Expanding Structure and Methods of Technology Acceptance Model of Population Census Data Processing: Structural Equation Model and Bayesian Approach

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Abstract: Problem statement: Technology Acceptance Model (TAM) is one of models that analyze user behavior to accept and use a new technology. SEM is the most statistical method which use in TAM analysis that provides the estimation strength of all hypothesized relationship between variables in a theoretical model. Consider to employing the standard SEM in TAM analysis which expected a large data, the sample size become a crucial problem. Population census data processing is Indonesian government statistical program that needs supporting a computer technology in order to obtain accurate data and less time processing. it is needed to understand the user acceptance in mandatory environment with limited users. **Approach:** Estimation SEM with Bayesian method is an alternative to solve the sample size problem. This paper studied the developing TAM in the implementation of census data processing system with limitation of sample size and extension of statistical methods of TAM's analysis with Structural Equation Model (SEM) Bayesian approach. The TAM theory of this study implemented the constructs of TAM3: subjective norm, output quality, result demonstrability, perception of external control, compatibility and experience, perceived ease of use, perceived of usefulness . The others constructs are organizational interventions: management support, design characteristic , training, organizational support. **Result:** The result have shown that from the model there are significant relations between first: management support to subjective norm, second: subjective norm to perceived of usefulness, third: training, perception of external control to perceived ease of use. Residual analysis show that residuals are close to zero. **Conclusion:** Estimation of TAM using SEM and Bayesian methods with MCMC and Gibbs Sampler algorithm could handle the small sample size problem. .

Key words: TAM, SEM, Bayesian, census data processing.

INTRODUCTION

Information Technology (IT) is a technology artifact, and it has not been coming in vacuum area. The implementation of information technology could be different in every field. How the IT reach the optimum performance will depend on the user's acceptance of the technology. Since 1980 more researchers have been focusing on the user's intention to use a new technology (Nan, Hua and Qing, 2008. Technology Acceptance Model (TAM) is one of models that analyze user behavior to accept and use a new technology. TAM has been implemented in many field studies. TAM became popular, because it is simple and easy to understand (King, 2006). As a theory, like an organic being, TAM has ceaselessly evolved (Lee, 2003).

Some researchers have expanded to find the progress of TAM. The studies have developed in a specific field or in a comprehensive study with Meta analysis. In conjunction with the progress of diffusion innovation technology, TAM's analysis has been employed in many areas of researches. It could be focus on theoretical perspectives or practical views. The goal of TAM studies is having explanation of user acceptance in a new technology and the restriction that induce the user acceptance. It performed an analysis of the implementation a new technology which fit with user requirement in different circumstance.

The literature study from 105 leading journals, showed the most common problems which became limitation in TAM researches can be grouped in some categories: the limitation of sample size, the homogeneity of samples, cultural dimension, the region of samples, moderating variables, missing data and specification of researches.

Consider to employing the standard SEM in TAM analysis which expected large data, the sample size become a crucial problem. It refers that standard SEM is following the normal distribution. In hence, it was probably that TAM research could involve a small sample size. In addition some specific

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technologies are used by specific users. It means that the sample could be in small numbers. Deng *et. al* (2005) refers to Haris and Shaubroeck suggested for Confirmatory Analysis, it recommended at least 200 samples. Im *et .al* (2007), mention that 161 samples is too small for 3 or 4 TAM constructs.

The second limitation of TAM research is homogeneity samples. It takes place when the research conducting for a specific technology which implemented in a specific area. Another limitation of TAM studies is data collection; the incomplete data or missing data can go up in measurement and analysis process. Incomplete data could not be ignored and need special handling based on the characteristics of missing data. TAM analysis under standard SEM will face some problems with this situation, especially for small samples. A further, the moderating variable analysis in TAM is needed in a study of two application on intention to use (Loo *et al*., 2009).

The common statistical methodologies of TAM analysis are 1) SEM: Im et. al (2008), Teo *et. al* (2009), Hung *et. al* (2009) 2) Partial Least Square (PLS): Nan *et. al* (2008) 3) Confirmatory Factor Analysis(CFA): Roca *et. al* (2006), Teo (2010) 4) Regression Analysis: Lee *et. al* (2009) 5) Path Analysis: Dishaw and Strong (1999) 6) Multivariate Analysis of Variance (Manova): Grienfield and Rohde (2009)

SEM is the most statistical method which use in TAM analysis. It provides the estimation strength of all hypothesized relationship between variables in a theoretical model (Maruyama, 1997). In TAM model, SEM explain causal relation and estimate the structural weight for PEU and PU. Verdagem and Verleye (2009) explain that SEM is an advance statistical testing, and it enable not only of the validation to theoretical model but also reduction of the list of 29 indicators in to measurement instrument of nine key indicators and it still covering the full conceptual model.

The statistical analysis of TAM is expanding from the simple analysis to complex analysis. It depends of the case study which is conducted by researches. In classical regression, analyzing standard SEM base on sample covariance matrix, and it depends heavily on asymptotic normality distribution. In some unique cases with small sample size, the sample covariance matrix will inadequate for model analysis and it will not be effective for analyzing a complex model. However the estimation of SEM will influence the precise of TAM analysis model.

An extension of SEM is developed by Lee (2007) using Bayesian methods. Different with standard SEM with sample covariance matrix analysis, the Bayesian method analysis is based on raw individual random observations. It has several advantages, first, the development statistical methods is based on the first moment properties of the raw individual observations, which is more simple than the second moment properties (maximum likelihood or generalized least square). Second it leads to direct estimation of the latent variables which better than classical regression. Third it gives more direct interpretation and can utilize the common technique in regression such us outlier and residual analysis (Lee, 2007). In inference perspective the attractive of Bayesian approach consist of : a) provide a unified framework of all problems of survey inference such as analytical estimate, small or large sample inference, ignorable sample selection methods and problems where modeling assumption play more central role such as missing data or measurements error, b) many standards design-based inference can be derive from Bayesian approach, c) allows the prior information about a problem to be incorporate in the analysis in simple and clear way, d) deals with nuisance parameter in a natural and appealing way, e) satisfied the likelihood principle, f) with modern computational tools make Bayesian analysis much more practically feasible than in the past (Little, 2003).

This paper studies the developing TAM in the implementation of census data processing system with limitation of sample size and extension of statistical methods of TAM's analysis with Structural Equation Model (SEM) Bayesian approach.

MATERIAL AND METHOD

Theoretical Model: TAM was derived from a theory that addressed the issues of how users come to accept and use a technology. Based on Theory of Action Reasoned (TRA) that was developed by Fishbein and Azjen (1975), in 1989 Fred Davis introduced TAM as a model that explained how users come to accept and use a technology (Alrafi, 2005). The aim of TAM is providing an explanation the determinants of computer acceptance. (Maholtra, Yogesh; Galetta, Dennis F, 1999). A Meta analysis of TAM by Lee (2000), explained that during the past eighteen years, the information system community considered TAM is a parsimonious and powerful theory. TAM has been implemented in many fields of technologies with different situation background (Lee, 2009).

In order to understand user's acceptance, TAM explain the external variables which influence the internal variables. The two keys of construct in TAM, are perceived ease of use (PEU) and perceived usefulness (PU).

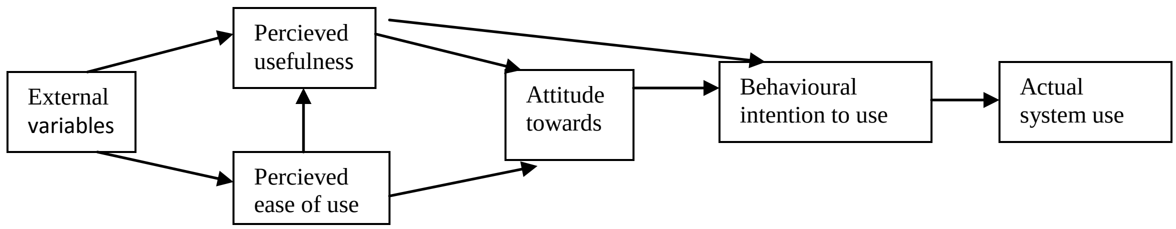

Fig. 1: Original Technology Acceptance Model

The chronological progress of TAM across four separate periods was presented by Lee (2009). This periods since 1986 to 2003. During 1986 to 1995 TAM was presented by Fred Davis. In 1992 Adams *et. al* studied about model validation of TAM, this study continued by Todd and Taylor (1995), Davis and Venkantesh (1996). After the introduction and validation period, TAM came to the extending period in 1994 to 2003. This studies performed by Straub (1994), and Gafen at al. (2003). The elaboration period start in 2000 by Davis and Venkatesh then continued by Venkatesh et. al in 2003.

In three decades the originally structure of TAM has been extended to TAM2 by Venkatesh and Davis (2000) and TAM3 by Venkatesh and Bala (2008). The extension of original TAM to TAM2 was extended in theoretical construct with putting social influence process (subjective norm, voluntariness and image) and cognitive instrumental process (job relevance, output quality, result demonstrability and perceived ease of use). TAM2 was proposed to better understanding the determinants of perceived usefulness with organizational intervention and how is it influence changes over time with increasing experience using the system.

Venkatesh and Bala (2008) combined TAM2 and the determinants of perceived ease of use (Venkatesh, 2000). TAM3 present a complete network the determinants of individual's IT adoption and use. The new relationship that wasposited in TAM3 is experience which moderate the relations (i) perceived ease of use and ease of perceived usefulness (ii) computer anxiety and perceived ease of use (iii) perceived of use and behavior intentions.

In TAM3, Venkatesh and Bala (2008) suggest to investigate the influence of organizational intervention. The implementation of intervention were classify into two categories: pre-implementation and post-implementation. This stage model is examined to identified user reaction during pre-implementation and post-implementation.

Pre-implementation intervention represent a set of organizational activities that take place during system development and deployment periods and it can potentially lead the greater acceptance of a system. This interventions are important for two interrelated reasons: (i) minimize of initial resistance to a new system and (ii) providing a realistic preview of the system so that potential user can develop an accurate perception regarding system features and how the system may help them perform their job (Venkatesh and Bala, 2008). Pre-implementation intervention was presented in five categories: design characteristics, user participation, management support, management and incentive alignment.

Post-implementation intervention represent a set of organizational, managerial, and support activities that take place after the deployment of a system to enhance the level of user acceptance of the system. The post-implementation intervention is important to help the user go through the initial shock and changes associated with the new system. Post-implementation intervention was presented in three categories: training, organizational support, and peer support.

Population Census Data Processing: Population census is a national statistical program, and it is performed by BPS Statistics Indonesia (government institution) once in ten years. One phase of population census process which needs support by computer is data processing. Data processing will transform the data textual (in questioner) to data digital (image). This data digital will be put in another process in order to obtain informations. The adoption of technology in population census data processing was taken in a mandatory environment. Even though, it is important to identify the empirical user acceptance in mandatory environment. The focus of this research is to examine empirical perceived ease of use and perceived of usefulness of users by the external variables. Behavioral Intention to Use and Actual Use are treated as a given condition as a consequences of mandatory environment. The external variables which are involved in the models are defined by observation research during population census data processing in 5 months. They are adjusted with the organization characteristics which performed the population census

Census Data Processing needs a specific system to be implemented. The objective of implementation system is reducing time processing and producing accurate data output. Data processing takes a long time because the quantity of the documents or questionnaires. The Indonesia Population Census 2010 involved more than 234 million individual data and they were written manually (handwriting) in questionnaire by official.

One phase of population census data processing is data capturing. It replace the manually process of data entry by key-in (the data entry officer entry by keyboard to computer) with the new system base on scanner data capturing. The speed of scanner is higher than the speed of data entry by officer. The problems of data capturing bay scanner emerge when the system should recognize the variation of handwriting in questionnaire. The system works by its threshold of handwriting. When it is out of the threshold, the system needs to verify with operator. If many data are under the threshold, then the system needs more time to produce valid data output.

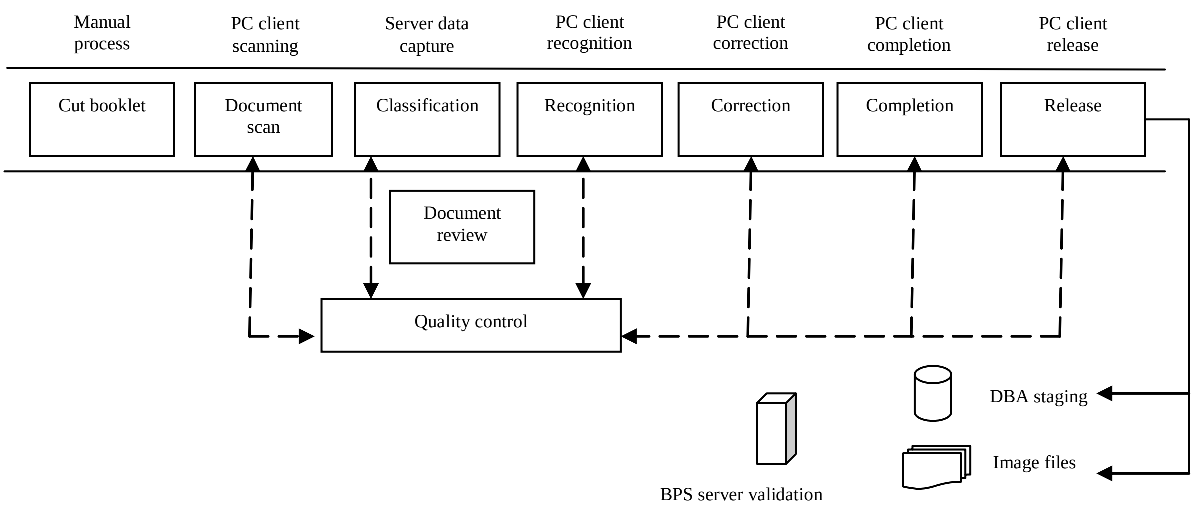

Fig. 2: Work flow of population census data processing

The complexity of new system (census data processing base on scanner) is compared by user with the manual system (key-in data entry). The system requires high skill of user to operate it. The iteration process as consequences of verifying and validation data processing was known by user as an obstacle of data processing. The decision makers and user have different perceived easy of use and perceived of usefulness of the new system.

Base on future research of Venkatesh and Bala (2008), the goal of this research was to examine the influence of organization intervention through pre-implementation and post-implementation.

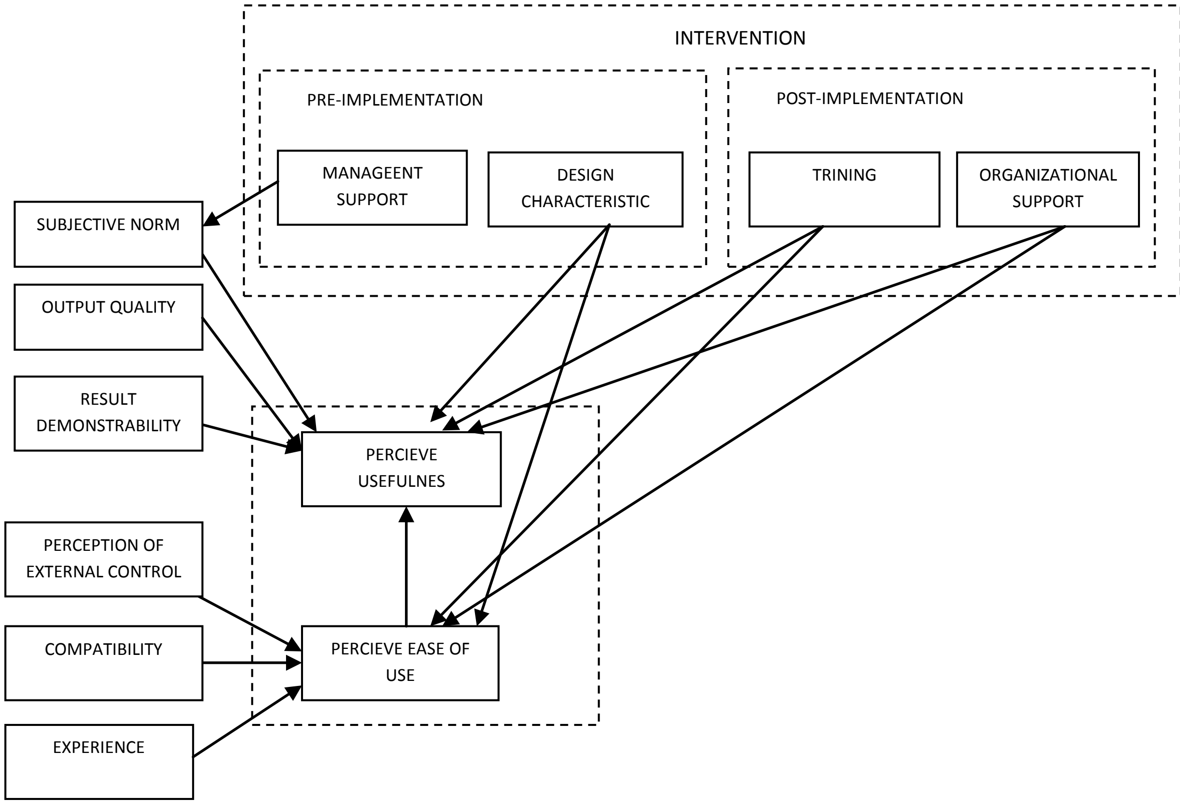

Fig. 3: TAM BPS Statistics Indonesia

The constructs of TAM BPS are subjective norm (SN), output quality (OQ), result demonstrability (RD, perception of external control (PEC), compatibility (COMP), experience (EXP), management support (MS), design characteristics (DC), training (TR), organizational support (OS), perceived of usefulness and perceived ease of use (PEU).

Bayesian Estimation of SEM: In Classic methodology of statistics, like as the GLS and ML, the methodology approaches are performed base on a covariance structure analysis framework in order to have analyzing the standard structural equation model. The statistical theory that associate with GLS and ML approach as well the computational algorithms are developed on the basis of the sample covariance matrix, S. Hence the estimator will heavily depend on asymptotic distribution of S, but unfortunately the real cases of data sometimes are complicated. Hence there is a strong demand of new statistical methods of handling more complex data structures. Lee (2007) refers to Berger (1985) and Condon (2003) explained that Bayesian estimation is well recognized as an attractive approach to analyze a wide variety of models.

Let M be an arbitrary SEM with a vector of unknown parameters of $\boldsymbol{\theta}$. Let $\mathbf{Y}$ be an observed data set or raw observation with a sample size n. In Bayesian approach $\boldsymbol{\theta}$ is considered to be random with a distribution, called prior distribution. Let $p(\mathbf{Y}, \boldsymbol{\theta}|\mathbf{M})$ be the probability density function of a joint distribution of $\mathbf{Y}$ and $\boldsymbol{\theta}$ under M, the behavior of θ under given data $\mathbf{Y}$ is described by the conditional distribution of $\boldsymbol{\theta}$ given $\mathbf{Y}$. This condition is called posterior distribution. Posterior distribution of $\boldsymbol{\theta}$ plays important role in the Bayesian analysis (Lee, 2007). And the Bayesian rule can be expressed with

$$\log p(\boldsymbol{\theta}|\boldsymbol{Y}, M) \quad \alpha \quad \log p(\boldsymbol{Y}|\boldsymbol{\theta}, M) + \log p(\boldsymbol{\theta}) \quad (1)$$

Prior distribution: The selection of prior distribution was base on previous research by Lee (2007). Corresponding to a measurement equation:

$$\boldsymbol{y_i} = \boldsymbol{\Lambda}\boldsymbol{\omega_i} + \boldsymbol{\varepsilon_i} \quad i = 1, \ldots, n \qquad (2)$$

where ω_i is distributed as $N(0,\Phi)$ and ε_i is distributed as $N(0,\mathbf{\Psi}_\varepsilon)$. Let Λ_k^T be *k*th row of Λ, a conjugate type prior distribution of $\mathbf{\Lambda}_k, \psi_{ek}$ will be $\psi_{ek}^{-1} \ \underline{\underline{D}}$ Gamma $[\alpha_{0ek}, \beta_{0ek}]$ and for $(\mathbf{\Lambda}_k|\boldsymbol{\psi}_{ek})$ is $(\mathbf{\Lambda}_k|\boldsymbol{\psi}_{ek})\ \underline{\underline{D}}\ N(\mathbf{\Lambda}_{0k}, \psi_{ek}\mathbf{H}_{0yk})$, where $\alpha_{0ek}, \beta_{0ek}$ and elements in Λ_{0k}, H_{0yk} are hyper parameters and $\mathbf{H}_{0yk}$ is a positive definite matrix. The conjugate prior of Φ is $\Phi^{-1}\ \underline{\underline{D}}\, W_q(\mathbf{R}_0, \rho_0)$. another conjugate prior which are employed in Bayesian analysis are:
$\alpha = \alpha\ \underline{\underline{D}}\ N(0,\mathbf{I})$, $\mathbf{\Lambda}_k = \Lambda_k\ \underline{\underline{D}}\ N(\mathbf{\Lambda}_{0k}, \psi_{ek}\mathbf{I})$, and $\mathbf{\Gamma} = \mathbf{\Gamma}\ \underline{\underline{D}}\ N(\mathbf{\Gamma}_0, \psi_\delta \mathbf{I})$, where $\mathbf{I}$ is identify matrices.

Posterior Analysis: Theoretically the mean of posterior distribution $(\boldsymbol{\theta}|\mathbf{Y})$ could be obtained via integration. But most of situation the integrations does not have a closed form. Lee (2007) employed the idea of data augmentation which proposed by Taner and Wong (1987). The idea of data augmentation is treat the latent quantities as hypothetical missing data and then augment the observed data with latent quantities so the posterior distribution will easily to analyze base on complete data set.

The idea of data augmentation was influenced by latent variables. For complex model, the posterior density $p(\boldsymbol{\theta}|\mathbf{y})$ was performed with $p(\boldsymbol{\theta},\mathbf{\Omega}|\mathbf{Y})$, where $\mathbf{\Omega}$ is as set of latent variables of model. With complete data set$(\mathbf{\Omega},\mathbf{Y})$, the conditional distribution which is involved in posterior analysis is $p(\mathbf{\Omega}|\boldsymbol{\theta},\mathbf{Y})$. MCMC was implemeted to simulate the obervation of $p(\boldsymbol{\theta},\mathbf{\Omega}|\mathbf{Y})$ and built the iterations for describe the probability density function of $p(\boldsymbol{\theta},\mathbf{\Omega}|\mathbf{Y})$ and $p(\mathbf{\Omega}|\boldsymbol{\theta},\mathbf{Y})$.

Samples and measure: We measured the indicators of latent variables using Likert scale in five scales ranging from "strongly agree" to "strongly disagree". After test the questioners, for the first model we have 32 indicators for 9 exogenous variables and 3 endogenous variables.

The samples of this research were taken from one of population census central data processing in Indonesia. The respondents are supervisors and administrators who understand the whole of data processing. Most of them have experience in population census central data processing in 2000 and they joined in population census central data processing training 2010. We spread 40 questioners and collected 37 questioners without missing data.

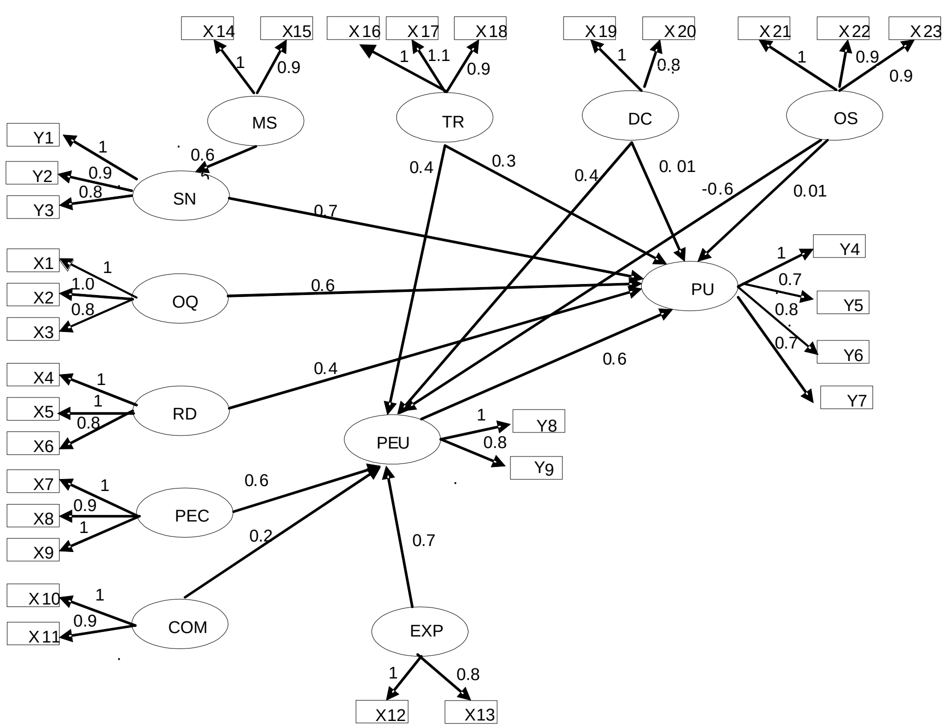

Fig.4: Structure of SEM TAM BPS Indonesia

Reliability and validity analysis: The reliability and validity of the measurement instrument was examined using Cronbach's alpha and product moment. The range of Cronbach alpha is 0.51 to 0.89. the lowest score of Cronbach alpha is Experience (0.511). Venkatesh and Davis (2000) did not measure directly the construct Experience. They analyze the influence of Experience based on Hartwick and Barki (1994) that found although subjective norm had significant effect on intentions prior to system development, the effect became non significant three months after the implementation.

Bayesian Estimation via WINBugs

WinBUGS software was employed to examine the estimated parameter in models. The measurements equations which used in conducting Bayesian analysis of SEMs are define by thirty two manifest variables in $y_i = (y_{i1} \dots y_{i32})^T$ and twelve latent variables in $\omega_i = (\eta_1 \dots \eta_3, \xi_1 \dots \xi_9)^T$ as follow:

$y_{i1} = \alpha_1 + \xi_{i1} + \varepsilon_{i1},\ y_{ik} = \alpha_k + \lambda_{k1}\xi_{i1} + \varepsilon_{ik}\quad k = 2,3$

$y_{i4} = \alpha_4 + \xi_{i2} + \varepsilon_{i4},\ y_{ik} = \alpha_k + \lambda_{k2}\xi_{i2} + \varepsilon_{ik}\quad k = 5,6$

$y_{i7} = \alpha_7 + \xi_{i3} + \varepsilon_{i7},\ y_{ik} = \alpha_k + \lambda_{k3}\xi_{i3} + \varepsilon_{ik}\quad k = 8,9$

$y_{i10} = \alpha_{10} + \xi_{i4} + \varepsilon_{i10}, y_{ik} = \alpha_k + \lambda_{k4}\xi_{i4} + \varepsilon_{ik}\quad k = 11$

$y_{i12} = \alpha_{12} + \xi_{i5} + \varepsilon_{i12}, y_{ik} = \alpha_k + \lambda_{k5}\xi_{i5} + \varepsilon_{ik}\quad k = 13$

$y_{i14} = \alpha_{14} + \xi_{i6} + \varepsilon_{i14}, y_{ik} = \alpha_k + \lambda_{k6}\xi_{i6} + \varepsilon_{ik}\quad k = 15,16$

$y_{i17} = \alpha_{16} + \xi_{i7} + \varepsilon_{i16}, y_{ik} = \alpha_k + \lambda_{k7}\xi_{i7} + \varepsilon_{ik}\quad k = 18$

$y_{i19} = \alpha_{18} + \xi_{i8} + \varepsilon_{i18}, y_{ik} = \alpha_k + \lambda_{k8}\xi_{i8} + \varepsilon_{ik}\quad k = 20,21$

$y_{i22} = \alpha_{20} + \xi_{i9} + \varepsilon_{i20}, y_{ik} = \alpha_k + \lambda_{k9}\xi_{i9} + \varepsilon_{ik}\quad k = 23$

$y_{i24} = \alpha_{23} + \eta_{i1} + \varepsilon_{i23}, y_{ik} = \alpha_k + \lambda_{k10}\eta_{i1} + \varepsilon_{ik}\quad k = 25,26$

$y_{i27} = \alpha_{27} + \eta_{i2} + \varepsilon_{i27}, y_{ik} = \alpha_k + \lambda_{k11}\eta_{i2} + \varepsilon_{ik}\quad k = 28$

$y_{i29} = \alpha_{29} + \eta_{i3} + \varepsilon_{i29}, y_{ik} = \alpha_k + \lambda_{k12}\eta_{i3} + \varepsilon_{ik}\quad k = 30,31,32$

Where $\varepsilon_{ik}, k = 1 \dots p$ is independently distributed as $N(0, \psi_{ek})$ and independent with ω_i. The structural equation as define:

$\eta_1 = \gamma_{12}\xi_9 + \delta_3$

$\eta_2 = \gamma_3\xi_3 + \gamma_4\xi_4 + \gamma_5\xi_5 + \gamma_7\xi_6 + \gamma_8\xi_7 + \gamma_{810}\xi_8 + \delta_2$

$\eta_3 = \gamma_1\xi_1 + \gamma_2\xi_2 + \gamma_6\xi_6 + \gamma_9\xi_7 + \gamma_{11}\xi_8 + \beta_1\eta_3 + \beta_2\eta_2 + \delta_1$

Where $\xi_i = (\xi_{i1} \dots \xi_{i9})^T$ is distributed as $N(0, \boldsymbol{\Phi})$ and δ_i distributed as $N(0, \psi_{\boldsymbol{\delta}})$, ξ_i and δ_i are independent.

The measurement equation is formulated as $y_i \underline{\underline{D}} N(\mu_{ik}, \psi_k)$ and structural equation is formulated by defining the conditional distribution η_i given $\boldsymbol{\xi_i}$ as $N(v_i, \psi_\delta)$ where v_i is appropriate with $v_i = \boldsymbol{\Gamma\xi}_i$. The conjugate priors which are used in this Bayesian estimation based on Lee (2007) :

$\Phi^{-1} \underline{\underline{D}}\ W\ \ (R[1{:}9,1{:}9],30)$

$$\Psi_{\mathrm{ek}}^{-1}\ \underline{\underline{D}}\ Gamma\ (10,8) \tag{4}$$

$$\Psi_{\delta}^{-1}\ \underline{\underline{D}}\ Gamma\ (10,8) \tag{5}$$

$\boldsymbol{\Lambda}_{0k}$ and $\boldsymbol{\Gamma}_0$ are taken 0.8 and 0.5, the free parameter $\alpha_1 = \cdots = \alpha_{31} = 0.0$

The estimation was performed by MCMC simulation using Gibbs Sampler method. The iteration was completed in 10.000 times.

RESULTS

Bayesian analysis via WinBUGS obtained estimate parameters: γ, ψ, ϕ. The range of λ is 0.737 to 1.11 . It shows that the coefficients relation are strong enough to latent variables.

The significant relations between latent variables are (i) management support to subjective norm, (ii) subjective norm to perceived of usefulness, (iii) perception of external control to perceived ease of use.

There are eleven relations between latent variables are not significant. They are (i) perceived ease of use to perceived of usefulness (ii) output quality to perceived of usefulness (iii) result demonstrability to perceived of usefulness (iv) compatibility to perceived ease of use (v) experience to perceived ease of use, (vi) training to perceived ease of use (vii) training to perceived of usefulness (viii) design characteristic to perceived ease of use (ix) design characteristic to perceived of usefulness (x) organizational support to perceived ease of use and (xi) organizational support to perceived usefulness. The residual analysis was performed to identify the goodness of the models. The mean of residual of model are near to 0.

DISCUSSION

For TAM BPS, the idea of future research of Venkatesh and Bala (2008) which involve the organizations interventions via pre-implementations and post-implementations will not always gives the significant relation to the user acceptance. Specially for relation between training and perceived of usefulness, characteristic to perceived of usefulness, perception of external control to perceived ease of use, compatibility to perceived ease of use, and experience to perceived ease of use. The strongest relation is subjective norm to perceived of usefulness. The organizations should performed the interventions base on the characteristics of users and the conditions of data processing process i.e. the procedures of data processing, the buildings etc.

CONCLUSION

The user acceptance of computer technology in population census data processing needs more adjustments and innovations specially for compatibility and perception of external control in order to get perceived ease of use. Experience has no significant relation to perceived ease of use, it means that the increasing experience of users does not make the increasing of user's perception of ease of use.

Organizational intervention with training and design characteristic has no significant relation to perceived of usefulness. it is needed to develop the innovation of design characteristics of the system and evaluation of the training.

The organizational intervention should be detail and more technical actions than procedural actions.

The limitations of TAM studies comes from the data conditions, i.e. small sample size which is difficult to analyze by SEM standard will be handled by Bayesian analysis. In Bayesian analysis, the estimation base on raw data and directly to latent variables will achieve the direct interpretation of the data. Data augmentation which is employed in the posterior analysis developed the analysis based on complete data set. The MCMC with Gibbs Sampler algorithm make the posterior analysis is simpler than the classical methodology with complex integrations.

Residual analysis obtained that the residual close to zero. It means that the goodness of fit of model is good enough.

REFERENCES

Alrafi, A., 2005. Technology Accceptance Model. pp. 1-12. (August 20 2010, from World Wide Web: http://www.mendeley.com/research/technology-acceptance-model-and-elearning)

Barret, P., 2007. Structural Equation Modelling : Adjudging Model Fit. *Personality and Individual Differences, 42*: 815-842.

Bollen, K., 1989. *Structural Equation with Latent Variable.* New York: John Wiley and Sons.

Chang, H., 2010. Task-Technology Fit and User Acceptance of Online Auction. *Human-Computer Studies, 68*: 69-89.

Chang, H., and Yang, H.M., 2010. Public Acceptance of The-Cyber Taipe Initiative and Cyber-Government Services. *Habitat International, 34*: 210-218.

Davis, F. D., 1989a. Percieved Usefulness, Percieved Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly, 13*: 319.

Davis, F. D. (1989b). User Acceptance of Computer Technology: A Comparison of Two Theoritical Models. *Management Science, 35*, 982-1003.

Davis, F., and Venkatesh, V. (1996). A Critical Assessment of Potential Measurement Biases in The Technology Acceptance Model: Three Experiment. *Human Computer Studies, 45*, 19-45.

Deng, X. D., 2005. A Muti-Group Analysis of Structural Invariance: An Ilustration Using The Technology Acceptance Model. *Information and Management, 42*: 745-759.

Dijk, J. P., Peters, O, and Ebbers, W., 2008. Explaining The Acceptance and Use of Government Internet Services: A Multivariate Analysis of 2006 Survey Data in The Netherlands. *Government Information Quarterly, 25*: 379-399.

Dishaw, M.T., and Strong D.M., 1999. Extending The Technology Acceptance Model with Task-Technology Fit Cunstructs. *Information and Management, 36*: 9-21.

Dunson, D. P., 2005. *Bayesian Structural Equation Modeling.* Statistical and Applied Mathematical Sciences Institute.

Engel, K. M., 2003. Evaluating the Fit of Structural Equation Model: Test of Significance and

Descriptive Goodness-of-Fit Measures. *Methods of Psycological Research, 8*: 23-74.

Gelman, Carlin, Rubin, and Stern., 2004. *Bayesian Data Analysis.* New York: Chapman and Hall.

Greenfield, G., and Rohde, F., 2009. Technology Acceptance: Not all organizations or workers may be the same. *International Journal of Accounting Information System, 10*: 263-272.

Gujarati, D., 2003. *Basic Econometrics.* Boston: McGraw-Hill Higher Education.

Gyampah, K.A., and Salam, A.F., 2004. An Extention of Technology Acceptance Model in An ERP Implementation Environmrent. *Information and Management, 41*: 731-745.

Haenlein, M., and Kaplan, A., 2004. A Beginners to Partial Least Square Analysis. *Understanding Statistics, 3(4)*: 283-297.

Hair, J,F., Black, W.C., Babin, B.J., Anderson, R.E., and Tatham, R.L., 2006. *Multivariate Data Analysis.* New Jersey: Pearson Education, Inc.

Hayduk, L., Cumming, G., Boadu, K.,Robinson, H.P., and Bouliane, S., 2007. Testing! Testing! one, two three-Testing The Theory in Structural Equation Models! *Personality and Individual Differences, 42*: 841-850.

Herman, K., and Dijk, K.V. (2002). *On Bayesian Structural Inference in a simultaneous Equation Model.* Econometric Institute Report EI.

Hu P.J., Clark, TH.K., and Ma, W., 2003. Examining Technology Acceptance by School Teachers: A Longitudinal Study. *Information and Management, 41*: 227-241.

Hu P.J., Clark, TH.K., and Ma, W., 2003. Examining Technology Acceptance by School Teachers: A Longitudinal Study. *Information and Management, 41*: 227-241.

Hung, S.Y., Chang, C.M., and Yu, T,J., 2006. Determinants of User Acceptance of The E-Government Services: The Case of Online Tax Filling and Payment System. *Government and Information Quarterly, 23*: 97-122.

Igbaria, M, 1993. User Acceptance of Microcomputer Technology: An Empirical Test. *Journal of Management Science, 21*: 73-90.

Im, I. K., Kim, Y. and Han, H.J., 2008. The Effect of Percieved Risk and Technology Type on User's Technology of Acceptance. *Information and Technology , 45*:1-9.

Iriawan, N., and Septin, P.A., 2006. *Statistics Data Processing with Minitab 14.* Yogyakarta: Andi Offset Indonesia.

Jiang X., and Mahadevan, S., 2009. Bayesian Structural Equation Modeling Method for Hierarchical Model Validation. *Realibility Engineering and System Safety, 94*: 796-809.

Jones, A. B., 2006. The Mediation of External Variables in The Technology Acceptance Model. *Information and Management System, 43*: 706-717.

Kass, R., and Raftery, A.E., 1995. Bayes Factor. *American Statistical Association , 90*: 430.

Kelava, A., and Brandt, H., 2009. Estimation of Nonlinier latent Structural Equation Models Using The Extended Unconstrained Approach. *Review of Psychology, 16*: 123-131.

Kenny, D., and Judd, C.M., 1984. Estimating The Nonlinier and Interactive Effects of Latent Variables. *Psychological Bulletin, 96*: 201-210.

King, W., and He, J., 2006. A Meta Analysis of The Technology Acceptance Model. *Information and Management, 43*: 740-755.

Klopping I.M., and McKinney, E., 2004. Extending The Technology Acceptance Model and Task-Technolohy Fit Model to Consumer E-Commerce. *Information and Technology, Learning and Performance, 22*:35-48.

Lederer, A., Maupin, D.J., Sena, M.P., and Zhuang, Y., 2000. The Technology Acceptance Model And The World Wide Web. *Decision Support System, 29*: 269-282.

Lee, S., 2007. Structural Equation Modeling A Bayesian Approach. England: John Wiley and Sons Ltd

Lee, S., and Song, S. Y., 2003. Maximum Likelihood Estimation and Model Comparison of Nonlinier Structural Equation Models with Continous and Polytomous Variables. *Computational Statistics and Data Analysis, 44*: 125-142.

Lee, S., and Song, S. Y., 2008. On Bayesian Estimation and Model Comparison of an Integrated Structural

Equation Model. *Computational Statistics and Data Analysis, 52*: 4814-4827.

Lee, Y., Kozar, K.A., and Larsen, K.R.T., 2003. The Technology Acceptance Model Past, Present and Future. *Communications of the Association for Information System, 12*: 752-780.

Lee, Y.C., Yoon, J.O., and Lee, I., 2009. Learners' Acceptance of E-Learning in South Korea: Theories and Result. *Computers and Educations, 53*: 1320-1329.

Lee, Y.C., Yoon, J.O., and Lee, I., 2009. Learners' Acceptance of E-Learning in South Korea: Theories and Result. *Computers and Educations, 53*: 1320-1329.

Legris, P. I., 2003. Why Do People Use Information Technology? A Critical Review of The Technology Acceptance Model. *Information and Management, 40*: 191-204.

Maholtra, Y., and Galetta, D.F., 1999. Extending the Technology Acceptance Model to Account for Social Influences: Theoritical Bases an Empirical Validation. *Proceedings of The 32nd Hawaii International Conference on System Science 1999*, (pp. 1-14). Hawaii.

Marcoulides, G. A, Chin,W.W., and Saunders, C., 2009. A Critical Look at Partial Least Square Modeling. *MIS Quarterly, 33*: 171-175.

Maruyama, G., 1997. *Basic of Structural Equation Modelling.* London: Sage.

Moosbrugger H., Engel S.K., Klein A., and Kelava A., 2010. Testing Multiple Nonlinier Effect in Structural Eqution Modelling: A Comparison of Alternative Estimation Approach. In T. Teo, and M. Khine, *Structural Equation Modelling in Educational Research: Concept and Application* (pp. 1-34). Rotterdam: NL:Sense Publisher.

Muthen, B., 2002. Beyond SEM: General Laten Variable Modelling. *Behaviormetrika, 29*: 81-117.

Nan, Z., and Hua, G. X., 2008. IDT-TAM integrated model for IT adoption. *Tsinghua Science and Technology, 27(9)*.

Nan, Z., Xun-Hua, G., and Qing, C.G., 2007. Extended Information Technology Initial Acceptance Model and Its Empirical Test. *System Enginering-Theory and Practice , 27*: 123-130.

Penny, W., Stephan, K.E., Mechelli, A., and Friston, K.J., 2004. Modelling Functional Integration: A Comparison of Structural Equation and Dynamic Causal Model. *NeuroImage, 23*: 264-274.

Raykov, T., Marcoulides,G.A., 2006. *A First Course in Structural Equation Modelling.* New Jersey: Lawrence Erlbaum Associate, Inc.

Roberts, P., and Handerson, R., 2000. Information Technology Acceptance in A Sample of Government Employees: A Test of The Technology Acceptance Model. *Interacting with Computers, 12*: 427-443.

Roca, C.J., Chiu, C.M., and Martinez, F.J., 2006. Understanding E-Learning Continuance Intention: An Extention of The Technology Acceptance Model. *Human- Computers* Studies, *64*: 683-696.

Suhartono, 2009. *Statistics Data Analysis with R.* Yogyakarta: Graha Ilmu Indonesia.

Schepers, J., and Wetzel, M., 2007. A Meta-Analysis of The Technology Acceptance Model: Investigating Subjective Norm and Moderating Effects. *Information and Management , 44*: 90-103.

Sun, H., and Zhang, P., 2006. The Role of Moderating Factors in User Technology Acceptance. *International Journal of Human-Computer Studies, 64*: 53-78.

Teo, T., Lee, B.C, Chai, C.S, and Wong, S.L., 2009. Assesing The Intention to Use Technology Among Pre-Service Teachers in Singapore and Malaysia: A Multigroup Invariance Analysis. *Computers and Education, 53*: 1000-1009.

Trkman, P., and Turk, T., 2009. A Conceptual Model for The Development of Broadband and E-Government. *Government Information Quarterly, 26*: 416-424.

Verdegem, P., and Varleye, G., 2009. User-Centered E-Government in Practice : A Comprehensive Model for Measuring User Satisfaction. *Government Information Quarterly, 26*: 487-497.

Venkatesh, V., and Davis, F., 2000. A Theoritical Extention of The Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science, 46*: 186-204.

Venkatesh, V., and Bala, H., 2008. Technology Acceptance Model 3 and Research Agenda on Intervention . *Decision Science, 39*: 273-315.

Wall, M., 2007. *Maximum Likelihood and Bayesian Estimation for Nonlinier Structural Equation Models.* Division of Biostatistics School of Public Health University of Minnesota.

Yuliar, S., and Anggorowati, 2006. Governance Teknology in Society: An Actor-Network Apporach. *Jurnal Sosioteknologi Fakultas Seni Rupa dan Desain ITB Indonesia*.

Zellner, A., 1995. Bayesian and Non-Bayesian Approach to Statistical Inference and decision making. *Journal of Computational and Applied Mathematics, 64*: 3-10.

Zellner, A., 1988. Bayesian Specification Analysis and Estimation of Simultaneous Equation Models Using Monte Carlo Methods. *Journal of Econometrics, 38*: 39-72.

Zellner, A., 1998. The Finite Sample Properties of Simultaneous Equation Estimates and Estimators Bayesian and Non-Bayesian Approach. *Journal of Econometrics, 83*: 185-212.