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Chronic Care in a Life Transition: Challenges and Opportunities for Artificial Intelligence to Support Young Adults With Type 1 Diabetes Moving to University

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Self-managing a chronic condition involves adapting management strategies to life's continual change. Among these changes, moments of significant life transition can render routine self-management practices obsolete without significant modification to the new context. In this study, we examine one significant life transition for young adults living with Type 1 Diabetes, the move from home to university, to understand how near future AI-enhanced technologies might provide opportunities and challenges for supporting care. From interviews with 24 students in the UK who had moved away from their childhood homes, we used sensemaking literature to frame the process of initial disruption to the rebuilding of self-care practices around a new lifestyle and support networks. By studying a significant life transition, we uncover implications for the design of T1D technology, particularly closed-loop systems, through AI enhancements and human-centred design approaches, then extrapolate for other significant life transitions and chronic conditions.

1 INTRODUCTION

Change is an ever-present challenge for those living with a chronic condition as it erodes the effectiveness of developed self-management processes, requiring constant adjustment to maintain. This effect is accentuated during significant life events, for example, moving house, starting a new job, or progressing to the next stage of education, where many aspects of life change. In the UK, an estimated 19 million people are living with chronic conditions [38]. With the resources of the National Health Service (NHS) becoming more thinly distributed, the individuals themselves perform the vast majority of the management of these conditions. In recent years, technology has empowered these individuals by improving the efficacy of their self-management and heightening their understanding of it. The ideal management of chronic conditions is personalised to an individual, as the many nuances of conditions mean different people will react differently to the same situations. Artificial intelligence (AI) can hone technology for personalised management to avoid the intensive manual adjusting process.

The applications of AI in chronic care technology are evident across various conditions, including diabetes, neck and back pain, dementia, migraines, heart failure, and chronic obstructive pulmonary disease [26, 72, 74, 115, 118, 120]. The uses within these cases range from recommendation generation to technology interfaces to event prediction, but all aim to assist in the self-management process. There has also been consideration of interactions with healthcare professionals and how they can be reduced through the use of AI in chatbots [48, 114]. Machine learning is an area of particular interest in chronic care with the continual increase in data available from digital devices [76, 89], with these machine learning techniques further supporting the personalisation of chronic care technology.

Type 1 Diabetes (T1D) is a condition that lends itself to AI-enhanced interventions due to the regularity of data streams, partly due to the rise of continuous glucose monitors (CGMs). However, there are times when the regularity of this data stream and established self-management practices are disrupted, causing particular challenges for data-reliant diabetes technologies. Therefore, we consider the case of young adults with T1D moving to university and the

implication this transition has on the design of AI systems for chronic conditions. In the UK, 50% of people attend higher education before the age of 30 [124]. This transition often involves moving to a new city with a different schedule, away from family and a known support network, all while learning to live independently and experiencing university life. All these changes bring cognitive burden, with a chronic condition only adding to this. Designing AI systems that consider life transitions, like the move to university, would decrease the burden of chronic conditions by making them easier to manage at a time when help is most needed.

We present findings from the thematic analysis of 24 semi-structured interviews with young adults living with T1D in the UK who have left their childhood home in the last five years to attend university. These findings revolve around the changes experienced in the transition to university that most impact self-management: changes in lifestyle and changes to support networks. From this analysis, we discuss challenges and opportunities for T1D digital interventions during life transitions, focusing on AI and the HCI community's roles within them. Sensemaking [82] frames the difficulties of T1D management created by the transition, the process of learning to manage around them and the wisdom gained from this process, with consideration of the wider implications across life transitions and chronic conditions.

2 RELATED WORK

2.1 Self-management and Shared Care for Chronic Conditions

Across health and care, various approaches are taken to design technology, including a wealth of work investigating the lived experience of people integrating care into their everyday lives (e.g. [51, 69, 75, 137]). In chronic care, self-tracking has been utilised for goal-directed self-management [116] and encouraged through pictorial tracking apps [5, 6]. There has also been work considering the context in which technologies are used, including the environmental context's [53], the social context's [96], and the cultural context's [87] impact on living with a chronic condition. While there is significant variation between different chronic conditions and the context in which self-management occurs, research has highlighted the differences and similarities of lived experiences with technologies across idiosyncratic conditions [7, 115]. Ongoing work in HCI prioritises understanding these lived experiences and utilises them in the design of new technology sensitive to the different contexts [136].

Much of adult self-management places a burden on the individual, but there are also elements of shared care. Investigation into such practices has uncovered a complex socio-technical context, where many different people influence care practices and experience [55, 121]. Moving towards more complicated sensor-based technologies, the availability of the internet-of-things has led to collective modification [142] and the interpretation of data from smart home devices within wider households [64]. Chronic care is not experienced in a social vacuum, including diabetes self-management.

2.2 T1D Self-management, Shared Care and Technology

T1D forms a valuable case study for chronic conditions due to the wide adoption of various technologies and the recent surge in the availability of data streams, the most significant of these being continuous glucose monitors (CGMs). These systems can assist in trend detection in historical data to aid future T1D management [80]. They are also linked to improved engagement with self-management, which in turn improves glycaemic control [130]. Those living with T1D are unable to produce sufficient quantities of the hormone insulin, vital in the body's regulation of blood glucose levels. As a result, they are forced to inject insulin to manage the numerous factors that impact blood glucose levels, which include diet, activity, alcohol intake, and illness, among others [37]. There is a stigma associated with T1D that is

particularly relevant during adolescence, and young adulthood [113], with work done to address this stigma through participatory design [86]. However, as explored by O'Kane et al., the increase in worn T1D technology has led some users to a dilemma of whether to hide or show the technology, highlighting their condition to others [96].

As part of self-management, individuals develop peer support networks to gain assistance from others [139], which allows for collaborative approaches to self-management. CGMs are often used in conjunction with systems that remotely share blood glucose readings to allow others to collaborate in shared care from a distance. Shared care has informed the design of technology in a broader chronic condition context [93], and by Toscos et al. in the relationships between children and parents in T1D management [129]. Collaboration is commonly seen between children and parents; however, as they grow, they transition to more independent management and take on more responsibility [16]. Education is essential in this transition to independence, and technology has been developed to assist with it, commonly designed with children in mind [65, 131].

The rise of self-tracking technology has made predictive technology for chronic conditions possible, as seen in Doryab et al.'s work on bipolar disorder, which utilises machine learning tools [33]. For diabetes, Katz et al. explore decision support systems [58], which face difficulty due to population-wide variation in self-management approach. Their work also considers the design of user interfaces within applications using mass data [57], highlighting the excessive cognitive load that gaining knowledge from mass data entails. One potential solution to this problem is automation in the tracking and interpreting stages, with Choe et al. finding it to reduce user burden [21]. For years, as medical regulation fails to keep pace with health technology development [135], DIY systems that utilise such automation have been in use, impacting self-management [60, 95]. This shift in the individual's expertise has raised the importance of customisation in self-management technology [2, 122], with machine learning used in a decision-support context [32]. The design of technology has also been shown to benefit from collaborative work and end-user involvement, such as co-designing machine learning applications for T1D self-management [7].

2.3 Sensemaking

A considerable part of the self-management of any chronic condition is learning. Limited contact with healthcare professionals means most of this comes from making sense of personal experiences to iterate and improve management strategies. The concept of sensemaking was developed to capture this process, with some of the first references coming from Russell et al. and Weick, in the contexts of data analysis [112] and organisational dynamics [140] respectively. The concept has been refined over time to be more future and actions orientated [42, 111, 141], and applied in numerous settings, from social interaction to data and analytics based, including data analysis, data visualisation, and cognitive task analysis [13, 63, 70, 101]. Sensemaking is viewed as more crucial at times of change when there is a more significant gap in knowledge and understanding and therefore is relevant in the design of systems used at these times [28]. In collaborative settings [88], particularly healthcare, collective understanding is reached from contrasting opinions through sensemaking when discussing and combining ideas [81, 90, 99].

Chronic condition management uses experiential learning to develop management strategies by drawing links between past events and their health outcomes [77, 80, 104], this can lead to digital interventions designed to support this experiential learning process [78, 79]. Personalisation becomes a vital component of these interventions to encompass the wide range of approaches and knowledge of self-management [29]. When applying sensemaking to chronic condition management, Mamykina et al. broke the experiential learning into three activities: 1) perception of new information, 2) development of inferences from the perceptions, and 3) putting inferences into practice during self-management [82]. With current technology, T1D management can be very data-focused, making earlier sensemaking

work particularly relevant. It has been used to highlight challenges in data analysis, the inability to identify clear trends and counterintuitive insights compromising trust in data [103].

2.4 The Impact of Life Transitions on T1D Management

Throughout a person's life, numerous transitions they go through will dramatically change their lifestyle, bringing with it several challenges [44]. Technology is a growing part of this change [46, 85] and has the potential to reduce some of the difficulties it brings [62]. For those with T1D, these transitions can require significant changes to management strategies to remain effective, which takes time to learn and adapt. Young adulthood is one of the most intense periods of life transition, with adolescence and changes to education, relationships and work all potentially impacting T1D management. In addition, during young adulthood, there are also T1D healthcare transitions, including diagnosis, complications and technology changes [108]. Transitions experienced at younger ages have been studied, focusing on gaining independence in T1D management from parents in childhood [16], and digital interventions that could be designed to help this transition [119].

Transitions are known to disrupt T1D management in young adults [47, 91]. The strategies young adults have developed to manage these disruptions have been studied, with a balanced approach to blood glucose management and social peer interventions found among them [54, 107]. Technology is also considered to be a tool that can alleviate some of the pressures that occur in transitions [106], which raises the potential for digital interventions to support young adults further in adapting their management strategies to a new context. One of the more heavily studied transitions in young adulthood is the shift from child to adult services. This move brings with it a reduction in contact time with health care professionals, access to technology and assistance in organising clinical contact. The same difficulties are found across other chronic conditions with implications on self-management [66]. Support groups have been found to assist with this transition [83], along with numerous interventions developed to help maintain effective T1D management during it [14, 117]. In the UK, the transition to university has been linked with poor health outcomes and low engagement with clinical care [61]. The current work focuses on the difficulties in the transition, which include a lack of routine [9], changes to food intake and the limited understanding of T1D peers have [49], which young adults adapt to while trying to live as normal a life as possible [8]. However, current work does not capture the range of social nuances or challenges for data-intensive T1D technologies created by the transition and stops short of directly proposing potential technological solutions to the challenges it raises.

2.5 The Future of T1D Technology

T1D technology has seen many advances in recent years with the introduction of the insulin pump, CGMs and, more recently, closed-loop systems. A closed-loop is a blood glucose monitoring system linked to an insulin delivery system, with an algorithm adjusting insulin dosage based on blood glucose and other factors without user intervention. These systems are hailed as the future of T1D technology and show the potential to significantly reduce the burden placed on those with T1D by automating the management process [40, 41, 68]. They are now commercially available from various manufacturers, with some covered by the UK's NHS in specific regions and within certain criteria. There has also been the development of DIY closed-loop systems linking existing technology with new algorithms, which are available open-source [34, 43, 50]. Future improvements to the systems may come from several directions, such as the inclusion of glucagon in a dual hormone system to both lower and raise blood glucose levels to automate balance [15, 35].

There is also continual work improving the algorithms found within closed-loop systems, which historically had relied on control engineering [24]. Currently, research is going into developing closed-loop systems and blood glucose

prediction algorithms that use machine learning techniques, such as reinforcement learning, to improve existing algorithms [36, 125]. These techniques allow for further personalisation of algorithms that can learn from the user to optimise control to an individual based on historical data. Another approach to closed-loop system improvement is including additional data sources, which often revolve around physiological data to factor physical activity into blood glucose algorithms [134]. This addition has been implemented into closed-loop systems that demonstrate effective management [23, 52, 109]. However, these systems require consistent data streams, consistent use, and algorithms trained based on historical data, and diabetes self-management even during routine daily life has been described as "out of sync with the normative temporal orders of everyday life" [39]. When someone goes through a major life transition, such as the move to university, the inputs to these technologies leveraging AI and ML become unreliable, potentially rendering the technology useless at precisely the time when it would be most helpful.

3 METHOD

To understand the potential impacts of a life transition on data-reliant technologies for chronic care, we conducted an interview study of the experience of moving to university whilst balancing Type 1 Diabetes self-care, using sensemaking to frame the thematic analysis.

3.1 Participants

Twenty-four young adults were recruited for an hour-long interview. To be included in the study, participants needed to be 18-25 years old, have been diagnosed with T1D, have been self-managing their T1D for over a year, live in the UK and have moved out of their childhood home in the last five years. Participants were recruited through Twitter, T1D university groups, word of mouth and with the help of the Juvenile Diabetes Research Foundation (JDRF), who also advertised it on their website and through their social media channels. As reimbursement for their time, participants were given £20 worth of shopping vouchers. While the inclusion criteria included people who left their childhood home for any reason, the participants recruited had all left home to attend university (50% of people attend university in the UK).

   Participants provided demographic information about themselves, shown in Table 1, through open text boxes in an online form. Where necessary, spelling was corrected, and numbers were rounded for consistency. There were 14 female (58.3%), 8 male (33.3%) and two non-binary (8.3%) participants. For self-identified ethnicities in an open text box, 23 (95.8%) identified themselves as White or British, and one participant (4.2%) identified themselves as Middle Eastern. There was a mean age of 21.5 years (±1.4 years) and a mean time since T1D diagnosis of 11.9 years (±4.5 years). All participants used CGMs, with 11 (45.8%) on multiple-dose injected insulin therapy (MDI) and 13 (54.2%) on insulin pumps. There were 3 (12.5%) participants using closed-loop systems.

3.2 Data Collection

After each participant completed a consent form, an interview was organised over Microsoft Teams. The first author, who has Type 1 Diabetes and left home for university six years ago, conducted the interviews. Interviews lasted up to an hour and were semi-structured using a pre-defined topic guide. The first two interviews were initially pilot interviews; however, only minimal changes were made to the topic guide in response to them, so they were included in the dataset. The topic guide covered T1D management, transitioning away from home, physical activity, wearable devices and closed-loop systems. During the interview process, it became apparent that three participants who had signed up did

Table 1. Participants' demographic information

Participant Number	Age	Gender	Ethnicity	Years since Diagnosis	T1D Management Devices
01	23	Male	White	5	CGM, MDI
02	20	Male	White - British	19	CGM, Insulin pump
03	22	Non-Binary	White British	17	CGM, Insulin pump, Closed-loop
04	21	Female	White British	4	CGM, MDI
05	20	Male	White British	19	CGM, Insulin pump, Closed-loop
06	24	Female	White British	4	CGM, MDI
07	19	Non-Binary	White British	10	CGM, Insulin pump
08	22	Female	White British	21	CGM, Insulin pump
09	23	Female	White British	13	CGM, Insulin pump
10	20	Male	White British	18	CGM, Insulin pump
11	21	Female	White	7	CGM, MDI
12	22	Female	White British	18	CGM, Insulin pump
13	19	Male	White British	3	CGM, MDI
14	19	Male	White British	6	CGM, Insulin pump
15	21	Female	White Welsh	10	CGM, MDI
16	21	Female	White	9	CGM, Insulin pump
17	20	Female	British	8	CGM, Insulin pump
18	24	Female	Middle Eastern	12	CGM, MDI
19	25	Female	White British	15	CGM, Insulin pump, Closed-loop
20	24	Female	White British	10	CGM, MDI
21	21	Female	White British	16	CGM, MDI
22	23	Male	British	12	CGM, MDI
23	21	Female	White British	14	CGM, MDI
24	22	Male	White British	15	CGM, Insulin pump

not have T1D, so they were excluded from the dataset. The interviews were recorded and then transcribed, after which the recordings were deleted.

3.3　Data Analysis

The interviews were analysed following the reflexive thematic analysis framework outlined by Braun and Clarke [10, 11], opting for an inductive and semantic approach. The transcripts were thematically coded over an iterative process using NVivo. Initially, five transcripts were randomly chosen, and two passes were made in which general codes were generated and then focused down by the first author. The remaining transcripts were read through and coded using those generated in the first five. The codes were edited, iterated on and expanded during the process. The codes were then grouped into themes and sub-themes, with those relevant to the transitional changes in T1D management selected. During the grouping process, links were drawn to the three sensemaking activities in chronic conditions outlined by Mamykina et al. [82], which became a framework for future iterations of grouping discussed and iterated on with all authors.

4 FINDINGS

In the findings, we present how the changes in lifestyle and support network that occur in the transition to university impact T1D management. For each sub-theme, we seperate the experiential learning into Mamykina et al.'s chronic condition sensemaking activities: 1) perception of new information in the initial disruption, 2) development of inferences from the perceptions during the transition, and 3) putting inferences into practice as part of self-management [82].

4.1 Changes in Lifestyle

The transition to university brings multiple changes in lifestyle impacting T1D self-care, which have been categorised into drinking habits, eating habits, sleeping patterns, physical activity habits, and routines.

4.1.1 Changes in Drinking Habits. Alcohol has an extended impact on blood glucose and often comes in sugar-filled drinks, so its consumption brings with it difficult to predict insulin requirements [37]. Participants commonly brought up alcohol when discussing the changes experienced in the move to a UK university. In most cases, this was associated with an increase in frequency and intensity: *"I obviously was drinking before I'd come to uni, but not to the same level"* (P14). This increase in alcohol consumption had a detrimental impact on T1D management: *"I definitely drank a lot more while I was at university and so sometimes I think it was a bit difficult to manage"* (P20). Despite this negative impact, wanting to fit in led to alcohol consumption nonetheless: *"you know it's really bad for your blood sugar and then at uni I was kind of like well everyone else is, you know I'm going to drink more"* (P21).

Due to being faced with new experiences around alcohol, young adults are forced to learn how to react: *"Going out, I hadn't done that at home, so that was something to learn"* (P06). P10 spoke of their process of learning through experience, *"just lots and lots of testing really. And then when you can see the trends just making small changes"*, but warned of being overzealous in this approach, *"if you change anything too quick, especially if you're drunk, it's, it's not a good recipe"*. P21 referred to the learning process as a *"trial by fire sort of thing"*, throwing themselves into the situation to have to adapt in the moment. Part of the learning process is *"trying to work out how [alcohol] really function, especially with different types of drinks"* (P13) and understanding these nuances to manage their T1D better in future. This also involved having more honest conversations with clinicians now that they were adults: *"my doctor, my guy just said to me like you're better going for like stronger spirits 'cause there's less carbs and that makes it a bit less complicated"* (P14). The initial alcohol induced self-care challenges changed over time, especially as the student progressed at university and the initial major transition to first year ends, *"I don't go drinking the same now, like I'm a fourth year"* (P06).

The learning culminates in numerous new strategies for managing T1D around alcohol. Some strategies concentrated on blood glucose preparation before a drinking session, which often involved food and insulin: *"I tend to definitely eat before I go"* (P08) and *"when I have like dinner, I'd probably just take like half of what I need"* (P11). Another commonly mentioned management strategy was the progression of drinks chosen on the night, which P16 detailed: *"I [...] drink drinks that don't really have any sugar in them, [...] earlier on, and then if we're out later I'll like drink like sugary drinks to [...] get a bit higher before I go to bed"*. However, all established strategies have their limitations, *"once you're like five drinks deep, that [...] doesn't always get maintained to be honest"* (P11), with alcohol itself a contributing factor to this. For P14 the prolonged impact of alcohol caused longer-term difficulties: *"I'm never gonna have a good bloods day [...] the next day"*.

At university, alcohol consumption often increases in frequency and intensity, sometimes brought about by social pressures. Through trial and error, young adults develop strategies around insulin management and drink choice, although the cognitive impact of alcohol can make this learning process more difficult.

4.1.2 Changes in Eating Habits. The timings and composition of meals will change the insulin required to manage it [37]. In the move to university, the young adults often had to take on the responsibility of organising meals from their parents: *"I need to figure out when I'm going to eat for myself because no one else is around"* (P03). As a result, the timings and content of these meals changed, which in turn impacted self-management: *"certainly with meal time to change up [...] and the nutritional content of meals wasn't quite the same. So no, it definitely made it more difficult."* (P10). P17 described this change as going from *"eating properly to not eating as properly. And, and it was definitely more like snacks rather than full on meals"* (P17). In contrast, some university students live in catered halls for the earlier years of their degree where food is provided for them, which brought other challenges to adapt to: *"I couldn't weigh anything. So, I think there was a lot of carb guesstimating going on, which probably wasn't the best"* (P23).

Young adults have to learn to manage this new diet, which involves *"getting used to like new foods that I was being exposed to"* (P02) and helps to build experiential knowledge to be applied in the future. P07 found the responsibility of planning meals brought with it the freedom to adjust the schedule to fit with T1D management: *"Sometimes with my meal times will be delayed like quite hours because I'm waiting for my bloods to come down"*. The same freedom also results in *"going out with like friends and stuff or getting food like on after nights out"* (P11), creating further scenarios to adapt to. For some, such as P02, it was beneficial to their T1D management to be more in control of the preparation, *"It's sort of great 'cause I know when I'm about to cook and during that process I can sort of scale out when I need to give the insulin"*. Taking a bigger role in preparation of meals led to better understanding of how to manage them.

From this learning, the young adults develop T1D management strategies, where the increased independence was found to allow for greater flexibility in timings and content of meals: *"if I'm running high, I'll probably tend to do something a bit more on the low carb side of things [...] if I'm running low, I'll probably have those extra carbs in my food"* (P03). It also means the timings of meals can be adjusted, although for P02, this created a dilemma with the wider health implications of T1D management decisions: *"is it worse to be starving yourself or is it worse to have slightly bad control for an hour or two?"* It is sometimes difficult to stick to the ideal management strategy, which can cause frustration when their more established T1D management practices dictate actions that go against in-the-moment personal preference, *"one thing that like diabetes, like really annoys me with. So, if I go low and really don't want to like have to eat"* (P11).

At university, the timings and content of meals change and young adults learn to utilise their agency to manage these changes, finding effective strategies in delaying meals and better understanding their preparation.

4.1.3 Changes in Sleeping Habits. During sleep, basal insulin is primarily at play, so when a person's sleep schedule changes their basal schedule needs to be adjusted to match it [37]. At university, there is a different set of pressures dictating when to sleep. As a result, the sleep pattern of young adults moving to university often changes, *"all of the sort of nature of when you're awake and you sort of sleep schedule changes"* (P10). The timings of sleep change but it also becomes *"a bit more erratic, um at uni"* (P16), with a shift to *"going to bed like a bit later"* (P03) and being *"allowed to sleep a lot later"* (P18). Often this contrasts with life before university: *"school, it's a little bit more structured, so it's like I'm gonna be waking up for 9:00 o'clock everyday [...] Whereas now I'm like I could sleep in like if I don't have lectures"* (P05).

The new sleep schedule disrupts previous T1D management practices, *"it just threw all the, the basal and the carb ratios a bit out of wack [...] I just put insulin in and it'd just send me low 'cause, 'cause the body wasn't quite adjusted to it"* (P10), so new strategies needed to be learned. These strategies need to reflect the variability in lecture timetables, which allows for more flexibility but can impact T1D management: *"I wake up whenever my first thing is so [...] having my routine be at different times every day I found really impacted my bloods"* (P07). Often this learning happens through

experience, such as P03 who found out the consequences of poorly managing sleep: *"I can go to bed at 4:00 o'clock in the morning if I wanted to and nobody bat an eye, except me in the morning when I'm kicking myself"*.

Over time, the young adults gain an understanding of the nuances of managing T1D around their new sleep schedule: *"On a normal day, it just plateaus if I don't do anything. But if I it feels like if I give a tiny amount of insulin it just suddenly drops"* (P02). P02 also highlights bringing in consistency where possible to make T1D management easier: *"I need a schedule for better control because then you can predict what's going to happen and you can set up background rates to work a bit better"*. Some participants had also linked out-of-range blood glucose levels with poorer sleep: *"like sugars definitely affect how much I sleep [...] if it's normal to low I can't sleep and if it goes high in the middle of the night then I can't wake up"* (P18). This link increases the importance of finding effective T1D management strategies around sleep, which is made difficult by the instability of university life.

At university, sleep patterns can be sporadic and variable, which often are in contrast to life prior to university. Young adults learn the negative impact this has on T1D management and begin to aim for a more consistent sleep pattern.

4.1.4 Changes in Physical Activity Habits. The blood glucose impact of physical activity varies depending on the activity type, the person doing it, and the context, making new activities hard to predict [37]. At university there are more opportunities to try different sports and exercise, *"I was in a city, so, um, gyms are more local"* (P06), as well as the freedom to choose what to do and not to do, *"I was a distance runner [...] and that sort of stopped when I moved away and, and became a bit more sedentary"* (P10). There is also a change in social activity, with dancing during 'clubbing' being common: *"this year I started going clubbing which obviously is physical activity that does not compare to anything else. Especially with the alcohol involved"* (P07). Numerous new household chores which were picked up in the transition from their childhood homes were also found to impact blood glucose levels, including cleaning, *"cleaning always makes my bloods go low"* (P07), tidying, *"when I'm tidying up [...] that definitely does seem to drop my blood sugar level"* (P17), packing, *"if I'm packing to go on holiday or going away for the weekend [...] definitely noticed them them drop"* (P24), and cooking, *"I did all the cooking and then by the end of it I was, you know, my blood sugar was really low"* (P21). Although participants had some experience with these chores, their usual or routine chores changed significantly when living independently for the first time. The use of transport also plays into physical activity and its impact on T1D management. Mode of transport can change based on new living situations and the location of the university, for instance in a city: *"because buses obviously are expensive and you don't have much money at all, so I did a lot of walking"* (P12).

The changes to physical activity had an impact on T1D management: *"I don't think I'd do as much. And I think that was probably having quite a big effect on my levels before I went to uni which isn't there anymore"*. Although, sometimes these impacts were more positive: *"I picked up hobbies and did more exercise and the exercise definitely seemed to help manage the diabetes"* (P08). Many of the changes to sport and exercise were a shift to more solitary activities, *"I was in the football team too, so I've, I've not been been doing much of that. I, I've, I guess started going to the gym"* (P10) and *"I played football every week but that was about it and this year I try and run like two or three times a week"* (P14). Participants also noticed the impact of travel on T1D management: *"moving to a city where you walk pretty much everywhere had a huge impact on my bloods"* (P07). P11 found these changes to the mode of transport advantageous at times: *"you can't drive back if you're low [...] which can sometimes lead to like highs instead, uhm, but because now I just walked the gym or I walked to netball it doesn't really matter"*.

Participants developed strategies to manage around the new activities they had picked up, *"especially for dance, taking my insulin pump off was something that helped me to manage um my level"* (P17). However, compared to sport and exercise, where participants had precise management strategies, *"a 60% basal rate two hours beforehand"* (P12), the majority of participants forget to factor household chores into T1D management: *"It's not like a defined sort of sports, I haven't like accounted for in the same way"* (P09). By contrast, P19 had learned to use it as a management tool: *"if I'm running a bit high, I'll just do a bit of cleaning as a way of bringing them down"*. The strategies developed for physical activity required consistent update as the young adult's lifestyle shifted over time: *"I don't go to the gym this year because I don't really have time"* (P21).

At university, new exercises, social activities and household chores are experienced, as well as changes to the mode of travel. These physical activities all have an impact on T1D management and young adults learn, in most cases, to adjust for them. However, some proved quite difficult, such as household chores, that they had less experience of before university.

4.1.5 Changes to Schedule and Routine. Activities of daily life and their patterns have a strong impact on basal insulin requirements and variations or changes to these patterns have a knock-on effect on that requirement [37]. Many factors contribute to daily routine and, in the transition to university, most of these change: *"I was sleeping at random times, eating at random times, drinking at random times and my blood sugars just didn't respond well"* (P04). There is often irregularity in schedule, *"our timetable each week is was normally different"* (P24), which adds to the difficulty of adapting and is often a stark contrast to life before the move: *"my blood sugar got a lot worse when I came to uni. I found it much easier to deal with at school when there was much more like a regular routine"* (P16).

Awareness of the quickly changing nature of university, *"I've got a gap between two lectures but then all of a sudden I'm called into a meeting"* (P05), teaches young adults to be adaptable. They move between different environments, each of which has different impacts on T1D management, *"I've moved back home for like two weeks and all of a sudden I'm going hyper a lot more"* (P05). Also, within the social side of scheduling, participants found there were consequences of overcommitting your time, *"if you're not really very good at being like no, I'm gonna stay in. Then sometimes you just see kind of the negative effects of that"* (P11).

Participants drew causal links between routine and T1D management, such as P22: *"when I'm busy, I'm in the motions of doing everything, including keeping a track on it. But if it's like a lazy day, then I'm probably not looking at as much"*. At times this was then implemented into strategy, for instance with medication changes: *"I always notice when I get home is that I suddenly have to up all of my Lantis for the evenings"* (P01). However, the changing nature of university means most end up adjusting their *"management to fit the schedule rather than the other way around"* (P16), which as P17 found was a continuous process: *"At one point, there was like I'd got into a routine that was definitely seemed to be working. Um and then [...] my lecture and seminar times changed so then it's just been trial and error since"*. The result is a more reactive strategy to T1D management where new scenarios will be regularly met but form learning opportunities to inform future management.

At university, lifestyle changes influence daily routine, which often consistently fluctuates with a new set of work or social pressures. Young adults learn adaptability to combat this and try to bring in consistency where possible.

4.1.6 Summary of Changes in Lifestyle. In the transition to university, a young adult's lifestyle goes through many changes, which has a knock-on effect on T1D management. The previously less documented of these are the consumption of alcohol (which is prevalent in a UK context), performing more household chores, the change in use of transport, and the role of social pressure in causing many of the schedule changes. The complex impacts of these factors on

T1D management are learned over time by the young adults, who must adapt their management strategies to the new setting.

4.2 Changes in Support Network

The move to university changes a young adult's support network, bringing independence and removing parental supervision. As a result, T1D needs to be explained to new people and new support networks need to be developed.

4.2.1 Increased Independence. Moving away from a support network forces independence on young adults managing T1D. In terms of the day-to-day management process, 14 of the 24 participants expressed they were already independently managing prior to university, *"throughout being teenager I very much could just controlled it myself"* (P19), and participants were comfortable with this process: *"I've always been quite happy just on my own and just me managing it"* (P17). However, there were still moments of realisation of the lack of support: *"that was probably the moment where it felt most like 'Oh my goodness, I'm not living at home anymore. I've got to look after myself'"* (P06). The independence also brings isolation, *"I don't actually know anybody with type one that I speak to about it, and so you can speak about it to people, but they don't fully understand"* (P19), and the loss of safety net, with P19 describing that at home *"if I didn't surface for a day I'd have someone knocking on my door saying 'where are you?'"* compared to now where they and their flatmates *"could go 36 hours without seeing each other and it not be a weird thing"*. If something does go wrong, the chance of it being noticed by anyone other than the person with T1D is diminished.

The participants learned that the prior ability to independently manage was vital, *"it was fortunate that I'd had it for so long because that wasn't an extra thing I was having to deal with"* (P02). They also came to realisations on the lack of knowledge in those around them: *"my friends knew I was diabetic [...] there wasn't really anyone that I, you know, rely on for actual, you know diabetes management support"* (P21). With this realisation came an increase in awareness and care of their management, *"I put a lot more effort into it [...] 'cause I still don't have that support constantly around me"* (P22). Outside typical daily management, there were additional difficulties to cope with: *"illness was one, for freshers' flu and stuff that's obviously harder to manage when you're on your own"* (P06).

As a result of the independence, participants found a better personal understanding of their management: *"I've gained just more of an understanding of my diabetes. Um again, because you are solely responsible for it"* (P19). From this understanding they were able to adjust their T1D management to comply with independent living, *"the good thing about kind of being in charge of myself is that I have complete control over my food"* (P06). P22 explained technology's role: *"[I] have that independence through using technology and things with my condition, I think it's been really helpful"*. For some, like P17, it also boosted confidence in their management ability: *"it's definitely helped me a lot. Let's say I'm definitely more independent and less kind of anxious about being on my own"*. This fed into the wider feeling across participants that independent management was necessary for the future, *"we have to live with this for the rest of our life, so we can't really depend on other people to tell us what to do"* (P23). However, the awareness was not necessarily linked with improved management, but instead with improved attitudes over time: *"I'd say the control overall maybe hasn't got better, but my attitudes got much better 'cause it's now definitely my responsibility. I definitely I need to be more proactive"* (P02).

At university, young adults find fewer people supervise what they do, so they have to take on more responsibility for their T1D management and gain understanding of their condition for the future.

4.2.2 Parents' Role in T1D Management at University. A major part of the difficulty of independence is no longer being in close contact with parents, who often form a major part of the support network, *"my mum, used to sort of look over*

my, um, blood sugar levels and stuff a bit more. And obviously I'm not at home, so she doesn't" (P21). This is particularly noticeable in elements of management, like carb counting for P14, who was *"used to just saying to mum [...] 'do you know how many carbs are in it' and she'd [...] go through and look at every ingredient".* The reduction in support brought with it negative consequences, *"Mum would usually like say 'dinner is 15 minutes away' and I'm like, 'oh, cool pre bolus.' But when you're cooking yourself, [...] I forgot my insulin"* (P12). There was also a view across several participants that their parents worried about their T1D management when they moved to university, *"my mum, um worries a lot about me"* (P05). One major recent development in T1D technologies is the ability to send blood glucose readings over the cloud, *"the [Abbott] LibreLink account stuff that if they wanted too, I think my parents have access to that"* (P10). This is a new way of connecting parents to their children with T1D and allows them to remotely monitor blood glucose readings. However, these systems bring with them challenges, *"she constantly talks to, texts me about it and she knows that it's really annoying [...] my blood will be like 3.1 and she'll be like, 'oh maybe it's your basal, or maybe it's your carb ratio' and I'm like, 'I don't wanna think about it right now'"* (P07). Taking over the more administrative elements of T1D management also caused difficulties, *"it was a bit more of a shock [...] the eye checks, have checks at the GP surgery, have the appointments with the diabetes nurse"* (P23). This work came as a surprise to many participants as it was commonly assisted by parents: *"my parents used to pick up my prescription, so it was less stressful before"* (P18).

Some participants learned the importance of keeping track of supplies through hard lessons: *"the first couple of months I was like 'Oh my God I've got like 2 days of insulin left. I need an emergency prescription'"* (P12). Events like this can be very dangerous, and participants began to understand the effort involved in avoiding it when they were solely responsible, *"it just took so much more time out of my life now because I didn't have someone else doing it for me"* (P07). Without parents around to complete these tasks, young adults are forced to learn to do it themselves: *"I relied on mum originally for working out the actual carbs content that I've had to learn and try and work out myself"* (P22). However, in some cases, it is difficult for parents to relinquish their role in T1D management, *"I basically said to her I need to manage this [...] this is like for me to control and not her [...] That was the best thing for it. Probably not her eyes, but my eyes"* (P06). At times, the lack of parental supervision was viewed as a benefit as *"it's kind of nice not to be nagged about things"* (P21), although the use of remote blood glucose tracking allowed parents to help: *"I mainly just use it at night time so that my parents can see my readings [...] if it alarms and I don't wake up, [...] they can like ring me [...] it definitely makes me feel a lot safer"* (P17). However, P14 found it allowed their parents to infer other information about what they're doing, which the participant did not want their parents to be aware of: *"It was it was like freshers and I was testing it like 6 in the morning to make sure she'd obviously she'd be messaging me like 'have you just got up or what?'. And 'nah still not gone to bed, Mum'".*

For some, sending readings was found to be a way of alleviating worry, *"they would definitely lose a lot more sleep, not knowing and worrying and stuff"* (P17). However, other participants felt it would only increase parent's worry, *"I don't think it'll be a good idea for anyone for me to send it to my mum. I think it would just cause everyone a lot of stress"* (P11), so resorted to removing parents from the system to avoid nagging, *"If I was gonna send it to anyone, it'd be my mum, but I don't want the hassle"* (P15), and to hide their management, *"I don't like the idea of someone can consistently watching it"* (P05). Parents did still maintain their role as a source of information, *"things relating to my diabetes, I probably would have called my mum and dad"* (P20), and a person to talk to if something is going wrong, *"There was one night when I went really high and I did ring mum like it was a stupid time like 2 in the morning, 'cause I was just panicking"* (P06).

At university, parents' role in T1D management changes because they are no longer around, so the young adult needs to take on this work. However, remote monitoring technology allows for some parent involvement, which in different situations provides reassurance but also privacy concerns.

4.2.3 Explaining T1D to People at University. Without parents around, others can be informed about T1D in case of emergency, *"making sure that like the friends that I've made it at uni knew that I was diabetic and like I just told them what to do if anything does go wrong"* (P24). However, this can be difficult as *"you have to establish your friends first before you can know, kind of who you need to educate"* (P16) and can cause anxiety *"I didn't really tell anyone I was diabetic either in the first year. I just just didn't want to. I was scared what they're going to say"*. While difficult, those that did explain T1D to others were met without prejudice, *"it's quite difficult when you tell people, but I did I told all my flatmate um and they're like, 'Oh yeah, it's fine'"* (P17). Some participants also wanted to raise awareness of T1D, *"I wanna make people around me understand it because it's always like frustrated me the lack of understanding that people have had"* (P09), which was often triggered by technology, *"a lot of the time, like people will see my sensor and ask about it"* (P13).

When trying to explain T1D to others, participants found there was little prior knowledge, with P09 finding a *"lack of understanding between the difference between like Type 1 and Type 2"* and *"people always being like 'what you don't look fat', uhm, which is not a helpful"*. As result some participants felt the need to combat the misunderstanding: *"I find it quite nice to explain to people what, what it is, especially like fight some of those misconceptions"* (P24). However, sometimes even after explanations, people struggle to understand T1D management: *"blood sugar is low once and this, uh, a girl I was with was like 'let me go get you insulin' and I was like 'no that's not what I need like you're gonna make it worse' [...] I just wouldn't really trust anyone else to help me with it"*. As a result, it reinforces independent T1D management and the careful development of a support network.

Over time misunderstandings can be broken down, with close friends beginning to pick up some of the nuances of T1D management, through exposure to it. This can start with just recognition of the condition, *"one of my friends for a few months before was like 'ohh [P24], you're diabetic'"* (P24). Over time the understanding builds, *"gradually like the longer I spend with people. And the closer I get with them, they generally start to [...] recognise when I'm going low just because of how I'm acting"* (P09). This learning can be from experience rather than from explanations, *"they don't necessarily know like whether I'm high or hypo, they just know like something's wrong. Uhm and then they like they kind of tell me to like stop and check and stuff"* (P09). Here the support network begins to reform, with less independence, as new people become part of it.

At university, young adults meet many new people, most of whom don't understand T1D, which results in the young adults needing to explain the complex condition. This can have mixed results, but eventually, as friendships form, understanding is found and support provided.

4.2.4 Assistance from Others with T1D Management. Having explained T1D to others at university, some begin to take roles in supporting management, *"I'd spoken to a few people in my halls, it was almost like they were learning with me sometimes, so they occasionally helped me out"* (P01). This can be helped with prior experience with T1D: *"one of my friends, her dad is diabetic, so like when we'd go out together, she'd be like, you know, 'make sure you do your blood sugar' like she'd know, which is quite nice"* (P21). However, in terms of exposure to new technology it was still family members that provided support: *"My mum is [...] always keeping an eye on new technology so she first found the Libre"* (P13) and *"my brother's diabetic, and he kept going on about how good it was [...] So I thought I'd give it another go"* (P02).

The support from others develops over time as they learn to assist with various areas of T1D management, from physically checking blood glucose levels, *"if I get very very drunk and I'm passed out, he'll come up to [...] see if everything is OK"* (P15), to emotional support, *"not really anything to do with my diabetes but just in general just providing like that emotional support"* (P20). The use of remote blood glucose tracking systems furthers the assistance they can provide, *"my other half have access to it so that is brilliant"* (P12). Also, the young adults find other sources for help researching

T1D technology, for P23 it was through support groups: *"I've then downloaded the app that, um, the rapid calc [...] was actually recommended to me by other people with type one diabetes through the support group"*.

The remote blood glucose tracking systems form effective safety nets to fulfil the role parents previously held: *"my housemate who I live with has access to my blood sugars all the time. So, if like I'm in my room and he's in his room and I'm not doing well, he can like just see how I'm doing"* (P03). P07 had furthered this system to include alerts so in the case of an adverse event someone else was aware: *"My flatmates have the alerts on for if my bloods are dangerously high or low just so they can come and check on me and see if I need anything."* Also, the sources of T1D support became more consistent, *"support group were really helpful because [...] any problems in that we can kind of just speak to each other about it"* (P23), and through such sources participants reached an equilibrium in responsibility for T1D management: *"it used to be that [parents would] look into it, and I wouldn't really, but now it's, it's more equal"* (P17).

At university, the new support network that forms still involves parents but also friends at university and support groups. The assistance provided includes research and management support, with remote monitoring sometimes utilised for this.

4.2.5 Summary of Changes in Support Network. The transition to university changes the people seen regularly, requiring more independent management, especially as the support network reforms. Expanding on previous findings, the change particularly impacts the more administrative side of T1D management, the process of explaining T1D to others and the role of remote monitoring technology. These elements combine to result in an updated support network with more independence for the young adult.

5 DISCUSSION

Much of the findings fit well with Mamykina et al.'s view of sensemaking in chronic care [82]. This is particularly seen in the trial and error in the move to university, the experiential learning to adapt to the changes, and then those experiences being translated over the longer term into T1D self-management knowledge. However, there were points when the nuances of learning to manage T1D in a new environment could not be completely explained by this framework. Physical activity changes were mainly adapted to, however, there were several participants who despite being aware of household chores impacting blood glucose levels, failed to learn from these events to generate strategies around them. Many lifestyle changes were made sense of and managed around, however, the support network changes were less straightforward to adapt to and change. The complex nature of developing relationships with people leads to inferences not being relevant for new situations and social pressure making young adults act outside of what the inferences would dictate to do. This leaves further work to be done in the area to capture the process of adapting to social changes to T1D management, particularly those that arise through major life transitions. However, it does uncover implications for supporting the lived experiences of life transitions through technology and human-centred approaches to design.

The findings outline several personal and unpredictable lifestyle changes that occur in the lived experience of moving to university. Many of the factors described in the findings are consistent with Balfe's work looking at this turbulent time for self-care, but this current research also expands on understanding the transition by considering the university experience of young adults in the UK with T1D [8, 9]. Balfe highlights the change in routine, expressing changes to diet, activity and drinking to be an inherent part of the move to university. The work here extends these findings by considering in more detail how each of these aspects of the experience changes self-management and showing the learning processes that follow. Similar themes were raised by Hill et al. when considering Canadian university students [49], implying some level of global generalisability to the findings. However this previous work has focused on policy

implications [82] or implications for nursing practices [8, 9], and where current research stops short is in suggesting implications for technology of these findings on the impacts of life transitions.

The experience of young adults when transitioning to university presents many challenges in T1D management that exceed those experienced in routine life. Potential solutions to many of these challenges lie in leveraging AI innovations, particularly in conjunction with closed-loop systems. However, there are significant challenges that AI may not be sufficient for, here a more human-centred approach may be able to present alternatives that aid during life transitions. Both these innovation routes are discussed in the context of the move to university, with broader implications for chronic care technology during life transitions.

5.1 AI's Role in the Future Development of T1D Technology during Life Transitions

Many of the future technological implications of the findings relate to closed-loop systems, as they are currently hailed as the direction T1D technology is taking. Although only three of the participants used such systems the experiences of all participants are relevant to its development through presenting scenarios it will face. Participants commented on how background rates and ratios were no longer relevant at university due to lifestyle changes, and most closed-loop algorithms rely on these parameters, particularly those utilising control engineering. This situation highlights the potential for systems that detect changes in the background rate and ratios and update them, which have been shown to improve glycaemic control in general use [27, 98, 126]. If this effect could be increased in periods of transition it could improve glycaemic management, for example, to capture a shift in sleep schedule without user intervention. However, this would require testing at times of dramatic shift in health data, with the potential of anomalous periods like fresher's week having a negative impact.

A similar issue arises for closed-loop systems that personalise their algorithm to the user over time. This is a form of concept drift, where ongoing changes result in the underlying data that a model is built upon no longer being relevant [132], which Tsymbal split into gradual and sudden types. The gradual form was considered by Torrent-Fontbona and Lopez in their case-based reasoning bolus insulin T1D recommender system, which updated its examples over time and increased time in the target glycaemic range when simulated [127]. However, sudden concept drift, seen in the initial disruption of a life transition, has seen too little consideration in system development considering its presence in the lived experience of chronic healthcare, as shown by this current study. Engaging an accelerated form of evolving the personalisation process during the transition may reduce its limitations, however, the ongoing changing nature of university may make these adjustments less reliable.

Part of the ongoing change that occurs at university is the shifts between locations and contexts, which shares similarities to Raj et al.'s findings in adolescence around school [105]. Much of their design implications are relevant also to a university context, which we add to here in the suggestion of setting up multiple profiles for different contexts, a common practice for insulin pump users. Here each context would be personalised to separately, which Doherty and Greaves tested for Type 2 Diabetes [31]. However, while this may optimise management further when moving between university and home during term holidays, the process would require additional user input and therefore be less appealing.

In contrast to additional manual user inputs, further data streams could be automatically inputted to closed-loops. Several subtle physical activities were mentioned throughout the interviews, such as dancing, commuting, or household chores, which people with T1D might not account for in their management. To account for these hidden physical activities, factoring physiological variables directly into closed-loop systems would be beneficial (and has been seen to improve glycaemic control [23, 52, 109]). This could be achieved without user input through potentially socially

acceptable wearable devices [97], which would not additionally burden [21] someone who is also managing a brand new lifestyle and social settings as part of a significant life transition.

Alcohol, which is heavily woven into the UK university experience, formed a common topic for participants, with a tendency for an increase in volume and regularity of its consumption. It has a significant impact on blood glucose levels, potentially lasting for a day after consumption [133] and can also bring with it a compromised mental state [20]. Most current interventions around alcohol for people with T1D focus on the education of its impact [102, 123], although Pesl et al. included alcohol as an input to an insulin bolus calculator [100]. Such work could be translated to a closed-loop system although also suffers from the limitations of adding additional manual user inputs as found by Katz et al. [56].

A significant problem for many of the suggestions made here is the lack of data available from life transitions to assess its effectiveness at these times. Part of the solution might be transfer learning: the process of using knowledge from a related area to improve learning in a new area [128], often used in a machine learning context. Systems could first be built from datasets of wider population groups to form an initial model or algorithm, which could, in turn, be specialised to a population, such as young adults going to university. Several pieces of work designing algorithms for closed-loop systems make use of transfer learning to improve their performance [73, 146, 147]. While this could amplify the use of relevant data, there is still a need for further data collection.

5.2 HCI's Role in the Future Development of T1D Technology during Life Transitions

While an advanced closed-loop system may be able to deal with day-to-day life, the extreme events that arise in the transition to university may be beyond it. The reliance of data-driven AI on consistent input data means that in many situations it is not possible to accurately predict future changes. For example, during an evening of drinking several participants referred to flexible strategies generated around drink choice to manage glucose content and the latent impact of alcohol. Closed-loop systems lack the ability to implement such strategies and are unlikely to even be aware of the quantity of alcohol consumed. There are also cases where the systems may break down and an over-reliance on it would have disastrous consequences without a support network overseeing management, such as the boyfriend who checked readings when his partner was deeply sleeping after getting very drunk. These cases suggest a human-centred approach to the design of such systems could be more beneficial than simply trying to automate the process to capture the extreme events and scenarios that fall outside typical T1D management. The findings here build on the work of others to contribute to this process and highlight avenues for further research.

The impact of the social context on T1D self-care shows similarities to O'Kane et al.'s work on the concealing or revealing of medical technology [96], for example, exposed technology being a trigger for explaining T1D to others. O'Kane et al. also found some people revealed technology on purpose to make it seem normal and educate others, similar to the participants who actively explained T1D to others to raise awareness of it. This research expands on O'Kane et al.'s work by looking at the social complexities inherent in a new life transition, the move to university. It highlights the process by which family, friends and new social connections are trusted with roles in T1D management as a result of disruptions to social routines, such as the social sharing of T1D treatment after a night of drinking. It also raises new triggers, beyond revealed technology, for conversations around T1D with others, including becoming a trusted flatmate or close friend at university. However, there is an underlying dilemma in this process as to when the right time to bring new people into the support network is.

Several findings relate to the use of remote monitoring and how it shapes the support networks that form at university. These findings extend those discussed in Kaziunas et al.'s 'Caring through data', which looks at the use of Nightscout, a remote monitoring system, by parents for their children and adolescents [59]. The work finds 'peace of mind' is

gained from the use of remote monitoring, which is also found here and elsewhere in literature [12]. However, in the university context, there is also a perceived increase in worry caused by the reduction in access and control parents have when young adults move away from their childhood home and parental care. Similarities between the research can be seen with parents invading privacy by being able to infer activity from the data, except at university this resulted in parents having their access to the system removed by the young adult. We can also see the shift as new people, such as flatmates, get access to the remote monitoring system and have a less controlling power/management dynamic.

These findings suggest the need for improved customisation of remote monitoring systems. This could include allowing users to limit the information they send to different people watching at different times of the day or only alerting during adverse events. There may be a role for AI within this as algorithms could be used to detect whether the user had already intervened to an adverse effect before warning others, reducing the 'nagging' some participants were concerned about. For diabetes, much work exists on hypoglycaemia prediction, which could be implemented in a remote setting [22, 144]; however, detection for treatment of hypoglycaemia without user input has had much less consideration.

Numerous assistive tools and recommender systems have been developed to support T1D management and education. These range from carbohydrate estimation [3, 4, 67, 110] to insulin dosage suggestion [71, 84] to diet and exercise recommendation [92, 143, 145]. Such tools are useful also in a university context to help prepare young adults for new experiences. While AI will play a role in the future development of many of these, there are some examples raised in the findings of complex socio-technical situations that just would not be possible. For example, the difficulties raised by almost all participants about taking responsibility for the administrative sides of T1D management (ordering and collecting prescriptions or attending appointments), where systems to warn users of low supplies or imminent appointments would be beneficial. Here the infrequency of such events and variability in challenges across users limits the potential of AI, particularly in personalising to an individual. Such technology would benefit from the human-centred design approach to target the needs of individuals and assist with management during life transitions.

5.3   Wider Implications for Chronic Conditions

Throughout the development of technology for chronic care, there is a drive to focus further on people's lived experiences of the conditions [94]. Much of this work is trending towards personalisation as a method to enable technology to directly support the difficulties each individual faces [18]. Such personalisation could be invaluable to the effectiveness of a system, shown across numerous chronic conditions [17, 19, 138]. Through increasing access to automatically collected data, systems can be developed to bring recommendations and assist in management [1, 25, 45]. However, events of dramatic change, such as life transitions, can cause difficulties for these data-driven technologies. As suggested in the personalisation of closed-loop algorithms for T1D management, life transition can change the underlying mechanisms of a chronic condition that result in a personalised system losing relevance. Consideration should be taken into such events and how personalised systems can be adapted to cope with dramatic life changes.

Many of the social implications of life transitions found here are going to be relevant across chronic conditions, including meeting ignorance in others and having to explain the condition to new people. While the specifics of management may change across chronic conditions, the difficulties of working out who to tell and who to build into the support network are universal. There is a need for further study in this area to understand how technology can meet these challenges and while AI may be a powerful tool in developing them, it will not be relevant to all situations. Paramount to this consideration is how technology adapts to life transitions to ensure that it does not add to the burden of self-management when the cognitive load is already stretched across numerous tasks.

6   LIMITATIONS

While many young adults in the UK go through similar experiences as part of life transitions, the participants lacked diversity in social economic backgrounds and ethnic backgrounds, impacting the applicability of the finding to the young adult population who do not move away from home for university. In addition, many participants had their university experience impacted by the COVID-19 pandemic, such as through online lectures, being sent home and lockdowns. So, while all participants highlighted experiences of university life unaffected by the pandemic, the findings must be viewed within the context of pandemic-related changes to the university experience.

7   CONCLUSION

The move to university brings numerous changes, many of which impact T1D management. It can be overwhelming for individuals to manage all these changes, and it often results in poorer T1D management in the young adult population [30]. From the interviews, the changes highlighted as having the most significant impact on T1D management were changes in lifestyle (drinking, eating, sleeping, physical activity and schedule) and changes in support network (gaining independence, losing parental support and explaining T1D to new people). These changes highlight some of the limitations of current technology and potential areas for the development of digital interventions. Many of the solutions suggested are based on data-intensive AI technologies, however, the findings also highlight scenarios where human-centred design approaches may be more applicable. Targeting life transitions, such as young adults with T1D moving out of home, is paramount to ensure that the interventions developed are usable at a time when numerous other activities and events are fighting for attention and adverse chronic condition management events are more likely.

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