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Associations between psychosocial needs, carbohydrate-counting behavior, and app satisfaction: A randomized crossover app trial on 92 adults with diabetes

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Abstract

In order to examine whether psychosocial needs in diabetes care are associated with carbohydrate counting and if carbohydrate counting is associated with satisfaction with diabetes apps' usability, a randomized crossover trial of 92 adults with type 1 or 2 diabetes requiring insulin therapy tested two top-rated diabetes apps, *mySugr* and *OnTrack Diabetes*. Survey responses on demographics, psychosocial needs (perceived competence, autonomy, and connectivity), carbohydrate-counting frequency, and app satisfaction were modeled using mixed effect linear-regressions to test associations. Participants ranged between 19 and 74 years old (mean 54) and predominantly had type 2 diabetes (70%). Among the three tested domains of psychosocial needs, only competence—not autonomy or connectivity—was found to be associated with carbohydrate-counting frequency. No association between carbohydrate-counting behavior and app satisfaction was found. In conclusion, perceived competence in diabetes care is an important factor in carbohydrate counting; clinicians may improve adherence to carbohydrate counting with strategies designed to improve perceived competence. Carbohydrate-counting behavior is complex; its impact on patient satisfaction of diabetes app usability is multifactorial and warrants consideration of patient demographics such as gender as well as app features for automated carbohydrate counting.

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Author Contributions

JSC and HNF wrote the manuscript. JSC created Figure 1. DM performed literature review and drafted the tables. HNF, DM, and JAW researched the data. JFW, TJA, and JAW contributed to the general discussion on the design and methodology, and they reviewed and edited the manuscript.

Keywords

Diabetes Mellitus; Mobile Applications; Motivation; Personal Autonomy; Self-Care

Self-care behaviors such as blood glucose (BG) testing and meal planning are vital to the management of diabetes mellitus.[1] Carbohydrate (carb) counting, a part of meal planning, is essential for determining the dosages of postprandial insulin therapy in people with type 1 diabetes (T1D)[2,3] and potentially for those with type 2 diabetes (T2D) to decrease episodes of post-meal hyperglycemia.[4–6] Carb counting is particularly important in T1D to prevent hypoglycemia from underestimating carb intake for a given dose of insulin.[7–10] It is associated with short-term improvements of hemoglobin A1c both in T1D[11] and T2D.[5,6]

Despite its importance in diabetes management, carb counting is difficult for patients to accurately perform and indefinitely sustain. Few patients with diabetes mellitus count carbs; for example, a study of Brazilians with T1D found that only 30.4% of respondents counted carbs.[12] A basic level of carb counting requires literacy and numeracy skills;[13] knowledge of the carb content of individual foods relative to their portion sizes;[14] and lifestyle habituation of monitoring behaviors using memory, paper logs, or electronic records.[6,15] These requirements are onerous, and errors in counting are frequent even with experienced patients.[16] Advanced levels of carb counting require further management of complex food combinations and restaurant meals, individual tailoring of food intake, and titration of mealtime insulin therapy.[14] Whether basic or advanced, counting carbs is “essentially a repetitive decision-making technique” that imposes a considerable long-term burden on the patient.[7] Studies of carb counting frequently find that participants fail to adhere to carb counting for longer than six months.[6,15]

Long-term nonadherence to carb counting might be explained by the Self-Determination Theory (SDT) on motivation. SDT posits that intrinsic motivation, internalized within a patient, is essential for long-term adherence to a task. Intrinsic motivation depends on the fulfillment of three psychosocial needs of self-determination in the domains of (1) self-perceived competence in the task, (2) autonomy, and (3) connectivity and relatedness with autonomy-supportive people (e.g., clinicians).[17,18] SDT has been successfully applied to patients both with T1D[19] and with T2D;[20,21] for example, patient competence and autonomy predict changes of hemoglobin A1c in patients with T2D.[20,21] However, to the authors’ knowledge, no studies have yet applied SDT to the behavior of carb counting.

Mobile health applications for diabetes (diabetes apps) can potentially improve diabetes care by assisting with counting carbs or sharing diet data with clinicians. For example, diabetes apps can identify foods by analyzing camera images[22] or audio recordings of dictated food descriptions[23] before looking up their carb content in nutrition databases and calculating carb-based insulin dosages.[24] Literature suggests that patients using some diabetes apps for carb counting are comparable in accuracy to certified dieticians.[22,25] Diabetes apps may improve patient knowledge and confidence in its practice by guiding and habituating the patient through carb counting.[26]

In spite of diabetes apps' potential to improve carb counting, there have been few studies of patient satisfaction with app usability.[27] Patients who experience poor app usability or dissatisfaction using the app to help them count carbs are unlikely to use them again. Recently, investigators examined the relationships between patients' psychosocial needs in diabetes care, as modeled by SDT, and their satisfaction with diabetes app usability.[28] Diabetes app satisfaction was predicted by all three psychosocial need domains from SDT —self-perceived competence, autonomy, and connectivity. That study did not specifically evaluate the relationship between carb-counting behavior and diabetes app satisfaction, whereas this study addresses this gap by answering whether carb-counting behavior contributes to diabetes app satisfaction.

The study's aims are to determine the association between (1) patients' psychosocial needs regarding motivation to perform diabetes self-care (as modeled by SDT) and their carb-counting behavior; and (2) patients' carb-counting behavior and their initial satisfaction with apps that support diabetes self-care, as first-time users of those apps. Greater fulfillment of psychosocial needs (competency, autonomy, and connectivity) is hypothesized to be associated with more frequent carb counting, and greater frequency of carb counting to be associated with greater app satisfaction.

Methodology

This study is part of a parent randomized crossover app trial[28] with participants with T1D- or T2D-required insulin therapy conducted in 2017 that tested *mySugr* and *OnTrack Diabetes*, two of the "best diabetes apps of 2016" as rated by *Healthline*.[29] Both apps support several functions related to counting carbs, including carb-data input, locating carb-data analysis reports, and sharing carb data via email.

Subjects and Procedures

Participants were recruited from July to November 2017 through study flier posting on Facebook, Craigslist, a federally qualified health center, a Veterans Affairs clinic, a university campus, and community bulletin boards in Minnesota. Interested individuals were screened by telephone, and those who met these criteria were enrolled: (1) age 18 years or older; (2) diagnosed with T1D or T2D; (3) currently using insulin therapy, with a duration of at least six months; (4) able to fluently read and speak English; (5) proficient with smartphones for functionality beyond phone calling, emailing, text messaging, or taking photographs; and (6) having used an Android smartphone for at least six months. Exclusion criteria were (1) having ever used *mySugr* or *OnTrack Diabetes*, and (2) having used any diabetes app within the past six months. Each participant signed an informed-consent form and received a $50 gift upon the study's completion. The Institutional Review Board of the University of Minnesota approved the study before its initiation (approval #MOD0001221).

Because age is a potential cofounder in user satisfaction with software applications,[30] participants were first stratified by age (≥ 56 and < 56 years, respectively). Between July 26 and November 30, 2017, participants in either stratum attended testing sessions held in public facilities such as private meeting rooms in public libraries. A statistician used a software program to randomly assign AB or BA app-testing orders, which were provided to each participant in an opaque, sealed envelope; the assignments were blind to investigators until the end of the study. Participants watched two YouTube training videos created by the app developers. Next, they practiced using one app and tested it following a study protocol checklist consisting of seven tasks: (1) enter carb intake for a meal; (2) enter an exercise activity; (3) enter an insulin dose; (4) enter a BG test result; (5) locate BG analysis reports by days of the week; (6) locate carb-intake analysis reports by meal; and (7) email a BG analysis report. A study Samsung 5S phone with cellular service was provided for these tasks. For the testing phase, the participant had a different task order than the practice phase that was randomized. After the first app test, participants completed an app satisfaction survey. During a 30-minute break between the first and second app tests, participants completed a background survey regarding their demographic characteristics, psychosocial needs, and desired app features to support self-care.

Measures

The study measured two outcome variables, three predictor variables, and several covariates. Outcome variables were frequency of carb counting and app satisfaction. Predictor variables were three psychosocial needs of self-care based on SDT. Covariates included patient characteristics, other self-care activities, and patient motivation. These variables are summarized in relation to the study's Aims in Figure 1.

Outcomes

The outcome variable for Aim 1 was the frequency of carb counting defined as the number of days of carb intake monitored in the given week, with responses ranging from 0 to 7 days. Carb counting was measured by answering the question, "On how many of the last SEVEN DAYS did you space carbs evenly through the day?"; this question was taken from the Summary of Diabetes Self-Care Activities by Toobert et al. (r >0.50).[31]

The outcome variable for Aim 2 was app satisfaction measured by the System Usability Scale (SUS) at the end of each app testing.[30] This instrument consists of 10 items on a 5-point Likert scale (from 0 for "strongly disagree" to 4 for "strongly agree"). Items alternate between positive statements (e.g., "I felt very confident using this app" and "I would like to use this app frequently") and negative statements (e.g., "this app is unnecessarily complex"). Final scores range between 0 and 100, where higher scores indicate greater satisfaction with the app's usability.[30] The SUS is used widely to evaluate the usability of consumer-facing products, and a study pooling multiple products found that the SUS exhibited good internal consistency, with Cronbach's α of this instrument to be at 0.91.[30]

Predictors

Predictor variables for Aim 1 were participants' psychosocial needs in diabetes care (competence, autonomy, and connectivity as modeled by SDT). Self-perceived competence in diabetes care was measured by the Perceived Competence Scale (PCS) for diabetes, which consists of four items measuring the participant's confidence or self-perceived capability in managing diabetes mellitus on a 7-point Likert scale (from 1 for "strongly disagree" to 7 for "strongly agree").[32] A similar three-item scale applied to participants with T2D exhibited good internal consistency, with Cronbach's α exceeding 0.80.[33] In this study, Cronbach's α of the PCS was 0.88. Self-perceived autonomy in diabetes care was measured by four survey items designed by the principal investigator (HF) and validated by four subject-matter experts: an endocrinologist, a physician researcher of diabetes mellitus, and two PhD-level nurses who were certified diabetes educators. These items measured participants' personal interest (a component of autonomy)[34] in identifying personal patterns or trends in BG test results and carb intake. Participants personally interested in self-care possess stronger feelings of autonomy, empowerment, and self-regulation regarding their self-care.[34] Survey responses are from 1 for "strongly disagree" to 5 for "strongly agree" to the statements describing personal interest. Cronbach's α of this instrument was acceptable at 0.74 in this study. Self-perceived connectivity with clinicians was measured by the short-form Health Care Climate Questionnaire (HCCQ), which consists of six items measuring perceptions regarding whether health care providers support autonomy or exert control over their participants, on a 7-point Likert scale (from 1 for "strongly disagree" to 7 for "strongly agree").[35] The HCCQ applied to participants with T2D exhibited good internal consistency, with Cronbach's α at 0.82.[33] Cronbach's α of the PCS was 0.94 in this study.

Covariates

Covariates included participant characteristics—such as age, gender, race/ethnicity, education level, phone model, smartphone comfort level, diabetes types, duration of diabetes diagnosis, duration of insulin therapy, and last known hemoglobin A1c—as well as self-care activities and patient motivation.

Covariates of self-care activities included the number of days (1) BG testing was performed and (2) blood glucose testing was prescribed. These were responses to questions from Toobert et al.'s Summary of Diabetes Self-Care Activities: "On how many of the last SEVEN DAYS did you test your blood sugar?" and "On how many times a day does your health care provider/primary care provider recommend you to test your blood sugar?"

The covariate of patient motivation was measured using the Treatment Self-Regulation Questionnaire (TSRQ), which consists of eight items evaluating intrinsic motivation to perform diabetes self-care and eleven items evaluating extrinsic motivation, on a 7-point Likert scale (from 1 for "strongly disagree" to 7 for "strongly agree").[33,35] Patient motivation was scored as a Relative Autonomous Motivation Index (RAMI), the average of extrinsic motivation items subtracted from the average of the intrinsic motivation items.[35]

Statistical Analysis

A regression model analysis (n=84) with 10% attrition (n=8) and 13 predictors with R^2 correlation of 0.20 and α of 0.0 was performed. Residual plots showed no evidence of heteroskedasticity. Analyses of t- and χ^2 tests were used to assess differences between groups in terms of participant characteristics. Paired t-tests of *mySugr* and *OnTrack Diabetes* usability scores showed significant differences ($P < 0.050$); thus, repeated-measure regression analyses were adjusted for app group and testing order with an interaction term. An α of 0.050 was set for statistical significance. All analyses were performed using R.[36] Figure 1 shows nine regression models for testing two aims.

Aim 1 (predictor of psychosocial need) was analyzed by a linear multiple regression model of analysis of variance (ANOVA). Models 1–3 were run separately; each model had one psychosocial need as a predictor and was adjusted for 12 covariates of patient characteristics: age, sex, education, phone model, smartphone comfort, diabetes type, diabetes duration, years of insulin use, hemoglobin A1c, days of BG testing performed, days of BG testing recommended by provider, and motivation. Smartphone brand and education variables were collapsed into dichotomous variables. Model formula was as follows:

- Fixed effect Model 1–3: frequency of carb counting ~ one of the psychological needs predictor + age + sex + education + phone model + smartphone comfort level + diabetes type + diabetes year + insulin use years + HbA1c + days tested BG + BG testing prescribed per day + motivation.

Aim 2A (predictor of carb counting as a continuous variable) used ANOVA with (1) random effect to account for repeated app testing, and (2) fixed effect for the frequency of carb-counting behavior and app effect and participant characteristics. The same covariates were used from Aim 1 as follows:

- Mixed effect Model 4: SUS ~ frequency of carb counting predictor + 12 covariates + [random effect (testing order + study ID) in repeated app testing] + app group.
- Fixed Model 5 for *mySugr* and Model 6 for *OnTrack Diabetes*: SUS ~ frequency of carb counting predictor + 12 covariates + app group.

Aim 2B (predictor of carb counting as a binary variable of frequent versus infrequent) used the same mixed model as Aim 2 using ANOVA. A separate analysis limited to app group was planned. A model with the same variables but in fixed effect per app group was also analyzed as follows:

- Mixed effect Model 7: SUS ~ frequent versus infrequent carb counting + 12 covariates + [random effect (testing order + study ID) in repeated app testing] + fixed effect app group.
- Fixed effect Model 8 for *mySugr* and Model 9 for *OnTrack Diabetes*: SUS ~ predictors of frequent versus infrequent carb counting + 12 covariates + fixed effect from app group.

Results

Ninety-two participants were recruited: forty-six from Facebook (50%), eight from patient referrals (9%), seven from a community clinic (8%), six from a university campus (7%), five from Craigslist (5%), four from a Veterans Affairs clinic (4%), three from diabetes support groups (3%) and seven from miscellaneous sites (8%).[28] Participants ranged in age between 19 and 74 years, with a mean age of 54. Table 1 summarizes their characteristics, which were predominantly white, female, beyond high school level in education, and with T2D. When participants were grouped by frequent versus infrequent carb counting (0–3 vs. 4–7 days weekly), their characteristics were generally similar, except in the number of days that a clinician prescribed BG testing, with 4.4 days in the frequent carb-counting group versus 3.3 days in the infrequent carb-counting group ($P = 0.007$).

Not all three psychosocial needs predicted the frequency of counting carbs. Only competence in diabetes care was associated with carb-counting behavior (Table 2, Model 1), whereas no such association was found with self-perceived autonomy or clinician connectivity (Models 2 and 3). Participants who rated high in diabetes care competence counted carbs more frequently ($P = 0.005$). A one-unit increase in competence score was associated with an increase of 0.8 days per week in carb counting ($P = 0.007$). Men counted carbs nearly 2 days fewer per week compared to women ($P = 0.0008$, 0.0027, and 0.0014 in Models 1, 2, and 3, respectively). The frequency of BG testing prescribed per day was associated with the frequency of counting carbs ($P = 0.0051$). Each additional BG test that was prescribed was associated with adding a half day of carb counting. Autonomy and connectivity in diabetes care were not associated with the frequency of carb counting; in the regression analysis model, the influence of gender and BG testing prescribed remained statistically significant.

The effect of carb-counting behavior on app satisfaction was not statistically significant. The frequency of carb-counting behavior or days of carb counting was not associated with SUS scores for diabetes app satisfaction in a mixed effect model (Model 4). This was also the case for the fixed effect model when the association was limited to one app at a time (Models 5 and 6). No statistically significant difference in app satisfaction was found between frequent and infrequent carb-counting groups (Model 7). The estimated effects of carb-counting frequency on SUS were small in magnitude (Models 4–9), corresponding to differences of 0.1 to 1.2 points on a scale ranging from 0 to 100. In contrast, app effect magnitude was much larger. The effect of the app (*mySugr* or *OnTrack Diabetes*) on satisfaction was approximately 12.5 points in Model 4 and Model 8 ($P < 0.0001$). Education influenced the degree of app satisfaction for one app only. For the *mySugr* app, education was significantly associated with app satisfaction (Model 8). Participants with education greater than high school were associated with a lower app satisfaction SUS score by 9.3 ($P = 0.0451$).

Discussion

This study was designed first to test the application of SDT on motivation to the important but difficult task of counting carbs by participants with diabetes. By extending a previous study,[28] this study took advantage of data from a diverse sample (n=92) that included African American, Native American, and Asian adults who required insulin therapy. Our hypothesis that participants' psychosocial needs in diabetes care as modeled by SDT would predict their carb-counting behavior was supported for one domain of psychosocial needs (self-perceived competence) but not supported in two other domains (self-perceived autonomy and self-perceived connectivity with autonomy-supportive clinicians). SDT has been successfully applied to participant self-care modalities for a variety of conditions,[37] and this study adds carb counting to that set.

The association between self-perceived competence and carb counting is consistent with the well-known finding that carb counting is a difficult behavior requiring literacy, knowledge, and experience—all of which are time consuming for participants to acquire and perform accurately.[3,6,14–16] Increased self-perceived competence was previously associated with improved glycemic control;[33] this study's findings suggest this may partially result from competence-associated improvements in adherence to carb counting and control, which in turn may improve glycemic control.[5,6,11]

Our results show that only self-perceived competence was associated with carb-counting behavior but not self-perceived autonomy or connectivity, in contrast with a previous study showing all three domains of SDT's psychosocial needs associated with improved glycemic control.[33] This inconsistency may reflect idiosyncrasies of carb counting and its difficulty. Glycemic control results from a complex mix of lifestyle behaviors, therapies, conditions, and unmodifiable factors,[38] of which adherence to carb-counting behavior is only one factor. Other lifestyle factors likely are more affected by self-perceived autonomy or connectivity.

When clinicians wish to improve their patients' adherence to carb counting, it may be optimal for them to focus on improving their self-perceived competence using strategies from SDT designed to increase self-perceived competence. These include setting specific tasks for counting carbs matched against the patients' own standards, giving feedback about how the patients achieved or did not achieve desired goals rather than giving generic praise or criticism, and providing general support and encouragement about the patient's own capability to count carbs.[39] By increasing patient knowledge, confidence, and self-perceived competence in carb counting, patients may become more intrinsically motivated to perform it over the long term.

These results also may illuminate previous findings that diabetes apps are associated with dietary monitoring.[26] Diabetes apps may guide patients through the tasks of accurate dietary monitoring, including carb counting, at their own paces, thus increasing their knowledge, confidence, and self-perceived competence in these self-care behaviors and with corresponding increases in long-term adherence. This difference is especially stark when diabetes apps are compared to patient memory and judgment or to paper-based records such as dietary-recall surveys and food diaries, which are frequently inconsistent and often underestimate the carb content of meals.[22,40,41] The relationship between the difficulty of accurate carb counting and self-perceived competence is yet to be empirically studied, but failure to perform accurate carb counting likely reduces a patient's confidence in counting their carbs. Even a small error in carb counting may significantly affect the risk of insulin-therapy-induced postprandial hypoglycemia, which may be psychologically traumatic to patients who survive such episodes[42] and may make them averse to future carb counting. By increasing the accuracy of a patient's carb counting, diabetes apps may thereby increase their self-perceived competence, motivation, and adherence to it.

App dissatisfaction likely increases nonadherence or cessation of app use, depriving patients of its benefits to carb-counting accuracy, self-perceived competence, and adherence. To date, app usability for diabetes care is poorly studied;[27] therefore, it is important to understand factors in diabetes app satisfaction. The previous study[28] examined effects of several patient characteristics on app satisfaction, including SDT's three domains of psychosocial needs in diabetes care. All three domains—self-perceived competence, autonomy, and connectivity —predicted greater satisfaction with two tested apps, m*ySugr* and *OnTrack Diabetes*. The present study extends these findings by testing whether current carb-counting behavior predicted patient satisfaction, but no statistically significant association was found between current carb-counting behavior and diabetes app satisfaction. This finding was unexpected, and it may result from limitations of the tested app design that lacked an electronic or automatic carb-counting function.

Carb-counting behavior encompasses numerous skills, including recall of nutrition information of foods and calculating content based on portion sizes,[13,14] and these skills are strongly impacted by several factors such as age and gender as well as social determinants of health such as education and income. It is thus difficult to demonstrate associations between diabetes app features, design, and accuracy; carb-counting adherence; and satisfaction.[43] This study found that education levels greater than high school predicted greater satisfaction with *mySugr* but not *OnTrack Diabetes*. Education level is a known factor in adherence to using apps to support self-care,[44] yet here its effects appeared in satisfaction with only one of two tested diabetes apps. The cause of this contrast is uncertain, but it may reflect differences in the apps' designs, such as intuitiveness of navigation and readability of text.

Limitations

Minimal carb-counting functionality was involved during the testing—accounting for the study's failure to distinguish an effect of carb-counting behavior on diabetes app satisfaction. *mySugr* and *OnTrack Diabetes* were selected based on their inclusion in a 2016 list of best diabetes apps as rated by a health-information website, *Healthline*;[29] since then, *mySugr* has remained in *Healthline*'s 2022 list of best diabetes apps,[45] and *OnTrack Diabetes* has been recommended by educators from the American Diabetes Association[46] and the University of Michigan.[47] Both *mySugr* and *OnTrack Diabetes* have a variety of app functions that support self-care in general but did not have automated carb-counting features, because their app features were limited to input and output of carb-intake data and sharing the carb-intake log via email. The absence of quality or any carb intake analysis report may have influenced patients' rating of app satisfaction and its association with carb-counting behavior.

In the last five years, cloud storage, machine learning, and artificial intelligence have advanced the development of carb-counting app functions. A summary of recent diabetes app studies by carb-counting app feature is given in Table 4. These app features included automated carb content analysis linked to a nutrition database,[23,25,43,48,49] visual food recognition based on machine-learning algorithms,[25,43] audio recognition of dictated food descriptions using natural-language processing,[23,48] augmented-reality overlays of food portion sizes,[50] and insulin dose calculation methods based on carb intake.[24] These advanced carb-counting features were not tested in this study. For example, *ServARpreg* and *Diet-A* are mHealth dietary apps that respectively provide augmented-reality overlays for meal portion size estimation and voice recognition of food descriptions for nutrient counting, and the users of both apps report high satisfaction.[48,50] *ServARpreg* was also found to promote greater self-care knowledge.[50] *Dietrometro* allows patients to choose standardized images that most resemble their meals, after which the app looks up their carb content from a nutrition database; using *Dietrometro* was associated with improved glycemic control in people with T1D.[49] Vasiloglou et al. (2018)[25] and Ladyzynski et al. (2018)[23] found that automated carb-counting resources can have comparable accuracy to dieticians.[23,25] Future studies should compare a variety of app features directly against each other in carb-counting accuracy; impact in health outcomes, including glycemic control and behavior change; financial cost; and usability experience by population (e.g., diabetes type and age group).

Finally, this study collected data only after each participant's single initial use of the diabetes app and not over time. It is possible that using the app over a longer period of time would make the effects of carb counting on diabetes app satisfaction more evident. There are no studies to the authors' knowledge that have examined the effects of carb counting on diabetes app usability and satisfaction over longer periods of time. Future work should therefore test the effects of specific diabetes app features and long-term usage of diabetes apps on self-perceived competence, autonomy, connectivity, and adherence to counting carbs.

Conclusion

In a randomized crossover trial that tested top-rated diabetes apps with adults with diabetes who are on insulin therapy, participants' self-perceived competence was associated with increased carb counting. To improve patient adherence to counting carbs, clinicians should focus on strategies from SDT designed for increasing self-perceived competence. Counting carbs is a complex behavior, and its impact on participant satisfaction with diabetes apps is a multifactorial problem warranting further study. As app functionality evolves, the capacity of apps to enhance data tracking and self-care behaviors is growing by using both passive and active data acquisition and reporting approaches. This app evolution will require additional studies on the ability of patients to use and incorporate these resources into their day-to-day management to better understand the human factors that drive app usage and disease management behavior and their relationship to SDT.

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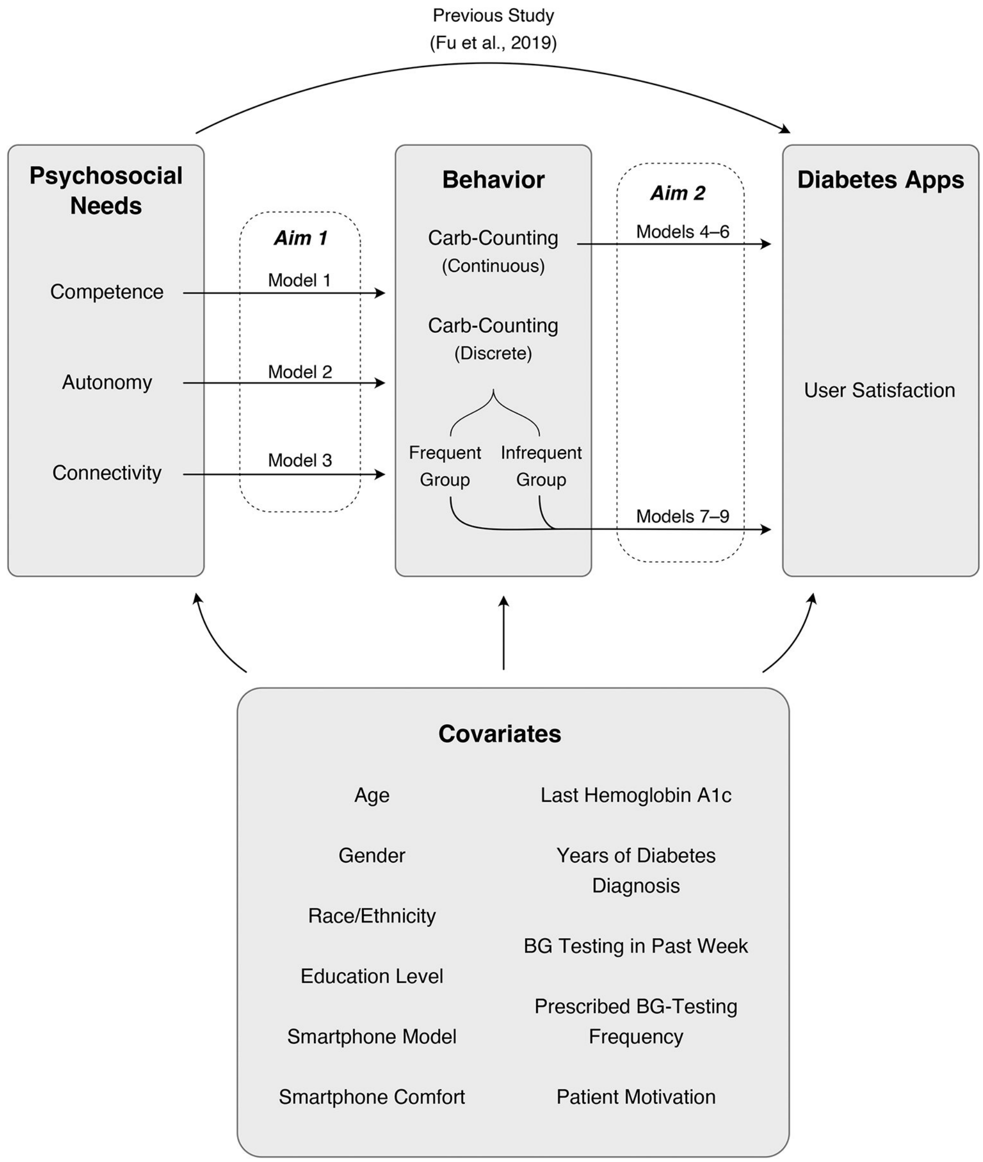

Figure 1:
Aims and statistical models.

Table 1:

Characteristics and comparison of carb-counting behavior groups.

Characteristics	Overall (*n*=92)	4–7 days (*n*=44)	0–3 days (*n*=48)	*P*-value
RAMI, mean (SD)	2.2 (1.4)	2.2 (1.5)	2.1 (1.2)	0.769
Competence	5.4 (1.2)	5.7 (1.0)	5.1 (1.3)	0.029 *
Autonomy	3.2 (0.7)	4.0 (0.5)	3.9 (0.8)	0.561
Connectivity	6.1 (1.3)	6.1 (1.1)	6.0 (1.4)	0.813
Days space carb / count carb (range 0–7)	3.3 (2.7)	5.8 (1.3)	1.0 (1.3)	<0.001 ***
Days space carb / count carb (*n* %)				
0	27 (29)	—	27 (56)	—
1	2 (2)	—	2 (4)	—
2	9 (10)	—	9 (19)	—
3	10 (11)	—	10 (21)	—
4	10 (11)	10 (23)	—	—
5	9 (10)	9 (20)	—	—
6	5 (5)	5 (11)	—	—
7	20 (22)	20 (45)	—	—
Age, years, mean (SD)	54 (13)	54 (14)	54 (12)	0.954
Age over 65, *n* (%)	20 (22)	8 (18)	12 (25)	0.590
Female, *n* (%)	54 (59)	30 (68)	24 (50)	0.119
Race, White vs non-White				0.164
White, *n* (%)	57 (62)	31 (71)	26 (54)	—
Black/African American, *n* (%)	23 (25)	7 (16)	16 (34)	—
Native American, *n* (%)	10 (11)	5 (11)	5 (10)	—
Asians, *n* (%)	2 (2)	1 (2)	1 (2)	—
Education > high school, *n* (%)	61 (66)	32 (73)	29 (60)	0.304
Education ≥ 4 years college, *n* (%)	30 (33)	15 (34)	15 (31)	0.946
Samsung phone, *n* (%)	44 (48)	22 (50)	22 (46)	0.849
Comfortable with smartphone, *n* (%)	57 (62)	27 (61)	30 (63)	1.0
T1D, *n* (%)	28 (30)	15 (34)	13 (27)	—
T2D, *n* (%)	64 (70)	29 (66)	35 (73)	—
HbA1c (%)	10.0 (18)	11.7 (25.9)	8.6 (2.0)	0.415
Diabetes duration years, mean (SD)	17 (11)	17 (12)	17 (11)	0.896
Insulin duration years, mean (SD)	12 (12)	12 (13)	13 (12)	0.660
Insulin use types, *n* (%)				
Insulin pump	14 (15)	5 (11)	9 (19)	—
Long- and short-acting injection	46 (50)	22 (50)	24 (50)	—
Long-acting injection	28 (30)	14 (32)	14 (29)	—
Short-acting injection	2 (2)	1 (2)	1 (2)	—
None (stopped use)	2 (2)	2 (5)	0 (0)	—
Days checked BG in the past week	5.7 (1.8)	5.9 (1.9)	5.6 (1.8)	0.557
0–3 days, *n* (%)	13 (14)	7 (16)	6 (12)	—

Characteristics	Overall (n=92)	4–7 days (n=44)	0–3 days (n=48)	P-value
4–7 days, n (%)	79 (86)	37 (84)	42 (88)	0.866
BG testing prescribed per day	3.8 (1.9)	4.4 (2.2)	3.3 (1.4)	0.007**
SUS for first app	61 (17)	61 (18)	61 (17)	0.967
SUS for second app	62 (18)	59 (17)	64 (19)	0.187

* $P < 0.050$.

** $P < 0.010$.

*** $P < 0.001$.

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Table 2:

Associations between psychosocial needs and carb-counting behavior.

Estimate	Model 1	Model 2	Model 3
Competence	0.8**	—	—
Autonomy	—	0.3	—
Connectivity	—	—	0.2
Age per 10 years	0.1	0.0	0.0
Men versus women	−1.9***	−1.8**	−2.0**
> High-school versus ≤ high-school education	0.7	0.7	0.7
Samsung versus not Samsung	−0.3	−0.1	−0.3
Smartphone comfort	0	−0.1	−0.0
T2D versus T1D	−0.6	−0.2	−0.2
Diabetes duration per 10-year	0.0	0.0	0.0
Insulin duration per 10-year	−0.1	−0.1	−0.1
HbA1c	0	−0.2	−0.2
Days tested BG in last 7 days	−0.2	−0.2	−0.1
BG testing prescribed per day	0.5**	0.5**	0.5**
Motivation	−0.2	0.0	0.0
Adjusted R^2	0.2	0.1	0.1

** $P < 0.010$.

*** $P < 0.001$

Table 3:

Associations between carb-counting behavior and app SUS.

Estimate	Effect of carb-counting behavior			Effect of frequent vs. infrequent carb counting		
	Model 4 Both apps (*n*=184)	**Model 5 *mySugr* (*n*=92)**	**Model 6 *OnTrack* (*n*=92)**	**Model 7 Both apps (*n*=184)**	**Model 8 *mySugr* (*n*=92)**	**Model 9 *OnTrack* (*n*=92)**
Carb-counting behavior	−0.2	−0.5	0.3	—	—	—
Frequent carb counting (vs. infrequent)	—	—	—	−1.2	−0.7	−0.1
Age per 10 years	−0.1	−0.1	−0.03	−0.1	−0.2	0.0
Men compared to Women	−0.6	−1.4	0.9	−0.4	−0.4	0.4
> High-school versus ≤ high-school education	−5.3	−9.0	−3.2	−5.2	−9.3*	−3.0
Samsung versus not Samsung	1.6	3.1	−0.2	1.5	3.1	0.2
Smartphone comfort	0.6	−0.6	2.1	0.7	−0.6	2.1
T2D versus T1D	−4.7	−4.0	−5.4	−4.0	−4.0	−5.4
Diabetes duration per 10-year	0.4	0.5	0.3	0.4	0.4	0.3
Insulin duration per 10-year	−0.1	−0.2	−0.1	−0.1	−0.2	−0.1
HbA1c	0.4	−0.8	1.7	0.5	−0.7	1.7
Days tested BG	−0.1	−0.8	1.7	0.6	−0.8	1.7
BG testing prescribed per day	−0.3	0.3	−1.2	−0.5	0.1	−1.1
Motivation	−0.5	−0.8	0.2	−0.4	−0.8	0.2
Testing order factor	0.3	−3.9	3.6	0.3	−4.1	3.5
App group factor	12.5***	—	—	12.5***	—	—
−Adjusted R^2	0.1	0.0	0.0	0.1[b]	0.0	0.0

*$P < 0.050$.

***$P < 0.001$.

Table 4:

Selected app features related to carb counting.

Carb counting	Author/country	User	App	App features	Findings/limitations
Automated image analysis of food photographs	Joubert et al. (2021) / France [43]	Medical students	*Foodvisor* and *Glucicheck*	• *Foodvisor* analyzes food photographs using a deep-learning algorithm, estimating food weight and carb content. • *Glucicheck* provides photos of precalculated carb content for users to match their meals.	• Mock testing. • Small carb-counting errors in *Foodvisor* (−7.2 ± 17.3 g; $P < 0.05$) and *Glucicheck* (1.4 ± 13.4 g; NS), compared to patients with T1D. • Limited to hospital meals.
	Vasiloglou et al. (2018) / Switzerland [25]	Dieticians	*GoCARB*	• Food photo analysis using a machine-learning algorithm to estimate food weight and carb content.	• Mock testing. • Similar absolute carb-counting errors in *GoCARB* (14.8 ± SD 9.73 g) compared to dieticians (14.9 ± 10.12 g with $P = 0.93$). • Limited by nonrandom meal selection, on a lack of mixed ingredient foods like sauces or soups.
Automated analysis of dictated speech describing food	Ladyzynski et al. (2018) / Poland [23]	Hospitalized adult patients with T1D	*VoiceDiab*	• Speech-to-text recognition of carb and portion sizes. • Link carb content for automatic calculation of insulin doses.	• Patient testing. • Similar carb counting between patients assisted by app compared to dieticians who did manual carb counting (e.g., breakfast estimates of 4.1 ± 0.9 versus 3.8 ± 0.8 carb exchange units). • Limited because patients must be knowledgeable of portion size.
	Lee et al. (2017) / South Korea [48]	High school students	*Diet-A*	• Speech-to-text recognition identifies carb and serving sizes. • Analysis of carb intake above recommended limit. Alert reminders to collect food data.	• Mock testing. • 61.9% of participants reported being satisfied with app, but >70% reported that it was burdensome to use the app or difficult to remember to use it. • Usability testing was limited to teenagers.
Education to estimate portion size	Brown et al. (2019) / Australia [50]	Pregnant women at 12–22 wk	*ServARpreg*	• Education module on portion sizes of carbs. Scan a barcode to get 3D virtual food image on a dinner plate.	• Patient testing with pregnant women. • 80% of participants reported an increase in carb awareness, and 72% of participants found it easy to use. • Limited by gender bias, questionable generalizability, and unknown health status of participants.
Food database	Briganti et al. (2021) / Italy [49]	Adults with T1D using insulin therapy	*Dietrometro*	• Provides images of foods in varying portion sizes for patients	• Patient testing.

Carb counting	Author/country	User	App	App features	Findings/limitations
				to choose the image that best matches their meals.	• App-assisted carb counting, when compared to no carb counting, showed increased time in optimal BG range (71.25 ± 9.75% vs. 52.32 ± 13.22%; $P < 0.001$), and decreased time above the range (31.25 ± 19.18% vs. 22.31 ± 10.89%; $P < 0.001$). • Limited by group difference in glycemic controls at baseline.

Abbreviation: NS, not statistically significant.