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스마트 패러독스를 해결하는 방법

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How to Solve the Smart Paradox

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요 약 모바일 메신저는 20세기 초반의 전화기, 1950~60년대의 텔레비전과 마찬가지로 사람들의 삶에 큰 변화를 유발하였다. 하지만 많은 연구자들은 모바일 메신저가 공동체의 삶과 사회적 관계를 향상시키는지 혹은 악화시키는지에 대해 갑론을박을 벌이고 있다. 본 연구는 국내 두 대학의 155명의 대학생들을 대상으로 모바일 메신저의 사용과 사용에 따른 영향(외로움)에 대해 설문조사하였다. 설문대상자들은 모두 모바일 메신저를 능숙하게 사용할 수 있으며, 자주 사용하는 대상자들이다. 연구결과 지나친 모바일 메신저의 사용은 자기 주변의 사람들과의 의사소통을 감소시키는 것으로 나타났으며, 이는 또한 외로움에 영향을 미치는 것으로 나타났다.

주제어 : 외로움, 스마트 패러독스, 모바일 메신저

Abstract The mobile instant messengers could change the lives of average citizens as much as did the telephone in the early part of the 20th century and television in the 1950s and 1960s. Researchers are debating whether the mobile instant messengers are improving or harming participation in community life and social relationships. For this study, 155 participants in two universities completed questionnaires pertaining to their own mobile instant messengers use and feelings of loneliness. We used survey data to examine the effects of the mobile instant messengers on social involvement and psychological well-being. In this sample, the mobile instant messengers were used extensively for communication. Results suggest that greater use of the mobile instant messengers were associated with declines in participants' communication with the people around which in turn creases their loneliness. These findings have implications for research and for the design of technology.

Key Words : loneliness, smart paradox, mobile instant messenger

1. Introduction

With the rapidly expanding reach of the mobile phone into most aspects of every life, we need to understand its social impact and the behaviors leading to this impact. The mobile instant messengers is becoming increasingly influential, but some observers have noted that heavy mobile instant messengers users seem alienated from normal social contacts and may even cut these off as the mobile instant messengers becomes the predominate social factor in their lives. The mobile instant messengers refer to a kind of

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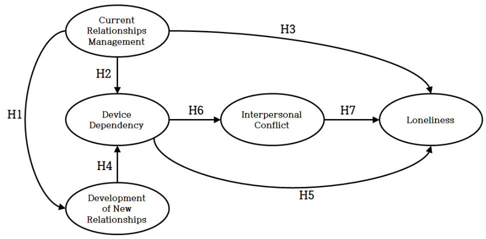
services that enable users to chat with others, share photo and video, call freely with voice or video, and offer local information using mobile network [18]. There are two dissimilar points of view. Some scholars argue that the mobile instant messengers is causing people to become socially isolated and cut off from genuine social relationships, as they hunker alone over their terminals or communicate with anonymous strangers through a socially impoverished medium. In this point of view, online relationships are shallow, illusory, and sometimes exploitative and hostile [16]. Such interactions compete with, and are established at the expense of, traditional face to face social relationships. Others argue that the mobile instant messengers lead to more and better social relationships by freeing people from the constraints of geography or isolation brought on by schedule. In this point of view, mobile instant messengers allow the formation of genuine personal relationships, free from the restrictions of age, occupation, proximity and physical appearance [16]. The goal of this article is to examine these issues and to report early empirical results of a field trial of mobile instant messengers use.

2. Literature Review

Loneliness is a condition that is widely distributed and severely distressing [34]. Despite the pervasiveness of loneliness, very little empirical research has been directed at the problem [29]. Loneliness exists to the extent that a person's network of social relationships is smaller or less satisfying than the person desires [24]. Thus, loneliness is a situation experienced by the individual as one where there is an unpleasant or inadmissible lack of quality of certain relationships [8]. In literature distinctions have been made between loneliness and aloneness or solitude [3]. Aloneness or solitude, when an individual deliberately chooses to be alone or to play by him or herself, is associated with a pleasant, positive, and sometimes even desirable situation [2]. Loneliness, on the other hand, refers to the discrepancy between a person's desired and actual social relationships [22]. Some have attempted to identify different components or types of loneliness. Weiss (1973) distinguished between emotional, stemming from the absence of an intimate figure or a close emotional attachment, and social loneliness stemming from the absence of a broader group of contacts, or an engaging social network on theoretical grounds [9]. Social loneliness specifically indicates a lack of companionship and is related to the number of close friends [3]. Social loneliness arises when people perceive their social relationships as unsatisfactory, or when they do not have accessible social networks or peer groups [2]. Emotional loneliness, in its turn, indicates a lack of intimacy with close friends and has nothing to do with the number of friendships [3]. Emotional loneliness arises when a partner relationship dissolves through widowhood or divorce and is characterized by intense feelings of sadness, emptiness, abandonment, and forlornness [2][9]. Various factor analytic studies have provided some evidence that the experience of loneliness can be partitioned into separable dimensions, but these factors have also been found to be highly correlated, and their antecedents and consequences have been found to be sufficiently overlapping that loneliness is generally conceptualized and measured as a unidimensional construct that varies primarily in its experienced intensity [8][22].



[Fig. 1] The Proposed Conceptual Model

〈Table 1〉 The Demographic Profile of Respondents

		Frequency	Ratio
Gender	Male	74	47.7
	Female	66	42.6
	No Response	15	9.7
Age	Average	25.3742	
Education	High School	6	3.8
	In Collage	2	1.3
	Collage	4	2.6
	In University	88 3 26	75.5
	University	23	14.8
	In Graduate	2	1.3
	Graduate	1	0.6
		155	100%

3. Analysis

3.1 Data Collection

We used a survey instrument to collect data from respondents. We use a student data for analysis. Student data can be informative and helpful in terms of mobile instant messengers. The sample thus consisted of undergraduate and graduate students. Each respondent was asked to indicate the level of agreement, using Likert seven-point scales anchored with strongly disagree (1) and strongly agree (7).

A total of 200 self-report questionnaires were distributed to students at two universities in Korea; of these, 165 (82.5 percent) were completed and returned, but 10 of them were incomplete, leaving 155 samples for data analysis. Finally, 155 questionnaires were analyzed, giving a response rate of 77.5% (mean age 25 yrs). All respondents constituted 74 (47.7%) male and 66 (42.6%) female. The general demographic information of respondents is shown in Table 1 in detail.

3.2 Factor Analysis

To examine the internal structure further, we conduct exploratory factor analysis (EFA) with the sample of 155 questionnaires to check whether the items adopted for the present study are appropriate using the Statistical Package for the Social Sciences (SPSS) as default.

Prior to factor analysis, the researcher must ensure that the data matrix has sufficient correlations to justify the application of factor analysis [10]. To do this, this research takes two approaches such as the Bartlett test of sphericity and the measure of sampling adequacy. In this research, the Bartlett test of sphericity finds that the correlations are significant at the 0.0001 level (see Table 2). This test indicates that the correlation matrix has significant correlations among at least some of the variables [10]. The measure of sampling adequacy (MSA) considers not only at the correlations, but also their patterns between variables [10]. The MSA values must exceed 0.50 for the overall test [10]. In this research, the overall MSA value falls in the acceptable range with a value of 0.808. This means that conducting factor analysis is appropriate.

Factor analysis carried out using principal axis factors (PAF) with Varimax rotation method and Kaiser Normalization on all the measurement scales, see Table 2. PAF will give us the best results, depending on whether your data are generally normally-distributed or significantly non-normal, respectively [Costello and Osborne, 2005]. Varimax rotation creates orthogonal factors with minimized high loadings of the measurement items on other factors [7]. On the other hand, non-orthogonal rotations such as the Direct Oblimin Method can produce a neater pattern of loading, and so they make the interpretation of the factors easier, but at the cost of increasing multicollinearity because of the loss of orthogonality [7].

Based on “rule of thumb”, factor loadings of 0.5 or higher should be considered in the interpretation of a factor with eigenvalues greater than 1.0 [5][33]. Five factors were selected through these procedures (see Table 2).

3.3 Common Method Bias Test

Common method variance (CMV) means the amount of spurious covariance shared among variables because of the common method used in collecting data [21]. Such method biases are problematic because they are one of the main sources of measurement error. Measurement error threatens the validity of the conclusions about the relationships between measures [26].

One of the most widely used techniques is Harman's one-factor (or single-factor) test for assessing common method variance in a single-method research design [21][26]. According to this approach, significant common method variance is assumed to exist if a single factor will emerge from the results of a principal component analysis, or one general factor will account for the majority of covariance among the measures in an unroated factor analysis [26]. The results showed five factors with eigenvalues greater than 1, with the first accounting for 29% of the total variance [17]. Thus, we can argue that the level of common method bias was not a serious problem in this research.

3.4 Reliability and Validity of Measurement Model

The reliability and validity of the constructs can be

<Table 2> Exploratory Factor Analysis

	Factor					Cronbach's Alpha
	1	2	3	4	5	
IC1	.130	.761	.023	-.014	.202	0.9155
IC2	.106	.875	.019	.027	.105	
IC3	.115	.853	.138	.015	.100	
IC4	.148	.886	.070	.058	.107	
IC5	.163	.788	.062	.100	.020	
IC6	.279	.526	.151	.193	-.061	
DD1	-.014	.090	.131	.283	.748	0.8834
DD2	-.012	.167	.287	.108	.601	
DD3	.023	.058	.058	.135	.872	
DD4	.074	.110	.044	.153	.763	
CRM1	.036	.047	.206	.603	.194	0.8810
CRM2	.046	.087	.031	.932	.173	
CRM3	.019	.083	.088	.784	.038	
CRM4	-.081	.034	-.010	.711	.263	
NRM1	.268	.058	.555	.112	.130	0.8891
NRM2	.191	.062	.774	.056	.108	
NRM3	.137	.080	.850	.067	.123	
NRM4	.215	.134	.775	.091	.086	
Lone1	.647	.110	.147	-.043	.113	0.9288
Lone2	.714	.194	.130	-.034	-.022	
Lone3	.761	.168	.066	.043	-.023	
Lone4	.812	.155	.198	.116	-.019	
Lone5	.700	.091	.059	-.024	-.001	
Lone6	.846	.074	.071	-.007	-.041	
Lone7	.762	.202	.321	.038	.017	
Lone8	.819	.018	.116	-.005	.101	
Eigenvalue	7.550	4.027	3.038	2.020	1.786	
% of Variance	29.037	15.487	11.685	7.768	6.869	
Cumulative %	29.037	44.524	56.209	63.977	70.846	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.					.808	
Bartlett's Test of Sphericity			Approx. Chi-Square		2911.070	
			Degree of Freedom		325	
			Significance		.000	

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.

demonstrated through measures of indicator reliability, internal consistency, construct, and discriminant validities.

Indicator reliability refers to the reliability of each of manifest variables [13]. Although no exact criterion value of 0.70 is oft-cited as a lower threshold [4][30]. Results of PLS loading analysis in Table 2 suggest satisfactory indicator reliability.

In general, Cronbach's alpha is preferred for assessing internal consistency because it does not depend on the assumptions required of other indices of reliability [25]. Thus, this study used the Cronbach's alpha for gauging the reliability of scale items. Reliability is defined as the ratio of true score variance to observed score variance [30]. Cronbach's alpha of 0.70 or higher is acceptable for social science research [23]. As shown in Table 2, all alphas were satisfied threshold value.

While Cronbach's alpha is the most widely used metric for addressing the reliability [30], Cronbach's alpha assumes that its items are perfectly correlated with their underlying construct [25]. Because this assumption is almost always unreasonable in practice, Cronbach's alpha tends to under-estimates reliability of latent variables [15][25]. Accordingly, this study measures composite reliability (CR) for assessing internal consistency. CR is a statistical technique for assessing reliability of composite scales and assesses whether the specified indicators are sufficient in their representation of their respective constructs [30]. Like Cronbach's alpha, an internal consistency reliability value above 0.7 is regarded as satisfactory, whereas a value below 0.7 indicates a lack of reliability [15]. As shown in Table 3, CR of all reflective measures is clearly above the recommended level of 0.7, confirming satisfactory reliability.

〈Table 3〉 PLS Loadings , Cross-Loadings, and Reliability

	CurrentRel	DeviceDepend	InterConflict	Loneliness	NewRel	AVE	CR
IC1	0.1596	0.2554	0.8112	0.2595	0.0519	.7072	.9350
IC2	0.1478	0.2015	0.877	0.2519	0.0808		
IC3	0.2484	0.2201	0.8864	0.2811	0.0727		
IC4	0.2054	0.2286	0.9051	0.3000	0.1169		
IC5	0.1608	0.1586	0.8488	0.2716	0.1313		
IC6	0.2283	0.0766	0.7003	0.3865	0.2077		
DD1	0.2587	0.8745	0.181	0.0578	0.4311	.7101	.9072
DD2	0.3772	0.7699	0.218	0.0977	0.2536		
DD3	0.2185	0.8776	0.1632	0.0909	0.3304		
DD4	0.1851	0.8441	0.1953	0.1026	0.3041		
CRM1	0.7461	0.2533	0.1572	0.3609	0.1727	.7213	.9115
CRM2	0.8804	0.2674	0.1827	0.3224	0.1469		
CRM3	0.889	0.2675	0.1892	0.3068	0.1683		
CRM4	0.8735	0.2765	0.2545	0.3529	0.1858		
NRM1	0.2616	0.3462	0.115	0.084	0.7937	.7051	.9051
NRM2	0.1489	0.3658	0.1478	0.0638	0.9066		
NRM3	0.1459	0.2371	0.1293	0.0324	0.8102		
NRM4	0.0926	0.3547	0.0597	-0.0435	0.8439		
Lone1	0.3688	0.0942	0.3417	0.8734	0.1331	.6605	.9395
Lone2	0.2318	-0.0065	0.1974	0.7635	-0.0171		
Lone3	0.2392	0.0227	0.2440	0.8405	-0.0175		
Lone4	0.4754	0.129	0.3748	0.8637	0.0714		
Lone5	0.3165	0.1441	0.1800	0.8192	0.0027		
Lone6	0.3131	0.1421	0.2230	0.7448	-0.0008		
Lone7	0.2689	0.0691	0.3427	0.7926	-0.0096		
Lone8	0.2624	0.0241	0.3019	0.7951	0.0635		

AVE: Average Variance Extracted / CR: Composite Reliability

〈Table 4〉 Test of Discriminant Validity

	CurrentRel	Dependence	InterConflict	Loneliness	NewRel
CurrentRel	0.8493				
Dependence	0.3144	0.8427			
InterConflict	0.2331	0.2256	0.8410		
Loneliness	0.3972	0.1019	0.3529	0.8127	
NewRel	0.1995	0.3964	0.1345	0.0445	0.8397

Diagonal values are the square root of AVEs.

Adequate convergent validity could be suggested by an AVE, and demonstrated by an AVE above 0.5 [25]. AVE refers to the amount of variance that is captured by the construct in relation to the amount of variance due to measurement error [6]. If AVE is less than 0.50, then the variance due to measurement error is larger than the variance captured by the respective construct [6][30]. As shown in Table 3, all AVE values are higher than an acceptable level of convergent validity. On the basis of this result, we can assert that the convergent validity of the construct is adequate [6].

AVE was used to gauge discriminant validity. To establish discriminant validity, we test to see if the square root of the AVE (Average Variance Extracted) of each construct is much larger than any correlation between this construct and any other construct [7]. To satisfy the requirements for discriminant validity, the square root of the AVE for each construct should be greater than the correlation between constructs. It means that the items share more common variance with their respectice constructs than any variance the construct shares with other constructs [30]. Table 4 shows an evidence of discriminant validity.

Collectively, the evidence suggests that the constructs demonstrate adequate measurement properties.

4. Results

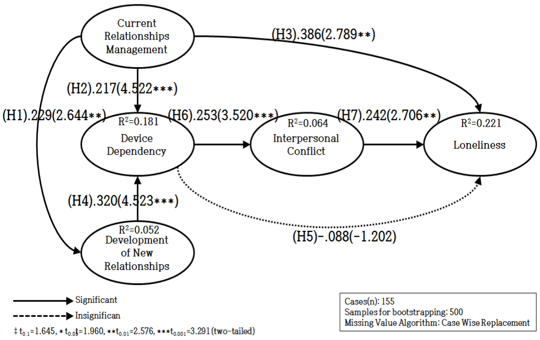
There are two reasons for choosing to use variance-based partial least squares (PLS) path modeling in this study. First, PLS is a strong approach for developing and refining theoretical models. In contrast to techniques for structural modeling such as AMOS and LISREL, PLS requires less demanding assumptions about theoretical closure in models and can produce unbiased estimates of parameters [28]. While covariance-based SEM (Structural Equation Modeling) is a confirmatory approach that focuses on the model's theoretically established relationships and aims at minimizing the difference between the model implied covariance matrix and the sample covariance matrix, PLS-SEM is a prediction-oriented variance-based approach that focuses on endogenous target constructs in the model and aims at maximizing their explained variance [11][12]. Second, PLS has special abilities that make it more appropriate than other techniques when analyzing small sample sizes. For robust PLS path modeling estimations, the minimum sample size should be equal to the larger of ten times the largest number of structural paths directed at a particular construct in the inner path model [1]. Based on this rule of thumb, we need at least 80 samples for estimating the proposed model.

This study used SmartPLS 2.0 M3 [27]. SmartPLS is a software application for the design of structural equation models (SEM) on a graphical user interface (GUI) [14]. These models can be measured with the method of partial least squares (PLS)-analysis [14].

R2 (The Coefficient of Determination) indicates the amount of variance explained by the independent variables [17]. Adequate PLS models contain dependent variables with at least 10% of their variance explained [31]. As shown in figure 2, the assessment of the latent variables in our proposed model reveals moderate to weak R2 values ranging between 0.052 and 0.221 of variance explained.

To assess a model's fit to the data, we used a global of fit (GoF) measure for PLS path modeling [32]. The measure can be interpreted with the following guidelines: 0.36 or above, large; 0.25 or above, medium; and 0.1 and above, small [35]. In this study, we obtained a GoF value of 0.305, which exceeds the cut-off value of 0.25 for medium effect of R2 and allows us to conclude that the model is a realistic representation of the data.

To test for significant of relationships between latent variables, t-values were calculated for path coefficients using 500 bootstrapping subsamples with 155 cases [31].



[Fig. 2] Results of PLS Path Modeling

Figure 2 reports the results of PLS-SEM analysis. We found that current relationships management had a positive effect on development of new relationships (β =0.229, p<0.01, two-tailed, Hypothesis 1 supported), device dependency (β=0.217, p<0.001, two-tailed, Hypothesis 2 supported), and loneliness (β=0.386, p<0.01, two-tailed, Hypothesis 3 supported). In addition, development of new relationships had a positive impact on device dependency (β=0.320, p<0.001, two-tailed, Hypothesis 4 supported). We also found that interpersonal conflict was influenced positively by device dependency (β=0.253, p<0.001, two-tailed, Hypothesis 6 supported). On the other hand, device dependency had no significant effect on loneliness (β=-0.088, two-tailed, Hypothesis 5 not supported). Finally, the results showed that interpersonal conflict significantly influenced loneliness (β=0.242, p<0.01, two-tailed, Hypothesis 7 supported).

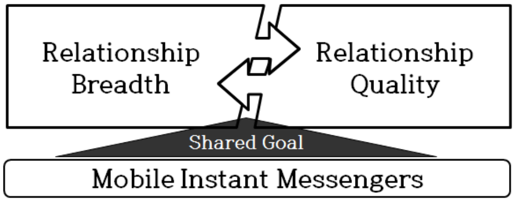
5. Conclusions and Implications

The purpose of this study is to explore the solution to reduce the smart paradox. The smart paradox refers to the increase in communications brought about by mobile instant messengers usage actually had negative effects on well-being [19][20].

The research results of this study are as follows: (1) Mobile instant messengers play an important role in building new relationships. However, this function may increase a device dependence of individuals, which in turn influence reducing communication around him or her.; (2) Reducing communication makes people feel lonely. In sum, mobile messengers contribute to extend relationship breadth, but are detrimental to depth of relationship (relationship quality).

These findings provide a picture of the consequences of using the mobile instant messengers. Greater use of mobile instant messengers was not associated with loneliness, whereas it affects indirectly on loneliness by increasing the interpersonal conflict. The solution for the smart paradox, then, is that learning how to deal with interpersonal conflict to maximize a relationship quality.

Dunbar's number is a suggested cognitive limit to the number of people with whom one can maintain stable social relationships. These are relationships in which an individual knows who each person is and how each person relates to every other person. This number was first proposed by British anthropologist Robin Dunbar, who found a correlation between primate brain size and average social group size. By using the average human brain size and extrapolating from the results of primates, he proposed that humans can only comfortably maintain 150 stable relationships. The core of his research is that the relationship quality is more important than the relationship breadth. Thus, mobile instant messengers must be used to increase based on the shared goal.



[Fig. 3] Implications of Our Study

The findings presented in this research are a nice starting point for future research, but it is important to keep the study's limitations in mind. We did not consider the possible effect of control variables on loneliness. By examining the effect of demographic variables on loneliness, future research may shed further light on the complex relationships linking gender, age, education and etc. Methodological limitations should also be acknowledged. One limitation is that the analyses relied on cross-sectional data. Therefore, we cannot draw conclusions about the causal directions underlying our results. Another issue is common method variance. It is important to consider the threat of same-source bias or common method variance. Collection of data for both the dependent variable and the independent variable from the same source is problematic, because it may sometimes inflate the magnitude of relationships between variables. Thus, post hoc statistical control of common method bias was conducted. The results of a Harmon one factor test suggested that common method variance was not likely to be a concern in this study. However, it appears that the explanations are post hoc in nature. For the limitation of a self-report survey, a better way to reduce the common method bias is to get information from separate sources. Finally, our model have relatively low explanatory power, accounting for between 5.2 (Development of New Relationships) and 6.4 (Interpersonal Conflict) percent. To improve the explanatory power of the model, more variables which are relevant to research model should be added the nomological network.

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