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Using mobile health technology to deliver decision support for self-monitoring after lung transplantation

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Abstract

Background—Lung transplant recipients (LTR) experience problems recognizing and reporting critical condition changes during their daily health self-monitoring. Pocket PATH®, a mobile health application, was designed to provide automatic feedback messages to LTR to guide decisions for detecting and reporting critical values of health indicators.

Objectives—To examine the degree to which LTR followed decision support messages to report recorded critical values, and to explore predictors of appropriately following technology decision support by reporting critical values during the first year after transplantation.

Methods—A cross-sectional correlational study was conducted to analyze existing data from 96 LTR who used the Pocket PATH for daily health self-monitoring. When a critical value is entered, the device automatically generated a feedback message to guide LTR about when and what to report to their transplant coordinators. Their socio-demographics and clinical characteristics were obtained before discharge. Their use of Pocket PATH for health self-monitoring during 12 months was categorized as low (≤25% of days), moderate (>25% to ≤75% of days), and high (>75% of days) use. Following technology decision support was defined by the total number of critical feedback messages appropriately handled divided by the total number of critical feedback messages generated. This variable was dichotomized by whether or not all (100%) feedback messages were appropriately followed. Binary logistic regression was used to explore predictors of appropriately following decision support.

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Authors'contributions: All authors made substantial contributions to the study. YJ was the principal author, conducting secondary analysis of data, interpreting data from the parent study and drafting the manuscript. SMS, ADD, SMH, and EAS contributed to the study concept, study design, data analysis, and interpretation of the findings.

Protection of human subjects protections: The parent study (NIH, NINR, R01 NR010711, PI: Annette DeVito Dabbs) has been approved and renewed by the University of Pittsburgh Institutional Review Board (IRB, PRO08070401). Since the current study only used de-identified data for secondary analysis, University of Pittsburgh classified this study as exempt (PRO15010376).

Results—Of the 96 participants, 53 had at least 1 critical feedback message generated during 12 months. Of these 53 participants, the average message response rate was 90% and 33 (62%) followed 100% decision support. LTR who moderately used Pocket PATH ($n = 23$) were less likely to follow technology decision support than the high (odds ratio [OR] = 0.11, $p = 0.02$) and low (OR = 0.04, $p = 0.02$) use groups. The odds of following decision support were reduced in LTR whose income met basic needs (OR = 0.01, $p = 0.01$) or who had longer hospital stays (OR = 0.94, $p = 0.004$). A significant interaction was found between gender and past technology experience (OR = 0.21, $p = 0.03$), suggesting that with increased past technology experience, the odds of following decision support to report all critical values decreased in men but increased in women.

Conclusions—The majority of LTR responded appropriately to mobile technology-based decision support for reporting recorded critical values. Appropriately following technology decision support was associated with gender, income, experience with technology, length of hospital stay, and frequency of use of technology for self-monitoring. Clinicians should monitor LTR, who are at risk for poor reporting of recorded critical values, more vigilantly even when LTR are provided with mobile technology decision support.

Keywords

Mobile health technology; Decision support; Health self-monitoring; Critical value reporting; Patient compliance; Lung transplantation

1. Introduction

Lung transplantation has been increasingly performed in persons with end-stage lung diseases and has improved their quality of life and survival [1–3]. However, survival rates of lung transplant recipients (LTR) are still lower than those of other solid organ recipients [3]. Up to 75% of LTR are affected by infection and 55% by acute rejection in the first year [4,5], which are risk factors for chronic rejection, the primary cause of death beyond the first year [6,7]. Prompt recognition of condition changes that are associated with complications is crucial for improving recipients' survival. In addition to their regular follow-up visits to the transplant center, LTR are highly encouraged to perform daily health self-monitoring of spirometry, vital signs, weight, and symptoms at home, and to report any early signs of complications to clinicians [8].

However, LTR often have problems recognizing critical condition changes and making decisions about when to contact clinicians [9]. Although all LTR receive discharge instructions for detecting and reporting critical condition changes during home self-monitoring, LTR find it challenging to identify the thresholds of critical values for multiple health indicators, for example, the lower or upper limits of blood pressures, and to recognize critical changes from their own personal baselines [9]. Considering the amount of self-monitoring data generated by all LTR, it would be too time-consuming for clinicians to track and screen critical values for each LTR [10]. Patient engagement in self-management is important for the improvement of health outcomes [11,12]. Providing direct decision support for LTR to recognize critical values and report them to the transplant team may help the recipients engage in their own care and facilitate early interventions for the improvement of quality of life and survival.

Electronic spirometry systems have been reported to be reliable and valid for LTR health self-monitoring [10,13–15]. However, most electronic spirometry systems have been designed to send self-monitoring data to clinicians for interpretation, and do not provide decision support for LTR [15–19]. A few systems provide reminders or alerts for LTR to take action, such as reassessing their forced expiratory volume in the first second (FEV_1) when the values fall below a reference value [17], or contacting the transplant center when symptoms worsen [20]. Kugler et al. [21] described one electronic spirometry system that provided specific traffic light colors to warn patients on how to interpret and respond to lowering FEV_1 values.

Pocket Personal Assistant for Tracking Health (Pocket PATH®) is a smartphone application, developed by a multidisciplinary research team from the University of Pittsburgh and Carnegie Mellon University to assist LTR to monitor health indicators including spirometry, temperature, blood pressure, pulse, weight, and symptoms. Automatic thresholds for reporting critical values for each health indicator were determined by clinicians and programmed in the device. A full description of features of Pocket PATH was published elsewhere [22]. Main features of Pocket PATH include direct data entry of health indicators, both logged and graphical displays of data over time, and automatic decision support. When a critical value is entered into the device, the application automatically generates a feedback message, providing specific decision support for LTR about when and what to report to their transplant coordinators [22].

However, patients may not always adhere to self-monitoring recommendations. Non-adherence to the medical regimen in transplant recipients has been widely reported [23–27]. It is unknown whether transplant recipients would follow self-monitoring recommendations delivered by mobile technology, especially when reporting critical values is the concern. It is important to identify the factors that may affect the degree to which LTR follow technology-generated decision support recommendations for reporting critical values, which may help develop effective solutions to improve the self-monitoring and early identification of complications. Although a previous study of transplant recipients reported that demographics, social support, and perceived health were not associated with non-adherence to the medical regimen [28], no studies have explored whether such factors predict response by LTR to technology decision support for reporting critical values.

No previous conceptual framework has been specifically utilized to identify factors associated with appropriate response to technology decision support for reporting critical condition changes during patient health self-monitoring. Based on a widely used technology acceptance model, the Unified Theory of Acceptance and Use of Technology (UTAUT) [29], and the literature [30,31], two exploratory models (Figs. 1 and 2) were proposed to guide this study. The models posit that socio-demographic factors and context-related facilitating conditions, such as clinical characteristics and health status, health control beliefs, self-care agency, and environmental factors, may affect responses by LTR to technology decision support for reporting critical values. In addition, the frequency of use of mobile technology for health self-monitoring may be associated with following technology decision support for reporting critical values. The models propose that use of mobile technology may be a potential moderator or a mediator of the relationships between predictors (socio-demographics and facilitating conditions) and appropriately following technology decision support, respectively.

Using the Pocket PATH intervention as an exemplar of a mobile health (mHealth) technology with decision-support features, the purposes of this study were to: (1) determine the degree to which LTR responded appropriately to mHealth technology-generated decision support feedback messages by reporting critical values, (2) explore predictors of appropriately following technology decision support during the first 12 months post-transplantation; and (3) assess whether the frequency of using the Pocket PATH intervention influenced the relationships between predictors and appropriately following technology decision support for reporting critical values.

2. Materials and methods

2.1. Study design and sample

A cross-sectional correlational design was utilized to analyze existing data from a randomized controlled trial evaluating the efficacy of Pocket PATH intervention compared to usual care for promoting self-monitoring during 12 months post-lung transplantation. The sample was comprised of 96 LTR who were from the Pocket PATH intervention group. All participants were recruited from December 2008 to December 2012 at the acute cardiothoracic unit of the University of Pittsburgh Medical Center. They were at least 18 years old, with no prior organ transplant, stable enough to be discharged from the hospital, likely to be involved in their own post-transplant care, and able to read and speak English. Details of the protocol have been published elsewhere [22,32]. The mean age of the sample was 57 years (*SD* = 14). Most were male (51%), white (93%), currently married (74%), unemployed (84%), with more than high-school education (56%), with their basic needs met by current household income (89%). More than half (54%) were re-hospitalized at some point during the first year post-discharge.

2.2. Procedure

LTR received a 30–60 min technology training session before discharge from the hospital. They were instructed to enter their spirometry data, vital signs, and symptoms into the daily checklist of Pocket PATH. The application was programmed to generate automatic feedback messages via the Smartphone prompting the LTR to take action, such as double checking the values, and reporting any of the following critical values: temperature >101° Fahrenheit (or 38.3° Celsius), blood pressure of systolic >160 or <88 or diastolic >100 mmHg, or pulse <60 or >120 beats/min [33].

Participants used Pocket PATH daily for self-monitoring of health indicators in 12 months post-discharge. Self-monitoring data were automatically uploaded to a secure server in the research site. Critical feedback messages were assessed and compared with cumulative data by project staff every 72 h [33]. Participants were informed that the transplant team was responsible for managing their clinical care [32].

2.3. Measures

The outcome for following technology decision support was operationalized as evidence of reporting critical values in response to feedback messages. According to an *a priori* data monitoring algorithm [33], confirmation about whether the LTR responded appropriately to a feedback message by reporting the critical value to the clinician was obtained by reviewing the transplant coordinators' progress notes. Appropriate responses were also considered when critical values were found to be entered in error, values returned to acceptable levels, or clinicians were already aware of values from other ways (such as clinical visits) [33]. The degree of following decision support was calculated as a percentage by dividing the number of feedback messages to which the LTR appropriately responded by the total number of feedback messages generated over the 12 months, multiplied by 100. As the distribution of this variable was severely left (negatively) skewed, this variable was dichotomized by whether or not recipients appropriately responded to all (100%) critical feedback messages. The threshold of 100% was chosen because the recipients are required to report all identified critical values during home self-monitoring according to standard care. In addition, this cut-off point can be used to evaluate whether or not the recipients were fully following the technology decision support.

Socio-demographic factors were measured at baseline (before discharge) and included for this analysis, *age* (years), *gender* (male vs. female), *marital status* (currently married vs. not-married), *education* (≤high school vs. >high school), *employment* (employed vs. unemployed), and *income* (current household income met basic needs vs. did not meet basic needs). *Race* was used as a sample descriptor, but was not included in the analysis because all participants who had critical values recorded were Caucasians. *Experience with technology* was calculated by summing scores for frequency of use of cell phone, personal digital assistant (PDA), other handheld device (e.g., MP3, digital camera, etc.), and a computer. The summed score ranged from 0 to 8, with higher scores indicating more technology experience.

Clinical characteristics were obtained from patient medical records and included for this analysis, *underlying lung disease* (obstructive vs. non-obstructive), *type of transplant procedure* (single vs. double), *re-intubation* (yes vs. no), *return to intensive care unit* (yes vs. no), *post-operative ventilator needs* (<48 h vs. ≥48 h), *length of ICU stay* (days), *length of hospital stay* (days), *discharge destination* (home vs. facility), and *re-hospitalization* (yes vs. no) during the 12 months post-discharge.

Health status included physical health and psychological distress post-transplantation. The *physical component summary* (PCS) of the Medical Outcomes Study Short Form-36 (SF-36) v2 [34], a reliable and valid self-report summary measure of physical health-related quality of life, was measured at 2, 6, and 12 months post-transplantation. Cronbach's alpha for the PCS in LTR was 0.83 [35]. An overall mean PCS score was calculated as the average of the PCS values at the 2, 6, and 12 months post-transplantation assessments and ranged from 0 to 100, with higher scores indicating better physical health.

Psychological distress was measured using the reliable and valid anxiety and depression subscales of the Symptom Checklist-90-Revised (SCL-90-R) at baseline, 2, 6, and 12 months [36]. Cronbach's alphas for the two subscales ranged from 0.80 to 0.88 in LTR [35]. The average scores for anxiety (10 items) and depression (13 items) were summed to generate a measure of general psychological distress, since anxiety and depression scores were highly correlated ($r = 0.68$ to 0.74, $p < 0.001$) in this study. An overall mean psychological distress score over the 12-month period was calculated as the average of the psychological distress values at the 2, 6, and 12 months post-transplantation assessments, with a range of 0–8, higher scores indicated more distress.

Health control beliefs were measured at baseline using the Multi-dimensional Health Locus of Control Scale [37]. Cronbach's alphas were reported to range from 0.67 to 0.78 for two subscales, including LTR [37–39]. The internality subscale (6 items) and externality subscale (6 items) assessed the extent to which LTR believed that their health outcomes were primarily their own responsibility or the responsibility of their health professionals, respectively. Scores for each subscale ranged from 6 to 36, higher scores indicated higher control beliefs.

Self-care agency, defined as the perceived ability to engage in self-care, was measured using the Perception of Self-Care Agency scale at baseline, 2, 6, and 12 months post-transplantation [40]. Cronbach's alpha of the scale was reported as 0.95 in LTR [41], and 1-week test-retest reliability was 0.85 [42]. An overall mean self-care agency score was calculated as the average of the total scores at the baseline, 2, 6, and 12 months post-transplantation assessments with a range of 53–265, higher scores indicated higher self-care agency.

Quality of recipient-caregiver relationship was measured at baseline using an adaptation of the Dyadic Adjustment Scale [43], with a reported Cronbach's alpha of 0.86 in LTR [41]. Only the sum score of the first 15 items was counted in this study, assessing any type of recipient-caregiver relationship. Scores ranged from 15 to 75, with higher scores indicating higher relationship quality.

Satisfaction with technology training was measured by the After-Scenario Questionnaire [44]. Cronbach's alpha was reported from 0.90 to 0.96 [44]. The average score of three items ranged from 1 to 7. Since the distribution of average scores was highly negatively skewed, the variable was dichotomized by the median score of 7 as fully satisfied (7) and less than fully satisfied (<7).

Use of Pocket PATH for health self-monitoring over the 12 months was measured by calculating the percentage of days with data recorded for any health indicator divided by the total number of participation days (adjusted for the days LTR were re-hospitalized and not expected to self-monitor), and multiplied by 100. Since the data were highly skewed (U- or L-shaped distribution), they could not be normalized through data transformation [45,46], therefore the use of Pocket PATH was categorized into three levels: low use (monitored ≤25% of days), moderate use (monitored >25% to ≤75% of days), and high use (monitored >75% of days).

2.4. Data analysis

Analyses were conducted using IBM® SPSS® Statistics (version 23.0, IBM Corp., Armonk, NY). Descriptive statistics were used to summarize sample characteristics and the outcome variable of appropriately following technology decision support. Mann-Whitney *U* tests (continuous variables) or Chi-Square/Fisher's Exact tests (categorical variables) were used to compare sample characteristics between groups of participants with and without critical values recorded, and between groups of participants who had 100% following decision support and who had less than 100% following decision support. Using a cutoff p-value < 0.25 [47,48], univariate binary logistic regression was conducted to screen for candidate predictors variables (socio-demographic factors, facilitating conditions) of the outcome variable, appropriately following technology decision support, for inclusion in the final multivariate (multiple predictors) binary logistic regression model. Interactions between predictor variables and multicollinearity were assessed. Deviation from the mean of continuous variables was introduced in the model to eliminate non-essential multicollinearity among continuous predictor variables due to inclusion of two-way interaction terms. Final parsimonious models were generated using backward elimination (using a $p < 0.05$ for the retention of a predictor variable in the model). The percent correct prediction of the binary logistic regression model, including sensitivity, specificity, and overall correct prediction, was evaluated based on a classification table (using the cutoff value of 0.50 for the predicted probability). Potential mediation and moderation effects of use of Pocket PATH on relationships between predictors and the outcome variables (Figs. 1 and 2) were assessed by simple mediation models (four steps of regression analyses between the causal variable, potential mediator, and outcome variable) and multiple regression analysis [49], respectively. The level of significance was set at $p < 0.10$ for the exploration of possible mediation and moderation effects.

3. Results

3.1. Summary of sample and appropriately following decision support for reporting critical values

Among 96 LTR participants, 53 (55%) recorded at least one critical value, prompting at least one critical feedback message during the first 12 months post-transplantation. The remaining 43 participants had zero critical value recorded. Between LTR with and without critical values recorded, socio-demographics and facilitating conditions did not differ ($p > 0.05$), except for external health control beliefs. LTR with at least one critical feedback message generated had stronger beliefs that their health outcomes were primarily their health care providers' responsibilities ($p = 0.03$). A significant difference in frequency of using of Pocket PATH was found between LTR with and without recorded critical values ($p < 0.001$). About 78% of LTR in the low use group (monitored ≤25% days) did not have any critical values recorded, whereas in the high use group (monitored >75% days) this percentage was only 5%. About 96% of LTR in the high use group had at least one critical value recorded during 12 months.

Those 53 participants who had critical values recorded were on average 59 years old, with moderate experience with technology. Most were male, married, unemployed, with more than high school education, and reported that their current household income met their basic needs. The majority were re-hospitalized at least once during the 12 months post-discharge. Most were identified as having moderate or high use of Pocket PATH for health self-monitoring (see Table 1).

Among the 53 participants, 33 (62%) followed all (100%) technology-generated decision support recommendations, reporting all critical values to clinicians, leaving 20 (38%) who reported less than 100% of recorded critical values (mean = 75%, range 0–98%, and mode = 50%). The overall average reporting rate was 90%. Participants who followed 100% technology decision support had significantly lower ICU stay and were less likely to return to ICU than those who followed less than 100% technology decision support (see Table 1).

3.2. Predictors of appropriately following decision support for reporting critical values

Univariate logistic regression modeling ($p < 0.25$) identified several candidate predictors for the final multivariate modeling of appropriately following technology decision support for reporting critical values, including gender ($p = 0.06$), income ($p = 0.20$), experience with technology ($p = 0.17$), LOS ($p = 0.07$), length of ICU stay ($p = 0.10$), and use of Pocket PATH for health self-monitoring in which the moderate use group was significantly different than the high use group ($p = 0.19$) in reporting recorded critical values. Since LOS and length of ICU stay were highly correlated ($r = 0.84$, $p < 0.001$), only LOS was included in the multivariate (multiple predictor) binary logistic regression model. The final parsimonious model included five predictor variables – gender, income, experience with technology, LOS, and use of Pocket PATH.

The parsimonious modeling results presented in Table 2 revealed that LTR whose income met their basic needs (OR = 0.01, $p = 0.02$), or with longer LOS (OR = 0.94, $p < 0.01$), were less likely to follow technology decision support for reporting critical values. A significant interaction of gender and experience with technology indicated that with increased experience with technology, the odds of following technology decision support for reporting critical values decreased in men but increased in women ($p = 0.03$). In addition, use of Pocket PATH for self-monitoring predicted the reporting of recorded critical values ($p = 0.02$), and the moderate use group was less likely to follow decision support than the high use group (OR = 0.11, $p = 0.02$). After adjusting the model by using the low use group as the reference, the moderate use group was also found to be less likely to follow decision support that the low use group (OR = 0.04, $p = 0.02$), which is not shown in Table 2. No interaction was found between use of Pocket PATH and any other predictors in the model.

According to the classification table generated in the final parsimonious logistic regression model, with the cutoff set at 0.5, the prediction for appropriately following decision support for reporting critical values during 12 months had a sensitivity of 87.9% and specificity of 75.0%, indicating a high proportion of correctly classified events (following 100% decision support) and nonevents (following less than 100% decision support). The false positive rate was 14.7%, and the false negative rate was 21.1%. The overall correct prediction was 83.0%.

33. Mediation or moderation effects of use of Pocket PATH

Use of Pocket PATH for self-monitoring was not a mediator of the relationships between gender, income, experience with technology, LOS and following decision support for reporting critical values during 12 months post-transplant ($p > 0.10$). In addition, use of Pocket PATH did not moderate any relationships between the above predictors and following decision support for reporting critical values during 12 months post-transplant ($p > 0.10$).

4. Discussion

The central aim of this secondary analysis was to explore responses of LTR to decision support recommendations delivered through Pocket PATH, a mHealth application. Findings revealed that among the 53 LTR who had any critical values recorded, the majority appropriately followed decision support for reporting critical values. However, only 33 (62%) of those reported all recorded critical values. No previous study has reported patients' following mHealth technology-based decision support recommendations for reporting critical condition changes. However, our results are comparable to patients' following self-care recommendations delivered by clinicians, such as nurses [50,51], and patients' adherence to advice (to contact the doctor or perform self-care) delivered by a web-based triage system [52].

This study also identified that certain predictors for appropriately following technology decision support, including socio-demographic factors (gender, income, and previous technology use), clinical factor (length of hospital stay), and the frequency of use of technology (Pocket PATH) for health self-monitoring. We also found that men and women may respond differently to technology-generated recommendations for reporting critical values, which was affected by their prior experience with technology. Specifically, with increased previous technology use experience, women were more likely to follow technology decision support for reporting critical values than men. Previous studies have reported inconsistent gender differences in mobile technology adoption [53–55]. Regarding health condition monitoring and symptom reporting, women were consistently shown to report more symptoms than men [56,57]. Prior experience with technology was generally found to be associated with increased technology acceptance [58], yet this study showed that an increased experience with technology may lead to differences between women and men when it comes to reporting critical condition changes based on technology-generated decision support.

Income was not included as an influential factor in the original Unified Theory of Acceptance and Use of Technology [29]. However, this study found that the low-income group (basic needs unmet by household income) was more likely to follow decision support for reporting critical values. This finding may be partially explained by evidence that low-income patients often have higher trust in their doctors and rely more on their doctors as the primary source of health information [59,60]. According to a report from Pew Research Center, mobile phones play an important role for assessing health information in those with low household incomes (less than $30,000) [61]; they are more likely to be smartphone-dependent, and therefore, they may tend to accept information generated by mobile technology, such as decision support recommendations.

Length of hospital stay, considered an indicator of patients' general health status, is a potential predictor of patients' acceptance of consumer health information technology [58]. Both better health and poorer health have been reported to be associated with increased acceptance of or adherence with technology use [19,62–64]. Specifically, Sabati et al. [65] found poor health status was a barrier to adherence to an electronic home monitoring system in LTR. Similarly, current study revealed that LTR with a longer hospital stay (poorer health status) followed decision support less often and reported critical condition changes at a lower rate.

Although use of mobile technology for health self-monitoring was not a mediator or a moderator of the relationships between predictors and appropriately following technology decision support, not surprisingly LTR who used Pocket PATH for self-monitoring more often were more likely to record more critical values and respond more appropriately to self-monitoring recommendations. It is interesting to note that although the low use group did not frequently use the technology for self-monitoring, if and when they used it, they tended toward following decision support for reporting critical condition changes. This finding may need to be further explored in future studies.

The study has several limitations. First, the sample size of LTR who recorded any critical values was small ($n = 53$); thus, the study may lack the power to reveal the true relationships between potential predictors and the outcome variable. Although univariate analyses and parsimonious modeling were conducted to decrease the number of predictors included in the final model, generalization of findings of this study needs to be confirmed in a larger sample. Second, some approaches for managing the variables in the study may have caused loss of information; for example, calculation of the overall mean scores for longitudinal variables, such as PCS and self-care agency, and categorization of variables such as use of Pocket PATH for self-monitoring and satisfaction with technology training due to data skewness. Also due to the high correlation between anxiety and depression, a composite variable, psychological distress, was created by summing the mean subscale scores. Third, this study only included the subgroup of 53 LTR who recorded critical values, and therefore had the potential to receive decision support recommendations. Forty-three LTR recorded no critical values, yet we were unable to determine if this was due to a limited use of Pocket PATH for self-monitoring or these LTR had no critical values to report. Fourth, in the absence of a specific theoretical framework regarding patients' responses to technology decision support, we adapted the UTAUT model to guide this study. It is possible that some potential predictors were missed in the consideration. However, the final model presented both high sensitivity (87.9%) and specificity (75%) in prediction for following decision support by reporting critical values. With an overall 83% of all cases correctly predicted, predictors identified in this study may be useful in future studies to further understand patients' behavior of following technology decision support.

5. Conclusion

Mobile health technology with decision support appears to be effective in promoting appropriate response behaviors for reporting of recorded critical values after lung transplantation; however, not all values were reported consistently and LTR with certain characteristics were less likely to respond. Appropriately following technology decision support was associated with their gender, income, experience with technology, length of hospital stay, and the frequency of use of mobile technology for health self-monitoring. Clinicians should more vigilantly monitor LTR who are at risk for poor reporting of critical values even when provided with mobile technology decision support. Tailored interventions may be needed to assist LTR to improve self-monitoring and early detecting and reporting of critical condition changes. Alternatively, automatic critical values reporting may be able to be added in the system design, especially for those recipients who are at high risk for poor reporting. The recipients' involvement in the verification of critical values still needs to be considered, and they should be allowed to choose their preferred ways to report the recorded critical values.

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Summary Points

What was already known

- Lung transplant recipients (LTR) face challenges in recognizing critical condition changes during health self-monitoring and may not know what and when to report to clinicians
- It is unknown how patients would respond to decision support recommendations delivered through mobile health technologies
- A conceptual framework to guide the examination of factors that predict patients' responses to technology-delivered decision support is lacking
- LTR, a population that is expected to perform daily self-monitoring, may benefit from decision support for recognizing and reporting critical condition changes to clinicians

What this study added to our knowledge

- LTR benefited from mobile technology decision support for the interpretation and reporting of critical condition changes to clinicians during daily health self-monitoring
- Appropriate responses by LTR to mobile technology decision support is significantly associated with gender, experience with technology, income, length of hospital stay, and self-monitoring frequency
- With the increase of prior experience with technology, the likelihood of LTR following decision support recommendations delivered through mobile health technologies for reporting critical condition changes increased in women, but decreased in men
- LTR who have high use of mHealth technology are more likely to respond appropriately to decision support recommendations

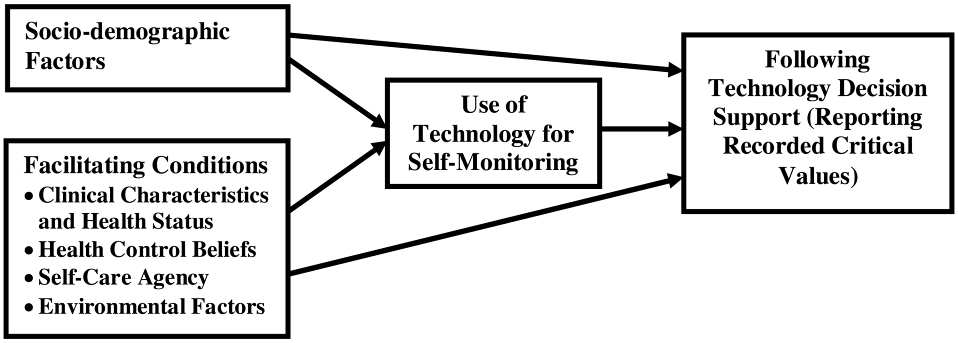

Fig. 1.

Exploratory research model 1: following technology decision support for reporting recorded critical values during health self-monitoring in lung transplant recipients (use of technology as a mediator).

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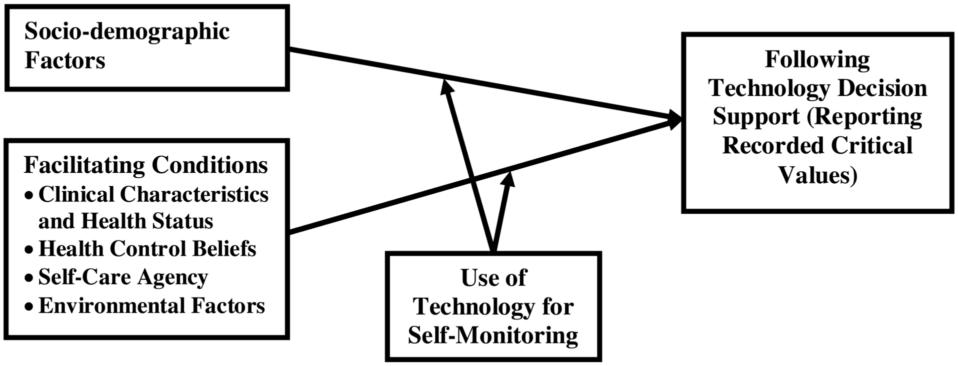

Fig. 2.

Exploratory research model 2: following technology decision support for reporting recorded critical values during health self-monitoring in lung transplant recipients (use of technology as a moderator).

Table 1

Summary of Sample with Feedback Messages Generated and Subgroups Following Technology Decision Support.

Characteristic		Total Sample (*n* = 53)	100% Following (*n* = 33, 62%)	<100% Following (*n* = 20, 38%)	*p*
	Mean (*SD*)				
Age (years)		59 (12)	58 (12)	61 (10)	0.33
Experience with Technology		5 (2)	6 (2)	5 (2)	0.17*
LOS (days)		29 (25)	24 (15)	38 (34)	0.08*
Length of ICU stay (days)		8 (11)	6 (9)	12 (13)	0.02**
		n (%)			*p*
Gender	Male	31 (59)	16 (52)	15 (48)	0.09*
	Female	22 (41)	17 (77)	5 (23)	
Marriage	Married	42 (79)	25 (60)	17 (40)	0.50
	Unmarried	11 (21)	8 (73)	3 (27)	
Employment	Unemployed	46 (87)	29 (63)	17 (37)	1.00
	Employed	7 (13)	4 (57)	3 (43)	
Education	>High School	28 (53)	18 (64)	10 (36)	0.75
	≤ High School	25 (47)	15 (60)	10 (40)	
Income	Met Basic Needs	46 (87)	27 (59)	19 (41)	0.23*
	Not Met Basic Needs	7 (13)	6 (86)	1 (14)	
Underlying Disease	Obstructive/COPD	30 (57)	18 (60)	12 (40)	0.70
	Non-obstructive	23 (43)	15 (65)	8 (35)	
Type of Transplant	Double	42 (79)	25 (60)	17 (40)	0.50
	Single	11 (21)	8 (73)	3 (27)	
Post-op Ventilator	<48 h	37 (70)	24 (65)	13 (35)	0.55
Needs	≥48 h	16 (30)	9 (56)	7 (44)	
Re-intubated	No	47 (88)	30 (64)	17 (36)	0.66
	Yes	6 (12)	3 (50)	3 (50)	
Return to ICU	No	49 (93)	33 (67)	16 (33)	0.02**
	Yes	4 (7)	0 (0)	4 (100)	
Re-hospitalized in 12 Months	Yes	43 (81)	28 (65)	15 (35)	0.48

Characteristic		Total Sample (n = 53)	100% Following (n = 33, 62%)	<100% Following (n = 20, 38%)	*p*
	Mean (*SD*)				
	No	10 (19)	5 (50)	5 (50)	
Use of Pocket PATH for Self-monitoring in 12 months	Low Use (≤25%)	9 (17)	6 (67)	3 (33)	0.42
	Moderate Use (>25% to ≤75%)	23 (43)	12 (52)	11 (48)	
	High Use (>75%)	21 (40)	15 (71)	6 (29)	

Notes: ICU: Intensive Care Unit; LOS: Length of Stay (in hospital).

* p-value<0.25.

** p-value<0.05.

Table 2

Parsimonious Logistic Regression Model for Predictors of Appropriately Following Technology Decision Support for Reporting Critical Values (n = 53).

Predictor	***b***	**SE (*b*)**	***p***	**OR**	**95% CI for OR**	
					Lower Limit	**Upper Limit**
Gender (Male)	-1.65	0.91	0.07	0.19	0.03	1.14
Income (Met Basic Needs)	-4.26	1.80	0.02*	0.01	<0.01	0.48
Experience with Technology	1.26	0.64	0.05*	3.53	1.01	12.36
LOS	-0.06	0.02	<0.01**	0.94	0.90	0.98
Use of Pocket PATH (Moderate Use)#	-2.22	0.93	0.02*	0.11	0.02	0.67
Gender*Experience with Technology	-1.58	0.75	0.03*	0.21	0.05	0.89

Notes: CI: Confidence Interval; LOS: Length of Stay (in hospital); OR: Odds Ratio; SE: Standard Error.

* *p*-value<0.05.

** *p*-value<0.01.

\# High use group as the reference.