Situational Awareness
Predicts Self-Management of Type 1 Diabetes
in Adolescents and Young Adults

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Abstract [250 words]

Objective: Using a hybrid closed-loop system with a continuous glucose monitor and insulin pump predicts higher time in target glucose range (TIR) for adolescents and young adults with type 1 diabetes (T1D). However, patients don't always use these systems effectively for self-management. Based on Two Minds Theory, we hypothesized that patients with better situational awareness and more automatic diabetes technology use would have higher TIR.

Methods: We recruited 20 patients with T1D from a diabetes specialty clinic. Participants used the Tandem X2 with Control-IQ technology (Control-IQ) hybrid closed-loop system. For 2 weeks they also completed daily surveys about T1D self-management, and triggered surveys whenever they interacted with Control-IQ. Surveys measured reasons for interacting with the system and perceived automaticity.

Results: Proactive reasons for interacting with Control-IQ, e.g., planning to eat, predicted higher TIR. Reactive interactions, e.g., responding to alerts, did not. In fact, participants had higher TIR when they interacted less often with Control-IQ and administered fewer manual boluses. Self-reported automaticity did not predict TIR, but perceived self-management did. Perceived high glucose was associated with higher TIR regardless of accuracy.

Conclusions: Adolescents who interacted less intensively and more proactively with a hybrid closed-loop system had better glucose control. Accurate perception of glucose mattered less than believing that glucose might be too high; it is possible that situationally aware participants perceived increases before glucose went out of range. Better measures of automaticity are needed. Hybrid closed-loop systems appear to support situational awareness that helps adolescents and young adults in self-managing T1D.

Keywords: adolescents; continuous glucose monitor; self-management; situational awareness; type 1 diabetes

Worldwide, there are nearly 100,000 new cases of type 1 diabetes (T1D) annually among people under age 15, adding to over 1 million existing cases at a growing rate (Patterson, 2019). Adolescents and young adults with T1D have the worst glycemic control of any group (Foster et al., 2019), and are at risk for complications including kidney disease, hypertension, neuropathy, and retinopathy (Dabelea et al., 2017). Unfortunately, T1D is difficult for many adolescents and young adults to self-manage, requiring alterations to activity and diet, self-monitoring, and medication adherence (Messer et al., 2022). Hybrid closed-loop systems can help adolescents and young adults to self-manage T1D (American Diabetes Association [ADA], 2024). These consist of a continuous glucose monitor (CGM), an insulin pump to deliver insulin, and an algorithm to automate the amount of insulin delivered. While these systems are useful, many people with diabetes find them difficult to use consistently or have difficulty changing their self-management behaviors in response to device feedback (Messer et al., 2020).

Although adolescents have varying levels of knowledge about diabetes disease processes and treatments, knowledge is not the only factor that affects self-management. Other important considerations include family and peer relationships, relationships with health professionals, living environment, general health status, comorbidities, and coping skills (Othman et al., 2020). Daily goal planning has also been suggested as an aspect of adolescents' T1D self-management (Wiebe et al., 2018). With respect to hybrid closed-loop insulin pump and CGM system use, adolescents perceive benefits for their health, daily activities, and mood, but also barriers including time, effort, pain, and embarrassment. Many adolescents have an ambivalent view of the continuous glucose feedback provided by CGM technology, regarding it as both "best friend" and "spy" (Messer et al., 2018). Those with more difficulty using CGM also report more family distress, diabetes-related distress, and symptoms of depression (Messer et al., 2020).

One potential benefit of hybrid closed-loop insulin pump/CGM system use is that it can help adolescents to develop *situational awareness*, a form of expertise recognizable based on an individual's ability to (a) perceive the most relevant details in a complex situation, (b) understand what these details mean, and (c) take appropriate action based on the most likely future states (Endsley, 1995; Fore & Sculli, 2013). One widely cited example is the 2009 incident in which pilot Chesley "Sully" Sullenberger safely landed U.S. Airways flight 1549 in the Hudson River, 4 minutes after the plane struck a flight of Canada geese. The airline's standard engine-failure checklist was designed for higher elevations, and the pilots' ability to recognize crucial nuances of the emergency was essential for its successful resolution (National Transportation Safety Board, 2010). Situational awareness may seem at first like a rational, cognitive approach to decision-making, but the speed at which it occurs suggests otherwise. Indeed, experts with high situational awareness actually devote *less* attention to their decisions than non-experts, and often perceive their selected course of action to have been the only one available (Klein, 2008).

The seeming automaticity of decision-making in people with high situational awareness can be explained by Two Minds Theory, a neurocognitive model that suggests health-related actions result from an *intuitive system* outside of conscious awareness (Cook, Schmiege, Reeder, Horton-Deutsch, Lowe, & Meek, 2018). This is distinct from the *narrative system* in the cerebral cortex that generates intentions and explanations for behavior. Although these systems operate simultaneously, the intuitive system takes precedence because it is faster and more efficient; the narrative system is often characterized as "slow" thought, which is helpful for deliberation but not in responding to the rapid-fire demands of everyday life (Kahneman, 2011). The best way to improve health behavior, therefore, is to pre-program healthier behaviors into the intuitive system so that they will occur automatically in challenging situations (Messer, Sousa, & Cook,

2019). Hybrid closed-loop insulin pumps/CGMs give feedback on glucose levels in real-world situations over time and may therefore be useful in developing situational awareness.

The purpose of the current study was to examine daily data from adolescents and young adults using a commercially available hybrid closed-loop insulin pump/CGM system to better understand their T1D self-management. In addition to the hybrid closed-loop system, participants used smartphone-based surveys to provide data about the context and thinking behind their interactions with the system. We combined data from multiple sources to identify the best predictors of glycemic control, which was quantified using a standard glycemic time-in-range (TIR) metric of 70–180 mg/dl (Battelino et al., 2019). We hypothesized that more automatic and proactive ways of interacting with the hybrid closed-loop system would be associated with higher TIR, in comparison with reactive responses, such as those initiated by system prompts.

Methods

Participants

Twenty adolescents and young adults with T1D were recruited from the University of Colorado's Barbara Davis Center for Diabetes, where they were receiving ongoing diabetes care. Participants' ages ranged from 15 to 25 (M = 18.5, SD = 2.98). Participants were 40% male (8/20), 10% transgender male (2/20), and 50% female (10/20). Twelve participants (60%) were White non-Hispanic, with 25% Hispanic or Latino (5/20, 3 of whom also had another non-White race or ethnicity), 5% Black (1/20), 5% Asian (1/20), 15% Native Hawaiian/Pacific Islander (3/20), and 10% other race or ethnicity (2/20). Their diabetes was generally well-controlled, with an average last HbA1c value of M = 7.27%, SD = 1.02. The American Diabetes Association HbA1c goal for most people with diabetes is < 7% (ADA, 2024).

All participants were already using a commercially available hybrid closed-loop system

to manage their diabetes at the start of the study, the t:slim X2 device with Control-IQ Technology (Tandem Diabetes Care, San Diego CA), referred to hereafter as *Control-IQ*. The Control-IQ system included an insulin delivery pump, a Dexcom G6 CGM sensor, and an algorithm for insulin delivery. Users were also asked to use the Tandem t:connect Mobile app, which allows the user to view glucose and insulin data, and to deliver a bolus of insulin.

Surveys were in English only, so patients who could not speak or read English were excluded, as were patients who required other forms of diabetes management. There were no exclusion criteria based on comorbidities or time since diagnosis. This research study was approved by the Colorado Multiple Institutional Review Board (protocol #22-1608).

Procedure

Adolescents or young adults with T1D were recruited in-person or via phone by research staff, and then enrolled via videoconference. If the participant did not already use the t:connect mobile app, a study coordinator helped them to install it. Participants were also introduced to surveys that could be completed from a link on their smartphone. The coordinator helped them to create a tile on their smartphone adjacent to the t:connect app, which linked to the triggered survey. This helped participants remember to complete a survey each time they looked at the app.

In addition to using the Control-IQ system, participants were asked to complete a short online survey each time they interacted with the t:connect app or their insulin pump. Surveys were administered using the REDCap secure data management system (Vanderbilt University, Nashville TN), and asked participants to categorize their reasons for interacting with the pump at that time. The survey also included a 4-item automaticity scale, which asked participants whether they made a conscious choice to check the pump or did it without thinking. Participants completed an average of 3.81 triggered surveys per day (SD = 2.09, range: 1.75 to 9.09) over the

course of the 2-week study, across a wide range of times (morning, afternoon, evening). Control-IQ data showed that users actually interacted with their pump an average of 8.97 times per day (*SD* = 4.95), so the percentage of pump checks that also had a survey completed was 42%.

A second type of survey, also administered via REDCap, asked about success in achieving one's diabetes self-management goals. That survey was completed each evening. Participants received a text message with the survey link at the appropriate time. Participants were highly adherent to this procedure, with *M* = 14.3 (*SD* = 2.03) surveys completed per person.

At the end of the 2-week study period, participants completed a 15-30-minute interview with a researcher (Xu et al., 2024), to discuss their diabetes self-management experiences. Participants were paid $25 each for enrollment and the end-of-study interview, and $10/day for each day on which at least 2 triggered surveys were completed — up to $190 for the full study.

Measures

Control-IQ Insulin Pump Data. The insulin pump and CGM sensor record separate data streams. For the Tandem t:slim X2 pump, this includes the delivery of insulin boluses either automatically by the algorithm or as initiated by the user and the delivery of alerts related to high or low glucose levels, low battery power, low insulin supply, or other potential problems. For this study, insulin pump data were obtained directly from the device manufacturer (Tandem Diabetes Care, San Diego CA) in a file that recorded each system event with a date/time stamp, type of event, and any details (e.g., alert ID number, user opening app, carbohydrate amount entered at the time of a meal, bolus amount given, blood glucose entered by the user). Some of these data are also summarized for patients and health care professionals in the commercially available t:connect app, using Tandem's proprietary algorithms. However, raw pump data, rather than algorithmically summarized data, were used for analysis in the current study.

Control-IQ CGM Data. The CGM component of the Control-IQ system is a Dexcom G6 sensor that samples the user's interstitial glucose level every 5 minutes. The sensor is worn continuously on the user's skin and is not removed for showers or at other times. It records data 24 hours per day for 10 days, at which time it must be replaced. Although adolescents do report some difficulties using CGM sensors (Messer, 2020), there were no noted adherence problems in this study. Values of 70–180 mg/dL were considered target in-range glucose levels for the calculation of time-in-range (TIR). The American Diabetes Association sets a goal of 70% of glucose values being in this range as a measure of overall glycemic control (ADA, 2024).

Triggered Surveys on Pump Interactions. The triggered survey consisted of a series of yes/no items on potential reasons for interacting with the pump, plus a 4-item automaticity scale. The 10 available reasons were: 1) responding to an alert, 2) giving a bolus, 3) thought that glucose was too high, 4) thought that glucose was too low, 5) just felt "off," 6) I check my glucose routinely, 7) just bored or curious, 8) planning to eat soon, 9) planning to exercise soon, and 10) planning another activity soon. There was also 11) an *other reason* category, but with no option to specify what the other reason was. Items were developed by expert T1D clinicians and researchers based on their understanding of common patient experiences. The experts considered some of these reasons to be more proactive and situationally aware (#s 2 and 8–10), rather than reactive (all other items). The 4-item automaticity scale had statements rated on a 7-point Likert-type scale ranging from 1 = *completely disagree* to 7 = *completely agree*. An example item is "I checked without thinking." These 4 items were grouped into a single scale with excellent internal consistency reliability (Cronbach's $\alpha = .94$), and were therefore averaged together for analysis. This was used as another measure of situational awareness, because activities of the intuitive system are expected to take place outside of conscious awareness (Cook et al., 2018).

End-of-Day Surveys on Diabetes Self-Management. The end-of-day survey consisted of 3 items that asked participants about their success with diabetes self-management: "I tried to make progress on my diabetes goals today," "I tried not to let others interfere with meeting my goals today," and "I was successful in managing my diabetes today." This scale was originally adapted from the Goal Systems Assessment Battery (Maes & Karoly, 2005) in reference to diabetes goals by Wiebe et al. (2018). It had moderate internal consistency reliability (Cronbach's $\alpha = .78$) both in the original study and in our sample. The 3 items were averaged together into a single diabetes self-management score, but were also considered separately.

Statistical Analysis

Data from multiple within-person daily data sources (insulin pump, CGM, triggered survey, and end-of-day survey) were combined into a single file. Data points were aggregated as either averages (for continuous data like glucose or carbohydrate values) or counts (for discrete data like system alerts or reasons for checking the pump) within persons, within study days, and within 6-hour time intervals. The 6-hour intervals were created as follows: 3 AM to 9 AM (morning/breakfast), 9 AM to 3 PM (daytime/lunch), 3 PM to 9 PM (evening/dinner), and 9 PM to 3 AM of the subsequent day (overnight). We then calculated descriptive statistics for TIR and potential predictor variables across all participants and time periods.

By comparing across data sources, we were able to assess the accuracy of users' glucose perceptions (e.g., "I thought my glucose was too high" or "I thought my glucose was too low"), based on actual CGM values just before the survey response. In this analysis we used a value of <70 mg/dL as the objective marker for "too low" and >180 mg/dL for "too high," corresponding to the lower and upper limits of the TIR measure (Battelino et al., 2019). We then calculated the percent accuracy of participants' perceived glucose within each 6-hour time period.

Finally, we used multilevel models in SPSS 29 (IBM: Armonk, NY) to determine which (a) survey responses, (b) alert types, and (c) other Control-IQ variables were the best predictors of TIR. These additional variables were selected because they predicted TIR in past research (Messer et al., 2023): prior blood glucose, intention to self-manage, social support, success self-managing diabetes, number of pump checks, number of boluses, and percentage of boluses with a carbohydrate entry. Models were group-mean centered, and potential predictors were tested as fixed effects with a diagonal covariance matrix. Candidate variables were examined individually using an uncorrected alpha level of .05, in order to identify all potentially important predictors for use in subsequent prediction or intervention research. All models compensated for missing data via maximum likelihood estimation. Power in multilevel models is based on both the number of participants and the number of observations: With 4 time periods in each of 14 days per person, $N = 20$, and $ICC = .30$ for observations within participants, we had an effective sample size of 64, yielding 80% power to detect small effects of $\beta = .36$ or greater. Initial data screening confirmed the clinical expectation that time of day would significantly predict TIR across participants, so we included time of day as a covariate in all subsequent analyses.

Results

Time of Day, But Not Day of Week, Predicted TIR

Based on clinical experience, we expected time of day to be a significant predictor of TIR. As shown in Figure 1, this was confirmed as a strong effect, $F(3, 862) = 76.4$, $p < .001$. Across all participants, the 3 to 9 AM time interval had the highest TIR, $M = 83.0\%$, $SD = 23.5$; followed by the 9 AM to 3 PM interval, $M = 65.0\%$, $SD = 26.4$; and the overnight 9 PM to 3 AM interval, $M = 57.8$, $SD = 31.8$. Across all participants, the lowest TIR was during the evening 3 to 9 PM interval, $M = 53.7\%$, $SD = 28.3$. Post hoc tests confirmed that each of these intervals had

significantly different TIR from the others, despite a high level of within-person variability. In contrast to this effect, number of days since the start of the study had no effect on TIR, $F(1, 868) = 1.38$, $p = .24$, and neither did the specific day of the week, or weekends in comparison to weekdays (all ps > .55). These findings suggest relatively little day-to-day variability in glycemic control, and an absence of reactive measurement effects where participants might have improved their initial self-management because they knew they were being monitored.

Automaticity Failed to Predict TIR

We also examined automaticity using the 4-item measure of whether participants' pump interactions were unconscious or premeditated. Scores were normally distributed, $M = 4.23$, $SD = 1.61$, and indicated a moderate degree of automaticity in users' interactions with their pump. However, automaticity did not predict TIR, $F(1, 136) = 0.19$, $p = .66$. This was also true for each of the 4 individual scale items when they were examined separately in sensitivity analyses.

Proactive Pump Interactions Predicted Better TIR

Because the 11 possible reasons for checking the pump were presented in "select all that apply" format, we used UpSet analysis (Lex & Gehlenborg, 2014) of combinations of reasons as well as individual reasons (Figure 2). The number of surveys completed per day was unrelated to days in the study, $F(1, 122) = 0.51$, $p = .48$, or time of day, $F(1, 128) = 0.37$, $p = .77$, so even though many pump interactions had no associated survey data, the available data are considered to reflect a relatively unbiased sample of participants' reasons for interacting with the pump.

Table 1 shows the relationship of individual reasons for checking the pump (frequency within a 6-hour period) to TIR. Only one participant-reported reason predicted TIR on its own: When participants checked glucose because they *intended to exercise soon* (reason #9), they had better TIR. Additionally, the *other reasons* item predicted better TIR. We unfortunately did not

provide a free-text field for this category, so it is difficult to interpret this finding; however, the *other reasons* choice was infrequently used (n = 95 out of 987 responses). Sensitivity tests were performed, looking at individual reasons for checking the pump with no time-of-day covariate, and looking at the use of each item as a percentage of surveys completed during that time period rather than as an absolute count, but no other predictive relationships were identified.

When considering reasons for checking the pump in combination, we found that the sum of all proactive reasons predicted higher (better) TIR, $F(1, 145) = 4.48$, $p = .04$. However, the sum of all reactive items did not, $F(1, 145) = 0.01$, $p = .94$. Three specific combinations of items also predicted TIR. First, reasons #6 (*I check my glucose routinely*) and #8 (*planning to eat soon*) in combination predicted lower (worse) TIR, M = 46%, than overall TIR for the same participants, M = 65%. Second, adding reason #2 (*giving a bolus*) predicted even lower TIR, M = 39% when all three reasons were selected. However, the 3-reason combination was rare, used only 20 times by just 3 participants. The 6 participants who used reasons #6 and #8 together (with or without reason #2) were no different overall from participants who did not, TIR M = 65% vs. 64%, but that combination predicted lower TIR at times when it occurred. This combination appears to identify specific high-risk times for people who have generally in-range glucose values, even though one of the reasons (#8) was considered to be a proactive one.

Finally, the specific combination of items #1 (*responding to an alert*) and #11 (*other reason*) was found to predict higher TIR on a within-person basis, even though reason #1 was considered reactive. This combination occurred only 32 times, all from 3 participants who had low TIR overall, M = 54% vs. 67% in the rest of the sample. The combination of items #1 and #11 therefore may be slightly protective, but only for a subgroup of participants who had lower TIR to start with. As noted above, the *other reason* category is difficult to interpret.

System Alerts Predicted Worse TIR

Table 2 shows the most common alert types and their effects on TIR. As in prior research (Messer, 2023), receiving more alerts for any reason predicted lower TIR, r = -.33. A subset of alerts were classified by the Control-IQ system as *alarms* that required urgent attention due to a stoppage of insulin delivery because of power loss, no insulin, etc. A higher number of alarm-type alerts also predicted lower TIR, r = -.11. When users acknowledged more of the alerts that they received, this also predicted TIR, but in this study it predicted lower TIR, r = -.22, which is the opposite direction from that seen in previous research (Messer, 2023). A shorter average length of time from an alert to a user response predicted higher TIR, r = .13, but the percentage of alerts that were automatically cleared by the system (when the condition prompting the alert no longer applied) had no relationship to TIR.

Besides alerts, the number of events where the pump ran out of battery power predicted lower TIR, r = -.12. Similarly, the longer it took for a user to correct the problem, the lower their TIR, r = -.22. The incidence of a low-battery alert indicating that power was *about* to run out predicted low TIR even more strongly than actual power failure, r = -.40. Events where the pump ran out of insulin also predicted lower TIR, r = -.17.

With regard to the specific types of alerts received, high blood glucose alerts predicted lower TIR, whether this was based on the Control-IQ system's pre-set "high" level, r = -.43, or based on a user-selected value, r = -.40. Although there was a strong correlation between these two versions of the high glucose rule, r = .40, the pre-set Control-IQ algorithm had a slightly stronger relationship to TIR. In the other direction, the Control-IQ algorithm's pre-set low glucose alert also predicted lower TIR, r = -.10, as did alerts based on a user-selected low glucose value, r = -.06. In contrast, the Dexcom CGM device's hard-coded low glucose alert,

which was set at a slightly lower level than the Control-IQ version, did not predict TIR.

Other Predictors of TIR

Participants' average glucose was significantly related to their TIR, as expected because TIR is based on glucose. As described in the Methods, we compared subjective perceptions of glucose to the participant's actual glucose reading immediately before the survey. We found that participants who perceived their glucose as too high were generally still within the target range, M = 165 mg/dL, SD = 52.4. Similarly, participants who "felt off" were also generally within the target range, M = 162 mg/dL, SD = 75.6. In contrast, participants who perceived their glucose as too low had high average glucose, M = 183 mg/dL, SD = 67.6. As shown in Table 3, perceived high glucose was strongly associated with higher TIR, even when that perception was inaccurate, r = .80. Similarly, a perception that something felt "off" predicted higher TIR, r = .89, even when glucose was actually in range. Underestimating one's current glucose did not predict TIR.

We also tested end-of-day survey variables as predictors of TIR, and found that overall self-management success was related to subsequent TIR. However, this effect was due to just one of 3 end-of-day survey items; a sensitivity analysis showed that only the item "I was successful in managing my diabetes today" had a significant relationship to TIR. We failed to replicate a prior finding about intention to self-manage, although the exact question wording was different in the current study. We also failed to replicate a prior finding about social support, although again the question wording was different — in this case "I tried not to let people interfere with meeting my goals" rather than "other people helped me in meeting my goals."

Finally, we tested three metrics derived from the Control-IQ system data that predicted TIR in past research (Messer, 2023). All of them again predicted TIR in the current, independent data set: The more often a participant interacted with their pump, the lower their TIR. Figure 3

illustrates the consistent nature of this relationship for all participants, regardless of their other characteristics. Similarly, the more manual boluses a participant delivered, the lower their TIR. And the more often a participant entered carbohydrates at the time they gave a bolus, the higher their TIR. As also seen in prior research, the actual carbohydrate *amount* entered was not related to TIR, $F(1, 507) = 0.54$, $p = .46$, only the behavior of entering carbohydrates with a meal.

Discussion

Although CGM devices can improve TIR for adolescents and young adults with T1D, some patients have better results than others (Jiao, Shen, & Chen, 2022). Situational awareness is a complex concept used to understand high-stakes decision-making in aviation, firefighting, and the military (Klein, 2008). Here, we examined situational awareness as a potential mechanism by which CGM use might affect glycemic control in T1D. Specific self-management behaviors that predicted higher (better) TIR were responding quickly to alerts, avoiding insulin pump problems such as low battery or low insulin, and entering a carbohydrate value when giving an insulin bolus for a meal. Participants who perceived themselves to be successful in self-managing diabetes based on an end-of-day survey also had better TIR on the subsequent day.

We found support for a role of situational awareness and unconscious actions in the successful self-management of T1D, based on habits developed through experience and practice. The superiority of habitual behaviors over alert-triggered actions was supported by three major findings: First, proactive reasons for interacting with the Control-IQ system were associated with higher TIR, but reactive interactions were not. Second, as in prior research (Messer et al., 2023), simply having more interactions with the Control-IQ system, delivering more manual boluses, and receiving more alerts from the pump all predicted lower, rather than higher, TIR. In this study, even responding to a higher percentage of alerts predicted lower TIR. Third, perceived

high glucose levels predicted higher TIR even though those perceptions were mostly inaccurate, while the number of high-glucose alerts predicted lower TIR. We interpret this pattern of results as evidence that situationally aware participants were able to identify times when their glucose was *likely* to exceed the target range, which allowed them to more actively manage their glucose levels and therefore prevent out-of-range values. In other cases where an alert occurred, glucose levels were already out of range. Parallel qualitative findings also support this interpretation, because proactive self-management is supported by self-reflective patterns of use (e.g., checking numbers at certain critical points in the day), attention to embodied signals, and deliberate adjustments to one's routines in order to achieve specific results (Xu et al., 2024). Additionally, entering carbohydrates when giving a bolus predicted higher TIR, which suggests that paying attention to one's diet may be more important than simply using the hybrid closed-loop system to dose insulin at mealtimes. Improving self-management around meals may be a good intervention target, because adherence to dietary guidelines is a particularly important strategy for improving TIR in adolescents and young adults with T1D (Chiang et al., 2018; Dominguez-Riscart et al., 2022). Specific meal-related self-management behaviors may include weighing food, checking food labels, and estimating carbohydrates even if precise data are not available.

By contrast, routinely checking the Control-IQ system was not helpful, and actually predicted lower TIR in combination with two specific self-management behaviors: checking when planning to eat, and checking when giving a bolus. Again, this finding paralleled qualitative results which suggested that reactive management was less helpful than proactive management. One possible explanation is that reactive management strategies are more vulnerable to disruption by everyday stressors, alarm fatigue, stress, or insufficient sleep. These hypotheses would be interesting to explore in future research. Despite these findings in support

of the concept of situational awareness, a scale that asked participants whether they had consciously chosen to interact with their pump or done it without thinking about it failed to predict TIR. This finding may reflect measurement problems, or may simply reflect the fact that people have poor insight into their own behaviors (Schwitzgebel, 2013).

Comparisons to Prior Research

We partially replicated prior findings (Messer et al., 2023) that more pump interactions and more alerts predicted lower TIR, and that entering carbohydrates with meals and timely responses to alerts predicted higher TIR. We failed to replicate a finding from the same study showing that underestimating one's current glucose level predicted lower TIR, but we did have a finding in the opposite direction showing that *over*estimating one's current glucose level predicted *higher* TIR. In contrast to these sensor-based findings, we were less successful in replicating prior survey studies' findings that intention to self-manage diabetes (Messer et al., 2022; Wiebe et al., 2018) and perceived social support (Messer et al., 2022) predicted successful self-management in T1D. In this study, only perceived success in self-managing diabetes was associated with next-day TIR. However, we used different question wording for the intention and social support items than prior investigators. One recent study suggests that social support in particular may have indirect effects on glycemic control by way of treatment adherence, and that separate measures of family versus peer support may each be useful in understanding this relationship (Almeida, Tavares, & Pereida, 2023). Better measures are likely needed to fully understand the effects of self-management intentions and social support.

Even though the concept of situational awareness implies *accurate* perception of current threats (Endsley, 1995), we found an inverse relationship between the accuracy of participants' glucose perceptions and their TIR. Additionally, we found that users' perceptions of high glucose

were generally not accurate. Their perceptions of low glucose were even less accurate, with most pump checks for perceived low glucose being associated with actual glucose readings above the target range. Users who perceived that they had high glucose or "just felt off" had higher TIR results despite these inaccuracies. But both high- and low-glucose alert messages predicted lower TIR. As described above, this pattern of findings suggests a more nuanced interpretation of accuracy: Situationally aware participants may accurately perceive times when they are *at risk* for hyperglycemia and take steps to prevent it, while those who wait for a CGM alert before taking action might have already missed the window to effectively counteract hypergylcemia.

Quantitative findings in this study aligned well with qualitative results obtained from the same participant group (Xu et al., 2024). For instance, *recognizing body signals* was a prominent qualitative theme that ties to our findings about perceived glucose. *Diet/carb tracking* was noted as an important self-management strategy; in the current analysis, 73% of user-initiated boluses were accompanied by a carb entry. Unfortunately, some boluses might have been due to users' reported *impatience with automated dosing*; efforts to correct for the perceived "slowness" of the algorithm might lead some users to over-administer insulin (Berget, Messer, & Forlenza, 2019). *Exercise* was noted as a self-management strategy in qualitative results but was an infrequently endorsed reason for checking the pump; one possible explanation is that it can be inconvenient to check the pump during exercise. Alternately, other self-management strategies, such as strategic snacking, may be more useful in the context of exercise. Some qualitative interviewees said they *checked routinely* or were just interested in their glucose level, and this was also a commonly endorsed quantitative item, although routine checking did not predict higher TIR. Other barriers noted in interviews included *getting sick* or *drinking alcohol*, which were not directly assessed in the quantitative survey. Some participants said they *rely on alerts* to detect high glucose, but we

found that this may be an ineffective self-management strategy. Some participants also noted that alerts could be a source of stress, leading to alert fatigue or desensitization. Interviewees said they *could not always respond to alerts* because of other activities (e.g., driving), which helps to explain the wide variability in alert response times; however, some participants' average responses were much faster than others' so there is also some between-person variability involved. We suggest elsewhere that more context-driven alerts related to specific behaviors (e.g., drinking, driving, sleeping) and a more glanceable format (e.g., during classes or exercise) may improve the usefulness of alerts (Xu et al., 2023). Finally, interviewees reported that *CGM data helped them control glucose*, and our quantitative data support this perception.

Limitations and Directions for Future Research

This study's primary limitation was sample size, which may limit the generalizability of findings. Participants were primarily White, and 25% were Hispanic, but results may not be representative of other demographic groups. In addition, patients were recruited from a specialty clinic on an academic medical campus and might have been more engaged or better-resourced than the average patient with T1D in other settings. Surveys used in this study were developed by clinical experts on the study team, and although instrument psychometrics were tested, there may be an advantage in future studies using previously validated tools for concepts such as mindfulness vs. automaticity. The end-of-day survey items about diabetes self-management should also be standardized and potentially expanded, to help reconcile conflicting results from studies that used different question wording. Finally, participants in this study knew they were being monitored and could have changed their behavior as a result, even though we found no direct evidence of reactive measurement. Future studies could address this by monitoring for a longer period of time, which typically washes out such effects (e.g., Cook et al., 2012).

Future intervention studies could build on our findings by capitalizing on methods such as structured practice and reflection that help people to move behaviors from conscious control to more habitual execution by the intuitive system (Messer, 2019). Structured environmental prompts such as those delivered by hybrid closed-loop insulin pumps and CGMs may be helpful in developing situational awareness, but the ultimate goal should be to help adolescents and young adults with T1D to become less dependent on those prompts. Overall, the current research suggests that proactive engagement in T1D self-management behaviors, perhaps especially those involving diet, is the most effective route to better diabetes control.

Conclusion

Overall, these results suggest that successful self-management of T1D by adolescents and young adults is a largely automatic process, and that more optimal glycemic outcomes are achieved by users who interact with their hybrid closed-loop system both a) proactively and b) more selectively. Users' specific self-management behaviors that predicted higher TIR include carbohydrate entry with meals, timely responding to alerts, and preventing system failures related to low power or low insulin. Users were generally good judges of their own success self-managing diabetes, as perceived success at the end of one day predicted TIR the next. Self-awareness of glucose levels may be important even when those perceptions are not accurate, because they can serve as a cue to self-management. CGM/hybrid closed-loop insulin pump system use may help adolescents and young adults with T1D to self-manage their diabetes, particularly if users' interactions with the device result in an increased situational awareness of T1D and a more proactive approach to managing it.

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Table 1. Reasons for Checking the Control-IQ System

Reason for checking the pump	Total # times endorsed	BG at time of use: *M* (*SD*)	Effect on TIR during the same 6-hour period
1. Responding to an alert	333	162 (58.2)	$F(1, 67) = 0.58$, $p = .45$ n.s.
2. Giving a bolus	530	184 (68.3)	$F(1, 52) = 2.25$, $p = .14$ n.s.
3. Thought glucose was too high	157	165 (52.4)	$F(1, 93) = 0.13$, $p = .72$ n.s.
4. Thought glucose was too low	89	183 (67.6)	$F(1, 118) = 0.46$, $p = .50$ n.s.
5. Just felt "off"	60	162 (75.6)	$F(1, 139) = 0.02$, $p = .88$ n.s.
6. I check my glucose routinely	198	164 (63.3)	$F(1, 138) = 0.23$, $p = .63$ n.s.
7. Just bored or curious	120	163 (63.8)	$F(1, 113) = 0.17$, $p = .68$ n.s.
8. Planning to eat soon	188	190 (75.3)	$F(1, 53) = 3.20$, $p = .08$ n.s.
9. Planning to exercise soon	19	144 (55.6)	$F(1, 135) = 6.06$, $p = .02$ *
10. Planning another activity soon	7	222 (83.1)	$F(1, 142) = 0.62$, $p = .43$ n.s.
11. Other reason for checking	95	152 (35.9)	$F(1, 96) = 6.60$, $p = .01$ **
Combination of reasons 1 & 2	104	174 (61.9)	$F(1, 1202) = 0.09$, $p = .76$ n.s.
Combination of reasons 2 & 8	147	200 (†)	$F(1, 1208) = 2.63$, $p = .11$ n.s.
Combination of reasons 6 & 8	35	255 (49.7)	$F(1, 1201) = 5.80$, $p = .02$ *
Combination of reasons 2 & 3	92	196 (73.7)	$F(1, 1203) = 0.01$, $p = .91$ n.s.
Combination of reasons 1 & 3	48	186 (†)	$F(1, 1200) = 0.55$, $p = .46$ n.s.
Combination of reasons 6 & 7	58	161 (55.6)	$F(1, 1211) < 0.01$, $p = .96$ n.s.
Combination of reasons 1 & 11	32	172 (64.4)	$F(1, 1204) = 5.81$, $p = .02$ *
Combination of reasons 1 & 4	29	180 (105.9)	$F(1, 1203) = 1.14$, $p = .29$ n.s.
Combination of reasons 4 & 5	18	†	$F(1, 1203) = 1.79$, $p = .18$ n.s.
Combination of reasons 2, 6, & 8	20	184 (†)	$F(1, 1201) = 4.16$, $p = .04$ *
Combination of reasons 1, 2, & 3	30	†	$F(1, 1200) = 0.31$, $p = .58$ n.s.

BG = blood glucose; TIR = time in range; n.s. = not significant; * $p \leq .05$; ** $p \leq .01$;
†insufficient data for calculation

Note. Effects on TIR were calculated using multilevel models with person as the level-2 clustering variable and date/time combinations as the level-1 cases within persons. For each person/date/time combination, we tested the total number responses of a given type as a predictor of TIR for that same person/date/time combination. In each analysis we controlled for the time of day, which was found to strongly predict TIR in a preliminary screening analysis.

Table 2. Alerts Generated by the Control-IQ System

Predictor Variable	*M* (*SD*) per time period	BG at time of event: *M* (*SD*)	Effect on TIR during the same 6-hour period
Control-IQ Alerts and Other Significant Events			
Number of CGM alerts or alarms received	3.92 (2.80)	197 (61.9) [any alert]	$F(1, 997) = 27.0$, $p < .001$ ***
Number of *alarms* in particular that were received	2.58 (1.99)	195 (72.5) [any alarm]	$F(1, 1141) = 13.0$, $p < .001$ ***
Percent of alerts acknowledged	25% (29.6)	207 (61.5) [user response]	$F(1, 997) = 27.0$, $p < .001$ ***
Percentage of alerts cleared automatically by system	51% (41.5)	202 (61.1) [if cleared]	$F(1, 1003) = 2.52$, $p = .11$ n.s.
Time for user to respond to an alert (minutes)	30.5 (150.9)	207 (61.5) [user response]	$F(1, 546) = 8.27$, $p = .004$ **
Number of incidents where pumping was suspended	0.20 (0.57)	194 (63.5) [suspended]	$F(1, 1202) = 12.1$, $p < .001$ ***
Time from pumping suspended to pumping resumed (minutes)	26.1 (29.7)	197 (66.6) [resumed]	$F(1, 177) = 5.74$, $p = .01$ **
Specific Content of Alert Messages			
Alert #50, system-determined high glucose	0.65 (1.00)	205 (55.7)	$F(1, 1211) = 318.5$, $p < .001$ ***
Alert #2, user-set high glucose	0.69 (0.91)	207 (58.1)	$F(1, 1213) = 165.6$, $p < .001$ ***
Alert #51, system-determined low glucose	0.43 (0.80)	179 (60.1)	$F(1, 1209) = 27.3$, $p < .001$ ***
Alert #1, CGM hard-coded “urgent low soon”	0.06 (0.27)	185 (62.0)	$F(1, 1207) = 2.71$, $p = .10$ n.s.
Alert #3, user-set low glucose	0.29 (0.65)	177 (58.6)	$F(1, 1213) = 6.39$, $p = .01$ **
Alert #0 or #17, low insulin	0.11 (0.36)	213 (62.3)	$F(1, 1201) = 24.1$, $p < .001$ ***
Alert #46, low battery	0.77 (0.99)	207 (58.9)	$F(1, 1213) = 163.7$, $p < .001$ ***

BG = blood glucose; CGM = continuous glucose monitor; TIR = time in range;
n.s. = not significant; ** $p \leq .01$; *** $p \leq .001$

Table 3. Other Potential Predictors of Time in Range

Predictor Variable	Effect on TIR during the same 6-hour period
Actual vs. Perceived Glucose Level	
Average *CGM-monitored* BG during the same timeframe	$F(1, 1177) = 3301.4$, $p < .001$ ***
Average *self-reported* BG during the same timeframe	$F(1, 632) = 461.1$, $p < .001$ ***
Underestimation of current glucose level (% of pump checks for perceived low glucose, where glucose was actually normal or high)†	$F(1, 17) = 0.43$, $p = .52$ n.s.
Overestimation of current glucose level (% of pump checks for perceived high glucose, when glucose was actually low or normal)†	$F(1, 18) = 18.6$, $p < .001$ ***
Inaccuracy of perception that something was "off," when checking without a specific direction for the expected problem†	$F(1, 9) = 45.4$, $p < .001$ ***
End-of-Day Survey Variables	
Overall success self-managing diabetes (mean of 3 items)	$F(1, 976) = 5.75$, $p = .02$ *
1. Intention to self-manage ("I tried to make progress on my diabetes self-management goals")	$F(1, 976) = 0.25$, $p = .62$ n.s.
2. Social support ("I tried not to let others interfere with my goals")	$F(1, 976) = 0.80$, $p = .37$ n.s.
3. Self-reported success ("I was successful in managing my diabetes today")	$F(1, 976) = 22.2$, $p \leq .001$ ***
Other Control-IQ System Variables	
Number of times checking the pump	$F(1, 1196) = 90.3$, $p < .001$ ***
Number of boluses given by the user	$F(1, 1204) = 81.9$, $p < .001$ ***
Percent of boluses with a carb entry	$F(1, 542) = 30.1$, $p < .001$ ***

BG = blood glucose; CGM = continuous glucose monitor; TIR = time in range;
n.s. = not significant; * $p \leq .05$; *** $p \leq .001$

†This subset of analyses did not control for time of day, because survey completion happened only during certain timeframes.

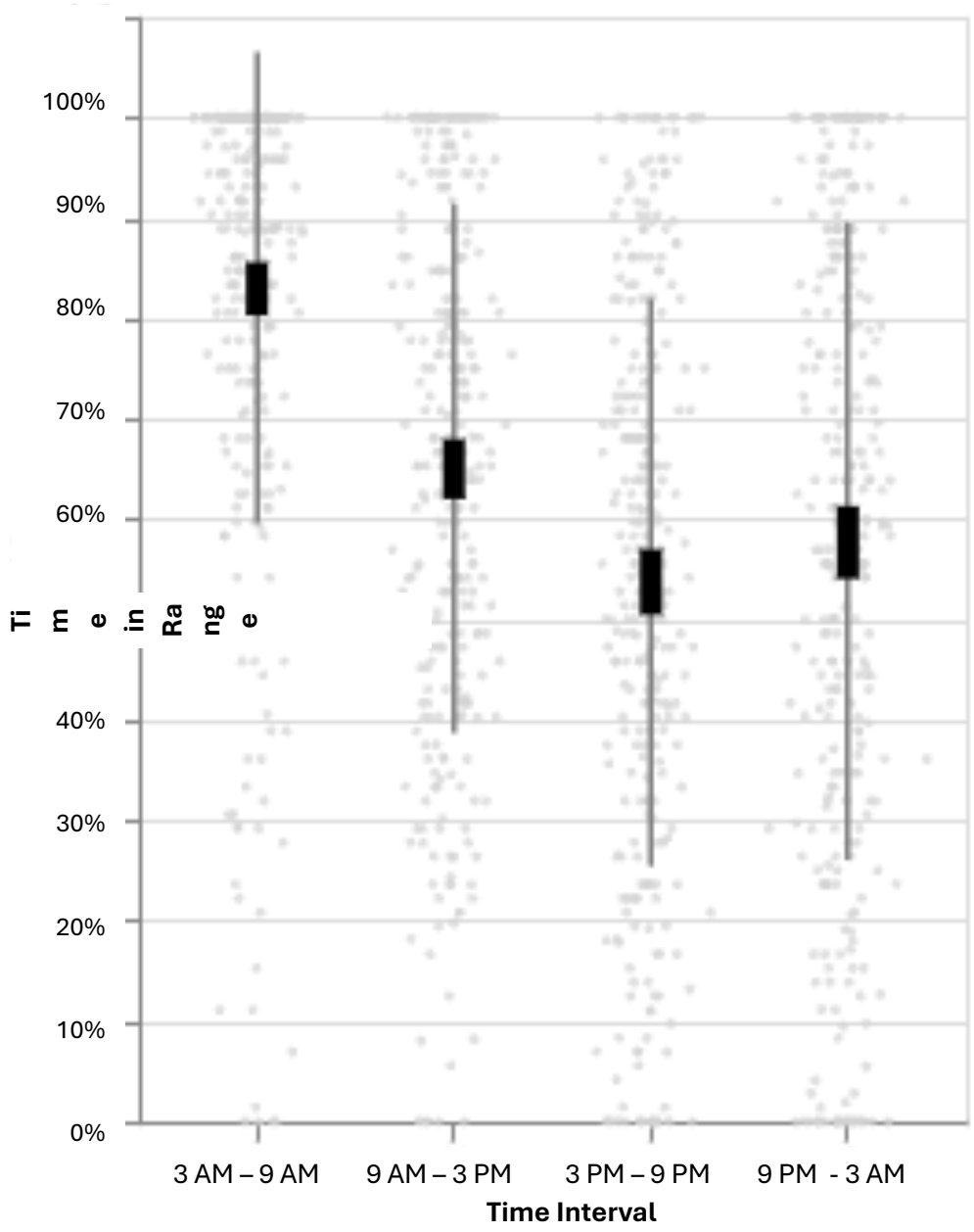

Figure 1. Boxplot illustrating the effect of time of day (four 6-hour intervals) on TIR, across all study dates and participants. Boxes represent TIR values for 50% of the data points in that timeframe, with the heavy central line representing the median. Whiskers represent the full range of values for most participants, with dots showing values for individual scores that were outliers in the data. These were seen particularly during the overnight time period, when TIR was generally good with infrequent exceptions.

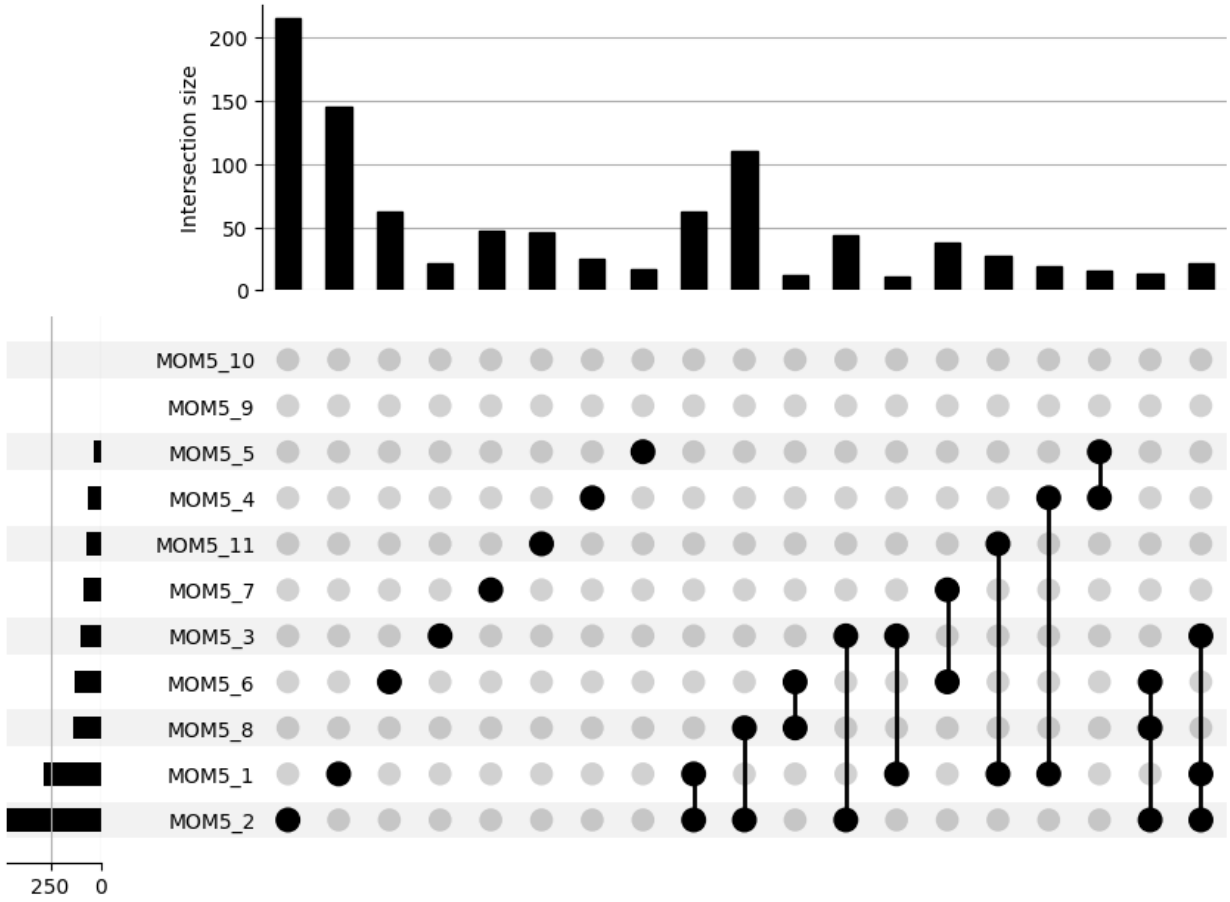

Figure 2. UpSet diagram (Lex & Gehlenberg, 2014) showing the frequency of each common survey response choice on its own (first 8 columns) and the 11 most common combinations of items among surveys completed in this study (remaining columns). The bars along the left-hand side of the figure show the overall frequency of each response choice, whether used on its own or in combination with other items. The dots and lines in the lower grid identify specific item/item combinations, including two 3-item combinations on the right side of the figure. Note that 2 of the individual response choices (#9: *planning to exercise*, and #10: *planning another activity*) were very rarely used, and therefore not included in this analysis.

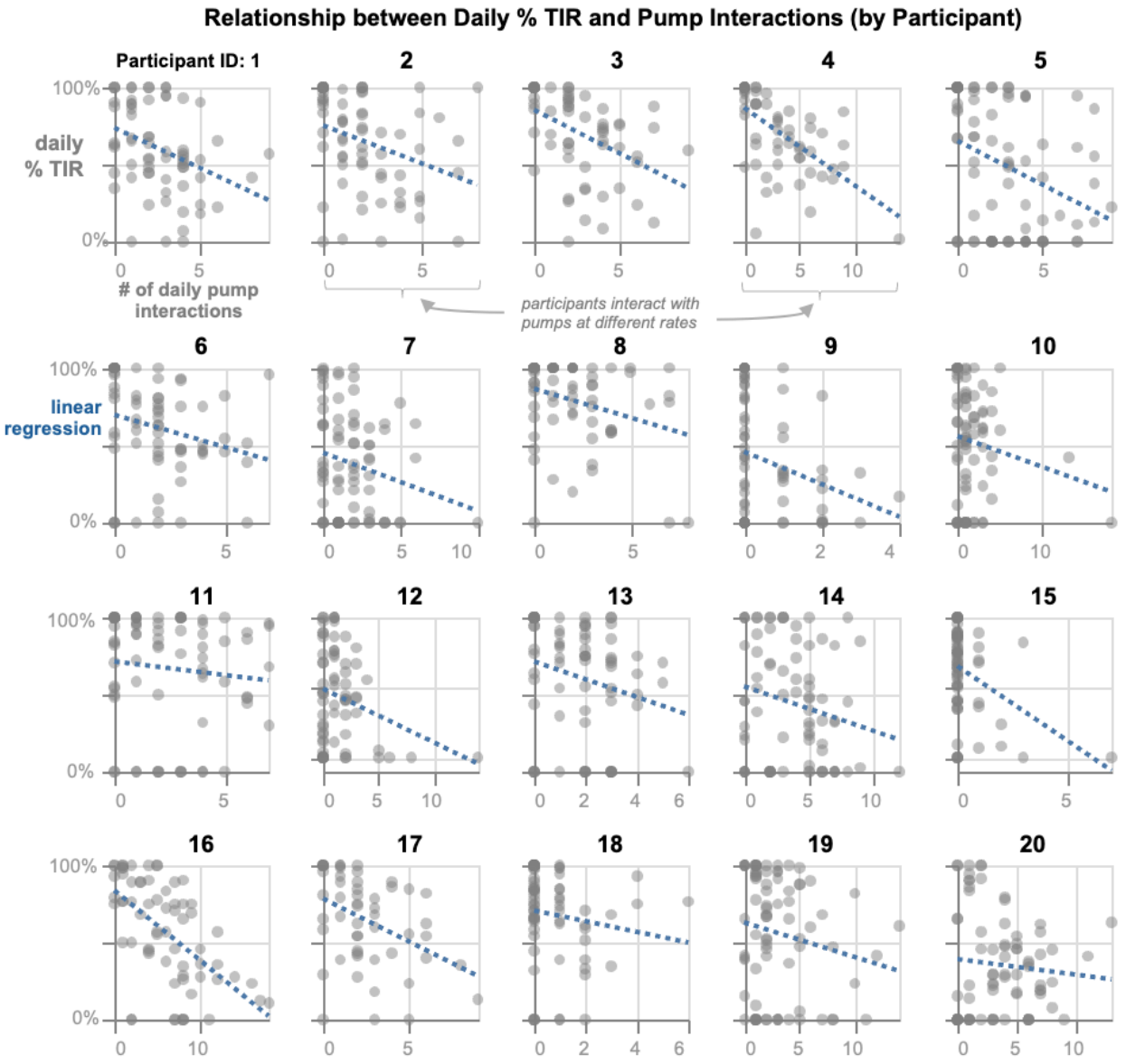

Figure 3. Individual regression plots showing the association between the number of pump interactions on a given day and the participant's TIR for that day. The number above each graph is the participant number. The individual regression lines shown on each participant's graph illustrate the consistent negative relationship between number of pump interactions and TIR. Note that the *x*-axis scale is different for each participant, because people varied widely in their range of total daily pump interactions over the course of the 2-week study.