Restructuring and Expanding Technology Acceptance Model 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 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 study 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. **Results:** 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: Information Technology (IT), Technology Acceptance Model (TAM), Structural Equation Model (SEM), Bayesian

INTRODUCTION

Information Technology (IT) is 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 (Zhang *et al.*, 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 and He, 2006). As a theory, like an organic being, TAM has ceaselessly evolved (Lee *et al.*, 2003).

Some researchers have expanded to find the progress of TAM (Samah *et al.*, 2011; Mohd *et al.*, 2011). 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 108 leading journals, show the most common problems which became limitation in TAM researches can be grouped in some

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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 small sample size. In addition some specific 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*. (2008), mention that 161 samples are 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.

The common statistical methodologies of TAM analysis are (1) SEM: Im *et al*. (2008); Teo *et al*. (2009); Hung *et al*. (2006) (2) Partial Least Square (PLS): Zhang *et al*. (2007) (3) Confirmatory Factor Analysis(CFA): Roca *et al*. (2006); Teo *et al*., (2009) (4) Regression Analysis: Lee *et al*. (2009) (5) Path Analysis: Dishaw and Strong (1999) (6) Multivariate Analysis of Variance (Manova): Greenfield 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. Verdegem and Varleye (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 as 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. There are more comparative studies of Bayesian method (Ahmed *et al*., 2010).

This study develop 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) using Bayesian approach.

MATERIALS AND METHODS

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) and Davis (1989) introduced TAM as a model that explained how users come to accept and use a technology. The aim of TAM is providing an explanation the determinants of computer acceptance

(Maholtra and Galetta, 1999). A Meta analysis of TAM 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 *et al.*, 2003).

Figure 1 shows the structure of original TAM. 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). Perceived Usefulness define the extent to which a persons believes that using the system will enhance his or her job performance and percieved ease of use define as the extent to which a person believes that using the system will be free of effort. Percieved usefulness is also influenced by percieved ease of use because other thing being equal, the easier the system is to use, the more usefull it can be. Consider to many empirical tests of TAM percieved usefulness has consistently been a strong determinant of usage intentions (Venkatesh and Davis, 2000).

The chronological progress of TAM across four separate periods was presented by Lee *et al.* (2003). This period since 1986-2003. During 1986-1995 TAM was presented by Hyndman and Davis (1992). After the introduction and validation period, TAM came to the extending period in 1994-2003. The elaboration period start in 2000 by Davis and Venkatesh (1996) then continued by Venkatesh and Bala (2008).

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 and Davis, 2000). TAM3 present a complete network the determinants of individual's IT adoption and use. The new relationship that was posited 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 represents a set of organizational activities that take place during system development and deployment periods. It can potentially lead the greater acceptance of a system. These 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.
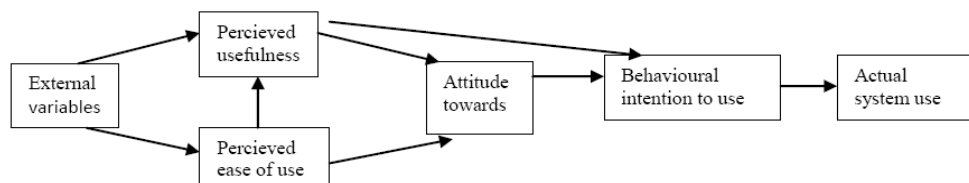

Fig. 1: Original technology acceptance model

One phase of population census process which needs support by computer is data processing. Data processing will transform the textual data (in questioner) to digital data (image). In order to obtain information's, this digital data will be put in to another process. 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 for 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.

Population 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 manually written (handwriting) in questionnaire by official.

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

Figure 2 shows the work flow of population census data processing. The computerized system start from the document scan process. In this stage, the textual data from questionare was captured and transformed to image file. Classification step is a process to clasify the images file from a block census to each group. Recognation is the process when each of the characters in image file was fit to the dictionary of the system. The correction and completion process need users (operator) to perform the process. In this stage each characters and image which is under the threshold value will be evaluated. Document review was employed to check

the precision of image file thus the character could be captured properly. Quality control was taken in every step and handle the quality of image file.

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 ease of use and perceived of usefulness of the new system.

Figure 3 shows the structure of TAM BPS Statistics Indonesia. This model propose the user acceptance of population census data processing system. The hypothesis of the model was investigated base on future research of Venkatesh and Bala (2008). 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). The goal of this research was to examine the influence of organization intervention through pre-implementation and post-implementation in mandatory environment.

Bayesian estimation of SEM: In Classic methodology of statistics, for instance the GLS and ML, the methodology approach 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. Hence the estimator will heavily depend on asymptotic distribution of 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.

Let M be an arbitrary SEM with a vector of unknown parameters of θ. Let Y be an observed data set or raw observation with a sample size n. In Bayesian approach θ is considered to be random with a distribution, called prior distribution. Let $P(Y,\theta|M)$ be the probability density function of a joint distribution of Y and θ under, the behavior of under given data Y is described by the conditional distribution of θ given Y. This condition is called posterior distribution. Posterior distribution of θ plays important role in the Bayesian analysis (Lee, 2007). And the Bayesian rule can be expressed with Eq. 1:

$$\log p(\theta \mid Y, M) \alpha \log p(Y \mid \theta, M) + \log(\theta) \qquad (1)$$
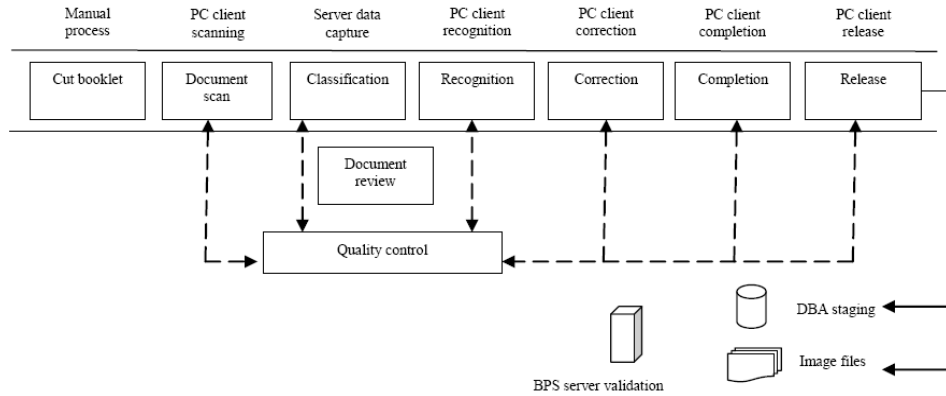
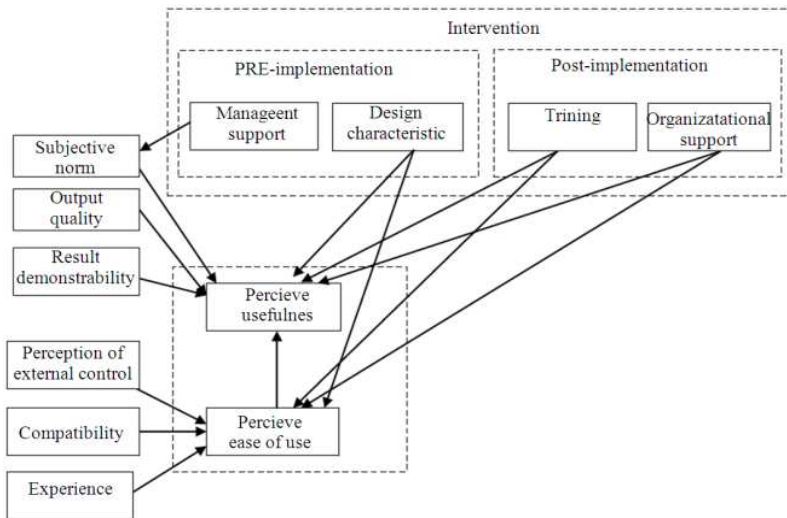Fig. 2: Work flow of population census data processing

Fig. 3: TAM BPS Statistics Indonesia

Prior distribution: The selection of prior distribution was base on previous research by Lee (2007). Corresponding to a measurement Eq. 2:

$$y_i = \Lambda_{\omega i} + \varepsilon_i \quad i = 1, \ldots, n \qquad (2)$$

where, ωi is distributed as $N(0, \Phi)$ and is distributed as $N(0, \psi_\varepsilon)$. Let Λ_K^T be kth row of Λ, a conjugate type prior distribution of Λ_K, ψ_{ek} will be $\psi_{ek}^{-1} \underline{D}$ Gamma $[\alpha_{0ek}, \beta_{0ek}]$ and for $(\Lambda_K | \psi_{ek})$ is $(\Lambda_K | \psi_{ek}) \underline{D} N(\Lambda_{0K}, \psi_{ek} H_{0yk})$, where $\alpha_{0ek}, \beta_{0ek}$ and elements in Λ_{0K}, H_{0yk} are hyper parameters and H_{0yk} is a positive definite matrix. The conjugate prior of Φ is $\Phi^{-1} \underline{D} W_q (R_0, P_0)$ another

conjugate prior which are employed in Bayesian analysis are: $\alpha = \alpha \underline{D} N(0,1)$, $\Lambda_K = \Lambda_K \underline{D}$ and $N(\Lambda_{0K}, \psi_{ek} I)$ and $\Gamma = \Gamma \underline{D} N(\Gamma_0, \Psi_\delta I)$, where I is identify matrices.

Posterior Analysis: Theoretically the mean of posterior distribution $(\theta | Y)$ 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. 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 $\rho\ (\theta\ |\ y)$ was performed with $\rho\ (\theta,\ \Omega|Y)$, where Ω is as setof latent variables of model. With complete data set $(\Omega,\ Y)$, the conditional distribution which is involved in posterior analysis is $\rho\ (\theta\ |\Omega,\ Y)$. MCMC was implemeted to simulate the obervation of and built the iterations for describe the probability density function of $\rho\ (\theta\ \Omega,\ Y)$ and $\rho\ (\theta|\Omega,\ Y)$.

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.

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. that 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 $yi = (y_{ik} \ldots y_{i32})$ and twelve latent variables in $\omega_I = (\eta_1 \ldots \eta_3, \xi_1 \ldots \xi_9)^T$ in as follow:

$$y_{i1} = \alpha 1 + \xi_{i1} + \varepsilon_{i1}\ , \alpha_\kappa + \lambda_{\kappa 1}\xi_{i1} + \varepsilon_{i\kappa}\kappa = 2,3$$

$$y_{i4} = \alpha_4 + \xi_{i2} + \varepsilon_{i4}\ , y_{i\kappa} = \alpha_\kappa + \lambda_{\kappa 2}\xi_{i2} + \varepsilon_{i\kappa}\kappa = 5,6$$

$$y_{i7} = \alpha_7 + \xi_{i3} + \varepsilon_{i7}\ , y_{i\kappa} = \alpha_\kappa + \lambda_{\kappa 3}\xi_{i3} + \varepsilon_{i\kappa}\kappa = 8,9$$

$$y_{i10} = \alpha_{10} + \xi_{i4} + \varepsilon_{i10}\ , y_{i\kappa} = \alpha_\kappa + \lambda_{\kappa 4}\xi_{i4} + \varepsilon_{i\kappa}\kappa = 11$$

$$y_{i12} = \alpha_{12} + \xi_{i5} + \varepsilon_{i12}\ , y_{i\kappa} = \alpha_\kappa + \lambda_{\kappa 5}\xi_{i5} + \varepsilon_{i\kappa}\kappa = 13$$

$$y_{i14} = \alpha_{14} + \xi_{i6} + \varepsilon_{i14}\ , y_{i\kappa} = \alpha_\kappa + \lambda_{\kappa 6}\xi_{i6} + \varepsilon_{i\kappa}\kappa = 15\ 16$$

$$y_{i17} = \alpha_{16} + \xi_{i7} + \varepsilon_{16}\ , y_{i k} = \alpha_\kappa + \lambda_{\kappa 7}\xi_{i7} + \varepsilon_{i\kappa}\kappa = 18$$

$$y_{i17} = \alpha_{16} + \xi_{i7} + \varepsilon_{i16}\ , y_{i\kappa} = \alpha_\kappa + \lambda_{\kappa 8}\xi_{i8} + \varepsilon_{i\kappa}\kappa = 20,21$$

$$y_{i22} = \alpha_{20} + \xi_{i9} + \varepsilon_{i18}\ , y_{i\kappa} = \alpha j + \lambda_{\kappa 9}\xi_{i9} + \varepsilon_{i\kappa}\kappa = 23$$

$$y_{i24} = \alpha_{23} + \eta_{i1} + \varepsilon_{i23}\ , y_{i\kappa} = \alpha_\kappa + \lambda_{\kappa 10}\eta_{i1} + \varepsilon_{i\kappa}\kappa = 25,26$$

$$y_{i27} = \alpha_{27} + \eta_{i2} + \varepsilon_{i27}\ , y_{i\kappa} = \alpha_\kappa + \lambda_{\kappa 11}\eta_{i2} + \varepsilon_{i\kappa}\kappa = 28$$

$$y_{i29} = \alpha_{29} + \eta_{i3} + \varepsilon_{i29}\ , y_{ik} = \alpha_\kappa \lambda_{\kappa 12}\eta_{i3} + \varepsilon_{i\kappa}\kappa = 30,31,32$$

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

$$\eta_1 = \Upsilon_{12}\ \xi_9 + \delta_3$$
$$\eta_2 = \gamma_3\xi_3 + \gamma_4\xi_4 + \gamma_5\xi_5 + \gamma_7\xi_6 + \gamma_8\xi_7 + \gamma_{10}\xi_8 + \delta_2$$
$$\eta_3 = \gamma_1\xi_1 + \gamma_2\xi_2 + \gamma_6\xi_6 + \gamma_9\xi_7 + \gamma_{11}\xi_8 + \beta_1\eta_3 + \beta_2\eta_2 + \delta_1$$

where, $\xi_i = (\xi_{i1} \ldots \xi_{i9})^T$ is distributed N $(0,\Phi)$ as δ_i and distributed as $N(0,\Psi_\delta)$, ξ_i and δ_i are independent.

The measurement equation is formulated as yi D (μ_{ik},Ψ_k)N and structural equation is formulated by defining the conditional distribution η_i given ξ_i as N (ν_i, ψ_δ) where ν_i is appropriate with $\nu_i = \Gamma\xi_i$ The conjugate priors which are used in this Bayesian estimation based on Lee (2007) Eq. 3-5:

$$\phi^{-1}\underline{D}W(R[1:9,1],30) \tag{3}$$

$$\psi_{ek}^{-1}\underline{D}gamma(10,8) \tag{4}$$

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

$\wedge_{0k}$ and Γ_0 are taken 0.8 and 0.5, the free parameter $\alpha_1 = \ldots = \alpha_{31} = 0.0$:

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

RESULTS

Figure 4 shows the result of Bayesian analysis via Win BUGS and obtained estimate parameters γ, ψ, ϕ.The range of λ is 0.737-1. 11 It shows that the coefficients relation is strong enough to latent variables.

The significant relations between latent variables are (i) management support to subjective norm, (ii) subjective norm to perceive of usefulness, (iii) erception of external control to perceived ease of use.
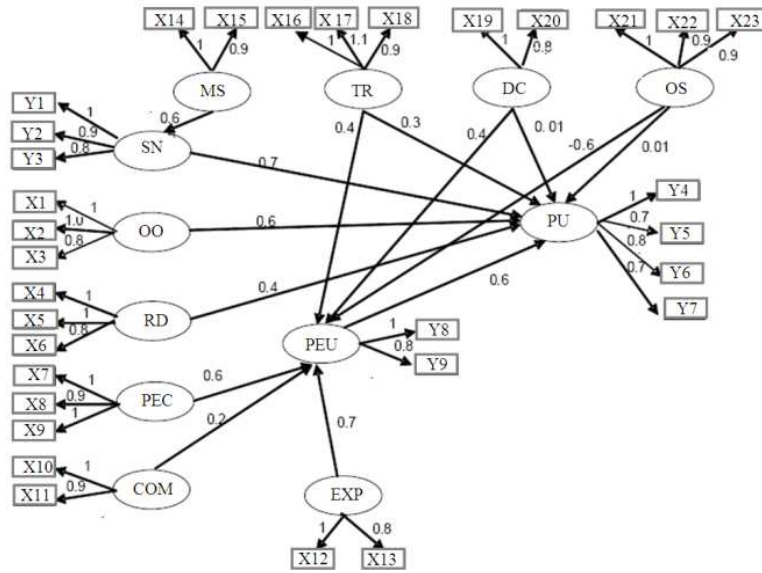
Fig. 4: Structure of SEM TAM BPS Indonesia

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 the future research 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, design 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 perceive 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 and buildings.

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 high 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 perceive of usefulness. It is needed to develop the innovation of design characteristics of the system and evaluation of the training. Theorganizational 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 method. 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 more simple than the classic methodology (for complex integrations). Additionally, the result also show that residual model are close to zero. It means that the goodness of fit of model is good enough.

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