

Estimating for Healthcare Cost Savings: Using AI-based Dietary Management Application*

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1. Introduction

Obesity is a major public health concern in developed countries. In Japan, lifestyle related diseases, including obesity, account for more than 30% of medical costs (Ministry of Health, Labour, and Welfare, 2018). Medical costs are 22.3% higher in obese groups than in non-obese groups (Kuriyama et al., 2002), and maintaining a 10% weight loss reduces lifetime medical costs by USD 2,200–5,300 (Oster et al., 1999). Asians, in particular, are more prone to diabetes after even a small increase in Body Mass Index (BMI) than other ethnic groups (Sone et al., 2004). Eating habits are also contributory to health problems such as mortality, obesity, hypertension, and cardiovascular disease (Owen & Corfe, 2017; Michaëlsson et al., 2020).

In this context, the Japanese government is increasing its assistance for research on the development of new service models and platforms for data management and utilization in serious lifestyle related diseases and nursing care prevention. In recent years, the widespread use of cloud computing and mobile devices (e.g., smartphones) has enabled the use of personal health records, which comprise medical, nursing, and health data of individuals, for various services with their consent. In addition, information and communication technology (ICT) and artificial intelligence (AI) are now being considered in the context of providing health interventions. The use of ICT and AI can potentially reduce the costs of traditional direct human interventions and reach a large number of people. Recently, health app usage has been promoted at the individual and insurance association levels to reduce medical costs. However, sufficient evidence has not yet been accumulated.

There are limited studies that simultaneously examine the health improvement effects and medical cost reduction effects of app usage using actual data (Zhai et al., 2014; Ministry of Health, Labour and Welfare, 2022), and clear evidence has not been obtained.

Okaniwa and Yoshida (2020a) conducted an experiment to test the effectiveness of AI-based health intervention. They used a smartphone-based diet management application for the intervention. Users captured photos of their meals with their smartphone camera, and the application analyzed the photos, determined the nutrients and calories in their meals, and calculated the meal balance score. It also delivered advice on balanced meals, supervised by nutritionists and created using an AI algorithm. The analysis revealed that the AI-delivered text advice intervention significantly lowered the participants BMIs by 2.6%. This study used the results from a previous study to estimate the effect of such an AI-delivered service on reducing medical costs.

In other words, this study estimated that the macro-medical cost savings of AI-delivered text message interventions are becoming more widespread (and thus, the prevalence of obesity is decreasing). This study provides preliminary material for new developments for future research in this field.

2. Data and Methods

Okaniwa and Yoshida (2020a) found that an AI-delivered text advice intervention significantly lowered participants' BMIs by 2.6% in three months. In this study, this estimate was used to examine the medical cost savings that could be achieved if people's health was improved using these interventions. Obesity increases the risk of diabetes, hypertensive diseases, and hyperlipidemia (Kadowaki et al., 1984; Ohnishi et

* This paper has substantially revised a discussion paper (Okaniwa and Yoshida, 2020b).

al., 2006; Kadowaki et al., 2006) and causes atherosclerosis (Iwabu et al., 2010). Interventions for obesity prevent the onset of these illnesses (Kosaka et al., 2005). If AI and human interventions, such as those examined in our study, become widely used, BMIs might decrease. This could reduce the prevalence of obesity in the population, and therefore, the number of people with obesity-related diseases. Thus, medical costs can also be reduced.

Estimating the number of people who will no longer be obese following such an intervention requires data on the BMI distribution of the population. BMI was calculated in units of kg/m², where kg is a person's weight in kilograms and m² is their height in meters squared. According to the Japan Society for the Study of Obesity (JSSO, 2011), obesity is considered by a BMI of 25 or higher and a visceral fat area ≥ 100 cm² (as measured by computed tomography). In this study, individuals with a BMI of 25 or higher were considered obese, and the number of people who could have their BMI reduced to below 25 by the intervention was estimated.

The BMI distribution of the population was obtained from the National Health and Nutrition Survey (NHNS, Kokumin Kenkou Eiyō Chōsa) in 2019. The distribution of each sample is shown in Figure 1. The BMI distribution at the time of the NHNS survey is represented in black; 25.8% of the total population was obese. The distribution in gray shows a projected 2.7% decrease in BMI after the AI health intervention. At this time, the percentage of obese individuals in the total population was 18.9%, representing a 26.6% decrease compared to before the intervention.

Finally, the effects on medical cost of reducing the number of obese individuals by approximately 26.6% were estimated. The medical cost-saving rate was calculated as follows:

Medical Cost Saving Rate for Each Disease:

$$MCSR = \frac{(M_i \times \rho_i \times \sigma)}{M_i} \quad (1)$$

Medical Cost Saving Rate for Total Diseases:

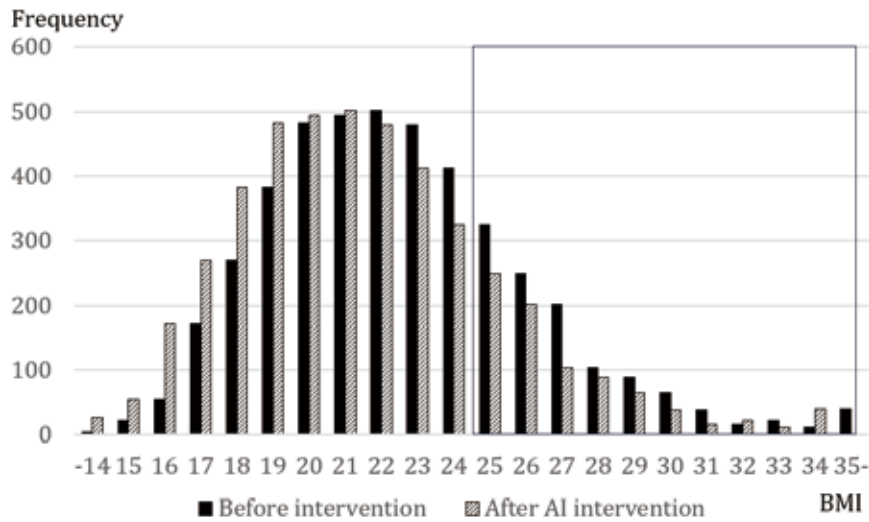
$$MCSRT = \frac{(M_i \times \rho_i \times \sigma)}{\sum_{i=1}^{122} M_i} \quad (2)$$

where M_i is the medical cost for each disease ($i=24$, diabetes; $i=51$, hypertensive diseases). Data for each health insurance association were obtained from the Fact-Finding Survey on Medical Benefits (Iryō-Kyūhū Jittai Chōsa) conducted in 2021. The survey

includes medical costs for 122 diseases. Diabetes and hypertensive diseases are strongly associated with obesity; however, not all patients treated for these diseases are obese. Therefore, data on the proportion of obesity in these diseases ($=\rho_i$) were needed. Furukawa and Nishimura (2007) found that 27.1% of patients with diabetes and 23.6% of patients with hypertensive disease were obese, using micro data from the NHNS. The medical costs caused by obesity before the intervention ($=M_i \times \rho_i$) were calculated by multiplying these numbers by the medical costs associated with each disease. As mentioned above, the number of obese individuals was estimated by the distribution of BMI reported by the NHNS, and the estimates of Okaniwa and Yoshida (2020a) were used to calculate the percentage reduction in obesity due to the intervention (σ). Here, the rate of decrease in the number of obese individuals was multiplied by each medical cost caused by obesity before the intervention ($=M_i \times \rho_i \times \sigma$) to calculate the medical cost savings rate of each cause of obesity after the intervention. Equation (1) represents the rate of reduction in the medical cost of diabetes or hypertensive diseases. Equation (2) represents the rate of reduction in total medical costs. Figure 2 presents an outline of the estimation.

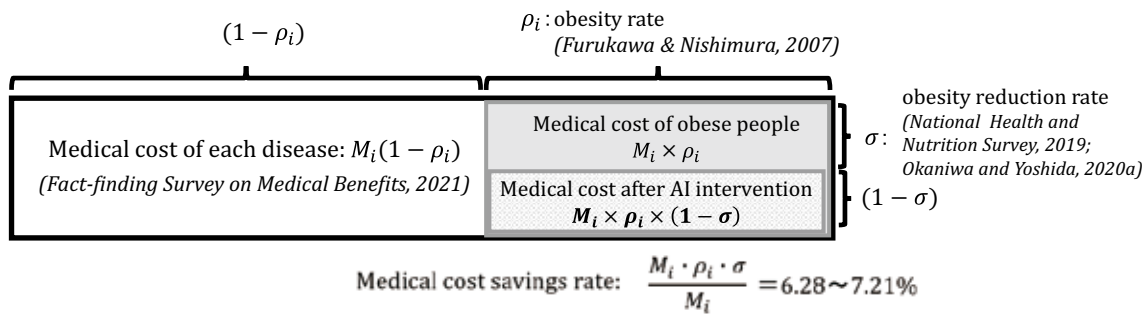
3. Estimation Results

Table 1 shows the estimates with respect to diabetes, based on BMI distribution data from the NHNS. Column (1) shows the medical costs for each health insurance association, collected from the Medical Benefits Survey (2021). Medical costs were divided into inpatient and outpatient costs. The total medical expenses for all the associations were JPY 1.04 trillion for diabetes. The medical expenses due to obesity are shown in column (2). These values were calculated by multiplying the medical cost in column (1) by ρ_i , based on Furukawa and Nishimura (2007), as described above. Column (3) shows the reduction rate of obese individuals resulting from AI intervention. Medical cost reductions after the intervention (shown in column (4)) were calculated by multiplying columns (2) and (3). The results showed that AI intervention could reduce medical costs by JPY 75 billion for diabetes. As shown in column (6), the estimated effects of AI intervention could reduce medical costs by 7.2% for diabetes. Column (7) shows these cost reductions



Source: Created by the authors based on the Ministry of Health, Labor, and Welfare (2019) National Health and Nutrition Survey.

Figure 1 : Distribution of BMI



Source: Created by the authors based on Furukawa & Nishimura (2007), the Ministry of Health, Labour, and Welfare (2019, 2021), and Okaniwa & Yoshida (2020a).

Figure 2: Outline of the estimation of medical cost savings

as a percentage of total medical cost. The largest predicted reductions in total medical costs for diabetes were observed by the National Health Insurance Association (NHI).

Similarly, Table 2 provides estimates related to hypertensive diseases based on the BMI distribution in the NHNS. The total medical cost for all associations in column (1) was JPY 1598 million. The total medical cost for all associations in column (1) is JPY 1.60 trillion. Multiplying this by the reduction rate of obese individuals due to AI intervention in column (3), the medical cost reduction after the intervention was calculated to be JPY 100 billion. It was estimated that AI intervention could reduce medical costs by 6.28% in column (6). The most significant reduction in total medical costs was observed in the late-stage medical care system for elderly with hypertensive diseases (column (7)).

4. Conclusion and Discussion

The purpose of this study was to provide a preliminary analysis of the impact of AI health intervention systems on reducing healthcare costs if they were to become widespread in the future. Using the BMI distribution data based on the NHNS, it was predicted that AI interventions would reduce obesity in the population by 26.6%. They are also predicted to reduce medical costs by 6.28–7.21% for diabetes and hypertensive diseases.

Currently, however, there are only a few studies on the effects of AI health interventions, and insufficient evidence to evaluate their impact. Due to this lack of data, only diabetes and hypertensive diseases caused by obesity were considered in this study. However, obesity can lead to several other diseases. It is also likely that people with a BMI of 25 or less included

Table 1. Estimated Medical Cost Savings (Diabetes)

Diabetes ($\rho=0.271$)		(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Medical cost of each disease (JPY)	Medical cost of each disease caused obesity (JPY)	Decrease rate of obese individuals through intervention	Medical cost savings by AI intervention (JPY)	Total medical cost (JPY)	Medical cost saving rate of each disease	Medical cost saving rate of total medical cost
		=Mi	=Mi $\cdot\rho$	= σ	=Mi $\cdot\rho\cdot\sigma$	= Σ Mi	=Mi $\cdot\rho\cdot\sigma$ / Mi	=Mi $\cdot\rho\cdot\sigma$ / Σ Mi
Total	Subtotal	1,043,304,286,930	282,735,461,758	0.266	75,207,632,828	28,979,584,591,290	7.21%	0.26%
	Hospitalized	233,422,286,900	63,257,439,750		16,826,478,973	15,167,573,506,140		0.11%
	Non-hospitalized	809,882,000,030	219,478,022,008		58,381,153,854	13,812,011,085,150		0.42%
Japan Health Insurance Association	Subtotal	184,657,880,790	50,042,285,694		13,311,247,995	5,290,046,065,940		0.25%
	Hospitalized	23,064,090,140	6,250,368,428		1,662,598,002	2,144,687,883,700		0.08%
	Non-hospitalized	161,593,790,650	43,791,917,266		11,648,649,993	3,145,358,182,240		0.37%
Health Insurance Societies	Subtotal	71,942,744,600	19,496,483,787		5,186,064,687	2,614,147,478,310		0.20%
	Hospitalized	8,120,835,200	2,200,746,339		585,398,526	996,208,373,070		0.06%
	Non-hospitalized	63,821,909,400	17,295,737,447		4,600,666,161	1,617,939,105,240		0.28%
Mutual Aid Associations	Subtotal	15,999,520,260	4,335,869,990		1,153,341,417	731,057,062,480		0.16%
	Hospitalized	1,924,790,150	521,618,131		138,750,423	300,526,188,880		0.05%
	Non-hospitalized	14,074,730,110	3,814,251,860		1,014,590,995	430,530,873,600		0.24%
National Health Insurance	Subtotal	317,596,426,140	86,068,631,484		22,894,255,975	7,641,156,635,000		0.30%
	Hospitalized	59,122,057,110	16,022,077,477		4,261,872,609	3,838,753,630,380		0.11%
	Non-hospitalized	258,474,369,030	70,046,554,007		18,632,383,366	3,802,403,004,620		0.49%
Medical care system for elderly in the latter stage of life	Subtotal	453,107,715,140	122,792,190,803		32,662,722,754	12,703,177,349,560		0.26%
	Hospitalized	141,190,514,300	38,262,629,375		10,177,859,414	7,887,397,430,110		0.13%
	Non-hospitalized	311,917,200,840	84,529,561,428		22,484,863,340	4,815,779,919,450		0.47%

Source: Calculated by the authors.

Notes: (1) Medical cost of each disease and (5) Total medical cost are based on the Ministry of Health, Labour, and Welfare (2021) “Fact-finding Survey of Medical Benefit,” (2) Medical cost of each disease caused by obesity is based on Furukawa & Nishimura (2007), and (3) Decrease rate of obese individuals through intervention is calculated from the BMI distribution based on the Ministry of Health, Labour, and Welfare (2019) “National Health and Nutrition Survey” and Okaniwa & Yoshida (2020a).

Table 2. Estimated Medical Cost Savings (Hypertensive diseases)

Hypertensive disease ($\rho=0.236$)		(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Medical cost of each disease (JPY)	Medical cost of each disease caused obesity (JPY)	Decrease rate of obese individuals through intervention	Medical cost savings by AI intervention (JPY)	Total medical cost (JPY)	Medical cost saving rate of each disease	Medical cost saving rate of total medical cost
		=Mi	=Mi $\cdot\rho$	= σ	=Mi $\cdot\rho\cdot\sigma$	= Σ Mi	=Mi $\cdot\rho\cdot\sigma$ / Mi	=Mi $\cdot\rho\cdot\sigma$ / Σ Mi
Total	Subtotal	1,598,127,622,320	377,158,118,868	0.266	100,324,059,619	28,979,584,591,290	6.28%	0.35%
	Hospitalized	176,103,051,260	41,560,320,097		11,055,045,146	15,167,573,506,140		0.07%
	Non-hospitalized	1,422,024,571,060	335,597,798,770		89,269,014,473	13,812,011,085,150		0.65%
Japan Health Insurance Association	Subtotal	230,002,001,100	54,280,472,260		14,438,605,621	5,290,046,065,940		0.27%
	Hospitalized	5,680,794,820	1,340,667,578		356,617,576	2,144,687,883,700		0.02%
	Non-hospitalized	224,321,206,280	52,939,804,682		14,081,988,045	3,145,358,182,240		0.45%
Health Insurance Societies	Subtotal	89,342,715,190	21,084,880,785		5,608,578,289	2,614,147,478,310		0.21%
	Hospitalized	1,696,507,250	400,375,711		106,499,939	996,208,373,070		0.01%
	Non-hospitalized	87,646,207,940	20,684,505,074		5,502,078,350	1,617,939,105,240		0.34%
Mutual Aid Associations	Subtotal	20,368,036,390	4,806,856,588		1,278,623,852	731,057,062,480		0.17%
	Hospitalized	414,198,980	97,750,959		26,001,755	300,526,188,880		0.01%
	Non-hospitalized	19,953,837,410	4,709,105,629		1,252,622,097	430,530,873,600		0.29%
National Health Insurance	Subtotal	379,092,215,690	89,465,762,903		23,797,892,932	7,641,156,635,000		0.31%
	Hospitalized	17,108,821,460	4,037,681,865		1,074,023,376	3,838,753,630,380		0.03%
	Non-hospitalized	361,983,394,230	85,428,081,038		22,723,869,556	3,802,403,004,620		0.60%
Medical care system for elderly in the latter stage of life	Subtotal	879,322,653,950	207,520,146,332		55,200,358,924	12,703,177,349,560		0.43%
	Hospitalized	151,202,728,750	35,683,843,985		9,491,902,500	7,887,397,430,110		0.12%
	Non-hospitalized	728,119,925,200	171,836,302,347		45,708,456,424	4,815,779,919,450		0.95%

Source: Calculated by the authors.

Notes: (1) Medical cost of each disease and (5) Total medical cost are based on the Ministry of Health, Labour, and Welfare (2021) “Fact-finding Survey of Medical Benefit,” (2) Medical cost of each disease caused by obesity is based on Furukawa & Nishimura (2007), and (3) Decrease rate of obese individuals through intervention is calculated from the BMI distribution based on the Ministry of Health, Labour, and Welfare (2019) “National Health and Nutrition Survey” and Okaniwa & Yoshida (2020a).

those with diabetes and hypertensive diseases; however, these people were excluded from the estimates made in this study. Therefore, the medical cost savings in this study are likely underestimated. Additionally, there is a need for updated data on disease prevalence.

Moreover, although this study focused on BMI, it is also necessary to validate body fat percentage (BFP), which represents body composition. BMI is a measure of the adult nutritional status. Although this is a simple indicator that can be calculated using height and weight alone, it is not a complete indicator of physical

status. This is because it does not consider other factors and does not accurately predict BFP (Barba et al., 2004; Moreno et al., 2006). However, BFP is a more reliable health indicator than BMI because it calculates fat as a percentage of body weight, and therefore actually represents body composition. The American College of Physicians states that BFP is more important than BMI for assessing a patient's health and mortality risk (Padwal et al., 2016). However, it is not possible to obtain BFP distribution data from other national surveys in Japan. BMI can be automatically calculated using height and weight information, whereas BFP is measured using an instrument that detects body fat. This difference in their measurement processes may explain why the BFP distribution data is not available.

Furthermore, this study focused on medical costs; however, in the future, both the costs and effectiveness of AI must be examined, including the development costs. Moreover, medical costs are disproportionately incurred by seriously ill individuals (Kazawa, 2020). Therefore, to reduce medical costs, a greater effect could be achieved by focusing on severely ill patients. Interventions that reduce the number of people who are likely to become severely ill in the future, along with improving the symptoms of those who are already severely ill, would be more effective in reducing healthcare costs. These are limitations of this study, and other associated analyses should be undertaken in the future to examine these issues further.

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Estimating for Healthcare Cost Savings: Using AI-based Dietary Management Application

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吉田 浩

人工知能（AI）や情報通信技術は目覚ましい発展を遂げており、医療・健康分野においても、人々の自発的な健康増進行動を促す介入システムへの応用が進んでいる。このような AI による健康介入システムの有効性や、活用に伴うマクロの医療費削減効果についてのエビデンスはいまだ端緒的である。本研究では、AI ベースの食事管理アプリに焦点を当て、このような健康介入システムが普及した場合のマクロの医療費削減額について、予備的な試算を行った。データは、厚生労働省（2021）『医療給付実態調査』、厚生労働省（2019）『国民健康栄養調査』を利用し、先行研究（Furukawa & Nishimura, 2007; Okaniwa & Yoshida, 2020）における推計値を参照しながら、AI 介入が普及し肥満者が減少した場合に、どの程度の医療費削減が可能かを試算した。その結果、糖尿病では7.2%、高血圧症では6.3%の医療費を削減することが示された。本稿は、試算の前提条件に一部制約があるものの、AI ベースの健康介入の意義をマクロの視点で捉えることで、社会的に望ましい健康介入システムの普及・導入可能性に向けた議論の材料を提供するものである。