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A New Measurement Method on Correlation Coefficient for Attribute Fuzzy Interval Data and Its Applications

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ABSTRACT

In general, the classical Pearson's correlation coefficient shall be applied to evaluate the relationship for two continue variable and the Spearmen correlation coefficient could be employed to measure the casual for two attribute variable. However, as the data are composed of qualitative attributed fuzzy interval values, it is hard to adopt above the traditional scheme calculation the attribute correlation coefficient. In this study, we present the simple calculation of attribute fuzzy interval correlation coefficient via the central and length of the attribute fuzzy interval observation and the attribute correlation coefficient of two variables. As such, this investigate is able to offer an improving measure of attribute fuzzy interval correlation from attribute fuzzy interval observation. Furthermore, we apply simulation study and empirical study to proof the validity of our proposal on attribute fuzzy interval correlation coefficient using data via the adult population survey (APS) of the global entrepreneurship monitor (GEM) in Taiwan.

Keywords: Attribute fuzzy interval-vale; Spearmen's correlation coefficient; Attribute fuzzy interval correlation coefficient

1. Introduction

In application statistical field, in general, the attributed observations should be taken into account under probability distribution and collected by single value for attribute variable. In fact, nevertheless, the attributed observations sometimes described by linguistic terms or service quality, for instance "unsatisfactory and satisfactory" or "weekly consumer flow," are only similarly comprehend or interval number of service, rather than equating with certain. Evaluate the attribute correlation coefficient between two attributed variables including fuzziness is a challenge to the traditional application statistical field. Such as, Kulak and

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Kahraman [8] proposed the scheme of the analytic hierarchy process (AHP) which is a multi-attribute method and decision-making set of alternatives. And this approach can be applied especially in large-scale problem where many criteria must be considered and where the evaluation of alternatives is mostly subjective.

Whereas the uncertain or two-valued logic world gets more and more collecting by management science, services and econometrics in recent years. In the analysis of the sampling survey, service industry, economics, however, most of them use the univariate attributed observation to study the pattern of the satisfactory, sale volume or the number of consumer for attribute fuzzy interval value. For instance, the categorical attribute data will be collected in supermarket, then the relationship of sales volume between of two goods can be studied [1, 2, 10].

Many researchers investigate the subject of the fuzzy correlation analysis and its application in the social or economic science fields [3, 4, 6, 7, 9]. Liu and Kao [9] proposed a mathematical programming approach to evaluate the fuzzy measures via Zadeh's extension principles. Moreover, this method should apply mathematical programming to compute the fuzzy correlation coefficient and its derivation is very probable. Gyenesei [5] proposed the fuzzy association rule which is easily understandable to a human because of the linguistic terms associated with the fuzzy sets. And this method of fuzzy association rule can decrease the field into a categorical one for the interval quantitative attributes data. Moreover, the method adopts linguistic terms to represent the revealed regularities and exceptions. However, with respect to study in the foregoing is considering the continue observation for fuzzy set. Consequently, this thesis will propose an approach of calculation attribute correlation coefficient for attributed fuzzy interval value.

In addition, formulas in these studies are quite complicated or required some mathematical programming which really limits the access of some researchers who do not have strong mathematical background. In this paper, we propose a simple computation of an attribute fuzzy correlation coefficient without using any programming and apply this scheme to various qualitative attribute data which have attributed fuzzy interval-valued data to detect any relationship among them.

The remainder of the paper proceeds as follows. The fuzzy interval correlation is elaborated in Section 2. Section 3 presents the computation approach of the attributed fuzzy interval correlation. Moreover, Section 4 using the simulation studies explain the performance of calculation for attributed fuzzy interval correlation coefficient and proposes its empirical studies in Section 5. Finally, the conclusions are drawn in Section 6.

2. Fuzzy Interval Correlation

In general, the attribute observation cannot adopt the classical Pearson's correlation coefficient to measure the relationship between two attribute variable.

As such, the traditional Spearmen's correlation coefficient will be considered and widely employed to evaluate the attributed relationship between the variables x and y in a sample. It explains the level of the relationship whether it is positive correlation, negative correlation or non-correlation. The Spearmen's correlation coefficient, ρ_s, is defined by the formula:

$$\rho_s = 1 - \frac{6\sum_{i=1}^{n}(Y - X)^2}{n(n^2 - 1)}.$$

In this case, the more positive ρ_s is, the more positive the association is. This also points out that when ρ_s is close to 1, an individual with a high value for one variable will likely have a high value for the other, and an individual with a lower value for one variable will likely to have a low value for the other. Besides, the more negative ρ_s is , the more negative the association is, this also denotes that an individual with a high value for one variable will likely have a low value for the other when ρ_s is close to -1 and conversely. When ρ_s is close to 0, its interpretation is that there is non-linear relationship between two variables. In practice, we will apply the distance of two attribute sample observation to extend Spearmen's correlation coefficient approach. The sample correlation coefficient r_s is illustrated as:

$$r_s = 1 - \frac{6\sum_{i=1}^{n}(y_i - x_i)^2}{n(n^2 - 1)}$$

Where (x_i, y_i) is the i^{th} pair observation value, $i = 1, 2, 3, \ldots, n$.

In terms of the scheme of Spearmen's correlation coefficient, it is applied to evaluate the relationship between two qualitative attribute variables. However, as the attributed fuzzy interval data can be developed and collected then the formula above is hard to employ to obtain the causal between two attribute fuzzy interval-value observations. In order to study the relationship between the attributed interval valued fuzzy numbers, we consider choosing samples from population X and Y. Each attribute fuzzy interval data for the centroids and length of the sample X and sample Y will be considered to compute the correlation coefficient. In addition, we also think of using the maximum value and minimum value of fuzzy interval data to measure the attribute fuzzy interval correlation coefficient.

3. Methodology

In this section, the definition of fuzzy mean with interval data will be introduced. Furthermore, there are three kinds of attribute fuzzy interval-value correlation which are based on the Spearmen's correlation as well as the extension principle Definition 1, Definition 2 and Definition 3. The vantages are that we can calculate different samples with fuzzy interval form for the attribute sample.

Definition 1 *Attribute Fuzzy Correlation Coefficient (AFCC)*

Let ($X_i = [a_i, b_i]$, $Y_i = [c_i, d_i]$, i = 1, 2, ..., n) be a sequence of attributed interval-value fuzzy sample on population Ω with its pair of centroid (cx_i, cy_i) and pair of area $\|x_i\| = \text{area}(x_i)$, $\|y_i\| = \text{area}(y_i)$.

$$cr_s = \frac{6\sum_{i=1}^{n}(cy_i - cx_i)}{n\left(n^2 - 1\right)} \text{ and } ar_s = \frac{6\sum_{i=1}^{n}(\|y_i\| - \|x_i\|)}{n\left(n^2 - 1\right)}$$

Then attribute fuzzy correlation is defined as:

$$\text{FC} = \beta_1 cr_s + \beta_2 ar_s, (\beta_1 + \beta_2 = 1)$$

We choose a pair of (β_1, β_2) depend on the weight of practical use. For instance, if we think the location correlation is much more important than that of e scale, (β_1 = 0.7, β_2 = 0.3) will be a good suggestion.

Definition 2 *The Center and Length Attribute Fuzzy Correlation Coefficient (CLAFCC)*

Let ($X_i = [a_i, b_i]$, $Y_i = [c_i, d_i]$, i = 1, 2, ..., n) be a sequence of paired attribute fuzzy interval-value sample on population Ω with its pair of centroid (cx_i, cy_i) and pair of area $\|x_i\| = \text{area}(x_i)$, $\|y_i\| = \text{area}(y_i)$.

$$cr_s = 1 - \frac{6\sum_{i=1}^{n}(cy_i - cx_i)}{n\left(n^2 - 1\right)},$$

$$\lambda ar_s = 1 - \frac{\ln(1 + |ar_s|)}{|ar_s|} \text{ where } ar_s = 1 - \frac{6\sum_{i=1}^{n}(\|y_i\| - \|x_i\|)}{n\left(n^2 - 1\right)}.$$

Then attribute fuzzy interval correlation is defined as:
(i) When $cr_s \geq 0, \lambda ar_s \geq 0$, fuzzy correlation = $(cr_s, \min(1, cr_s + \lambda ar_s))$.
(ii) When $cr_s \geq 0, \lambda ar_s < 0$, fuzzy correlation = $(cr_s - \lambda ar_s, cr_{xy})$.
(iii) When $cr_s < 0, \lambda ar_s \geq 0$, fuzzy correlation = $(cr_s, cr_s + \lambda ar_s)$.
(iv) When $cr_s < 0, \lambda ar_s < 0$, fuzzy correlation = $(\max(-1, c_{xy} - \lambda ar_s), cr_s)$.

Definition 3 *Attribute Fuzzy Interval Correlation Coefficient (AFICC)*
Let $X_{ji} = [a_i, b_i]$ and $Y_{ji} = [c_i, d_i]$, i = 1, 2, ..., n, be a sequence of paired attribute fuzzy sample on population Ω. Let:

$$r_s = 1 - \frac{6\sum_{i=1}^{n}(y_i - x_i)}{n\left(n^2 - 1\right)}, (x, y) = \{(a,c),(b,d)\}.$$

Then attribute fuzzy interval correlation is $[r_{low}, r_{up}]$ with $r_{low} = \bar{r} - s_r$ and $r_{up} = \bar{r} + s_r$,

where $r_{up} = \bar{r} + \frac{s_r}{\sqrt{2}}$, $r_{low} = \bar{r} - \frac{s_r}{\sqrt{2}}$, $\bar{r} = \frac{\sum_{(x,y)\in\{(a,c),(b,d)\}} r_s}{2}$ and $s_r = \sqrt{\sum_{(x,y)\in\{(a,c),(b,d)\}} \left(r_{x,y} - \bar{r}\right)^2}$.

4. Simulation studies

The method of the Mote Carlo simulation is used to discuss the performance of the approach by Definition 1, Definition 2 and Definition 3 in this section. For the simulation stages, we consider employing the discrete distribution to generate the attributed fuzzy interval value data figuring out the lowest observation and highest observation via the discrete distribution where the discrete include the Poisson, binomial, negative binomial, hyper-geometric, discrete uniform. The simulation procedure of evaluation the attribute fuzzy correlation is described below and the result is listed in Table 1.

Step 1: Generate the attribute data, X, with the central distribution where central distribution contain the Poisson, binomial, negative binomial, hyper-geometric, discrete uniform.

Step 2: Generate attribute fuzzy interval-value set via attribute data, X, with successive 2 points e_1 and e_2, the lowest price $X - e_1$, and highest price $X + e_2$, by area distribution which is same distribution with central distribution.

Step 3: Let $Y = aX + e$, compute the fuzzy data set Y by the attribute fuzzy data set X and error term.

Step 4: Compute the fuzzy interval correlations from the attribute fuzzy interval data set, X and Y, by Definition 1, Definition 2 and Definition 3.

Table 1. The attribute fuzzy interval correlations coefficient with Definition 1, Definition 2 and Definition 3.

a	Central / Area	Binomial (30, 0.2)	Poisson (5)	Negative binomial (100, 0.2, 10)	Hyper-geometric (100, 40, 60)	Discrete uniform (0, 5)
1	Binomial	0.41^1 (0.56, 0.60)^2 (0.42, 0.45)^3	0.45^1 (0.62, 0.66)^2 (0.51, 0.55)^3	0.68^1 (0.68, 0.96)^2 (0.93, 0.98)^3	0.36^1 (0.49, 0.53)^2 (0.36, 0.39)^3	0.32^1 (0.45, 0.48)^2 (0.32, 0.35)^3
	Poisson	0.38^1 (0.49, 0.53)^2 (0.37, 0.40)^3	0.39^1 (0.54, 0.58)^2 (0.42, 0.45)^3	0.08^1 (0.10, 0.14)^2 (0.10, 0.11)^3	0.36^1 (0.50, 0.54)^2 (0.37, 0.41)^3	0.32^1 (0.43, 0.47)^2 (0.32, 0.34)^3
	Negative binomial	0.20^1 (0.27, 0.30)^2 (0.20, 0.22)^3	0.03^1 (0.04, 0.07)^2 (0.02, 0.03)^3	0.46^1 (0.64, 0.67)^2 (0.47, 0.51)^3	0.03^1 (0.03, 0.06)^2 (0.01, 0.02)^3	0.02^1 (0.02, 0.05)^2 (0.01, 0.02)^3
	Hyper-geometric	0.39^1 (0.54, 0.57)^2 (0.41, 0.45)^3	0.45^1 (0.62, 0.66)^2 (0.51, 0.55)^3	0.68^1 (0.95, 0.98)^2 (0.92, 0.98)^3	0.32^1 (0.44, 0.48)^2 (0.36, 0.39)^3	0.36^1 (0.49, 0.52)^2 (0.36, 0.40)^3
	Discrete uniform	0.54^1 (0.75, 0.79)^2 (0.67, 0.72)^3	0.45^1 (0.62, 0.66)^2 (0.51, 0.55)^3	0.05^1 (0.06, 0.10)^2 (0.05, 0.06)^3	0.32^1 (0.43, 0.47)^2 (0.36, 0.40)^3	0.38^1 (0.54, 0.57)^2 (0.42, 0.45)^3
3	Binomial	0.53^1 (0.74, 0.77)^2 (0.59, 0.71)^3	0.58^1 (0.80, 0.84)^2 (0.64, 0.76)^3	0.69^1 (0.97, 0.99)^2 (0.98, 0.99)^3	0.50^1 (0.68, 0.72)^2 (0.54, 0.58)^3	0.48^1 (0.67, 0.70)^2 (0.47, 0.62)^3
	Poisson	0.50^1 (0.70, 0.73)^2 (0.53, 0.68)^3	0.53^1 (0.73, 0.77)^2 (0.56, 0.67)^3	0.16^1 (0.22, 0.26)^2 (0.21, 0.23)^3	0.51^1 (0.71, 0.75)^2 (0.56, 0.63)^3	0.47^1 (0.65, 0.69)^2 (0.42, 0.61)^3
	Negative binomial	0.46^2 (0.64, 0.67)^3 (0.42, 0.65)^4	0.09^2 (0.12, 0.15)^3 (0.02, 0.18)^4	0.55^2 (0.77, 0.80)^3 (0.64, 0.69)^4	0.07^2 (0.08, 0.11)^3 (0.01, 0.11)^4	0.05^2 (0.06, 0.09)^3 (0.01, 0.06)^4
	Hyper-geometric	0.53^1 (0.74, 0.78)^2 (0.53, 0.75)^3	0.55^1 (0.77, 0.81)^2 (0.63, 0.70)^3	0.69^1 (0.97, 0.98)^2 (0.97, 0.98)^3	0.51^1 (0.71, 0.74)^2 (0.46, 0.67)^3	0.50^1 (0.70, 0.74)^2 (0.53, 0.65)^3
	Discrete uniform	0.64^1 (0.89, 0.92)^2 (0.82, 0.88)^3	0.58^1 (0.80, 0.84)^2 (0.61, 0.76)^3	0.13^1 (0.17, 0.20)^2 (0.11, 0.15)^3	0.53^1 (0.73, 0.77)^2 (0.63, 0.68)^3	0.54^1 (0.75, 0.79)^2 (0.53, 0.70)^3
5	Binomial	0.55^1 (0.76, 0.79)^2 (0.67, 0.70)^3	0.59^1 (0.82, 0.87)^2 (0.72, 0.77)^3	0.70^1 (0.98, 0.99)^2 (0.98, 0.99)^3	0.52^1 (0.72, 0.76)^2 (0.54, 0.63)^3	0.50^1 (0.70, 0.74)^2 (0.58, 0.60)^3
	Poisson	0.52^1 (0.73, 0.76)^2 (0.56, 0.68)^3	0.54^1 (0.76, 0.80)^2 (0.65, 0.69)^3	0.25^1 (0.33, 0.37)^2 (0.14, 0.25)^3	0.54^1 (0.75, 0.78)^2 (0.62, 0.66)^3	0.50^1 (0.69, 0.73)^2 (0.57, 0.63)^3
	Negative binomial	0.57^2 (0.79, 0.83)^3 (0.50, 0.82)^4	0.12^2 (0.17, 0.20)^3 (0.03, 0.21)^4	0.57^2 (0.78, 0.82)^3 (0.65, 0.73)^4	0.09^2 (0.11, 0.15)^3 (0.04, 0.12)^4	0.08^2 (0.09, 0.15)^3 (0.05, 0.07)^4

Table 1. The attribute fuzzy interval correlations coefficient with Definition 1, Definition 2 and Definition 3 (Continued).

α	Central / Area	Binomial (30, 0.2)	Poisson (5)	Negative binomial (100, 0.2, 10)	Hyper-geometric (100, 40, 60)	Discrete uniform (0, 5)
	Hyper-geometric	0.60[1] (0.83, 0.87)[2] (0.73, 0.78)[3]	0.57[1] (0.79, 0.83)[2] (0.70, 0.75)[3]	0.70[1] (0.98 0.99)[2] (0.98, 0.99)[3]	0.55[1] (0.76, 0.80)[2] (0.66, 0.68)[3]	0.53[1] (0.72, 0.75)[2] (0.62, 0.66)[3]
	Discrete uniform	0.64[1] (0.90, 0.93)[2] (0.85, 0.88)[3]	0.59[1] (0.82, 0.86)[2] (0.72, 0.76)[3]	0.16[1] (0.21, 0.25)[2] (0.12, 0.22)[3]	0.57[1] (0.79, 0.83)[2] (0.68, 0.75)[3]	0.56[1] (0.78, 0.82)[2] (0.62, 0.77)[3]
7	Binomial	0.57[1] (0.79, 0.82)[2] (0.69, 0.71)[3]	0.60[1] (0.83, 0.87)[2] (0.73, 0.78)[3]	0.70[1] (0.98, 0.99)[2] (0.98, 0.99)[3]	0.53[1] (0.74, 0.77)[2] (0.61, 0.64)[3]	0.51[1] (0.71, 0.75)[2] (0.59, 0.61)[3]
	Poisson	0.55[1] (0.73, 0.77)[2] (0.57, 0.71)[3]	0.55[1] (0.77, 0.81)[2] (0.66, 0.70)[3]	0.31[1] (0.42, 0.46)[2] (0.39, 0.44)[3]	0.54[1] (0.75, 0.79)[2] (0.61, 0.69)[3]	0.51[1] (0.70, 0.74)[2] (0.59, 0.63)[3]
	Negative binomial	0.62[1] (0.87, 0.90)[2] (0.78, 0.84)[3]	0.14[1] (0.18, 0.22)[2] (0.05, 0.21)[3]	0.57[1] (0.79, 0.83)[2] (0.68, 0.73)[3]	0.11[1] (0.14, 0.17)[2] (0.07, 0.13)[3]	0.09[1] (0.11, 0.15)[2] (0.07, 0.09)[3]
	Hyper-geometric	0.60[1] (0.84, 0.88)[2] (0.74, 0.77)[3]	0.58[1] (0.80, 0.84)[2] (0.65, 0.77)[3]	0.70[1] (0.98, 0.99)[2] (0.98, 0.99)[3]	0.56[1] (0.78, 0.82)[2] (0.65, 0.72)[3]	0.54[1] (0.74, 0.78)[2] (0.62, 0.67)[3]
	Discrete uniform	0.65[1] (0.90, 0.94)[2] (0.84, 0.90)[3]	0.59[1] (0.83, 0.87)[2] (0.73, 0.77)[3]	0.17[1] (0.22, 0.26)[2] (0.15, 0.23)[3]	0.59[1] (0.81, 0.85)[2] (0.70, 0.78)[3]	0.56[1] (0.78, 0.83)[2] (0.68, 0.71)[3]
9	Binomial	0.57[1] (0.79, 0.83)[2] (0.67, 0.74)[3]	0.60[1] (0.84, 0.87)[2] (0.75, 0.79)[3]	0.70[1] (0.98, 0.99)[2] (0.98, 0.99)[3]	0.53[1] (0.74, 0.78)[2] (0.60, 0.66)[3]	0.52[1] (0.71, 0.75)[2] (0.56, 0.65)[3]
	Poisson	0.55[1] (0.74, 0.78)[2] (0.70, 0.74)[3]	0.56[1] (0.77, 0.81)[2] (0.68, 0.72)[3]	0.38[1] (0.51, 0.55)[2] (0.44, 0.54)[3]	0.54[1] (0.75, 0.79)[2] (0.62, 0.69)[3]	0.51[1] (0.71, 0.75)[2] (0.58, 0.64)[3]
	Negative binomial	0.65[1] (0.90, 0.93)[2] (0.85, 0.87)[3]	0.09[1] (0.19, 0.23)[2] (0.08, 0.22)[3]	0.58[1] (0.79, 0.84)[2] (0.66, 0.74)[3]	0.11[1] (0.15, 0.18)[2] (0.05, 0.17)[3]	0.10[1] (0.12, 0.16)[2] (0.09, 0.11)[3]
	Hyper-geometric	0.61[1] (0.84, 0.88)[2] (0.75, 0.78)[3]	0.58[1] (0.81, 0.84)[2] (0.66, 0.78)[3]	0.70[1] (0.98 0.99)[2] (0.98, 0.99)[3]	0.56[1] (0.78, 0.82)[2] (0.68, 0.75)[3]	0.54[1] (0.75, 0.79)[2] (0.64, 0.68)[3]
	Discrete uniform	0.65[1] (0.90, 0.94)[2] (0.84, 0.91)[3]	0.59[1] (0.83, 0.88)[2] (0.72, 0.78)[3]	0.17[1] (0.22, 0.26)[2] (0.16, 0.25)[3]	0.59[1] (0.82, 0.86)[2] (0.72, 0.77)[3]	0.57[1] (0.79, 0.83)[2] (0.69, 0.72)[3]

Note: [1]Denote the computed value with daily maximum and minimum price of various stocks of the electric machinery by Definition 1.
[2]Denote the computed value with daily maximum and minimum price of various stocks of the electric machinery by Definition 2.
[3]Denote the computed value with daily maximum and minimum price of various stocks of the electric machinery by Definition 3.

We can obtain the results from Table 1 as follows. First, when a increases from 1 to 9, the value of the attribute fuzzy interval correlation coefficient by Definition 1, Definition 2 or Definition 3 is also increasing. Hence, the relationship between two attribute fuzzy interval data will be evaluated by the result of attribute fuzzy interval correlation coefficient. Second, the value of the attribute fuzzy interval correlation coefficient by Definition 1, Definition 2 and Definition 3 in different central distribution get a similar result under the same area distribution. In other words, the relationship between two attribute fuzzy interval-value data will be evaluated by this study proposes the scheme of calculation the attribute fuzzy interval correlation coefficient. In recent years, more and more customer service will be attached importance to explain the satisfactory. Therefore, we can apply the calculation approach of fuzzy interval correlation coefficient for attribute fuzzy interval data to describe the relationship between different situations.

5. Empirical studies

In the field of survey, the traditional statistical principle is not an ideal employment in the data of service industry or economic which has the pattern of attribute fuzzy interval-value data. Therefore, in order to study the correlation between the two variables for attributed fuzzy interval-value data in sampling survey. In this section, we apply the empirical examples to illustrate the performance of two attributed fuzzy interval data of the adult population survey (APS) of the global entrepreneurship monitor (GEM) with the schemes at Section 3. And the entrepreneurial propensity, entrepreneurial experience and entrepreneurial perception by attribute fuzzy interval data in this survey will be applied to explain the effect for entrepreneurs and business owners. The result is shown in Table 2.

Table 2. Correlations interval based on the attributed fuzzy interval data of entrepreneurial propensity, entrepreneurial experience and entrepreneurial perception for new entrepreneurial and business owner.

Fuzzy correlation	AFCC	CLAFCC	GAFICC
entrepreneurial propensity	0.986 ($\beta_1 = 0.7, \beta_2 = 0.3$)	(0.991, 1.000)	(0.929, 0.936)
entrepreneurial experience	0.992 ($\beta_1 = 0.7, \beta_2 = 0.3$)	(0.996, 1.000)	(0.936, 0.948)
entrepreneurial perception	0.979 ($\beta_1 = 0.7, \beta_2 = 0.3$)	(0.983, 1.000)	(0.934, 0.949)

In Table 2, we get the results as follows:

(i) In the entrepreneurial propensity, the attribute interval correlation coefficient of entrepreneurial propensity with AFCC, CLAFCC and GAFICC are high and positively significance correlated. This result shows that the business owner think that the entrepreneurial propensity may improve the business profit, then the new entrepreneurial has also similar thought.

(ii) The attribute correlation interval of entrepreneurial experience for new entrepreneurial and business owner is high and positively significance correlated by the approach of AFCC, CLAFCC and GAFICC. This result represents the new entrepreneurial and business owner, which has the high acknowledgement each other for entrepreneurial experience. In other words, the business owner think that the entrepreneurial experience is important for business, then the new entrepreneurial has also similar thinking for business management.

(iii) The attribute correlation interval of entrepreneurial perception for new entrepreneurial and business owner is high and positively significance correlated by the approach of AFCC and CLAFCC. This result denotes that the new entrepreneurial and business owner, which has the high recognizing each other for entrepreneurial perception. On the other hand, the business owner think that the business performance shall be improved by entrepreneurial perception, then the new entrepreneurial has also same thinking for business management.

6. Conclusion

Taking into account the statistical numerical data of uncertainty will be collected and analyzed in the domains of the sampling survey, service science, economics and management science. And the statistical numerical data of uncertainty can be collected by the qualitative attribute data, for example, if we want to survey that the numbers of owning car for married people which is qualitative attribute form or interval-value data. Nevertheless, the traditional mathematical computation and statistical principle are hard to be employed. Hence, how to use the method of effect to calculate the relationship between the uncertain observations is important and interesting issue.

In addition, data in the sampling survey, service science or management science are often in the form of attribute fuzzy interval. If we use above data to measure the relationship via the method of traditional correlation coefficient which achieve this false accuracy to do causal analysis or measurement, it may lead to the deviation of the causal judgment, the misleading of the decision strategy, or the exaggerated difference between the predicted result and the actual data.

Thus our presented the methods of evaluation the relationship between two attribute fuzzy interval data, which are profitable the application of sampling survey or decision making. On the other hand, this thesis applies a natural scheme to compute the causal for the attribute fuzzy interval measures based on the classical definition of Spearmen correlation coefficient which are easy and straightforward. In this study, we apply the simulation study to explain that the attribute interval correlation coefficient can measure the level of variation relationship for attribute fuzzy interval value. And the satisfaction of dimension in sampling survey will be described in empirical study. Therefore, with the methodology developed in this paper, a more realistic correlation is obtained, which provides the decision maker with more sound and unbiased information thus enhancing decision maker more confident to make better strategies.

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