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Cost of Illness – Acquired Brain Injury in Queensland Children: Evidence from a Population- Based Study

Junya Fang

School of Economics, The University of Queensland, Brisbane, Queensland, Australia, 4067, China

junya.fang@uqconnect.edu.au

ABSTRACT

Background: Traumatic brain injury (TBI) affects 280-1373/100,000 young people globally each year, with non-traumatic acquired brain injury (ABI) affecting an additional 82.3/100,000 [1]. ABI leads to long-term negative impacts on patients, families, and society, costing the global economy around US$400 billion annually [2]. Objective: This study estimates the direct (hospitalisation) and indirect (opportunity costs from bed-days) costs of children with ABI. It also analyses factors influencing hospital length of stay, helping guide resource allocation. Methods: Using an incidence-based, bottom-up approach, average length of stay is used to estimate medical costs. Regression analyses (linear, logit, and ordered logit models) were used to assess factors influencing length of stay and ABI severity. Results: In 2020, 5667 new ABI cases in Queensland incurred $0.112 billion in total costs. The cost per mild case was $15,863.41, while severe cases averaged $300,049.61. Mild cases represented 75% of total costs. ICU stay length and ventilatory support duration were significant factors in cost analysis. Conclusion: Preventing secondary injury should be a priority in ABI care.

KEYWORDS

Cost-of-illness study; Acquired Brain Injury (ABI); Direct cost; Burden of disease; Incidence-based analysis (bottom-up approach)

1. INTRODUCTION

1.1. Introduction and Background

Healthcare resources are scarce, and their allocation is a major challenge for healthcare systems. The goal of resource allocation is to maximize outcomes and economic benefits [3]. Cost-of-illness (COI) analysis is a valuable tool that helps decision-makers understand the financial impact of diseases at both individual and societal levels. COI studies provide key information for setting healthcare prices and policies [4]. They are particularly useful for governments, as they show the financial burden of diseases on public programs like Medicare and Medicaid, aiding in the efficient allocation of resources to specific diseases or prevention efforts. This study focuses on the economic burden of Traumatic Brain Injury (TBI) and Acquired Brain Injury (ABI), analyzing both direct and indirect costs to inform resource allocation strategies [5].

ABI is one of the most common causes of death or disability among children [6]. TBI is a significant subset of ABI, and globally, it affects between 280 and 1373 per 100,000 young people annually. Non-traumatic ABI affects an additional 82.3 per 100,000 young people [1]. These injuries not only

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lead to physical disability but also impose long-term economic and social burdens on families and society [7]. The global economic impact of TBI is estimated to be around $400 billion annually [2].

1.2. Economic Concepts

Health economics provides a framework for allocating limited healthcare resources to meet diverse healthcare needs. COI studies play an important role in guiding these allocations, especially in the case of high-burden diseases like ABI and TBI [5]. A key concept in this study is scarcity—healthcare resources are limited relative to the population's needs [8]. This scarcity often leads to competition for high-value resources such as hospital beds and advanced medical technologies, especially in cases involving complex conditions like ABI and TBI [9, 10].

The study aims to identify which stages of TBI, and ABI care should be prioritized to achieve the most effective outcomes while maximizing the benefits to the healthcare system. Accessibility to healthcare resources is another important factor. Patients living in rural and remote areas often face barriers to accessing high-quality care, which can lead to delayed treatment and worse outcomes [10]. Patients in these areas may incur additional costs, such as transportation and accommodation, which contribute to the overall financial burden of the illness. Delays in treatment may also result in more severe health outcomes, increasing the need for intensive healthcare interventions.

Opportunity cost is another critical economic concept in this analysis. In healthcare, opportunity cost refers to the trade-offs that arise when allocating limited resources. For example, using a hospital bed for one patient may mean that another patient has to wait for treatment, thereby increasing the overall cost to the system [11]. Bed days, or the number of days a patient stays in a hospital, are a significant component of healthcare costs and reflect the opportunity costs associated with patient care. The length of hospital stays for ABI and TBI patients can significantly influence the total cost of treatment and the allocation of resources.

Despite their usefulness, COI studies have limitations. They do not measure the benefits of treatment but focus solely on costs. However, they can indicate which diseases or health conditions require more resources for prevention and treatment [12]. Understanding the economic burden of ABI and TBI is essential for improving resource allocation decisions, reducing the healthcare burden, and enhancing the quality of life for affected individuals and their families.

1.3. Acquired Brain Injury (ABI) and Traumatic Brain Injury (TBI)

ABI refers to any brain injury that occurs after birth, including those caused by strokes, tumors, infections, or oxygen deprivation [13]. TBI, a subset of ABI, results from external physical forces such as falls, traffic accidents, or violence. TBI can involve both open (penetrating) and closed (non-penetrating) injuries, and children are at a higher risk due to their smaller size and larger head-to-body ratio. These injuries can cause a range of complications, including concussions, skull fractures, hematomas, and axonal damage [14].

Beyond the initial injury, ABI and TBI can also lead to secondary complications, such as brain swelling, increased intracranial pressure, and cerebral hypoxia, which can exacerbate cognitive and physical impairments [15]. These injuries affect the maturation of the central nervous system in children, leading to long-term cognitive deficits, including impairments in memory, language, and attention [16].

Children with ABI and TBI often experience difficulties in school and later employment, which further adds to the economic burden. In addition to cognitive impairments, these children may struggle with emotional, social, and behavioral challenges, making it difficult for them to integrate into society [17]. The impact on families is also significant, as they must provide long-term care and support, often at great financial and emotional cost.

In some cases, the effects of TBI persist into adulthood, increasing the risk of conditions such as Alzheimer's disease and dementia [18]. Patients with severe TBI may suffer from permanent disabilities, such as speech impairments or paralysis, requiring lifelong rehabilitation and care [19]. This places a heavy burden on both families and the healthcare system, making it essential to estimate the lifetime costs of treating ABI and TBI.

2. METHODOLOGY

2.1. Method

A cost of illness (COI) study estimates resource costs for treating diseases and aids policymakers in comparing economic and disease burdens [20, 21]. The study will estimate annual economic costs of acquired brain injury (ABI) in children (<18 years) using incidence-based analysis (bottom-up approach).

2.1.1. Direct costs:

The incidence-based approach can estimate the lifetime costs of a condition from its onset until its disappearance (cure or death) and estimate the number of new cases of death or hospitalization in a given year and apply the lifetime cost estimate to those new cases [20]. These estimates may then be used to compute incremental cost-effectiveness or cost-utility ratios, comparing the new treatment with current treatments. For this research, the incidence-based approach can capture the burden of disease in new diagnostic cases and estimate discounted costs and health gains with alternative interventions [22].

$$\text{Incidence rate} = \frac{\text{Number of new cases of disease (health event) during a specified period}}{\text{Time each person at risk was observed totalled for all persons}} \times 10$$

Figure 1. Incidence Rate Calculation Formula

This study uses a bottom-up approach to estimate economic costs, collecting data at the patient level after admission. The process has two steps: (1) measure health inputs and (2) estimate unit costs for medical services [21 Data sources include admissions, emergency, non-admissions, transfers, and mortality datasets. The main admission dataset, covering patient demographics, ICD codes, ICU stay, and respiratory equipment use, will be the primary focus.

Direct medical costs include hospitalization, diagnostics, treatment, rehabilitation, and medical supplies [20 Step one involves collecting data from children aged 0–18 admitted to Queensland hospitals between 2012 and 2021. Step two uses this data to estimate the number of TBI and ABI patients, average costs by severity, and total costs using average unit costs and length of stay.

Three options were considered for classifying disease severity: (1) ICD-10 codes, though multiple codes per patient complicated severity assessment; (2) consciousness levels using ICD-10 S06 codes, though not all patients had these codes; and (3) classified patients by length of stay (LOS), grouping them into categories: less than 7 days, 7 to 30 days, and more than 30 days. This method was deemed most appropriate, as LOS is a strong indicator of healthcare utilization and severity [23]

2.1.2. Treatment cost per case

Upon admission, children with TBI incur significant costs depending on severity. Canadian data shows emergency care costs $253.37, ICU care $1,212.07/day, and operating rooms $1,129.11/hour, totaling $12,429.22 for typical cases [24]. ICU and operating theater use contribute the most to costs,

especially for severe cases. Early intervention and rehabilitation can reduce costs and optimize resource use.

2.1.3. Public price lists in Queensland hospitals:

Due to limited cost breakdowns in the dataset, this study uses Queensland's public health cost list, covering medical care, imaging, surgery, and medication. As of July 2021, long-stay costs are $1,784/day, with a base rate of $6,871 [25]. The average cost per ICU bed day is $4,375 [26]. ICU bed days cost $4,375. In public hospitals, most costs are covered by Medicare, but patients in private hospitals bear more, especially for ICU care [27]

Hospital Group	Type	Long Stay Per Day Rates
All hospitals excluding Group X	Medical	$1,784
All hospitals excluding Group X	Intervention	$2,346

Figure 2. [25] Long Stay Per Day Rates for Medical and Intervention Services

Hospital Group	Base Rate
All hospitals excluding Group X	$6,871

Figure 3. [25] Base Rate for Hospital Stay

2.1.4. Non-acute care costs

Non-acute care, particularly for children with mild TBI, represents a major cost [28]. Research has found that 53% of total costs occur within the first year, with psychological distress contributing to the financial burden [29]. Another study reported that psychological care costs are 2.8 times higher for patients experiencing distress [29]. After 12 months, as patients enter the convalescence phase, costs such as rehabilitation, assisted accommodation, and personal care become significant. These costs range from $20,961 for moderate TBI to $343,526 for severe TBI over six years [30].

Sub and Non-Acute Item No. Code	Description	Max Fee Excl. GST
99801	Maintenance	$1,841 per day
99802	Rehabilitation – Same Day	$1,159 per day
99803	Rehabilitation - Overnight	$1,860 per day
99804	Palliative	$1,737 per day

Figure 4. [25] Sub and Non-Acute Care Service Fees

2.1.5. Total treatment costs

TBI places a heavy economic burden, with head injury hospitalizations costing Australia nearly half a billion dollars over ten years [31]. Lifetime costs per case for moderate to severe TBI range from $2.5 to $4.8 million, with 19% covered by the government [32]. Total treatment costs are calculated based on case numbers and severity.

2.2. Indirect Costs

Indirect costs include productivity losses due to morbidity and mortality, and opportunity costs. For children with ABI, indirect costs stem from parental absenteeism and reduced productivity due to caregiving [20, 33]. As children age, disability-related premature death leads to further productivity losses. To focus on opportunity costs, this study estimates the costs of prolonged hospital stays, which could prevent other patients from using healthcare resources. Using the willingness-to-pay method, this paper will estimate opportunity costs by: (i) determining the bed days lost due to TBI & ABI, (ii)

calculating the average cost per bed day, and (iii) estimating the total opportunity cost of extended stays.

2.2.1. Extended length of stay

This article will calculate the mean estimate of additional stay and the standard deviation first and then use the Gamma distribution. The Gamma distribution is a two-parameter distribution, including the shape parameter α and the scaling parameter β. The shape parameter α represents the occurrence times of events, and the scaling parameter β represents the average time required for the occurrence of an event [34, 35]. The product $\mu = \alpha\beta$ is the average time required for the event to occur, which is the expected value (mean) of the Gamma distribution [34, 35]. Thus, the gamma distribution can wait for the K-time event to occur, and it can help us estimate the additional length of stay. In health analysis, it is often possible to use logarithmic gamma regression to estimate the length of stay (LOS) because the length of stay is always constrained to a positive number.

This study used estimates of the independent effect of the main admission dataset on length of stay (LOS). It is because the cost of treatment should vary between levels. Therefore, here, the study should estimate the LOS separately according to the class division. The simulated gamma distribution parameters (a and β) are calculated using the mean length of stay u (standard deviation s), $a = \frac{u^2}{s^2}$ and $\beta = \frac{s^2}{u^2}$ it is used to derive the values of a and β. This allows the prediction of future extended bed days and also the calculation of the opportunity cost by multiplying the mild, moderate, and medium times of the extended bed days.

2.2.2. Average cost per bed days

The data of average cost per bed days can be obtained from the Queensland Hospitals Statistics dataset. And the opportunity cost of bed days can be approximated by the average number of cases per bed day.

2.2.3. Opportunity costs

The total value of bed days lost to the TBI & ABI for each stage is then calculated as the product of the number of bed days lost and the average cost per bed day. The lost bed day is estimated based on the number of TBI & ABI cases and the average extended LOS per case. Since prolonged LOS is produced by the Gamma distribution and the number of TBI & ABI cases is produced by the beta distribution. Therefore, the opportunity cost, which is the prolonged LOS, TBI & ABI cases and cost per bed day is generated by a mixed distribution.

The high incidence of mild TBI contributed greatly to the overall disability from TBI at the population level. Thus, mild TBI prevention strategies are particularly important and cannot be thought of as a low-cost, temporary problem with little or no long-term sequelae [36]. The use of health resources for cognitive, psychological, and emotional disorders should be improved, and follow-up for mild TBI is necessary. It will help the child's prognosis and adjustment to school and future social situations.

3. REGRESSION ANALYSIS

After calculating the direct and indirect costs, this study found that a large proportion of the costs incurred depend on the length of stay in hospital. Therefore, this study will then use regression to analyze which factors will influence the length of stay.

3.1. Model Introduction

3.1.1. Multiple linear regression models.

A multiple linear regression model as well as a logit model and an ordered logit model are used to analyze the length of stay of the data set. Two datasets will be involved in the analysis. The first is the primary hospitalization dataset. The second is the emergency admissions dataset. With the main admissions dataset, the main objective is to identify the factors influencing length of stay. The dependent variable is length of stay and the independent variables are age, gender, area of residence, length of stay in Level 6 Intensive Care Unit - minutes and duration of Continuous Ventilatory Support – minutes. Here the length of ICU and duration of cvs are taken as a logarithm, and create new InICU and Incvs variables. Taken these two variables' logarithms are checking their elasticity, which means, how much the left-hand explanatory variable (length of stay of the patient) will increase for every one-percent increase in the log variable (ventilation equipment and ICU minutes of use).

The study began with a multiple linear regression model to identify the independent variables that had a significant influence on the dependent variable. The study then formulated five hypotheses.

Hypothesis 1: All other things being equal, the longer the ICU is used, and the longer the patient's stay in hospital.

Hypothesis 2: All other things being equal, the longer the respiratory equipment is used, the longer the patient's hospital stay.

Hypothesis 3: All other things being equal, the longer the gender of the patient, the longer the patient's hospital stay.

Hypothesis 4: All other things being equal, the younger the age, the longer the patient's hospital stay.

Hypothesis 5: All other things being equal, the more remote the patient's place of residence, the longer the patient's length of stay.

Equation 1:

$$\boldsymbol{Yit} = \boldsymbol{\beta 0} + \boldsymbol{\beta 1 Zit} + + \boldsymbol{uit} + \boldsymbol{\epsilon it} \quad (1)$$

Equation 2:

$$\boldsymbol{Yit} = \boldsymbol{\beta 0} + \boldsymbol{\beta 1 Xit} + \boldsymbol{\beta 2 Zit} + \boldsymbol{uit} + \boldsymbol{\epsilon it} \quad (2)$$

Equation 3:

$$\boldsymbol{Yit} = \boldsymbol{\beta 0} + \boldsymbol{\beta 1 Xit} + \boldsymbol{\beta 2 Zit} + \boldsymbol{\beta 3 Sit} + \boldsymbol{\beta 4 Ait} + \boldsymbol{\beta 5 Dit} + \boldsymbol{\beta 6 Eit} + \boldsymbol{uit} + \boldsymbol{\epsilon it} \quad (3)$$

Equation 1 and 2 are used as a reference, these hypotheses are mainly focus is on equation 3:

In the regressions, Yit represents patient length of stay, with independent variables including ventilator use time ($\boldsymbol{Xit}$), ICU time ($\boldsymbol{Zit}$), gender ($\boldsymbol{Sit}$), age ($\boldsymbol{Ait}$), residence area ($\boldsymbol{Dit}$), and mode of admission ($\boldsymbol{Eit}$). The dataset is panel data, and a fixed effects model is used. The first equation assesses ICU's effect on length of stay, while the second adds ventilator use time. The third includes all variables. Age groups are divided into 5-year intervals, and areas of residence are categorized as Inner Regional, Major Cities, Outer Regional, Remote, and Very Remote. Admissions are classified as elective or emergency, based on prior scheduling or ambulance arrival.

3.2. Logit Regression Model

A binary logit model was used to identify factors influencing the length of stay for severe ABI patients. The model evaluated the probability of a severe ABI (coded as 1, otherwise 0) affecting hospital stay. Marginal effects analysis was applied to assess the impact of a 1% increase in independent variables on severity. As the explanatory variable is binary, a linear regression model was not appropriate.

Patients were grouped by hospital stay duration: less than 7 days, 7-30 days, and over 30 days. The first regression examined the effect of ICU hours on severe patients' length of stay.

$$\ln\left(\frac{P}{1-P}\right) = a_0 + a_{i\ \text{severe}} + \delta_1 \ln\ ICU + \varepsilon_i \tag{4}$$

$a_i\ severe$ indicates whether the i patient with severe ABI。$\delta_i$represents the control variable. εi denotes other factors that are difficult to observe that may have an impact on the sample, i.e. random error terms.

$$\ln\left(\frac{P}{1-P}\right) = a_0 + a_{i\ \text{severe}} + \delta_1 \ln\ ICU + \delta_2 \text{lncvs} + \varepsilon_i \tag{5}$$

The second group added the logarithm of minutes of respiratory equipment use to the first group as a control variable.

$$\ln\left(\frac{P^4}{1-P}\right) = a_0 + a_{i\ \text{severe}} + \delta_1 \ln\ ICU + \delta_2 \ln\ cvs + \delta_{3\ \text{gender}} + \delta_{4\ \text{agegroup}} + \delta_{5\ \text{distance}} + \delta_{6\ \text{admission_mode}} + \varepsilon_i(3) \tag{6}$$

The third group again builds on the second group with the addition of gender, age and distance of residence to the control variables.

Besides, since admission mode is also a 0-1 variable, emergency admission is 1 and elective admission is 0. Therefore, this study also used a logit model to analyze whether the proximity of the area of residence had an effect on admission mode to hospital. Because the asric-eric variable represents access to medical resources and services. Some studies have shown that the distance to the hospital will affect the rate of emergency visit and hospitalization of patients [37]. For example, patients living in very remote areas may harder to go to the hospital in time or be reluctant to go to the hospital. They would rather heal at home or be taken to hospital by ambulance if they got seriously ill [37]. Therefore, it is also valuable to discuss the causal relationship between area of residence (i.e., distance) and admission mode. The formula is as follows.

$$\ln\left(\frac{P^{\ell}}{1-P}\right) = a_0 + a_{i\ \text{elect_status}} + \delta_{1\ \text{distance}} + \varepsilon_i \tag{7}$$

3.3. Ordered Logit Model

Finally, ordered logit models were used to analyses the factors influencing the degree of disease. In medical research, it is inevitable to encounter variables with such a progressive relationship as mild patients becoming moderate or severe due to secondary impairment. As it is no longer a two-class outcome, the ordinary binary logistics regression is no longer applicable when studying the relationship between other factors and such ordered dependent variables. So, this study used an ordered logit model further to the second step. On the basis of the binary logistic regression, we understand the linear relationship between the log probability logit (Y) and x for the dependent variable Y. This was extended to the case where the dependent variable has k classifications (1, 2, 3...k progressive relationships).

$$\log\ it(p_j) = \ln\left(\frac{p_j}{1-pj}\right) = \alpha_j + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{n^2} x_{n^2} \tag{8}$$

In the above equation p_j represents the cumulative probability of Y taking the first j values.

$$p_j = p(y \le j \mid x) = \begin{cases} \frac{\exp(\alpha_j+\beta x)}{1+\exp(\alpha_j+\beta x)}, \text{ when } 1 \le j \le k-1 \\ 1, \text{ when } j = k \end{cases} \tag{9}$$

Setting a j will transform the multiclassification problem into a binary classification problem with classification objectives of {1,…. ,j } and { j+1,... ,k}, the logit defined on the basis of these two classes represents the logarithm of the cumulative probability of belonging to the k-j classes with respect to the cumulative probability of dominance of the previous j classes, and is therefore called the cumulative dominance model. For example, when Y takes the values 1,2,3, i.e. light to moderate severity, the logit model is

$$\mathbf{P}1 = p(y = 1 \mid x) = \frac{\exp(a_1+\beta_x)}{1+\exp(a_1+\beta_x)} P1 = p(y = 1) = \mathrm{P}1 \quad (10)$$

$$\mathbf{P}2 = p(y \leqslant 2 \mid x) = \frac{\exp(a_2+\beta_x)}{1+\exp(a_2+\beta_x)} P2 = p(y = 2) = \mathrm{P}2 - \mathrm{P}1 \quad (11)$$

$$\mathbf{P3} = p(y \leq 3 \mid x) = 1, P_3 = p(y = 3) = 1 - P_2 \quad (12)$$

The first model represents the relationship between the probability p and x for the first value take from y; the second model represents the relationship between the cumulative probability p and x for the first two values take from y. These two models have different constant terms and identical regression coefficients.

The probability of y taking the first value p (1) = p1, the probability of y taking the second value p(2) = p - p1 and the probability of y taking the third value p(3) = 1 - p2. They have different intercepts and the same slope, so are a family of J-1 parallel straight lines. Therefore, the assumptions of the model will also be involved, and the ordered logit model requires a parallelism test of the data.

When P>a, the original hypothesis of parallelism is accepted. Otherwise, some values of the dependent variable should be combined to reduce the number of values taken by the dependent variable, so that the parallelism of the multi-categorical logistic regression model holds.

The final formula is as follows:

$$P(Y = \Theta|\mathrm{X}) \frac{e^{(\beta_0+\sum_{k=1}^{k}\beta_k X_k)}}{1+e^{(\beta_0+\sum_{k=1}^{k}\beta_k X_k)}} \quad (13)$$

Where: Θ = { }; X is a vector of explanatory variables. The selection of all core explanatory variables and control variables are InICU, Incvs, gender, distance （aria_desc), and mode of admission (elect_status).

3.4. Statistical Analysis

Stata Statistics version 17 (64-bit) was used to analyse the data. Costs per person and total costs were expressed as mean with 95% confidence intervals (CIs). Differences between mild and moderate/severe ABI costs were tested using a significance t-test with the significance level set at $p< 0.05$, $p< 0.01$ and $p< 0.1$.

4. RESULTS

4.1. Direct Cost

4.1.1. ABI & TBI average length of stay

From June 2020 to June 2021, there were 5,667 new cases of ABI and TBI among children in Queensland, resulting in an incidence rate of 0.4%. Of these cases, 5,362 were mild, 278 were moderate, and 27 were severe. This means that 94.62% of the new patients were mild, 4.91% were

moderate, and only 0.48% were severe. The average length of stay (LOS) for mild cases was 1.36 days (95% CI: 1.34-1.39), with a median of 1 day. Moderate cases had an average LOS of 13.03 days (95% CI: 12.87-13.18), with a median of 11 days. Severe cases had an average LOS of 49.49 days (95% CI: 49.02-49.96), with a median of 43 days. Among the 5667 patients, 108 required psychological treatment: mild cases received an average of 1.80 days, moderate cases received 14.01 days, and severe cases received 41.47 days of psychological care. For ICU use, patients with LOS <7 days had a mean duration of 34 hours in the ICU, while those with LOS between 7 and 30 days spent 126 hours in the ICU, and patients with LOS over 30 days spent an average of 17.81 days in the ICU.

Information on new patient admissions from June 2020 to June 2021			
	Average length of stay (day)	sd	95% Confidence interval[CI]
LOS≤7	1.36 days	0.97	1.34-1.39 days
7<LOS≤30	13.03 days	5.93	12.87-13.18 days
LOS>30	49.49 days	18.06	49.02-49.96 days
	Average number of psychiatric care days (day)	sd	95% CI
LOS≤7	1.8 days	1.49	1.76-1.84 days
7<LOS≤30	14.01 days	6.24	13.85-14.18 days
LOS>30	41.47 days	14.69	41.08-41.85 days
	Average length of stay in ICU (min/hr/day)	sd	95% CI
LOS≤7	2044.5 mins≈34 hr≈1.42 days	1670	2001-2088 mins
7<LOS≤30	7541 mins≈126 hr≈5.23 days	7214.61	7353-7728 mins
LOS>30	25659.46 mins≈428 hr≈17.81 days	27642.21	24940-26379 mins
	Average duration of Continuous Ventilatory Support (min)	sd	95% CI
LOS≤7	2170 mins ≈36.17 hr≈1.51 days	2136.9	2114.72-2225.99 mins
7<LOS≤30	8082.25 mins≈134.70 hr≈5.61 days	7489	7887.27-8277.24 mins
LOS>30	18633.08 mins≈310.55 hr≈12.84 days	18094.57	18161.97-19104.19 mins

Figure 5. Patient Admission Data from June 2020 to June 2021: Length of Stay, ICU, and Ventilatory Support

4.1.2. Australia one year cost per person

The direct cost per person is discussed separately at different levels. Firstly, for patients with a mild hospital stay of less than 7 days. Their average length of stay is 1.36 days. As this is a short stay, only the base rate of $6,871 is used to calculate the cost. This means that the average cost per person for a minor patient is approximately $6,871. The average length of ICU stay for a mild patient is 1.42 days and the ICU cost per bed day is $4375. The average length of respiratory equipment use is 1.51 days, and the maintenance fee is $1841 per day. Based on this, the cost for a mild patient is $15,863.41 per day.

Secondly, the average length of stay for patients with moderate $7 < LOS \leq 30$ is 14.01, which can be considered a Long Stay Outlier. Add the long stay per day rate for medical and intervention, which is $4130, to the base rate. In addition to the base rate, the average length of stay in the ICU for moderate patients is 5.23 days and the average length of stay for respiratory equipment is 5.61 days, so the total cost for severe patients is $69,031.56.

The calculation for severe patient is same as above, only need add extra-long stay per day rate based on long stay per day rate. The average length of stay is 49.49 days; Thus, the average ICU LOS was 17.81 days, and the average respiratory time was 12.84 days, plus the ICU and maintenances costs, giving a total single person cost of $300,049.61.

4.1.3. Queensland ABI & TBI one-year total cost.

In 2020-2021, there were 5,362 cases of mild disease, 278 cases of moderate disease, and 27 cases of severe disease. The total cost for a year can then be calculated as:

5362 x \$15,863.41+278 x \$69,031.56+ 27 x \$300,049.61= \$112,351,717.6≈ \$11.2 million (14)

The proportion of mild ABI is (5362 x \$15,863.41)/ \$112,351,717.6x 100% ≈ 75.71% Therefore, based on the main admission dataset, Queensland spends \$11.2 million per annum on ABI costs, which includes the cost of general admissions, ICU admissions, ancillary treatment and life-sustaining services. It is important to note that mildly ABI patients are the most significant source of cost, although the cost is less, the 94.62% of patients are mildly ABI, resulting in, 75.71% of the cost from mildly ABI patients.

Direct costs			
	LOS⩽7	7<LOS⩽30	LOS>30
Average length of stay (day)	1.36 days	14.01 days	49.49 days
Average length of stay in ICU (day)	1.42 days	5.23 days	17.81 days
Average usage time of respiratory equipment (day)	1.51 days	5.61 days	12.84 days
ICU cost per bed day	\$4,375.00	\$4,375.00	\$4,375.00
Base Rate	\$6,871.00	\$6,871.00	\$6,871.00
Maintenance fee	\$1,841.00	\$1,841.00	\$1,841.00
Long Stay per day rate	\$0.00	\$4,130.00	\$4,130.00
Extra Long Stay per day rate	\$0.00	\$0.00	\$828.00
Cost per person	\$15,863.41	\$69,031.56	\$300,049.61
Total cost in one year	0.112billion		

Figure 6. Direct Costs by Length of Stay (LOS) Category

4.2. Indirect Cost

4.2.1. Total number of extended bed days by grade

The number of extended bed days is first calculated from the gamma distribution and is discussed in a hierarchical manner. The shape parameter a of the gamma distribution specifies the number of events you are modelling, while the scale parameter β indicates the average time between events. Mild ABI patient's mean LOS is 1.36 and standard deviation is 0.97. Through $\alpha = \frac{u^2}{s^2}$ and $\beta = \frac{s^2}{u^2}$, The α = 1.97, β = 0.51. Gamma distribution in moderate ABI patients mean LOS is 13.03 and standard deviation is 5.93,Thus, α = 4.83, β = 0.21. Lastly, the final mean LOS for the Severe ABI patient is 49.49 and standard deviation is 18.06. It gives α=7.51 and β=0.13. These are consistent with gamma distribution. Besides, the study can also derive additional bed-days by comparing between the different grades. And the prolonged expectation for patients with severe disease is set at 30%. For example, a mild patient who is admitted to hospital and encounters inappropriate treatment and care will be at risk of secondary impairment and becoming moderate or severe. The difference between moderate and mild mean LOS can then also be considered as extend bed-days.

Thus, the extended bed days for mild patients is 11.67 bed-days; and the extended bed- days for moderate patients is 36.46 bed-days. Moreover, the extended bed-days for severe patients is 64.34 days.

4.2.2. Total opportunity cost by grade

After calculating the extended bed-days, these were multiplied by the case sample size to assess costs. Since this analysis focuses on extended stays, the base rate is excluded. The discussion centers on the per-person fee for long stays, totaling \$4130 (\$1784 + \$2346).

Consequently, the costs for extended stays are as follows: \$48,197 per person for mild ABI patients; \$150,579.8 per person for moderate ABI patients; \$265,680 per person for severe ABI patients. Overall, the potential loss could reach up to \$0.3 billion if opportunity costs are considered for each patient.

4.3. Regression Results

4.3.1. Multiple linear regression model: Risk factors for length of stay

The results from Figure 6, Model 3, indicate that InICU has a p-value < 0.01, significant at the 1% level, leading to the rejection of hypothesis 1. This implies a causal relationship between ICU time and patient length of stay, with a coefficient of 26.0234. Thus, for every 1% increase in ICU time, the length of stay increases by approximately 26.02 days.

Although the Incvs variable is not significant, suggesting that the duration of respiratory equipment use does not notably impact hospital length of stay, it still aids in recovery and preventing secondary injuries. Additionally, the p-value for gender is < 0.01, also significant at the 1% level, indicating that female patients have a significantly shorter length of stay compared to male patients.

The p-value for age group is < 0.1, significant at the 10% level, meaning that as patients cross each 5-year age group, their length of stay increases by 12.36 days. However, the area of residence and admission pattern did not significantly affect length of stay.

	(1) Model_1	(2) Model_2	(3) Model_3
lnICU	10.5488***	23.5028***	26.0234***
	(1.1002)	(6.6329)	(6.8693)
lncvs		-6.7734	-7.1490
		(5.8349)	(5.6872)
sex1			-29.8137***
			(9.0813)
agegroup			12.3572*
			(7.1789)
aria_desc1			5.9778
			(5.9764)
elect_st~1			-0.6012
			(6.6070)
_cons	-70.7240***	-1.3e+02***	-1.8e+02***
	(8.9139)	(18.7786)	(32.0604)
N	1877	892	750
adj. R-sq	0.371	0.663	0.657

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Figure 7. Regression Analysis of Factors Influencing Length of Stay

	(1) Model_l1	(2) Model_l2	(3) Model_l3
severe			
lnICU	1.2888***	2.4066***	2.4598***
	(0.0915)	(0.2636)	(0.3070)
lncvs		-0.4166**	-0.3387*
		(0.1853)	(0.2057)
sex1			0.2275
			(0.2661)
agegroup			-0.0208
			(0.0897)
aria_desc1			0.1181
			(0.1405)
elect_st~1			-0.6376
			(0.6733)
_cons	-13.2295***	-20.4120***	-21.3336***
	(0.8600)	(1.7852)	(2.4212)
N	1877	892	750
adj. R-sq			

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Figure 8. Logistic Regression Analysis of Factors Influencing Severe ABI Outcomes

Average marginal effects Number of obs = 750
Model VCE: Robust

Expression: Pr(severe), predict()
dy/dx wrt: lncvs lnICU sex1 agegroup aria_desc1 elect_status1

	dy/dx	Delta-method std. err.	z	P>|z|	[95% conf.	interval]
lncvs	-.0258854	.0159745	-1.62	0.105	-.0571947	.005424
lnICU	.1880026	.0182319	10.31	0.000	.1522687	.2237365
sex1	.0173848	.0202778	0.86	0.391	-.0223588	.0571285
agegroup	-.0015889	.0068438	-0.23	0.816	-.0150025	.0118247
aria_desc1	.0090263	.0106002	0.85	0.394	-.0117497	.0298023
elect_status1	-.0487296	.0515778	-0.94	0.345	-.1498201	.052361

Figure 9. Average Marginal Effects of Factors on Probability of Severe ABI

4.3.2. Logit model results: Risk factors for severe ABI

A stepwise regression analysis was conducted using Stata 17 with a binary logit model on observed data, focusing on severe illness outcomes (0-1). The results in Figure 7 indicate that in Model_l3, the InICU variable has a p-value < 0.01, significant at the 1% level, suggesting that each 1% increase in ICU time raises the probability of severe illness by 145%.

Additionally, the duration of continuous ventilatory support has a p-value < 0.05, significant at the 5% level, with a negative coefficient. This implies that longer ventilator use decreases the likelihood of developing severe acute brain injury (ABI), potentially by maintaining oxygen delivery and minimizing secondary neurological damage [7]. Other control variables did not show significant effects on severe ABI development.

Figure 8 presents marginal effects analysis, revealing that a 1% increase in ICU time correlates with an 18.80% increase in severe illness probability. However, there may be reverse causation, as sicker patients may require longer ICU stays. Conversely, a 1% increase in continuous ventilatory support

is linked to a 2.5% reduction in severe illness probability, highlighting the importance of timely ventilatory support in preventing serious secondary injuries. Thus, treatment and care aimed at avoiding secondary injury are crucial for patient recovery and cost reduction.

4.3.3. Logit model: the effect of distance on admission mode

Figure 9 results indicate that distance positively and significantly affects emergency admissions (p-value < 0.01). This suggests that patients living farther from healthcare facilities are more likely to be admitted as emergencies rather than electively. Elective admissions require coordination among hospitals, general practitioners, and other parties, which may deter patients with limited access to medical resources from choosing this option. While previous regression analysis did not show a significant effect of admission pattern on length of stay, the causal relationship between distance and admission mode remains informative.

	(1) Model_14
elect_st~1	
aria_desc1	**0.1556*** **
	(0.0401)
_cons	**1.3756*** **
	(0.0791)
N	**40331**
adj. R-sq	

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Figure 10. Logit Regression Analysis of Admission Mode and Area of Residence

4.3.4. Ordered Logit model: The impact factors of disease degree

The ordered logit model results indicate that InICU (p-value < 0.01) and Incvs (p-value < 0.01) significantly influence disease progression at the 1% significance level. The coefficient for ICU is greater than that for Incvs, suggesting that ICU has a more substantial effect than ventilation. Specifically, a 1% increase in ICU usage correlates with a 210% increase in the probability of worsened disease severity. In contrast, the negative coefficient for ventilation duration implies that longer ventilation leads to improved disease severity. Other variables showed no significant effects.

Table 1. Ordered Logit Regression Analysis of Factors Affecting Stay Duration

(1)		(2)	(3)
Model_lS		Model_l6	Model_l7
stay			
lnICU	1. 2105*** (0.0567)	2.6817*** (0.3551)	3.0959*** (0.2498)
lncvs		-0.6216*** (0.2194)	-0.8378*** (0.1611)
sexl			-0.1000
			(0.1799)
agegroup			-0.0167
			(0.0619)
aria_descl			0.0074
			(0.1017)
elect_st~1			-0.5088
			(0.4942)
/			
cutl	9.3016*** (0.4625)	17.2399*** {1.4856}	18.5791*** (1.3359)
cut2	12.5417*** (0.5329)	21.2269*** {1.6675}	22.7811*** (1.5059)
N	1877	892	750
adj. R-sq			
Standard errors in parentheses * p<0.1, ** p<0.05, *** p<0.01			

5. CONCLUSION

In 2020–2021, there were 5,667 new cases of ABI in Queensland, with a total first-year cost estimated at $11.2 million. Mild cases accounted for 75% of the total cost, with an average cost of $15,863.41 per person. Moderate and severe cases had costs of $69,031.56 and $300,049.61 per person, respectively. The extended length of stay for mild to severe cases ranged from 11.67 to 64.34 bed days, contributing to opportunity costs. Key factors influencing length of stay were ICU duration and gender, with males staying longer than females. In a binary logit model, ICU time increased the likelihood of severe ABI by 145%, while more time on a ventilator reduced the severity risk. Marginal effects analysis showed that every 1% increase in ventilator use decreased the risk of severe ABI by 2.5%. This highlights the critical role of respiratory support in preventing secondary injuries and improving outcomes.

6. DISCUSSION

This study uses data from a population-based ABI incidence study to report the direct and indirect costs of ABI in Queensland during the first year, based on ABI severity. Direct costs for mild, moderate, and severe ABI were $15,863.41, $69,031.56, and $300,049.61 per person, respectively. While the cost per case of mild TBI is lower, it accounted for 75% of the total cost due to its high incidence (95% of cases). These results provide critical information for health service planning and policy development.

However, limitations exist. The dataset lacks detailed severity classification and relies on hospital length of stay instead of GCS scores, potentially causing bias. Additionally, the cost data is

aggregated, so individual service costs cannot be precisely followed, reducing accuracy. The dataset also doesn't consider non-healthcare indirect costs, such as caregiver time and productivity losses during a child's hospital stay, likely underestimating the true economic burden of ABI in Queensland.

Given the high number of mild ABI cases, this condition carries a significant economic burden. Policymakers should focus on prevention and early intervention to reduce secondary injuries. Although there are limitations in the regression analysis due to fewer variables, the study provides valuable insights into the cost of ABI in Queensland.

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