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Emotions and Dynamic Assemblages: A Study of Automated Social Security Using Qualitative Longitudinal Research

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In this paper we argue that qualitative longitudinal research (QLLR) is a crucial research method for studying automated decision-making (ADM) systems as complex, dynamic digital assemblages. QLLR provides invaluable insight into the lived experiences of users as data subjects of ADMs as well as into the broader digital assemblage in which these systems operate. To demonstrate the utility of this method, we draw on an ongoing, empirical study examining Universal Credit (UC), an automated social security payment used in the United Kingdom. UC is digital-by-default and uses a dynamic, means-testing payment system to determine the monthly amount of claim people are entitled to.

We first provide a brief overview of the key epistemological challenges of studying ADMs before situating our study in relation to existing qualitative analyses of ADMs and their users, as well as qualitative longitudinal research. We highlight that, thus far, QLLR has been severely under-utilized in studying ADM systems. After a brief description of our study, aims and methodology, we present our findings illustrated through empirical cases that demonstrate the potential of QLLR in this area.

Overall, we argue that QLLR provides a unique opportunity to gather information on ADMs, both over time and in real time. Capturing information real-time allows for more granular accounts and provides an opportunity for gathering in situ data on emotions and attitudes of users and data subjects. The ability to record qualitative data over time has the potential to capture dynamic trajectories, including the fluctuations and uncertainties comprising users' lived experiences. Through the personal accounts of data subjects, QLLR also gives researchers insight into how the emotional dimensions of users' interactions with ADMs shapes their actions responding to these systems.

CCS Concepts: • **Social and professional topics → Computing / technology policy**;

Additional Key Words and Phrases: Automated Social Security, Digital Social Security, Qualitative Research, Longitudinal Research, Interviews

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1 INTRODUCTION

In 2018 a report by the United Nations' Rapporteur on extreme poverty and human rights sounded an alarm on the global rise of automated decision-making systems (ADMS) in government services and daily life [4]. ADMS, which may deploy simpler rule-based algorithms making if-then decisions or more complex data mining and machine learning processes, can now be found in policing, social security and child services. The UN report voiced concern about the powerful capacities of these systems to socially sort citizens and structure their behavior while largely escaping public scrutiny and democratic oversight.

Many studies have similarly raised critical questions around ADMS in both public and private sectors [82]. ADMS that use statistical data mining can sort people into categories based on consumer preferences or unwanted behavior that can be problematically generalized across certain populations [6]. Further, ADMS can nudge or steer people towards predefined behaviors or preferences, and, as a result, these systems may guide, delimit or foreclose users' choices or options without their knowledge [36]. Literature has also focused on how ADMS threaten to weaken the discretion of humans or enact decisions without any human involvement or oversight [78]. Finally, scholars have written about the opaqueness of ADMS and that they can pose a challenge to individuals' or collective due process rights to query their decisions – to know what information they store, the steps leading to decisions made and their accuracy and legality in terms of unlawful discrimination [22]. ADMS ultimately raise questions about governance, particularly when interrogating them may be challenged by intellectual property claims and confidentiality clauses.

In addition to concerns around surveillance, agency, discretion, and governance [77], there are epistemological challenges that scholars often face when studying ADMS [31] [37] [28]. In the private sector, recommendation engines on social media and search engines are often tightly guarded by trade secrets. In the public sector, controversial systems such as predictive policing and welfare fraud may be difficult to access as governments protect public authority or are wary of citizens gaming these tools [76]. Scholars have subsequently introduced innovative methods for studying ADMS, including those that interrogate the more technical dimensions of underlying data [11] [51], or through interviews with users about their knowledge and experience of engaging with ADMS.

In this paper we present our experience using qualitative longitudinal research (QLLR) to understand an ADMS through users who interact with it over an extended time period. QLLR provides invaluable insight into the lived experiences of users of ADMS as well as into the broader digital assemblage in which these systems operate. To demonstrate the utility of this method, we draw on an ongoing, empirical study examining Universal Credit (UC), an automated social security payment used in the United Kingdom. UC uses a dynamic, means-testing payment calculation to determine the monthly amount of claim people are entitled to. In this study we use serial interviews plus phone texts as prompts for soliciting feedback from users. We argue that QLLR provides a unique

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opportunity to gather information on ADMS, both over time and in situ. Capturing information over time allows for more granular accounts of dynamic trajectories. Through the personal accounts of users reacting in situ, QLLR also gives researchers insight into the emotional dimensions of users' interactions with ADMS.

In the following literature review, we cover the challenges scholars have confronted while studying ADMS, how scholars have studied users of ADMS to overcome these challenges, and the value and drawbacks of longitudinal research.

2 EPISTEMOLOGICAL CHALLENGES OF STUDYING ADMS

Several scholars have addressed the difficulties of studying opaque computational processes. Private companies make opacity a part of their business model to protect intellectual property and keep competitive advantage, and coding and engineering processes often go undocumented or are simply not available to the public [37]. Public access itself does not address whether lay people can understand the complex technical components comprising ADMS [20]. The opacity of some ADMS may even be a matter of design intention: programmers set out to hide the seams of systems so that users can use them functionally without spending much effort to understand complicated underlying processes [31].

The complex, heterogenous nature of ADMS as part of larger social and technical systems make them difficult to delimit both conceptually and as an object of study [5]. ADMS and algorithmic systems are dynamic, unstable and contextual in their performance, socially bounded and often serve a range of uses and users [17] [64]. Teams of engineers and UX designers oversee ADMS, and they are also shaped by internal institutional policies, external standards, social norms, laws and the feedback loop of user interaction. For this reason, Kitchin [37] argues that studying such systems at a single point in time may result in very narrow understandings of their possibilities: one instance of an ADMS' performance cannot be extrapolated to comprise all possible instances, so studies should engage with such system over time and across various scenarios. In the context of machine learning in public sector decision-making, Veale et al [75] likewise recommend that ADMS be studied "in vivo, in the messy, socio-technical contexts" (p.10) in which they exist. ADMS are even hard to pin down disciplinarily. Critical algorithm studies has asked how scholars in the humanities and social science view their object of study as non-technical experts and how they understand their objects of study differently from engineers and designers [64].

A slate of research approaches addresses some of these challenges, particularly around system opacity. To bring greater transparency to these systems, scholars draw on techniques such as algorithmic audits [11] [51], documentation, impact assessments and reverse engineering (changing data inputs to see differences in outputs) [63]. An interest within HCI communities is to expose users to underlying processes through explainable AI techniques (XAI) to put them up to critical scrutiny and public debate [1]. These approaches can shed light on the underlying datasets and models of ADMS and their disparate and possibly unjust impacts across populations. Studies are also exploring whether more transparency by design can lead to greater public trust of these systems [38].

From the social sciences we find qualitative studies that seek greater understanding by focusing on engineers and designers [35] [64] and on the people who deploy ADMS; many are concerned with how these systems affect the discretion of those, such as public servants, who enact them [61] [79]. Social scientists have also set out to capture public attitudes towards ADMS and general awareness and understandings of how particular ADMS work [50]. Studies have asked if public data literacy and feelings of trust might increase public acceptance or shape ideas about the governance of ADMS [66] [44].

Another area of scholarship studies users and data subjects of ADMS. We go through this subset of research next by focusing on qualitative studies that set out to understand ADMS through their users.

3 QUALITATIVE STUDIES OF ADMS AND THEIR USERS

Qualitative research provides insight on the experiential aspects of life, along with "the sensations, atmospheres and narratives of real life", as opposed to quantitative methods, which focus on generating "precise, objective and generalizable findings" [45](p.ix). Qualitative research emphasizes "the depth of understanding and the deeper meanings of human experience" while producing more tentative findings [62] (p.627). For the purposes of this study, researching ADMS qualitatively through the experiences of their users can give unique insights into how they work. Users' interactions are likely to elicit unexpected system behaviors shedding light on their operations, and studying users can provide insight into the power dynamics of ADMS as users contest their decisions (if they can) or play any role in governance or design [2] [65]. Excavating the experiences, emotions and misconceptions of user communities can also helpfully inform the design of ADMS to make them more sensitive to user needs.

Many qualitative user studies of ADMS rely on interviews with users about their awareness – whether they realize a decision was automated or not – and how accurately they understand ADMS processes [31]. In a study of users of instant loan platforms in India, Ramesh et al [60] used interviews to ask people about their experience with instant loan apps and their notions of justice around relatively easy borrowing. Studies have asked how Airbnb hosts experience algorithmic evaluation [33], how Uber and Lyft drivers' feel about the algorithmic management of ridesharing platforms [42], and whether Instagram influencers' believe shadowbanning takes place [13]. Interviews have also been part of experimental studies probing how people feel towards a range of commercial applications using ADMS, focusing on their concerns related to perceptions of justice [7] [41]. Qualitative studies have also used digital methods to scour and analyze online data, such as Twitter or Instagram posts, to understand user expectations towards social media feeds and shadowbanning [16] [67].

Qualitative studies of ADMS users have deployed interviews alongside creative methods, such as design prompts, to explore how well people understand online recommender algorithms. Eslami et al interviewed people about their comprehension of the Facebook

News Feed's curation algorithm, asking how satisfied they are by it and their folk theories of how it works [24] [23] [59]. Another study by this research team asked how people understood the Yelp review filtering algorithm and their attitudes towards it once the algorithm became clearer from a design prompt [25]. Alvarado et al [5] introduced sensitizing activities, which they define as hands-on exercises to "sensitize participants to the existence of these algorithmic systems" to elicit design suggestions. Studies have used workshops inspired by participatory methods to understand the concerns of affected communities navigating the child social security system [10] [68].

We identify two features of these studies that shape the kind of data that can be collected. One is that the majority of these studies capture a snapshot of users' experiences or memories at one point in time. Another feature is that many of these studies ask users to respond to prompts created by the researchers – for instance, by exposing algorithms at work or responding to design scenarios – rather than capturing user experience from in situ, real-life interactions that are not internal to the study.

In the next section we look at how QLLR studies can collect data by capturing trajectories of user experience and in situ reactions to ADMs encountered in users' everyday life.

4 QUALITATIVE LONGITUDINAL STUDIES

Longitudinal can mean a variety of different time frames depending on the aim of the research, with a common minimal design being two interviews conducted with each participant at two separate points in time (also often called a panel study) [12] [48]. The focus of QLLR is to track participants' real time trajectories [18] [52] and trace change over time [56]. QLLR can facilitate trust and confidence with participants [48] [32] [43] and gives participants the freedom to retell their stories over the course of the study, however they think communicates their situation best [58]. QLLR can capture how dynamics unfold "at each research contact change, and the effects of change" may be "explored with participants" [73].

QLLR has a long tradition in fields such as anthropology, criminology, psychology, health studies, education and youth studies [32]. According to Thomson [71], this approach gained the attention of social scientists on a wider scale in the mid-2000s, aligning with the 'temporal turn' in research interests, particularly in the English-speaking world. In the last two decades the method has seen advances in particular areas, including social security and social policy research. People often interact with social services over a long period of time, so scholars in these areas find QLLR highly beneficial because of its ability to capture the dynamic, changing relationship between an individual and these services [15] [43]. QLLR studies have examined recipients of social benefits [55] [19], lone parent families [58] [48], homelessness [80] [15], welfare conditionalities [47] [18] and punitive welfare sanctions [81]. Griffiths et al [30] traced couples as they interact with Universal Credit over a three-year period. Griffiths offers one of the few published academic accounts reporting on the effects of UC automation, drawing on this longitudinal research [29].

A small number of scholars have used QLLR to study ADMS. User experience (UX) researchers of smart home heating technologies have used serial user interviews [40]. Ziewitz et al [83] traced people being scored by an automated credit scoring system through monthly diaries, diary-interviews and fieldnotes over the course of a year. Scholars have also applied ethnographic methods to offer richly detailed analyses of ADMS [34] in the context of automated social security [26], fairness of hiring systems [74], video surveillance [53] and predictive policing [9].

We argue that the advantages of QLLR can illuminate the complex, unfolding features and relationships comprising opaque digital assemblages. ADMS are dynamic, and QLLR can capture how these changes affect users' interactions with these systems and their impacts on users' lives. Longitudinal methods do not need to rely solely on participants' recollections of past events but can generate data near real-time, when memories and emotions are reactive and fresh. Additionally, this method enables participants to reflect on events they may have spoken about, then share additional information to retell their story. QLLR also facilitates trust between the participants and researchers, which can lead to more in-depth information and provide researchers with more context to interpret data with. Finally, QLLR enables researchers to iterate data collection by asking follow-up questions or gathering data on additional questions that may have come to light during or after the initial stage of data collection, or even changing the research design if necessary. QLLR researchers can share with the participants how their story is presented in research outputs and give them an option to reflect on it and share their thoughts and comments. Moreover, this method allows researchers to reflect on their research and their role during the research process to make changes accordingly. We argue that the dual nature of QLLR, bringing together the advantages of qualitative and longitudinal methods, can prove to be an invaluable addition to the pool of methods researchers use to study automated decision making.

5 CONTEXT: UNIVERSAL CREDIT IN THE UK

Administered by the Department for Work and Pensions (DWP), Universal Credit is the UK's largest social security payment. DWP introduced UC in 2012, and it is set to replace some of the previous benefits by 2024. The DWP terms UC 'digital-by-default' [27] since recipients apply for and receive payments through an online account. The account also acts as the primary mode of communication with DWP staff (though people unable to maintain the online account can opt to interact solely by phone). UC is a means-tested and conditional benefit; to qualify, some claimants must work or look for work for a certain number of hours per week, based on their capability to work and certain life circumstances, such as having dependents.

This study focuses on an essential automated decision-making feature of UC: its dynamic payment algorithm. UC uses automation to determine the amount of money claimants receive each month, based on calculating data points collected during a prior monthly assessment period. The monthly assessment period is a personalized unit of time based on the day a person applied for the benefit – for instance, if a person applies on February 15th, their assessment period will be from the 15th of a given month until the 14th of the next month. Claimants' start with a 'minimum standard allowance' based on their age and relationship status (either single or living with a partner) and other factors such as disability or number of dependents. Payments will then be adjusted negatively depending on monthly earnings and deductions. Deductions include repayments for advance claims the claimant may have been granted in the past, past overpayments from UC and third-party deductions made at the request of a creditor, including rent arrears, utility arrears, Council tax bill arrears, child support maintenance and fines by UC.

For those working, the adjustments to UC based on monthly earnings happen automatically through a data exchange with the HMRC's (HM Revenue and Customs) Real Time Information (RTI) system. Employers report their employees' earnings using payroll software to RTI for tax purposes, and DWP accesses this stream of data daily. A report by Human Rights Watch [72] uses the metaphor of a camera to describe how RTI affects the UC monthly assessment period:

> If the RTI system is a camera, the assessment period functions like a timer that tells it when to take a photo. The resulting snapshot is the earnings data that Universal Credit's algorithm uses to calculate an individual's benefit payment for that month.

UC considers all income that is reported to HMRC or self-reported by the claimant to UC during each monthly assessment period, and the UC payment decreases accordingly. After the monthly assessment of earnings, most claimants in the UK receive their payment once a month. In Scotland, people can choose to receive their monthly pay in two, approximately bi-weekly instalments.

One goal of UC's month-to-month calculation, based on actual earnings, is to eliminate some of the problems claimants faced with UK's legacy social security systems. A previous benefit, Working Tax Credits, had based claimants' monthly payment on an average of earnings from the past year as reported to HMRC, and this average could over- or under-estimated the benefit owed if a claimants' earnings changed. The discrepancies in reported versus actual earnings led claimants into debt to DWP if their earnings fell and rose but their tax credit payment stayed the same. UC aims to eliminate over- or under-payments to claimants – and falling into arrears to DWP – and reduce the burden on claimants to report changes in earnings [49].

DWP publishes very little documentation about UC's performance data, "despite the evidence that the Universal Credit team have built up a modern analytics capability where real-time data would be the expectation" [57] (p.70). Likewise, it does not publish any public domain data about its digital services, with the exception of blog and a smattering of one-off research projects [3] nor about their source code [57]. While DWP has consulted the researchers of this project and asked us for updates on our findings in the form of reports, they did not agree to formal interviews about how the system works. Conducting research that can account for the experiences of people who claim Universal Credit is particularly crucial given DWP's lack of transparency about how they study and understand the user experience. As will be shown later through the use of screenshots, our research gained insight into the interaction between claimants and social security agents, a largely unseen aspect of social security.

In the following sections, we demonstrate how QLLR methods focused on users of ADMS can be a powerful approach to collect data about systems, such as UC, that are highly complex and pose problems of access.

6 METHODS

The data presented in this paper is from an ongoing qualitative, longitudinal panel study conducted as part of a larger project exploring the lived experiences of recipients of UC.

Our panel study commenced in mid-2022 and is expected to run until the end of 2023; this paper reports on data collected in the first six-month period of the study from participants who were recruited in 2022. The study applies two distinct methods of qualitative data collection for each participant: 1. semi-structured interviews and 2. bi-weekly prompted updates sent over phone text asking about participants' interactions with UC.

We recruited twenty-six participants through local charities by participating in their in-person events and by advertising the study on their social media and mailing lists. Participants take part in the study over six or twelve months and were interviewed at the beginning of this period as well as after six months. Participants also receive text message prompts from the researchers roughly every two weeks asking for any updates on their interactions with UC. Participants used different methods to convey information: sending messages and sometimes screenshots of their interactions and UC accounts. Five participants at some point phoned the researchers to explain their situation rather than text. If asked for advice, researchers pointed participants to their case managers, work coaches and a local advice charity. The exception was a participant who had significant financial troubles, and the researchers believed that the participants' children were at serious risk. On this occasion the researchers recommended a specific financial aid the participant could apply for.

We gave participants a £25 shopping voucher after their first interview and a second one for a second interview at the six-month period to reimburse them for their time. The first interviews with each participant lasted for approximately forty-five minutes and were conducted either online or in person at local charity offices, cafés or at the University of Edinburgh. Follow up interviews lasted 15-30 minutes. The four participants whose quotes are used below reviewed and consented to their quotations and the representation of their stories.

Data collection for this study was not without challenges. Two participants never responded to the prompts and were eventually removed from the study. Twenty-one respondents provided us with relevant data about their interactions with Universal Credit; the rest, despite replying to prompts, either did not share any information that was related to the study or did not experience any problems with UC during the first six months.

We refer to our participants by pseudonyms. As some of our data was based on text messages and screenshots from our participants, quotes from these data sources often contain incorrect spelling or grammar. In order to preserve the original voice of our participants, we kept these as they were, unless changes were crucial for intelligibility.

The results of our study cannot be interpreted without taking the limitations of this study into consideration. Firstly, as is often the case with qualitative research, our sample was not representative, so the findings are not generalizable. Secondly, the language of the interviews and data collection in general was English; therefore, our study only includes participants who were able to speak in English at least on a conversational level. Thirdly, our sample has a high number of participants who identify as female, thus, the views of male and non-binary participants are less pronounced in our dataset.

Researchers received ethics approval for the study from the University of Edinburgh.

7 FINDINGS

Despite the growing body of creative, multi-method and ethnographic approaches for studying ADMS, QLLR panel studies – tracing a cohort of participants as they interact with systems over time – remains vastly under-utilized. Here we focus on how this method offers unique insights into UC through user accounts of two distinct but related features of UC's automated payment: the RTI-UC data pipeline and the fixed monthly assessment period. In this section we highlight the experiences of four participants to illustrate these issues. Presenting data from a smaller number of participants allows us to share their story in greater detail and showcase the value of the in-depth information our method can provide. Additionally, we demonstrate how our method was able to follow these participants' stories over time and offer insight at different stages.

7.1 HMRC's Real-Time Information (RTI) system

The RTI to UC data pipeline, as mentioned, entails the flow of data from claimants' employers to HMRC, where it becomes aggregated in its Real Time Information system. Though the data is collected for tax purposes, HMRC shares this data with UC daily, and UC uses it to adjust claimants' monthly UC payment.

As is the case with many vital infrastructures when they break down [69], the pipeline became most visible to claimants when errors were made at some point in these data exchange processes. RTI error rates are endemic to the system. The UK's National Audit Office (NAO) reported in 2018 that UC is "sensitive to any change in claimants' monthly income" and "employers sometimes supply information [to RTI] that is late or which contains errors"[54] (p.61). NAO estimated that in 2017-18, UC made overpayments of 7.2 percent and underpayments of 1.3 percent in part for this reason. [54] A result of these errors are fluctuations in claimants' pay, making it difficult to budget and plan.

Participants' accounts detail the steps they took to rectify these errors. In some cases, claimants contacted their employer and UC to report the error, but they then had little agency over the timing of its correction. The only data seen as relevant by UC to rectifying the pay calculation is the HMRC RTI data, not any evidence offered by the claimant.

Gaja, a white Polish woman in her late 40s raising two children, experienced an RTI error during the course of the study. In her first interview in June 2022, she described her case as relatively simple, telling us, "for me personally it works great," even though working at a charity as a case worker she had seen problems with the pay calculation affecting her clients.

In October 2022 Gaja reported over a text that she had received more payment from UC than anticipated and assumed her earnings had not been reported to HMRC, resulting in larger-than-usual UC entitlement; she wrote, "Something was not reported to [HMRC] and I told them [UC] that my award is too high, but, they can't do anything about it, need to wait for hmrc information."

Gaja was not worried about budgeting but understood such mistakes could pose problems for others:

> I've got far too much money that I need to return [to UC], not really changing anything if you are aware of the mistake, this could be a different story if I wouldn't understand how they work and spend all the money.

She pursued the matter with UC, then told us in early November, "they [UC] are still waiting for my employer to send the report so far no news." By late November she was still waiting for an update on the case.

When we interviewed Gaja a second time in January, she told us that HMRC had finally reported the September earnings two months later in December, and the overpayment from UC would now be deducted automatically from her future UC payments. Her employer told GaJa they had reported the earnings on time, so she never received an explanation for the delay and assumed that the mistake was due to her holding two jobs, and that HMRC had not registered the wages for one. Gaja shared that she did not feel she could affect or speed up the process:

> I've informed universal credit that this will be a mistake in payment. But they didn't ask me about my wage slip or anything like that, they just said that it will clear up when they clear up because they need to listen to HMRC and not what I'm going to say.

Gaja told us she was satisfied with how the situation was resolved and still much preferred UC, with its month-to-month calculations, to the older system used by Tax Credits, based on retrospective earnings data that so often led to overpayments and debt.

Another participant in our study expressed more distress when she found an RTI error. Emily, who identifies as Black Caribbean and white, is a single mother of two children in her late thirties. She works as an administrator for a center that provides a safe place for children to meet parents they do not live with. In her first interview she was very unhappy with Universal Credit, highlighting that in the approximately three years she had been receiving it, she never felt supported and had received conflicting and wrong information on her case from case workers and work coaches. She had also encountered difficulties reclaiming childcare costs.

In mid-January 2023, Emily shared over a text that her employer made an error reporting her salary in November 2022, and as a result she received £300 less in her January payment than she was entitled to. Emily wrote, "I know the whole system [. . .] is an absolute shambles. They are causing more hardship, it's a horrible situation." Emily shared screenshots of her exchange with her UC case manager after she reported the error in December. Her case manager told her that they would not be able to take action until January – UC needed to wait for confirmation from HMRC, which, in turn, needed a report

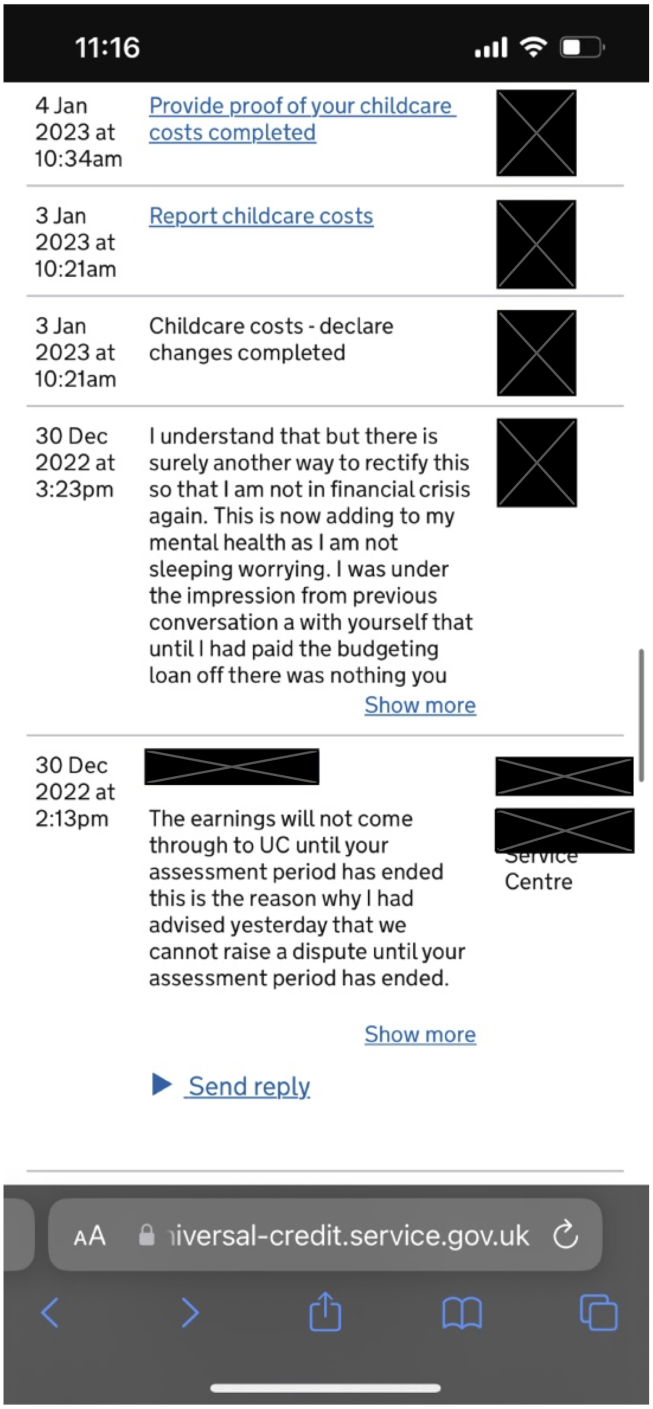

Fig. 1. Screenshot of Emily's interaction with her case manager

from Emily's employer. At the end of December, she wrote to her case manager: "There is surely another way to rectify this so that I am not in financial crisis again. This is now adding to my mental health as I am not sleeping worrying." (See Fig. 1)

By mid-January Emily was distraught, texting us, "So I'm currently waiting for that dispute to be resolved as I am once again out of pocket and struggling because of an error."

When we checked in at the end of January, Emily let us know, happily, that the error has been fixed thanks to her employer's swift response: "My employer were very helpful and contacted HMRC at speed and UC put the difference into my account on Friday. [. . .] My work has been amazing, thankfully."

Despite this, Emily had experienced difficulties during this two-month period of uncertainty, writing, "Just frustrating [that] I had to get an advance on my wage from my work to survive."

7.2 Universal Credit's monthly assessment period

In addition to RTI-related errors, UC's dynamic monthly payment presents another challenge for some working claimants. Noted previously by the Child Poverty Action Group [14] and Human Rights Watch [72], a punitive discrepancy can occur when a claimant's monthly assessment period, which reflects the amount of earnings a person receives within its time frame, is not in alignment with the period of work covered by the earnings. For most claimants, particularly those paid monthly, the UC assessment period will not pose problems. However, according to DWP's own analysis, around 25 percent of claimants will find their benefits reduced because they are paid every two or four weeks. People who are not paid monthly but rather every two or four weeks will encounter certain assessment periods over the course of a year that capture two payments at once, one at the beginning and one at the end of the period. For instance, someone who receives their wage every four weeks will receive two sets of wages in one assessment period, roughly once every 13 months, and may receive reduced or no UC payment following this. DWP, well aware of this problem, calls these dual temporalities "different earning patterns" in their guidance on their official website. We detail what two users reveal about UC by interrogating the effects of the fixed assessment period on their payment.

Fiona, a white Scottish woman, is a single mother in her late thirties with two children. She works as a cleaner for a school that pays her every four weeks. In her first interview she told us she was experiencing significant difficulties understanding the UC payment calculation and anticipating her monthly payment. At the beginning of August – six weeks after her first interview – she reported that she was trying to get information from UC, both through her online account and the phone helpline, regarding her entitlement. Fiona worried that, due to being paid every four weeks, she would not get her entitlement in an upcoming month. She wrote to us via text, "I tried phone uc to be told [to] write my worries and questions online, so i have done this yesterday and waiting on response." Knowing far in advance whether she would get her entitlement especially mattered as her children are "not entitled to school meals so [she would] need to make sure [her] kids have lunch money".

Throughout August, September and October we received frequent, instant updates from Fiona on her interactions with different UC case workers as she tried to understand when she would not receive a UC payment. Fiona's updates included screenshots of messages she exchanged with case managers and phone calls elaborating her worries and confusion. (See Fig. 2)

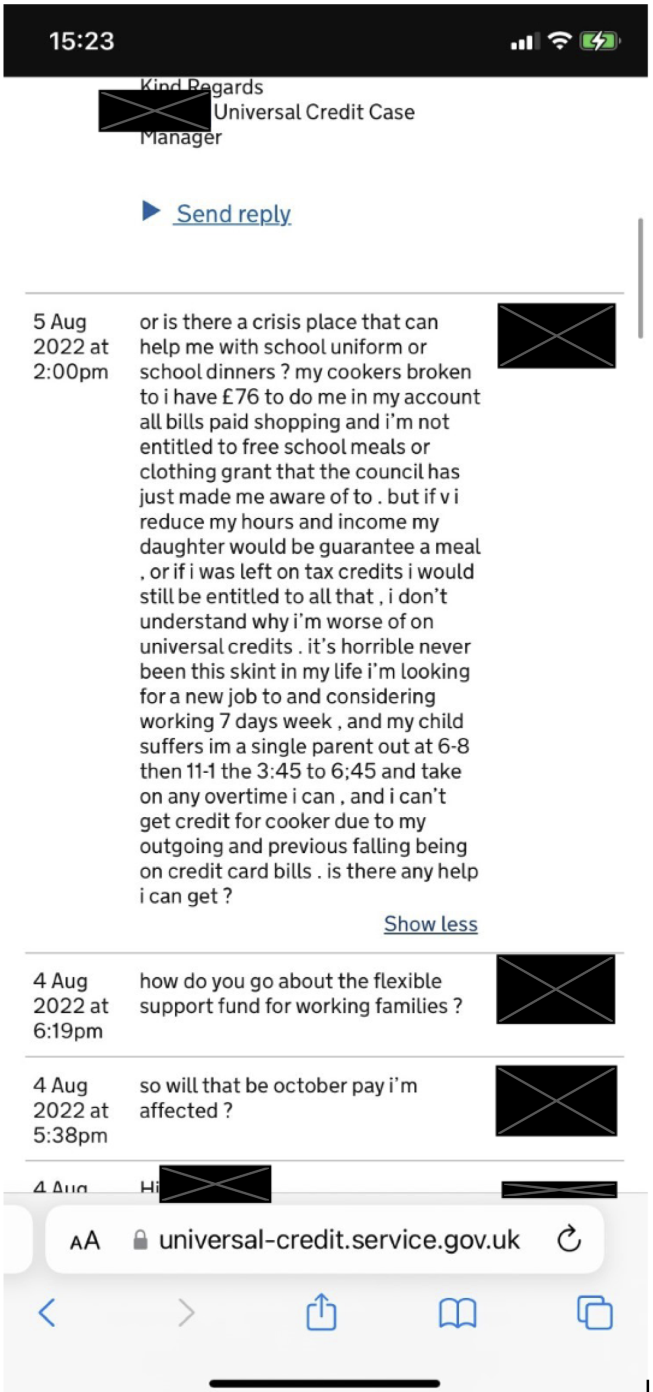

Fig. 2. Screenshot of Fiona's interaction with her case manager

At the end of September, Fiona shared that she still had not received a definitive answer regarding the month she would not receive UC payment: "I don't know if it will be november or december or both i don't get paid , it's horrible." In October she wrote, "the system is hellish".

She finally learned she would not receive UC payment in November from her UC statement that month, sent only a few days before her payment would have been put in her bank account. She wrote over text, "I'm not getting a november pay it's come up £0 no one told me."

Throughout, she interacted with several different case managers. In our second interview in mid-January 2023, she told us how frustrating and impersonal these interactions were: "Even [just] the same person replying to me would be better than a half assed conversation." She described her experience during the previous three months, saying, "I keep emailing them and writing, 'Good afternoon, could someone help me understand the calculation behind this madness?'." She shared that she had borrowed money from her son to "to keep [her] head above water until [she] get[s] paid."

Conflicts between employers' payment policies and the UC assessment period can happen as people start new jobs or change their working hours. Jennifer, a white Scottish woman, is a single mother of two children in her early thirties who worked 16 hours a week as a family support worker when we first interviewed her in June 2022. Overall, Jennifer seemed content with UC, though she had once experienced a mix-up with her wage-reporting that she said had been quickly resolved.

In July she left her job due to mental health difficulties. UC required her to look for 25 hours of work to qualify for the benefit, and by October she found a 16 hour-a-week contract serving school dinners. She worried this change in employment would affect UC's automated payment since her new employer had not yet paid her first wages for the month of October. In mid-October she sent a text to say she feared she would receive no UC payment the following month: "If [my wage payment] doesn't fall into the window that [UC] create. 21 to 21st of each month I wont receive any uc payment." If she was paid for her October hours and November hours in the same month, then her combined earnings could put her over the threshold to qualify for UC, resulting in no UC payment in November.

When we interviewed Jennifer again in January, she informed us that, indeed, her employer's late October pay had resulted in a "dip" in UC – though her November payment "wasn't zero, no, it just wasn't as high as what [she] thought". She expressed her frustration with UC's rigid assessment period and how it accounts for when you are paid according to HMRC, but not the period you actually worked:

> I'd waited a long time for my first wage so it looked like they had paid me twice. [...] They put it in the same month so it looked like I got more which is a really frustrating part of universal credit.

Jennifer also partly blamed herself for her changing circumstances; she had quit the school dinner post in early December to take another job in January as a pupil support assistant – a position she was excited about and felt more qualified for – for 25 hours a week. Reflecting on her two jobs Jennifer told us, "It is partly my fault, I have leapt from job to job in such a short amount of time."

8 DISCUSSION

Drawing on these accounts, we argue that QLLR brings advantages to user studies, and in this section, we focus on how it captures 1) the unfolding, dynamic processes endemic to ADMS and 2) in situ, affective dimensions of users' encounters.

8.1 Capturing ADMS as a process

Kitchin writes that "algorithms are rarely fixed in form and their work in practice unfolds in multifarious ways"[37]. A longitudinal approach captures just how multifarious and volatile UC's automated payment algorithm is: not only did participants recount unique experiences with it, but their individual encounters with UC over the first six-month period proved highly dynamic. Claimants such as Gaja, who had otherwise no trouble with the UC payment, encountered problems after the study started. Through screenshots shared with us, we could get a view of how users interacted with their case managers, work coaches and employers to resolve errors or seek information about upcoming payments, and we could discuss with participants their reflections on these encounters.

This approach - capturing ADMS as a process - gave us insight into problems around UC's accountability. ADMS in the public sector can be seen as "operating outside the scope of traditional oversight and public accountability mechanisms" [10], which underlines the need for innovative ways to examine these tools and their consequences. Thanks to the temporal element of our method, we gathered valuable insight on procedural technicalities of data exchange between UC and the RTI and the difficulties users face when they are subject to a mistake. This method allowed us to establish granular timelines for RTI error resolution that could be difficult for participants to recount from memory. We found that claimants face, on average, a two-month period of uncertainty and vacillating pay until DWP redresses the issue. We also found that even when claimants find the issue resolved they are not always able to discover the origins of the error.

Longitudinal research also has the advantage of allowing the study to be iterative and responsive to participants. Speaking to participants for a second interview helped us bridge gaps found during the first iteration of data analysis, particularly as we tried to establish timelines around UC errors. We also built trust with participants, which impacted the depth and detail of the information received during data collection. Though we never requested them, several participants, as mentioned, shared screenshots of their online chats with DWP. This type of data is valuable because researchers who do not qualify for UC cannot access the system directly – this data gave us a unique window into how DWP addresses errors and handles questions from claimants.

8.2 Emotions and ADMS

QLLR allows researchers to gather data as users react in near-real-time and in situ to ADM systems, capturing the emotional dimensions of users' interactions. Such an approach goes well with the theoretical lens of lived experience, a framework that sets out to understand peoples' subjective, embodied reactions to everyday events and considers how a person's identity – including their race, gender, and class – shape these experiences and ways of knowing the world[8][46][21][39]. As mentioned in the literature review, several studies have asked users about their basic comprehension of algorithmic systems, and some include questions about feelings of fairness and justice [60]. More work is needed to capture the lived experiences of users, including their emotional reactions as they interact with ADMs.

In our study participants expressed a range of emotions towards UC, from frustration and desperation to gratitude and relief. Their emotions intensified in the face of an error or when confronting a large change in UC pay due to circumstances out of their control – at these points, participants spent a great deal of affective energy on UC to sort out the error or anticipate for months when their UC payment would dip or not arrive at all. Participants expressed real fears of material scarcity affecting their children at these times. Our study traced these trajectories of emotions, capturing as participants first reacted with confusion and annoyance at a UC behavior or a decision they did not understand, then relief if the issue is resolved, or resignation, anger and helplessness if they could pursue the matter no further.

Literature on lived experience is helpful for being attentive to how subjectivity and emotions are situated in a person's social context, shedding light on its structural inequalities. In this regard, claimants expressed how they at times felt powerless when questions about payment went unanswered and unaddressed and because UC prioritizes certain forms of evidence – such as HMRC data – over the type claimants could supply. UC in this way shapes users' sense of self and agency as they interact with it. Stark [70] makes a direct link between affect and the normative values shaping digital technologies' development and use. Affect, Stark argues, "infuse(s) the norms and values of particular digital platforms…and/or shape subjective and social reactions to particular technologies" (p.122). In our study people reacted emotionally to their powerlessness when they could not anticipate their entitlement. With UC's unpredictable, fluctuating monthly pay, we find a design that can inflict emotional, as well as material, difficulties due to its unintelligibility.

9 CONCLUSIONS

As an automated social service, Universal Credit is notoriously difficult to study because of its complexity, dynamic responses to users' heterogenous circumstances and the reluctance of DWP to engage with researchers. Universal Credit also shares many features with other ADMS when it comes to problems concerning accountability and intelligibility to users. UC's dynamism calls for novel methods, and qualitative longitudinal research can serve as a capable tool to contribute more holistic understanding. We used our empirical study to demonstrate how QLLR captures granular information on basic features of UC: the data exchange pipeline led by the Real-Time Information system and the automated monthly assessment period. Through screenshots we obtained a quasi-archive of events that complemented the accounts of participants and revealed features of the UC system otherwise opaque to researchers not on the benefit. Lastly, by capturing emotions in situ and over time, we gained insight into how users experience power imbalances due to their lack of voice and the system's unintelligibility at times. We invite researchers to build on this method in future studies of ADM systems.

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