Factors Affecting Internet Banking Pre-Usage Expectation Formation

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Abstract

Self-service technologies appeal to service providers because they can standardize service delivery, reduce labor and service costs, and reach new consumers who are unreachable through the bricks-and-mortar channels. Our focus in this paper is on Internet banking. Scholars have proposed a variety of different models to explain the factors affecting Internet banking initial use intention formation that are supported by their own data, making it difficult to compare these models systematically. We use extant literature to propose a model of factors affecting Internet banking initial use intention formation. To test our model, we applied random-effect meta-analytic structural equation modeling method to data reported in 26 primary empirical studies of Internet banking pre-usage. The results of our analysis show that the combined total effects of three dimensions of trust are more prominent than perceived usefulness and perceived ease-of-use in enticing the consumers towards initial use of the Internet banking.

1. Introduction

The world average growth rate in Internet access from 2000 to 2011 was more than 500% [29]. Increasing universal access to information and communication technology (ICT) coupled with rapid advances in technological capabilities present the global community with the potential to increase the standard of living for end-users [21]. As a case in point, self-service technologies (SSTs) (e.g., airline check-in systems, tax preparation and submission systems, automated banking machines, online investment trading systems, and Internet banking) enable consumers' use without direct interaction with, or face-to-face assistance from service provider employees. This application of ICT appeals to service providers because it can standardize service delivery, reduce labor and service costs, expand the options for delivery, and reach customers who are unreachable through other channels [21]. SSTs also appeal to consumers with benefits such as cost savings, greater control over service delivery, reduced wait times, higher perceived levels of customization, and convenient access to services without time or space constraints. Notwithstanding its advantages, many consumers with Internet access are not using SSTs. Our focus in this paper is on the initial use intention of Internet banking. A study in 2008 shows that in Canada, the world leader in Internet banking usage, one out of three Internet users were not using Internet banking [18, 19]. About half of Internet users in the Netherlands, the second most intensive user of Internet banking in the world, and more than 56% of the Internet users in the USA were not using Internet banking. This can be explained in light of diffusion of innovation theory. According to Rogers [55], information about the existence of innovations, such as Internet banking, flows through social systems where potential adopters are situated. This information is processed by potential adopters to form perceptions about the characteristics of the innovation. Such perceptions, among other contextual factors, then serve as the drivers for innovation adoption decisions [55]. Considering that SSTs, such as Internet banking, are "technological interfaces that enable customers to produce a service independent of direct service-employee involvement" [47] (p. 50), to entice usage of Internet banking, it is crucial for the service providers to know about factors that affect consumers' expectation formation towards Internet banking adoption.

Adoption of an innovation by consumers involves a process that occurs over time and consists of a series of stages, with actions and decisions occurring at each stage [31]. The question addressed in this paper is: what factors affect adoption of Internet banking at the pre-usage stage. We found 26 primary empirical studies that have proposed a variety of different models to explain the factors affecting Internet banking pre-usage expectation formation. To synthesize the literature, we use meta-analytic techniques and structural equation modeling (MASEM). MASEM refers to methods focused on contrasting and combining results from different studies, in the hope of identifying patterns among study results, sources of disagreement among those results, or other interesting relationships that may come to light in the context of multiple studies [13]. To this end, in section 2, we propose a research model pertaining to factors affecting Internet banking pre-usage expectation

formation. Next, we apply MASEM to analyze our proposed research model with data collected from 26 independent studies that constitute 6714 cases. Findings from our analyses are presented in section 4. The paper concludes with a discussion of the findings and their implications for practice and theory.

2. Theoretical Foundation

The research model underlying this study draws on the theory of diffusion of innovation [55]. Based on innovation diffusion theory, a significant outcome is an individual's decision whether to accept or reject to adopt the innovation. Three innovation characteristics – *relative advantage, complexity*, and *compatibility* – have been related consistently to adoption [2, 61]. *Relative advantage* captures the extent to which a potential adopter views the innovation as offering an advantage over previous ways of performing the same task [2]. Relative advantage is similar to the notion of usefulness in the technology acceptance model [16]. Rogers' [55] notion of *complexity*, the second innovation characteristic, is similar to ease of use construct in technology acceptance model (TAM) that pertains to the degree to which a potential adopter views usage of the target technology to be relatively free of effort [22]. Innovations that are perceived to be easier to use have a higher likelihood of being accepted and used by potential users [2].

Drawing on TAM [22], perceived usefulness and perceived ease of use expectations affect consumers' initial use intention. Furthermore, the less effort that consumers expect to invest in using the technology the more useful they perceive it to be [22]. Thus, we can postulate the following three hypotheses.

H1: Consumers' perceived usefulness of Internet banking positively affects their initial use intention of Internet banking.

H2: Consumers' perceived ease of use of Internet banking positively affects their initial use intention of Internet banking.

H3: Consumers' perceived ease of use of Internet banking positively affects their perceived usefulness of the Internet banking.

The third innovation characteristic that affects pre-usage expectations is *compatibility* [55, 61]. Compatibility is a multidimensional construct defined as the degree to which using an innovation is consistent with the existing sociocultural values and beliefs, past and present experiences, and needs of potential adopters [55]. Innovations are inherently uncertain and risky and there is no guarantee that their adoption will in fact produce the anticipated benefits [2]. Compatibility captures the degree of disruption and magnitude of change the individual is likely to

experience when using a new technology [30]. An innovation that is less compatible is more uncertain to the potential consumers [55]. Uncertainty makes consumers reluctant to engage in online exchange relationships with service providers, especially for high-involvement SSTs such as Internet banking [53]. To that end, Rogers described the innovation-diffusion process as "an uncertainty reduction process" [55] (p. 232). *Trust, personal innovativeness,* and *social influence* are considered as factors that mitigate uncertainty in the adoption of SSTs [20, 25, 43].

Trust is crucial in many of the economic activities that involve uncertainty in regard to their outcomes [25]. This is even more the case with Internet banking – a sector that consumers can perceive as being high risk [46] – because the temporal and the spatial separation between the consumers and the physical bank does not allow consumers to evaluate the transactional situation as in a face-to-face interaction with the physical bank personnel. In this paper, we use four pertinent dimensions of trust that affect consumers' intention to use SST: (i) trust in the online vendor (i.e., trust in the Internet bank), (ii) trust in the offline vendor (i.e., trust in the traditional brick-and-mortar bank), (iii) structural assurances, and (iv) consumers' propensity to trust.

(i) Trust in the Internet bank – Through the lens of social exchange theory, consumers' interactions with the Internet bank can be viewed as being composed of costs paid (i.e., risks) and rewards received (i.e., benefits of the interaction). Consumers' initial use intention of Internet banking depends on whether their perception of rewards gained exceed incurred cost of using the SST [23]. Perceived risk, the negative attribute, and perceived benefit, the positive attribute, are fundamental aspects of consumer decision-making because consumers make decisions to maximize their benefits relative to their risks [33]. However, in the Internet banking context, consumers' relative rewards/benefits cannot be guaranteed by means of any legal contract. Thus, trust in the Internet bank is essential to mitigate uncertainty to entice the consumer using it [23]. To this end, we postulate the following hypothesis.

H4: Consumers' trust in the Internet bank positively affects their initial use intention of Internet banking.

(ii) Trust in the physical bank – Because consumers do not have much experience with the Internet bank prior to initial use, they are likely to draw upon their trust in the physical bank to infer about the operations of the Internet bank [15]. Thus, having high trust in the physical bank could lead the consumer to have both a high trust in the Internet bank and a high intention to use the Internet banking. Based on this justification, we

postulate the following two hypotheses.

H5: Consumers' trust in the physical bank positively affects their initial use intention of Internet banking.

H6: Consumers' trust in the physical bank positively affects their trust in the Internet bank.

(iii) Structural Assurances – The smooth and secure processing of online transactions depends on the functioning of the hardware and software as well as on the security of the data exchange services including the cryptographic protocols that are used. Internet banks can mitigate consumers' uncertainty about the security and privacy of their technological infrastructure and services by providing structural assurances. This includes safety nets, guarantees, regulations and security recourses in place to promote a sense of security and privacy about the pertinent technological infrastructure used. Thus, lack of structural assurances increases the uncertainty about the security and privacy of online interactions and transactions with the Internet bank that hinder consumers' initial use intention [34, 40]. Moreover, consumers' trust in the Internet bank is influenced by the extent of structural assurances built into the online system [34, 46]. To this end, we postulate the following two hypotheses:

H7: Structural assurances built into the Internet bank positively affect consumers' initial use intention of Internet banking.

H8: Structural assurances built into the Internet bank positively affect consumers' trust in the Internet

banking.

(iv) Consumers' propensity to trust – This dimension of trust represents a consumer's general tendency to trust others, which is a personal trait [45]. Consumers with higher tendency to trust others are expected to develop higher trust in the Internet bank. [45]. Thus, we postulate the following hypothesis.

H9: Consumers' propensity to trust positively affects consumers' trust in the Internet bank.

Personal innovativeness represents the degree to which an individual is willing to try out a new innovation [2]. Agarwal and Prasad [2] contend that most proximate influence on an individual's cognitive interpretations of information technology is factors related to the individual. They described personal innovativeness as symbolizing the risk-taking propensity that exists in certain individuals and not in others. More innovative individuals are more active information seekers about new ideas and have the ability to cope with higher levels of uncertainty and develop more positive intentions toward innovation adoption [55]. Findings from prior research suggest that personal innovativeness positively affects perceived ease of use and usefulness of ICT innovation [43, 55]. Thus, we postulate the following hypotheses.

H10: Consumers' innovativeness positively affects their perceived ease of use of the Internet banking.

H11: Consumers' innovativeness positively affects their perceived usefulness of the Internet banking.

Social influence, which has been regarded as an
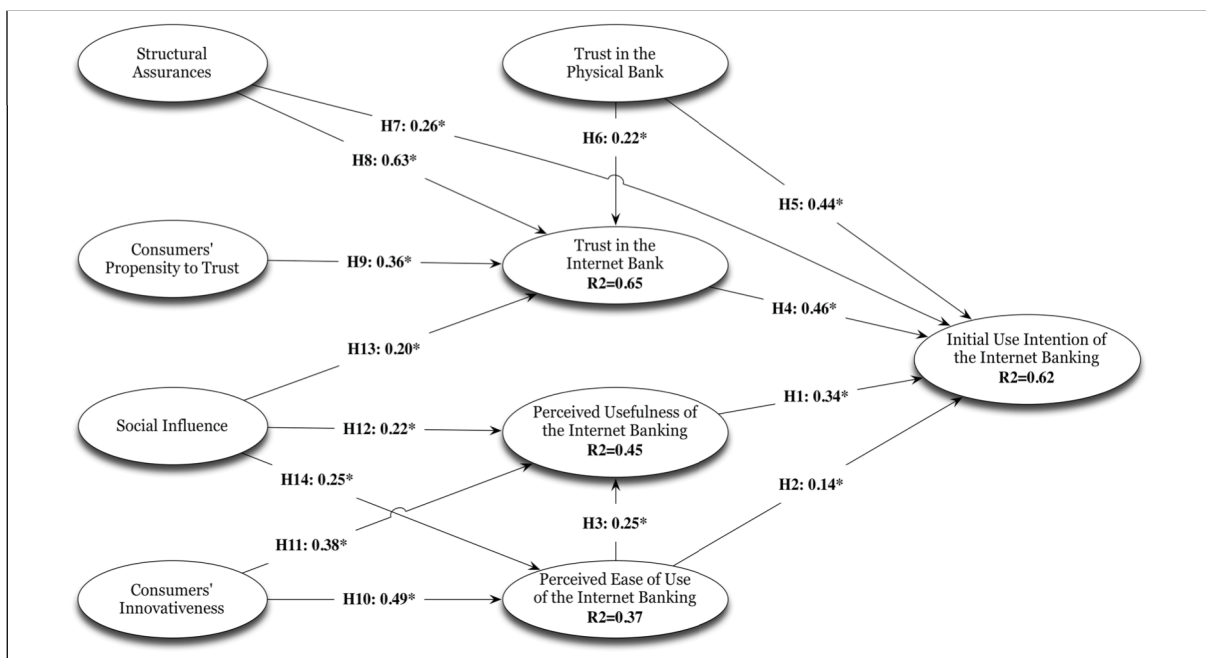
Note 1: N=6714; k=26; NS: Non-Significant; *: Significant at p<0.05
Note 2: df=12; RMSEA=0.02; CFI=0.98; TLI=0.95

Figure 1- Structural model of the proposed Initial use intention of the Internet banking

important element in innovation diffusion literature [55], also mitigates consumers' uncertainty in use of SST [43]. Social influence in this study refers to perceived influence from social networks and important others for/against a certain behavior [43]. The justification is that an innovation, such as Internet banking services, creates uncertainty about the expected outcomes for potential adopters. Since, potential adopters are generally uncomfortable with uncertainty, they tend to interact with their social network to consult on their adoption decisions [43].

TAM2 [62] shows that three mechanisms—*compliance*, *identification* and *internalization*—facilitate social influence on the adoption of ICT. *Compliance* represents a situation in which an individual performs a behavior in order to gain certain rewards or avoid punishment. *Identification* refers to an individual's belief that performing a behavior elevates his or her social status because important referents believe the behavior should be performed. *Internalization* is defined as the incorporation of referents' beliefs into one's own belief structure [62]. TAM2 posits that social influence positively influences perceived usefulness. Furthermore, there is empirical evidence that social influence positively affects trusting beliefs towards a technological innovation [41]. Based on social information processing theory and the social influence mechanisms of internalization and identification, before any direct experience of the technology (i.e., pre-usage stage), the potential adopter's perceived ease of use is affected by social influences [43]. For instance, if an Internet banking service is socially believed to be hard to learn and hard to use, it will inevitably affect a consumer's perceived ease-of-use of the service. Based on the above justifications, we postulate the following hypotheses.

H12: Social influences positively affect consumers' perceived usefulness of the Internet Banking.

H13: Social influences positively affect consumers' trust in the Internet Banking.

H14: Social influences positively affect consumers' perceived ease-of-use of the Internet Banking.

As elaborated in the next section, we subject our stated hypotheses to MASEM based on data from 26 primary empirical studies comprising 6714 cases of consumers who had access to, yet did not have actual usage experience with Internet banking.

3. Methodology

We draw on the quantitative method of meta-analytic structural equation modeling (MASEM) [11, 49] to test our stated hypotheses in this study. Using correlation matrices cumulated from existing pertinent studies, MASEM calculates the pooled correlation matrix, and applies the structural equation modeling (SEM) technique to assess a set of hypotheses in a theoretical model [49].

Application of MASEM to assess our hypotheses has several advantages over conducting a primary study:

1) Accumulation of multiple samples through MASEM increases the sample size and bolsters a model test's statistical power relative to that of single-sample studies [49]. MASEM can therefore detect valid effects that studies with modest sample sizes fail to detect [49]. By cumulating studies before model estimation, taking into account uneven sample sizes, our meta-analysis can generate more robust model estimates

2) Meta-analytical corrections for statistical artifacts, such as unreliability, improve the accuracy of parameter estimates [49].

3) A joint SEM and meta-analytic approach in MASEM embodies a more powerful test of theory than either technique might achieve alone. Neglecting interdependency among measured effects, meta-analytic estimates of individual relationships between variables imprecisely capture the unique effect size of the relationship, whereas sampling error may influence SEM estimates derived from a single sample [49]. Together, meta-analytical artifact corrections yield more credible empirical data for SEM analysis, which more accurately assesses structural parameters (given a correctly specified model) [49].

As per the following steps, we identified 365 studies related to Internet Banking Pre-Usage. We used a set of criteria, detailed below, to select a subset of these studies for inclusion in our MASEM. We subject our research model (depicted in Figure 1) to MASEM based on data from 26 pertinent empirical studies comprising 6714 cases of consumers who have access to, but have not had actual usage experience with Internet banking.

3.1. Literature search and criteria for inclusion

To identify studies that could potentially supply data to validate our research model depicted in Figure 1, we searched electronic databases (e.g., Informs, AIS, ACM, ScienceDirect, InterScience, Factiva, Gale Cengage, Palgrave Macmillan, Extenza, Metapress, Highwire Press, Sage, Emerald, IEEE), database aggregators (e.g., EBSCOhost, JSTOR, Scholar's Portal, Google Scholar), and digital theses libraries (e.g., Center for Research Libraries dissertations, EThOS, NDLTD, ProQuest, WorldCat). To that end, we used as search terms several variations of "internet banking" (i.e., "electronic banking", "online banking",

"self-served banking", "retail banking"), "adoption", "acceptance", and "usage". Bibliographies of identified studies were also scanned to locate additional studies. Because it is widely accepted that journals are more likely to publish studies with significant effect sizes, we considered conference proceedings, working papers, and dissertations in order to minimize the potential of biasing our data [49]. We also posted requests to various listservs (e.g., AOM's OCIS and IDT, AIS ISWorld,). The search initially yielded 365 studies broadly discussing Internet banking. The studies were then examined for inclusion in our data set. Not all the studies retrieved were appropriate for inclusion in the meta-analysis. Recognizing this, Rosenthal [56] recommended that researchers assess information quality in the primary studies by (i) establishing criteria for inclusion, (ii) using a multiple-rater technique to evaluate data from primary studies, and (iii) assessing inter-rater reliability [49]. To that end, we included only studies in which (1) the context was Internet banking adoption in business to customer (B2C) sector, (2) the respondents had unrestrained access to the Internet banking channel but had not used it, (3) the analysis was quantitative and provided sample sizes, reliabilities, and correlations, or sufficient data to compute these measures, (4) measurements exhibited average reliability (Cronbach's alpha) of at least 0.70 [49], and (5) measurement instruments for a given construct were consistent with the reference operationalizations. Applying these criteria resulted in inclusion of 26 primary studies in our analysis (see Table 1).

3.2. Coding of data from primary studies

To facilitate MASEM analysis, we followed the data-coding procedure specified by Cheung [11]. Accordingly, we coded a 9x9 matrix of bivariate correlations (among the nine factors in the proposed research model depicted in Figure 1) for each study based on the bivariate correlations supplied by each study. "NA" was coded for any missing pairings in the respective study and the missing data were identified for each matrix so that the missing values would not affect pooled correlations [49]. Sample sizes and measurement reliabilities were also coded for each study.

3.3. Evaluation of measurement invariability for the constructs in our research model

Table 1– The effect-sizes from the primary studies used in the estimation of hypotheses															
Studies[1]	Country[2]	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11	H12	H13	H14
[1]	JO	0.74	0.60	0.81	0.40			0.31			0.54	0.55	0.52	0.47	0.45
[3]	SA	0.78	0.73	0.77	0.67			0.32			0.73	0.73	0.30	0.28	0.31
[5]	MY		0.11	0.70											
[8]	HK			0.71											
[9]	UK	0.64	0.57	0.71				0.24					0.48		
[10]	HK	0.69	0.41	0.52									0.50		0.28
[16]	TW			0.22											
[14]	TW	0.63	0.37	0.56		0.31									
[17]	VN	0.33	0.17	0.55				0.55							
[58]	MY	0.51	0.55										0.42		0.64
[34]	US						0.16		0.39	0.26				0.34	
[37]	HK	0.18	0.35	0.70											
[38]	US							0.56							
[39]	KR			0.83		0.69		0.62							
[40]	TW	0.69	0.55					0.10					0.41		0.32
[42]	Int'l			0.38	0.06	0.60	0.19	0.39	0.53						
[32]	CN	0.23	0.32	0.79	0.49				0.76						
[44]	CN			0.52				0.10							
[51]	NZ	0.44	0.37	0.61				0.64							
[53]	PK	0.75	0.29	0.69											
[59]	CN	0.62	0.52	0.29		0.55									
[63]	TW	0.68	0.75												
[64]	NZ			0.76					0.63						
[57]	YE		0.70	0.30											0.53

[1] Note 1 – 24 out of 26 studies have been presented in this table because the two other studies (i.e., [24, 60]) provided the required effect sizes for the relationships that have not been hypothesized in our proposed research model.
[2] Note 2 – Due to space limitations, the countries names have been presented by their ISO 3166-1 alpha-2 codes (http://www.iso.org/iso/country_codes/iso_3166_code_lists/country_names_and_code_elements.htm).

Drawing on Hunter and Schmidt [28], prior studies have identified sources of artifacts that potentially distort meta-analytic tests of new theory: (1) non-independence of data sets, (2) coding errors, (3) measurement error, (4) multicollinearity, (5) missing studies, and (6) type II error [49]. We took rigorous precautions to address the foregoing seven concerns. As elaborated next, we assessed and corrected for the artifacts in order to be confident that the final parameter estimates are a result of the relationships hypothesized in our theoretical models rather than artifacts.

3.3.1. Ensuring independence of data sets – Non-independence of data sets would violate an important assumption in meta-analytic computations [49]. Therefore, we applied the following criteria to ensure the independence of data sets. We included only one data set if two or more studies used the same sample to ensure the independence of data sets—an important assumption in meta-analytic computations [49]. Conversely, for studies that presented two separate samples for two different contexts, we retained two separate data sets. As a result of applying the preceding criteria, our sample for the proposed research model depicted in Figure 1 contained 26 studies (k) comprised of 6714 cases (N) for MASEM. An asterisk (*) in the reference section marks each study contributing data.

3.3.2. Assessing and correcting coding error – As recommended by Rosenthal [56], we employed an inter-rater reliability test in order to assess (i) the selection and independence of primary study samples, (ii) the mapping of construct operationalizations (i.e., measurement) in each primary study to the operationalization in our study, and (iii) the coding of data from primary studies. To that end, the two authors independently coded data from each primary study and evaluated the data according to the preceding criteria. For example, each rater independently mapped constructs from prior studies to our operationalized constructs and coded correlations, reliabilities and sample sizes from each primary study. We then assessed inter-rater reliability. Average agreement was 90% and the inter-rater reliability measure, Kappa, was acceptable at 0.81 [49]. Disagreements were resolved by discussion and we proceeded only when unanimous agreement was obtained with respect to the coding.

3.3.3. Correcting for measurement error – We next corrected primary studies' reported effect sizes for measurement error, as recommended by Hunter and Schmidt [28]. We coded the corrected effect size matrices in a single file for our proposed research model, and used metaSEM package [12] in R 2.15.1 [54] to compute the pooled correlation matrix. Mean measurement reliabilities are all above 0.70, as recommended by Nunnally [50].

3.3.4. Assessing Multicollinearity – We reviewed the pooled correlation matrices for multicollinearity. The purpose of checking for multicollinearity was to make sure that the constructs are distinct. Based on the extant literature, we know that the constructs in our proposed research model are well-established distinct constructs. Nevertheless, we tested for the multicollinearity by checking the correlation coefficients and also by calculating variance inflation factor (VIF) [48]. All antecedent pairs in our both pooled correlation matrices exhibited $r<0.84$ and VIF<3.3 [48]. Hence, we were satisfied that the data did not violate the SEM assumption of independence of constructs (i.e., absence of multicollinearity).

3.3.5. Assessing potential missing-studies artifacts – The potential exists for a "file drawer problem" in which studies that find non-significant effects for our hypothesized relationships are not identified [49]. We calculated the "fail-safe" K; that is, the number of missing studies with non-significant results (null findings) that would need to exist for the correlations for our respective hypotheses to be rendered non-significant. The high fail-safe Ks for our hypotheses provide confidence in the robustness of our results with respect to possible missing studies.

3.3.6. Assessing Type II error – An important component of statistical test is the notion of statistical power, defined as the probability that the results of a statistical test will not lead to acceptance of the null hypothesis when it is in fact false (i.e., Type II error) [49]. To assess the risk of Type II error, we identified the power of pooled correlations for each of our hypotheses based on respective pooled sample sizes [49]. Because the results of our power analyses exceed 0.80, we are confident that our data sets for both of our models have sufficient power to reject rather than accept null hypotheses that are truly false [49].

3.4. Assessing the amount of variances across studies included in the meta-analysis

There are two models used in meta-analysis, the fixed-effects model and the random-effects model. These two models make different assumptions about the amount of variances across studies (i.e., heterogeneity of effect-sizes across studies), and these assumptions lead to different definitions and calculations for the pooled effect-sizes [7]. Under the fixed-effects model, it is assumed that there is one true population effect-size, which is shared by all the studies that are included in the meta-analysis (i.e., the effect-sizes across studies are homogenous). It follows that the pooled effect-size is our estimate of this population effect-size and any variation across the studies are considered as sampling errors. By contrast,

under the random-effects model, it is assumed that the true population effect-size could vary from study to study (i.e., the effect-sizes across studies are heterogeneous by nature) and the studies included in the meta-analysis are assumed to be a random sample of the relevant population-level distribution of effect-sizes and the pooled effect-size estimates the mean effect-size in this distribution [7]. To that end, assessing and considering the amount of variances across studies is important for selecting the appropriate meta-analysis model for calculations. Cheung and Chan [13] and Cheung [11] caution that ignoring variances across studies is questionable for MASEM analysis and that unless homogeneity of effect-sizes across studies is substantiated, using the fixed-effects model could be problematic. To that end, we have taken rigorous precautions to address this concern. We assessed the level of between-study variances present in our data set. Whereas between-study variances (i.e., heterogeneity) among effect-sizes supplied by primary studies is to be expected in meta-analyses, Cheung and Chan [13] and Cheung [11] recommend that (i) unless we can confirm that the effect-sizes supplied by primary studies demonstrate adequate level of homogeneity, we should use random-effects model for the meta-analysis, and (ii) use the existing heterogeneity across studies in weighting the pooled correlations during the structural modeling test of the proposed model (described in section E). First, we followed Cheung's [11] test of heterogeneity for meta-analyses: we assessed the level of heterogeneity of the effect-sizes across studies using metaSEM package [12] in R 2.15.1 [54]. In assessing the heterogeneity of the effect-sizes, we drew on the SEM goodness of fit indices, as proposed by Cheung and Chan [13] and Cheung [11], in which root mean square error of approximation (RMSEA) of 0.08 or less, and comparative fit index (CFI) and Tucker-Lewis Index (TLI) of 0.9 or above indicate homogeneous effect-sizes and any other values indicate heterogeneous effect-sizes across studies. Following Cheung and Chan [13] and Cheung [11], the fixed-effects model is justifiable only when there is an acceptable level of homogeneity across effect-sizes. Otherwise random-effects model is the appropriate method for the meta-analysis. The metaSEM results for the *assessment of heterogeneity* level demonstrate heterogeneous effect-sizes across the studies in our meta-analysis (RMSEA=0.193, TLI=0.82, CFI=0.86). Therefore, we used random-effects model for our meta-analysis, as recommended in the literature [11, 13, 26]. Next, we retained the asymptotic covariance matrix (ACM) outputs. The ACM captures any heterogeneity that exists in our pooled correlation matrix based on the variance and covariance between effect-sizes reported in the primary studies [49]. The ACM enables us to correct for the existing heterogeneity by weighting pooled correlations during evaluation of the research model.

3.5. Evaluation of the research model using SEM

Per MASEM procedures, proposed by Cheung and Chan [13], this step refers to the parameter estimation of the structural model using SEM and the meta-analytically pooled data from existing studies. SEM computes fit statistics (e.g., RMSEA) to evaluate the goodness-of-fit of a theoretical model. The objective of evaluating the goodness-of-fit is to reject a misspecified model and retain an acceptably specified and parsimonious model for interpretation [27]. To that end, following the MASEM approach by Cheung [11], we implemented generally weighted least squares (GWLS – Also called asymptotically distribution-free (ADF) estimation [13]) estimation method in metaSEM package [12] in R 2.15.1 [54] in order to compute the goodness-of-fit statistics and the structural parameters of our research model using the meta-analytic data [49]. As recommended by Cheung and Chan [13] and Cheung [11], we evaluated three complementary fit indices: the absolute fit index RMSEA, the relative fit index CFI, and the parsimonious fit index TLI. Values of the RMSEA 0.08 or less, CFI of at least 0.90, and TLI of at least 0.90 indicate very good model fit [27].

4. Results

The results of SEM analysis of our proposed research model with GWLS as the estimation method are presented in Figure 1. The fit statistics show that our proposed research model exhibits very good fit to the meta-analytic data (i.e., RMSEA=0.02; CFI=0.98; TLI=0.95). Path coefficients (i.e., estimated beta values) and their significance levels are presented for each path in Figure 1 along with the R^2 for the four endogenous variables. The results of our analyses show that all 14 stated hypotheses are supported at $p<0.05$.

5. Discussions and Implications

Self-Service Technologies such as Internet banking enable consumers to use services without direct interaction with the physical provider's personnel. Thus, service providers such as banks must better understand issues that can facilitate/inhibit use of SST by consumers with different personal characteristics, experience, and capabilities, under different situational contexts. Based on extant literature, we have proposed a theoretical model (depicted in Figure 1) as a lens to explore factors

Table 2 – Total effects of each of eight factors on initial use intention of the Internet banking			
Factors Affecting Initial Use Intention	Direct Effect	+ Indirect Effect	= Total Effect[*]
Structural Assurances	0.26	0.29	**0.55**
Trust in the Physical Bank	0.44	0.10	**0.54**
Trust in the Internet Bank	0.46	-	**0.46**
Perceived Usefulness of the Internet banking	0.34	-	**0.34**
Consumers' Innovativeness	-	0.24	**0.24**
Perceived Ease of Use of the Internet banking	0.14	0.09	**0.23**
Social Influence	-	0.22	**0.22**
Consumers' Propensity to Trust	-	0.17	**0.17**

Note – Based on Preacher and Kelley's [52] guidelines the direct and indirect effect sizes computed from our MASEM are based on standardized beta-values.

affecting consumers' initial use intention of Internet banking. Our MASEM of 26 primary empirical studies in Internet banking confirms the significance of perceived usefulness and perceived ease-of-use of the SST on its adoption by the consumers in the pre-usage stage. Furthermore, the results of our MASEM indicate that our three hypothesized factors to reduce the uncertainty in the adoption of SST (i.e., trust, innovativeness, and social influence) significantly affect consumers' initial use intention of the SST.

Bollen [6] stresses that it is important to look not only at direct effects (i.e., indicated by path coefficients in our model, depicted in Figure 1), but also at total effects in interpreting results in a structural equation model. Total effects indicate the combined effect of any direct path from a given factor (e.g., trust in the physical bank) to our dependent construct (i.e., initial use intention of Internet banking), as well as any indirect effects transmitted through other intervening factors [4]. For example, in our model, trust in the physical bank has a direct effect on initial use intention of Internet banking (0.44) as well as an indirect effect through trust in the Internet bank (0.10). The combination of these two effects is reflected in the total effect of trust in the physical bank on initial use intention of Internet banking (0.54), which means that one standard deviation increase in trust in the physical bank results in a 0.54 standard deviation increase in initial use intention of Internet banking [35, 36]. We have calculated the total effects of all of our eight factors on initial use intention of Internet banking, which are depicted in Table 2. Our results show that three dimensions of trust (i.e., structural assurances, trust in the physical bank, and trust in the Internet bank) have the largest total effects on the initial use intention of the Internet banking. Unlike the dominant trend in the literature that considers perceived usefulness and perceived ease of use as the most prominent factors towards the initial use intention, our results (depicted in Table 2) indicate that the combined total effects of three dimensions of trust are more prominent in enticing the consumers towards initial use of Internet banking. This is plausible considering the high risk associated with the Internet banking context [46].

In this paper, we have made two significant contributions to research. First, by fine-tuning a nomological model and calculating the total effects of its attributes on initial use intention of Internet banking, we have been able to shed light on the relationships among the factors as well as their relative prominence in contributing to consumer adoption of an Internet-based SST innovation (depicted in Figure 1). We assessed our nomological model using random-effect MASEM, which to our knowledge is unprecedented in Information Systems and constitutes our second contribution to research.

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7. References[1]

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