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Estimating Medical Cost Savings from Supporting Health Behavior Using AI and ICT in Japan*

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ABSTRACT

The fields of artificial intelligence (AI) and information and communication technology (ICT) are currently witnessing remarkable progress, and they are now being applied to systems that encourage people to engage in voluntary health promotion behaviors. In the future, health intervention systems will likely be replaced by AI. The development of such AI-based health intervention systems is still in its infancy, however, and there is little evidence of their effectiveness. The purpose of this study is to estimate the macro health care cost savings that would result from the widespread use of AI-based health intervention systems. This study to estimates the healthcare cost reductions that could be achieved if AI interventions were to spread and the number of obese people were to decrease, based on the estimates of Okaniwa and Yoshida (2020). It was estimated that AI interventions could reduce medical costs for diabetes and hypertensive diseases by 8.2% and 7.2%, respectively. The findings of this paper could contribute to providing preliminary material for new developments in future research in this field.

JEL classification: D91, H51, I10

Keywords: AI, ICT, medical cost savings, health intervention, BMI

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1. INTRODUCTION

Obesity is a public health threat in developed countries. In Japan, lifestyle-related diseases, including obesity, account for more than 30% of medical costs (Ministry of Health, Labour and Welfare, 2018a). 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 one's lifetime medical costs by US$2,200-5,300 (Oster et al., 1999). Asians, in particular, are more prone to diabetes following even a small increase in Body Mass Index (BMI), compared to other ethnic groups (Sone et al., 2004).

In this context, the Japanese government is stepping up its assistance for research into the development of new service models and platforms for data management and utilization for serious lifestyle-related diseases and nursing care prevention. In recent years, the widespread use of cloud computing and mobile devices (e.g., smartphones) has made it possible to utilize personal health records (PHRs), which comprise the medical, nursing, and health data of individuals, for various services, with the consent of the individual. In addition, information and communication technology (ICT) and artificial intelligence (AI) are now being considered in the context of providing health interventions. Using ICT and AI could potentially reduce the costs of traditional direct human interventions, and could reach a large number of people. However, there is little evidence regarding the effectiveness of AI-based health intervention systems.

Okaniwa and Yoshida (2020) conducted an intervention experiment[1] and tested the effectiveness of AI-based health interventions. In the experiment, they used a smartphone-based diet management application (app) for the intervention. Users took photos of their meals with their smartphone's camera, and the app analyzed the photos, determined the nutrients and calories in their meals, and calculated a meal balance score. The app also delivered advice on balanced meals, supervised by nutritionists, and created by the AI's algorithm. The analysis revealed that the intervention from the AI-delivered text advice significantly lowered the participants' BMIs by 2.6%. This paper uses the results from this previous study to estimate the effect such an AI-delivered service on reducing medical costs. In other words, this study estimated the macro medical cost savings of AI-delivered text message interventions becoming more widespread (and thus the prevalence of obesity decreasing). This paper will contribute to providing preliminary material for new developments in future research in this field.

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[1] The experiment was conducted for three months, from February to April 2020. The subjects were recruited from 102 users of asken Inc.'s diet management app. For details of the experiment, please refer to Okaniwa and Yoshida (2020).

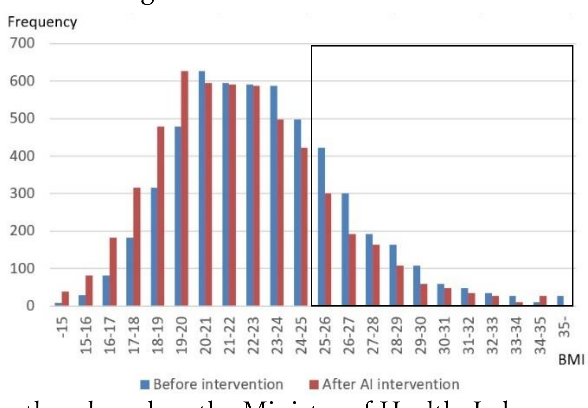
2. DATA AND METHODS

Okaniwa and Yoshida (2020) 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 achieve if people's health were to be improved using these interventions. Obesity increases the risk of diabetes, hypertensive diseases, and hyperlipidemia (Kadowaki et al., 1984; Ohnishi et al., 2006; Kadowaki et al., 2006) and causes atherosclerosis (Iwabu et al., 2010). Obesity interventions have been found to prevent the onset of these illnesses (Kosaka et al., 2005). If AI and human interventions, such as those examined in our study, were to become widely used, people's 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 could be reduced.

Estimating how many people would no longer be obese following such an intervention requires data on the BMI distribution of the population. BMI is calculated in units of kg/m^2, where kg is a person's weight in kilograms and m^2 is their height in meters, squared. According to the Japan Society for the Study of Obesity (JSSO, 2011), obesity comprises by a BMI of 25 or higher and a visceral fat area ≥100 cm^2 (as measured by computed tomography). In this paper, individuals with a BMI of 25 or higher were considered to be obese, and the number of people who could have their BMI reduced to below 25 by the intervention was estimated.

The population's BMI distribution was obtained from the National Health and Nutrition Survey (NHNS, *Kokumin Kenkou Eiyou Chousa*) from 2018. The distributions of each sample are shown in Figure 1. The BMI distribution at the time of the NHNS survey is represented in blue, with 25.8% of the total population being obese. The distribution in red shows a projected 2.6% decrease in BMI after the AI health intervention. At this time, the percentage of obese people in the total population would be 17.9%, representing a 30.3% decrease in the number of obese people, compared to before the intervention.

Figure 1: Distribution of BMI



Source: created by the author, based on the Ministry of Health, Labor, and Welfare (2018b) National Health and Nutrition Survey.

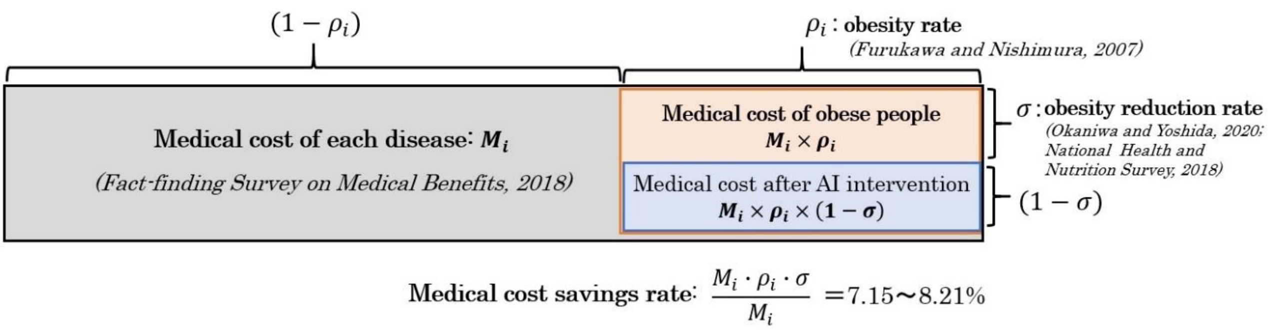
Finally, the effects of reducing the number of obese people by approximately 30% on medical costs was estimated. The medical cost-saving rate was calculated as follows:

$$Medical\ Cost\ Saving\ Rate\ for\ each\ diseases = \frac{(M_i \times \rho_i \times \sigma)}{M_i} \quad \cdot\cdot\cdot (1)$$

$$Medical\ Cost\ Saving\ Rate\ for\ total\ diseases = \frac{(M_i \times \rho_i \times \sigma)}{\sum_{i=1}^{122} M_i} \quad \cdot\cdot\cdot (2)$$

where M_i is the medical cost of 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 (*Iryou-Kyuuhu Jittai Chousa*) in 2018. Diabetes and hypertensive diseases are highly associated with obesity, but 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 had 27.1% of diabetic patients and 23.6% of hypertensive disease patients are obese, respectively, 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 each disease's medical costs. As mentioned above, the number of obese people was estimated by the distribution of BMI reported by the NHNS, and the estimates of Okaniwa and Yoshida (2020) were used to calculate the percentage reduction in obesity due to the intervention (σ). Here, the rate of decrease in the number of obese people 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 each medical cost for diabetes or hypertensive diseases. In addition, equation (2) represents the rate of reduction in total medical costs. Figure 2 shows an outline of the estimation.

Figure 2: Outline of the estimation of medical cost savings



Source: created by the author.

3. ESTIMATION RESULTS

Table 1 shows the estimates based on the BMI distribution data from the NHNS. This section focuses on diabetes and hypertensive diseases. First, column (1) shows the medical costs for each health insurance association, collected from the Medical Benefits Survey (2018). The total medical expenses for all associations were 1.01 trillion yen for diabetes and 1.59 trillion yen for hypertensive diseases. Of these, 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 people resulting from AI intervention. The medical cost reductions after the intervention (shown in column (4)) were calculated by multiplying columns (2) and (3). The results show that AI intervention by AI could reduce medical costs by 83 billion yen for diabetes and by 114 billion yen for hypertensive diseases. As shown in column (6), the estimated effects of AI intervention could therefore reduce medical costs by 8.2% for diabetes and 7.2% for hypertension. Column (7) shows these cost reductions as a percentage of the total medical cost. The predicted largest reductions in total medical costs were seen in the National Health Insurance Association (NHI) for diabetes and in the medical care system for elderly individuals in the latter stage of life for hypertensive diseases.

Table 1: Estimated Medical Cost Savings

JPY one thousand		(1) Medical cost of each disease	(2) Medical cost of each disease caused obesity	(3) Decrease rate of obesity people by intervention	(4) Medical cost saving by AI intervention	(5) Total medical cost	(6) Medical cost saving rate of each disease	(7) Medical cost saving rate of total medical cost
		=Mi	=Mi* ρ	= σ	=Mi* ρ * σ	= Σ Mi	=Mi* ρ * σ / Mi	=Mi* ρ * σ / Σ Mi
Data Source		Fact-finding Survey on Medical Benefits(2018)	Furukawa and Nishimura(2007)	Calculated besed on NHNS(2018) and Okaniwa and Yoshida (2020)		Fact-finding Survey on Medical Benefits(2018)		
Diabetes (ρ =0.271)	Total	1,014,147,332	274,833,927	30.3%	83,274,680	26,875,248,488	8.21%	0.31%
	Japan Health Insurance Association	169,615,856	45,965,897		13,927,667	4,788,672,926		0.29%
	Health Insurance Societies	51,042,420	13,832,496		4,191,246	1,882,990,969		0.22%
	Multual Aud Associations	7,914,165	2,144,739		649,856	356,871,793		0.18%
	National Health Insurance	336,558,610	91,207,383		27,635,837	7,718,579,168		0.36%
	Medical care system for elderly in the latter stage of life	449,016,281	121,683,412		36,870,074	12,128,133,631		0.30%
Hypertensive disease (ρ =0.236)	Total	1,594,677,453	376,343,879		114,032,195	26,875,248,488	7.15%	0.42%
	Japan Health Insurance Association	216,395,278	51,069,286		15,473,994	4,788,672,926		0.32%
	Health Insurance Societies	64,811,753	15,295,574		4,634,559	1,882,990,969		0.25%
	Multual Aud Associations	10,240,136	2,416,672		732,252	356,871,793		0.21%
	National Health Insurance	412,817,131	97,424,843		29,519,727	7,718,579,168		0.38%
	Medical care system for elderly in the latter stage of life	890,413,155	210,137,505		63,671,664	12,128,133,631		0.52%

Source: Estimations are based on the Ministry of Health, Labour and Welfare (2018c) Fact-finding Survey of Medical Benefit, the Ministry of Health, Labour and Welfare (2018b) National Health and Nutrition Survey, Furukawa and Nishimura (2007), and Okaniwa and Yoshida (2020).

4. CONCLUSIONS AND DISCUSSION

The purpose of this paper is to provide a preliminary analysis of the impact of AI health intervention systems on reducing health care costs, if they were to become widespread in the future. Using the BMI distribution data based on the NHNS, here it is predicted that AI interventions would reduce obesity in the population by 30.3%. AI interventions are also predicted to reduce medical costs by 7.15-8.21% for diabetes and hypertensive diseases.

Currently, however, there are few studies into the effects of AI health interventions, and there is insufficient evidence to evaluate their impact. Due to this lack of data, only diabetes and hypertensive diseases were to be caused by obesity in this study. However, obesity can cause many other diseases. It is also likely that people with a BMI of 25 or less include people with diabetes and hypertensive diseases, but these people were excluded from the estimates made in this paper. Therefore, the medical cost savings in this study are likely underestimations.

Moreover, although this study focused on BMI, it is also necessary to validate the body fat percentage (BFP), which represents body composition. BMI is a measure of nutritional status in adults. Though it is a simple indicator, which can be calculated from 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). On the other hand, BFP is more reliable as a 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 has stated that BFP is more important than BMI for assessing a patient's health and mortality risk (Padwal et al., 2016). However, it was not possible to obtain the distribution data of BFP from other national surveys in Japan. BMI can be calculated automatically using height and weight information, whereas BFP is measured using an instrument that detects fat in the body. This difference in their measure processes may explain why the distribution data of BFP is not available.

Furthermore, this study focuses on medical costs, but in the future, both the costs and effectiveness of AI must be examined, including development costs. Furthermore, medical costs are disproportionately spent on those who are seriously ill (Kazawa, 2020). In terms of reducing medical costs, therefore, a greater effect may be achieved by focusing on those who are severely ill. 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 health care costs. These are the limitations of this study, and in the future, other associated analyses should be undertaken to further examine these issues.

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