원 저

스마트폰 과의존 관리를 위한 모바일 건강관리 어플리케이션 수용 모델

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〈Abstract〉

Mobile Health Applications Adoption for the Management of Smartphone Overdependence

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Purposes: The convenience of smartphones have lead to people's overdependence on devices, which may cause obstacles in daily life. It is useful to manage smartphone overdependence by using mobile health applications. We aimed to investigate the acceptance of mobile health applications designed to help in the management of smartphone overdependence.

Methodology/Approach: We developed the extended model based on the Unified Theory of Acceptance and Use of Technology 2. The modified model had six hypotheses with six variables: result demonstrability, performance expectancy, effort expectancy, social influence, perceived risk, and behavioral intention to use. We randomly included 425 smartphone users in an online survey in 2020. A structural equation model was used to estimate the significance of the path coefficients.

Findings: Performance expectancy and social influence had a very strong direct positive association with behavioral intention to use. Result demonstrability had a direct positive association with performance expectancy. Perceived risk had a strong direct negative association with performance expectancy. Performance expectancy and social influence were the main factors directly influencing the acceptance of mobile health applications for the management of smartphone overdependence.

Practical Implications: We demonstrated smartphone users' acceptance of mobile health applications for smartphone overdependence management. Based on these results, we could develop mobile health applications more effectively.

Key Words: Smartphone Overdependence, Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), Technology Acceptance Model, Mobile Health Applications

Ⅰ. Introduction

The convenience of smartphones in our daily lives has lead to people's overdependence on these devices. Smartphone overdependence may cause many obstacles in daily life, creating negative

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consequences and social problems. Mobile health applications(mHealth apps) are proposed as a promising solution to overcome smartphone over-dependence. mHealth apps have been developed to help in the prevention, management, and diagnosis of smartphone overdependence[1, 2]. Lin et al. [3] highlighted that an app-incorporated diagnosis demonstrates substantial accuracy in the diagnosis of smartphone addiction[3]. Accordingly, we must be realistic and formulate a gradual plan to successfully introduce a mHealth apps service to the public.

We need to ensure that smartphone users actively participate in the acceptance of applications for smartphone dependence management. To convince smartphone users to adopt smartphone dependence applications, it is important to understand their perception. An accurate understanding of smartphone user's needs is essential if a smartphone application service is to successfully take hold in healthcare environment. This is mainly because the country's medical service is gradually becoming more active and user-focused.

Previous studies have been conducted to retest the original technology acceptance model(TAM) and Unified Theory of Acceptance and Use of Technology 2(UTAUT2) in the healthcare context [4-9], highlighting its value in the contexts of healthcare and new technologies[10-14].

The aim of this study is to provide a pragmatic explanation of key factors that affect the behavioral intention to use mHealth apps in the management of smartphone overdependence. To achieve the objective, this study proposed a user adoption model applicable to smartphone users' adoption of mHealth apps. The proposed model included crucial factors in UTAUT2 and previous qualitative studies explaining users' attitude toward technology acceptance. Here, we attempted to investigate the acceptance of mHealth apps designed to help in the management of smartphone overdependence.

Ⅱ. Theoretical background

We based our research model on UTAUT2 and TAM which proposes a method to evaluate user acceptance[15, 16]. The goal was to predict information technology acceptance before users adopt the system. The models have proven to be a successful method in predicting and explaining the use of various new technologies. It used a set of two variables(performance expectancy, effort expectancy) employed in many contexts of technology acceptance. Previous studies have employed UTAUT2 in diverse ways, using the variables of performance expectancy, effort expectancy, and extensional variables. In addition, UTAUT2 and TAM have been used as a method of evaluating user acceptance in the healthcare industry[4, 9, 17-20].

Ⅲ. Research model and hypotheses

We reviewed the literature on technology acceptance in the healthcare industry. Several qualitative studies explained the key factors that instill positive perceptions toward technology in the context of real healthcare. Based on the literature review, we developed the research model(Figure 1). The proposed model included six constructs: behavioral intention to use, effort expectancy, performance expectancy, social influence, result demonstrability, and perceived risk. Table 1 defined each construct.

Performance expectancy, effort expectancy in UTAUT2 were important variables in technology acceptance. Performance expectation in the

<Table 1> Definition of constructs

Construct	Definition	Reference
Result demonstrability	The degree to which an user perceives that they precisely could deliver its outcome in others after using mHealth apps	[21]
Performance expectancy	The degree to which an user believes the use of mHealth apps could improve management of smartphone overdependence	[4, 15, 22]
Effort expectancy	The degree to which an user perceives the ease of use the mHealth apps	[15, 23]
Social influence	The degree to which an important others believe he or she should use the mHealth apps	[23]
Perceived risk	The degree to which an user perceives uncertainty regarding the application, its cost and privacy	[4, 24]
Behavioral intention to use	The smartphone user's behavioral intention to use the application	[16, 23]

UTAUT2 has the same meaning with TAM's perceived usefulness. Effort expectancy was the same as TAM's perceived ease of use. In addition, two other variables were crucial in the healthcare context. In this study, performance expectancy meant the degree to which an user believes the use of mHealth apps could improve management of smartphone overdependence. Effort expectancy was the degree to which an user perceives the ease of use the mHealth apps. Previous studies showed the positive effect of performance expectancy and effort expectancy on behavioral intention to use[18, 21-23]. Furthermore, some studies indicated that effort expectancy directly influences performance expectancy[22-25]. As in previous studies, this study assumed that effort expectancy and performance expectancy for mHealth app's users of would affect their intention to use. It is also assumed that the easier the mHealth app is, the more useful it will be for users.

Therefore, hypotheses 1, 2, and 3 were proposed as follows:

H1: Effort expectancy will have a positive effect on behavioral intention to use.

H2: Effort expectancy will have a positive effect on performance expectancy.

H3: Performance expectancy will have a positive effect on behavioral intention to use.

In this research, results demonstrability meant the degree to which an user perceives that they precisely could deliver its outcome in others after using mHealth apps. In the extended TAM models(TAM2 and TAM3), result demonstrability was related to performance expectancy[26, 27]. In the healthcare context, the positive effect of result demonstrability on performance expectancy has been confirmed[5, 28, 29].

Also, in the case of the mHealth app, it is not a simple app, but an app that manages smartphone dependence. That is why it is necessary to use this to communicate results to psychiatric counseling or other related people and to utilize them. It was also hypothesized that the better the app usage results were communicated to people such as psychiatric counselors, the higher the app usage performance would be. Therefore, hypothesis 4 was proposed as follows:

H4: Result demonstrability will have a positive effect on performance expectancy.

It was useful to manage smartphone over-dependence by using mHealth apps. However, this was unfamiliar to smartphone users, which may strengthen their negative perceptions of such applications in terms of cost and privacy. For instance, mHealth apps managed sensitive user information such as smartphone usage time[30]. In this study, perceived risk referred to the degree to which an user perceives uncertainty regarding the application and privacy. Previous studies have confirmed issues pertaining to privacy[31, 32]. The perception of risks such as privacy is a very important issue in the introduction of mHealth apps as in previous studies. Therefore, hypothesis 5 was proposed as follows:

H5: Perceived risk will have a negative effect on performance expectancy.

Social influence played an influential role in technology acceptance decisions and usage. In this study, social influence referred to the degree to which an important others believe he or she should use the mHealth apps. Previous studies confirmed the positive effects of social influence on behavioral intentions to use a product or service[20, 33, 34]. In case of South Korea, social concerns and people's interest in smartphone overdependence have been very high in recent years. It was determined that the social influence of mHealth apps will affect the use the apps to reduce dependence on smartphones. Thus, hypothesis 6 was proposed as follows:

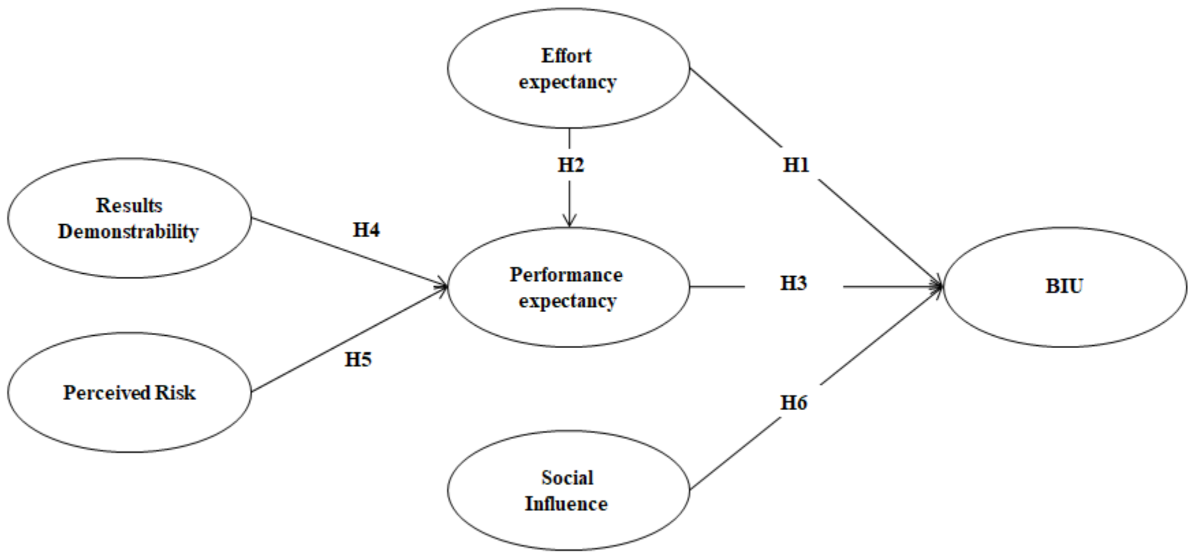
H6: Social influence will have a positive effect on behavioral intention to use.

The research model of this paper was shown in Figure 1.

Ⅳ. Methods

The study data were obtained from adult smartphone users. We conducted an online survey from March 2-13, 2020, and collected data from 547 adult smartphone users. We excluded 122 respondents because of incomplete answers, and finally included the responses of 425 participants in the analysis.

All questions were measured based on a five-point Likert scale. R(version 3.6.1.) was used as the statistical analysis software program in this research. Furthermore, a structural equation model(SEM) was employed to identify causal relationships between the model parameters. We used the R package lavaan for SEMs(version



<Figure 1> Research model

0.6-5) (http://cran.r-project.org/web/packages/lavaan/)[35].

The study procedures were carried out in accordance with the Declaration of Helsinki and were approved by the Institutional Review Board of C University (IRB number: MC20QISI0005). Participants' data were de-identified.

Ⅴ. Results

1. Demographics

In total, 206 (48.5%) males and 219 (51.5%) females participated in this study(Table 2). Respondents' age ranged from 19 to 73 years, and 340 (80%) were aged between 19 and 39 years.

<Table 2> Respondent characteristics

Characteristics	Items	Frequency	Percentage
Gender	Male	206	48.5
	Female	219	51.5
Age	Less than 30 years	176	41.4
	30-39 years	164	38.6
	More than 40 years	85	20.0
Education	High school graduate or lower	56	13.2
	Graduate school (including student) or higher	369	86.8
Job	Office worker, administrative position, professional technician	242	56.9
	Service industry, agricultural worker, production employee	54	12.7
	Student	75	17.6
	Other (including unemployed/housewife)	54	12.7
Location	Seoul	131	30.8
	Capital area (Gyeonggi-do Province / Incheon)	148	34.8
	Non-capital area	146	34.4
Average monthly salary	Less than USD 816.66	15	3.5
	USD 816.66-1,633.32	56	13.2
	USD 1,633.32-2,449.98	90	21.2
	USD 2,449.98-3,266.64	84	19.8
	More than USD 3,266.64	180	42.4
SMA[a]experience	Yes	204	48.0
	No	221	52.0
Smartphone usage time	1 hour-6 hours	266	62.6
	6-12 hours	119	28.0
	12-18 hours	30	7.1
	18-24 hours	10	2.4
	Total	425	100.0

[a] SMA: Smartphone management app. Exchange rate for Korean won to US dollars was 1,224.50 wons in 2020.

<Table 3> Overall fit of the confirmatory factor analysis model

Model-fit index	Recommended value	Scores
Chi-square/degree of freedom (X^2/df)	≤ 3.00	1.848
Comparative fit index (CFI)	≥ 0.90	0.963
Tucker-Lewis index (TLI)	≥ 0.90	0.956
Root mean square error of approximation (RMSEA)	≤ 0.08	0.045

Furthermore, 369 respondents have obtained a graduate school or higher education(86.8%); and 242(56.9%) respondents were office workers, in an administrative position, or working as a professional technician. In addition, 279 (65.6%) respondents lived in the capital area including Seoul, 180(42.4%) earn an average monthly salary of more than $ 3,266.64(approximately one USD 1,224.50 wons at the time of writing in 2020), and 204 (48%) had experience using a smartphone overdependence management application. Finally, 266(62.6%) respondents used a smartphone for 1 to 6 hours a day.

2. Confirmatory Factor Analysis

A confirmatory factor analysis(CFA) was conducted to test the reliability and validity of the measures. The following model-fit measures were used to assess the goodness-of-fit of the measurement model: Chi-square/degree of freedom (X^2/df), comparative fit index(CFI), Tucker-Lewis index(TLI), and root mean square error of approximation(RMSEA). Table 3 summarized the overall fit values of the CFA model. In this study, the fit indices were within the acceptable range. The overall results were: X^2/df(1.848), CFI(0.963), TLI(0.956), and RMSEA(0.045).

The internal consistency values for all constructs

<Table 4> Measurements: Confirmatory factor analysis.

Construct	Items	Component						Commu-nality	Cronbach's alpha	AVE[a]	CR[a]
		1	2	3	4	5	6				
BIU	BIU01	**.824**	.131	.169	-.041	.186	.071	.766	0.866	0.584	0.880
	BIU02	**.810**	.021	.139	-.100	.140	-.032	.706			
	BIU03	**.742**	.126	.239	-.031	.297	.086	.720			
	BIU04	**.729**	.146	.227	-.035	.254	.026	.672			
	BIU05	**.636**	.037	.285	-.186	-.008	-.082	.528			
RD	RD01	.131	**.870**	.083	-.067	.103	.055	.800	0.887	0.528	0.854
	RD02	.049	**.865**	.164	-.047	.093	.079	.795			
	RD03	.079	**.841**	.167	.031	.110	.097	.763			
	RD04	.097	**.784**	.081	.023	.085	.105	.650			
PE	PE01	.213	.061	**.793**	-.130	.159	.039	.722	0.813	0.670	0.925
	PE02	.140	.182	**.768**	-.148	.126	.063	.684			
	PE03	.264	.135	**.716**	-.012	.067	.094	.614			
	PE04	.252	.136	**.689**	-.037	.084	-.061	.568			
PR	PR01	-.165	.064	-.110	**.854**	.004	-.162	.799	0.756	0.560	0.800
	PR02	-.241	-.021	-.171	**.800**	.029	-.055	.732			
	PR03	.079	-.076	-.008	**.746**	-.175	-.029	.600			
SI	SI01	.308	.096	.068	-.089	**.789**	-.012	.739	0.775	0.555	0.843
	SI02	.419	.106	.099	-.055	**.752**	-.004	.764			
	SI03	.077	.245	.335	-.045	**.687**	.076	.658			
EE	EE01	.010	.106	.102	-.082	-.042	**.849**	.752	0.662	0.500	0.703
	EE02	.009	.167	-.016	-.126	.083	**.832**	.744			
Eigenvalue		3.423	3.088	2.691	2.059	1.998	1.518				
% of Variance		16.298	14.703	12.812	9.804	9.513	7.230				
Cumulative %		16.298	31.002	43.814	53.618	63.132	70.362				

[a]AVE: Average Variance Extracted, CR: Construct Reliability

RD:Resultdemonstrability,PE:Performanceexpectancy,EE: Effort expectancy, SI: Social influence, PR: Perceived risk, BIU: Behavioral intention to use were significant, ranging from 0.662 to 0.887(0.866 for behavioral intention to use, 0.887 for result demonstrability, 0.813 for performance expectancy, 0.756 for perceived risk, 0.775 for social influence, and 0.662 for effort expectancy). The internal consistency values for all constructs were greater than 0.6[36] (Table 4).

We evaluated the convergent validity(CR) of each construct. The criterion for assessing adequate convergent validity was the average variance extracted(AVE)[37]. The AVE scores were greater than 0.5, which is the minimum recommended score[38]. CR was adequate when constructs have a CR value greater than 0.7[39]. In this study, the CR scores were greater than 0.7, the minimum recommended score. Thus, acceptable levels of the validity of the instrument were confirmed.

Table 5 reported the AVE for each construct and the square of the correlations between each construct[40]. The results supported the discriminant validity of each construct, as the AVE of each was greater than that of the corresponding inter-construct squared correlation.

3. Hypotheses Testing

The overall model fit was evaluated using the four common fit measures: X^2/df, CFI, TLI, and RMSEA again. Table 6 summarized the overall fit values of the research model. The overall results were: Chi-square/degree of freedom(X^2/df:2.562), CFI(0.930), TLI(0.919), and RMSEA(0.061). All values were with in acceptable levels.

Figure 2 showed the results of the standardized path coefficients and t-value in the research model. Table 7 summarized the results. The structural path diagram supported the relationships postulated H3, H4, H5, and H6.

As predicted, H3 was supported. Performance expectancy has a positive effect on behavioral intention to use(β = 0.455, $p < 0.001$). According to H4, result demonstrability positively affected performance expectancy, which was supported by a positive path coefficient(β = 0.377, $p < 0.001$). H5, namely that perceived risk positively affects performance expectancy, was supported by a positive path coefficient (β = −0.318, $p < 0.001$).

<Table 5> Discriminant validity

Construct	BIU	PE	RD	PR	SI	EE
BIU	**0.584**					
PE	0.381	**0.670**				
RD	0.097	0.148	**0.528**			
PR	0.084	0.098	0.003	**0.560**		
SI	0.484	0.231	0.129	0.039	**0.555**	
EE	0.013	0.030	0.110	0.091	0.013	**0.500**

Average variance extracted (AVE) is shown on the diagonal; square correlations are off-diagonal.
RD: Result demonstrability, PE: Performance expectancy, EE: Effort expectancy, SI: Social influence, PR: Perceived risk, BIU: Behavioral intention to use

<Table 6> Overall fit of the research model

Model-fit index	Recommended value	Scores
Chi-square/degree of freedom (X^2/df)	≤ 3.00	2.562
Comparative fit index (CFI)	≥ 0.90	0.930
Tucker-Lewis index (TLI)	≥ 0.90	0.919
Root mean square error of approximation (RMSEA)	≤ 0.08	0.061

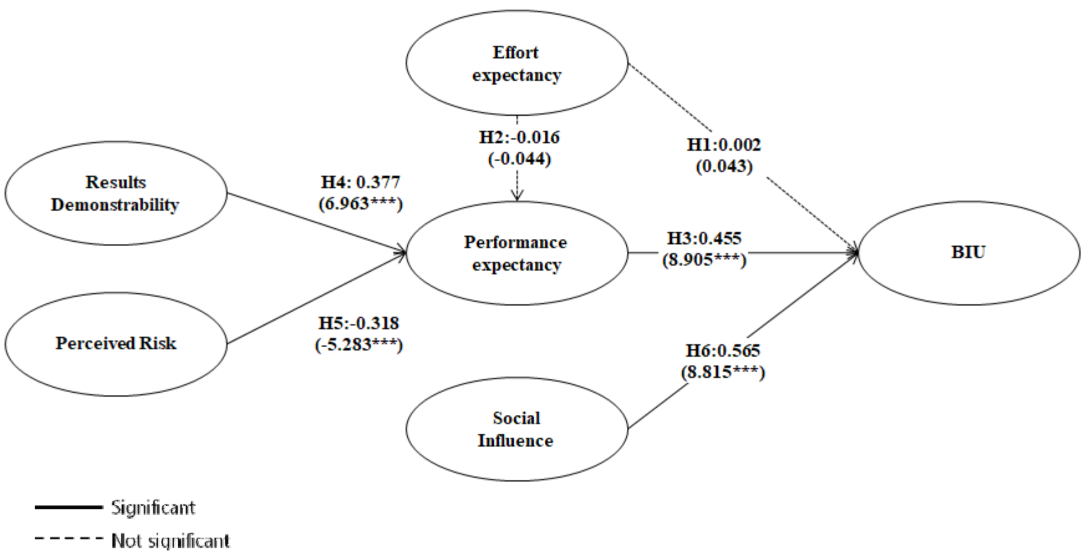
H6 that social Influence positively affects behavioral intention to use was supported by a positive path coefficient(β =0.565, p 〈 0.001). Unexpectedly, however, H1 and H2 were rejected.

4. alternative model

We set up an alternative model to verify the optimized research model, and compared it with the results of the research model. To create an alternative model, two hypotheses were added based on the existing research(RD→BIU, PR→BIU).

There are two hypotheses for alternative model: 1) Result demonstrability will have a positive effect on behavioral intention to use[41, 42]. 2) H: Perceived risk will have a positive effect on behavioral intention to use[43, 44].

The alternative model had a smaller Chi–square value of 3.8 and 2 degrees of freedom compared to the research model. However, at the significance level of 0.05 and 2 degrees of freedom, the Chi–square value is 5.991, so the research model is superior to the alternative model. In other words, the alternative model reduced the number of degrees of freedom by 2 compared to the research model, but the decrease in the Chi–square value (3.8) did not decrease enough to



<Figure 2> Results of the hypotheses tests

***$t_{0.001}$=3.291

<Table 7> Structural model results

Hypotheses	Path	Estimate	Standard Error	Z–value	p	Findings
H1	EE→BIU	0.002	0.008	0.043	0.966	n.s
H2	EE→PE	–0.016	0.074	–0.044	0.965	n.s
H3	PE→BIU	0.455	0.055	8.905	0.000	Supported
H4	RD→PE	0.377	0.056	6.963	0.000	Supported
H5	PR→PE	–0.318	0.083	–5.283	0.000	Supported
H6	SI→BIU	0.565	0.094	8.815	0.000	Supported

*** p 〈 0.001.

RD: Result demonstrability, PE: Performance expectancy, EE: Effort expectancy, SI: Social influence, PR: Perceived risk, BIU: Behavioral intention to use

<Table 8> Comparison of the fit index between research model and alternative model

	Fit index	Research model	Alternative model	Difference
x^2 fit	x^2	466.2	462.4	3.8
	Degrees of freedom	182	180	2
	p	0.000	0.000	$p<.05$

offset the decrease in the degrees of freedom (5.991), so it can be considered that the research model is superior.

Ⅵ Discussion and conclusion

We determined the acceptance of mHealth apps in helping with the management of smartphone overdependence. Based on the results of this study, we draw the following conclusions.

Both performance expectancy and effort expectancy have been conceived as crucial factors in the acceptance of new technology[12, 31, 45, 46], and it was emphasized that performance expectancy and effort expectancy lead to the behavioral intention to use[47, 48]. However, in this study, effort expectancy had no direct effect on behavioral intention to use and performance expectancy. Here, most respondents were aged less than 40 years(80%), and 317 respondents(74.5%) were office workers, in an administrative position, working as professional technician, or students. Since these respondents were familiar with using smartphone or mHealth apps, ease of use may not have been an important factor in using the application. According to Ma et al. [49], smartphone usage behavior varies according to demographic characteristics. For example, users who were younger with a higher education and higher economic status were more likely to accept the use of smartphones[49] and use mHealth apps. Thus, ease of use would not be an important factor in choosing to use a mHealth app.

Nevertheless, performance expectancy was important in choosing to use a mHealth app. In this case, how effectively the mHealth app managed smartphone overdependence was the main reason to choose and use a smartphone management application. Accordingly, we must develop an effective service and contents for smartphone overdependence such as a smartphone usage report, alarm views for smartphone over-dependence status, and a smartphone overdependence prediction tool.

Previous studies confirmed result demonstra-bility as a crucial factor in performance expectancy[26, 50]. Our result were the same as in previous studies that the perception of result demonstrability was a significant determinant of performance expectancy. A mHealth app must be developed to ensure help understanding and the intuitive use of its service contents. However, some research fields still view that result demonstrability directly affects the intention to use the technology[42]. In a future study, it is worth proving again whether this point is consistent with the context of this study.

We found that perceived risk had a positive effect on performance expectancy. A study has proposed that perceived risk directly had a positive effect on the acceptance of new technology[31]. Another study proposed that perceived risk was not an main UATUT predictor, but a contextual predictors[51]. This is different from the results of some existing studies. However, many consumers were concerned about their sensitive and private data in the health context[52]. The smartphone application for smartphone overdependence collected and uses privacy information such as smartphone usage time and time slot. Thus, mHealth apps must ensure that this information is adequately protected if users are to perceive them as useful in managing smartphone overdependence. Accordingly, application providers must find solutions to safely manage users' information and share these to protect privacy.

Previous studies confirmed the effect of social influence on the intention to use medical information technology[21]. We found that the perception and interest of surrounding people greatly affected the use and diffusion of the application. Social influence was needed to optimize the implementation of the application among smartphone users. Specifically, when the application was used in treating smartphone overdependence, the recommendations of medical staff and the hospital will influence the intention to use the application. Ultimately, we believe this application will become more widespread as smartphone users reduce their smartphone usage.

This study had some limitations. First, most respondents were aged less than 40 years (80%). According to previous research[49], smartphone usage behavior varies with demographic characteristics. Future research should thus collect data from people of all ages. In addition, future research will be able to validate the research model by using age as a control variable. Second, TAM and UTAUT2 model included various factors. We did not use facilitation condition, hedonic motivation, price value, and habit as a crucial factor in this study, and future research could employ this and other variables. Third, over the past few years, research on smartphone overdependence has been conducted in various ways, and various programs have been developed[53, 54, 55, 56]. However, only 48% of respondents had experience using mHealth apps for smartphone overdependence management. The rest have no experience with related applications. Future research could collect data from users experienced in using related mHealth apps. Fourth, in case of previous study, the moderating role such as gender and age were verified[57], but this study did not include this in the model hypothesis. It is judged that further research is necessary to verify this. Finally, this study focused on identifying the relationship between each construct from the perspective of smartphone overdependence management. In the case of TAM2, TAM3, and UTAUT2, the research model can be set by sufficiently considering external variables. Future research can be conducted taking this into consideration.

This study demonstrated smartphone users' acceptance of mHealth apps for the management of smartphone overdependence. Based on these results, we can more effectively develop mHealth apps.

Disclosure Statement

There is no conflict of interest occurred in this paper.

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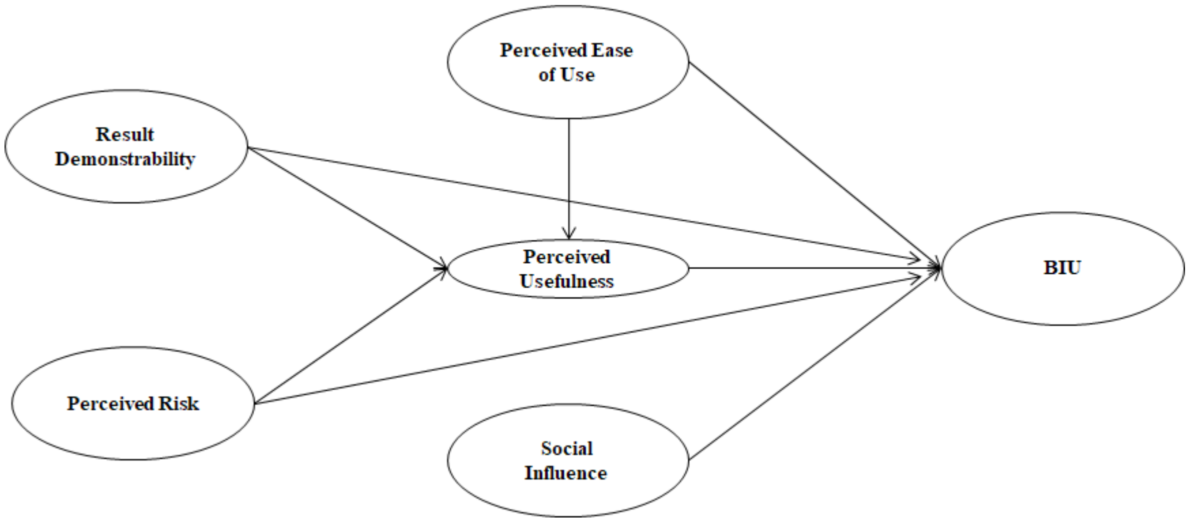
〈Appendix〉 Alternative model (부록)



〈Appendix〉 Questionnaire (부록)

Behavioral intention to use

I am willing to use the mHealth apps.

I plan to use the mHealth apps in the future.

When I have a chance to use the mHealth apps, I am willing to actually use it.

If the mHealth apps become paid, I am willing to use it.

I will recommend the mHealth apps to friends.

Result demonstrability

It is not difficult for me to talk to the medical staff about the results of using the mHealth apps.

I can easily talk to others about the results of using the mHealth apps.

I can clearly talk about the results of using the mHealth apps.

The results of using the mHealth apps can be communicated to medical staff or other people.

I can communicate the results of using the mHealth apps to the medical staff or others.

Performance expectancy

The mHealth apps will help to manage smartphone usage.

If I use the mHealth apps, it will be effective in managing smartphone usage.

If I use the mHealth apps, I will be able to reduce unnecessary smartphone use.

Using the mHealth apps will make it easier to manage smartphone usage.

Effort expectancy

I think the mHealth apps are easy to understand and simple.

It hope be good if the learning(installation, setup, operation) to use the mHealth apps was easy.

Overall, I think the mHealth apps will be easy to use.

Social influence

People who influence me are likely to think, “I should use the mHealth apps.”

My family and friends will think “I should use tthe mHealth apps”.

People around me will think positively that I use the mHealth apps.

Perceived risk

I'm not sure about the service how much the mHealth apps will help you in managing your smartphone usage.

I wonder if I can get the service I want through the mHealth apps.

If you receive insufficient or incorrect health information through the mHealth apps, it seems rather harmful to me.

한글 초록

연구목적: 스마트폰의 편리함은 사람들로 하여금 스마트폰 과의존을 불러 일으켜 일상생활에 여러 가지 문제를 일으킨다. 이에 모바일 헬스케어 앱을 활용하여 이를 관리하는 것은 매우 유용하다. 본 연구는 스마트폰 과의존을 관리하는데 도움이 될 수 있는 모바일 헬스케어 앱에 대한 사용자들의 수용에 대한 연구를 진행하였다.

연구방법: 우리는 확장된 통합기술수용모형 모델을 기반으로 확장된 연구모델을 개발하였다. 총 6개의 변수(사용의도, 성과기대, 노력기대, 사회 영향, 인지된 위험, 결과실증성)를 기반으로 6개의 가설을 설정하였다. 온라인 서베이를 실시하여 총 425명의 스마트폰 사용자들의 데이터를 수집하였다. 6개의 가설은 구조방정식 모형을 통해 검증하였다. 또한 최적화된 연구모형 확인을 위해 대안모델을 설정하고 결과를 비교하였다.

결과: 성과기대와 사회 영향력이 앱 사용의도에 가장 직접적으로 영향력이 강하게 나타났다. 결과실증성은 성과기대와 정의 관계를 지니고 있었다. 인지된 위험은 성과기대와 부의 관계를 가지고 있었다. 성과기대와 사회 영향력이 스마트폰 과의존을 관리하는데 유용한 모바일 헬스케어 앱 도입에 가장 큰 영향을 미치는 변수로 나타났다.

함의: 우리는 스마트폰 과의존을 관리하는데 필요한 모바일 헬스케어 앱 도입에 필요한 사용자들의 도입 요인을 살펴보았다. 이를 기반으로 보다 효과적인 모바일 헬스케어 앱 개발을 할 수 있을 것이다.

중심단어: 스마트폰 과의존, 확장된 통합기술수용모형, 기술수용모델, 모바일 헬스케어 앱