Seoul Metropolitan Area, Republic of Korea

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ABSTRACT

Introduction: The COVID-19 pandemic heightened individuals' risk perception and increased their protective behaviors to minimize unnecessary contact with others. While existing studies have explored behavioral changes in response to the pandemic, few have examined the dynamic interplay between risk perception, protective behaviors, and contextual factors, largely due to the limitations of short-term or cross-sectional data.
Methods: This study used 80 repeated cross-sectional surveys conducted throughout the pandemic to track the risk perception and protective behavior of Koreans. We adopted a one-way ANOVA model and a conceptual SEM to examine the differences in risk perception and protective behavior across various socio-demographic groups. The variables considered were individuals' risk perception, protective behaviors, and the external environment such as the number of confirmed cases and government quarantine measures for exploring their associations with public transit usage.
Results: The results indicate that individuals' risk perception is significantly influenced by their surrounding environment. Individuals with heightened risk perception are likely to adopt preventive measures, which in turn impact their public transit ridership. We also provide compelling evidence on how risk perception and protective behavior related to COVID-19 evolved over time, influenced not only by public health policies but also by individuals' socio-demographic characteristics. Last, this study empirically demonstrates the occurrence of *psychic numbing* resulting from repeated exposure to a persistent threat.
Conclusions: These findings underscore the importance of adaptive public health strategies and targeted communication to address the varying perceptions across different socio-demographic groups, contributing to a more resilient public transit system. This study highlights the importance of adaptive transit operations, sustained safety measures, and continuous public engagement during future pandemics.

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1. Background

A perceived risk, referring to susceptibility to a certain threat, has long been associated with one's behavioral patterns (Brewer et al., 2004). He relationship between individuals' risk perception and their specific behaviors during hazardous events has been a well-established area of inquiry in the fields of emergency management and social psychology (Bourque et al., 2013). The interrelations between individuals' perceptions of risk and their behaviors in situations such as hurricanes (Ng, 2022; Demuth et al., 2016), floods (Terpstra, 2011; Shao et al., 2017), earthquakes (Ao et al., 2021), and biological diseases (Jiang et al., 2009; Chan et al., 2020), as well as the factors influencing them, have all been the focus of substantial research. These studies have shown that socio-demographic features including age (Kim et al., 2015), gender (Yong et al., 2019; Cvetković et al., 2018), occupation (Mızrak et al., 2023), and education level (Faryabi et al., 2023), previous experiences (Papagiannaki et al., 2019; Ng, 2023; Kim et al., 2024a), and political orientation (Bourque et al., 2013; Chung et al., 2022; Kim et al., 2021) are strong factors influencing individuals' risk perception, their behaviors, and the association between the two.

The COVID-19 pandemic heightened individuals' risk perception (Dryhurst et al., 2022) and increased their engagement in protective behaviors to minimize unnecessary contact with others (Lüdecke et al., 2020; Resnicow et al., 2021). As of 2025, the virus has claimed approximately 7 million lives out of approximately 778 million reported cases worldwide, underscoring its unprecedented contagiousness and mortality. Initially, the virus was perceived globally as a novel and unfamiliar disease, provoking heightened fear and amplifying risk perception among individuals and across societies (Haas, 2020). However, the prolonged nature of the threat gradually led to a decline in public sensitivity. For instance, in the Republic of Korea, the Omicron variant began spreading from December 1, 2021, resulting in tens of thousands of confirmed cases daily. Yet, despite the exponential rise in infections, public concern diminished as individuals grew accustomed to the situation and increasingly viewed government-imposed quarantine policies as excessive or burdensome (Kim et al., 2024b).

Previous studies have investigated how COVID-19 transmission affected various daily activities, including outdoor engagements (Park et al., 2022; Michelini et al., 2021), social gatherings (Lio et al., 2021), and public transit usage (Qi et al., 2023; Parker et al., 2021). However, relatively few studies have comprehensively examined how individuals' risk perception and protective behaviors evolved over the course of the pandemic in conjunction with external contextual factors—such as confirmed case counts and policy responses. Furthermore, much of the existing literature has relied on short-term or cross-sectional data, limiting its ability to capture

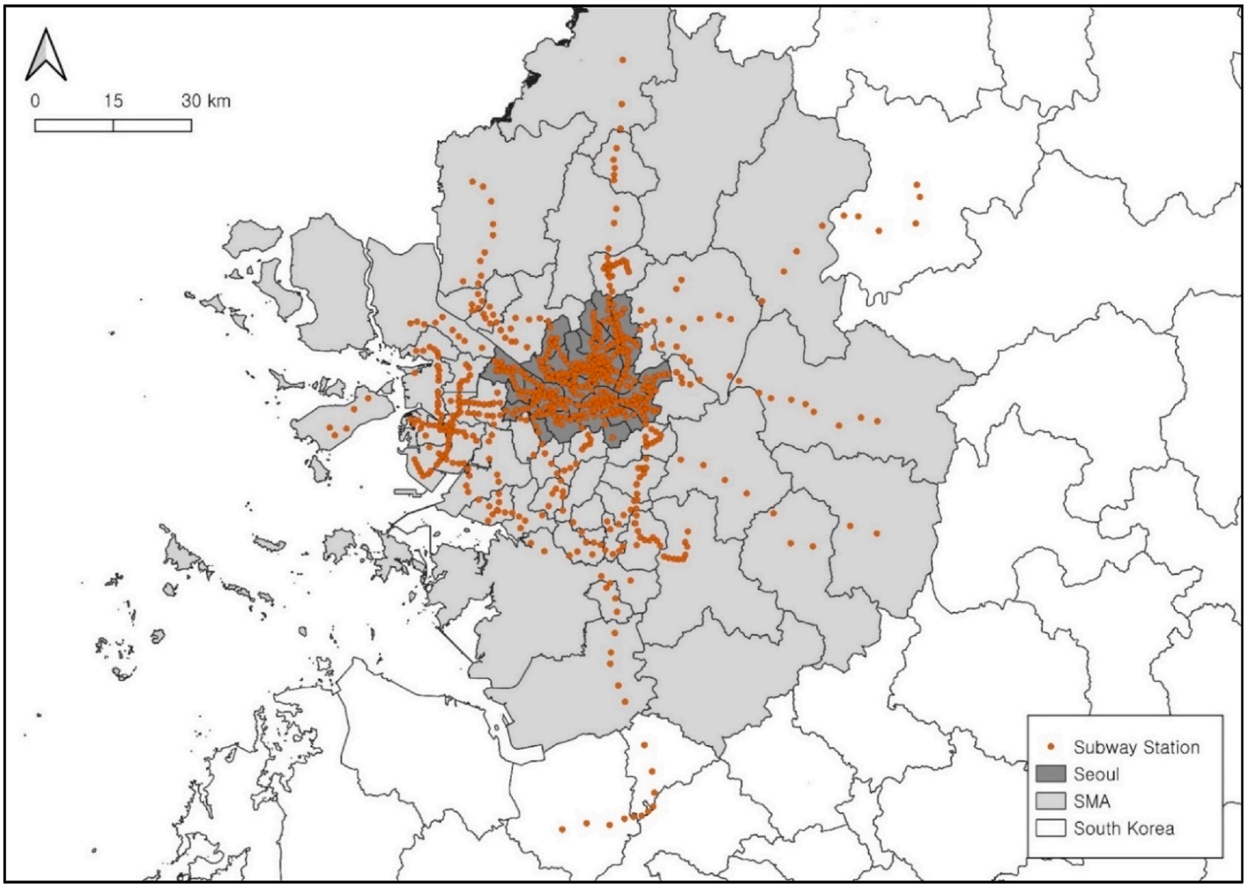

Fig. 1. Subway station network in the Seoul Metropolitan Area.

dynamic changes over time or to explore how psychological and behavioral responses adapt to ongoing threats. This research gap may stem from the variability in individuals' risk perceptions and protective behaviors during the COVID-19 period (Thu et al., 2020), as these interactions are strongly influenced by the evolving nature of virus transmission (Fatima et al., 2023).

This study addresses this gap by adopting a longitudinal approach based on 80 repeated cross-sectional surveys conducted in the Republic of Korea. The survey data track changes in individuals' risk perception and protective behavior over a three-year period, allowing for a detailed analysis of temporal patterns at the individual level. By focusing on public transit ridership—a critical aspect of urban mobility—this study investigates how behavioral responses are shaped not only by individual perceptions but also by broader environmental and policy conditions. It further explores how these relationships vary across socio-demographic groups and how they differ before and after the emergence of the Omicron variant.

By capturing long-term behavioral dynamics and incorporating both internal and external variables, this research overcomes the temporal and contextual limitations of earlier studies. It contributes to a more nuanced understanding of public responses to pandemics and offers valuable insights into future transportation and public health policy under prolonged conditions of crisis.

2. Methods

2.1. Study area

The Seoul Metropolitan Area (SMA), which includes Seoul, Incheon, and Gyeonggi-do Province, is one of the world's largest metropolitan regions (Kim et al., 2023). Home to more than half of South Korea's total population—approximately 26 million residents (Chang et al., 2007)— the SMA features a dense public transportation network that facilitates rapid movement both within and between its subregions. As of 2020, the area comprises 30 subway lines and 712 stations (Fig. 1), with an average daily ridership of 9 million, equivalent to about 35 % of the SMA's population (Kim et al., 2022). Due to its high population density and mobility, the region was particularly vulnerable to the spread of COVID-19, accounting for up to 80.5 % of all confirmed cases in the country (Choi et al., 2021). Government-enforced quarantine measures were also heavily concentrated in the SMA (Park et al., 2023), making it a suitable setting for investigating the relationship between citizens' perceived COVID-19 risk and their behavioral responses.

2.2. Data

A series of repeated cross-sectional surveys were conducted to examine changes in the risk perception and protective behaviors of Korean individuals throughout the COVID-19 pandemic. Since these factors can be influenced by the surrounding social environment,

Table 1
Survey questionnaire and corresponding possible responses.

Variable		Survey question	Possible responses
Socio-demographic traits	Gender	What is your gender on your resident registration?	Male Female
	Age	How old are you?	20–29 30–39 40–49 50–59 More than 60
	Education level	What is the highest degree of schooling you have completed?	Less than a high-school graduate A college degree or higher
	Occupation	What do you do for a living?	Office worker Salesman Field job Student, housewife Unemployed
	Marital status	What is your marital status?	Single Married
	Child status	Do you have children?	No Yes
	Type of residence	What type of house do you currently live in?	Single-family house Apartment Multi-family house
	Political orientation	Is your political ideology orientation conservative or progressive?	11-point Likert scale (0 = very progressive stance; 10 = very conservative stance)
Risk Perception	Severity	How serious is the COVID-19 infection in Korea according to your perception?	5-point Likert scale (1 = not at all; 5 = very serious)
	Infection possibility	How likely do you think you are to be infected with COVID-19?	5-point Likert scale (1 = not at all; 5 = very likely)
Protective Behavior	Refrain from outdoor activity	Do you refrain from outdoor activities now when compared to before the COVID-19 pandemic?	4-point Likert scale (1 = not at all; 4 = very much so)
	Refrain from using public transit	Do you refrain from eating out now when compared to before the COVID-19 infection spread?	4-point Likert scale (1 = not at all; 4 = very much so)

we also collected data on the number of COVID-19 cases, the levels of social distancing according to prescribed policies, and public transit usage, with a particular focus on subway ridership. All data used are geographically anchored within the Seoul Metropolitan Area (SMA) in Korea.

2.2.1. Repeated cross-sectional surveys

Since the initial detection of COVID-19 on January 20, 2020, in Korea, a total of 80 biweekly repeated cross-sectional surveys were conducted from February 2020 to April 2023 to investigate the temporal dynamics of Korean citizens' risk perception and protective behaviors during the pandemic. Each wave comprised 1000 respondents aged 19 and above, selected through stratified random sampling based on gender, age, and region, and the surveys were administered with support from Hankook Research, a leading polling firm in Korea. While the overall dataset includes approximately 80,000 responses (80 surveys × 1000 respondents), the present study focuses exclusively on 40,734 completed responses from participants residing in the Seoul Metropolitan Area (SMA) to ensure consistency with the geographical scope of transit and epidemiological data.

The surveys were meticulously designed to collect information on respondents' socio-demographic characteristics, risk perception, and protective behaviors in response to the spread of COVID-19. The specific survey items are listed in Table 1. The questionnaires gathered individual details such as gender, age, education level, occupation, marital status, child status, type of residence, and political orientation. In addition, respondents were asked about their perception of COVID-19 risk—specifically the perceived severity of the outbreak and the likelihood of infection—as well as their preventive behaviors, such as avoiding outdoor activities and using public transit.

2.2.2. COVID-19 infection cases and social distancing policy in Korea

This study collected the daily number of confirmed COVID-19 cases as officially reported by the Ministry of Health and Welfare in Korea. Drawing on insights from a previous study (Sprengholz et al., 2023), we calculated the mean number of confirmed cases over the seven days preceding each survey conducted during the study period. Research conducted in Korea has shown that individuals' risk perception is more strongly associated with the natural logarithm of confirmed COVID-19 cases rather than the absolute number, indicating a manifestation of *psychic numbing* (Kim et al., 2024b). Accordingly, we define the variable *infection* as the natural logarithm of the 7-day average of confirmed cases preceding each survey.

The second variable considered in this study is the social distancing policy in Korea. The Ministry of Health and Welfare implemented social distancing levels based on the severity of COVID-19 to reduce outdoor activities (Ministry of Health and Welfare, 2022). As part of the government's proactive quarantine measures, the early stages of the social distancing campaign comprised three phases: enhanced social distancing (March 22 to April 19, 2020), eased social distancing (April 20 to May 5, 2020), and a transition to distancing in daily life (May 6 to August 22, 2020). However, these initial policies were criticized for lacking systematic categorization (Yeon et al., 2022). In response, the Korean government introduced a structured five-level scheme, ranging from levels 1 to 3, with intermediate levels of 1.5, 2, and 2.5. In July 2021, a new four-level distancing system was implemented, ranging from levels 1 to 4. All social distancing restrictions were lifted on April 18, 2022, following the widespread prevalence of the Omicron variant. A distinct social distancing level is assigned to each survey period, resulting in 80 time points defined by the variable *social distancing*.

2.2.3. Public transit ridership

We use subway ridership data from the Seoul Open Data Plaza (https://data.seoul.go.kr/) to examine the association between perceived COVID-19 risk and public transit usage. The data includes the daily number of passengers boarding and disembarking at all subway stations within the SMA region. These figures are aggregated to estimate weekly ridership corresponding to each survey period.

2.3. Statistical method

In outlining the research methodologies employed to understand Koreans' perspectives on COVID-19 risk, we focus on key aspects such as risk perception, protective behavior, and factors influencing actual public transit ridership. First, an ANOVA model is employed to examine variations among respondents based on their socio-demographic characteristics. Next, we introduce a structural equation model (SEM) grounded in Social Cognitive Theory (SCT) to elucidate the relationships between individuals' risk perception and protective behavior, as well as their subsequent impact on public transit usage.

2.3.1. ANOVA model

A one-way ANOVA model is adopted to examine differences in risk perception and protective behavior across various socio-demographic groups. Specifically, we formulate four null hypotheses (NH) as follows.

NH1: The perceived severity of COVID-19 does not significantly vary according to respondents' socio-demographic characteristics before and after the emergence of the Omicron variant.
NH2: The perceived likelihood of infection does not significantly vary according to respondents' socio-demographic characteristics before and after the emergence of the Omicron variant.
NH3: The behavior of refraining from outdoor activities does not significantly vary according to respondents' socio-demographic characteristics before and after the emergence of the Omicron variant.

NH4: Public transit usage does not significantly vary according to respondents' socio-demographic characteristics before and after the emergence of the Omicron variant.

2.3.2. Social cognitive theory (SCT)-based SEM

Social Cognitive Theory (SCT), initially introduced by Bandura (1986), is widely recognized as a robust framework for analyzing behavioral patterns. According to SCT, human behavior is influenced, regulated, and shaped by both personal factors (e.g., self-efficacy) and environmental conditions (e.g., the social environment) (Chiu et al., 2006). As SCT-related research has advanced, extended models have been proposed to provide a more comprehensive understanding of the determinants of behavior. One such expanded SCT model, applied to the context of public transit ridership, suggests that individuals' behavioral patterns are shaped by their personal characteristics, environmental contexts, and outcome expectations (Short et al., 2013).

The extended SCT comprises four key factors: social environment (SEN), self-efficacy (SE), outcome expectation (OE), and behavior patterns (BP) (Short et al., 2013; Wang et al., 2021). According to SCT, BP represents a spectrum of behavioral responses that reflect acceptance, adoption, and willingness to engage in specific actions. SEN encompasses external factors that influence an individual's personal traits and BP, including both social relationships and physical surroundings. Consequently, SEN can exert a direct influence on an individual's BP. As a component of personal factors, SE functions as a cognitive driver that initiates the execution of specific behaviors. For example, individuals may avoid certain actions when they perceive a lack of confidence, as guided by their internal cognitive appraisal. SE not only has a direct effect on BP but also exerts an indirect effect through its influence on OE. OE acts as a mediating variable between SE and BP, capturing individuals' expectations about the outcomes of specific behaviors. These expectations are shaped by a variety of factors, such as perceived risks, anticipated benefits, and personal values. The trade-off between perceived benefits and risks is a critical determinant in shaping BP.

Ten hypotheses are proposed to investigate the factors influencing public transit ridership during the COVID-19 pandemic. Drawing upon a diverse array of data sources—including individuals' risk perception and protective behaviors obtained from surveys, COVID-19 case data, and government quarantine policies—these hypotheses are formulated based on the extended Social Cognitive Theory (SCT) (Bandura, 1986; Wang et al., 2021), which posits that public behavior is shaped by personal traits and environmental conditions. Building on these theoretical foundations, the proposed hypotheses are presented below.

H1. An increase in COVID-19 infections will lead to stricter enforcement of government quarantine policies.

H2. An increase in COVID-19 infection cases will be associated with heightened individual risk perception.

H3. The implementation of quarantine policies will influence individuals' risk perception.

H4. An increase in COVID-19 infections will encourage individuals to adopt more protective behaviors.

H5. The implementation of quarantine policies will affect individuals' protective behaviors.

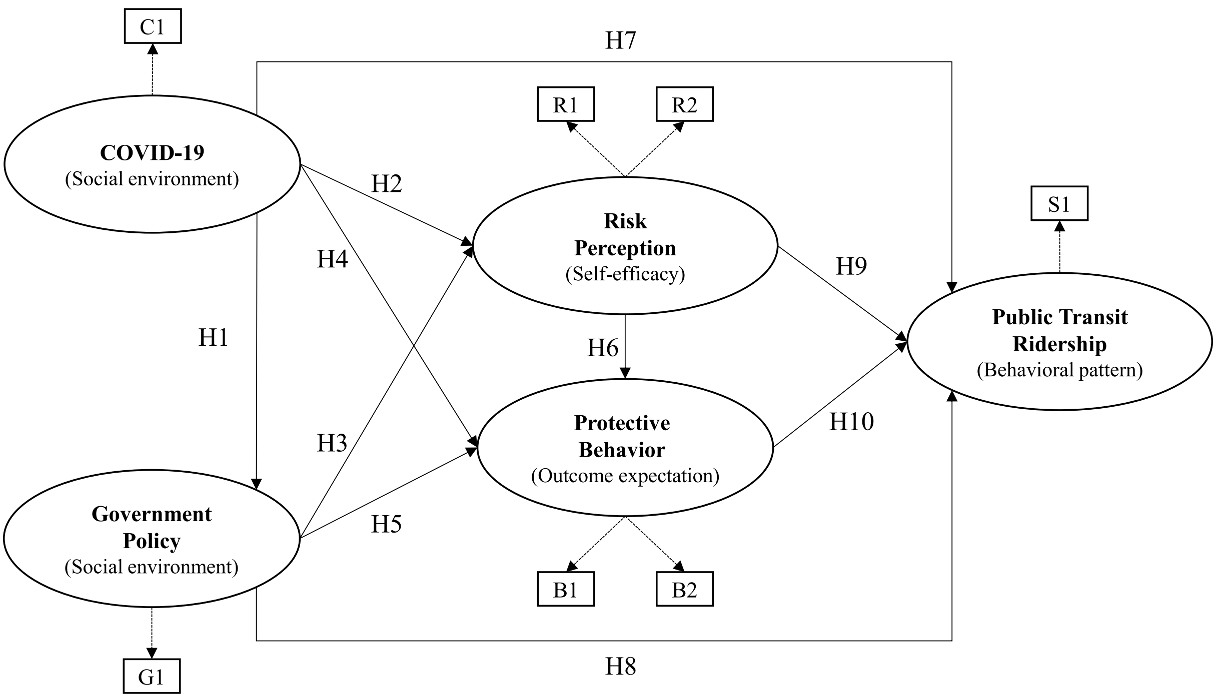

Fig. 2. Conceptual SCT-based PLS-SEM for examining the public transit ridership.

H6. An increase in COVID-19 infections will have a direct impact on public transit ridership in Seoul Metropolitan Area (SMA).

H7. Individuals who perceive COVID-19 as highly risky are more likely to engage in preventive behaviors.

H8. The implementation of quarantine policies will directly affect public transit ridership in SMA.

H9. Individuals with heightened risk perception are less likely to use public transit in SMA.

H10. Individuals who intend to adopt preventive measures are less likely to use public transit in SMA.

A Structural Equation Model (SEM) is developed to test the proposed hypotheses, as illustrated in Fig. 2. The conceptual model consists of two components: the structural model and the measurement model. The structural model delineates the relationships among the latent variables, whereas the measurement model specifies the relationships between each latent variable and its associated manifest variables. To validate the ten hypotheses, the structural model includes five latent variables: *COVID-19, Government Policy*, *Risk Perception*, *Protective Behavior*, and *Public Transit Ridership*. Relevant manifest variables are selected to represent each latent construct, drawing from the three data sources mentioned earlier—survey data, COVID-19 infection records, and government policy documents. Care is taken to ensure that both the structural and measurement models meet established criteria for model fit and reliability. Table 2 presents a comprehensive overview of the variables used in constructing the PLS-SEM, including the names and symbols of both latent and manifest variables, their corresponding symbols, explanations, and corresponding data sources.

The two research phases—pre-Omicron and post-Omicron—are categorized based on the emergence of the Omicron variant. The pre-Omicron period includes 47 surveys conducted between February 2020 and December 2021, prior to the detection of the variant. The post-Omicron period comprises 33 surveys conducted between January 2022 and April 2023, after the variant's emergence. To compare the factors influencing public transit ridership before and after the emergence of Omicron, two separate Structural Equation Models (SEMs) are developed. These models examine the roles of individuals' risk perception and protective behaviors in shaping transit usage across the two phases.

The partial least squares (PLS)-based SEM approach is employed to evaluate the conceptual model. As a variance-based SEM method, PLS-SEM is well-suited for identifying causal relationships among latent variables through estimated path coefficients (Henseler et al., 2016). The model is developed using SmartPLS 4, a widely used software tool for conducting PLS-SEM analysis (Wong, 2013). Given that PLS-SEM does not require the assumption of multivariate normality, a nonparametric bootstrapping procedure is applied to assess the statistical significance of path estimates. A total of 10,000 bootstrap subsamples are generated, which is considered sufficient for deriving stable parameter estimates and constructing 95 % confidence intervals (Wong, 2013). The relationships among the latent variables are visualized using path coefficients (β), along with their corresponding significance levels, assessed at the 99 % confidence level.

3. Results

3.1. Descriptive analysis

3.1.1. Descriptive statistics

Table 3 presents the descriptive statistics of risk perception and protective behaviors across various socio-demographic groups. In terms of gender, females reported higher mean values for both perceived severity (M = 3.622) and perceived infection possibility (M = 2.975) compared to males (M = 3.464; M = 2.881), and correspondingly showed greater adherence to protective behaviors, including refraining from outdoor activities (M = 3.384) and public transit use (M = 2.894). This suggests that women were generally more risk-sensitive and cautious in their behavioral responses during the pandemic.

Age-based differences revealed that perceived severity was highest among older adults aged 60 and above (M = 3.592), while younger respondents in their 20s also demonstrated elevated levels of both risk perception and protective behaviors. Notably,

Table 2
Variables used in constructing the SEM-based conceptual model.

Latent variable	Manifest variable	Symbol	Explanation	Data source
COVID-19	Infection	C1	The natural logarithm of the mean value for confirmed COVID-19 cases in the seven days preceding each survey	Ministry of Health and Welfare
Government Policy	Social distancing	G1	Social distancing level reported by the Ministry of Health and Welfare in Korea government	
Risk Perception	Severity	R1	Perceived severity of COVID-19 infections in Korea on a 5-point Likert scale	Hankook Research
	Infection possibility	R2	Possibility of contracting COVID-19 infection individually, on a 5-point Likert scale	
Protective Behavior	Refrain from outdoor activity	B1	Refraining from outdoor activity compared to before the COVID-19 infection spread	
	Refrain from using public transit	B2	Refraining from using public transit compared to before the COVID-19 infection spread	
Public Transit Ridership	Subway ridership	S1	The mean value of the subway ridership in the SMA in the seven days preceding each survey	Seoul Open Data Plaza

Table 3
Survey questionnaire and corresponding possible responses.

Socio-demographic traits		N	Risk Perception		Protective Behaviors	
			Severity	Infection possibility	Refrain from outdoor activity	Refrain from using public transit
Gender	Male	19,709	3.464	2.881	3.202	2.771
	Female	21,025	3.622	2.975	3.384	2.894
Age	20–29	6973	3.567	2.934	3.214	2.473
	30–39	6929	3.59	3.001	3.27	2.821
	40–49	8016	3.553	2.979	3.346	2.966
	50–59	8102	3.514	2.897	3.313	2.916
	More than 60	10,714	3.52	2.868	3.315	2.92
Education level	Less than a high-school graduate	22,126	3.592	2.936	3.284	2.87
	A college degree or higher	18,608	3.476	2.92	3.313	2.78
Occupation	Office worker	11,470	3.487	2.951	3.297	2.694
	Salesman	6671	3.534	2.941	3.226	2.864
	Field job	3849	3.494	2.933	3.195	2.875
	Student, housewife	9425	3.614	2.923	3.4	2.966
	Unemployed	4837	3.576	2.9	3.281	2.835
Marital status	Single	17,150	3.549	2.908	3.237	2.642
	Married	23,584	3.542	2.945	3.338	2.973
Child status	No	25,209	3.539	2.934	3.332	2.976
	Yes	15,525	3.556	2.922	3.237	2.604
Type of residence	Single-family house	3340	3.587	2.925	3.282	2.864
	Apartment	24,661	3.524	2.93	3.309	2.883
	Multi-family house	11,574	3.574	2.932	3.273	2.727
Political orientation	Liberal (0–4)	11,555	3.45	2.836	3.314	2.806
	Conservative (6–10)	11,563	3.56	2.944	3.269	2.802

respondents in their 30s had the highest levels of refraining from outdoor activities (M = 3.338), and those in their 40s reported the highest mean score for avoiding public transit (M = 2.976).

Education level also showed clear gradients, with individuals holding a college degree or higher perceiving less severity (M = 3.524) and being less avoidant of public transit (M = 2.883) than those with lower educational attainment. Similarly, variations were observed by occupation and political orientation, where unemployed individuals and those identifying as politically progressive tended to express higher risk perception and adopt stronger protective behaviors. These results suggest that socio-demographic factors significantly influence individuals' risk appraisal and behavioral responses to COVID-19.

3.1.2. Temporal trends in perceived risk and protective behaviors

Fig. 3 illustrates the temporal trends in perceived COVID-19 risk and the number of confirmed cases across the survey periods. During the pre-Omicron phase, the perceived severity of COVID-19 remained substantially higher than both the perceived likelihood of infection and the actual number of confirmed cases. However, in the post-Omicron phase, perceived severity declined, while the perceived likelihood of infection remained relatively stable compared to the pre-Omicron period. While this decline in perceived severity may partially reflect the clinical characteristics of the Omicron variant—particularly its lower severity among vaccinated individuals—it also appears to coincide with a broader psychological pattern observed over time. Specifically, the decoupling between perceived susceptibility and perceived severity began before the widespread public recognition of Omicron's clinical profile. This pattern aligns with psychological theories such as *psychic numbing*, which posit that repeated exposure to a persistent threat may diminish perceived severity regardless of actual medical risk (Kim et al., 2024b).

The temporal relationship between protective behaviors and the number of confirmed COVID-19 cases is illustrated in Fig. 3. Protective behaviors exhibited a relatively linear trend throughout the survey period. In the early stages of the pandemic, individuals reported moderate levels of avoidance behaviors, with scores of approximately 3.5 for refraining from outdoor activities and 3.0 for reduced public transit usage. However, these behaviors gradually declined over time as the virus continued to spread, and the pandemic became prolonged. This trend suggests that, over time, individuals began to prioritize a return to normalcy over strict adherence to infection-avoidance behaviors (Loft et al., 2022).

3.2. Model results

3.2.1. ANOVA results

As shown in Table 4, gender and age were identified as key variables that produced statistically significant differences in both risk perception and protective behavior. Female respondents exhibited higher perceptions of both the severity and likelihood of COVID-19 infection compared to males, and were consequently more likely to refrain from going out and using public transportation during the pandemic. Notably, the gender gap in risk perception widened during the Omicron period. In contrast, the relationship between age and perceived risk or protective behavior was more nonlinear than gender. Compared to younger adults (ages 20–39), middle-aged individuals (ages 40–59) generally reported lower levels of risk perception. However, respondents aged 60 and older demonstrated

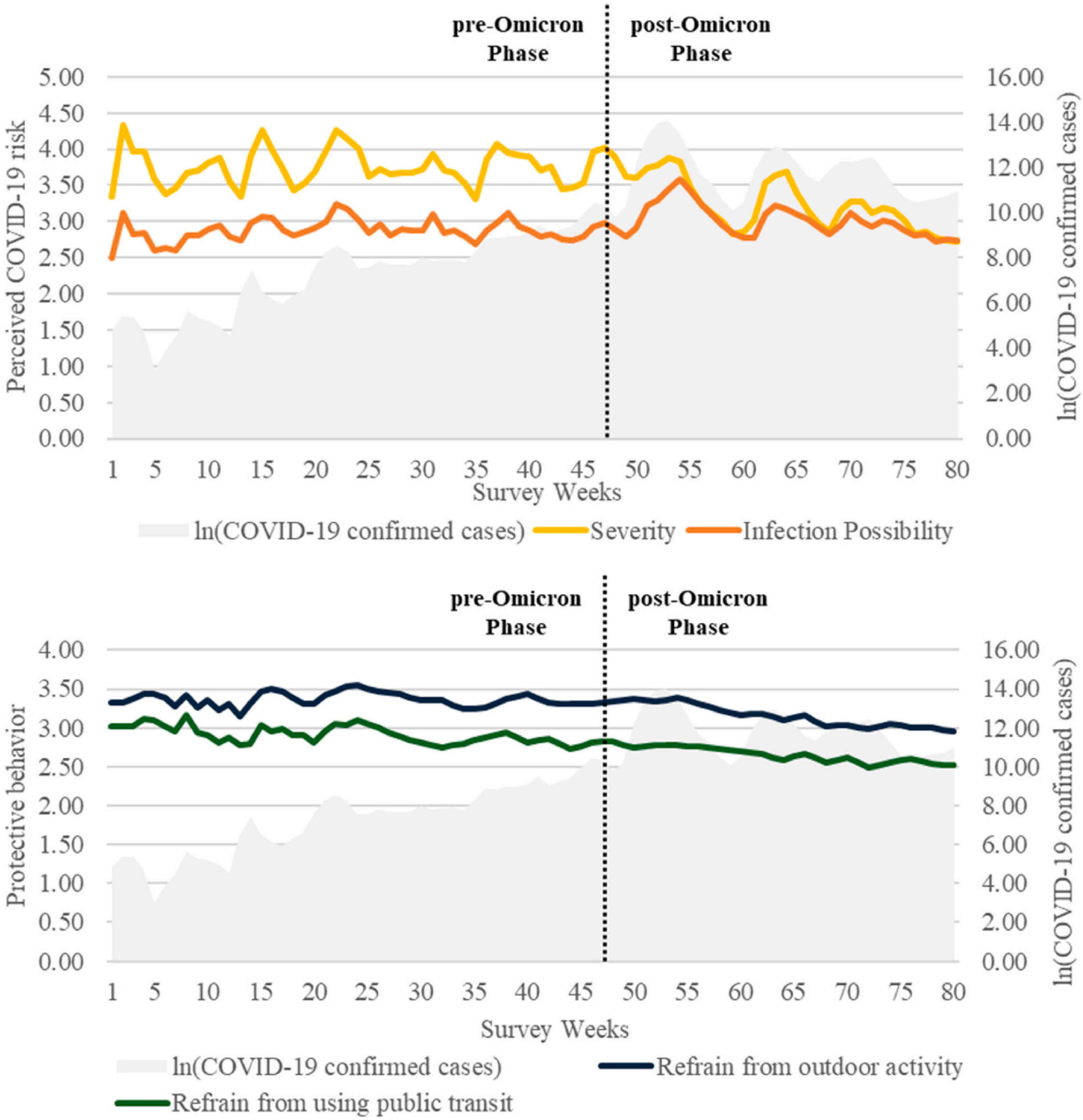

Fig. 3. Perceived severity and infection possibility and protective behaviors to refrain from outdoor activity and using public transit.

greater awareness of the virus's risks than other age groups. In terms of protective behavior, both middle-aged and older adults were more likely to avoid outdoor activities and public transit usage than younger individuals.

Risk perception and protective behavior also varied significantly according to respondents' education level and occupation. Individuals with a college degree or higher exhibited lower levels of risk perception compared to those with less than a high school education. This finding suggests that educational attainment is closely linked to access to factual information about COVID-19, which in turn influences perceived risk and protective behaviors (Rattay et al., 2021). With respect to occupation, students and homemakers showed the highest levels of risk perception and behavioral awareness regarding COVID-19, followed by unemployed individuals.

Political orientation was another significant factor affecting perceived severity and likelihood of infection. Interestingly, responses from progressive and conservative groups reversed before and after the emergence of the Omicron variant. This shift appears to be more closely associated with a change in political leadership during that period than with the characteristics of the virus itself. While political orientation did not result in significant differences in protective behavior, the findings highlight that political ideology can

Table 4
ANOVA results of risk perception and protective behavior based on socio-demographic information.

Socio-demographic traits		Risk Perception: Severity Pre-Omicron	Risk Perception: Severity Post-Omicron	Risk Perception: Infection possibility Pre-Omicron	Risk Perception: Infection possibility Post-Omicron	Protective Behavior: Refrain from outdoor activity Pre-Omicron	Protective Behavior: Refrain from outdoor activity Post-Omicron	Protective Behavior: Refrain from using public transit Pre-Omicron	Protective Behavior: Refrain from using public transit Post-Omicron
Gender	Male	3.683[b]	3.132[b]	2.838[b]	2.947[b]	3.271[b]	3.050[b]	2.856[b]	2.585[b]
	Female	3.831[b]	3.312[b]	2.910[b]	3.071[b]	3.456[b]	3.227[b]	2.987[b]	2.694[b]
Age	20–29 (Ref)	3.796	3.189	2.867	3.045	3.274	3.070	2.568	2.244
	30–39	3.800	3.262[b]	2.939[b]	3.098[a]	3.332[b]	3.125	2.923[b]	2.584[b]
	40–49	3.730[b]	3.279[b]	2.910[a]	3.086	3.410[b]	3.202[b]	3.038[b]	2.805[b]
	50–59	3.718[b]	3.216	2.842	2.978[b]	3.383[b]	3.166[b]	2.992[b]	2.760[b]
	More than 60	3.761[a]	3.195	2.835	2.912[b]	3.409[b]	3.134[a]	3.033[b]	2.703[b]
Education Level	Less than a high-school graduate	3.807[b]	3.265[b]	2.891[b]	3.004	3.352[b]	3.132	2.955[b]	2.680[b]
	A college degree or higher	3.687[b]	3.167[b]	2.850[b]	3.022	3.388[b]	3.157	2.874[b]	2.587[b]
Occupation	Office worker (Ref)	3.692	3.182	2.873	3.068	3.364	3.145	2.769	2.527
	Salesman	3.753[b]	3.217	2.890	3.015[a]	3.301[b]	3.063[b]	2.948[b]	2.681[b]
	Field job	3.691	3.206	2.900	2.981[b]	3.247[b]	3.090	2.948[b]	2.724[b]
	Student, housewife	3.828[b]	3.267[b]	2.872	3.006[b]	3.470[b]	3.229[b]	3.077[b]	2.710[b]
	Unemployed	3.803[b]	3.254[b]	2.859	2.959[b]	3.355	3.130	2.926[b]	2.648[b]
Political Orientation	Liberal	3.582[b]	3.240[b]	2.741[b]	2.988	3.373	3.175[b]	2.888	2.614
	Conservative	3.877[b]	3.121[b]	2.933[b]	2.959	3.356	3.094[b]	2.898	2.605

[a] $p < 0.05$.
[b] $p < 0.01$.

shape individuals' perception of the same infectious threat (Ju et al., 2022).

3.2.2. PLS-SEM results

In the pre-Omicron period, all hypothesized paths were found to be statistically significant except for the path from *Government Policy* to *Risk Perception*, as shown in Fig. 4. Among the social environment variables, *COVID-19* exhibited statistically significant positive path coefficients with *Government Policy* ($\beta = 0.641$), *Risk Perception* ($\beta = 0.464$), and *Public Transit Ridership* ($\beta = 0.421$), while showing a significant negative association with *Protective Behavior* ($\beta = -0.653$). This indicates that an increase in confirmed COVID-

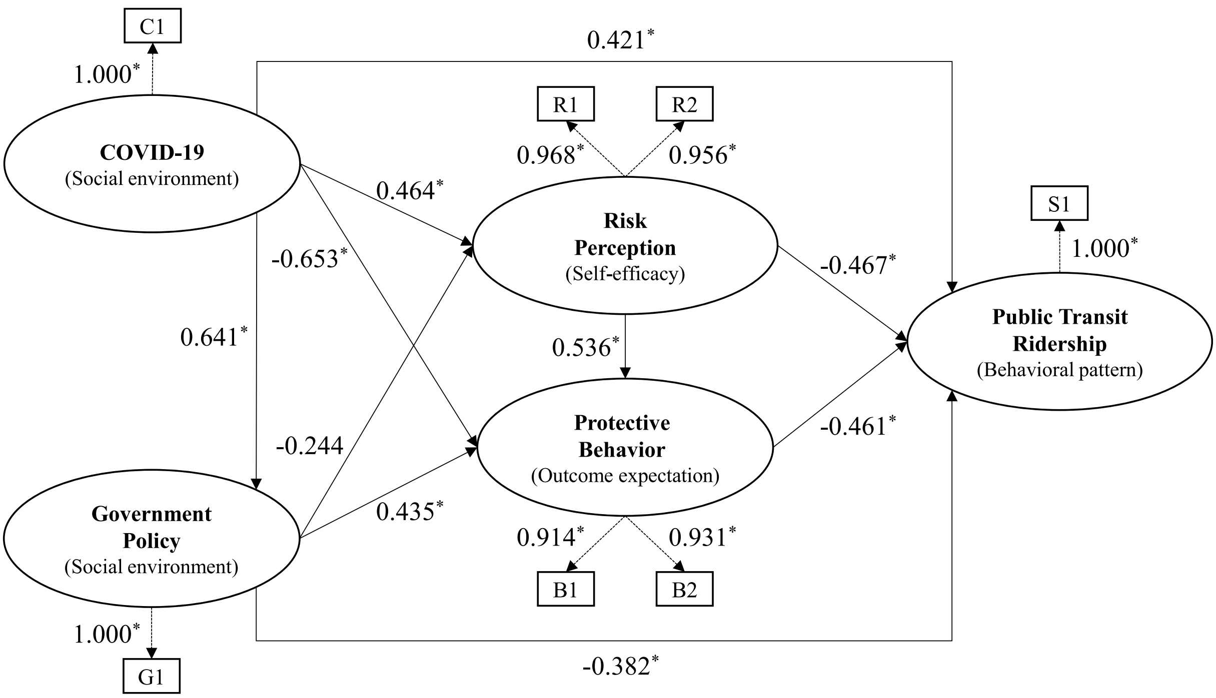

Fig. 4. PLS-SEM results in the pre-Omicron phase (*p < 0.01).

19 cases was associated with stronger policy enforcement and heightened risk perception, as expected. However, contrary to expectations, public transit ridership also increased alongside rising case numbers. This trend aligns with the negative path coefficient between *COVID-19* and *Protective Behavior*, suggesting a decline in precautionary actions despite worsening pandemic conditions.

The other social environment variable, *Government Policy*, exhibited a positive path coefficient with *Protective Behavior* and a negative path coefficient with *Public Transit Ridership*. This suggests that the government's quarantine measures were effective in reducing individuals' outdoor activities, particularly their use of public transportation. The latent variable *Risk Perception* had a positive influence on *Protective Behavior*, while negatively affecting *Public Transit Ridership*. Notably, *Protective Behavior* functioned as a mediating variable between *Risk Perception* and *Public Transit Ridership*. This indirect relationship indicates that individuals with heightened risk perception are more likely to adopt preventive measures, which in turn lead to a decline in public transit usage.

The PLS-SEM results for the post-Omicron period revealed notable disparities compared to the pre-Omicron period, as illustrated in Fig. 5. All paths leading to *Public Transit Ridership* became statistically insignificant, in contrast to the significant associations observed during the pre-Omicron phase. In addition, the paths from *COVID-19* to *Government Policy*, and from *Government Policy* to *Protective Behavior*, also lost statistical significance. However, one notable exception was the path from *Government Policy* to *Risk Perception*, which emerged as statistically significant. This finding suggests that prolonged exposure to the pandemic may have led individuals to internalize risk perceptions shaped by government policy, indicating a form of habituation to COVID-19-related information. In post-Omicron phase, the exponential increase in infections was observed, as shown in Fig. 3. Nevertheless, given that *Risk Perception* did not exert a statistically significant influence on both *Protective Behavior* and *Public Transit Ridership*, it can be inferred that a phenomenon of *psychic numbing* may have occurred.

The two PLS-SEM models yield the following key insights. First, individuals' risk perception is consistently shaped by their surrounding social environment across both time periods. Second, protective behaviors are positively associated with individuals' level of risk perception, regardless of the phase. These findings suggest that individuals are more likely to perceive the risk of COVID-19 when directly confronted with environmental cues or threats. Those with heightened risk perception tend to be more inclined to adopt preventive measures. However, with the emergence and spread of the Omicron variant in Korea, the influence of both risk perception and the social environment on public transit ridership diminished, indicating a decoupling between perceived risk and actual behavioral outcomes in mobility decisions.

3.2.3. PLS-SEM model fits

This study validated the suitability of the PLS-SEM models by adopting statistical criteria proposed in previous research (Chang et al., 2016; Memon et al., 2014; Jeong et al., 2020). A sample size is considered sufficient when it is at least ten times the maximum number of paths directed toward any latent variable in the model (Chang et al., 2016). In this study, the maximum number of incoming paths to a latent variable—*Protective Behavior*—was three; thus, the sample sizes for both periods exceeded the minimum required threshold. Second, the overall model fit for each PLS-SEM was assessed using four statistical indicators: the Standardized Root Mean Square Residual (SRMR), the squared Euclidean distance (d_ULS), the geodesic distance (d_G), and the Normed Fit Index (NFI) (Chang

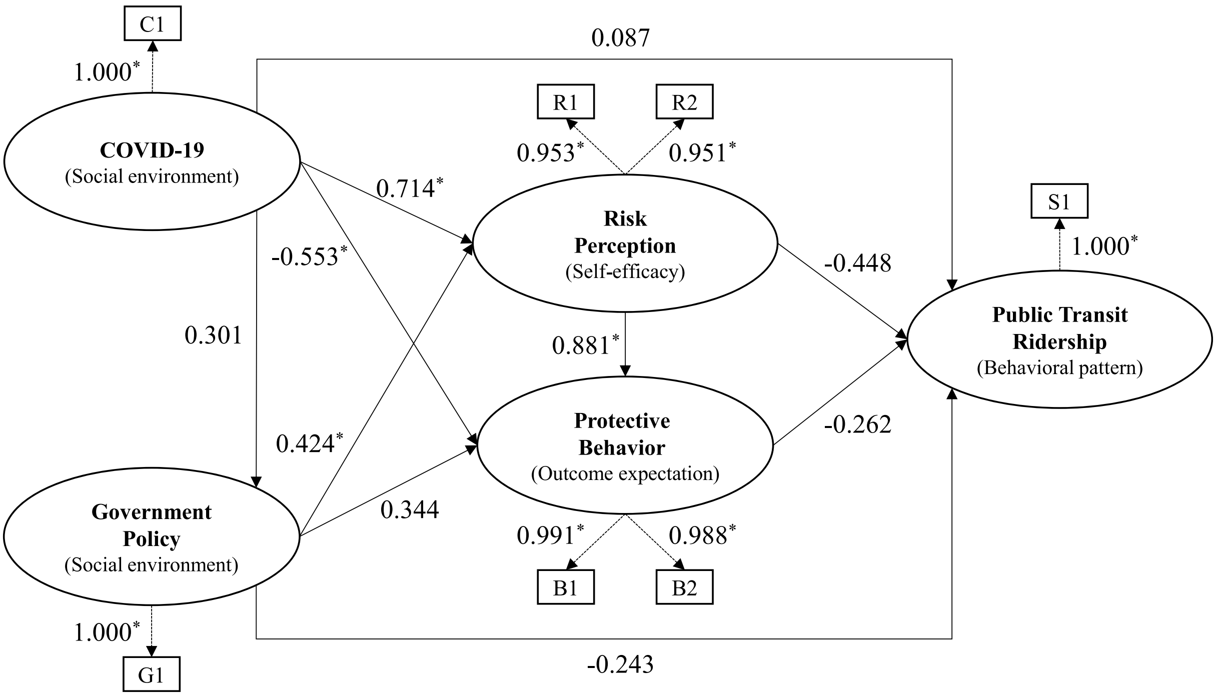

Fig. 5. PLS-SEM results in the post-Omicron phase (*p < 0.01).

et al., 2016; Memon et al., 2014; Jeong et al., 2020). The results, presented in Table 4, confirm that the obtained values fall within the recommended thresholds, indicating an acceptable model fit.

To evaluate the suitability of the measurement model in the two PLS-SEM analyses, we assessed internal consistency reliability, convergent validity, and discriminant validity in accordance with established guidelines (Chang et al., 2016; Memon et al., 2014; Jeong et al., 2020). Internal consistency reliability, which reflects the degree to which the manifest variables consistently explain their associated latent variable, was assessed using Cronbach's alpha and composite reliability (CR). As shown in Table 5, all latent variables met the threshold for internal consistency, with both Cronbach's α and CR values exceeding 0.7 in the pre- and post-Omicron phases. In addition, convergent validity was confirmed through the average variance extracted (AVE). All AVE values surpassed the recommended minimum of 0.5, thereby indicating that the latent variables adequately explain the variance in their respective indicators in both phases.

Discriminant validity evaluates whether each manifest variable is more strongly associated with its corresponding latent variable than with other constructs, typically assessed through cross-loading scores. As shown in Table 6, the selected manifest variables demonstrated good discriminant validity, particularly during the pre-Omicron phase, with higher cross-loadings observed for their respective latent variables. For example, the cross-loadings of manifest variables R1 and R2 were 1.000 and 0.853, respectively, indicating the strongest and second-strongest associations with the latent variable Risk Perception. Similarly, manifest variables B1 and B2 recorded the highest and second-highest cross-loading scores for Protective Behavior, both showing strong positive associations. Although in the post-Omicron phase, C1—rather than R1—showed the second-highest loading under Risk Perception, other manifest variables still demonstrated strong alignment with their intended constructs. Taken together, these results affirm the discriminant validity of the measurement models and support the overall suitability of the two PLS-SEM models.

4. Discussion and conclusion

This study provides important insights into the factors influencing public transit ridership during the COVID-19 pandemic, with a focus on the Seoul Metropolitan Area (SMA) in the Republic of Korea. In contrast to previous research that primarily examined short-term or fragmented time periods, this study utilizes a long-term, repeated cross-sectional survey design to capture the evolving dynamics of risk perception and protective behavior over a span of more than three years. This comprehensive approach enables a nuanced understanding of how public transit ridership was shaped by individuals' perceptions of COVID-19 risk, their behavioral responses, and their surrounding social environment. The findings offer clear evidence of distinct changes in public transit usage patterns, particularly before and after the emergence of the Omicron variant.

The key contributions of this study can be summarized as follows. First, the application of the extended Social Cognitive Theory (SCT) provides a robust theoretical framework for understanding the determinants of public transit ridership. By incorporating constructs such as social environment, self-efficacy, and outcome expectations, the study clarifies the complex interactions between external environmental factors, perceived risk, protective behaviors, and actual transit use. The findings underscore the critical influence of the number of confirmed cases, government quarantine policies, and individuals' risk perception and behavioral responses in shaping public transit usage.

Second, this study provides compelling evidence on how risk perception and protective behavior related to COVID-19 evolved over time, influenced not only by public health policies but also by individuals' socio-demographic characteristics. The PLS-SEM results showed that government quarantine policies had a direct and significant impact on public transit ridership; stringent measures implemented in the early stages of the pandemic effectively contributed to a decline in ridership.

Moreover, socio-demographic factors such as age, gender, education level, occupation, and political orientation significantly shaped individuals' risk perception and protective behaviors. For instance, females exhibited higher levels of risk perception and were more likely to avoid using public transit than males. Similarly, while younger individuals perceived higher risk levels, older individuals were more likely to avoid public transportation, reflecting a greater tendency toward protective behavior despite lower perceived risk. These findings align with prior research suggesting that socio-demographic characteristics play an important role in influencing public transit usage during health crises (Qi et al., 2023; Hu et al., 2021).

Third, this study empirically demonstrates the occurrence of *psychic numbing* resulting from repeated exposure to a persistent threat. Descriptive analysis revealed that, despite the exponential increase in confirmed COVID-19 cases during the post-Omicron period, both risk perception and protective behaviors declined (see Fig. 3). Furthermore, the PLS-SEM results provided additional empirical support for this phenomenon: perceived risk did not exert a statistically significant influence on either protective behavior or public transit ridership, thereby reaffirming the presence of *psychic numbing* in the post-Omicron phase (see Fig. 5).

In the early stages of the pandemic, even a small number of confirmed cases could provoke alarm and fear, as COVID-19

Table 5
Results of the measurement of fit for PLS-SEM.

Latent variable	Manifest variable	Pre-Omicron phase			Post-Omicron phase		
		Cronbach's α	CR	AVE	Cronbach's α	CR	AVE
Risk Perception	R1 R2	0.921	0.938	0.864	0.897	0.898	0.814
Protective Behavior	B1 B2	0.826	0.832	0.707	0.979	0.989	0.966

Table 6
Results of cross-loadings for PLS-SEM.

(a) Pre-Omicron phase

Cross-loadings		COVID-19	Government Policy	Risk Perception	Protective Behavior	Public Transit Ridership
Manifest variable	C1	**1.000**	0.641	0.318	−0.230	0.130
	G1	0.641	**1.000**	0.055	0.049	−0.158
	R1	0.258	0.063	**1.000**	0.437	−0.577
	R2	0.341	0.037	**0.853**	0.309	−0.417
	B1	0.054	0.218	0.427	**0.795**	−0.670
	B2	−0.416	−0.117	0.264	**0.885**	−0.684
	S1	0.130	−0.158	−0.540	−0.804	**1.000**

(b) Post-Omicron phase

Cross-loadings		COVID-19	Government Policy	Risk Perception	Protective Behavior	Subway Ridership
Manifest variable	C1	**1.000**	0.301	0.842	0.292	−0.439
	G1	0.301	**1.000**	0.639	0.740	−0.697
	R1	0.683	0.708	**0.953**	0.637	−0.724
	R2	0.924	0.507	**0.951**	0.571	−0.599
	B1	0.343	0.787	0.689	**0.991**	−0.723
	B2	0.228	0.672	0.560	**0.988**	−0.660
	S1	−0.439	−0.697	−0.696	−0.700	**1.000**

represented a novel threat to humanity. However, over time, as mass infections became more common and individuals grew accustomed to the ongoing risk, many developed fatigues toward government quarantine policies and exhibited signs of *psychic numbing*, becoming less sensitive to the threat of the disease. Following the emergence of the Omicron variant, public transit usage gradually recovered despite the continued spread of the virus, suggesting that individuals had come to perceive COVID-19 as a more familiar and manageable issue. This finding is particularly novel in that it extends the understanding of public transit usage fluctuations during the pandemic from a psychological perspective—an area that has been largely overlooked or only phenomenologically addressed in prior studies (Ahangari et al., 2020; Tiikkaja et al., 2021).

These findings offer important implications for transportation planning during future pandemics. First, transportation authorities should establish adaptive criteria for adjusting public transit supply based on pandemic severity. For example, during the early stages of an outbreak, transit services may be scaled down, with reallocated resources supporting safer alternatives such as bicycles and e-scooters, which are generally perceived as lower-risk modes. As public risk perception stabilizes and demand for transit increases, services should be flexibly expanded in response to evolving mobility needs.

Second, transit operators must prioritize sustained safety measures and ensure transparent communication with the public to foster trust. This may include enhanced sanitation protocols, mandatory mask requirements, and the deployment of digital technologies for real-time monitoring of safety compliance. By incorporating these strategies, policymakers and transit agencies can more effectively manage public transit use and enhance safety during pandemics, contributing to the development of more resilient urban transportation systems. This study provides foundational knowledge that can inform future research aimed at exploring innovative, health-conscious mobility solutions in the context of infectious disease outbreaks.

Third, policymakers should account for the effects of *psychic numbing* when formulating quarantine policies. As public sensitivity to risk diminishes over time, continuous public engagement—such as consistent messaging on the importance of preventive behaviors—can help counteract desensitization and sustain protective actions.

CRediT authorship contribution statement

Seunghoo Jeong: Writing – original draft, Funding acquisition, Formal analysis, Conceptualization. **Minjun Kim:** Writing – review & editing, Visualization, Project administration, Methodology, Formal analysis, Conceptualization. **Min-Kyu Kim:** Software, Resources, Investigation, Data curation. **Ji-Bum Chung:** Writing – review & editing, Validation, Conceptualization.

Ethics statement

Participants were recruited with their informed consent in accordance with the Korean Statistical Act, through online survey panels managed by Hankook Research, a leading polling firm in South Korea. The researchers accessed and utilized the survey data in collaboration with Hankook Research. The questionnaire used in the survey will be provided as supplementary material upon request.

Data availability

The data that support our study findings are available from the corresponding author upon reasonable request.

Disclosure of interest

The authors completed the ICMJE Disclosure of Interest Form (available upon request from the corresponding author) and disclosed no relevant interests.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Seunghoo Jeong reports financial support was provided by Korea Railroad Research Institute. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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