Validation for the Diversity of Usage in M-Commerce among Countries by ICOMP

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Abstract

This paper conducted the validation of diverse usage in m-commerce services among the countries. In order to determine whether there is a discrepancy between samples, this study proposed a new approach based on ICOMP to perform model selection and variables clustering. According to the ICOMP criteria, the model selection implied that there is heterogeneity between samples. The variable clustering, whatever within a group or with all twenty variables, indicated that there are differences in ranking the most relevant variables between samples. That is, whatever model selection or variables clustering, all results based on the proposed approach support that there were discrepancies in using m-commerce services among the countries.

Characters of both the ICOMP approach and the grey relational analysis in distinguishing the diverse usage were discussed. In short, both approaches can conclude there are discrepancies between the samples. The grey relational analysis is good to determine the preferences within a sample; and the ICOMP approach can determine the best fitting models for samples. The contribution of this paper towards the field in tow folds: the new approach to analyze the discrepancy; and the validation.

Keywords: M-commerce, ICOMP, Model selection, Variable clustering.

1 Introduction

Although it can provide the last mile connection to an individual, mobile commerce (m-commerce) did not bloom yet. Homogeneous services may not be able to attract the same attention from different user groups among countries. By the information-theoretic measure of complexity (known as ICOMP), this paper validated the diversity of usage in m-commerce among countries.

1.1 Background for the Problem

M-commerce is still in its infancy although the rate of increase mobile phone subscribers in developed countries is gradual in recent years [1]. One reason for the infancy might be there is a lack of “killer” application(s) for m-commerce. In fact, applications in handheld devices looked quite similar in the markets all over the world. It agreed that organizations often followed “collective norms,” then headed to “homogeneity in structure, culture, and output” [2]. That is, firms will imitate what “success” they believed in the industry.

Nippon Telephone and Telegraph’s (NTT) wireless operations, DoCoMo (NTT DoCoMo) might be the first one to enjoy success in m-commerce. Anwar [3] induced some critical issues about the market expansion and global strategy for NTT DoCoMo. None of them was application-related; but one of the issues addressed that the know-how in i-mode may not be able to easily shift to the other countries because the lifestyle and demands are quite different from each other. Rosenbloom and Larsen [4] showed that there is a relationship between culture and channel communication in international channels. That is, if a firm would like to have business with certain customers by mobile devices, then their culture will be definitely a matter.

Basically, m-commerce could be treated as the use of wireless technology, particularly handheld mobile devices and mobile Internet, to facilitate transaction, information search, and user task performance in consumer, business-to-business, and intra-enterprise communications [5-6]. Broad definitions of m-commerce had been employed to explore the potential benefits of the wireless technology. Skiba et al. [7] defined m-commerce as “the use of mobile hand-held devices to communicate, inform, transact and using text and data via connection to public or private networks.” They specifically list any kind of service that can be provided by the mobile device, thus expanding its mere commercial character through communicative and informative services.

The foundation of m-commerce, or mobile Internet, has unique strengths over the stationary Internet, because

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users may access the Internet wherever and whenever they want [8]. With these strengths, proponents claimed that m-commerce would surpass e-commerce in growth and scale [9]. But it had not happened yet, and the evolutions of m-commerce seem different from countries. Lee et al. [10] first confirmed that there were differences of preference in m-commerce among countries by a grey relational approach. Grounded in the framework proposed by Lehner and Watson [11], they grouped applications into four categories then evaluated the preferences. Furthermore, the discrepancies raised interesting questions to the field: are these three samples homogeneous or heterogeneous? And, which application is the most relevant among the different countries under such a framework?

Therefore, this paper conducted the validation for the diverse usage in m-commerce by ICOMP and comparing the results with those in [10] by the grey relational approach. Multi-sample clustering and variables selection with ICOMP are the approaches we used to validate whether diverse usage existed. In order to find the best-fitting model and the applications contributing most to the difference among these samples, two arguments are made in this paper. They are:

1. Can these samples be a homogeneous sample?
   Although we already knew preference differed from each other in the previous research, to distinguish whether the data are homogeneous or heterogeneous may be a more fundamental task. If they are not, what is the best-fitting model for them?
2. The preference for applications may not necessarily represent the same rank in contributing difference among samples. Which application(s) contributed most to the difference among samples?

1.2 About for the Approach

ICOMP was proposed by Bozdogan [12-13] which had broadly accepted in fields (e.g., [14-16]). According to Bozdogan [17], a rationale for ICOMP as a model selection criterion is that it combines a badness-of-fit term with a measure of complexity of a model by taking into account the interdependencies of the parameter estimates, as well as the dependencies of the model residuals. Even though there were several approaches for determining the difference, e.g., discriminant analysis or cluster analysis [18], the primary reason for employing ICOMP to analyze the diversity here is that the sample sizes were different.

To check whether the data is homogeneous or heterogeneous is very important in many scenarios. Analytically, to group the heterogeneous samples into homogeneous sets of samples is usually necessary to reduce the dimension of variables and the number of groups simultaneously. In literatures, the Analysis of Variance (ANOVA) is a widely used model for comparing two or more univariate samples, where the familiar *Student's t* and *F* statistics are used for formal comparisons among two or more samples. For cases with multiple samples, the Multivariate Analysis of Variance (MANOVA) is a popularly used model for comparing two or more multivariate samples. However, the formal analysis involved in ANOVA or in MANOVA is not revealing or informative. For this reason, in any problem where a set of parameters is to be partitioned into groups, we may employ a practical statistical procedure or procedures that would use some sort of statistical model to aid in comparisons of various collections of comparable groups or samples, identify the homogeneous groups from the heterogeneous ones, and determine which groups or samples should be clustered together.

Bozdogan [19] suggested that through Multi-Sample Cluster Analysis (MSCA) as an alternative to Multiple Comparison Procedures (MCP's) and through the use of model-selection criteria, all sufficiently simple partitions of groups consistent with the data, and also the best clustering among the alternative clusters, should be found. Based on this idea, he proposed an enumerative clustering technique to generate all possible choices in clustering alternatives of groups or samples on the computer using efficient combinatorial algorithms without forcing an arbitrary choice among the clustering alternatives. This work proposed a framework, which incorporated and extended the procedure of analyzing information complexity proposed by Bozdogan for the model selection and variables clustering, in order to conduct the validation with the survey data.

Grey relational analysis is good at showing the preference for the applications in each sample respectively but it can hardly to tell which application is the most influential in telling difference between samples. In fact, the most popular application in each sample may not be the one contributing most to the difference between samples. Since the abundance of irrelevant variables may mask the objectives of the study, and because they effect the information in the rest of the data that can unnecessarily increase the size of the search space and accuracy of classification of the data set, the choice of variables to represent the patterns in the whole dataset affects several aspects of pattern classification. In this paper, ICOMP was employed to distinguish the applications by ranking them with the contribution to the difference among samples based on the use of correlations as similarity measures, and applying the minimum pair-wise correlation as a measure of similarity between two clusters of variables.

1.3 Data and Results

In comparison, the data collected by Lee et al. [10] was used for the analyses. The ICOMP criteria were employed to determine the homogeneous or heterogeneous between samples. Since there were twenty applications in four groups, a genetic algorithm was used to find the optimization of ICOMP criteria in the fitness function for clustering these applications under the proper model, which was determined previously. According to the Stirling Number of the Second Kind (SNSK), the total number of clustering alternatives with a set of 20 variables will be 5.1724×10^{13}. The huge alternatives space is the reason why an efficient searching algorithm, such as a genetic algorithm, is necessary in order to find the optimal alternative.

Although different approaches carried out different results from the same data, they all agreed that the diversity of usage in m-commerce among countries existed. The ICMOP criteria in model selection indicated that data should be treated as three heterogeneous samples instead of one homogeneous sample. It fundamentally implied that the usage in m-commerce was different among these three countries. Furthermore, the ICOMP criteria in variable selection provided the rank of contributing most to the differences between samples, and those ranks differed from the preference ranking in the grey relational analysis. Therefore, it is appropriate to conclude that the grey relational approach is useful to determine the preference, and the ICOMP criteria are helpful to identify the best-fitting model and those important variables of the model.

The rest of this paper is organized as follows. In the coming section, the proposed approach, i.e., conducting model selection with ICOMP and variables clustering by ICOMP, will be briefly introduced. Results of the model selection and variables clustering are demonstrated in the third section for a comparison with those by the grey relational analyses. Discussions about the meaning to global expansion, and the comparison of both approaches in determining difference between samples are in beginning of the forth section. The validation of diversity usage is also discussed in that section. The conclusions of this study are in the last section.

2 The Proposed Approach

ICOMP, the information-theoretic measure of complexity, was proposed by Bozdogan [12-13]. It is based on the structural complexity of an element or set of random vectors via a generalization of the information-based covariance complexity index of van Emden [17]. For a general multivariate linear or nonlinear model defined by

$$\text{Statistical model} = \text{Signal} + \text{Noise} \tag{1}$$

ICOMP is designed to estimate a loss function:

$$\begin{aligned}\text{Loss} = {} & \text{Lack of fit} + \\ & \text{Lack of parsimony} + \\ & \text{Profusion of complexity}\end{aligned} \tag{2}$$

in several ways. The third term in Equation (2) represents the interdependencies or the correlations among the parameter estimates and the random error term of a model.

2.1 The ICOMP(IFIM)

A general approach to ICOMP, referred to as ICOMP(IFIM), exploits the asymptotic optimality properties of the maximum likelihood estimators (MLEs), and uses the information-based complexity of the inverse-Fisher information matrix (IFIM) of a model. For a multivariate normal linear or nonlinear structural model, the general form of ICOMP(IFIM) was defined as

$$\begin{aligned}&\text{ICOMP(IFIM)} = \\ &-2\log \mathrm{L}(\hat{\theta}) + 2\,\mathrm{C}_1(\hat{F}^{-1}(\hat{\theta})),\end{aligned} \tag{3}$$

and

$$\begin{aligned}\mathrm{C}_1(\hat{F}^{-1}) = 0.5\dim(\hat{F}^{-1})\log(\mathrm{tr}(\hat{F}^{-1}) \\ /\dim(\hat{F}^{-1})) \\ -0.5\log|\hat{F}^{-1}|\end{aligned} \tag{4}$$

where $\hat{\theta}$ is the maximum likelihood estimator of θ, L represents the likelihood function, and C_1 denotes the maximal information complexity of $\hat{F}^{-1}$, the estimated IFIM.

The first component of ICOMP(IFIM) in Equation (3) measures the lack of fit of the model, and the second component measures the complexity of the estimated IFIM, which gives a scalar measure of the celebrated Cramér-Rao lower bound matrix, which takes into account the accuracy of the estimated parameters and implicitly adjusts for the number of free parameters included in the model.

2.2 Model Selection with the ICOMP(IFIM)

For the test of homogeneity in multi-sample models, K-sample independent data matrices $\mathbf{X}_g$ ($n_g$xp), g = l, 2, ..., K, where the rows of $\mathbf{X}_g$ are independent and identically distributed (i.i.d.) Np($\boldsymbol{\mu}_g$, $\boldsymbol{\Sigma}_g$), g = 1, 2, …, K, were considered. In terms of the parameters $\boldsymbol{\theta} = (\boldsymbol{\mu}_1, \boldsymbol{\mu}_2, \ldots, \boldsymbol{\mu}_K, \boldsymbol{\Sigma}_1, \boldsymbol{\Sigma}_2, \ldots, \boldsymbol{\Sigma}_K)$ he models were covariances model, one-way multivariate analysis of variance (MANOVA) model, and complete homogeneity model. In multivariate data analysis, the assumption of equality of covariance matrices causes serious problems as testing the equality of mean vectors.

In order to tackle those problems, the equality of covariance matrices against the alternative that not all covariance matrices are equal should be tested first. If the groups or samples can differ in covariance matrices regardless of the mean vectors, then in terms of the parameters test of homogeneity of covariances model is

$$M_1 : \theta = (\mu_1, \mu_2, ..., \mu_K, \Sigma_1, \Sigma_2, ..., \Sigma_K) \tag{5}$$

with m = Kp+Kp(p+l)/2 parameters, where K is the number of groups, and p is the number of variables. If K normal populations are with different mean vectors $\boldsymbol{\mu}_g$, g = l, 2,..., K, but each population has the same covariance matrix $\boldsymbol{\Sigma}$, i.e., the groups or samples can differ only in their mean vectors; then in terms of the parameters the MANOVA model is

$$M_2 : \theta = (\mu_1, \mu_2, ..., \mu_K, \Sigma, \Sigma, ..., \Sigma) \tag{6}$$

with m = Kp+p(p+l)/2 parameters. In the case of a complete homogeneity model, in terms of the parameters, the model is

$$M_3 : \theta = (\mu, \mu, ..., \mu, \Sigma, \Sigma, ..., \Sigma) \tag{7}$$

with m = p+p(p+ l)/2 parameters.

Given the data obtained from surveys takes the following form:

$$X(n \times p) = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_K \end{bmatrix} \tag{8}$$

where

$X_g = n_g$ observations for the gth group.

$X_g \in R^{n_g * p}, 1 \le g \le K$

K = number of groups

p = number of variables

Under the hypothesis which is a test of homogeneity of covariances models can be defined to represent the K

group observations; based on Dillon et al. [14], the log likelihood of the parameters is given by:

$$\log L(\mu_g, \Sigma_g; \mathbf{X}) = -0.5(np\log(2\pi) + \sum_{g=1}^{K} n_g \log\left|\Sigma_g\right| + np) \tag{9}$$

2.3 Variables Clustering by the ICOMP(IFIM)

For clustering and subset selection of variables, the asymptotical inverse fisher information matrix for the multivariate normal model is as follows [20]:

$$\hat{F}^{-1} = \operatorname{diag}\begin{bmatrix} \frac{n}{n_g}\hat{\Sigma}_g & 0 \\ 0 & \frac{2}{n_g} D_p^+(\hat{\Sigma}_g \otimes \hat{\Sigma}_g) D_p^{+}{}' \end{bmatrix} \tag{10}$$

where $\otimes$ denotes the Kronecher product and D_p^+ is the Moore-Penrose inverse of the duplication matrix D_p, and that $D_p^+ = (D_p' D_p)^{-1} D_p$. In operating the complexity measure on the estimated inverse-Fisher information matrix, ICOMP(IFIM) is given by [20]:

$$\begin{aligned} \mathrm{ICOMP(IFIM)} &= np\log(2\pi) + n*(\log\left|\hat{\Sigma}\right| + tr\left(\hat{\Sigma}^{-1}S\right)) + .5*p(p+3)*\log \\ &\left(\frac{tr(\hat{\Sigma}) + \frac{1}{2n}\left(tr(\hat{\Sigma}^2) + \left(tr(\hat{\Sigma})^2 + 2\sum_j (\hat{\sigma}_{jj}^2)^2 \right)\right)}{0.5 * p(p+3)} \right) - \\ &p\log(2) + 0.5*p(p+1)*\log(n) - (p+2)*\log\left|\hat{\Sigma}\right| \end{aligned} \tag{11}$$

where S = dim ($\hat{F}^{-1}$) = rank ($\hat{F}^{-1}$)

A major practical difficulty in clustering and subset selection of variables is the computational burden entailed in exhaustive subset search. Let p be the number of variables and k represents the number of clusters (or partitions). The number of ways of clustering a set of p variables into k nonempty clusters is known as the Stirling Number of the Second Kind (SNSK), or a Stirling set number, which can be computed from the sum [21],

$$S(p,k) = \frac{1}{k!}\sum_{j=0}^{k}(-1)^j \binom{k}{j}(k-j)^p \tag{12}$$

For the dataset used in this paper, the total possible clustering alternatives are 5.1724×10^{13}, because 20 variables were considered. It indicated that to enumerate all possible clustering alternatives is a mission impossible. The best way to handle such a situation would be the implementation of a genetic algorithm to speed up the searching process. A genetic algorithm (GA) is a stochastic search algorithm based on concepts of biological evolution, natural selection, genetics, and evolution. They are widely applied to solving problems where vast numbers of possible solutions exist. A GA treats information as a series of codes on a binary string, where each string represents a different solution to a given problem.

This study employed GA as a searching method, guided by the use of ICOMP criteria as the fitness function, along with the other criteria to help select the appropriate subset selection of variables from the vast model space. Population size represents the searching range in iteration (generation). Larger population size can converge faster; that is, the optimum will be found by less iteration (generation). A brief description of the GA based procedure employed in this study was outlined as follows. More details can be found in [20].

Step 1: To develop the encoding scheme for the various possible combinations of variables in order to represent the possible subsets composing the genotypic space.
Step 2: Generating the initial population of subset of variables.
Step 3: To employ ICOM(IFIM) as a fitness function to evaluate the performance of any subset.
Step 4: The proportional selection mechanisms based on the ICOMP(IFIIM) was employed to select fitter models.
Step 5: Producing offspring that compose the next generation.

3 Data Analyses with ICOMP

In order to compare the results by Lee et al. [10], the same data were used in this study. The data were collected from three countries by the same questionnaire with appropriate translations. Sample sizes differed from each other, and there were 85 valid responses in Taiwan, 182 in the US, and 142 in Germany. The discrepancy in sample sizes would be very challenging for the analysis by most of conventional approaches and it is one of the reasons that the ICOMP approach was used to conduct the analysis. The results of model selection and variable clustering with ICOMP(IFIM) were performed in this section in order to validate the diversity of usage and compare the discrepancies based on different approaches.

3.1 Identification of the Best Fitting Parametric Model

First of all, this study examined whether the datasets are homogeneous or heterogeneous by different parametric models. That is, three parametric multivariate normal models, varying $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$, varying $\boldsymbol{\mu}$ and common $\boldsymbol{\Sigma}$, common $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$, with five combinations of sample clustering were considered, where the $\boldsymbol{\mu}$ represents location parameter and $\boldsymbol{\Sigma}$ is the dispersion matrix. ICOMP(IFIM) is the criterion to evaluate the fitness of models with different combinations of clustering, and the smallest value of ICOMP(IFIM) represents the best fit alternative.

Based on the proposed approach, the results of model selection are listed in Table 1. According to the assumptions of varying or common in samples' mean and covariance, M1, M2, and M3 represent the different parametric models respectively. In order to figure out the best fitting parametric model for the three samples, five alternatives for different clustering combination are used to conduct the analysis. For example, alternative 1 in table 1 indicated that all the three samples were clustered as there was only one sample. Since there was only one sample for this alternative, the ICOMP(IFIM) values for different parametric model are all the same.

According to the ICOMP(IFIM) values, the three samples are heterogeneous because the alternative 5 in model 1, clustering the three samples individually with different $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$, received the smallest value in all alternatives. Therefore, the model with varying mean vectors and covariance matrices is the best fitting model for the analysis of the m-commerce usage data. Due to the covariance heterogeneity, we cannot haphazardly assume that the covariances are equal and entertain the MANOVA model, or the test of complete homogeneity model and assume that data come from a single population.

3.2 Multisample Cluster Analyses -- All Variables

On the basis of the heteroscedastic model, the most relevant variables between these samples can be determined by the proposed approach. The best subset of variables, which received the smallest ICOMP(IFIM) value, is the most relevant variables between the samples, and it contributes less to the differences between the samples.

Table 1 Identification of the Best Fitting Parametric Model

Alternatives	Clustering	M1	M2	M3
1	(1,2,3)	23633.4459	23633.4459	23633.4459
2	(1,2)(3)	22903.7839	23456.1391	23609.6701
3	(1,3)(2)	22884.6332	23579.4928	23610.3929
4	(2,3)(1)	22970.9130	23460.3975	23605.8191
5	(1)(2)(3)	22159.6383*	23355.0144	23580.3351

Note: 1. M1 (varying $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$); M2 (varying $\boldsymbol{\mu}$ and common $\boldsymbol{\Sigma}$); M3 (common $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$)
2. *Global minimum of ICOMP(IFIM), which indicate the best fitting model

In order to verify the discrepancy, two levels of variable clustering were performed in this study. In the first level, all twenty variables were taking into account. The most relevant service among countries was selected based on the associate ICOMP(IFIM) values. With the same procedure, the subsequent relevant services can be determined from each run after removing the currently most relevant service from the decision variables. It is worthwhile to notice that different combination of samples may have different selection on the currently most relevant service. That implicated the level of relevance for a service could be different among samples.

Table 2 listed the five most relevant services across the multisample clustering structure based on the associate ICOMP(IFIM) values. According to the results, x_{11} is the most relevant variable between samples, whatever in which pair of samples. That is, there is less heterogeneity in the means and variances/co-variances on this service (chat rooms) between samples. Similar ranking structures can be observed in the pairs of Taiwan and Germany, the US and Germany, and all of the three countries. x_7 and x_{17}, which represented the service of corporate information and shopping respectively, contributed more to the differences between samples, except in the pair of Taiwan and the US. In the same context, x_8 and x_{12}, which represented the service of stock market data and video conferencing respectively, contributed more to the differences between Taiwan and the US only.

It is worthwhile to notice that comparing different values in different columns here is meaningless because they are computed within the combination based on the best fitting process.

3.3 Multisample Cluster Analyses -- Variables by Groups

Four groups of services, which were defined by Lehner and Watson [11], were taking into account in the second level of variables clustering. Clustering variables by groups can distinguish the contributions in the associate group. Again, ICOMP(IFIM) served as the criterion in selecting the most relevant cluster of variables between samples. By removing the most relevant variable from each run, the most relevant variables were ranked.

The first group, for the category of Information and Data Access, included the following eight services:

X_1: News
X_2: City Guides
X_3: Directory
X_4: Maps
X_5: Traffic
X_6: Weather
X_7: Corporate Information
X_8: Stock Market Data

The five most relevant services between samples in the first group were listed in Table 3. According to the ICOMP(IFIM) values, similar ranking structures can be

Table 2 Five Most Relevant Variables among Countries -- All Twenty Variables

Rank	Among C_1, C_2, and C_3		Among C_1 and C_2		Among C_1 and C_3		Among C_2 and C_3	
	Variable	ICOMP	Variable	ICOMP	Variable	ICOMP	Variable	ICOMP
1	X_{11}	1065.9474	X_{11}	764.9074	X_{11}	502.7524	X_{11}	863.7435
2	X_{18}	1158.2619	X_{19}	772.0421	X_{18}	579.7842	X_{18}	944.1125
3	X_{12}	1185.7149	X_{18}	792.3068	X_{12}	585.3742	X_{12}	968.5244
4	X_8	1210.5263	X_7	821.3844	X_8	605.3162	X_8	971.4276
5	X_{19}	1219.8698	X_{17}	825.5734	X_{17}	625.7603	X_{19}	997.8513

Note: 1. C_1: Taiwan; C_2: the US; C_3: Germany
2. ICOMP here is the abbreviation of ICOMP(IFIM)

Table 3 Five Most Relevant Variables among Countries -- Information and Data Access

Rank	Among C_1, C_2, and C_3		Among C_1 and C_2		Among C_1 and C_3		Among C_2 and C_3	
	Variable	ICOMP	Variable	ICOMP	Variable	ICOMP	Variable	ICOMP
1	X_8	1210.5263	X_7	821.3844	X_8	605.3162	X_8	971.4276
2	X_7	1238.2291	X_1	834.2670	X_7	648.0261	X_7	1006.8904
3	X_2	1319.7880	X_2	842.4386	X_2	689.7457	X_2	1107.3679
4	X_6	1347.8789	X_8	844.0553	X_6	702.6127	X_6	1126.4945
5	X_1	1359.3833	X_3	856.3090	X_1	723.9429	X_1	1160.6323

Note: 1. C_1: Taiwan; C_2: the US; C_3: Germany
2. ICOMP here is the abbreviation of ICOMP(IFIM)

observed in the pairs of Taiwan and Germany, the US and Germany, and all of the three countries. The x_3, which represented the service of weather, contributed more to the differences between samples, except in the pair of Taiwan and the US. In the same context, x_6, which represented the service of directory, contributed more to the differences between Taiwan and the US only, but not in all other pairs.

The second group, dedicated to the category of Communication and Interaction, had four services as follows; they were:

X_9: Short messaging
X_{10}: E-Mail
X_{11}: Chat rooms
X_{12}: Video conferencing

The three most relevant services between samples in this category were listed in Table 4. An exact same ranking structure can be observed in all the pairs. It implied that the usage of e-mail contributed most to the differences between samples.

The third group, for the category of Entertainment, consisted of the following three services:

X_{13}: Download/listen to Music
X_{14}: Play Games
X_{15}: Download Video

The two most relevant services between samples in this category were listed in Table 5. According to the ICOMP(IFIM) values, similar ranking structures can be observed in the pairs of Taiwan and Germany, the US and Germany, and all of the three countries. The x_{13}, which represented the service of download/listen to music, contributed more to the differences between samples, except in the pair of Taiwan and the US. In the same context, x_{15}, which represented the service of download video, contributed more to the differences between Taiwan and the US only, but not in all other pairs.

Five services were classified into the forth group, the category of Transactions. They were:

X_{16}: Banking
X_{17}: Shopping
X_{18}: Auctions
X_{19}: Mobile wallet
X_{20}: Booking and reservations

The four most relevant applications between samples in the forth category were listed in Table 6. The same ranking structure can be observed in the pairs of the US and Germany, and all of the three countries. Similar but different ranking structures exist in the pair of Taiwan and the US as well as in the pair of Taiwan and Germany. It is

Table 4 Three Most Relevant Variables among Countries -- Communication and Interaction

Rank	Among C_1, C_2, and C_3		Among C_1 and C_2		Among C_1 and C_3		Among C_2 and C_3	
	Variable	ICOMP	Variable	ICOMP	Variable	ICOMP	Variable	ICOMP
1	X_{11}	1065.9474	X_{11}	764.9074	X_{11}	502.7524	X_{11}	863.7435
2	X_{12}	1185.7149	X_{12}	817.2068	X_{12}	585.3742	X_{12}	968.5244
3	X_9	1381.9797	X_9	830.1205	X_9	756.2552	X_9	1177.6372

Note: 1. C_1: Taiwan; C_2: the US; C_3: Germany
2. ICOMP here is the abbreviation of ICOMP(IFIM)

Table 5 Two Most Relevant Variables among Countries -- Entertainment

Rank	Among C_1, C_2, and C_3		Among C_1 and C_2		Among C_1 and C_3		Among C_2 and C_3	
	Variable	ICOMP	Variable	ICOMP	Variable	ICOMP	Variable	ICOMP
1	X_{15}	1311.2248	X_{14}	894.6963	X_{15}	646.6252	X_{15}	1068.2541
2	X_{14}	1329.8042	X_{13}	907.1277	X_{14}	664.9788	X_{14}	1099.7394

Note: 1. C_1: Taiwan; C_2: the US; C_3: Germany
2. ICOMP here is the abbreviation of ICOMP(IFIM)

Table 6 Four Most Relevant Variables among Countries -- Transactions

Rank	Among C_1, C_2, and C_3		Among C_1 and C_2		Among C_1 and C_3		Among C_2 and C_3	
	Variable	ICOMP	Variable	ICOMP	Variable	ICOMP	Variable	ICOMP
1	X_{18}	1158.2619	X_{19}	772.0421	X_{18}	579.7842	X_{18}	944.1125
2	X_{19}	1219.8698	X_{18}	792.3068	X_{17}	625.7603	X_{19}	997.8513
3	X_{17}	1231.6210	X_{17}	825.5734	X_{19}	669.7088	X_{17}	1011.6916
4	X_{20}	1331.5306	X_{20}	855.0083	X_{20}	698.5459	X_{20}	1109.4955

Note: 1. C_1: Taiwan; C_2: the US; C_3: Germany
2. ICOMP here is the abbreviation of ICOMP(IFIM)

clear that the x_{16} and x_{20}, which represented the services of banking as well as booking and reservations respectively, contributed most to the differences between each pair of samples.

It is worthwhile to emphasize that all ranking structures are based on the heteroscedastic model recommendation. That is, there is less heterogeneity in the means and variances/covariances for the most relevant variable in each category. The general conclusion is that there are more heterogeneity in the means and variances/covariances for the other variables within the category.

4 Discussions

Since the ICOMP(IFIM) values indicated the three samples should be modeled individually, the realization of the results support the following three point of views. First, the recommendation based on ICOMP(IFIM) distinguishes the existence of diverse usages in m-commerce services among countries. According to the results, heterogeneous models are recommended for the three samples. The results also carried out the most relevant services in each group between countries. Second, it is interesting to compare the ICOMP approach with the grey relational analyses in telling the difference. Since both of approaches can make a distinction between samples, it will benefit researchers to discuss the pros and cons of these two approaches. Third, m-commerce differed from e-commerce in some ways. Usually, a service in e-commerce can be assumed to serve globally once it is online. The services in m-commerce may not repeat a similar success in the same way, even though they were popular in one country. In other words, the results implied that localization of services in m-commerce should be considered more seriously in its global expansion.

4.1 Validation the Diversity Usage

Results of model selection and variable clustering in the previous section show that Taiwan, the US, and Germany did use services in m-commerce diversely. The global minimum of ICOMP(IFIM), i.e., the model selection criteria, in Table 1 is located on the first model with varying mean vector and covariance matrices. The samples from each country must be grouped independently. That is, the global minimum indicated these three samples cannot be treated haphazardly as the covariance are equal and entertain the MANOVA model (the second model), or the test of complete homogeneity model (the third model) and assume that data came from a single population. In other words, there is heterogeneous covariance among samples, and any two or all of these three samples should not be clustered as one homogeneous group. Hence, the usage of services in m-commerce is different from each other's based on the results of model evaluation.

The smaller ICOMP(IFIM) value in a variable clustering implies it is a more relevant variable between two samples. Under the recommendation of heterogeneous models for all three samples, the most relevant variable among twenty variables is "Chat Room." It indicated this service is the most expendable variable in building individual models for the samples. When all twenty variables were taken into account for any two samples with heterogeneous models, the results of variable clustering would be slightly different from each other. Since two out of the first five most relevant variables are different from the other groups, the ranking of relevant variables between Taiwan and the US is more different than those in the pair of Taiwan and Germany as well as in the pair of US and Germany.

Originally, Lehner and Watson [11] proposed six groups of applications in m-commerce. Two of them were not used in this study because one was very rare and another was basically going to cover everything else. In the four groups used here, the differences in variable clustering among samples are slightly different according to Table 3, 4, 5, and 6. In the "Transactions" category (as shown in Table 6), the ranking of the most relevant variables are different in all three pairs. It indicates that the three different heterogeneous models should be used respectively in such a group of services. Even though the results of a variable clustering are the same in the "Communication and Interaction" category (as shown in Table 4), it is not necessary to have just one heterogeneous model for all three cases. More details are needed to identify whether the model for each case is the same but with different coefficients or anything else.

According to Table 3 for the "Information and Data Access" category, the most relevant variable among all three samples is "Stock Market Data," then "Corporate Information," "City Guide," "Weather," and "News" in descending order. The other three variables, "Directory Services," "Maps," and "Traffic," contributed more to the differences among those three pairs of samples. The ranking of the first five variables is the same as those between Taiwan and Germany, and also those between the US and Germany. It implies that the models for Taiwan and the US samples may have more differences than that for the Germany sample in this category. And there is a similar situation in the group "Entertainment" (as shown in Table 5). An overall picture of the diverse usage in m-commerce among the countries is that the discrepancy between Taiwan and the US may differ more from those between Taiwan and Germany, and those between the US and Germany.

4.2 Comparison between the Two Approaches in Telling the Difference

Since two different approaches had been used to validate the diverse usage in m-commerce services among the countries, it can benefit the field by distinguishing how these two approaches work. In validating diversity of the usage, the ICOMP approach provided different recommendations from those by grey relational analyses although they all ranked variables by their own ways. The concepts, computation procedures, results based on these two approaches, and also the relative pros and cons in validating the diversity were briefly compared in the following context. In general, the grey relational analyses can be used to establish the preferences that make it easy to tell the differences among samples; and the ICOMP approach will select an appropriate statistical model first, and then select relevant variables under a recommended model.

One of the most famous characters in grey theory was it can be used to examine the relationship among factors in an observable system where the information available is uncertain or incomplete. That is, a grey system can be built for answering specific research questions as there is no way to identify all affecting factors [22]. In validating the diversity, there is a seven-step procedure for getting the grey relational grades to rank the preferences [10]. All computations can be finished within an Excel worksheet because they are subtraction, addition, and comparison. Results came from the grey relational analyses show the relativism basically. Such "internal" results can tell the ranking of variables within a sample but cannot be used to compare the discrepancies among two samples.

For example, the five most important applications in Taiwan by grey relational analysis were "Short messaging," "Download/listen to Music," "Traffic," "Booking and Reservations," and "City Guides." For the case in the US, the five most important applications were "Short messaging," "e-Mail," "Maps," "Traffic," and "Download/listen to Music." The five most important applications in Germany were "Short messaging," "e-Mail," "Directory Services," "News," and "Maps." Even though the "Short messaging" is the most preferred services in all of three countries, there is no information about whether the "Short messaging" is more preferred in Taiwan than in the US or in Germany. In some cases, the missing information is important because it may indicate that there are other variables more important than the listed variables.

The basic idea of ICOMP approach in validating the diversity was the use of ICOMP(IFIM) as the criteria for model selection and then variables clustering. It combined a badness-of-fit term with a measure of complexity of a model by taking into account the interdependencies of the parameter estimates as well as the dependencies of the model residuals [17]. When the number of combination of variables is large, the calculation in variables clustering is more complicated than that in model selection. A genetic algorithm will be involved to search the optimal in such cases. Results by the ICOMP approach in model selection can only indicate what kind of the parameter model it is for the data. Therefore, variable clustering is necessary for getting more information about the discrepancies.

Even though both grey relational analyses and variables clustering by ICOMP(IFIM) rank the variables, there are fundamentally different from each other. An intuitive concept about that is an ICOMP approach deals model or variables selection among samples, but what a grey relational analysis does is ranking variables within a sample. Once the relation between samples is getting interested, we may like to know which variables are important to build such models for telling the discrepancy. For example, the five most relevant variables for all twenty variables in order are "Chat Room," "Auctions," "Video Conferencing," "Stock Market Data," and "Mobile Wallet" according to Table 2. What it implied is that they contributed less to the differences between the pairs of samples. If we are going to build appropriate models in order to tell the different behavior between samples, those most relevant variables may be the most expendable. That is the reason why there is the grey relational analysis, but the ICOMP approach is still recommended.

4.3 The Meaning to Global Expansion in M-commerce

M-commerce differed from e-commerce in some ways. The interface, connection, and even contents could look quite similar under e-commerce in a certain way, especially by a personal computer. The two most important characteristics of m-commerce, i.e., mobile devices and wireless network, make it different from e-commerce (e.g., [5-7]). Since m-commerce committed a ubiquitous service, the users' operating environment had more significant impact on it. Such impacts are not only on the connection or capabilities of mobile device, but also on the usage and business behavior. For example, traffic information may not be so valuable that every user in different areas will pay the wireless connection fee to get it by their mobile devices. It may be just valuable for those drivers who were stuck in traffic and hurried to find a way out.

In e-commerce, it always implied to serve globally once a service was online. It might be not true in m-commerce for many reasons. The results in this paper supported the idea about that m-commerce differed from e-commerce especially in global expansion. We believed that localized services make more sense in m-commerce because it provides the last mile connection to a person.

If the discrepancy is ignored, it is hard to get success in the other country. For example, NTT DoCoMo had tried to export the i-mode abroad since 2001 [3], but it still had not achieved the success it got in Japan yet. That is, even though the services are very popular in one country, they may not be able to guarantee another success in the other countries. The validation of diverse usage in m-commerce among the countries suggests that when enterprises consider a global expansion in m-commerce, they have better realized that there were different usages in m-commerce among counties.

5 Conclusions

This paper validated the diversity of usage in m-commerce among the countries, by using ICOMP(IFIM) as criteria to performed model selection and variable clustering. Heterogeneous, i.e., varying mean vectors and covariance matrices, models for the three samples are recommended according to the model selection results. The results based on variables clustering show that most of the relevant variables between the samples are different. That is, whatever based on model selection or on variables clustering, the results all agree with the diversity of usage in m-commerce services among the countries.

In comparison with the grey relational analysis, the proposed approach can explain the discrepancy in a more insightful way. The usage as well as the pros and cons of both approaches were discussed. In short, the grey relational analysis is good to determine the preference within a sample; and the proposed ICOMP approach can identify the best fitting parametric model and carry out multisample cluster analysis for the samples.

The promising ubiquity of m-commerce got attentions but did not be carried out so far. Applications for e-commerce can always be assumed to serve globally once they are online. The same assumption may not be true in m-commerce due to the existence of diverse usage. Since it may limit an international expansion of the services, the service provider should treat the diverse usage more seriously rather than just duplicated what they had to another country.

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