Comparative Study of Inpatient Utilization between Automobile Insurance and National Health Insurance in Korea

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ABSTRACT

Comparative study of Inpatient Utilization between Automobile Insurance and National Health Insurance in Korea

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Background: South Korea operates the National Health Insurance (NHI) system, which provides universal coverage to all citizens, along with an automobile insurance (AI) system that includes private liability insurance offering full coverage without patient cost-sharing. These structural and institutional differences offer divergent incentives for both patients and providers, potentially shaping distinct patterns of healthcare utilization. Particularly, the combination of a fee-for-service payment model and full coverage under AI increases the risk of moral hazard, provider-induced demand, and unnecessary care. Despite growing concerns—especially regarding rising expenditures in traditional Korean medicine under AI—empirical comparisons of inpatient utilization between AI and NHI remain limited, and evaluations of recent policy efforts to reduce excessive hospitalization are scarce. This study aims to address these gaps by comparing inpatient healthcare utilization across insurance types and empirically evaluating the impact of the December 2022 policy that strengthened claims review for mild-condition hospitalizations.

Methods: This retrospective cohort study used national claims data from 2018 to 2024, focusing on the five most frequently claimed diagnostic groups under AI, which account for approximately 72% of total AI expenditures. First, inpatient episodes for these conditions under both NHI and AI were extracted and matched 1:1 based on sex, age, medical department, primary diagnosis, surgery status, ICU stay, and admission timing, to ensure comparability between groups. Generalized estimating equations (GEE) were employed to account for repeated admissions. Second, a Difference-in-Differences (DID) analysis assessed the effect of the strengthened claims review policy implemented in December 2022. A Difference-in-Difference-in-Differences (DDD) analysis was also conducted to evaluate heterogeneous effects by targeted diagnosis groups. Primary outcomes included length of stay, total expenditure per episode, and per diem expenditure.

Results: Compared to NHI patients, AI patients had 2% longer hospital stays (exp(β) = 1.02, 95% CI: 1.01–1.03), 9% higher total inpatient expenditures (exp(β) = 1.09, 95% CI: 1.08–1.10), and 10% higher per diem expenditures (exp(β) = 1.10, 95% CI: 1.09–1.10). Among NHI patients, those receiving traditional Korean medicine care had 24% longer stays than those receiving Conventional medicine (exp(β) = 1.24, 95% CI: 1.21–1.27), while under AI, traditional Korean medicine care was associated with 40% higher medical costs (exp(β) = 1.40, 95% CI: 1.37–1.42). Following the policy implementation in December 2022, the average length of stay for AI patients decreased by approximately 6% (exp(β) = 0.94, 95% CI: 0.92–0.96), and total expenditure per episode declined by around 9% (exp(β) = 0.91, 95% CI: 0.89–0.93). However, the DDD analysis showed limited effects among the specifically targeted diagnostic groups.

Conclusions: This study empirically analyzed the characteristics of inpatient healthcare utilization and the effects of policy interventions under the automobile insurance (AI) system, which has been relatively understudied in Korea. Even after rigorous matching to adjust for differences in patient characteristics between the two insurance types, utilization under AI was significantly higher than under National Health Insurance (NHI). This suggests that in a zero cost-sharing system like AI, both provider- and patient-side moral hazard may arise. The analysis of policy effects further indicates that, even in a system without patient cost-sharing, policy interventions can partially mitigate excessive hospitalizations. The limited effects observed in the triple-difference analysis may be attributable to the non-disclosure of the targeted diagnosis groups.

To enhance the sustainability of the insurance system and promote the efficient allocation of healthcare resources, it is essential to establish clear policy objectives to address moral hazard and to develop a systematic framework for continuous monitoring and evaluation.

Keywords: Automobile insurance, Healthcare utilization, patient cost-sharing, Moral hazard, Difference-in-Difference-in-Differences analysis

1. INTRODUCTION

1.1. Background

Korea's healthcare system is fundamentally shaped by two institutional characteristics: the third-party payer model and the fee-for-service reimbursement system. Under the third-party payer model, medical providers are reimbursed by insurers after delivering care, reducing informational asymmetry between patients and providers. However, this structure may also diminish sensitivity to medical expenditures and foster excessive demand and supply of services, a classic manifestation of moral hazard. [1] Furthermore, the fee-for-service payment method imposes a high financial risk on insurers and makes it structurally difficult to control total medical expenditures.

The National Health Insurance (NHI) system is a single-payer public insurance program that covers nearly the entire Korean population. It requires copayments from patients, serving as a built-in mechanism to curb unnecessary medical utilization. In contrast, Automobile Insurance (AI) is a mandatory liability insurance for bodily injury. The "Bodily Injury I" component provides full reimbursement for traffic-related injuries without any cost-sharing, creating a fundamentally different set of incentives.

This divergence in benefit design serves as an institutional foundation for inherent differences in healthcare utilization behavior. [2] Specifically, Article 4 of the Medical Fee Standards for Automobile Insurance emphasizes the provider's duty to deliver all necessary treatment to restore traffic accident victims to their pre-injury state. [3] This legal requirement makes it difficult to define clear endpoints for care, and often legitimizes prolonged treatment, even for minor injuries. As a result, both providers and patients have incentives to prolong treatment. When coupled with a fee-for-service model, this structure can exacerbate moral hazard, potentially leading to longer lengths of stay and higher expenditures among AI patients compared to NHI patients with similar conditions. [4,5]

These concerns are supported by foundational economic theories. Arrow (1963) and Pauly (1968) provided early theoretical justifications for inefficiencies arising from insurance coverage.[4,6] The principal-agent theory further explains how asymmetric information enables providers to influence the volume of care delivered based on financial incentives. [7]

Such institutional and economic incentives manifest in various ways in the healthcare delivery system. One notable example is the increasing dominance of traditional Korean medicine (TKM) hospitals in the AI sector. The lack of clear clinical guidelines, full coverage of medical costs, and high patient acceptance of repetitive treatments such as acupuncture and cupping have enabled traditional Korean medicine hospitals to establish a favorable billing environment within AI. In some institutions, over 60% of inpatient revenue is derived from AI claims. This has been further facilitated by lenient claims review standards and simplified administrative processes.[8]

This situation has raised concerns about overutilization and potential abuse. According to a report by the Health Insurance Review and Assessment Service (HIRA), inpatient expenditures at KM hospitals are significantly higher than those at Conventional medicine hospitals, despite fewer total visits.[9]

Although various attempts have been made to curb overspending and insurance fraud in AI, fragmented governance structures—involving the Ministry of Land, Infrastructure and Transport (MOLIT), insurance companies, and HIRA—have hindered coherent policy development and enforcement.

Recent efforts to address these issues include policy measures such as mandatory submission of medical documentation for long-term treatment (introduced in September 2021) and restrictions on the use of premium hospital rooms (enforced from November 2022). However, the scope of these measures remains limited, and their effectiveness has yet to be properly evaluated.

In this context, a more comprehensive policy was introduced in April 2022 and implemented in December 2022, aimed at strengthening claims review criteria for inpatient care of patients with mild conditions (e.g., sprains, strains). While this policy sought to reduce unnecessary admissions and curb expenditures, empirical evidence on its effectiveness remains limited.

The institutional disparities between NHI and AI, including differences in cost-sharing and incentive structures, give rise to fundamentally divergent utilization patterns. [10] Even for the same diagnosis, AI patients often exhibit longer hospital stays and higher medical expenditures than NHI patients—differences attributable to the structural incentives embedded in each system.

However, comparative studies on inpatient healthcare utilization between the National Health Insurance and Automobile Insurance systems have been limited, and few empirical attempts have been made to systematically examine the differences between the two systems.

Accordingly, this study aims to analyze the heterogeneity in healthcare utilization arising from differences in institutional structure and cost-sharing mechanisms, and to evaluate the effectiveness of recently implemented claims review reforms in the automobile insurance system. The ultimate goal is to provide empirical evidence to support sustainable insurance operations and more efficient resource allocation.

1.2. Study Objective

This study aims to examine the impact of insurance type on inpatient healthcare utilization in South Korea. Specifically, the study focuses on comparing automobile insurance and national health insurance with respect to key utilization indicators to identify how differences in insurance design influence healthcare behavior. In addition, this study seeks to evaluate the policy effectiveness of the December 2022 reform that strengthened claims review criteria for mild-condition hospitalizations under automobile insurance.

The detailed research objectives are as follows:

(1) To compare inpatient healthcare utilization between patients covered by automobile insurance and those covered by national health insurance.

(2) To investigate how patterns of healthcare utilization differ depending on key factors related to medical service use, such as provider type, diagnosis category, and hospital level.

(3) To assess changes in inpatient healthcare utilization following the implementation of the December 2022 policy aimed at strengthening the review criteria for hospitalization costs of automobile insurance patients with mild conditions.

(4) To examine the differential impacts (heterogeneous effects) of the 2022 policy by comparing changes in inpatient utilization between the target and non-target diagnosis groups.

2. LITERATURE REVIEW

2.1. Policy Background

2.1.1. Structural Comparison between National Health Insurance and Automobile Insurance

Korea established the foundation of its liability compensation system for automobile accidents under the influence of the legal frameworks of Germany and Japan. In 1963, the Automobile Damage Compensation Guarantee Act (Law No. 1314) was enacted and promulgated, institutionalizing the principle that automobile operators bear strict liability for bodily injury or death caused by traffic accidents. This legislation marked a departure from the conventional negligence-based liability under civil law, and mandated that vehicle owners purchase bodily injury liability insurance, thereby formalizing the structure of compulsory liability insurance. Since its enactment, the Act has undergone successive amendments to gradually expand the scope of compensation, while maintaining the core principle of operator responsibility.[11]

Automobile Insurance (AI), initially introduced by the private sector in 1924, was subsequently formalized through the aforementioned legislation. The provision of unlimited compensation under the "Bodily Injury I" clause, combined with the complete absence of patient cost-sharing, has created a structural environment prone to moral hazard and excessive utilization of medical services.

In contrast, the National Health Insurance (NHI) system was introduced in 1963 with the enactment of the Medical Insurance Act and expanded in 1977 to include employees of large firms. With the implementation of the National Health Insurance Act in 1999, previously fragmented insurance schemes were integrated into a unified national program, providing coverage for nearly the entire Korean population. [12]

NHI is financed through contributions from employers, employees, and the self-employed, and includes a copayment mechanism that functions as a self-regulatory deterrent to overutilization. In contrast, AI reimburses all medical expenses related to traffic injuries in full, without requiring any copayment from patients. This fundamental difference in benefit design generates distinct behavioral incentives for both patients and providers. [10]

While AI serves a social protection role by ensuring prompt compensation for traffic accident victims, its administration by profit-oriented private insurers gives it the characteristics of both a social insurance scheme and a private insurance model, reflecting its hybrid nature. [8]

In addition, while the NHI system distinguishes between reimbursable and non-reimbursable services, thereby limiting the scope of covered care, the AI system offers a broader range of benefits. Specifically, AI covers not only services reimbursed by NHI but also additional services beyond NHI's coverage criteria. [13]

- All services reimbursed by NHI
- Services that do not conform to NHI reimbursement standards or are not explicitly listed as NHI-covered services
- Additional services recognized under the Industrial Accident Compensation Insurance scheme

For items not specifically priced, reimbursement is determined by:

- The most comparable procedure and relative value score in the NHI fee schedule

- The actual cost incurred by the provider for non-standard items such as certain materials or medications

There are also notable differences in administrative oversight. NHI is governed by the Ministry of Health and Welfare and subject to strict cost control and claims review by the Health Insurance Review and Assessment Service (HIRA). In contrast, AI falls under the jurisdiction of the Ministry of Land, Infrastructure and Transport. Although HIRA is entrusted with the claims review process, the level of oversight in AI is considerably more lenient, making it more vulnerable to inefficiency, overutilization, and moral hazard.

These institutional differences and structural incentives may result in substantial disparities in healthcare utilization patterns—such as length of stay and total expenditures—even among patients with identical diagnoses, depending on their insurance type.

Table 1. Comparative overview of social insurance and automobile insurance

Category	Social Insurance	Private Insurance	Automobile Insurance	
			Bodily Injury I	Bodily Injury II
Purpose of the System	Basic coverage (shared social risk)	Individual needs (personal risk)	Basic coverage (victim & personal risk)	Individual needs (personal risk)
Administering Entity	Government / Public Agency	Private Insurers	Private Insurers	
Public Responsibility	Present	Absent	Absent	
Operational Goals	Social benefit	Profit generation	Profit generation	
Entitlement Principle	Legal entitlement	Contractual entitlement	Legal/contractual entitlement	Contractual entitlement
Enrollment Requirement	Mandatory No risk selection	Voluntary Risk selection	Mandatory No risk selection	Voluntary Risk selection

2.1.2. Moral hazard and Principal-agent Problems

One of the core challenges in healthcare insurance systems is moral hazard. Moral hazard refers to the tendency for individuals to consume more healthcare services when they are insulated from the costs, a phenomenon well-documented in the field of health economics.[4,6] Moral hazard is the change in health behavior and consumption of health services because of insurance coverage. [14] When patients are shielded from the financial consequences of care, they are more likely to utilize services beyond what they would have otherwise chosen under cost-sharing conditions.

Koohi Rostamkalaee et al. (2022) further classify moral hazard into two mechanisms: ex-ante moral hazard, where insurance coverage reduces individuals' preventive behaviors and promotes unhealthy habits, and *ex-post moral hazard*, where the insured increase their consumption of healthcare services after illness due to reduced price sensitivity. [14]

Barati et al. (2018) complement this classification by identifying moral hazard not only in terms of timing (ex-ante and ex-post) but also by actor. They distinguish between consumer-side moral hazard, where insured individuals overutilize services due to the lack of financial responsibility, and provider-side moral hazard, where healthcare providers, exploiting informational asymmetry, induce unnecessary care for financial gain. This framework highlights how both patient behavior and provider incentives contribute to inefficiencies in insured healthcare environments.[15]

Stiglitz (1987) identifies three conditions necessary for moral hazard to arise: the presence of risk, insurance, and imperfect or asymmetric information. The healthcare sector is a paradigmatic example of an environment where all three factors coexist. In this context, moral hazard manifests in two forms: patients may overuse healthcare services due to the absence of out-of-pocket costs, and providers may deliver services that are not clinically necessary in pursuit of financial gain. [16]

Empirical evidence supporting the concept of moral hazard is provided by the RAND Health Insurance Experiment. [2] The study demonstrated that healthcare utilization significantly decreases as cost-sharing increases and, conversely, rises markedly under full insurance coverage. These findings underscore the role of patient cost sensitivity in moderating demand and suggest that insurance schemes with no cost-sharing—such as Korea's automobile insurance—may structurally incentivize overutilization.

In Korea, the NHI system incorporates a copayment mechanism that functions as a demand-side control to discourage excessive use. In contrast, AI covers all medical expenses related to traffic accidents with no patient cost-sharing, while operating under a fee-for-service (FFS) reimbursement model. This combination creates strong utilization incentives for both patients and providers. Patients face no financial barriers to seeking or prolonging treatment, and providers are reimbursed in full regardless of the frequency, duration, or intensity of care.

This dynamic is further explained by principal-agent theory, which highlights how information asymmetry between patients (principals) and providers (agents) can lead to provider-induced demand. Providers—who possess superior clinical knowledge and decision-making authority—may act in their own financial interest rather than solely in the interest of patients, particularly in settings with weak monitoring and regulation. This phenomenon lies at the core of the physician-induced demand hypothesis in health economics. provider-induced demand describes situations in which providers, leveraging their informational advantage, influence patient decisions and expand the utilization of medical services beyond what would be medically necessary or desired under conditions of full information.[17]

The automobile insurance system in Korea is particularly conducive to provider-induced demand due to the absence of volume restrictions and full reimbursement under a fee-for-service model. Notably, utilization review is either limited or inconsistently applied, and institutional mechanisms such as utilization caps—which could otherwise curb excessive care—are lacking. This environment grants providers considerable flexibility in billing, especially in traditional Korean medicine, where clinical guidelines are not standardized. Such regulatory gaps create systemic conditions that allow for the frequent provision of high-cost, high-volume care. [18] Reflecting these structural characteristics, the share of medical expenditures for traditional Korean medicine under AI surpassed that of Conventional medicine in 2020 and accounted for approximately 60% of all inpatient costs by 2023. This pattern aligns with theoretical predictions that provider behavior responds to financial incentives. It also highlights the practical implications of unregulated reimbursement schemes in driving high-volume, high-cost practices.

Table 2. Comparison of medical expenditures and utilization share between western and traditional Korean medicine under Automobile Insurance

(KRW:1,000,000/%)

Year	2017	2018	2019	2020	2021	2022	2023
Conventional medicine	1,112,389	1,150,603	1,173,981	1,096,169	1,030,325	986,476	1,003,276
	65.4	60.3	53.5	48.8	42.9	39.1	39.1
Traditional Korean Medicine	589,111	756,225	1,019,180	1,150,845	1,369,535	1,536,470	1,563,521
	34.6	39.7	46.5	51.2	57.1	60.9	60.9

source: HIRA, Statistical Indicator of Medical expenses under Automobile Insurance (2025)

2.2. Previous Studies

2.2.1. Studies on Inpatient Healthcare Utilization

Length of stay (LOS) is defined as the number of days a patient remains hospitalized from the date of admission to the date of discharge. [19] The most commonly used method for calculating LOS is the subtraction of the admission date from the discharge date. [20] LOS and medical expenditure are widely recognized as core indicators in the measurement of healthcare utilization. LOS serves two primary functions: it is used for cost estimation and as a performance indicator. It is considered a key metric for evaluating hospital efficiency and cost management, as exemplified by the National Health Service. [21] LOS is also one of the most important components of hospital resource consumption and has long been regarded as a key performance indicator in hospital management. [22] The Centers for Medicare & Medicaid Services (CMS) in the United States regard LOS as an important indicator for assessing healthcare efficiency, quality, cost, and patient safety. [23,24] Likewise, the OECD and the WHO have also identified LOS as a critical indicator of hospital efficiency, particularly in high-income countries. [25]

A systematic review categorized the determinants of LOS using Donabedian's framework of structure, process, and outcome. Structural factors include admission timing, [26] bed availability, [27] care pathways, [28] and the efficiency of support services. [29] Patient-related characteristics such as age, comorbidities, [30] and social relational factors also influence LOS. [31,32] Process-related factors include provider characteristics as well as teamwork and communication among medical staff. [30,33-35] Outcome-related determinants include complications acquired during hospitalization, [31] treatment outcomes, and patient satisfaction. [36]

According to a systematic review on factors influencing inpatient expenditure, [37] the determinants can be categorized across four levels: patient, clinical, hospital, and systemic. At the patient level, variables such as disease severity, comorbidities, and age significantly affect costs.[38] Clinical factors such as the type of treatment (e.g., surgery), ICU admission, and frequency of medical interventions have also been identified as key cost drivers. [39,40] At the hospital level, institutional characteristics such as hospital size and ownership status (e.g., public vs. private) have been shown to influence average inpatient costs.[41,42] Furthermore, payment mechanisms—particularly the fee-for-service model—are known to incentivize higher service volumes and contribute to overall expenditure increases. [43]

Table 3. factors affecting medical expenditure based on literature review (Goetghebeur, 2003)

category	factors	mechanism of influence	references
Patient-related factors	Severity of illness, comorbidities, older age	Higher clinical complexity leads to increased resource use and costs	Rosko & Mutter (2008)
Clinical characteristics	Type of treatment (e.g., surgery, ICU), frequency of interventions	Intensive treatments and complex procedures are associated with higher costs	Mechanic (2014); Alexander et al. (2003)
Hospital-level factors	Teaching status, hospital size, ownership (private/public)	Teaching and larger hospitals often incur higher average costs due to educational and administrative functions	Koenig et al. (2003); MedPAC (2014)
Market and geographic factors	Regional healthcare costs, market competition, provider density	Higher costs in monopolistic or resource-abundant areas	Cutler & Scott Morton (2013)
Payment system factors	Reimbursement model (e.g., fee-for-service, capitation)	Fee-for-service may incentivize overutilization and increase overall costs	Berenson et al. (2011)
Technological innovation	Adoption of advanced technologies, high-cost drugs and devices	New technologies improve outcomes but often raise upfront costs	Newhouse (1992); Chandra & Skinner (2012)
Administrative and operational factors	Billing costs, administrative overhead, inefficiency	High administrative burden contributes significantly to inpatient cost growth	Woolhandler & Himmelstein (2014)

2.2.2. Studies on cost sharing, moral hazard, and healthcare utilization

Many studies have reported that moral hazard contributes to increased healthcare utilization. Zweifel (2000) argued that health insurance reduces patients' cost sensitivity, thereby increasing the likelihood of overutilization. [5] Similarly, insurance design is associated with increased unnecessary healthcare use, [44] while Trottmann et al. (2012) showed that expanded coverage can lead to higher healthcare demand when both demand- and supply-side cost sharing are considered.[45] Courbage and Nicolas (2021) further suggested that high-deductible health plans (HDHPs) may suppress moral hazard, as individuals enrolled in such plans tend to engage more in preventive behaviors. [46] This implies the presence of self-regulatory mechanisms in healthcare utilization, whereby individuals may moderate their use of care and enhance prevention in the absence of moral hazard.

However, other studies have indicated that the effects of cost-sharing are mixed or limited. For example, while deductible-based mechanisms may reduce overuse, the effects are not uniform across all population groups and may exacerbate health inequities.[47] Recent findings have challenged the traditional framework of moral hazard by showing that no cost-sharing policies—though potentially conducive to overuse—can also improve adherence to essential medications, enhance clinical outcomes, reduce emergency visits and hospitalizations, and ultimately lead to lower long-term healthcare expenditures. [48,49] Furthermore, one study reported that no cost-sharing enhanced health equity at the time, while posing relatively low risk of traditional concerns over overutilization.[50]

Regarding physician-induced demand, studies have suggested that physician density, provider payment mechanisms, and expanded insurance coverage can incentivize unnecessary service provision, contributing to higher healthcare spending.[51] When Medicare reimbursement rates were changed, Rice (1983) observed increases in the intensity of procedures and diagnostic testing. [52] These findings suggest that when conditions enable supply-side inducement, increases in healthcare utilization can quickly follow. Notably, Saul (2006) reported that physician-induced demand resulted in Medicare expenditures exceeding $40,000 per patient in some cases. [53]

2.2.3. Studies on Automobile Insurance in Korea

Research on automobile insurance in South Korea has been relatively limited. Prior to 2013, inconsistent review criteria and differing interpretations across institutions frequently led to disputes among stakeholders. [54] In response, scholars emphasized the need to centralize claims review under the Health Insurance Review and Assessment Service to enhance the structural efficiency of the system.[55] Earlier studies also examined issues of moral hazard in the context of automobile insurance, particularly with regard to pricing policies and violations of traffic regulations. [56]

Following the delegation of claims review to HIRA, research efforts have primarily focused on identifying the causes of increasing medical expenditures and assessing the effectiveness of review centralization. For instance, Hong et al. (2020) identified a surge in the number of patients receiving traditional Korean medicine as a major contributor to rising expenditures under automobile insurance. He also noted that inpatient care in Conventional medicine was being substituted by outpatient services, and that the increase in non-covered services in traditional Korean medicine further contributed to the rise in costs. [57] The decline in inpatient care and the shift toward outpatient services following HIRA's involvement was regarded as a partial positive outcome of the review reform.

Kim et al. (2016) reported that centralization helped reduce settlement amounts, total indemnity payments, and administrative costs.[58] However, he also observed a sharp increase in outpatient visits and rising expenditures in long-term care hospitals and traditional Korean medicine institutions, suggesting that the expected cost-saving effects were only partially realized. [58]

Similarly, Kim (2016) found that claims centralization led to short-term behavioral changes among providers, resulting in a significant reduction in the number of service days, inpatient admissions, and outpatient expenditures. [59]

Despite these developments, empirical studies on medical utilization under automobile insurance remain scarce. Ko et al. (2011) examined the patterns and characteristics of inpatient care based on sex, age, and length of stay.[60] Han (2019) conducted an empirical analysis on the utilization patterns of traditional Korean medicine under automobile insurance, noting that such services were more commonly used for minor conditions than for severe ones. Several studies have similarly reported that rising expenditures in traditional Korean medicine are a major driver of overall cost increases in the automobile insurance system.[18,61-63]

While many of these studies have focused on the increasing costs of traditional Korean medicine, few have accounted for the structural differences between automobile and national health insurance.

3. MATERIAL AND METHODS

3.1. Framework of the Study Design

This study adopted a multi-component longitudinal cohort design grounded in theoretical perspectives on moral hazard and provider behavior within health insurance systems. According to these theories, patients with no or minimal cost-sharing are more likely to overutilize healthcare services, particularly under fee-for-service payment models. Accordingly, this study was designed to evaluate time-series patterns in healthcare utilization by type of insurance. The analysis used national cohort data from 2018 to 2024, and a matched dataset was constructed based on the most frequently occurring diagnoses under automobile insurance to enable valid comparisons between national health insurance and automobile insurance.

The analysis uses national cohort data from 2018 to 2024 and consists of two components:

First, comparison by insurance type: A longitudinal comparison if healthcare utilization between patients covered by automobile insurance (AI) and those covered by national health insurance (NHI) to assess differences in inpatient healthcare utilization.

Second, policy evaluation using difference-in-differences (DID): A DID analysis was conducted to estimate the impact of a policy implemented on December 1, 2022, which strengthened claims review procedures for mild-condition hospitalizations under the automobile insurance system.

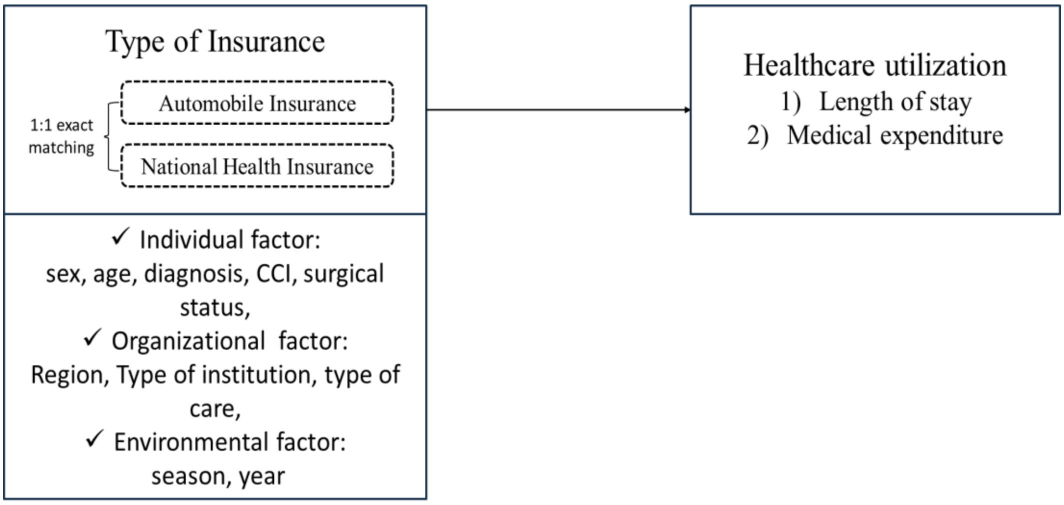


Figure 1. Conceptual framework of the study

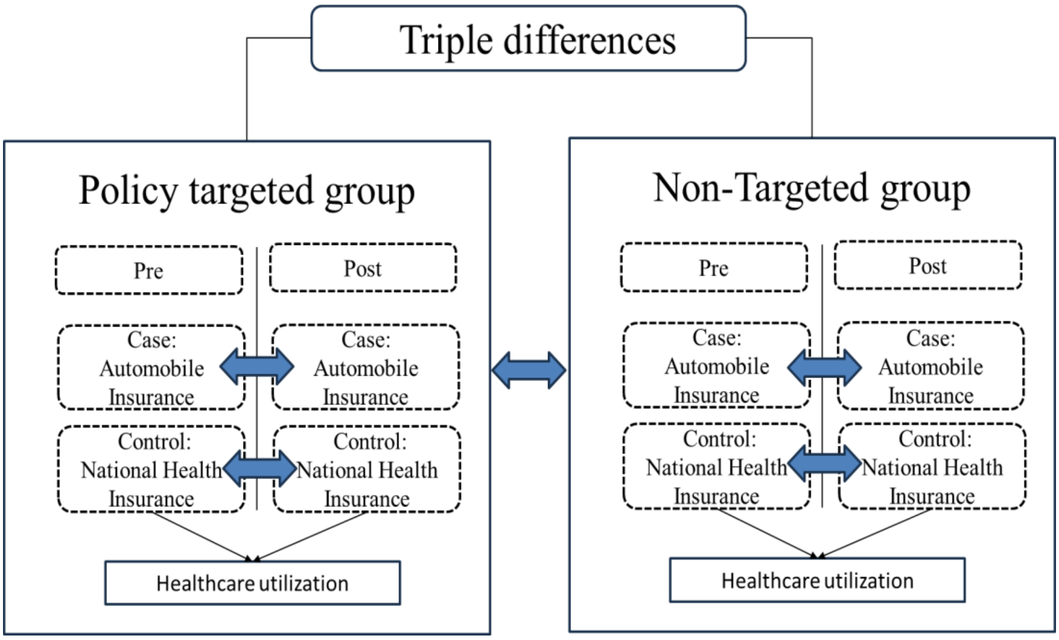


Figure 2. Analytical structure of the triple differences

3.2. Data Source and Study Population

3.2.1. Data Source

The data used in this study were obtained from the Health Insurance Review and Assessment Service (HIRA) of Korea. The dataset includes inpatient claims from both national health insurance and automobile insurance from January 1, 2018 to December 31, 2024. It includes patient-level information such as age, sex, diagnosis codes (based on ICD-10), hospitalization dates, total cost per episode, and institutional characteristics such as hospital type, region, and medical specialty.

3.2.2. Study Population

The study population consisted of patients who were hospitalized under either automobile insurance (AI) or national health insurance (NHI) between January 1, 2018, and December 31, 2024. The analysis was restricted to hospitalization episodes associated with the five most frequent diagnoses under AI claims, specifically injury-related conditions coded as S13, S33, S06, S22, and S82 based on the ICD-10 classification (e.g., dislocations, sprains, intracranial injuries, and fractures of the spine and lower extremities). Hospitalization episodes were defined based on admission dates, and consecutive hospitalizations with a one-day gap between discharge and readmission were considered part of the same episode. Each episode was consolidated into a single observation per hospitalization. As a result, a total of 4,177,531 episodes under AI and 2,722,604 episodes under NHI were constructed.

To establish comparable groups, exact matching was first performed between the AI (case) and NHI (control) groups based on sex, age, season, diagnosis, year, severity, and surgical status. Among these exactly matched pairs, additional refinement was conducted using a propensity score difference of less than 0.1 (caliper), calculated via logistic regression incorporating sex, age, comorbidity, diagnosis, region, type of medicine, surgical status, and severity. Finally, 1:1 greedy nearest-neighbor matching without replacement was applied by selecting controls with the smallest PS difference.

The following exclusion criteria were applied: records with missing values in any matching variable, hospitalizations with zero length of stay or zero medical expenses, and cases with incomplete linkage between patient and institution codes. After applying these criteria, a total of 296,102 hospitalization episodes were included in each group for the final analysis

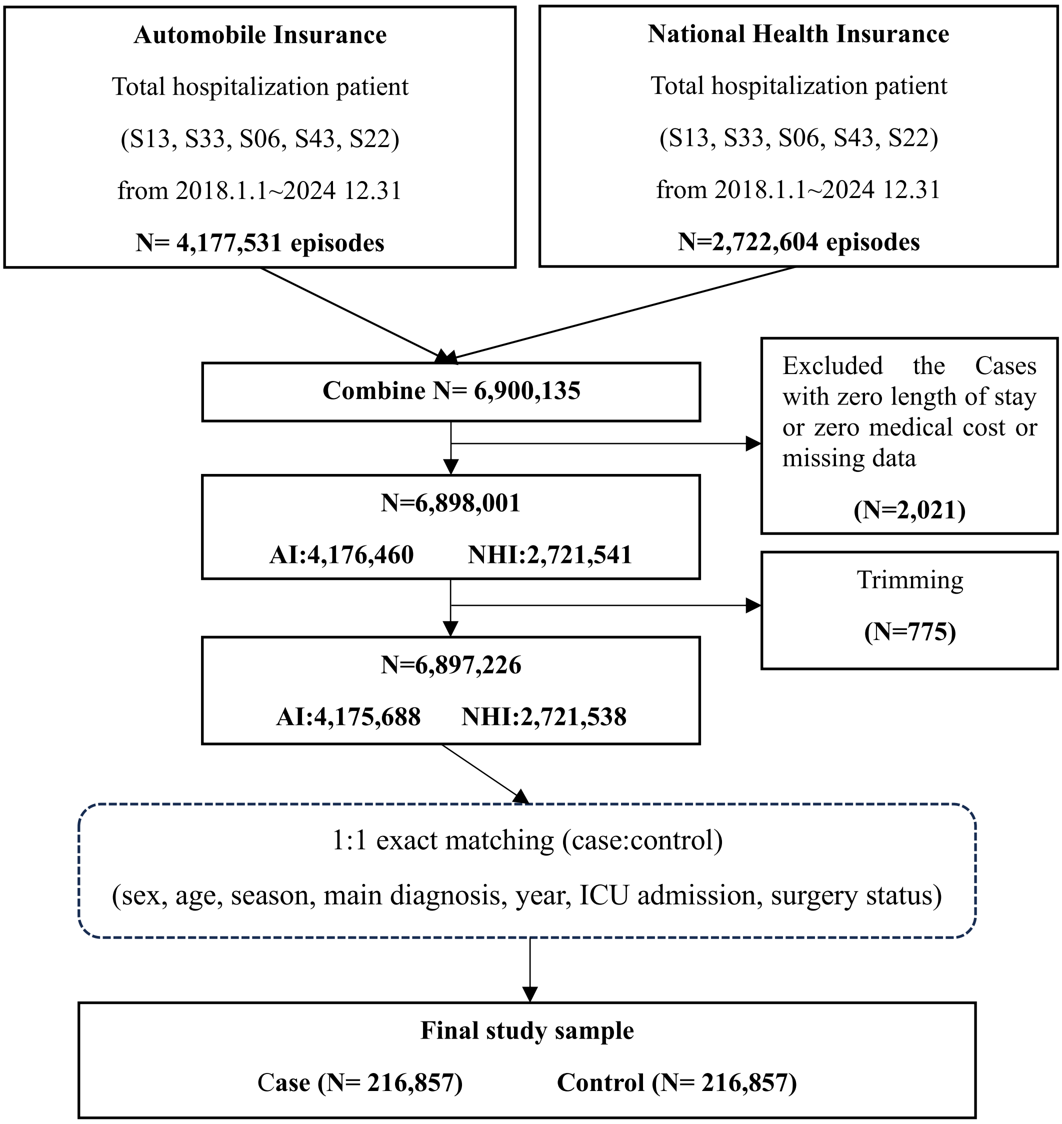


Figure 3. Flowchart of the study participants

3.3. Definition of Variables

3.3.1. Dependent Variable

In this study, inpatient healthcare utilization was analyzed using three main indicators: (1) the number of inpatient episodes, (2) the average length of stay (LOS) per episode.

Length of stay (LOS) was defined as the number of days from hospital admission to discharge within each episode. If the admission and discharge occurred on the same day, it was counted as one day and considered a single episode. Total medical expenditure was defined as the total amount of reimbursed healthcare costs per inpatient episode. Per diem expenditure was calculated by dividing the total medical expenditure for each episode by the corresponding length of stay.

3.3.2. Independent Variable

3.3.2.1. The variable of Interest

The first interesting variable was the type of insurance. Hospitalizations due to traffic accidents were covered by automobile insurance, while other types of hospitalizations were covered by the National Health Insurance (NHI). The type of insurance not only reflects the reason for hospitalization—whether it was related to a traffic accident—but also serves as a proxy for patients' out-of-pocket expenses. Automobile insurance fully covers inpatient care, resulting in no out-of-pocket payment for patients, whereas NHI involves partial cost-sharing, the amount of which varies by hospital type and type of care provided.

The second interesting variable was the policy intervention aimed at strengthening the review of claims for mild-condition hospitalizations. The policy was officially announced on April 18, 2022, and was implemented for claims submitted on or after December 1, 2022. Accordingly, the grace period of approximately seven months was excluded from the analysis. The post-intervention period was defined as December 1, 2022, to December 31, 2024, while the pre-intervention period spanned from January 1, 2018, to April 17, 2022.

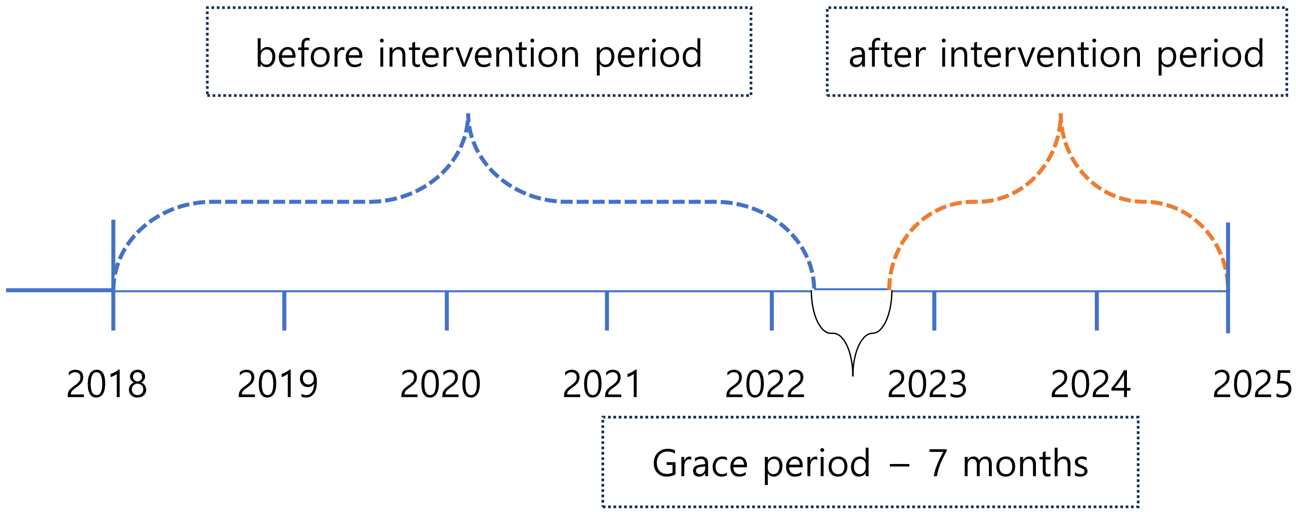


Figure 4. Timeline of policy implementation including pre-intervention, grace period, and post-intervention phases (2018–2024)

3.3.2.2. Covariates

The covariates in this study included sex, age, primary diagnosis, region, type of institution, type of care, ICU admission, Surgical Status, Charlson Comorbidity Index (CCI), season, and year. The CCI was measured using diagnostic codes from the three years prior to the admission date, based on the Charlson Comorbidity Index scoring algorithm using the International Classification of Diseases, 10th Revision (ICD-10). The scores were categorized into four levels (0, 1, 2, and ≥3) and used to adjust for comorbidities. A comorbid condition was identified if it appeared as a primary or secondary diagnosis in at least one inpatient claim or in three or more outpatient visits.

Table 4. Definition of covariates

Variable	Definition
Sex	Male, Female
Age	~19, 20~29, 30~39, 40~40, 50~59, 60~69, 70~
Principal Diagnosis	S13(neck level), S33 (lumbar spine and pelvis), S06 (Intracranial injury), S22 (fracture of rib, sternum, thoracic spine), S82 (Fracture of lower leg, including ankle)
Region	Capital city (Seoul, Metropolitan, Province
Type of institution	Tertiary hospital, General hospital, Clinic
Type of care	Conventional medicine, Traditional Korean medicine
ICU Admission	Yes, No
Surgical status	Yes, No
Charlson Comorbidity Index	0, 1, 2, ≥3
Season	Spring (Mar-May), Summer (Jun–Aug), Fall (Sep–Nov), Winter (Dec–Feb)
Year	2018, 2019, 2020, 2021, 2022, 2023, 2024
Quarter	1~28 (from the first quarter of 2018 to the fourth quarter of 2024)

3.4. Statistical Methods

To examine the distribution of the study population by general characteristics and outcome variables, chi-square tests were performed. General characteristics were summarized as frequencies and percentages for categorical variables, and as means with standard deviations for continuous variables.

To compare inpatient healthcare utilization for high-frequency diagnoses under automobile insurance with those under national health insurance, exact matching was first conducted on sex, age, season, diagnosis, year, severity, and surgical status. Propensity scores were then estimated using sex, age, comorbidity, diagnosis, region, and type of medicine (traditional Korean medicine vs. conventional medicine). Among these exactly matched pairs, pairs with a propensity score difference less than 0.1 (caliper) were selected, and finally, 1:1 greedy nearest-neighbor matching without replacement was applied. The balance between the matched groups was evaluated descriptively.

This study examined differences in inpatient healthcare utilization between patients covered by automobile insurance and those under national health insurance using nationwide claims data from 2018 to 2024. The three primary outcome variables were: length of stay (LOS), total inpatient medical expenditure, and average per diem expenditure.

Based on the generalized linear model (GLM) framework, generalized estimating equations (GEE) were used to compare differences in medical utilization between automobile insurance beneficiaries (case group) and national health insurance beneficiaries (control group). GEE extend the GLM framework to account for within-subject or within-cluster correlation in repeated measures data, providing robust standard errors and valid population-averaged estimates even when the specified correlation structure is not perfectly correct. [64]

GLMs allow for flexible specification of various outcome distributions, such as normal, binomial, Poisson, and gamma, as well as appropriate link functions, making them suitable for analyzing non-normally distributed data.[65] In this study, the outcome variables were continuous and positively skewed; therefore, a gamma distribution with a log link function was applied. Because the same patient could be included multiple times across different years, a GEE approach was adopted to account for intra-patient correlation and to enable robust estimation of population-averaged effects for non-normally distributed outcomes. These models were implemented using the PROC GENMOD procedure in SAS to perform GEE analysis.[66]

To account for within-subject correlations due to repeated admissions from the same patient over time, the patient ID was specified as the subject variable, and an independent working correlation matrix was assumed. Although this structure does not explicitly model intra-subject correlations, it provides consistent parameter estimates under the correct specification of the mean model. The models adjusted for the following covariates: sex, age group, disease code, department, type of care, hospital type, region, ICU admission, surgical status, Charlson Comorbidity Index (CCI), season, and calendar year. The GEE model used in this study is specified as follows:

$$g(E[Y_{it}]) = \beta_0 + \beta_1 (Case_{it}) + \gamma' X_{it}$$

g: log link function

Y: dependent variable for individual i at time t

$E[Y_{it}]$: Expected value of the outcome variable

i: individual (i=1,2,…, n)

t: time period (year)

$\boldsymbol{\beta_0}$: intercept

Case: A binary indicator variable coded as 1 for the case group (automobile insurance) and 0 for the control group (national health insurance).

$\boldsymbol{\gamma'}$: coefficients for covariates

$\boldsymbol{X_{it}}$: covariates (sex, age, region, principal diagnosis, type of institution, type of care, ICU admission, surgical status, CCI, Season, year)

Second, to evaluate the impact of the policy that strengthened claim reviews for mild inpatient cases under automobile insurance, both a Difference-in-Differences (DID) analysis and a Difference-in-Difference-in-Differences (DDD) analysis were conducted. The DID analysis was performed to estimate the average policy effect, whereas the DDD analysis was employed to examine the differential effects between policy-targeted and non-targeted groups. [67,68] Insurance type (automobile vs. national health insurance), policy period (pre- vs. post-intervention), and diagnosis group (policy-targeted vs. non-targeted) were used as key comparison factors. The dependent variable was modeled using a gamma distribution with a log link function. All analyses were conducted using GEE implemented via the GENMOD procedure to account for potential intra-cluster (within-group) correlations and to obtain robust population-averaged estimates. [69] To estimate the policy effect, an interaction term between insurance type and policy period was included in the DID model. [70] To examine the heterogeneity of the policy effect, interaction terms among insurance type, policy period, and diagnosis group were incorporated into the DDD model. [67,70]

The DID model used in this study are specified as follows:

$$g(E[Y_{it}]) = \beta_0+\beta_1 Post_t+\beta_2 Case_i+\beta_3(Case_i \times Post_t)+ \beta_4 Time_t+\gamma' X_{it}$$

g: log link function

Y: dependent variable for individual i at time t

E$[Y_{it}]$: Expected value of the outcome variable

i: individual (i=1,2,…, n)

t: time period (quarter)

β_0: intercept

Post: Indicator for the post-policy period (1 = post-policy, 0 = pre-policy)

Case: a binary indicator variable coded as 1 for the case group (automobile insurance) and 0 for the control group (national health insurance)

Time: time variable (quarter)

γ': coefficients for covariates

X_{it}: vector of covariates (sex, age, region, principal diagnosis, type of institution, type of care, ICU admission, surgical status, CCI, Season, year)

The DDD model used in this study are specified as follows:

$$g(E[Yit]) = \beta_0+\beta_1(Post_t) +\beta_2(Case_i) +\beta_3(Targt_i) +\beta_4(Case_i\times Post_t)+\beta 5(Case_i \times Target_i)+\beta_6(Post_t\times Target_i)+\beta_7(Case_i\times Post_t\times Target_i)+\beta_8 Time_t+\gamma' Xit$$

g: log link function

Y: dependent variable for individual i at time t

E[**Y*it***]: Expected value of the outcome variable

i: individual (*i*=1,2,…, n)

t: time period (quarter)

β_0: intercept

Post: Indicator for the post-policy period (1 = post-policy, 0 = pre-policy)

Case: a binary indicator variable coded as 1 for the case group (automobile insurance) and 0 for the control group (national health insurance)

Target: indicator for diagnosis group (1 =policy target diagnosis group, 0 = non-target diagnosis group)

Time: time variable (quarter)

β_7: triple interaction term coefficient representing the DDD effect

γ': coefficients for covariates

X_{it}: vector of covariates (sex, age, region, principal diagnosis, type of institution, type of care, ICU admission, surgical status, CCI, Season, year)

All statistical analyses were performed using SAS software version 9.4 (SAS Institute Inc., Cary, NC, USA), and statistical significance was defined as a two-sided p-value < 0.05.

3.5. Ethics Statement

This study was reviewed and approved by the Institutional Review Board of Yonsei University Health System in accordance with the principles of the Declaration of Helsinki (IRB no. 4-2024-1021). Furthermore, as the National Health Insurance data and Auto Insurance data we used for analysis does not contain personally identifiable information, the informed consent requirement was exempted.

4. RESULTS

4.1. General Characteristics of the Study Population

Table 4 presents the general characteristics and distributions of the study population after propensity score matching (PSM). The balance of covariate distributions between the case and control groups was assessed using standardized mean differences (SMDs). An SMD value less than 0.1 was considered indicative of sufficient balance between groups. Changes in SMDs before and after matching are reported in Supplementary Table 1.

After 1:1 propensity score matching, the number of observations in both the automobile insurance (case) and national health insurance (control) groups was 296,102. Among them, the number of males was 298,888 in the case group and 293,316 in the control group. The average length of stay per inpatient episode was 14.7 days for the automobile insurance group and 14.8 days for the national health insurance group. The average total medical cost per episode was KRW 2,468,847 for the automobile insurance group and KRW 2,309,774 for the national health insurance group. The average cost per day was KRW 193,345 for the automobile insurance group and KRW 181,343 for the national health insurance group.

Table 5. General characteristics of study subjects after matching

Variables	Total		Case (N=216,857) Auto insurance		Control (N=216,857) National health insurance		SMD
	N	%	N	%	N	%	
Total	**433,714**	**100**	**216,857**	**50**	**216,857**	**50**	
SEX							
Male	223,358	51.50	111,679	51.50	111,679	51.50	0.0000
Female	210,356	48.50	105,178	48.50	105,178	48.50	
AGE							
~29	64,894	14.96	32,447	14.96	32,447	14.96	0.0000
30~39	40,574	9.36	20,287	9.36	20,287	9.36	
40~49	53,312	12.29	26,656	12.29	26,656	12.29	
50~59	72,854	16.80	36,427	16.80	36,427	16.80	
60~69	83,556	19.27	41,778	19.27	41,778	19.27	
70~	118,524	27.33	59,262	27.33	59,262	27.33	
Principal Diagnosis							
S13 (neck level)	73,214	16.88	36,607	16.88	36,607	16.88	-0.0143
S33 (lumbar spine and pelvis)	108,238	24.96	54,119	24.96	54,119	24.96	
S06 (Intracranial injury)	100,968	23.28	50,484	23.28	50,484	23.28	

S22 (fracture of rib, sternum, thoracic spine)	78,000	17.98	39,000	17.98	39,000	17.98	
S82 (Fracture of lower leg, including ankle)	73,294	16.90	36,647	16.90	36,647	16.90	
Region							0.0000
Capital city	139,971	32.27	70,575	32.54	69,396	32.00	
Metropolitan	141,529	32.63	70,845	32.67	70,684	32.59	
Province	152,214	35.10	75,437	34.79	76,777	35.40	
Type of institution							0.0000
Tertiary hospital	149,735	34.52	68,801	31.73	80,934	37.32	
General hospital	208,642	48.11	101,698	46.90	106,944	49.32	
Clinic	75,337	17.37	46,358	21.38	28,979	13.36	
Type of Care							-0.0143
Conventional medicine	311,221	71.76	154,913	71.44	156,308	72.08	
Traditional Korean medicine	122,493	28.24	61,944	28.56	60,549	27.92	
ICU Admission							0.0000
0	431,316	99.45	215,658	99.45	215,658	99.45	
1	2,398	0.55	1,199	0.55	1,199	0.55	
Surgery							0.0000
0	354,482	81.73	177,241	81.73	177,241	81.73	
1	79,232	18.27	39,616	18.27	39,616	18.27	
Charlson Comorbidity Index							0.0000

0	268,680	61.95	132,766	61.22	135,914	62.67	
1	94,018	21.68	47,434	21.87	46,584	21.48	
2	47,923	11.05	24,484	11.29	23,439	10.81	
3 or higher	23,093	5.32	12,173	5.61	10,920	5.04	
Season							0.0000
1 (spring)	106,268	24.50	53,134	24.50	53,134	24.50	
2	109,552	25.26	54,776	25.26	54,776	25.26	
3	109,142	25.16	54,571	25.16	54,571	25.16	
4	108,752	25.07	54,376	25.07	54,376	25.07	
Year							0.0000
2018	64,898	29.93	32,449	14.96	32,449	14.96	
2019	65,336	30.13	32,668	15.06	32,668	15.06	
2020	62,094	28.63	31,047	14.32	31,047	14.32	
2021	60,154	27.74	30,077	13.87	30,077	13.87	
2022	59,344	27.37	29,672	13.68	29,672	13.68	
2023	60,070	27.70	30,035	13.85	30,035	13.85	
2024	61,818	28.51	30,909	14.25	30,909	14.25	

4.2. Comparison of Healthcare Utilization by Insurance Type

4.2.1. Length of Stay

4.2.1.1. Average length of stay by insurance type

Table 5 presents the comparison of average length of stay (LOS) between automobile insurance and national health insurance across major demographic and clinical characteristics. Overall, the average LOS was longer in the automobile insurance group (15.76 days) than in the national health insurance group (14.52 days). Among diagnostic categories, S13, S33, and S06 showed longer LOS under national health insurance, whereas S82 and S22 showed longer LOS under automobile insurance. For example, in the case of S82 (Fracture of lower leg, including ankle), the average LOS was 28.11 days under automobile insurance and 14.94 days under national health insurance, representing the largest difference among the diagnoses. Under national health insurance, S06 (Intracranial injury) had the longest LOS (23.44 days). Among patients admitted to the intensive care unit (ICU) during hospitalization, the average LOS was longer in the automobile insurance group (21.45 days) compared to the national health insurance group (16.37 days). Similarly, for those who underwent surgery, the average LOS was 19.96 days under automobile insurance, which was longer than the 12.81 days under national health insurance. Differences in LOS between the two insurance groups were statistically significant across most subgroups, including sex, age, type of medical institution, and type of care ($p < 0.0001$).

Table 6. Average length of stay by insurance type and patient characteristics

	Length of stay					
	Case Auto insurance		p-value	Control National health insurance		p-value
	Mean	SD		Mean	SD	
Total	15.76	38.64		14.52	43.19	
SEX			0.0090			<0.0001
Male	15.55	36.01		15.98	41.25	
Female	15.98	41.25		13.81	38.90	
AGE			<0.0001			<0.0001
~29	10.14	16.36		8.59	17.56	
30~39	11.61	21.60		11.23	32.52	
40~49	12.28	20.34		12.89	33.48	
50~59	13.87	24.94		14.99	43.47	
60~69	15.39	26.91		16.82	51.05	
70~	23.24	63.18		17.70	52.48	
Principal Diagnosis			<0.0001			<0.0001
S13 (neck level)	6.98	5.49		8.97	14.31	
S33 (lumbar spine and pelvis	7.32	11.15		10.21	11.45	
S06 (Intracranial injury)	19.90	67.25		23.44	83.11	
S22 (fracture of rib, sternum, thoracic spine)	18.74	21.64		13.75	21.92	
S82 (Fracture of lower leg, including ankle)	28.11	39.06		14.94	21.12	
Region			<0.0001			<0.0001
Capital city	16.30	42.87		14.32	46.90	
Metropolitan	16.11	41.26		15.43	44.66	
Province	14.92	31.19		13.85	37.99	
Type of institution			<0.0001			<0.0001
Tertiary hospital	15.45	22.68		10.13	15.86	
General hospital	17.17	51.85		18.63	59.50	
Clinic	13.13	17.67		11.61	8.15	
Type of Care			<0.0001			0.0054

Conventional medicine	17.20	42.76		14.35	45.92	
Traditional Korean medicine	12.16	25.22		14.93	35.18	
ICU Admission			<0.0001			0.0005
0	15.73	38.71		14.51	43.29	
1	21.45	23.67		16.37	18.10	
Surgery			<0.0001			<0.0001
0	14.82	41.04		14.90	47.09	
1	19.96	24.81		12.81	16.98	
Charlson Comorbidity Inde:			0.00			<0.0001
0	15.87	35.12		12.70	33.67	
1	15.12	40.33		14.39	39.46	
2	16.03	48.59		20.91	70.36	
3 or higher	16.53	45.40		23.93	73.83	
Season			<0.0001			0.9252
1 (spring)	15.85	36.29		14.60	44.67	
2	15.14	35.27		14.46	43.91	
3	15.53	34.67		14.44	41.13	
4	16.53	46.99		14.56	43.01	
Year			<0.0001			<0.0001
2018	14.84	20.72		14.41	43.15	
2019	15.63	27.70		14.10	40.38	
2020	16.07	34.69		14.54	40.48	
2021	16.38	41.73		14.67	42.62	
2022	15.79	41.53		14.36	44.91	
2023	14.66	40.47		13.58	38.35	
2024	16.97	55.33		15.94	51.26	

4.2.1.2. GEE analysis of factors associated with length of stay

Table 7 presents the results of the generalized estimating equation (GEE) analysis on length of stay. The model included the primary independent variable (type of insurance) along with covariates such as sex, age, diagnosis, region, hospital type, ICU admission, Surgical status, Charlson Comorbidity Index (CCI), season, and year.

Insurance type was significantly associated with the length of stay. Patients covered by automobile insurance had slightly longer hospital stays compared to those covered by national health insurance (exp(β) = 1.02, 95% CI: 1.01–1.03). Length of stay increased with age, with patients aged 70 and older staying approximately 72% longer than those under 30 years old (exp(β) = 1.72). Regarding the principal diagnosis, compared to patients with S13 (injury at the neck level), those diagnosed with S06 (intracranial injury), S22 (fracture of the rib, sternum, or thoracic spine), and S82 (fracture of lower leg, including ankle) had significantly longer lengths of stay, with exp(β) values of 2.36, 2.07, and 2.74, respectively. In terms of region, patients living in metropolitan and provincial areas had slightly longer hospital stays compared to those in the capital city, with metropolitan areas showing the largest difference (exp(β) = 1.10). Compared to tertiary hospitals, patients treated in general hospitals (exp(β) = 1.78) and clinics (exp(β) = 1.58) had significantly longer hospital stays. ICU admission and surgery were also associated with longer hospital stays. Patients admitted to the ICU had 24% longer stays (exp(β) = 1.24), and patients who underwent surgery had stays that were 10% longer than those who did not (exp(β) = 1.10). Higher CCI scores were associated with increased length of stay. Patients with a CCI score of 3 or higher stayed approximately 18% longer than those with a score of 0 (exp(β) = 1.18). Season and year were not major predictors of length of stay.

Table 7. Results of generalized estimating equation Analysis factor associated length of stay

Variable	Length of stay	
	EXP(ß)	95%CI
Insurance Type		
Auto Insurance	1.02	(1.01 - 1.03)
National Health Insurance	1.00	
SEX		
Male	1.00	
Female	0.98	(0.97 - 0.99)
AGE		
~29	1.00	
30~39	1.17	(1.15 - 1.20)
40~49	1.25	(1.23 - 1.27)
50~59	1.37	(1.35 - 1.39)
60~69	1.49	(1.46 - 1.52)
70~	1.72	(1.69 - 1.76)
Principal Diagnosis		
S13 (neck level)	1.00	
S33 (lumbar spine and pelvis)	1.03	(1.02 - 1.04)
S06 (Intracranial injury)	2.36	(2.31 - 2.42)
S22 (fracture of rib, sternum, thoracic spine)	2.07	(2.04 - 2.10)
S82 (Fracture of lower leg, including ankle)	2.74	(2.70 - 2.78)
Region		
Capital city	1.00	
Metropolitan	1.10	(1.08 - 1.11)
Province	1.02	(1.01 - 1.03)
Type of institution		
Tertiary hospital	1.00	
General hospital	1.78	(1.74 - 1.81)
Clinic	1.58	(1.56 - 1.60)
Type of Care		
Conventional medicine	1.00	
Traditional Korean medicine	1.00	(0.98 - 1.02)

ICU Admission		
0	1.00	
1	1.24	(1.17 - 1.30)
Surgery		
0	1.00	
1	1.10	(1.09 - 1.12)
Charlson Comorbidity Index		
0	1.00	
1	1.02	(1.00 - 1.03)
2	1.13	(1.11 - 1.16)
3 or higher	1.18	(1.14 - 1.22)
Season		
1 (spring)	1.00	
2	0.99	(0.98 - 1.01)
3	0.99	(0.97 - 1.00)
4	1.01	(0.99 - 1.03)
Year		
2018	1.00	
2019	0.99	(0.97 - 1.01)
2020	1.03	(1.00 - 1.05)
2021	1.02	(1.00 - 1.04)
2022	0.97	(0.95 - 0.99)
2023	0.93	(0.91 - 0.95)
2024	1.02	(0.99 - 1.04)

4.2.1.3. Results of subgroup analysis of factors associated with length of stay by insurance type

Table 8 presents the results of the subgroup analysis on factors associated with length of stay, stratified by type of insurance. The results are presented as exponentiated coefficients (exp(β)) derived from the GEE model.

When stratified by diagnosis group, patients with S13 (neck level) (exp(β) = 0.86, 95% CI: 0.84–0.88), S33 (lumbar spine and pelvis) (exp(β) = 0.73, 95% CI: 0.72–0.74), and S06 (intracranial injury) (exp(β) = 0.94, 95% CI: 0.91–0.98) showed a tendency for shorter lengths of stay under automobile insurance compared to national health insurance. In contrast, patients with S22 (fracture of ribs, sternum, and thoracic spine) and S82 (fracture of lower leg, including ankle) had longer lengths of stay under automobile insurance.

Among those admitted to general hospitals, patients under automobile insurance had significantly longer hospital stays (exp(β) = 1.40, 95% CI: 1.38–1.43). Conversely, in hospitals (as opposed to general hospitals), the length of stay was 17% shorter under automobile insurance (exp(β) = 0.83, 95% CI: 0.82–0.84).

Regarding the type of care, patients receiving Conventional medicine services under automobile insurance tended to have longer hospital stays (exp(β) = 1.18, 95% CI: 1.17–1.20), whereas those receiving Traditional Korean medicine had shorter stays (exp(β) = 0.71, 95% CI: 0.70–0.72).

Table 8. Result of subgroup analysis stratified by independent variables

Variable	Length of stay		
	National health insurance (ref)	Auto Insurance	
		Estimate	95%CI
SEX			
Male	1.00	0.99	(0.98 - 1.01)
Female	1.00	1.06	(1.04 - 1.08)
AGE			-
~29	1.00	1.13	(1.09 - 1.17)
30~39	1.00	0.98	(0.94 - 1.01)
40~49	1.00	0.92	(0.89 - 0.95)
50~59	1.00	0.91	(0.89 - 0.93)
60~69	1.00	0.91	(0.88 - 0.93)
70~	1.00	1.22	(1.20 - 1.25)
Principal Diagnosis			
S13 (neck level)	1.00	0.86	(0.84 - 0.88)
S33 (lumbar spine and pelvis)	1.00	0.73	(0.72 - 0.74)
S06 (Intracranial injury)	1.00	0.94	(0.91 - 0.98)
S22 (fracture of rib, sternum, thoracic spine)	1.00	1.37	(1.34 - 1.39)
S82 (Fracture of lower leg, including ankle)	1.00	1.86	(1.83 - 1.89)
Region			-
Capital city	1.00	1.11	(1.09 - 1.13)
Metropolitan	1.00	0.95	(0.93 - 0.97)
Province	1.00	1.01	(1.00 - 1.03)
Type of institution			-
Tertiary hospital	1.00	1.40	(1.38 - 1.43)
General hospital	1.00	0.83	(0.82 - 0.84)
Clinic	1.00	0.99	(0.97 - 1.00)
Type of Care			-
Conventional medicine	1.00	1.18	(1.17 - 1.20)
Traditional Korean medicine	1.00	0.71	(0.70 - 0.72)
ICU Admission			-
0	1.00	1.02	(1.01 - 1.03)

1	1.00	1.28	(1.18	-	1.39)
Surgery				-	
0	1.00	0.92	(0.91	-	0.93)
1	1.00	1.54	(1.52	-	1.57)
Charlson Comorbidity Index				-	
0	1.00	1.13	(1.12	-	1.15)
1	1.00	0.95	(0.93	-	0.97)
2	1.00	0.83	(0.80	-	0.85)
3 or higher	1.00	0.80	(0.77	-	0.84)
Season				-	
1 (spring)	1.00	1.04	(1.01	-	1.06)
2	1.00	0.99	(0.97	-	1.01)
3	1.00	1.02	(1.00	-	1.04)
4	1.00	1.03	(1.00	-	1.05)
Year				-	
2018	1.00	1.01	(0.98	-	1.03)
2019	1.00	1.05	(1.03	-	1.08)
2020	1.00	1.03	(1.01	-	1.06)
2021	1.00	1.05	(1.02	-	1.08)
2022	1.00	1.03	(1.00	-	1.06)
2023	1.00	0.97	(0.94	-	1.00)
2024	1.00	0.94	(0.91	-	0.97)

4.2.2. Medical Expenditure

4.2.2.1. Average medical expenditure of by insurance type

Table 9 presents the average total medical expenditure per inpatient episode, stratified by insurance type and patient characteristics. Overall, the average expenditure in the automobile insurance group was KRW 3,243,878, which was higher than that in the national health insurance group (KRW 2,755,776).

Across all insurance types, medical expenditure generally increased with age. The highest average cost was observed among patients aged 70 and older (KRW 4,755,499), while the lowest was among those aged 29 or younger.

Among diagnostic groups, the highest average expenditures were observed in patients with intracranial injury (S06) and fractures of the ribs, sternum, and thoracic spine (S22). In particular, for S22, the average cost in the automobile insurance group was KRW 5,152,721—substantially higher than in the national health insurance group (KRW 2,889,790). A similar pattern was observed for patients with lower leg fractures (S82), where the automobile insurance group incurred an average cost of KRW 3,405,329 compared to KRW 2,303,331 in the national health insurance group.

By region, the highest average expenditure in the automobile insurance group was observed in metropolitan areas (KRW 3,466,501), while the lowest was found in provinces. In all regions, the automobile insurance group had higher average costs than the national health insurance group.

Regarding the type of medical institution, tertiary hospitals showed the highest average expenditure (KRW 5,886,318 for automobile insurance and KRW 3,777,982 for national health insurance), followed by general hospitals and clinics.

In terms of care type, conventional medicine incurred higher costs than traditional Korean medicine in both insurance groups, with consistent trends.

Patients who were admitted to the intensive care unit (ICU) had substantially higher costs: KRW 22,821,083 in the automobile insurance group and KRW 15,256,864 in the national health insurance group. Similarly, patients who underwent surgery had higher expenditures in the automobile insurance group (KRW 8,347,951) compared to the national health insurance group (KRW 4,908,394).

Table 9. Average medical expenditure by insurance type and patient characteristics

Variable	Medical expenditure					
	Case		p-value	Control		p-value
	Auto insurance			National health insurance		
	Mean	SD		Mean	SD	
Total	3,243,878	8,755,825		2,755,776	7,721,901	
SEX			<0.0001			<0.0001
Male	3,505,508	9,363,566		3,137,251	8,857,423	
Female	2,966,076	8,051,262		2,350,721	6,270,557	
AGE			<0.0001			<0.0001
~29	2,288,978	6,979,115		2,288,978	6,979,115	
30~39	2,462,674	6,500,422		2,462,674	6,500,422	
40~49	2,504,686	6,323,195		2,504,686	6,323,195	
50~59	2,733,906	6,711,655		2,733,906	6,711,655	
60~69	3,136,903	7,499,044		3,136,903	7,499,044	
70~ 6	4,755,499	12,275,368		4,755,499	12,275,368	
Principal Diagnosis			<0.0001			<0.0001
S13 (neck level)	991,079	1,644,643		1,164,247	2,680,621	
S33 (lumbar spine and pelvis)	1,050,426	1,983,096		1,171,998	1,197,488	
S06 (Intracranial injury)	5,718,437	15,732,277		5,859,881	14,679,864	
S22 (fracture of rib, sternum, thoracic spine)	5,152,721	6,648,353		2,889,790	3,383,592	
S82 (Fracture of lower leg, including ankle)	3,405,329	5,793,344		2,303,331	3,815,954	
Region			<0.0001			<0.0001
Capital city	3,302,223	8,449,376		2,863,044	8,379,794	
Metropolitan	3,466,501	9,821,469		2,970,907	8,280,036	
Province	2,980,221	7,930,213		2,460,762	6,456,934	
Type of institution			<0.0001			<0.0001

Tertiary hospital	5,886,318	12,821,778		3,777,982	8,394,247	
General hospital	2,382,278	6,628,896		2,461,227	8,101,685	
Clinic	1,212,307	1,457,998		987,906	909,227	
Type of Care			<0.0001			<0.0001
Conventional medicine	3,799,914	10,078,797		3,147,667	8,595,533	
Traditional Korean medicine	1,853,310	3,412,141		1,744,105	4,626,858	
ICU Admission			<0.0001			<0.0001
0	3,135,034	8,413,792		2,686,273	7,529,494	
1	22,821,083	27,352,487		15,256,864	20,752,011	
Surgery			<0.0001			<0.0001
0	2,103,041	6,128,499		2,274,634	7,450,086	
1	8,347,951	14,824,092		4,908,394	8,509,437	
Charlson Comorbidity Index			<0.0001			<0.0001
0	3,479,961	8,957,078		2,526,670	6,386,300	
1	2,808,721	8,165,409		2,563,051	7,209,408	
2	2,888,079	8,495,748		3,669,673	11,389,632	
3 or higher	3,080,299	9,172,281		4,467,845	13,070,414	
Season			0.1242			0.0902
1 (spring)	3,265,115	8,599,646		2,776,791	7,972,862	
2	3,195,435	8,627,042		2,741,221	7,824,872	
3	3,307,318	8,749,726		2,809,479	7,360,366	
4	3,208,256	9,037,229		2,696,006	7,722,356	
Year			<0.0001			<0.0001
2018	2,642,947	6,312,441		2,182,362	5,770,810	
2019	2,910,341	7,149,056		2,366,355	6,128,001	
2020	3,145,135	8,528,025		2,647,877	7,141,279	
2021	3,435,297	10,359,573		2,845,985	7,522,103	
2022	3,396,362	8,918,900		2,891,543	8,424,076	
2023	3,361,121	8,770,116		2,885,840	7,455,877	
2024	3,879,874	10,605,300		3,533,222	10,682,535	

4.2.2.2. GEE Analysis of Factors Associated with Medical Expenditure

Table 10 presents the results of the GEE analysis for inpatient medical expenditure per episode. The model included the interesting variable (type of insurance), along with covariates such as sex, age, diagnosis, region, type of hospital, ICU admission, Surgical status, Charlson Comorbidity Index (CCI), season, and year.

The average inpatient medical expenditure per admission for patients covered by automobile insurance was statistically significantly higher—by 9%—compared to that of patients covered by national health insurance (exp(β) = 1.09, 95% CI: 1.08–1.10).

Regarding demographic characteristics, female patients had significantly lower medical expenditures than male patients (exp(β) = 0.94, 95% CI: 0.93–0.95), and medical expenditure increased with age. In particular, patients aged 70 years or older showed the highest expenditure, with an exp(β) of 1.67 (95% CI: 1.64–1.70).

By principal diagnosis, compared to patients with S13 (injury at the neck level), those with S06 (intracranial injury) had more than threefold higher medical costs (exp(β) = 3.26, 95% CI: 3.18–3.34), followed by S82 (fracture of the lower leg, including ankle) with an exp(β) of 2.57 and S22 (fracture of the rib, sternum, or thoracic spine) with an exp(β) of 1.95.

In terms of hospital type, medical expenditure was significantly lower in general hospitals and clinics compared to tertiary hospitals, by 18% (exp(β) = 0.82, 95% CI: 0.81–0.84) and 44% (exp(β) = 0.56, 95% CI: 0.56–0.57), respectively. By type of care, expenditures for traditional Korean medicine were significantly higher than for conventional medicine, with a 29% difference (exp(β) = 1.29, 95% CI: 1.28–1.31).

Patients admitted to intensive care units incurred over twice the cost of those who were not (exp(β) = 2.32, 95% CI: 2.18–2.48), and medical expenditures were also significantly higher among patients who underwent surgery (exp(β) = 2.06, 95% CI: 2.03–2.09).

Table 10. Results of Generalized estimating equation analysis of factors associated medical expenditure

variable	Medical Expenditure	
	EXP(ß)	95%CI
Insurance Type		
Auto Insurance	1.09	(1.08 - 1.10)
National Health Insurance	1.00	
SEX		
Male	1.00	
Female	0.94	(0.93 - 0.95)
AGE		
~29	1.00	
30~39	1.19	(1.16 - 1.21)
40~49	1.24	(1.22 - 1.26)
50~59	1.33	(1.30 - 1.35)
60~69	1.44	(1.41 - 1.46)
70~	1.67	(1.64 - 1.70)
Principal Diagnosis		
S13 (neck level)	1.00	
S33 (lumbar spine and pelvis)	1.01	(0.99 - 1.02)
S06 (Intracranial injury)	3.26	(3.18 - 3.34)
S22 (fracture of rib, sternum, thoracic spine)	1.95	(1.92 - 1.98)
S82 (Fracture of lower leg, including ankle)	2.57	(2.53 - 2.62)
Region		
Capital city	1.00	
Metropolitan	1.05	(1.03 - 1.06)
Province	0.88	(0.86 - 0.89)
Type of institution		
Tertiary hospital	1.00	
General hospital	0.82	(0.81 - 0.84)
Clinic	0.56	(0.56 - 0.57)
Type of Care		
Conventional medicine	1.00	

Traditional Korean medicine	1.29	(1.28 - 1.31)
ICU Admission		
0	1.00	
1	2.32	(2.18 - 2.48)
Surgery		
0	1.00	
1	2.06	(2.03 - 2.09)
Charlson Comorbidity Index		
0	1.00	
1	1.02	(1.01 - 1.04)
2	1.14	(1.11 - 1.17)
3 or higher	1.21	(1.17 - 1.25)
Season		
1 (spring)	1.00	
2	1.00	(0.99 - 1.02)
3	1.00	(0.99 - 1.02)
4	1.00	(0.99 - 1.02)
Year		
2018	1.00	
2019	1.09	(1.07 - 1.11)
2020	1.24	(1.22 - 1.27)
2021	1.33	(1.30 - 1.35)
2022	1.33	(1.30 - 1.36)
2023	1.34	(1.31 - 1.37)
2024	1.49	(1.45 - 1.53)

4.2.2.3. Results of Subgroup Analysis of Factors Associated with Medical Expenditure by Insurance Type

Table 11 presents the results of the subgroup analysis on factors associated with medical expenditure, stratified by type of insurance.

When analyzed by diagnosis, inpatient medical expenditure under automobile insurance was significantly higher than that under national health insurance.

For S13 (injury at the neck level), the exponentiated coefficient (exp(β)) was 1.71 (95% CI: 1.60–1.81). For S22 (fracture of ribs, sternum, and thoracic spine), the exp(β) was 1.43 (95% CI: 1.43–1.48), and for S82 (fracture of lower leg, including ankle), the exp(β) was 1.80 (95% CI: 1.68–1.73), all indicating significantly higher expenditures under automobile insurance.

By hospital type, inpatient medical expenditure was 1.26 times higher in tertiary hospitals (95% CI: 1.24–1.28) and 1.09 times higher in clinics (95% CI: 1.07–1.10) under automobile insurance compared to national health insurance. For medicine services, expenditure was also higher under automobile insurance, with an exp(β) of 1.13 (95% CI: 1.11–1.14). Patients admitted to the ICU had 47% higher expenditures under automobile insurance (exp(β) = 1.47, 95% CI: 1.32–1.63). Likewise, patients who underwent surgery had 54% higher expenditures (exp(β) = 1.54, 95% CI: 1.51–1.57).

Table 11. Result of subgroup analysis stratified by independent variables

Variable	Medical expenditure		
	National health insurance (ref)	Auto Insurance	
		EXP(ß)	95%CI
SEX			
Male	1.00	1.05	(1.04 - 1.07)
Female	1.00	1.14	(1.12 - 1.15)
AGE			
~29	1.00	1.20	(1.16 - 1.25)
30~39	1.00	1.10	(1.06 - 1.14)
40~49	1.00	1.03	(1.00 - 1.06)
50~59	1.00	0.99	(0.96 - 1.02)
60~69	1.00	0.98	(0.95 - 1.00)
70~	1.00	1.23	(1.20 - 1.25)
Principal Diagnosis			
S13 (neck level)	1.00	1.71	(1.54 - 1.90)
S33 (lumbar spine and pelvis)	1.00	0.92	(0.91 - 0.93)
S06 (Intracranial injury)	1.00	0.84	(0.81 - 0.88)
S22 (fracture of rib, sternum, thoracic spine)	1.00	1.43	(1.40 - 1.46)
S82 (Fracture of lower leg, including ankle)	1.00	1.80	(1.77 - 1.83)
Area of residence			
Capital city	1.00	1.17	(1.15 - 1.20)
Metropolitan	1.00	1.04	(1.02 - 1.06)
Province	1.00	1.07	(1.05 - 1.09)
Type of institution			
Tertiary hospital	1.00	1.26	(1.24 - 1.28)
General hospital	1.00	0.96	(0.95 - 0.98)
Clinic	1.00	1.09	(1.07 - 1.10)
Type of Care			
Conventional medicine	1.00	1.13	(1.11 - 1.14)

Traditional Korean medicine	1.00	1.00	(0.98 - 1.02)
ICU Admission			
0	1.00	1.09	(1.07 - 1.10)
1	1.00	1.47	(1.32 - 1.63)
Surgery			
0	1.00	0.98	(0.97 - 0.99)
1	1.00	1.54	(1.51 - 1.57)
Charlson Comorbidity Index			
0	1.00	1.22	(1.21 - 1.24)
1	1.00	1.01	(0.99 - 1.04)
2	1.00	0.85	(0.82 - 0.88)
3 or higher	1.00	0.79	(0.75 - 0.83)
Season			
1 (spring)	1.00	1.11	(1.09 - 1.13)
2	1.00	1.07	(1.05 - 1.09)
3	1.00	1.09	(1.07 - 1.11)
4	1.00	1.10	(1.07 - 1.12)
Year			
2018	1.00	1.12	(1.09 - 1.15)
2019	1.00	1.15	(1.12 - 1.18)
2020	1.00	1.10	(1.07 - 1.13)
2021	1.00	1.12	(1.09 - 1.16)
2022	1.00	1.11	(1.07 - 1.14)
2023	1.00	1.03	(1.00 - 1.06)
2024	1.00	0.98	(0.95 - 1.01)

4.2.3. Subgroup Analysis

4.2.3.1. Subgroup analysis stratified by type of insurance and type of care

Table 12 presents the results of the subgroup analysis of medical utilization by type of insurance and type of care. This GEE analysis also included covariates such as sex, age, diagnosis, region, type of hospital, ICU admission, surgery status, Charlson Comorbidity Index (CCI), season, and year.

Among patients receiving traditional Korean medicine care, compared to conventional medicine under national health insurance, traditional Korean medicine under national health insurance was associated with a 24% longer length of stay (exp(β) = 1.24, 95% CI: 1.21–1.27) and a 32% higher total medical expenditure (exp(β) = 1.32, 95% CI: 1.29–1.35). Patients who received conventional medicine under automobile insurance had a 15% longer length of stay (exp(β) = 1.15, 95% CI: 1.13–1.17) and a 10% higher total medical expenditure (exp(β) = 1.10, 95% CI: 1.08–1.12), compared to those who received conventional medicine under national health insurance.
In contrast, patients who received traditional Korean medicine under automobile insurance had an 8% shorter length of stay (exp(β) = 0.92, 95% CI: 0.91–0.94) but a 40% higher total medical expenditure (exp(β) = 1.40, 95% CI: 1.37–1.42), compared to those who received conventional medicine under national health insurance.

Table 12. Subgroup analysis of health utilization by insurance type and type of care

variable	Length of stay		Medical expenditure	
	EXP(ß)	95%CI	EXP(ß)	95%CI
Conventional medicine under National health insurance (ref)	1.00		1.00	
Traditional Korean medicine under **National health insurance**	1.24	(1.21 - 1.27)	1.32	(1.29 - 1.35)
Conventional medicine under **Automobile insurance**	1.15	(1.13 - 1.17)	1.10	(1.08 - 1.12)
Traditional Korean medicine under **Automobile insurance**	0.92	(0.91 - 0.94)	1.40	(1.37 - 1.42)

4.2.3.2. Analysis of per diem expenditure

Table 13 presents the results of the GEE analysis for inpatient medical expenditure per day. The model included the main variable of interest, insurance type, along with covariates such as sex, age, principal diagnosis, region, type of hospital, ICU admission, surgical status, Charlson Comorbidity Index (CCI), season, and year.

The average per diem medical expenditure for patients covered by automobile insurance was 10% higher than that for patients covered by national health insurance, and this difference was statistically significant (exp(β) = 1.10, 95% CI: 1.09–1.10).

Regarding the principal diagnosis, taking cervical spine injury (S13) as the reference category, patients with intracranial injury (S06) had 28% higher per diem expenditure (exp(β) = 1.28, 95% CI: 1.27–1.29), whereas patients with fractures of the ribs, sternum, or thoracic spine (S22) and fractures of the lower leg including the ankle (S82) showed lower per diem expenditures (exp(β) = 0.98, 95% CI: 0.97–0.99 and exp(β) = 0.97, 95% CI: 0.97–0.98, respectively).

Compared to the capital region, other regions showed lower per diem expenditures: metropolitan areas (exp(β) = 0.93, 95% CI: 0.92–0.93) and provinces (exp(β) = 0.86, 95% CI: 0.85–0.86). By hospital type, when tertiary hospitals were used as the reference, general hospitals and clinics had 55% (exp(β) = 0.45, 95% CI: 0.45–0.45) and 68% (exp(β) = 0.32, 95% CI: 0.32–0.32) lower per diem expenditures, respectively.

Traditional Korean medicine was associated with a 21% higher per diem expenditure compared to Conventional medicine (exp(β) = 1.21, 95% CI: 1.21–1.22). ICU admission (exp(β) = 1.97, 95% CI: 1.88–2.07) and surgery (exp(β) = 2.08, 95% CI: 2.06–2.10) were both strongly associated with higher per diem expenditure.

Table 14 presents the results of the subgroup analysis on factors associated with per diem expenditure, stratified by type of insurance.

Excluding S06 (exp(β) = 0.96, 95% CI: 0.95–0.98), all other diagnoses showed a tendency for higher per diem medical expenditure under automobile insurance compared to national health insurance.

By hospital type, there was no significant difference in per diem expenditure between insurance types in tertiary hospitals and clinics. However, in general hospitals, per diem expenditure under automobile insurance was approximately 18% higher than under national health insurance (exp(β) = 1.18, 95% CI: 1.17–1.19).

For traditional Korean medicine, per diem expenditure was 44% higher under automobile insurance than under national health insurance (exp(β) = 1.44, 95% CI: 1.41–1.47).

Table 13. Results of Generalized estimating equation analysis of factors associated with per diem expenditure.

Variable	Per diem expenditure	
	EXP(ß)	95%CI
Insurance Type		
Auto Insurance	1.10	(1.09 - 1.10)
National Health Insurance	1.00	
SEX		
Male	1.00	
Female	0.96	(0.96 - 0.96)
AGE		
~29	1.00	
30~39	1.04	(1.03 - 1.04)
40~49	1.02	(1.01 - 1.03)
50~59	1.00	(0.99 - 1.01)
60~69	1.01	(1.00 - 1.02)
70~	1.05	(1.05 - 1.06)
Principal Diagnosis		
S13 (neck level)	1.00	
S33 (lumbar spine and pelvis)	1.00	(1.00 - 1.01)
S06 (Intracranial injury)	1.28	(1.27 - 1.29)
S22 (fracture of rib, sternum, thoracic spine)	0.98	(0.97 - 0.99)
S82 (Fracture of lower leg, including ankle)	0.97	(0.97 - 0.98)
Region		
Capital city	1.00	
Metropolitan	0.93	(0.92 - 0.93)
Province	0.86	(0.85 - 0.86)
Type of institution		
Tertiary hospital	1.00	
General hospital	0.45	(0.45 - 0.45)

Clinic	0.32	(0.32 - 0.32)
Type of Care		
Conventional medicine	1.00	
Traditional Korean medicine	1.21	(1.21 - 1.22)
ICU Admission		
0	1.00	
1	1.97	(1.88 - 2.07)
Surgery		
0	1.00	
1	2.08	(2.06 - 2.10)
Charlson Comorbidity Index		
0	1.00	
1	1.00	(0.99 - 1.00)
2	1.00	(0.99 - 1.01)
3 or higher	1.01	(1.00 - 1.02)
Season		
1 (spring)	1.00	
2	1.02	(1.01 - 1.02)
3	1.02	(1.02 - 1.03)
4	1.00	(0.99 - 1.01)
Year		
2018	1.00	
2019	1.09	(1.08 - 1.10)
2020	1.21	(1.20 - 1.23)
2021	1.30	(1.29 - 1.31)
2022	1.39	(1.38 - 1.41)
2023	1.47	(1.46 - 1.48)
2024	1.53	(1.52 - 1.54)

Table 14. Result of subgroup analysis stratified by independent variables on Per diem expenditure

variable	National health insurance	per diem expenditure	
		Auto Insurance	
	(ref)	EXP(ß)	95%CI
SEX			
Male	1.00	1.09	(1.08 - 1.10)
Female	1.00	1.11	(1.10 - 1.12)
AGE			
~29	1.00	1.12	(1.10 - 1.13)
30~39	1.00	1.19	(1.17 - 1.20)
40~49	1.00	1.17	(1.15 - 1.18)
50~59	1.00	1.12	(1.11 - 1.13)
60~69	1.00	1.08	(1.07 - 1.10)
7	1.00	1.03	(1.02 - 1.04)
Principal Diagnosis			
S13 (neck level)	1.00	1.19	(1.18 - 1.20)
S33 (lumbar spine and pelvis)	1.00	1.27	(1.26 - 1.28)
S06 (Intracranial injury)	1.00	0.96	(0.95 - 0.98)
S22 (fracture of rib, sternum, thoracic spine)	1.00	1.06	(1.05 - 1.07)
S82 (Fracture of lower leg, including ankle)	1.00	1.02	(1.01 - 1.03)
Area of residence			
Capital city	1.00	1.08	(1.07 - 1.09)
Metropolitan	1.00	1.14	(1.12 - 1.15)
Province	1.00	1.09	(1.08 - 1.10)
Type of institution			
Tertiary hospital	1.00	1.00	(0.99 - 1.01)
General hospital	1.00	1.18	(1.17 - 1.19)
Clinic	1.00	1.00	(0.99 - 1.01)
Type of Care			-
Conventional medicine	1.00	0.99	(0.98 - 0.99)
Traditional Korean medicine	1.00	1.44	(1.41 - 1.47)
ICU Admission			

0	1.00	1.10	(1.09 - 1.10)
1	1.00	1.41	(1.30 - 1.52)
Surgery			
0	1.00	1.09	(1.08 - 1.09)
1	1.00	1.13	(1.11 - 1.15)
Charlson Comorbidity Index			
0	1.00	1.12	(1.12 - 1.13)
1	1.00	1.09	(1.08 - 1.10)
2	1.00	1.03	(1.01 - 1.05)
3 or higher	1.00	1.00	(0.98 - 1.02)
Season			
1 (spring)	1.00	1.10	(1.09 - 1.11)
2	1.00	1.11	(1.10 - 1.12)
3	1.00	1.09	(1.08 - 1.11)
4	1.00	1.10	(1.09 - 1.11)
Year			
2018	1.00	1.12	(1.10 - 1.13)
2019	1.00	1.10	(1.09 - 1.11)
2020	1.00	1.08	(1.07 - 1.10)
2021	1.00	1.10	(1.09 - 1.11)
2022	1.00	1.11	(1.09 - 1.12)
2023	1.00	1.21	(0.93 - 1.57)
2024	1.00	1.09	(1.08 - 1.11)

4.3. Policy Impact on Healthcare Utilization: Difference-in-Difference-in-Differences (DDD) Analysis

4.3.1. General Characteristic of Study Population

Table 15 presents the general characteristics of the dataset used for the policy effect analysis. It describes the baseline characteristics of the sample, excluding the grace period (April 18 to November 30, 2022) following the announcement of the reinforced medical cost review policy on April 17, 2022. The total number of inpatient episodes is n = 394,027.

Among them, 196,854 episodes were in the case group, with 133,799 episodes in the pre-policy period and 63,055 episodes in the post-policy period. The control group included 197,193 episodes, of which 133,989 occurred before and 63,184 after the policy implementation.

Table 16 presents the mean values of outcome variables before and after the policy implementation, as well as by policy-targeted (S13, S33, S06) and non-targeted diagnosis groups (S22, S82).

Table 15. Distribution of covariates by insurance type and policy period

Variables	Total		Case (Automobile insurance)				Control (National health insurance)			
			pre policy		post policy		pre policy		post policy	
	N	%	N	%	N	%	N	%	N	%
Total	**394,027**	**100**	**133,799**	**68.0**	**63,055**	**32.0**	**133,989**	**68.0**	**63,184**	**32.0**
SEX										
Male	202,826	51.5	68,687	51.3	32,675	51.8	68,690	51.3	32,774	51.9
Female	191,200	48.5	65,112	48.7	30,379	48.2	65,299	48.7	30,410	48.1
AGE										
~29	59,161	15.0	20,647	15.4	8,929	14.2	20,636	15.4	8,949	14.2
30~39	36,981	9.4	12,821	9.6	5,660	9.0	12,851	9.6	5,649	8.9
40~49	48,532	12.3	16,654	12.4	7,600	12.1	16,677	12.4	7,601	12.0
50~59	66,332	16.8	23,032	17.2	10,107	16.0	23,078	17.2	10,115	16.0
60~69	75,664	19.2	25,258	18.9	12,566	19.9	25,273	18.9	12,567	19.9
70~ 6	107,357	27.2	35,387	26.4	18,193	28.9	35,474	26.5	18,303	29.0
Region										
Capital city	127,212	32.3	43,364	32.4	20,702	32.8	42,576	31.8	20,570	32.6
Metropolitan	128,546	32.6	43,645	32.6	20,630	32.7	43,598	32.5	20,673	32.7
Province	138,269	35.1	46,790	35.0	21,723	34.5	47,815	35.7	21,941	34.7

Type of institution										
Tertiary hospital	136,231	34.6	43,293	32.4	19,344	30.7	49,933	37.3	23,661	37.4
General hospital	189,331	48.1	60,162	45.0	31,943	50.7	65,428	48.8	31,798	50.3
Clinic	68,465	17.4	30,344	22.7	11,768	18.7	18,628	13.9	7,725	12.2
Type of Care										
Conventional medicine	283,626	72.0	98,199	73.4	42,879	68.0	99,049	73.9	43,499	68.8
Traditional Korean medicine	110,401	28.0	35,600	26.6	20,176	32.0	34,940	26.1	19,685	31.2
ICU Admission										
0	391,716	99.4	133,475	99.8	62,222	98.7	133,665	99.8	62,354	98.7
1	2,311	0.6	324	0.2	833	1.3	324	0.2	830	1.3
Surgery										
0	321,972	81.7	108,766	81.3	52,080	82.6	108,949	81.3	52,177	82.6
1	72,055	18.3	25,033	18.7	10,975	17.4	25,040	18.7	11,007	17.4
Charlson Comorbidity Index										
0	243,261	61.7	80,251	60.0	39,857	63.2	82,068	61.2	41,085	65.0
1	86,081	21.8	30,796	23.0	12,614	20.0	30,338	22.6	12,333	19.5
2	43,667	11.1	15,099	11.3	7,185	11.4	14,573	10.9	6,810	10.8
3 or higher	21,018	5.3	7,653	5.7	3,399	5.4	7,010	5.2	2,956	4.7

Season										
1 (spring)	97,051	24.6	33,313	24.9	15,079	23.9	33,588	25.1	15,071	23.9
2	94,586	24.0	31,942	23.9	15,349	24.3	31,952	23.8	15,343	24.3
3	93,853	23.8	31,734	23.7	15,190	24.1	31,710	23.7	15,219	24.1
4	108,537	27.5	36,810	27.5	17,437	27.7	36,739	27.4	17,551	27.8
Policy-targeted group										
0 (S22, S82)	137,180	34.8	46,860	35.0	21,655	34.3	46,793	34.9	21,872	34.6
1 (S13, S33, S06)	256,847	65.2	86,939	65.0	41,400	65.7	87,196	65.1	41,312	65.4

Table 16. Mean values of outcome variables by insurance type

Variables	Length of stay				Medical expenditure			
	Case		Control		Case		Control	
	mean	SD	mean	SD	mean	SD	mean	SD
Policy								
Before (2018.1. ~ 2022.4.)	15.75	33.01	14.50	42.54	3,036,255	8,210,061	2,531,221	6,790,791
After (2022.12. ~ 2024.12.)	14.05	26.24	12.99	26.59	3,366,813	8,271,159	2,921,525	7,195,197
Policy-targeted group								
0 (S22, S82)	23.01	29.21	14.18	20.01	4,196,109	6,175,625	2,555,345	3,558,944
1 (S13, S33, S06)	11.04	31.14	13.93	44.96	2,579,464	9,091,255	2,710,233	8,173,778

4.3.2. Length of Stay

Table 17 presents the results of the difference-in-differences (DID) analysis estimating the effects of the enhanced claims review policy for mild-condition hospitalizations on the length of stay (LOS), stratified by insurance type and policy-targeted diagnosis group. The model included key covariates such as sex, age, region, hospital type, CCI, ICU admission, surgery status type of care, type of institution, season and time. The interaction term of Insurance type × Policy indicated a 6% decrease in length of stay for automobile insurance patients after policy implementation (Exp(β)=0.94, 95% CI: 0.97–0.99).

Table 18 presents the results of the difference-in-difference-in-differences (DDD) analysis estimating the effects of the enhanced claims review policy for mild-condition hospitalizations on the length of stay (LOS), stratified by insurance type and policy-targeted diagnosis group. The model included key covariates such as sex, age, region, hospital type, CCI, ICU admission, surgery status type of care, type of institution, season and time.

Compared to national health insurance, automobile insurance was associated with a 63% longer length of stay (Exp(β)=1.63, 95% CI: 1.61–1.66). The policy-targeted diagnosis group showed a 6% shorter stay than the non-targeted group (Exp(β)=0.94, 95% CI: 0.92–0.96).

The three-way interaction (Insurance × Policy × Group) was significant (Exp(β)=1.06, 95% CI: 1.01–1.11).

Table 17. Difference-in-Differences Estimates of the Impact of Policy Implementation on length of stay

variable	Length of stay	
	Exp(ß)	95%CI
Policy †		
before (2018.1. ~ 2022.4.)	1.00	
after (2022.12. ~ 2024.12)	0.34	(0.30 - 0.38)
Case		
Auto insurance	1.04	(1.02 - 1.05)
Control		
National health insurance	1.00	
Case*Policy		
(difference, case-control)	0.94	(0.92 - 0.96)
SEX		
Male	1.00	
Female	0.98	(0.97 - 0.99)
AGE		
~29	1.00	
30~39 3	1.16	(1.14 - 1.19)
40~49 4	1.25	(1.23 - 1.27)
50~59 5	1.36	(1.33 - 1.38)
60~69 6	1.48	(1.45 - 1.50)
70~ 7	1.68	(1.65 - 1.71)
Principal Diagnosis		
S13 (neck level)	0.83	(0.81 - 0.85)
S33 (lumbar spine and pelvis)	0.37	(0.37 - 0.38)
S06 (Intracranial injury)	0.76	(0.75 - 0.77)
S22 (fracture of rib, sternum, thoracic spine)	0.38	(0.38 - 0.39)
S82 (Fracture of lower leg, including ankle)	1.00	
Region		
Capital city	1.00	

Metropolitan	1.09	(1.08 - 1.11)
Province	1.03	(1.01 - 1.04)
Type of institution		
Tertiary hospital	0.66	(0.65 - 0.66)
Secondary hospital	1.10	(1.09 - 1.11)
Clinic	1.00	
Type of Care		
Conventional medicine	1.00	
Traditional Korean medicine	1.02	(1.01 - 1.04)
ICU Admission		
0	1.00	
1	1.30	(1.23 - 1.37)
Surgery		
0	1.00	
1	1.12	(1.11 - 1.14)
Charlson Comorbidity Index		
0	1.00	
1	1.02	(1.00 - 1.03)
2	1.13	(1.10 - 1.16)
3 or higher	1.18	(1.14 - 1.22)
Season		
Spring	1.00	
Summer	1.01	(0.99 - 1.03)
Fall	0.99	(0.97 - 1.02)
Winter	1.01	(0.99 - 1.03)

† Excludes the 7-month grace period between policy announcement and implementation

* The model includes a time variable defined by quarters

Table 18. Difference in difference in differences (DDD) estimates of policy effects on length of stay by insurance type and policy-targeted diagnosis group

Variable	Length of stay			
	Exp(ß)	95%CI		
Policy				
Before (2018.1. ~ 2022.4.)	1.00			
After (2022.12. ~ 2024.12.)	0.34	(0.95	-	1.52)
Insurance Type				
Auto insurance (case)	**1.63**	**(1.61**	**-**	**1.66)**
National health insurance (control)	1.00			
Policy-targeted group				
Group 1 (S13, S33, S06)	**0.94**	**(0.92**	**-**	**0.96)**
Group 0 (S22, S82)	1.00			
Insurance × Policy × Policy-targeted group (DDD)	**1.06**	**(1.01**	**-**	**1.11)**
SEX				
Male	1.00			
Female	0.94	(0.93	-	0.95)
AGE				
~29	1.00			
30~39	1.16	(1.13	-	1.19)
40~49	1.25	(1.22	-	1.28)
50~59	1.40	(1.37	-	1.43)
60~69	1.55	(1.52	-	1.58)
70~ 7	1.88	(1.84	-	1.92)
Region				
Capital city	1.00			
Metropolitan	1.06	(1.04	-	1.07)
Province	0.98	(0.96	-	0.99)
Type of institution				
Tertiary hospital	1.00			
Secondary hospital	1.63	(1.60	-	1.66)
Clinic	1.29	(1.27	-	1.31)
Type of Care				

Conventional medicine	1.00			
Traditional Korean medicine	0.86	(0.85	-	0.88)
ICU Admission				
0	1.00			
1	1.61	(1.51	-	1.72)
Surgery				
0	1.00			
1	1.20	(1.18	-	1.22)
Charlson Comorbidity Index				
0	1.00			
1	0.98	(0.96	-	0.99)
2	1.14	(1.11	-	1.18)
3 or higher	1.22	(1.17	-	1.27)
Season				
1 (spring)	1.00			
2	0.95	(0.91	-	1.00)
3	0.91	(0.86	-	0.97)
4	1.02	(0.98	-	1.07)

† Excludes the 7-month grace period between policy announcement and implementation

* The model includes a time variable defined by quarters

Figure 5 illustrates the trend in average length of stay over time during the study period (2018-2024). Figure 6 presents the trends in average length of stay for policy-targeted and non-targeted diagnosis groups by insurance type.

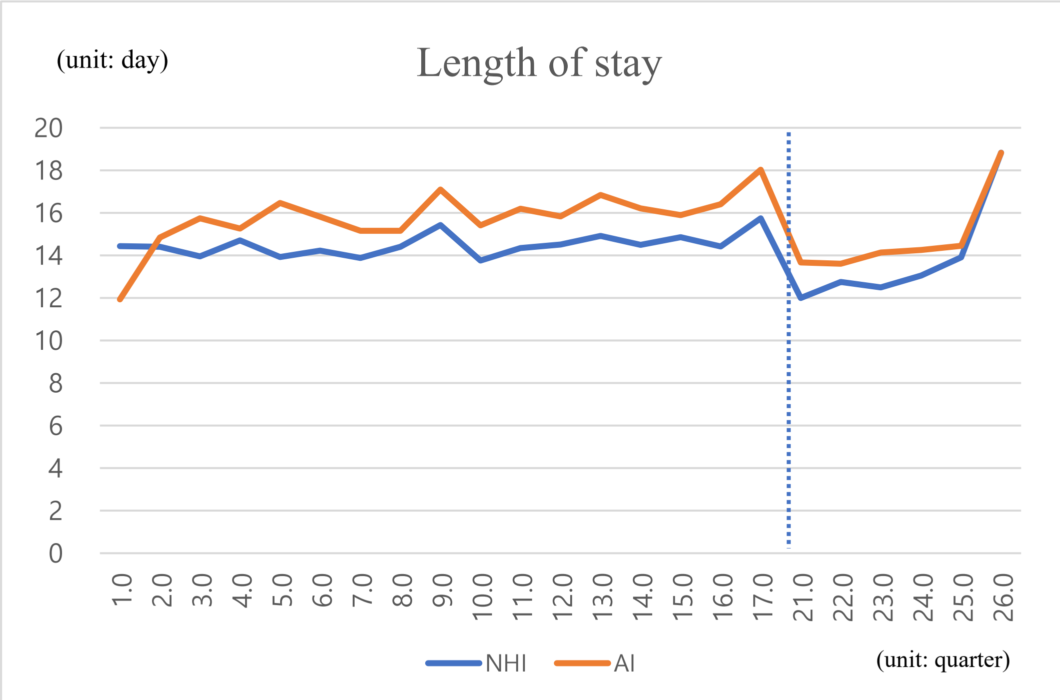
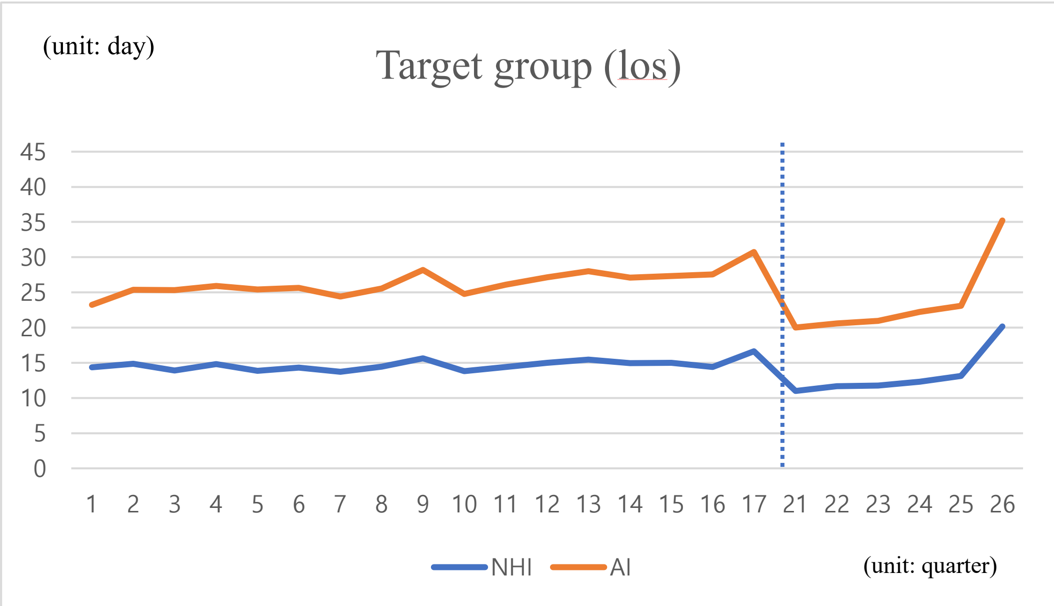


Figure 5. Quarterly trends in average length of stay by insurance type before and after policy implementation



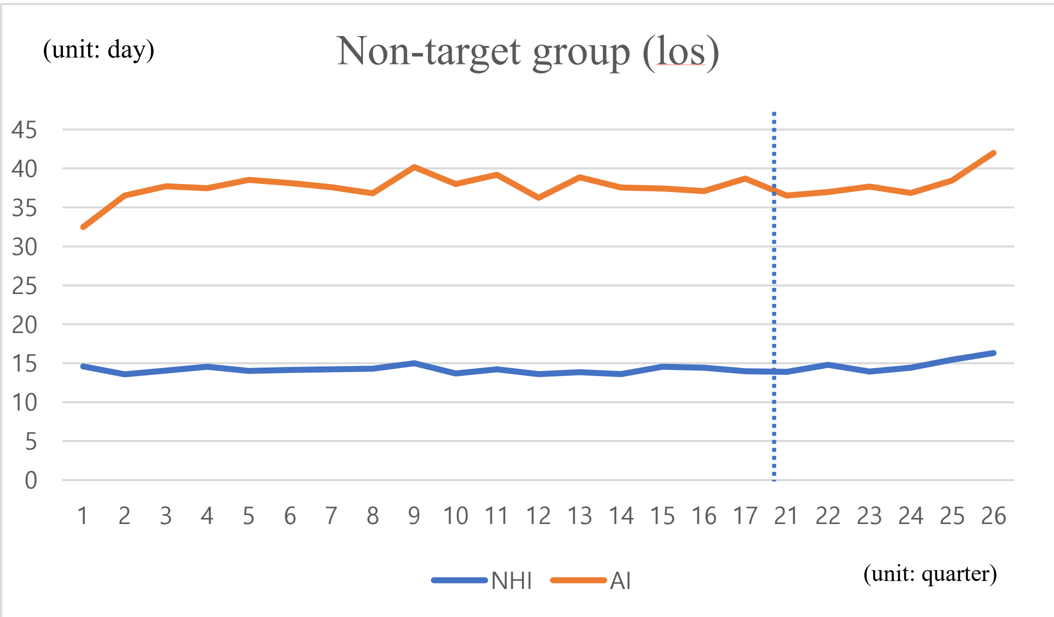


Figure 6. Quarterly trends in length of stay by policy-targeted group and insurance type

4.3.3. Medical Expenditure

Table 19 presents the results of the difference-in-differences (DID) analysis estimating the effects of the enhanced claims review policy for mild-condition hospitalizations on medical expenditure, stratified by insurance type and policy-targeted diagnosis group. The model included key covariates such as sex, age, region, hospital type, CCI, ICU admission, surgery status type of care, type of institution, season and time. The interaction term of Insurance type × Policy indicated a 9% decrease in medical expenditure for automobile insurance patients following policy implementation (Exp(β)=0.91, 95% CI: 0.89–0.93).

Table 20 presents the results of the difference-in-difference-in-differences (DDD) analysis estimating the effects of the enhanced claims review policy for mild-condition hospitalizations on medical expenditure, stratified by insurance type and policy-targeted diagnosis group. The model included key covariates such as sex, age, region, hospital type, CCI, ICU admission, surgery status type of care, type of institution, season and time.

Compared to national health insurance, automobile insurance was associated with a 65% higher medical expenditure (Exp(β) = 1.65, 95% CI: 1.62–1.68).

The policy-targeted diagnosis group exhibited a 15% higher expenditure than the non-targeted group (Exp(β) = 1.15, 95% CI: 1.13–1.18).

The three-way interaction term (Insurance × Policy × Diagnosis Group) was not statistically significant, indicating that the policy did not result in a differential change in medical expenditure across insurance types for the targeted versus non-targeted diagnosis groups (Exp(β) = 0.98, 95% CI: 0.93–1.03).

Table 19. Difference-in-Differences Estimates of the Impact of Policy Implementation on Medical Expenditure

variable	Medical expenditure		
	Exp(ß)	**95%CI**	
Policy †			
before (2018.1. ~ 2022.4.)	1.00		
after (2022.12. ~ 2024.12)	0.33	(0.29	0.37)
Case			
Auto insurance	1.12	(1.10	1.13)
Control			
National health insurance	1.00		
Case*Policy			
(difference, case-control)	0.91	(0.89	0.93)
SEX			
Male	1.00		
Female	0.94	(0.93	0.95)
AGE			
~29	1.00		
30~39 3	1.18	(1.16	1.20)
40~49 4	1.23	(1.21	1.26)
50~59 5	1.31	(1.29	1.34)
60~69 6	1.42	(1.40	1.45)
70~ 7	1.64	(1.61	1.67)
Principal Diagnosis			
S13 (neck level)	0.39	(0.39	0.40)
S33 (lumbar spine and pelvis)	0.40	(0.39	0.40)
S06 (Intracranial injury)	1.22	(1.20	1.25)
S22 (fracture of rib, sternum, thoracic spine)	0.76	(0.75	0.77)
S82 (Fracture of lower leg, including ankle)	1.00		
Region			
Capital city	1.00		

Metropolitan	1.04	(1.03	1.05)
Province	0.88	(0.87	0.89)
Type of institution			
Tertiary hospital	1.82	(1.79	1.84)
Secondary hospital	1.44	(1.42	1.46)
Clinic	1.00		
Type of Care			
Conventional medicine	1.00		
Traditional Korean medicine	1.31	(1.30	1.33)
ICU Admission			
0	1.00		
1	2.43	(2.27	2.60)
Surgery			
0	1.00		
1	2.09	(2.06	2.13)
Charlson Comorbidity Index			
0	1.00		
1	1.02	(1.01	1.04)
2	1.13	(1.11	1.16)
3 or higher	1.20	(1.16	1.24)
Season			
Spring	1.00		
Summer	1.01	(0.99	1.03)
Fall	0.99	(0.97	1.01)
Winter	1.00	(0.98	1.03)

† Excludes the 7-month grace period between policy announcement and implementation

* The model includes a time variable defined by quarters

Table 20. Difference in difference in differences (DDD) estimates of policy effects on medical expenditure by insurance type and policy-targeted diagnosis group

Variable	Medical expenditure			
	Exp(ß)	95%CI		
Policy				
Before (2018.1. ~ 2022.4.)	1.00			
After (2022.12. ~ 2024.12.)	**1.88**	**(1.47**	**-**	**2.39)**
Insurance Type				
Auto insurance (case)	**1.65**	**(1.62**	**-**	**1.68)**
National health insurance (control)	1.00			
Policy-targeted group				
Group 1 (S13, S33, S06)	**1.15**	**(1.13**	**-**	**1.18)**
Group 0 (S22, S82)	1.00			
Interaction term				
Insurance × Policy	**0.96**	**(0.93**	**-**	**0.98)**
Insurance × Policy-targeted group	**0.53**	**(0.52**	**-**	**0.55)**
Policy × Policy-targeted group	**0.85**	**(0.82**	**-**	**0.88)**
Insurance × Policy × Policy-targeted group (DDD)	0.98	(0.93	-	1.03)
SEX				
Male	1.00			
Female	0.88	(0.86	-	0.89)
AGE				
~29	1.00			
30~39	1.17	(1.14	-	1.21)
40~49	1.25	(1.22	-	1.28)
50~59	1.37	(1.34	-	1.40)
60~69	1.53	(1.50	-	1.57)
70~	1.91	(1.87	-	1.96)
Region				
Capital city	1.00			
Metropolitan	1.01	(0.99	-	1.03)

Province	0.82	(0.81	-	0.84)
Type of institution				
Tertiary hospital	1.00			
Secondary hospital	0.71	(0.70	-	0.73)
Clinic	0.41	(0.40	-	0.42)
Type of Care				
Conventional medicine	1.00			
Traditional Korean medicine	1.03	(1.01	-	1.05)
ICU Admission				
0	1.00			
1	3.14	(2.85	-	3.45)
Surgery				
0	1.00			
1	2.25	(2.20	-	2.30)
Charlson Comorbidity Index				
0	1.00			
1	0.97	(0.96	-	0.99)
2	1.16	(1.12	-	1.20)
3 or higher	1.26	(1.21	-	1.32)
Season				
1 (spring)	1.00			
2	0.95	(0.90	-	1.00)
3	0.92	(0.86	-	0.98)
4	1.03	(0.98	-	1.08)

† Excludes the 7-month grace period between policy announcement and implementation

* The model includes a time variable defined by quarters

Figure 7 illustrates the trend in average medical expenditure over time during the study period (2018-2024). Figure 8 presents the trends in average medical expenditure for policy-targeted and non-targeted diagnosis groups by insurance type.

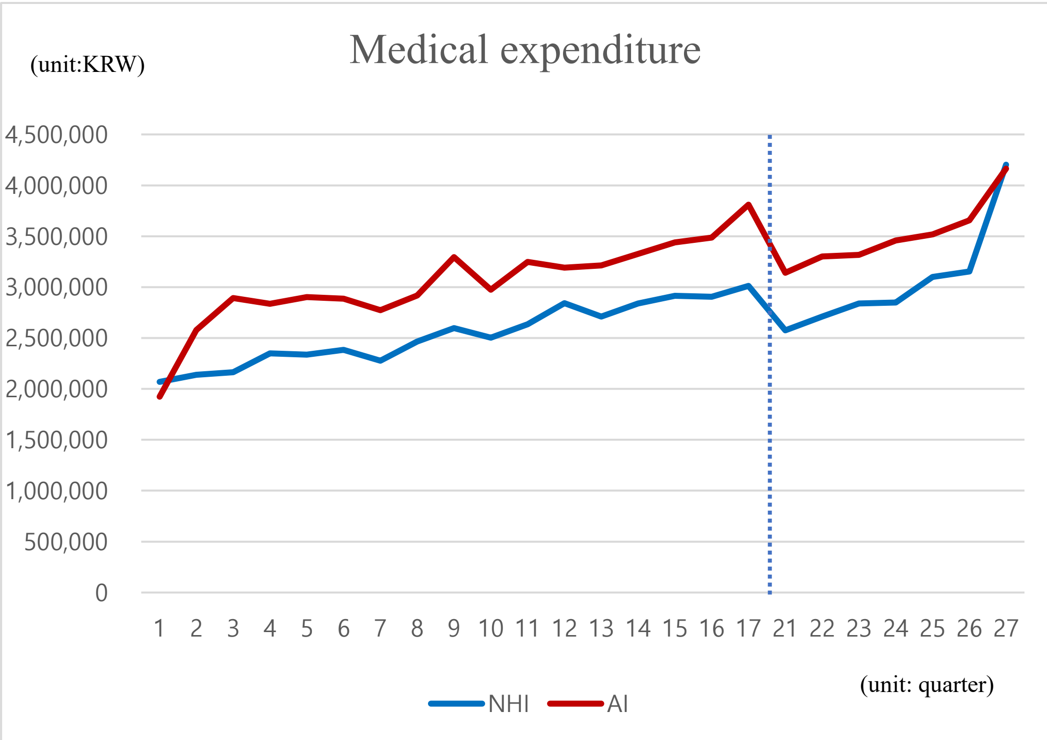


Figure 7. Quarterly trends in average medical expenditure by insurance type before and after policy implementation

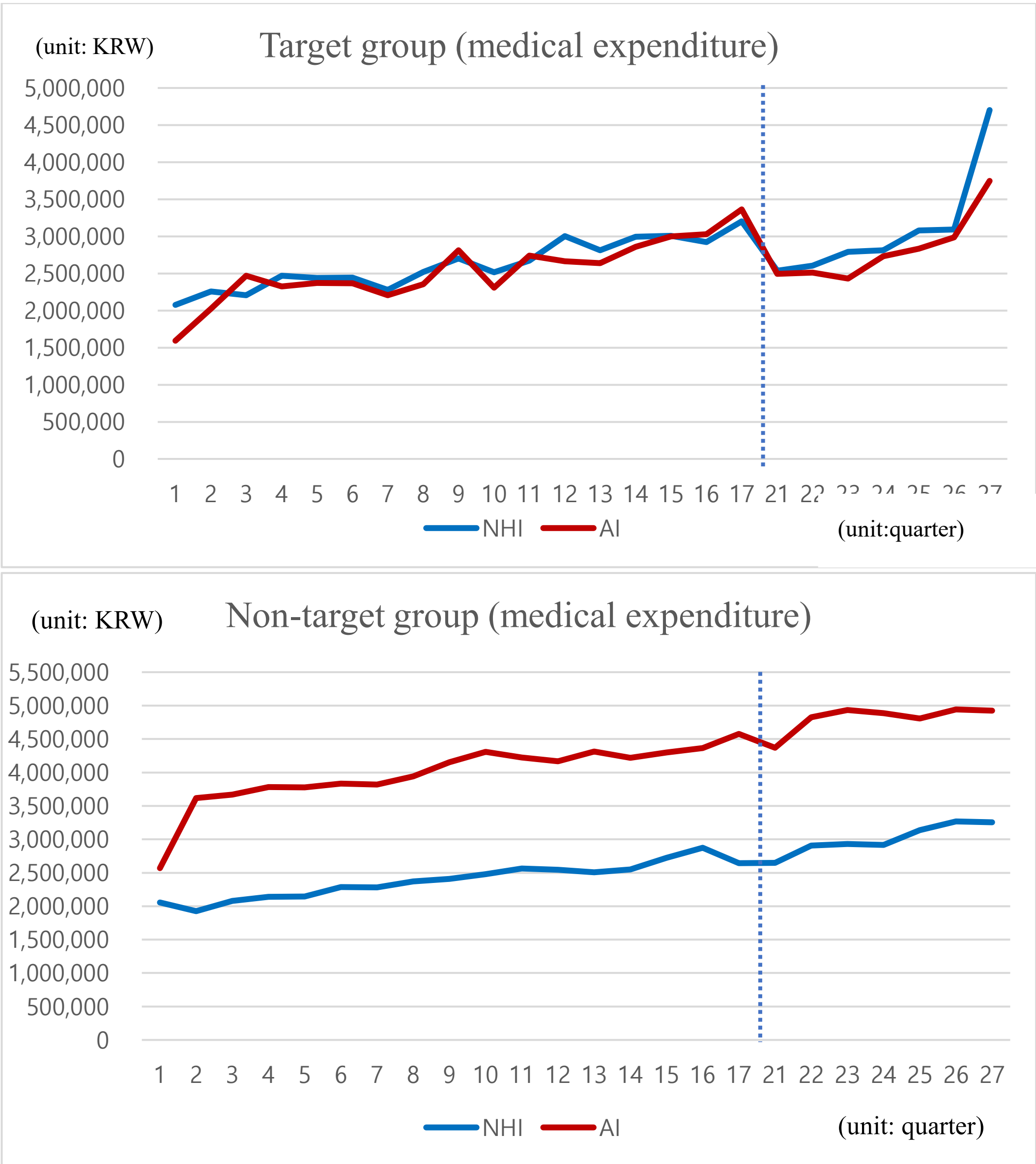


Figure 8. Quarterly trends in average medical expenditure by policy-targeted group and insurance type

5. DISCUSSION

5.1. Discussion of the Study Methods

This study adopted a longitudinal comparative design to evaluate differences in inpatient healthcare utilization between automobile insurance (AI) and national health insurance (NHI). To minimize selection bias and enhance the comparability between groups, the study population was restricted to patients hospitalized with the five most frequently claimed diagnoses under AI. These five diagnoses accounted for approximately 72% of total AI inpatient expenditures in 2023, thus ensuring the analysis reflects policy areas with substantial financial impact. Among them, three diagnosis groups were subject to the December 2022 policy intervention, while the remaining two served as non-targeted control conditions, enabling a comparative policy impact evaluation.

To construct a balanced cohort, exact matching was first conducted based on sex, age, admission year and month, and diagnosis codes. This was followed by 1:1 propensity score matching using a greedy algorithm without replacement, with a caliper width set at 0.1 standard deviations of the logit score. The propensity score model included covariates such as sex, age, Charlson Comorbidity Index (CCI), type of care (conventional medicine vs. traditional Korean medicine), region, and type of hospital. This approach helped balance observed covariates and reduce treatment selection bias.

The main outcomes—length of stay and total inpatient expenditure—were analyzed using Generalized Estimating Equations (GEE). By specifying the patient ID as the clustering unit and applying an exchangeable correlation structure, the model accounted for intra-subject correlation due to repeated or correlated episodes within individuals. This approach reduced the risk of underestimating standard errors and mitigated the inflation of statistical significance.[71,72]

To estimate the causal effect of the 2022 policy, the study employed a Difference-in-Difference-in-Differences (DDD) design by incorporating three dimensions: insurance type (AI vs. NHI), time period (pre- vs. post-policy), and diagnosis group (targeted vs. non-targeted). The DDD framework allows for the control of unobserved time-invariant confounders and group-specific heterogeneity, thereby improving causal identification.[73] Notably, compared to standard DID, the DDD design is more robust to bias from unobserved time-varying confounders.[74] This analytical approach was tailored to evaluate the impact of a policy implemented in December 2022, which strengthened the claim review process for mild-condition inpatient admissions. By comparing changes across insurance type, time period, and diagnosis group, the study aimed to isolate and estimate the net effect of the policy intervention, independent of contemporaneous secular trends or group-specific dynamics

One consideration in the study design is the notable reduction in sample size resulting from the combined use of exact matching and propensity score matching. The initial dataset included 4,177,531 AI and 2,722,604 NHI inpatient episodes, which was ultimately refined to 216,857 matched episodes per group. While such reduction is an inherent trade-off of applying strict matching criteria to enhance comparability and reduce bias, it may have implications for statistical power and generalizability. That said, the extensive size of the original dataset helped ensure that the final matched cohort remained sufficiently large to support robust comparative analyses. Moreover, the matching strategy was carefully structured—exact matching was applied to clinically essential variables, while broader contextual factors were balanced through propensity score matching—thereby achieving covariate balance while minimizing unnecessary sample attrition.

In summary, this study applied a rigorous, multi-layered methodological approach to address the inherent biases in observational data. By integrating episode-level outcome measures, a balanced matched cohort, and a quasi-experimental DDD design, the analysis provides strong evidence for causal inference on differences in inpatient utilization and policy impact between AI and NHI. Future studies should consider linking administrative claims with clinical outcomes or patient-reported outcome measures (PROMs) to further assess the appropriateness and quality of care associated with observed utilization patterns.

This study has some limitations. First, although 1:1 exact matching was performed based on variables such as sex, age, diagnosis, and admission timing to control for observed covariates, the possibility of unmeasured confounders—such as patient preferences, institutional characteristics, and provider discretion—cannot be entirely ruled out. Second, due to the limitations of claims data, important patient-level information such as socioeconomic status, clinical outcomes, and the appropriateness of care could not be included. Third, the unit of analysis was confined to inpatient episodes, without consideration of outpatient follow-up or long-term health outcomes. This limits the ability to comprehensively assess differences in the entire care pathway by insurance type. Fourth, the analysis was restricted to the top five most frequently claimed diagnostic groups under Automobile Insurance, which may limit the generalizability of the findings to broader inpatient populations or other disease groups. However, these five groups account for approximately 72% of total inpatient expenditures in AI (based on 2023 data), [9] suggesting that the findings reflect the core patterns of utilization. Fifth, there are structural differences in the fee schedules between AI and NHI. For example, AI does not apply a decreasing rate schedule for room charges, whereas NHI has implemented such a system during certain periods. In addition, the institutional add-on fee rates differed between the two systems until 2023. Although exact matching was conducted based on department and diagnostic group, medical institutions were not directly matched by type or level (e.g., clinic, hospital, general hospital). Nevertheless, in the matched sample, the proportion of patients treated at general hospitals was substantially higher in the NHI group than in the AI group. Given that general hospitals typically have higher reimbursement rates, this difference may have partially offset the relative fee advantage of AI. To mitigate these structural discrepancies, this study applied exact matching at the department and diagnostic group levels.

Despite these limitations, the study offers several notable strengths. First, it utilized six years of nationally representative claims data to systematically compare inpatient healthcare utilization between AI and NHI. Second, the use of propensity score matching enhanced the comparability between the two groups. Third, advanced statistical methods—such as Generalized Estimating Equations (GEE), Difference-in-Differences (DID), and Difference-in-Difference-in-Differences (DDD)—were applied to control for confounding factors and to strengthen causal inference. In particular, the DDD model enabled the adjustment of complex pre-post policy changes and unobserved heterogeneity, leading to more credible estimates of policy effects. Fourth, stratified analyses were conducted by diagnostic category, type of care, and type of provider, generating policy-relevant insights.

Collectively, these findings provide empirical evidence on how structural differences in insurance design influence patterns of healthcare utilization and provider behavior. This study offers an empirical basis for future policy reforms to enhance the efficiency and equity of the automobile insurance system in Korea.

5.2. Discussion of the Results

In this study, differences in inpatient healthcare utilization between Automobile Insurance and National Health Insurance in South Korea were examined, focusing on insurance type and provider characteristics. Nationwide cohort data from 2018 to 2024 were used, and Generalized Estimating Equations were applied to analyze inpatient length of stay and total medical expenditure. To evaluate the impact of the 2022 policy reform that strengthened cost review mechanisms, a Difference-in-Differences and Difference-in-Difference-in-Differences approaches were employed, comparing policy-targeted and non-targeted diagnosis groups by insurance type and time period.

First, compared to patients under the National Health Insurance (NHI), patients covered by Automobile Insurance (AI) had a 2% longer length of stay and 9% higher average medical expenditure per episode. Consequently, the cost per day of hospitalization (i.e., intensity of care) was 10% higher for AI patients. While part of these differences may be attributable to the higher fee schedules and facility-type-specific surcharges under AI, the persistent gap in care intensity—even after matching on major confounders—suggests that institutional design features may influence provider behavior. [43,75]

These findings raise the possibility of both consumer-side moral hazard and provider-side incentive effects. On the patient side, the near elimination of out-of-pocket payments under AI may reduce cost sensitivity, potentially weakening self-regulation and increasing utilization. [2,76] On the provider side, the absence of cost sensitivity among patients increases the likelihood of inefficient use of medical resources, potentially resulting in supplier-induced demand. [77] This phenomenon is especially prominent in inpatient care settings, where provider discretion is greater than in outpatient care. In the context of an agent–principal relationship characterized by information asymmetry, providers, acting as agents for their patients, may distort clinical decisions in ways that maximize their own financial gains. Therefore, these differences are likely to reflect a combination of structural pricing mechanisms and behavioral responses on the part of both providers and patients within the current reimbursement framework.[15,54]

Due to structural differences in benefit coverage between the two insurance systems, direct comparisons may be inherently limited. Specifically, while the National Health Insurance (NHI) includes a range of non-covered (non-reimbursed) services that require out-of-pocket payment, Automobile Insurance (AI) generally covers all inpatient services without patient cost-sharing. This fundamental design difference lowers access barriers for AI patients and may inherently contribute to higher utilization, independent of other behavioral or institutional factors.

Second, subgroup analysis revealed that overall medical utilization under Automobile Insurance was higher than under National Health Insurance in tertiary general hospitals. This may be explained by the higher expected profits from AI patients, owing to these hospitals' ability to provide high-cost treatments and benefit from higher reimbursement rates. In contrast, at the general hospital level, both length of stay and medical expenditure were lower under AI than under NHI. These findings suggest that, even within the same insurance type, hospitals may exhibit different strategic responses depending on their classification. In tertiary general hospitals, where patients tend to present with more severe conditions, the intensity of claims review may be relatively lower. Meanwhile, general hospitals may be more sensitive to regulations surrounding long-term admissions and could thus differentially adjust length of stay and treatment intensity in response.[63]

Third, in terms of type of care, traditional Korean medicine showed 29% higher average medical expenditure than Conventional medicine. When comparing across insurance types, the patterns diverged: traditional Korean medicine under Automobile Insurance incurred 40% higher costs than Conventional medicine under National Health Insurance, despite having shorter lengths of stay. This suggests that traditional Korean medicine under AI may be characterized by high-cost, short-duration intensive treatment. In contrast, traditional medicine under NHI exhibited both longer hospital stays and higher average expenditures compared to Conventional medicine under NHI. These findings indicate that even within the same type of treatment, the duration of hospitalization can differ substantially depending on the insurance scheme. This may reflect providers' behavioral responses to differences in regulatory burden, such as claims review for length of stay. It also implies that supplier-induced demand may shift toward domains with less stringent oversight.[17,52]

Fourth, in diagnosis-level comparisons, milder conditions (S13, S33, S06) and more severe conditions (S22, S82) demonstrated different patterns. Compared to S13, all other conditions were associated with longer lengths of stay and higher costs. These differences were more pronounced when analyzed by insurance type. Among the mild conditions, S33 and S06 were associated with shorter lengths of stay under AI than under NHI, and their average expenditures were 8% and 16% lower, respectively. However, contrasting results emerged in terms of care intensity: S33 under AI showed a 27% higher cost per day compared to NHI, marking the largest disparity in care intensity among the five diagnoses. In contrast, S06 also showed lower intensity under AI, suggesting that even among mild conditions, care patterns varied by diagnosis. For more severe conditions, S22 and S82 were associated with significantly greater utilization under AI: length of stay was 37% and 86% longer, respectively, and medical expenditures were 43% and 80% higher than under NHI. These trends were consistent in cost per day as well. This differential pattern highlights how medical utilization behaviors vary between policy-targeted (S13, S33, S06) and non-targeted (S22, S82) diagnosis groups.

Fifth, to assess whether these divergent utilization patterns were attributable to the strengthened claims review policy for mild-condition hospitalizations implemented in December 2022, a Difference-in-Difference-in-Differences analysis was conducted. In response to concerns over excessive use of automobile insurance for mild conditions, the Health Insurance Review and Assessment Service introduced stricter claims reviews for cases categorized under vague terms such as "sprains and strains." the DDD results indicated that the policy-targeted diagnosis group experienced a shorter length of stay compared to the non-targeted group. Additionally, the Difference-in-Differences (DID) term for insurance type and policy period showed that the post-policy increase in length of stay was smaller under AI than NHI. However, the three-way interaction term (Insurance × Policy × Policy-targeted group) revealed that the length of stay for the targeted group increased marginally relative to the non-targeted group after policy implementation. This somewhat counterintuitive result may reflect that, although the targeted diagnoses are generally milder and associated with shorter hospitalizations, the strengthened claims review may have discouraged unnecessary admissions while allowing longer, clinically necessary admissions to persist. In other words, some appropriate hospitalizations for mild conditions may have remained or even lengthened, leading to a marginal net increase in average length of stay among the targeted group compared to the non-targeted group.

Sixth, in the policy-targeted diagnosis group, changes in medical expenditures for AI patients were not statistically significant. This suggests that after the implementation of the policy, inpatient medical expenditures for targeted conditions under AI did not decline or rise significantly compared to non-targeted conditions or NHI patients. In other words, while the policy may have slightly moderated the overall growth in medical expenditures for AI patients, it appears to have had limited effect in directly reducing costs for the targeted diagnoses. This limited impact may stem from the fact that the policy did not clearly specify which diagnoses were targeted, instead using a broad and vague category such as "sprains and strains." As a result, differential responses between the targeted and non-targeted groups may not have materialized. Furthermore, if only a small number of cases were actually subjected to claims review, the policy may have lacked sufficient enforcement to generate meaningful changes in expenditure. Therefore, the 4% smaller increase in total medical expenditure for AI patients relative to NHI patients—identified in the DID analysis—can be interpreted as reflecting the general cost-containment effect of the policy, rather than a targeted impact on specific diagnosis groups.

5.3. Policy Implications

This study empirically identified differences in inpatient healthcare utilization between Automobile Insurance and National Health Insurance, thereby illustrating how structural heterogeneity between the two systems affects actual patterns of medical use. Based on these findings, this study provides an analytical foundation for understanding the characteristics and limitations of the AI system and proposes the following policy implications for improving the system and designing more effective regulatory strategies.

First, to manage healthcare utilization under AI more efficiently, a structural overhaul of the insurance scheme is necessary. The current design fosters an environment that simultaneously promotes provider-induced demand and consumer moral hazard, potentially leading to excessive hospitalization and increased intensity of care. In fact, even after adjusting for patient and institutional characteristics, care intensity under AI was approximately 10% higher than under NHI. Furthermore, efforts to control inpatient costs through claims review may generate a "balloon effect," whereby the length of stay is reduced but the intensity of care per day increases. Additionally, the differential surcharge rates applied to the same diagnosis depending on the type of insurance can distort provider incentives to hospitalize patients. Therefore, aligning reimbursement levels, fee structures, and claims review standards with those of NHI could help ensure consistency across systems and promote both the efficiency and sustainability of AI.

Second, a targeted monitoring system is needed to reflect utilization patterns by combinations of insurance type, type of care, and diagnostic group. In particular, it is necessary to develop standardized clinical protocols that clearly define the scope and criteria for appropriate treatment by diagnosis. These protocols could function not only as tools for post-hoc claims review, but also as mechanisms for preemptive assessment and guidance of appropriate care. Additionally, considering the practical reality that healthcare institutions and providers often operate across multiple insurance schemes, regulations targeting one type of insurance may inadvertently incentivize utilization shifts to another. As such, an integrated and coherent policy design that accounts for cross-system interactions is essential.

Third, it is necessary to move beyond a retrospective cost-control model and introduce institutional flexibility that enhances consumer choice and promotes autonomous, responsible healthcare use. For example, the default coverage under AI could be limited to Conventional medicine, while traditional Korean medicine could be included as an optional service with additional premiums. Such a differentiated design would improve both the efficiency and accountability of healthcare utilization and serve as a mechanism to encourage rational decision-making among consumers.

6. Conclusion

This study analyzed differences in inpatient healthcare utilization between automobile insurance (AI) and national health insurance (NHI) in South Korea using nationwide claims data from 2018 to 2024, focusing on the five most frequently claimed diagnostic groups under AI. The results showed that AI patients had longer average lengths of stay and higher total and per diem medical expenditures compared to NHI patients.

In particular, the strengthened claims review policy for mild-condition hospitalizations, introduced in December 2022, appears to have contributed to a reduction in overall healthcare utilization among AI patients. After policy implementation, the average length of stay decreased by approximately 7%, and total medical expenditure per episode decreased by around 4%. These findings suggest that even within a zero cost-sharing system such as AI, policy intervention can partially mitigate excessive hospitalizations. In contrast, no statistically significant change was observed in per diem expenditure, indicating that the reduction in total expenditure was likely achieved through shorter hospital stays rather than reduced care intensity.

The triple-difference (DDD) analysis assessing differences across three dimensions revealed limited effects of the policy on the targeted diagnosis group. Given that the specific targeted conditions were not publicly disclosed, the observed decrease in healthcare utilization among AI patients may be better explained by a general deterrent effect of the policy rather than by selective reductions in targeted diagnoses. This broader effect likely stems from behavioral adjustments by both providers and patients.

This study not only provides empirical evidence of quantitative differences in inpatient healthcare utilization but also underscores the structural vulnerabilities inherent in insurance systems without patient cost-sharing. The strengthened claims review policy implemented in late 2022 demonstrated a modest reduction in overutilization; however, its effect appears to have been driven more by generalized behavioral deterrence than by direct intervention targeting specific conditions. This highlights the importance of transparency and clearly defined policy targets in the design and implementation of regulatory measures.

Furthermore, the findings of this study empirically confirm that the structural features of insurance design—particularly the presence or absence of cost-sharing—play a pivotal role in shaping patterns of healthcare utilization. The observed disparities between AI and NHI reflect the presence of both provider-induced and patient-side moral hazard, thereby raising important implications for the equity, efficiency, and long-term sustainability of healthcare financing. Accordingly, policymakers should consider not only strengthening regulatory oversight but also pursuing structural reforms that realign incentives among stakeholders across the system.

This study seeks to address a gap in the existing literature by examining the characteristics of healthcare utilization and policy responsiveness under the automobile insurance (AI) system—an area that has received relatively limited scholarly attention—within a comparative institutional framework alongside the National Health Insurance (NHI) system. Furthermore, it empirically confirms the presence of moral hazard arising from the behaviors of both providers and patients within an insurance structure that lacks patient cost-sharing.

To enhance the long-term sustainability of the AI system and improve the efficiency of healthcare utilization, it is imperative to establish structural mechanisms that can effectively deter unnecessary use driven by moral hazard. In addition, to improve the effectiveness of claims review policies, it is essential to clearly define the scope of targeted conditions and to implement a systematic framework for long-term monitoring and policy evaluation.

ABBREVIATIONS

AI: Automobile Insurance
NHI: National Health Insurance
LOS: Length of Stay
GEE: Generalized Estimating Equations
PSM: Propensity Score Matching
DID: Difference-in-Differences
DDD: Difference-in-Difference-in-Differences
CCI: Charlson Comorbidity Index
FFS: Fee-for-Service
HDHP: High-Deductible Health Plan
KRW: Korean Won
TKM: Traditional Korean Medicine
WM: Conventional medicine

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APPENDICES

Appendix 1. Weighted index applied to calculate CCI score

n.	Conditions	ICD-10 Codes	Weight
1	Acute myocardial infarction	I21, I252	1
2	Congestive heart failure	I50	1
3	Peripheral vascular disease	I702, I73	1
4	Cerebral vascular disease	I60, I61, I62, I63, I64, I69	1
5	Chronic pulmonary disease	J42, J43, J44, J45, J46, J47, J60, J61, J62, J63, J64, J65, J66, J67, J701, J703	1
6	Connective tissue disease	M05, M06, M30, M31, M32, M33, M34, M35, M36, M45	1
7	Peptic ulcer	K25, K26, K27, K28	1
8	Mild liver disease	B18, K704, K711, K7131, K714, K715, K73, Z944	1
9	Severe liver disease	K703, K717, K721, K729, K743, K744, K745, K746, I85, I864, I982	3
10	Diabetes without chronic complication	E100, E101, E106, E108, E109, E110, E111, E116, E118, E119, E120, E121, E126, E128, E129, E130, E131, E136, E138, E139, E140, E141, E146, E148, E149	1
11	Diabetes with chronic complication	E102, E103, E104, E105, E107, E112, E113, E114, E115, E117, E122, E123, E124, E125, E127, E132, E133, E134, E135, E137, E142, E143, E144, E145, E147	2
12	Hemiplegia	G041, G114, G801, G81, G82, G830, G831, G832, G833, G834, G839	2
13	Chronic renal disease	N18, Z940, Z491, Z492, Z992, T861	2
14	Cancer without metastasis	C00, C01, C02, C03, C04, C05, C06, C07, C08, C09, C10, C11, C12, C13, C14, C15, C16, C17, C18, C19, C20, C21, C22, C23, C24, C25, C26, C30, C31, C32, C33, C34, C37, C38, C39, C40, C41, C43, C45,C46, C47, C48, C49, C50, C51, C52, C53, C54, C55, C56, C57, C58, C60, C61, C62, C63, C64, C65, C66, C67, C68, C69, C70, C71, C72, C73, C74, C75, C76, C81, C82, C83, C84, C85, C88, C90, C91, C92, C93, C94, C95, C96, C97	2
15	Metastatic carcinoma	C77, C78, C79, C80	6
16	AIDS	B20, B21, B22, B24	6

Appendix 2. General characteristics of study subjects before matching

Variable	Total		Case Auto insurance		Control National health insurance		SMD
	N	%	N	%	N	%	
Total	6,897,226	100.0	4,175,688	60.5	2,721,538	39.5	
SEX							
Male	3,652,305	53.0	2,447,626	35.5	1,204,679	17.5	0.2902
Female	3,244,921	47.0	1,728,062	25.1	1,516,859	22.0	
AGE							
~19	1,155,223	16.7	847,775	12.3	307,448	4.5	0.6364
30~39	921,745	13.4	716,403	10.4	205,342	3.0	
40~49	1,060,542	15.4	759,923	11.0	300,619	4.4	
50~59	1,373,716	19.9	870,715	12.6	503,001	7.3	
60~69	1,250,221	18.1	676,268	9.8	573,953	8.3	
70~	1,135,779	16.5	304,604	4.4	831,175	12.1	
Principal diagnosis							
S13 (neck level)	994,013	14.4	469,289	6.8	524,724	7.6	0.6364
S33 (lumbar spine and pelvis)	2,243,467	32.5	2,111,155	30.6	132,312	1.9	
S06 (Intracranial injury)	856,745	12.4	151,014	2.2	705,731	10.2	
S43 (shoulder gridle)	2,006,377	29.1	1,340,160	19.4	666,217	9.7	
S22 (fracture of rib, sternum, thoracic spine)	796,624	11.5	104,070	1.5	692,554	10.0	
Region							
Capital city	2,430,070	35.2	1,570,488	22.8	859,582	12.5	0.6364
Metropolitan	2,166,488	31.4	1,278,742	18.5	887,746	12.9	
Province	2,300,668	33.4	1,326,458	19.2	974,210	14.1	
Type of institution							
Tertiary hospital	1,624,843	23.6	512,376	7.4	1,112,467	16.1	0.6364

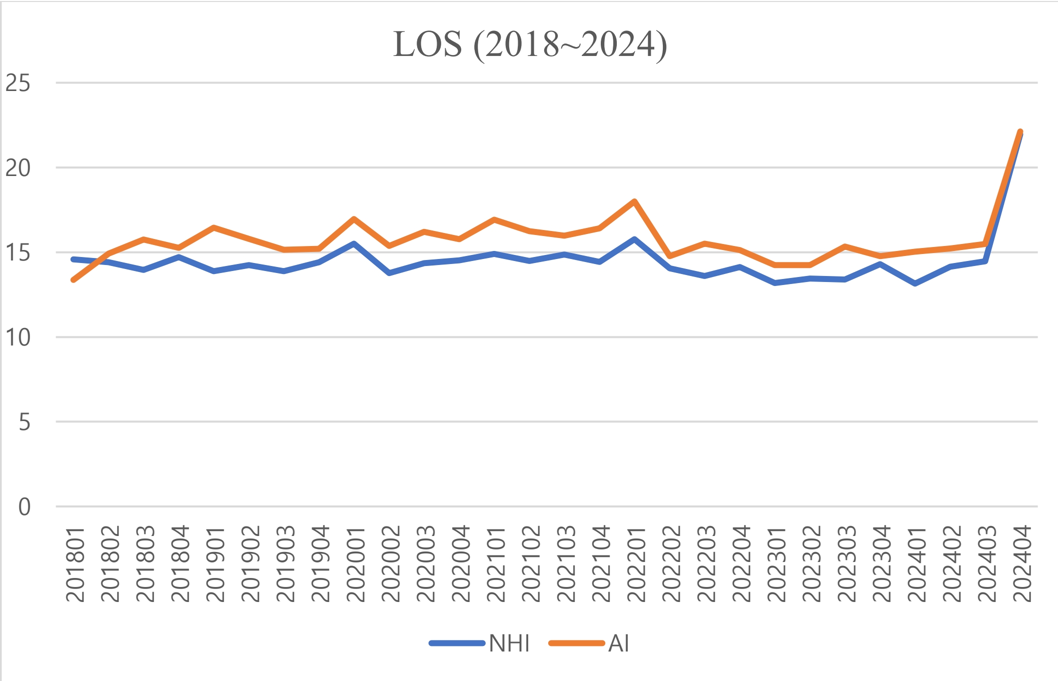
Secondary hospital	3,558,704	51.6	2,298,491	33.3	1,260,213	18.3	
Clinic	1,713,679	24.8	1,364,821	19.8	348,858	5.1	
Type of Care							
Conventional Medicine	4,389,689	63.6	2,081,107	30.2	2,308,582	33.5	0.804
traditional Korean medicine	2,507,537	36.4	2,094,581	30.4	412,956	6.0	
ICU Admission							
0	6,884,171	99.8	4,173,088	60.5	2,711,083	39.3	0.6364
1	13,055	0.2	2,600	0.0	10,455	0.2	
Surgery							
0	6,046,739	87.7	4,083,713	59.2	1,963,026	28.5	0.7694
1	850,487	12.3	91,975	1.3	758,512	11.0	
Charlson Comorbidity Index							
0	5,984,281	86.8	3,775,844	54.7	2,208,437	32.0	0.2902
1	562,087	8.1	262,618	3.8	299,469	4.3	
2	236,555	3.4	101,575	1.5	134,980	2.0	
3 or higher	114,303	1.7	35,651	0.5	78,652	1.1	
Season							
1 (spring)	1,638,052	23.7	981,164	14.2	656,888	9.5	0.6364
2	1,736,335	25.2	1,044,747	15.1	691,588	10.0	
3	1,785,201	25.9	1,116,350	16.2	668,851	9.7	
4	1,737,638	25.2	1,033,427	15.0	704,211	10.2	
Year							
2018	1,021,478	14.8	604,033	8.8	417,445	6.1	0.6364
2019	1,042,335	15.1	634,409	9.2	407,926	5.9	
2020	970,634	14.1	593,910	8.6	376,724	5.5	
2021	953,775	13.8	591,678	8.6	362,097	5.2	
2022	941,913	13.7	577,948	8.4	363,965	5.3	
2023	964,479	14.0	577,240	8.4	387,239	5.6	
2024	1,002,612	14.5	596,470	8.6	406,142	5.9	

Appendix 3. Validation of the relative parallel trends assumption for triple differences.

Variable	**Case * Group *Time**		
	ß	**SE**	***p*-value**
Length of stay	0.0067	0.0043	0.1217
Medical expenditure	0.0071	0.0039	0.0676
Per diem expenditure	0.0051	0.0027	0.0551

* Results are based on the pre-policy period

Appendix 4. Total trends of length of stay.



Appendix 5. Triple difference (DDD) analysis results for per diem medical expenditures

Variable	**Per diem expenditure**		
	Exp(ß)	**95%CI**	
Policy			
Before (2018. ~ 2022.4.)	1.00		
After (2022.12. ~ 2024.)	**1.50**	**(1.34**	**1.67)**
Insurance Type			
Auto insurance (case)	**1.03**	**(1.02**	**1.04)**
National health insurance (control)	1.00		
Policy-targeted group			
Group 1 (S13, S33, S06)	**1.08**	**(1.07**	**1.09)**
Group 0 (S22, S82)	1.00		
Interaction term			
Insurance × Policy (DID)	1.01	(0.99	1.02)
Insurance × Policy-targeted group	**1.11**	**(1.09**	**1.12)**
Policy × Policy-targeted group	1.02	(1.00	1.03)
Insurance × Policy × Policy-targeted group (DDD)	0.99	(0.97	1.02)
SEX			
Male	1.00		
Female	0.96	(0.95	0.96)
AGE			
~29	1.00		
30~39	1.03	(1.02	1.04)
40~49	1.02	(1.01	1.03)
50~59	1.00	(1.00	1.01)
60~69	1.03	(1.02	1.04)
70~	1.08	(1.07	1.09)
Region			
Capital city	1.00		
Metropolitan	0.92	(0.92	0.93)

Province	0.86	(0.85	0.86)
Type of institution			
Tertiary hospital	1.00		
Secondary hospital	0.42	(0.42	0.42)
Clinic	0.29	(0.29	0.30)
Type of Care			
Conventional medicine	1.00		
Traditional Korean medicine	1.19	(1.18	1.20)
ICU Admission			
0	1.00		
1	2.07	(1.98	2.18)
Surgery			
0	1.00		
1	2.12	(2.10	2.14)
Charlson Comorbidity Index			
0	1.00		
1	0.99	(0.98	0.99)
2	1.00	(0.99	1.01)
3 or higher	1.01	(0.99	1.02)
Season			
1 (spring)	1.00		
2	0.99	(0.98	1.01)
3	0.99	(0.98	1.00)
4	0.99	(0.98	1.00)

Korean Abstract (국문 요약)

한국의 자동차보험과 국민건강보험의 입원 의료이용 비교 연구

연세대학교 일반대학원 보건학과

김수진

서론: 한국은 전국민을 보장하는 국민건강보험과, 본인부담이 없는 민간 책임보험을 포함한 자동차보험 제도를 함께 운영하고 있다. 이러한 제도적·구조적 차이는 환자와 의료 제공자 모두에게 서로 다른 의료 이용 유인을 제공하며, 결과적으로 의료 이용 패턴에도 영향을 미칠 수 있다. 특히 자동차보험은 행위별 수가제와 전액 보장 구조가 결합되어 도덕적 해이, 공급자 유인 수요, 과잉진료의 위험이 높다. 그럼에도 불구하고 자동차보험과 건강보험 간 입원 의료이용 차이를 실증적으로 비교한 연구는 제한적이었으며, 자동차보험의 과잉입원을 억제하기 위한 정책 효과를 평가한 연구도 부족하다. 따라서 이 연구는 보험 종류에 따른 입원 의료이용 특성을 비교하고, 2022 년 시행된 경증질환 입원료 심사 강화 정책의 효과를 실증적으로 분석함으로써, 의료자원의 효율적 활용, 제도의 지속가능한 제도 마련의 정책적 근거를 마련하고자 한다.

연구방법: 이 연구는 2018 년부터 2024 년까지의 전국 단위 청구자료를 활용한 후향적 코호트 연구로, 자동차보험에서 가장 많이 청구된 상위 5 개

진단군(전체 진료비의 72% 해당)을 분석 대상으로 하였다. 첫째, 2018 년부터 2024 년까지 5 개 질환으로 입원한 건강보험 및 자동차보험 환자를 추출 한 후, 성별, 연령, 진료과, 주진단명, 수술여부, 중환자일 입원 여부, 입원 시기 등을 기준으로 매칭하여 두 그룹의 환자 간의 비교가능성을 확보하였다. 또한 환자의 반복 입원을 고려하기 위해 일반화 추정 방적식 모형을 적용하였다. 둘째, 2022 년 12 월부터 시행된 자동차보험의 경증 입원심사 강화정책의 영향을 평가하기 위해 이중차이분석(DID)을 실시하였고, 정책 적용 대상여부를 고려한 삼중차이분석(DDD)을 실시하였다. 모든 분석은 입원기간과 진료비 그리고 일당진료비를 주요 결과변수로 설정하여 수행되었다.

연구결과: 자동차보험 환자는 국민건강보험 환자에 비해 입원일수는 2% (exp(β) = 1.02, 95% CI: 1.01–1.03) 더 길고, 에피소드당 입원진료비는 9% (exp(β) = 1.09, 95% CI: 1.08–1.10), 일당 진료비는 10% (exp(β) = 1.10, 95% CI: 1.09–1.10) 더 높았다. 건강보험의 의과에 비해서, 건강보험의 한의과는 입원일수가 24% 높았고(exp(β) = 1.24, 95% CI: 1.21–1.27), 자동차보험의 한의과는 진료비가 40% 높았다(exp(β) = 1.40, 95% CI: 1.37–1.42). 2022 년 12 월 경증 입원 심사 강화 정책 이후, 자동차보험 환자의 평균 입원일수는 약 6%,(exp(β) = 0.94, 95% CI: 0.92–0.96), 입원당 총 진료비는 약 9%(exp(β) = 0.91, 95% CI: 0.89–0.93)로 유의하게 감소하였다. 삼중차이분석 결과, 정책 대상 질환군의 효과는 제한적으로 나타났다.

결론: 본 연구는 국내에서 상대적으로 연구가 부족했던 자동차보험 제도 하 입원 의료이용의 특성과 정책 효과를 실증적으로 분석하였다. 두 보험 이용 환자 특성 보정을 위한 엄격한 매칭 후에도, 자동차보험의 이용이 건강보험도 환자보다 유의하게 높았다. 이는 자동차보험과 같은 본인부담이 없는

구조에서 공급자 및 환자 모두에서 도덕적 해이가 존재할 수 있음을 시사한다. 또한 정책효과 분석 결과는 환자 본인부담이 없는 구조에서도 정책개입은 과잉입원의 일정 부분 완화할 수 있음을 보여주며, 삼중차이 분석의 제한적 결과는 대상군 비공개 때문일 가능성이 있다. 향후 제도의 지속가능성을 높이고 의료자원의 효율적 배분을 실현하기 위해서는 도덕적 해이에 대한 명확한 정책 목표를 설정하고, 이를 지속적으로 관찰하고 평가할 수 있는 체계적인 관리 시스템 구축이 요구된다.

핵심어 : 자동차보험, 의료 이용, 도덕적 해이, 무본인부담, 삼중차이분석