



# The Study of Annual Health Examination Result by Using Testing Fuzzy Hypotheses with Fuzzy P-Value

Paothai Vonglao

Department of Applied Statistics, Faculty of Science, Ubon Ratchathani Rajabhat University

Corresponding author. E-mail address: paothai2508@gmail.com

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## Abstract

The research aimed to study a health evaluation method from the annual health examination by an application of testing fuzzy hypotheses. The fuzzy p-value is used for the testing. The reason that we need to apply the fuzzy hypotheses testing, because classical hypotheses testing can not test the difference between a population mean with an interval of constant. The participants were 136 recipients who had an annual health examination in Ubon Ratchathani Rajabhat University in 2015. Research instrument was the simplified forms with result recorded from a laboratory examination in an annual health examination. Statistics used in data analysis were testing fuzzy hypotheses by using fuzzy p-value and percentage. The method of health diagnosis was the testing fuzzy hypotheses by using fuzzy p-value consisted of the followings : 1) Set the fuzzy hypotheses to insist the results from laboratory in the annual health examination. 2) Set fuzzy significant level. 3) Define the test statistic. 4) Finding the fuzzy p-value. 5) Compare the fuzzy p-value with the fuzzy significant and 6) Make decision. Most of the results from laboratory in annual health examination were in normal value with degree 0.8627–1.0. The study indicated that the values of cholesterol was higher than normal value with degree 1.

**Keywords:** Annual health examination, Testing Fuzzy Hypotheses, Fuzzy p-value, Fuzzy Set.

## Introduction

An annual health examination is a medical screening that can protect the diseases found from the examination. In addition the examination allows physicians to identify risky factors of the occurrence of diseases. The examination can improve quality of life by adjusting some health's habits (Karusun, Sawanyavisuth, & Chaiear, 2007). In Thailand the government launches a practice for annual health examination. The goals of the practice were to extend life expectancy, reduce the risk of physical illness and improve quality of life. The health examination for persons who were older than 34 years old consisted of 2 steps (Supason, 2008). Step 1 : The physicians asked questions from recipients on background such as age, career, congenital disease, illness of family members, eating habit, drug use and doing exercise. The physician examined physical body such as observing, listening, touching with hands and knocking

without medical instruments. The examination allowed the physician to identify the abnormal of physical conditions on some organs such as skin, eye, ear, nose, mouth, neck and joints. Step 2: Laboratory examination which include 1) to examine blood cell and find the blood count intensity or hematocrit (HCT) to evaluate the anemia condition. The normal value of HCT for male is 38%–54% and 36%–52% for female 2) to examine the performance of kidney to check blood urea nitrogen (BUN) and creatinine. The BUN and creatinine values evaluate the deformation of kidneys. The normal value of BUN is 7–18 mg/dl and 0.6–1.3 mg/dl for creatinine. 3) to examine the level of uric acid to evaluate Gout risks. The normal value of uric acid level is 2.6–7.2 mg/dl. 4) to examine the performance of liver to examine the enzyme level of liver in blood which includes Alanine aminotransferase (ALT), Asparate aminotransferase (AST) and Alkaline phosphatase (ALP). The enzyme are used to evaluate the deformation of bile duct and liver. The



normal value of ALT for male is 30–65 U/L and 26–69 U/L for female. The normal value of AST for male is 15–37 U/L and 13–46 U/L for female. The normal value of ALP for male is 50–136 U/L and 28–126 U/L for female. 5) Plasma glucose examination to find sugar level in the blood after fasting (Fasting Blood Sugar: FBS). The FBS value is used to evaluate diabetes risk. The normal value of

FBS is 70–110 mg/dl. 6) Cholesterol and Triglyceride examination to find cholesterol and triglyceride level in the blood. The examination can predict the risk of coronary artery and myocardial infarction disease. The normal value of cholesterol is 0–200 mg/dl and triglyceride is 30–150 mg/dl. (Regional Health Promotion Center 7 Ubon Rachathani, 2016).

**Table 1** The normal value of health index in annual health examination.

health examination	health index	The normal value of health index
Anemia condition	HCT of male	38%–54%
	HCT of female	36%–52%
Performance of kidney	BUN	7–18 mg/dl
	Cr	0.6–1.3 mg/dl
Gout risks	Uric acid	2.6–7.2 mg/dl
Performance of liver	ALT of male	30–65 U/L
	ALT of female	26–69 U/L
	AST of male	15–37 U/L
	AST of female	13–46 U/L
	ALP of male	50–136 U/L
	ALP of female	28–126 U/L
Diabetes	FBS	70–110 mg/dl
Cholesterol and Triglyceride	Cholesterol	0–200 mg/dl
	Triglyceride	30–150 mg/dl

Generally, the study of results from the laboratory examination attend to find the percentage of the deformity of health index among recipients. For example, Karusun et al. (2005) studied the result of annual health examination of the person in faculty of medicine, Khonkean University. The study found that the percentage of staff with higher 200 mg/dl of cholesterol were 82.6 and 85.2 for officers and nursing service staff respectively, and 25% for the anemia person. However, the result from the study merely explained the health condition of the samples but not inferring the health condition of population. Moreover, the quantitative data result from laboratory examination is possibly beneficial for analysis when using parametric statistics. The testing hypotheses is an important statistical method that appropriate for the analysis. However, in classical statistics, testing

hypotheses can be applied when the hypotheses are crisp. For example, in one population case when we test the difference between a population mean with a constant, the ordinary null hypothesis stipulate the population mean that is precisely equal to the constant. The hypothesis testing can not test the difference between a population mean with an interval of constant. Because of the normal value of the result from the laboratory examination are an interval of constant, we can not use the hypothesis testing to test whether the recipient have deformity health or not. However, testing fuzzy hypotheses is available for the testing in that case.

The fuzzy hypotheses mean the imprecise quotation about parameter. Parchami, Ivani, & Mashinchi, (2011) compared difference between classical hypotheses and fuzzy hypotheses by using



example. For the example, suppose that  $\theta$  is the proportion of a population which has a disease. In classical statistics, when we would like to test our believe about the  $\theta$ , one use hypotheses of the form  $H_0 : \theta = 0.15$  versus  $H_1 : \theta \neq 0.15$  or the form  $H_0 : \theta \leq 0.15$  versus  $H_1 : \theta > 0.15$  and so on. However, we would sometimes attend to test more realistic hypotheses about the  $\theta$  such as  $\theta$  is *small*, *very small*, *large*, *approximately 0.5* and so on. Therefore, more realistic formulation of the hypotheses might be (for exam) :  $\tilde{H}_0 : \theta$  is *small* versus  $\tilde{H}_1 : \theta$  is *not small*. We call such hypotheses as fuzzy hypotheses. In addition, they also gave example to promote fuzzy hypotheses is more appropriate than classical hypotheses. For the example, suppose we would like to test a population mean with a constant,  $\mu_0$ . In classical statistics, we use hypotheses of the form  $H_0 : \mu = \mu_0$  versus  $H_1 : \mu \neq \mu_0$ . Obviously, in this example, if the sample mean is slightly different from  $\mu_0$ ,  $H_0$  is still acceptable. On the other hand if the sample mean is considerable different from  $\mu_0$ ,  $H_0$  is rejected. Thus it is reasonable to accept null hypothesis if  $\mu$  is close to  $\mu_0$  ( $\mu \cong \mu_0$ ) and to reject it if  $\mu$  is far from  $\mu_0$  ( $\mu \not\cong \mu_0$ ). Therefore, the fuzzy hypotheses is appropriate for the such hypotheses, the form of fuzzy hypotheses are  $H_0 : \mu \cong \mu_0$  versus  $H_1 : \mu \not\cong \mu_0$ .

There are many scholars who have studied about fuzzy testing since Zadeh (1965) presented the notion of fuzzy set. Taheri (2003) presented the trends in fuzzy statistics, in which he (she) illustrates data analysis by using fuzzy set theory to test vague hypotheses. Tanaka, Okuda, & Asai, (1979) studied on decision in statistical model that obtain the approach to test hypotheses by using fuzzy data analysis. Casals, Gil, & Gil, (1986) extended both Neyman–Pearson and Bayes theories to test hypotheses when the available data are fuzzy. Watanabe and Imaizumi (1993) presented a fuzzy statistical testing of fuzzy

hypotheses, in which they illustrate an approach for fuzzy hypotheses testing. The approach is based on condition about fuzzy critical region and a fuzzy conclusion. Arnold (1996, 1998) presented an approach to test fuzzy hypotheses and testing hypotheses with crisp data, in which he provided new definition for probability of type *I* and type *II* errors. Taheri and Behboodian (1999, 2001) worked on Neyman–Pearson Lemma for fuzzy hypotheses testing and a Bayesian approach to test fuzzy hypotheses. Their work presented fuzzy hypotheses testing when the observations are crisp and new definition for probability of type *I* and type *II* errors. In addition they also presented fuzzy hypotheses testing when the observation are ordinary. Buckley (2005) proposed the fuzzy statistics for hypotheses testing, in which he produced a fuzzy test statistic by using a set of interval confidence. Filzmoser and Viertl (2004) presented the approach for crisp hypotheses testing when the observation are fuzzy by using fuzzy p-value. Denoeux, Masson, & Hébert, (2005) obtained nonparametric testing by a rank-based statistic approach when data are fuzzy. The fuzzy p-value is used to test in the approach. Geyer and Meeden (2005) presented hypotheses testing by using a fuzzy confident interval and fuzzy p-value. They founded that the testing is optimality of uniformly most powerful (UMP) and uniformly most powerful unbiased (UMPU) test. Parchami and Mashinchi (2008) investigated the problem of testing fuzzy hypotheses based on a fuzzy p-value method, when data are crisp. They also presented an approach for comparing the fuzzy p-value with the given fuzzy significance level, and obtaining an index of acceptance for the null hypothesis. In addition they gave the useful numerical example to illustrate the performance of the method. Parchami et al. (2011) also presented an application of testing fuzzy hypothesis. They introduced the approach of testing fuzzy hypotheses by using fuzzy p-value for soil study on the



bioavailability of cadmium. The as above studies motivate me to apply the testing fuzzy hypotheses to study the result from laboratory examination in an annual health examination.

As above mention, this research attend to find a new method to study the result from laboratory examination in an annual health examination of staff at Ubon Rachathani Rajabhat University. The testing fuzzy hypotheses by using fuzzy p-value will be applied to study the result. The benefit of this research is a new testing hypotheses approach and the information about health situation of the staff at Ubon Rachathani Rajabhat University.

**Research Objective**

The purposes of this research were:

1. To study the result from laboratory examination in an annual health examination by using testing fuzzy hypotheses with fuzzy p-value.
2. To evaluate the health situation of the staff at Ubon Rachathani Rajabhat University by applying testing fuzzy hypotheses .

**Methods and Materials**

**Participants**

The population included 865 staff at Ubon Rachathani Rajabhat University. The sample were 136

recipients who had an annual health examination at Ubon Rachathani Rajabhat University in 2015.

**Data collection**

This research collected data from the simplified form that recorded the results from laboratory examination in an annual health examination of the recipients at Ubon Rachathani Rajabhat University on 2015.

**Data analysis**

This research analyzes data according to the research objectives. The content analysis is used to study the testing fuzzy hypotheses by using fuzzy p-value. The testing fuzzy hypotheses using fuzzy p-value is used to evaluate the health situation of the staff in Ubon Rachathani Rajabhat University.

1. The preliminary concepts of testing fuzzy hypotheses.

1.1 Fuzzy set theory

Parchami and Mashinchi (2008) concluded the concept of fuzzy set as: Let  $X$  be a universal and  $A$  is a functions from  $X$  to  $[0,1]$ ,  $A: X \rightarrow [0,1]$ , we call  $A$  is fuzzy set on  $X$ . Let  $F(X)$  be the set of all  $A$  so  $F(X) = \{A|A: X \rightarrow [0,1]\}$ . In particular, let  $\mathfrak{R}$  be the set of real number. We use the following notation represent fuzzy set and set of the fuzzy set.

$$F_C(\mathfrak{R}) = \{A|A: \mathfrak{R} \rightarrow [0,1], A \text{ is a continuous function} \},$$

$$F_S(\mathfrak{R}) = \{S(a,b)|a,b \in \mathfrak{R}, a \leq b\}, \text{ where } S(a,b)(x) = \begin{cases} 1 & \text{if } x \leq a \\ (x-b)/(a-b) & \text{if } a < x \leq b \\ 0 & \text{if } x > b \end{cases}$$

$$F_B(\mathfrak{R}) = \{B(c,d)|c,d \in \mathfrak{R}, c \leq d\}, \text{ where } B(c,d)(x) = \begin{cases} 0 & \text{if } x < c \\ (x-c)/(d-c) & \text{if } c \leq x < d \\ 1 & \text{if } x \geq d \end{cases}$$

$$F_T(\mathfrak{R}) = \{T(a,b,c)|a,b,c \in \mathfrak{R}, a \leq b \leq c\}, \text{ where } T(a,b,c)(x) = \begin{cases} (x-a)/(b-a) & \text{if } a < x \leq b \\ (x-c)/(b-c) & \text{if } b < x \leq c \\ 0 & \text{elsewhere} \end{cases}$$

Note:  $T(a,a,a)$  will denote the indicator function of  $a, I_{\{a\}}$

**Definition 1** Let  $A \in F_C(\mathfrak{R})$ , then

- (1) A is called normal, if there exists  $x \in \mathfrak{R}$  such that  $A(x) = 1$ .
- (2) A is called convex, if  $A(\lambda x + (1-\lambda)y) \geq \min(A(x), A(y))$ ,  $\forall x, y \in \mathfrak{R}, \forall \lambda \in [0,1]$ .

1.2 Testing fuzzy hypotheses

To test the fuzzy hypotheses we need to understand the following key definitions: **Definition 2** Fuzzy hypothesis means any hypothesis that is in the form “ $\tilde{H} : \theta$  is  $H$ ” where  $H : \Theta \rightarrow [0,1]$  is a

(3) The support of  $A$  is the crisp set given by  $\text{Supp}(A) = \{x | A(x) > 0\}$ .

(4) The  $\delta$ -cut of  $A$  is the crisp set given by  $A_\delta = \{x | A(x) \geq \delta\}$ , for any  $\delta \in (0,1]$ .

fuzzy set of parameter space  $\Theta$  with membership function  $H$ . (Taheri & Behboodan, 1999)

According to definition 2, let  $\theta$  be the parameter of normal distribution if we want to test “ $\theta$  is approximately 0.5”. We can represent the message by fuzzy set,  $H = T(0,0.5,1)$ , so the fuzzy hypothesis for testing “ $\theta$  is approximately 0.5” is

$$“\tilde{H} : \theta \text{ is } H”$$

**Definition 3** Let the fuzzy hypothesis “ $\tilde{H} : \theta$  is  $H$ ” be such that

- (1)  $H$  is a monotone function of  $\theta$ ,
- (2) there exists  $\theta_1 \in \Theta$  such that  $H(\theta) = 1$  for  $\theta \geq \theta_1$  (or for  $\theta \leq \theta_1$ ),
- (3) the range of  $H$  contains the interval  $(0,1]$

Then  $\tilde{H}$  is called a one-sided fuzzy hypothesis.

**Definition 4** Let the fuzzy hypothesis “ $\tilde{H} : \theta$  is  $H$ ” be such that

(1) There exists an interval  $[\theta_1, \theta_2] \subset \Theta$  such that  $H(\theta) = 1$  for  $\theta \in [\theta_1, \theta_2]$  And  $\inf\{\theta : \theta \in \Theta\} < \theta_1 \leq \theta_2 < \sup\{\theta : \theta \in \Theta\}$ ,

(2)  $H$  is an increasing function of  $\theta$  for  $\theta \leq \theta_1$  and decreasing for  $\theta \geq \theta_2$

(3) the range of  $H$  contains the interval  $(0,1]$

Then  $\tilde{H}$  is called a two-sided fuzzy hypothesis.

**Definition 5** The boundary of the hypothesis  $\tilde{H}$  is a fuzzy subset of  $\Theta$  with membership function  $H_b$ , defined as follows:

- (1) If  $\tilde{H}$  is one-sided and  $H$  is increasing then  $H_b(\theta) = \begin{cases} H(\theta) & \text{for } \theta \leq \theta_1 \\ 0 & \text{for } \theta > \theta_1 \end{cases}$
- (2) If  $\tilde{H}$  is one-sided and  $H$  is decreasing then  $H_b(\theta) = \begin{cases} H(\theta) & \text{for } \theta \geq \theta_1 \\ 0 & \text{for } \theta < \theta_1 \end{cases}$
- (3) If  $\tilde{H}$  is two-sided then  $H_b(\theta) = H(\theta)$

The process of testing fuzzy hypotheses begins with fuzzy hypotheses assignment as follows:  $\tilde{H}_0 : \theta$  is  $H_0(\theta)$  versus  $\tilde{H}_1 : \theta$  is  $H_1(\theta)$ , where  $H_0$  and  $H_1$  are membership function that used to represent the quotation about parameter that one would like to test.

To test the fuzzy hypotheses we let a random sample,  $X = (X_1, X_2, X_3, \dots, X_n)$  from a probability (density) function,  $f(x, \theta)$  with unknown  $\theta \in \Theta$ . Such a test is usually dependent on a test statistic  $T(X)$ , in a nonrandomized test the space of possible



values of the test statistic  $T$  is decomposed into a rejection region and acceptance region. The regions are

dependent on  $\tilde{H}_0$  and  $\tilde{H}_1$  which usually take one of the following forms:

$$T \leq t_l, \tag{1}$$

$$T \geq t_r, \tag{2}$$

$$T \notin (t_1, t_2) \tag{3}$$

Where  $t_l, t_r, t_1$  and  $t_2$  are certain qualities of the distribution of  $T$ . In testing precise hypotheses, we can respectively find the p-value according to the

regions (1),(2) and (3) by a function of null hypothesis as follows:

$$\text{p-value} = P_{\theta_0}(T \leq t), \tag{4}$$

$$\text{p-value} = P_{\theta_0}(T \geq t), \tag{5}$$

$$\text{p-value} = \begin{cases} 2P_{\theta_0}(T \geq t) & \text{if } t \geq m, \\ 2P_{\theta_0}(T \leq t) & \text{if } t < m, \end{cases} \tag{6}$$

Where  $\theta_0$  is the boundary of the null hypothesis and  $m$  is the median of the distribution of  $T$ . Then we can reject null hypothesis if the obtained p-value is less than the given significance level  $T$  (Parchami et al., 2011).

In testing fuzzy hypotheses, Parchami and Mashinchi (2008) defined the fuzzy p-value as the fuzzy set  $\tilde{P}$  on  $[0,1]$ . They also characterize the fuzzy set by its  $\delta$ -cut for any critical region of the relations in (4)-(6) as follows:

$$\tilde{P}_\delta = [P_{\theta_2(\delta)}(T \leq t), P_{\theta_1(\delta)}(T \leq t)], \tag{7}$$

$$\tilde{P}_\delta = [P_{\theta_1(\delta)}(T \geq t), P_{\theta_2(\delta)}(T \geq t)], \tag{8}$$

$$\tilde{P}_\delta = \begin{cases} [2P_{\theta_1(\delta)}(T \geq t), 2P_{\theta_2(\delta)}(T \leq t)] & \text{if } t \geq m_r, \\ [2P_{\theta_2(\delta)}(T \leq t), 2P_{\theta_1(\delta)}(T \geq t)] & \text{if } t \leq m_l, \end{cases} \tag{9}$$

Where  $\delta$ ,  $\theta_1(\delta)$  and  $\theta_2(\delta)$  are such that  $(\tilde{H}_{ob})_\delta = [\theta_1(\delta), \theta_2(\delta)]$ ,  $\delta \in (0,1]$ ,  $\tilde{H}_{ob}$  is the boundary of  $\tilde{H}_0$  and:

$$m_l = \inf \{m : m \in \text{Supp}(\tilde{m})\},$$

$$m_r = \sup \{m : m \in \text{Supp}(\tilde{m})\},$$

in which fuzzy set  $\tilde{m}$  is the median of the distribution of the test statistic under the boundary of null hypothesis,  $\tilde{H}_{ob}$ . The membership function of the fuzzy set is  $\tilde{m}(m) = \tilde{H}_{ob}(\theta)$ . From the above

mention, we can construct the fuzzy p-value by its  $\delta$ -cuts. After that, one may also consider the significance level as a fuzzy set to compare with the fuzzy p-value. If the fuzzy p-value is less than given fuzzy significance level, then  $\tilde{H}_0$  is rejected, otherwise  $\tilde{H}_0$  is accepted. Holena (2001, 2004) defined the fuzzy significance level, and Yuan (1991) defined the appropriate to obtain the fuzzy sets comparison. The two definitions are as follows:



**Definition 6** A fuzzy significance level is any fuzzy set  $\tilde{S}$  on  $(0,1)$ .

**Definition 7** Let  $\tilde{A}, \tilde{B} \in F_C(\mathfrak{R})$  be normal and convex. The truth degree of “ $\tilde{A}$  is greater than  $\tilde{B}$ ” is defined to be:

$$D(\tilde{A} \succ \tilde{B}) = \frac{\Delta_{\tilde{A}\tilde{B}}}{\Delta_{\tilde{A}\tilde{B}} + \Delta_{\tilde{B}\tilde{A}}}, \tag{10}$$

Where  $\Delta_{\tilde{A}\tilde{B}} = \int_{a_{\tilde{A}_\delta}^+ > a_{\tilde{B}_\delta}^-} (a_{\tilde{A}_\delta}^+ - a_{\tilde{B}_\delta}^-) d\delta + \int_{a_{\tilde{A}_\delta}^- > a_{\tilde{B}_\delta}^+} (a_{\tilde{A}_\delta}^- - a_{\tilde{B}_\delta}^+) d\delta,$

And  $a_{\tilde{A}_\delta}^+ = \sup\{x : x \in \tilde{A}_\delta\}, a_{\tilde{A}_\delta}^- = \inf\{x : x \in \tilde{A}_\delta\}.$

From the above two definitions, given the fuzzy significance level  $\tilde{S}$ , and  $\tilde{P}$  is fuzzy p-value, if  $D(\tilde{P} \succ \tilde{S}) \geq 0.5$  then testing fuzzy hypotheses accept  $\tilde{H}_0$  with the truth degree of acceptance,  $D(\tilde{P} \succ \tilde{S})$ . On the other hand, if  $D(\tilde{P} \succ \tilde{S}) < 0.5$  then reject  $\tilde{H}_0$  with the truth degree of rejection,  $D(\tilde{P} \prec \tilde{S}) = 1 - D(\tilde{P} \succ \tilde{S})$ .

2. Computational procedure

As the preliminary concepts of testing fuzzy hypotheses, this research studies the result from laboratory examination by using testing fuzzy hypotheses with the fuzzy p-value according to the following computational procedure:

Step 1. fix the membership function of null hypothesis,  $\tilde{H}_0$  to represent the normal value of each examination laboratory result and compute the membership function of its boundary,  $\tilde{H}_{0b}$ .

Step 2. Compute the left and right end point of the  $\delta$ -cut of  $\tilde{H}_{0b}$ , i.e.  $\theta_1(\delta)$  and  $\theta_2(\delta)$  where  $\tilde{H}_{0b} = [\theta_1(\delta), \theta_2(\delta)]$ , for all  $\delta \in (0,1)$ .

Step 3. Regarding the forms of the presented rejection region according to the relations (1)-(3),

compute the  $\delta$ -cuts of fuzzy p-value,  $\tilde{P}_\delta$  by Eqs. (7)-(8) for all  $\delta \in (0,1]$ .

Step 4. Give the fuzzy significance level,  $\tilde{S}$ , and compute the truth degree,  $D(\tilde{P} \succ \tilde{S})$  by Eq. (10), if  $D(\tilde{P} \succ \tilde{S}) \geq 0.5$  then accept  $\tilde{H}_0$  with degree of acceptance,  $D(\tilde{P} \succ \tilde{S})$  that mean the population have normal health situation. On the other hand, if  $D(\tilde{P} \succ \tilde{S}) < 0.5$  then reject  $\tilde{H}_0$  with the truth degree of rejection,  $D(\tilde{P} \prec \tilde{S}) = 1 - D(\tilde{P} \succ \tilde{S})$  that mean the population have deformity health situation.

3. The data analysis process

The process of data analysis is based on the computational procedure as mentioned above. There are 6 steps in the process of data analysis. They are as follows:

Step 1. The hypotheses are defined as “The result from laboratory of annual health examination is in normal value”. Then the fuzzy hypotheses are defined to represent the hypotheses as follows:

$\tilde{H}_0$  :  $\mu$  is in normal value.

$\tilde{H}_1$  :  $\mu$  is bigger than the normal value.



Where  $\mu$  is the population mean of the result from laboratory examination. Let  $H$  is membership function of  $\mu$ , it is reasonable to set  $H$  as  $T(a,b,c)$ . Actually,  $a$  and  $c$  are based on the

normal value of health index. Where  $a$  is the lower of normal value,  $c$  is the upper of normal value and  $b = (a + c)/2$ . So the fuzzy hypotheses are presented as follows:

$$\tilde{H}_0 : \mu \text{ is } H = T(a,b,c).$$

$$\tilde{H}_1 : \mu \text{ is bigger than } H = T(a,b,c).$$

Step 2. The fuzzy significant level is set as  $S = T(0, .05, 0.1)$ .

$S^2$  were calculated by using data from 136 recipients who were the sample.

Step 3. The test statistic is set as  $\bar{X}$ , based on central limit theorem the distribution of  $\bar{X}$  is approximately normal distribution with mean  $\mu$  and

Step 4. The  $\delta$ -cut of fuzzy p-value is calculated based on formula (8) that lead to interval of the following forms.

approximate variance by  $\frac{S^2}{n}$ . Where  $\bar{X}$  and

$$P_\delta = \left[ \int_{\frac{\bar{x} - \mu_1(\delta)}{s/\sqrt{n}}}^{\infty} (2\pi)^{-1/2} \exp\left(-\frac{z^2}{2}\right) dz, \int_{\frac{\bar{x} - \mu_2(\delta)}{s/\sqrt{n}}}^{\infty} (2\pi)^{-1/2} \exp\left(-\frac{z^2}{2}\right) dz \right].$$

Where  $\mu_1(\delta)$  and  $\mu_2(\delta)$  are calculated based on

$\tilde{H}_0$  that lead to the formula as follows:

$$\mu_1(\delta) = a + (b - a)\delta \text{ and } \mu_2(\delta) = c - (b - a)\delta \text{ for all } \delta \in (0, 1].$$

The fuzzy p-value,  $\tilde{P}$  is constructed by its  $\delta$ -cut. Obviously, one can obtain graph of fuzzy p-value that horizontal axis is the  $\delta$ -cut of fuzzy p-value while vertically axis is  $\delta, \delta \in (0, 1]$ . For example, the graphs are shown as figure 1-2.

hand if  $D(P \succ S) < 0.5$  the reject  $\tilde{H}_0$  with degree  $1 - D(P \succ S)$ .

Step 5. The fuzzy p-value and the fuzzy significant level are compared by using definition 7. The application of definition 7 need to construct graph of fuzzy p-value and fuzzy significant level. Then regions of the graphs will be calculated according to definition 7. Finally, we obtained the decision degree,  $D(P \succ S)$ .

All of the calculations and graphs in this research have been carried out by using MATLAB software. The programs are available upon request.

**Result**

Step 6. Making decision, if  $D(P \succ S) \geq 0.5$  then accept  $\tilde{H}_0$  with degree  $D(P \succ S)$  on the other

The new method to study the result from laboratory in annual health examination is testing fuzzy hypotheses which consists of 6 steps as follows:

- 1) fix fuzzy hypotheses which represents the believe about the result from laboratory in annual health examination.



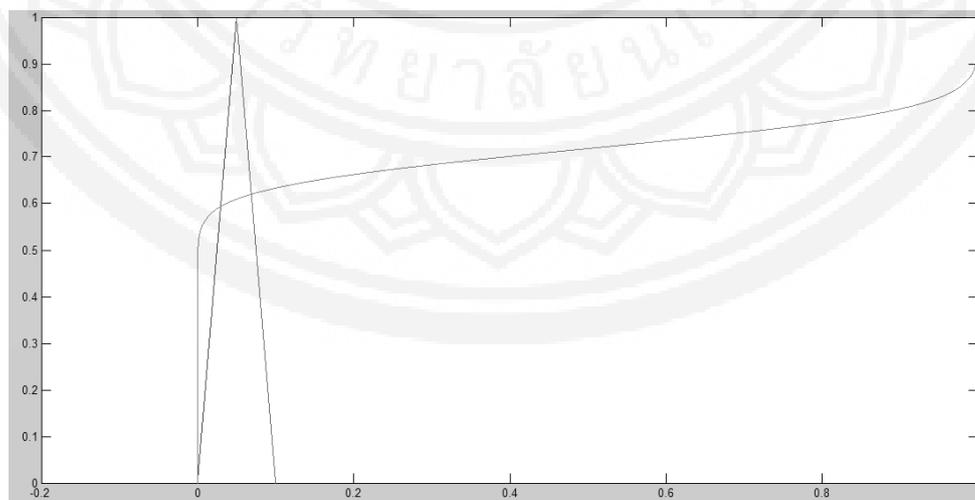
- 2) Set fuzzy significant level.
- 3) Define the test statistic.
- 4) Finding the fuzzy p-value.
- 5) Compare the fuzzy p-value with the fuzzy significant level.
- 6) Making decision.

The majority of results from laboratory in annual health examination of the samples were in normal value

as in Table 2. The result from testing fuzzy hypotheses showed that the population mean of health index from laboratory were in normal value with degree 0.8627-1.0, but only the cholesterol level which was higher than normal value with degree 1 as in Table 3. In the Figure 1-2 showed the comparing of the fuzzy p-value and the fuzzy significance level to test some health index, HCT for male and female.

**Table 2** Frequency and percentage of the sample classified by health index and health situation

Health index	Health situation					
	Lower		Normal		high	
	Frequency	percent	frequency	percent	frequency	percent
HCT of male	1	2.6%	38	97%	-	-
HCT of female	13	13.4%	83	85.3%	-	-
BUN	3	2.2%	124	91.1%	8	5.9%
Cr	7	5.2%	128	94.8%	-	-
Uric acid	-	-	119	88.1%	16	11.9%
ALT of male	23	59%	15	38.5%	1	2.6%
ALT of female	79	81.4%	14	14.4%	3	3.1%
AST of male	2	5.1%	32	82.1%	5	12.8%
AST of female	6	6.2%	85	87.6%	5	5.2%
ALP of male	5	12.8%	33	84%	1	2.6%
ALP of female	1	1%	93	95.9%	2	2.1%
FBS	-	-	120	88.9%	15	11.1%
Cholesterol	-	-	37	27.4%	98	72.6%
Triglyceride	1	0.7%	115	85.2%	19	14.1%



**Figure 1** Comparing of the fuzzy p-value and the fuzzy significance level for HCT testing of male.

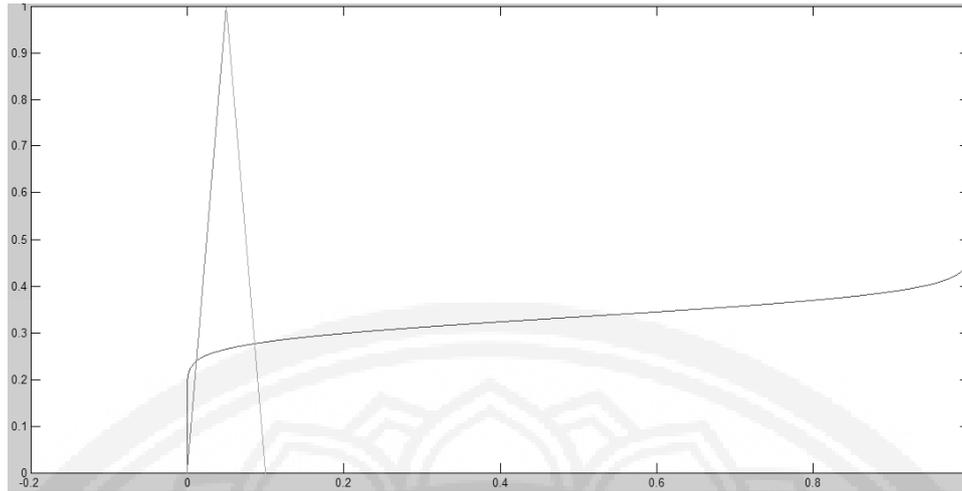


Figure 2 Comparing of fuzzy p-value and the fuzzy significance level for HCT testing of female.

Table 3 The result of testing fuzzy hypotheses for each result from laboratory.

Result	$\bar{X}$	S.D.	$\tilde{H}_0$	$D(P > S)$	Decision on $\tilde{H}_0$	Decision degree
HCT of male	43.74	3.31	$T(38,46,54)$	0.9676	Accepted	0.9676
HCT of female	38.67	3.32	$T(36,44,52)$	0.9938	Accepted	0.9938
BUN	12.15	3.58	$T(7,12.5,18)$	0.9431	Accepted	0.9431
Cr	0.75	0.16	$T(0.6,0.95,1.3)$	0.9972	Accepted	0.9972
Uric acid	5.51	1.59	$T(2.6,4.9,7.2)$	0.8987	Accepted	0.8987
ALT of male	31.10	16.36	$T(30,47.5,65)$	1.0000	Accepted	1.0000
ALT of female	20.14	24.75	$T(26,47.5,69)$	1.0000	Accepted	1.0000
AST of male	25.82	7.38	$T(15,26,37)$	0.9411	Accepted	0.9411
AST of female	22.07	18.69	$T(13,29.5,46)$	0.9835	Accepted	0.9835
ALP of male	70.67	20.87	$T(70,90,110)$	0.9867	Accepted	0.9867
ALP of female	63.15	21.71	$T(0,100,200)$	0.9697	Accepted	0.9697
FBS	96.58	11.84	$T(30,90,150)$	0.8627	Accepted	0.8627
cholesterol	221.58	37.28	$T(28,77,126)$	0.000	Rejected	1.000
triglyceride	101.71	57.47	$T(70,90,110)$	0.9124	Accepted	0.9124

**Discussion**

This research aims to propose an alternative method to study the result from laboratory in annual health examination. The testing fuzzy hypotheses with fuzzy p-value are used in the study. The process of the method resembles an application of testing fuzzy hypotheses to the study of soil on the bioavailability of cadmium that proposed by Parchami et al. (2011). The process of testing fuzzy hypotheses is similar to

the process of testing hypotheses in classical statistics. However, the fuzzy hypotheses is likely more accurate than crisp hypotheses. Especially, testing hypotheses in classical statistics is only a specific case for the testing fuzzy hypotheses. Both of the testing hypotheses in classical statistics and the testing fuzzy hypotheses provide us information in decision making process whether to accept null hypothesis at any significance level or not. In other word, the testing help us to decide at various confident levels. However, testing



fuzzy hypotheses provide useful information on the degree of decision that effectively interpret testing hypotheses. In case the study investigate whether parameter is in an interval or not, the testing hypotheses in classical statistics is not practical. On the other hand, testing fuzzy hypotheses is practical. As same as in this research on investigating whether population mean of the result from laboratory is in an interval of normal value. The testing fuzzy hypotheses by using p-value is appropriated for evaluating because null fuzzy hypotheses can be controlled to support the interval. In addition, the fuzzy p-value keeps all information from the hypotheses and sample. Thank to the reason, the result of testing fuzzy hypotheses in this research is considered reliable. The reliability of the result is also confirmed by comparing sample mean of laboratory result and the interval of normal value. In addition, the results from the testing fuzzy hypotheses were relatively complied with the result analyzed by the percentage. Moreover, the decision degree are according to the total of lower and normal percentage.

### Conclusion and Suggestion

An annual health examination is very important for everybody. The diseases found from the examination can be early protected while physicians can identified risky factors of disease and its occurrence. The annual health examination actively improves the quality of life by changing for healthy habits. The popularity statistic for studying result from laboratory in the examination is frequency and percentage. As of the limitation of the percentage in reference and the result from laboratory are quantitative data, therefore this research aims to propose testing hypotheses to study the result. However, normal value of the result is in interval form, the testing hypotheses in classical statistics is impracticable. This research need to propose the testing fuzzy hypotheses to study the result from laboratory. The process of the testing fuzzy hypotheses consist of

6 steps as: 1) Creating the fuzzy hypotheses that represent the believe about the result from laboratory in annual health examination. 2) Setting fuzzy significant level. 3) Defining the test statistic. 4) Finding the fuzzy p-value. 5) Comparing the fuzzy p-value with the fuzzy significant and 6) Making decision. The almost all result from laboratory in annual health examination of the staff in Ubon Rachathani University are in normal value with degree of 0.8627-1.0. The research shows that only cholesterol that is higher than normal value with degree 1. The result from testing fuzzy hypotheses has been found reliable and according to the result from data analysis by using percentage. Thank to the reliability of the testing fuzzy hypotheses, the method can be applied for other problems that resemble the annual health examination. In addition, a comparison study in the result from the testing fuzzy hypotheses between triangular null hypotheses and trapezoidal null hypotheses should be conducted.

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