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A Structural Equation Model to Predict the Social-Cognitive Determinants Related to Physical Activity in Iranian Women with Diabetes Mellitus

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ABSTRACT

Background: Lifestyle-modification programs including physical activity are essential for both treatment and prevention of Type 2 Diabetes Mellitus (T2DM). However, factors associated with physical activity among patients are poorly understood. This study applied Social-Cognitive Theory (SCT) for predicting determinants of physical activity among women with T2DM in Iran, 2013.

Methods: In this cross-sectional study, partial least square path modeling (PLS-PM) was used as an estimation technique for structural equation model. This model specified hypotheses between components of Social-cognitive Theory on physical activity behavior. A random sample of 300 women with T2DM was selected, and completed SCT constructs instrument. Data were analyzed using statistical software WarpPLS Ver. 4.0.

Results: The model explained 26% of the variance in physical activity. Self-regulation, task self-efficacy and barrier self-efficacy were significantly direct predictors of physical activity among women with T2DM. Task self-efficacy, social support and modeling had significantly indirect effects on physical activity behavior (P<0.001).

Conclusions: Our findings showed evidence for adequacy of a theoretical framework that could be used to predict physical activity behavior among women with T2DM.

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Introduction

Diabetes mellitus is the fourth great cause of death in most of countries; an estimated 285 million adults suffered from diabetes worldwide in 2010, and this number is expected to rise to 438 million by 2030[1]. It is estimated that the prevalence of diagnosed diabetes among population over 30 years is 7.3% in Iran[2].

Lifestyle-modification programs including physical activity (PA) have been shown to prevent of type 2 diabetes mellitus (T2DM)[3]. Although physical activity have positive effects on various aspects of health in patients with diabetes, but many diabetics compared with no diabetics have low levels of mobility (34% vs. 40%)[2].

To develop related policies and effective interventions, it is necessary to identify factors that could be changed to improve PA behavior[4]. To present behavior predictors, decrease disability, and enabling individual to adapt to health promoting behaviors, Social-cognitive Theory (SCT) has been introduced[5].

Different personal factors including demographic variables, attitude, social, and environmental factors affect performing PA[6] and directly and indirectly predict PA[2,7].

Jinis et al determined the power of SCT constructs in predicting PA and providing a structural model in patients with spinal injury. They showed that self-regulation construct directly predicted performing PA in their patients. In addition, self-efficacy and outcome expectations described PA indirectly through self-regulation[8]. In Plotnikoff's study, self-efficacy was predictor of PA among patients with type 1 and type 2 diabetes. Self-efficacy and self-regulation were direct predictors of PA. In addition, self-efficacy, outcome expectations and social support predicted self-regulation, which, in turn, predicted PA[9].

In the previous study, authors identified direct effects of social-cognitive factors influencing PA behavior using regression technique. They did not identify the role of latent variables and multiple dependent variables on each other and the behavior PA[10].

In some studies multiple regressions was used to assessing the predictors of PA in patients. The present study provides, perhaps comprehensive understanding of determinant relationships with each other or in combination with effect on PA behavior. The role of social-cognitive factors was based on assessing SCT that determines factors of behavior (such as PA) and examines in interaction with each other.

Structural Equation Model (SEM) compared to multiple regression have some advantages including more flexible assumptions, using confirmatory factor analysis to reduce measurement error by considering several variables observed for each of hidden variables, and the ability to test models with multiple dependent variables. SEM comprises a group of estimation algorithms that account for the complexity of SCT. The relationship between several components can be analyzed in a SEM with the combination of factors and multiple regression analysis [11].

The aim of this study was to provide SEM to predict SCT on PA and propose a method for empirical analysis of situations that involve multiple inter-relationships among several composites. It also aimed to discover the most effective or the strongest social-cognitive factors, demographic and medical variables of PA behavior among women with T2DM.

Methods

Design and setting

Participants of this cross-sectional study were recruited from diabetes clinics in health centers in Mashhad City, Iran in 2013. The required sample size for the study was estimated to be 300 people. This estimation was based assumptions for similar study, given correlation coefficient of self-efficacy with physical activity (r=0.16), 95% confidence and power of 80% [2].

Procedure

Study population was selected based on two-stage cluster sampling technique[10]. The diabetes women eligible for participation in the study were given oral information about the project and were assured that contribution was anonymous. Oral consent was obtained from patients and the study was approved by the Research Ethical Committee of Mashhad University of Medical Sciences.

Patients were enrolled based on the following inclusion criteria, women with T2DM (based on exciting health evidence), Iranian nationality, the age of 35- 65 years, willingness to participate in the study, having T2DM more than 6 month and performing physical activity. Patients with diabetes complications, insulin therapy, were excluded from the study.

Measures

Data collection was performed using a validated and localized questionnaire[10,13]. Content validity was concluded by utilizing experts' opinions, and calculation of Content Validity Ratio (CVR). Internal and external consistency of questionnaires was estimated using Cronbach' alpha index and test–retest respectively. Details of these findings have been mentioned in previous study[10].

The questionnaire consisted of three sections as follows: 1) questions about demographic characteristics such as age, gender, marital status, level of education, 2) short form of International Physical Activity Questions (IPAQ) [12], and 3) question related to SCT constructs. the third section (SCT) contained; self-regulation with two questionnaires (6 and 4 questions about goal setting and action planning respectively), barrier self-efficacy with 10 questions ,task self-efficacy with 4 questions (range 4-20), outcome expectations with 4 questions, modeling with 10 questions, 10- question short form of depression with one question added by experts to assess anxiety to assess affective state, social support with 10 questions and perceived environmental with 7 questions. All questions (except depression and planning questions that were measured using 4-point Likert type style) were scored based on the 5-point Likert type style from strongly disagree to strongly agree.

The physical activity was assessed with 7-items that asked patients to state the intensity of (severe, moderate, and light), and duration of physical activity. Using Metabolic Equivalent of (MET) level of consumed energy in terms of intensity of activity is determined[12].

Data analysis

Social–cognitive model of physical activity specifies the relationship between effective variables on physical activity (Figure 1).This model is consistent with theoretical models in preceding studies[8, 14], which provides a theoretical framework for our study.

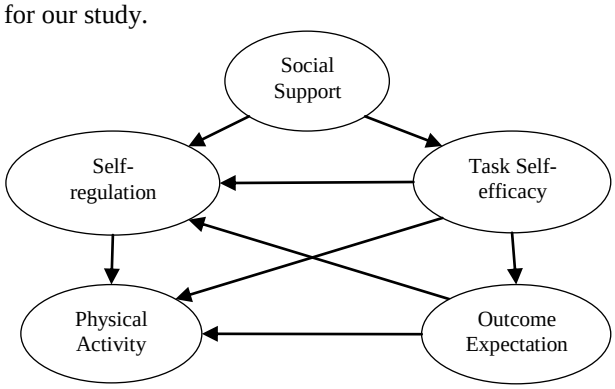

Figure 1: Basic theoretical model of Social-cognitive theory for physical activity

Fit of the social–cognitive model of physical activity behavior was examined using latent variable structural equation model (SEM) (Figure 2). We used R^2 and the path coefficients to test the fit of the model. Before carrying out the SEM analysis, normality of variables was examined. To do SEM in non-normal distributions and small sample size of the data Partial least square path modeling (PLS-PM) was used [15, 16].

PLS-PM is a technique of SEM where the share of the variance explained for one or several endogenous constructs specified in the SEM is maximized through a series of ordinary least squares regressions[17]. It is a component-based estimation method, which is an iterative algorithm that separately analyzes the blocks of the measurement model and then estimates the path coefficients in the structural model. PLS-PM is regarded as a "soft modeling" approach, without strong assumptions for the distributions, the sample size and the measurement scale[18]. WarpPLS 4.0 was used to model the social-cognitive theory using the Warp3 PLS regression algorithm. PLS analyzes structural equation models with

multi-item variables that contain direct, indirect, and interaction effects. PLS provides a powerful technique for appraising a structural model and measurement model because of the minimal needs on measurement scales, sample size, and residual distributions[15]. Handling both formative and reflective indicators PLS can be used not only for theory confirmation, but also for suggesting where relationships might or might not exist and for suggesting propositions for later testing. The combined analysis of the measurement and the structural model enables measurement errors of the observed variables to be analyzed as an integral part of the model, and factor analysis to be combined in one operation with hypothesis testing[19]. All the indicators in the model were treated as reflective indicators of their respective constructs. Statistical significance was set at $P<0.05$.

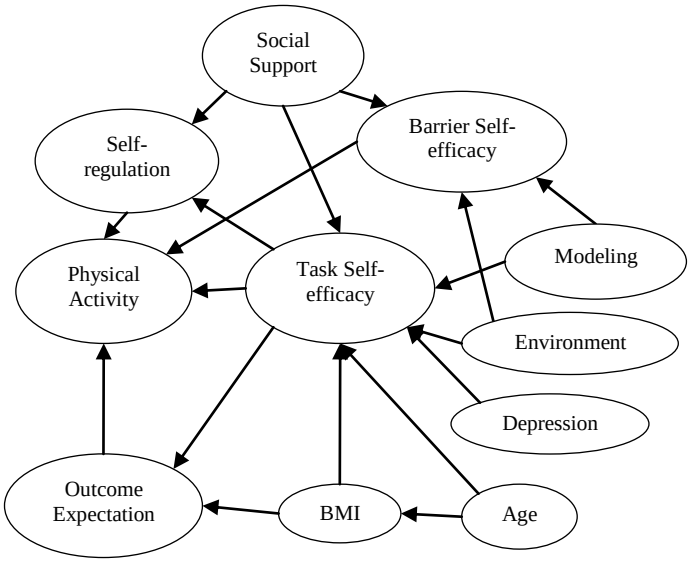

Figure 2: A structural equation model of the social– cognitive theory of physical activity among women with type 2 diabetes

Model Fit

The social-cognitive model was also evaluated for goodness of fit in order to determine how well the social-cognitive model will explain specific situations. The WarpPLS 4.0 provides three basic model fit indices that are average path coefficient (APC), average R^2 (ARS) and average variance inflation factor (AVIF) [21]. APC is the average of all the path coefficients in the inner model. WarpPLS takes all the path coefficients and averages them. WarpPLS then calculates a *P* value with the significance cut-off as the classic 0.05. ARS is the same as the average of the R^2 of the inner model. AVIF is the average of the variance inflation factors of the paths of the inner model. AVIF is a measure of multi co linearity. Furthermore, WarpPLS 4.0 provides other indices including Average full co linearity VIF (AFVIF), Average adjusted R-squared (AARS), TenenhausGoF (GOF), Simpson's paradox ratio (SPR) and R-squared contribution ratio (RSCR).

Effect Size

An effect size is the measure of the extent to which an exogenous (independent) latent variable as a significant influence on an endogenous (dependent) latent variable[20].

Mathematically effect size can be determined using the following notation:

$$f^2=\frac{R_1^2-R_*^2}{1-R_1^2}$$

Where f^2=effect size , R_1^2= coefficient of determination of the full model and R_*^2 =coefficient of determination when a dependent variable is removed[22].

Results

Participants

Participants had the mean of age 52.49 ±7.12 years, body mass index (BMI) 30 ±4.17, and hemoglycolized hemoglobin (HbA1C) 7.67 ±1.68, and the median of diabetes duration, 48 months. Forty-seven percent (N=141) of participants in this sample were classified as obesity (BMI > 30), and 41.7% (N=125) overweight. Table 1 shows other descriptive statistics in this study. Correlations between demographic variables and physical activity of study patients are reported in Table 2.

Table 1: The distribution of demographic Variables in study subjects (n=300)

Variable	Number	Percent
Level of Education		
Low Literacy	49	16.3
Elementary	127	42.3
Middle school	55	18.3
High school diploma	58	19.3
Academic education	11	3.7
Employment status		
Housewife	286	95.3
Employed	14	4.7
Marital status		
Married	262	87.3
Widowed	30	10.0
Divorced	8	2.7
Income level ($)		
<166 ($)	92	43.6
≥166	119	56.4

Table 2: Correlations between study variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12
1. Self-regulation	1.000											
2. Modeling	0.558	1.000										
3. Social support	0.500	0.501	1.000									
4. Barrier self-efficacy	0.543	0.555	0.397	1.000								
5. Depression	-0.232	-0.360	-0.220	-0.340	1.000							
6. Perceived environment	0.304	0.338	0.202	0.188	-0.104	1.000						
7. Physical environment	0.239	0.206	0.380	0.204	-0.081	0.090	1.000					
8. Task self-efficacy	0.596	0.596	0.470	0.613	-0.379	0.227	0.211	1.000				
9. Outcome expectation	0.242	0.352	0.158	0.380	-0.226	0.168	0.096	0.334	1.000			
10. Physical activity	0.534	0.462	0.457	0.429	-0.214	0.266	0.204	0.573	0.211	1.000		
11. Body mass index	-0.028	-0.101	0.025	-0.088	0.124	-0.032	0.040	-0.037	0.000	-0.118	1.000	
12. Age	-0.114	-0.129	-0.067	-0.114	0.072	-0.059	0.061	-0.090	-0.085	-0.124	-0.006	1.000

Evaluation of the Structural Model

The measurement model resulted in a good model fit (APC=0.189; *P*<0.001), (ARS=0.264; *P*<0.001), (AARS=0.256; *P*<0.001), AVIF=1.1290, AFVIF=1.506, GOF=0.433, SPR=0.947, RSCR=0.998.

Figure 3 shows the results of assessment and hypothesis testing. There were statistically significant direct effects between (a) self-regulation and PA, (b) task self-efficacy and PA, (c) barrier self-efficacy and PA. Outcome expectation had non-significant direct effect on PA.

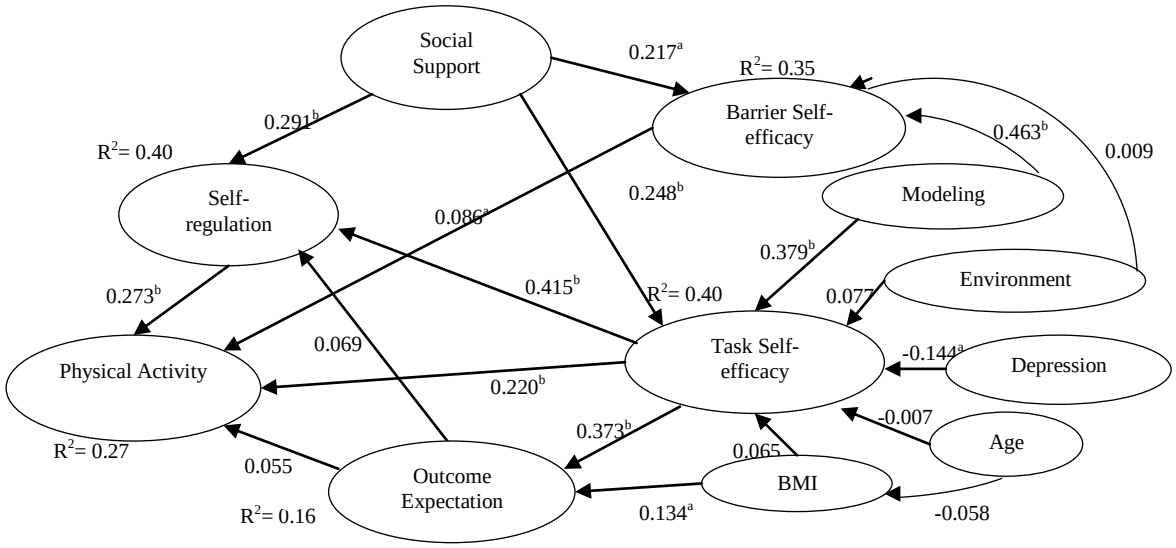

Figure 3: Structural equation analysis of the social–cognitive model of physical activity, Standardized direct effect coefficients [a]*P*<0.05, [b]*P*<0.001

Direct, indirect, and total effect path coefficients are listed in Table 3. Within the model, task self-efficacy had the strongest total effect on PA ($\beta_{(total)}$ =0.361) and then self-regulation ($\beta_{(total)}$=0.273), Social support ($\beta_{(total)}$ =0.188), Modeling ($\beta_{(total)}$=0.177), Barrier self-efficacy ($\beta_{(total)}$ =0.086). Outcome expectations ($\beta_{(total)}$ = 0.074), BMI ($\beta_{(total)}$ =0.033), Perceived environment ($\beta_{(total)}$ =0.028) had positive effects on PA behavior. Greater age was associated with lower levels of physical activity ($\beta_{(total)}$ =−0.004). Besides, depression had a negative effect on PA behavior ($\beta_{(total)}$=-0.052, *P*=0.099) (Table 3).

The results of path coefficients in presented model showed modeling had the greatest direct effect on barrier self-efficacy, also modeling had a moderate direct effect on task self-efficacy and influenced PA behavior by barrier self-efficacy and task self-efficacy. Task self-efficacy had a strong direct effect on self-regulation (β=0.415, *P*<0.001), and then on outcome expectation (β=0.373, *P*<0.001). Indeed, task self-efficacy influenced PA behavior by self-regulation and outcome expectation in the sample. The direct effect of Task self-efficacy (β=0.220, *P*<0.001) was higher than indirect effect (β=0.141, *P*<0.050) on PA. Self-regulation directly predicted PA, which mediated by task self-efficacy, social support, and outcome expectancies (Figure 3).

Social support indirectly predicted PA through its effect on self-regulation; Task self-efficacy, and barrier self-efficacy (Figure 3).

Outcome expectations had a small total effect on PA, which did not reach (direct, indirect and total effects) significance. Moreover, Perceived environment and BMI indirectly predicted PA which none of their effects on PA were significant (Table 3).

Table 3: Direct, indirect (based on coefficients illustrated in Figure 3), and total effects related to physical activity in the social-cognitive model

Variable	Direct effect	*P* value	Indirect effect	*P* value	Total effect	*P* value
Barrier self- efficacy	0.086	0.041	No path	-	0.086	0.041
Self-regulation	0.273	0.001	No path	-	0.273	0.001
Outcome expectation	0.055	0.133	0.019	0.296	0.074	0.068
Task Self-Efficacy	0.220	0.001	0.141	0.002	0.361	0.001
Depression	No path	-	-0.052	0.099	-0.052	0.099
Body mass index	No path	-	0.033	0.250	0.033	0.250
Social Support	No path	-	0.188	0.001	0.188	0.001
Modeling	No path	-	0.177	0.001	0.177	0.001
Perceived Environment	No path	-	0.028	0.283	0.028	0.283
Age (yr)	No path	-	-0.004	0.464	-0.004	0.464

Coefficient of Determination

The variance explained (R^2) are demonstrated for each endogenous variable in the model (Figure 3). The R^2 value related to self-regulation is 0.40. This implies that the independent variables (social support, task self-efficacy, outcome expectation), pointing at self-regulation (the dependent variable), are explaining the dependent variable (self-regulation) by almost 40% and is a suitable moderate threshold for an endogenous variable with few exogenous variables. Similarly, task self-efficacy is influenced by social support, modeling, environment, depression, age and BMI. The R^2 value of task self-efficacy was 40%. In the same way, R^2 observed for barrier self-efficacy was 0.35 and this factor

is influenced by social support, modeling and environment (Figure 3).

The R^2 accounted for PA was 0.27 and this factor is probably influenced by self-regulation, task self-efficacy, barrier self-efficacy, and outcome expectations.

Moreover, the model explained 0.16 of the variance in outcome expectations, which this factor is influenced by Task self-efficacy and BMI.

Effect size

Based on Figure 3, The R^2 values for self-regulation, task self-efficacy, barrier self-efficacy and for physical activity were 0.40, 0.40, 0.35, and 0.27 respectively. We showed the effect size of each independent variable using the f^2 values.

The effect size of age on BMI was 0.003, BMI on outcome expectation 0.002, task self-efficacy on outcome expectation 0.141, task self-efficacy on self-regulation 0.238, social support on self-regulation 0.143, outcome expectation on self-regulation 0.018, social support on barrier self-efficacy 0.093, modeling on barrier self-efficacy 0.259, environment on barrier self-efficacy 0.001, age on task self-efficacy 0.001, BMI on task self-efficacy 0.004, social support on task self-efficacy 0.118, modeling on task self-efficacy 0.216, environment on task self-efficacy 0.017, depression on task self-efficacy 0.050 and the effect size of task self-efficacy on PA was 0.099, outcome expectation on PA 0.012, self-regulation on PA 0.0125, barrier self-efficacy on PA 0.032. The effect size of outcome expectation (0.018) suggests that outcome expectation has a small effect on self-regulation. Both the task self-efficacy and social support relationships have a moderate effect on self-regulation. Similarly, all independent variables except modeling have weak influences on task self-efficacy.

Discussion

The present study showed an overall good fit between the proposed model and the data. If the *P* values associated with APC, ARS and AARS are lower than 0.05, AVIF and AFVIF are lower than 5, GOF is greater than 0.36, SPR is greater than 0.7 and RSCR is greater than 0.9 then a model is determined to have a good fit with the sample data[21]. In our findings, self-regulation was potential variable to exert significant direct effect on physical activity. Similarly, in a study by Ginis et al, self-regulation was a direct predictor of physical activity among people with spinal cord injury[8]. In Anderson's study, self-regulation was potential predictor and direct effect on physical activity in adults in Virginia[14]. Bandura emphasizes that utilization of self-regulation strategies (i.e., ability to self-monitor and evaluate their behavior) is necessary for goal setting and planning to adopting and maintaining an active lifestyle[23].

Furthermore, the current study suggests that independent of self-regulatory behaviors, two type of self-efficacy (task self-efficacy and barrier self-efficacy) have effect on physical activity. Task self-efficacy has important effect on physical activity that directly and indirectly effect on PA behavior. In the result of Anderson's study[14], and whiteetal.[24] self-efficacy influenced physical activity both directly and indirectly. Furthermore, consistent with Plotnikoff's study results, self-efficacy had a direct effect on PA[9]. In a study by Ginis et al, task self-efficacy had significantly indirect effect on PA[8].

According to the social-cognitive theory, self-efficacy is a direct determinant of behavior. In addition, self-efficacy has indirect effects on behavior through its influence on outcome expectations and self-regulatory strategies. Individuals with higher levels of self-efficacy will expect favorable results from physical activity and will be more likely to implement the self-regulatory behaviors related to PA[5]. The funding of model showed barrier self-efficacy had significant direct effect on PA. This is in agreement with previous investigation of Dunlop who found barrier self-efficacy had positive direct effect on PA[7]. Lee et al in a study aiming to apply the theory of self-efficacy of overcoming psychological obstacles to increase physical activity in the elderly, revealed that barrier self-efficacy in exercise has a strong correlation with the amount of physical activity in the elderly[25]. Barrier self-efficacy was important predictor of PA[26]. Perceived social support was another predictor of participants' physical activity in the present study. Social support was a direct determining factor of physical activity in diabetic patients[9] and in Anderson et al[14] study, family social support had indirect effect on physical activity; its indirect effect on behavior was through self-efficacy and self-regulation strategies. In an investigation by Tulloch, social and physical environment were indirect predictors of physical activity through self-efficacy and outcome expectations[27]. However, in some studies perceived social support was not correlated with physical activity[28]. Social support is the interpersonal positive or negative encouragement and feedback that others provide about a behavior[29]. Those who receive positive advice and feedback may gain additional self-efficacy to adopt or maintain a behavior.

Our funding showed, outcome expectations had direct and indirect effects on PA, although these effects were not significant. In the Plotnikoff's study, this construct was imperative predictor of PA among people with diabetes[9]. Result of White's study showed outcome expectations, contributed to physical activity behavior in middle-aged and older adults[24].

The current findings suggest that vicarious experience or modeling had indirect effect through task self-efficacy on physical activity. Bandura emphasizes that modeling is effective on self-efficacy (one of the sources of building self-efficacy is modeling through the observation of others) and outcome expectation [29].

The results also show that, depression a weak indirectly and inversely effect on PA, its effect was through task self-efficacy on PA. Blanchard found mood to be significantly associated with task self-efficacy and barrier efficacy[30]. Bandura has proposed that personal recognition of mood arousal in a specific behavior may predict future confidence in performing an activity [29].

Based on findings environment construct influenced physical activity indirectly via task and barrier self-efficacy. Environment factors play an important role in social-cognitive theory. They directly affect self-efficacy, outcome expectations and behavior [29]. Several studies have indicated the associations between Physical environments, both perceived and objectively variables and PA[28, 30]. In this study, biological and personal factors including age, and body mass index (BMI), none of them was significantly affected on physical activity, BMI had a weak and non-significant indirect effect on PA through outcome expectations and task

self-efficacy, and age had a weak indirect and inverse effect on PA through task self-efficacy. White et al reported that among participants in their study, older age was associated with fewer disability limitations and a decline in physical activity[24].

This study was the first to apply structural equation modeling to examine a comprehensive theoretical model of incorporating social-cognitive theory constructs and demographics as predictors of PA among women with T2DM in Iran. Our funding highlighted the value of using a model of Social-cognitive Theory constructs to predict physical activity in patients with T2DM, especially the construct of self-regulation, self-efficacy and their relationship with PA behavior. The observed inter-relationships among these constructs may provide direction for developing physical activity-enhancing experiments. In particular, interventions that involve causal manipulations of self-regulatory skills may produce changes in physical activity and help direct the development of interventions. also these skills may be influenced by self-efficacy (both task and barrier self-efficacy) and outcome expectations, interventions should also focus on targeting sources of self-efficacy that people have positive expectations regarding the consequences of physical activity participation. Furthermore, social support may indirectly promote physical activity through self-regulation and task self-efficacy that should be considered for designing interventions. For example, family was participating in develop plans and goal setting for physical activity. Finally, these results provide partial support for the social-cognitive model (both direct and indirect relationships) for physical activity proposed on social-cognitive theory.

Our study was not without limitations. First, we used self-report questioner of all variables. Second, it is difficult to make causal inferences due to the cross-sectional data.

There is a great need to continue research in the area of physical activity interventions to help people to adopt and maintain their behavior. Future studies should examine to replicate this model in diabetic patients and other populations in order to understand whether the SCT model provides a useful framework for the understanding of the social-cognitive processes underlying this behavior.

Conclusions

The SEM approach allowed us to confirm the adequacy of an overall framework of SCT. We used comprehensive constructs of SCT and demographic variables in theoretical model. However, in order to improve understand physical activity behavior and design more beneficial interventions may be needed to examine broader models.

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Conflict of interest statement

None declared.

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