Patient-Provider Communication Technologies, Patient Preferences and Medication Adherence: An In-depth Analysis

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***Abstract*— Communications between a patient and their health service provider are essential in ensuring sustained engagement and achievement of optimal clinical outcomes. To generate valuable insight on how to optimize interactions with patients, and to preserve both adherence and patient satisfaction, this study analyses different patient-provider communication modalities, user preferences, and medication adherence across a range of covariates. To evaluate how patient-provider communications relate with these covariates, and to adherence, we identify which Channel of Communication (CoC) is used by the patient to confirm every medication delivery. This is used to display preference as well as how successful each CoC is. In this study, we define adherence as the Percentage of Days Covered (PDC) by medication stock. Three CoCs are covered in this study: phone calls, email, and portal (a web platform), all of which enable the user to confirm medication deliveries, enabling them to have the required medication stock, in alignment with their doctor's prescription. Through this analysis, we find that each CoC has a significant influence on medication adherence, with portal users having relatively better adherence for any given month (PDC reduction of 6.7-6.8% for phone users, compared to portal users). Additionally, the use of the portal increases by 4.7% month on month, whilst phone call use decreases by 4.6%. We opine that the impact seen in portal usage is due to patients growing in familiarity with digital health solutions, as well as the benefit attained via digital health means. Furthermore, this study shows that patients who are consistent with their preferred CoC attain greater adherence than those with inconsistent CoCs. In any given month, patients who continue to use a CoC that was an initially stated preference typically have a PDC 6.1-6.3% greater than their counterparts with inconsistent CoC preferences. The insights gained around the temporal nature of patient behavior and communication preferences will allow for their health service providers to better support their patients, with dynamic and tailored interventions. Such tailored services are consequently better positioned to improve adherence, patient outcomes and satisfaction.**

***Keywords- medication adherence; healthcare; homecare; communication; engagement; digital health*.**

I. INTRODUCTION

Efficient and reliable patient-provider communication has been shown to positively influence adherence [1]. Whilst tailored communication has been acknowledged by many as having a major influence on medication adherence and overall health outcomes [2], the channel through which such tailored communication is made available to the patient is equally crucial. With the escalation in the variety of communication tools available today, including web portals, apps, automated text and email messaging, phone calls and many more, healthcare providers have an arsenal of communication channels at their disposal to effectively communicate with their patients. Furthermore, patient-centered communication is believed to drive engagement, trust, and improvement in health outcomes [3]. Such patient-centered communication encompasses patient preferences, amongst other factors, with respect to how healthcare is delivered. It is crucial therefore to have a deeper understanding of patterns in patient behavior and preferences with a view to ensuring that relevant communication is delivered in a format, and through a channel, that benefits engagement and drives persistent medication adherence. To this end, this study seeks to analyse the communication patterns for chronic disease patients who have their medicines (which they self-administer) delivered to them. The reasoning behind this is to identify the communication channel's impact on medication adherence behaviors, as well as how communication channel preferences can evolve over the length of a patient's time on service/treatment. Insight from these analyses would support the optimization of interventions that are designed to ensure patient engagement in their care and ultimately improve medication adherence over a sustained period. To this end, the Research Questions (RQ) and hypotheses for this study include:

RQ1: Does the Channel of Communication (CoC) used influence patient adherence?

Hypotheses:

H_0 Channel of communication does not affect adherence.

H_1 Channel of communication affects adherence.

RQ2 How dynamic are patient communication preferences?

Hypotheses:

H_0 Patient communication preferences are static over time.

H_1 Patient communication preferences are dynamic and change throughout time on service.

RQ3 Does inconsistency in communication preference influence patient adherence?

Hypotheses:

H_0 Inconsistency in communication preference does not affect adherence.

H_1 Inconsistency in communication preference affects adherence.

The structure of this paper is as follows: Section II outlines the importance of this study, whilst Section III provides a review into other studies with comparable objectives. Section IV details the data that is utilized within this study, leading into Section V where each RQ is evaluated and discussed. Finally, Section VI concludes our findings and provides suggestions for future work.

II. BACKGROUND

The World Health Organisation (WHO) suggests that adherence is affected by healthcare system or provider-patient relationship, amongst other factors [4]. Many studies have focused on the quality of physician communication and patient adherence, finding a strong positive relationship between the two [5]. Intuitively, provider communication and patient adherence are inextricably linked. The healthcare provider is the patient's initial contact point at diagnosis, the executor of any changes to treatment regimen, and the support should any difficulties arise with the condition or therapy. Resultantly, ensuring that the patient-provider relationship is strong is a primary goal of communication and is fundamental in active patient engagement [6].

Providing flexibility in the way that a patient accesses support is crucial in ensuring their long-term engagement, not least because it accommodates patient choice and changing preferences. Interestingly, despite a common belief that face-to-face interactions are superior to digital communication forms for patient outcomes, other studies have pointed out the paucity of data to support this view [7]. Notably, technological developments have resulted in a fundamental shift in health service delivery approaches, with the increasing popularity of digital forms of communication. For instance, 68% of the UK now advocate for the use of digital health technology within the NHS [8], with £2 billion in funding recently allocated to support the transition to electronic patient records within the NHS [9]. Aside from the increased convenience and accessibility made possible through digital communication options, some studies have demonstrated that technological advancements, like AI-driven SMS communication of tailored messages are associated with higher medication adherence rates [10].

Health Literacy and Adherence

If patients are not self-motivated to learn, it is very likely that their healthcare provider will be the source of any accrued knowledge around their condition. The complexities inherent to patient adherence necessitate some formal modelling to segment and understand the processes at play. Whilst impossible to focus on all factors (both internal and external to the patient) that influence non-adherence, streamlining the communication and decision-making phases of the patient's health journey (Figure 1) can potentially enhance health literacy and, ultimately, their likelihood to adhere to their prescribed medication [11]. Health literacy is the patient's ability to obtain, process, communicate and understand basic health information and services [12].

The Dunn-Conard health literacy instructional model is founded on the grounds that the monitoring and control of chronic health conditions is complex and requires a high level of patient involvement [13][14]. Whilst bolstering all the factors listed in Figure 1 would be the most beneficial for patient outcomes, this study primarily focuses on assessing the impact of patient-provider communications on adherence. To understand the behavioral mechanisms behind patient-provider communication, Table I assesses the relationship through a COM-B model, which postulates that performing a behavior is linked to capability, opportunity, and motivation [15].

Whilst communication regarding the delivery of medication may not seem complex, it is multi-faceted in its behavioral components. Several factors can deter patients from ordering their medication on time. For example, patients may not have the capability to communicate with their homecare provider. Usually, these patients would be assisted by a carer, or through bespoke facilitation by a Clinical Homecare provider. However, in some circumstances, this may not be the case. Equally, patients may have limited access to the technological mediums required to place an order for their medication. Many Clinical Homecare

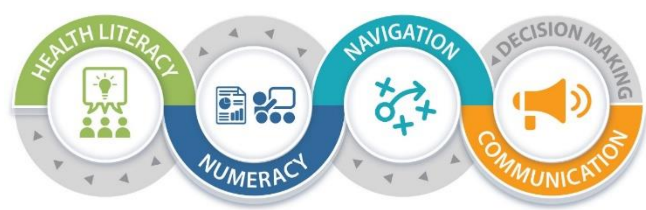

Figure 1. Dunn-Conard Health Literacy Model

TABLE I. COM-B MODEL OF COMMUNICATION BEHAVIOR

	Capability	**Opportunity**	**Motivation**
Definition	*The individual's physical and psychological capacity to engage in the behavior.*	*All factors lying outside the individual that make performance of the behavior possible or prompt it.*	*All brain processes that energize and direct behavior.*
Behaviors	Understanding the communication methods available to them.	Access to channels of communication.	Self-efficacy and willingness to engage with the provider.
	Psychological capability to communicate i.e. disabilities and mental health considered.	Severity of condition/regimen complexity	Condition-specific factors i.e. immediacy of side-effects, tangibility of medication efficacy.
	Common language of communication.		Cues for action from the homecare provider.

Note. All statements in italics are definitions taken from Michie et al. (2011) [15]. General model applied in Jackson et al. (2014) [17]

providers in the UK are transitioning to digital communication channels. Some patients may not have access to an internet-capable device, although this is a very small subset of the UK, where 97.8% use the internet, up from 56.5% in 2002 [16]. Lastly, patients must also be motivated to order their medication, whereby their motivation to do so may be impacted by a number of factors. For example, if non-adherence to medication has no immediate side-effects, adherence to medication has immediate side effects, or a patient is not provided sufficient cues from their Clinical Homecare provider, they may be less motivated to order and take their medication [17]. Ultimately, it is essential to understand why patients may have less than 100% adherence to provide solutions. This study does not granulate communication into the factors listed in Table I but does assess the overall impact of communication channel choice on non-adherence to medication in patients with chronic conditions. The granular take on communication in Table 1 should be explored further in future research.

III. RELATED WORK

Studies elsewhere have found that poor adherence to medication is linked to negative clinical outcomes and increased utilization of healthcare resources, and it is estimated that poor medication adherence costs NHS England approximately £1bn annually [28][29]. However, measuring adherence, particularly in a chronic disease setting, is often challenging given that approaches such as clinician observation of medicine intake or biological testing for presence of the therapy, are neither economically nor logistically sustainable. Approaches to measuring adherence can largely be grouped into subjective, indirect, and direct categories, as shown in Table II.

This study measures adherence using pharmacy records, and more specifically, the Proportion of Days Covered (PDC). Simply put, this is the percentage of days within a time period that a patient has access to the medication that they are prescribed.

PDC data is obtained from a UK-based Clinical Homecare organisation, focusing on patients who self-administer subcutaneous injections across respiratory, rheumatology, dermatology, and gastroenterology therapy areas. This form of adherence was chosen due to its conservatism, which other pharmacy-based metrics like medication possession ratio (MPR) fail to exercise. The PDC metric has been advocated for by various bodies (e.g., the Pharmacy Quality Alliance (PQA)) as the preferred quality indicator for estimating adherence to therapies for chronic diseases [30].

The literature is sparse on communication modality and its effect on adherence, however, a 2021 study found that agency with regards to digital reminder modality had a positive effect on patient adherence in asthma patients [31]. Studies in

TABLE II. METHODS OF MEASURING MEDICATION ADHERENCE

Measurement Category	**Types of measurement**	**Author/ year**
Subjective	Self-reported questionnaires Homecare providers perception of adherence	Gupta et al., 2016 [18] Nguyen et al., 2014 [19] Alili et al., 2016 [20]
Indirect	Pharmacy records Pill counting Electronic monitoring devices	Gupta et al., 2016 [18] Denicolò et al., 2021 [21] Mackridge & Marriott, 2007 [22] Lam & Fresco, 2015 [23] Paterson et al., 2017 [24]
Direct	Direct observed therapy Digital pills Chemical adherence testing	Lane et al., 2019 [25] Gupta et al., 2016 [18] Denicolò et al., 2021 [21] Pitt, 2009 [26] Patel et al., 2010 [27]

adjacent domains looked at the preference in communication modality and physical activity in patients with musculoskeletal disorders and adherence in HIV, finding a preference for printed materials and text messaging respectively [32][33].

To our knowledge, this study appears to be the first of its kind to assess the impact of communication channel on patient adherence across several chronic diseases and medication types, in a Clinical Homecare setting, using a larger patient cohort than other studies in adjacent domains.

IV. METHODOLOGY

The data used within this study is comprised of patients who are enrolled in a UK-based Clinical Homecare service. All data has been pseudonymized and processed in compliance with General Data Protection Regulation. All data processing is conducted using Python and the Pandas library, all statistical analysis is conducted using STATA 18.1.

A. Study Data

The data used within this study focuses on specific medications which cover a range of conditions (gastrointestinal, respiratory, dermatological, rheumatoid, and ophthalmic indications). This representative sample contains 30,102 patients, with all patient-provider communications logged from their initialization on the service, beginning in 2018, until January 2024. This timestamped data contains the CoC, which can be phone calls, direct email communication and the use of an online portal (which can be accessed directly by the patient or be encouraged through email/text one-time links). All these CoCs can be used to confirm a medication delivery, which is what will be measured in this study to establish the patient's preference.

A patient's stated CoC preference is collected when they join the service. Patient revealed preferences will be identified by establishing the CoC that was used to confirm every patient's medication delivery. It is worth noting that in the absence of any delivery confirmation, when one would be expected, the Clinical Homecare provider will telephone the patient to confirm the delivery.

Demographic data is also collected in addition to the communication and delivery data, specifically, age, gender, diagnosis, location and whether the patient is on a patient support program.

B. Data cleaning and processing

Prior to data processing, redundant communication data is removed, such as logged questionnaire activity.

We primarily wish to identify how consistent a patient's initial preference for a CoC is with the communication behavior they exhibit over their time on service. To capture and analyse this behavior, whenever a patient receives medication stock, the CoC that led to this delivery is recorded. Through identification of which CoCs have been used to confirm an upcoming medication delivery, we can analyse its relationship with both adherence and initial stated preferences.

The data is processed monthly, for the statistical analysis, to ensure a high-level of granularity. The timepoint when a patient has their first communication with their Clinical Homecare provider, marks the beginning of their Length Of Service (LOS). After this period, the CoC used by the patient to confirm each medication delivery is considered as a successful CoC.

Panel data is configured by establishing a timeline for each patient, where their monthly communication behavior is recorded. In addition to this, other variables such as whether this CoC matches stated preference, total medication deliveries, and the percentage of successful deliveries that used a stated preference are created. It is worth noting that not every month has a delivery, with most deliveries having a frequency of 8 weeks or longer. The months without delivery data are left null and omitted from our models. This monthly data is also pooled to produce one data point per patient, for every patient's full time on service (up until the current date). This produces cross-sectional data, from which alternative research questions can be answered.

To answer the research questions, PDC values were calculated at each month and across the whole service duration to establish how changing preferences influence monthly adherence, as well as their overall relationship. To calculate PDC, the timestamp of a medication delivery and the number of days' worth of medication the delivery contains is recorded. This provides a patient timeline, which displays the quantity of medication that each patient should have at any given date, further details of this technique have been provided in a previous study [34]. The data allows for the stockpiling of medication (when a patient receives an additional delivery before their current medication stock has depleted, these stock values are added together), as this is common behavior for chronic disease patients [35][36]. Finally, a variable to describe each patient's approximate level of economic deprivation is created using UK-based Index of Multiple Deprivation (IMD) data [37]. This variable is inputted as a percentile.

C. Dataset outline

To better understand the data utilized in this study, this section covers the demographics and descriptive statistics of the patients within the sample. Table III displays the number of deliveries that have resulted from each CoC, as well as the number of patients that state an initial preference for each CoC.

The summary statistics on dichotomous demographics and disease-specific variables are presented in Table IV. Patient receives Enhanced Services (PES) stipulates whether the patient receives additional nurse visits to support treatment compliance.

The summary statistics for the continuous demographic variables are presented in Table V, where all patients have data for each variable.

TABLE III. COMMUNICATIONS OUTLINE

CoC	Initial Preference	Total Successful Uses
Portal	24,976	125,065
Calls	3,597	178,974
Emails	8,171	1,067

V. RESULTS AND DISCUSSION

This section will cover each of the research questions and hypotheses outlined in the Introduction and discuss the statistical methodologies that have been used to answer these questions. In addition, analysis and discussion of these results is provided.

RQ1: DOES CHANNEL OF COMMUNICATION USED INFLUENCE PATIENT ADHERENCE?

- H_0 Channel of communication does not affect adherence.
- H_1 Channel of communication affects adherence.

A. Results

It is important to understand how CoC affects adherence within the sample. For example, as many healthcare service providers transition to digital-first communication strategies to aid with optimization, labor-force allocation, and costs, it is important to know if patient outcomes are affected. Whilst the Clinical Homecare provider that is the subject of this study have kept traditional communication methods available to their patients, the default option for arranging deliveries is now through the patient portal, which is the reference category for the analysis shown in Table VI. Panel 1 uses a random effects panel regression to establish the effect of CoC on adherence, each month. Panel 2 uses an identical model, with additional demographic and diagnosis covariates to confirm the relationship observed in Panel 1.

In Panel 1, the coefficient for calls is $\beta = -0.0667$, with a standard error of 0.00116, and the coefficient for emails is $\beta = 0.0924$, with a standard error of 0.000660. Both effects are highly significant at the $p < 0.01$ level. In Panel 2, the effect sizes increase to $\beta = -0.0680$ for calls, and $\beta = 0.110$, with standard errors of 0.00127 and 0.00242 respectively. Both effect sizes are significant at the $p < 0.01$ level. This is indicative that people who use calls to arrange their medication are predicted to have lower adherence, whilst patients that use emails to arrange their medication are predicted to have higher adherence and are robust to the inclusion of demographic and diagnosis covariates.

TABLE IV. PATIENT DEMOGRAPHIC AND DIAGNOSES DESCRIPTIVE STATISTICS

Category	Variable	Frequency
Gender	Male	13,034
	Female	12,846
PES	Yes	10,055
	No	20,047
Disease	Atopic Dermatitis	12,776
	Hidradenitis Suppurativa	472
	Juvenile Arthiritis	225
	Psoriasis	3,268
	Crohn's Disease	2,928
	Eosinophilic Eosophagitis	10
	IBD (Inflammatory Bowel Disease)	48
	Ulcerative Colitis	950
	Uveitis	225
	Severe Asthma	3,647
	Axial Spondyloarthritis	1,518
	Rheumatoid Arthritis	3,181

TABLE V. CONTINUOUS DEMOGRAPHIC VARIABLES DESCRIPTIVE STATISTICS

Variable	Frequency	Median	Standard Deviation
Age	30,097	47	17.856
IMD	30,097	46	24.031
LOS	30,097	20	18.457

TABLE VI. PANEL DATA MODEL: CoC AND ADHERENCE - DIRECT EFFECTS (PANEL SAMPLE)

Variable	Panel 1		Panel 2	
	Coefficient	Std. Error	Coefficient	Std. Error
CoC: Call	-0.0667***	0.00116	-0.0680***	0.00127
CoC: Email	0.0924***	0.000660	0.110***	0.00242
Gender			-0.00345**	0.00167
Age			0.000667***	0.0000501
IMD			0.0000305	0.0000342
PES			0.00371**	0.00170
Hidradenitis Suppurativa			-0.0146**	0.00712
Juvenile Arthritis			-0.0179	0.0146
Psoriasis			-0.0145***	0.00307
Crohn’s Disease			-0.00468	0.00337
Eosinophilic Esophagitis			0.0134	0.0218
IBD			0.0434**	0.0174
Ulcerative Colitis			0.0227***	0.00493
Uveitis			-0.0113	0.0115
Severe Asthma			0.0396***	0.00219
Axial Spondylarthritis			-0.00766*	0.00450
Rheumatoid Arthritis			-0.0167***	0.00334
Chi^2	40415.250		33920.440	
$p > chi2$	0.000		0.000	
# Observations	285,621		230,687	
# Patients	28,311		23,820	

Note: Panel regression models with random effects and robust standard errors. Outcome variable: Monthly PDC (100% days covered=1, 0% days covered=0). Panel 1 regresses monthly communication type (Portal=omitted category) and Panel 2 includes covariates age (in years), gender (Female=omitted category), IMD (Index of Multiple Deprivation in percentiles), PES (tailored interventions (with homecare provider interactions at pre-determined intervals) designed to improve treatment adherence/compliance), and diagnosis (Atopic Dermatitis=omitted category) (*** p<0.01, **p<0.05, *p<0.1).

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B. Discussion

Whether a given CoC was an initial preference or not, the CoC that is used, has significant influence on a patient's behavior. This is evidenced by the coefficients displayed in Table VI, which shows that at any given month, patients who utilize calls to confirm their deliveries have a PDC 6.67% - 6.80% (range dependent on predictive model) lower than portal users. Whilst patients that confirm deliveries via email have a PDC 9.24%-11.0% greater than those using portal. These findings are indicative of the crucial role of patient engagement, as the use of portal and email requires more patient engagement than receiving a phone call, showing a level of commitment to their treatment which is directly correlated with increased adherence (i.e., PDC). Whilst these objective findings are useful for a Clinical Homecare provider looking to drive better patient engagement, understanding the motive for that communication preference is vital.

Patients using call, for example, may be calling because of a missed delivery, looking for an immediate resolution. On occasion, this missed delivery could result in a lower PDC. Likewise, the Clinical Homecare provider within this study prioritizes communicating with patients via phone call when a patient is at risk of being overdue for their medication, due to the immediacy offered in resolving the situation.

The relationship between email usage and PDC in this study may also have been influenced by the relative infrequency of emails compared to communications using the portal, or call. 41.04% of communications were through the portal, 58.60% through calls, and 0.37% through email. Further analysis shows that the maximum number of communications any patient has through email is 1, indicating that email is unlikely to be a consistent CoC for a patient, and used sporadically for specific events only.

RQ2: How dynamic are patient communication preferences?

- H_0 Patient communication preferences are static over time.
- H_1 Patient communication preferences are dynamic and change throughout time on service.

C. Results

Understanding how patient behavior evolves over time is vital in establishing effective healthcare provisions. To model changing patient communication behaviors, we ran mixed-effects logistic regression analysis on revealed communication preferences over time. This model was chosen as it is preferential for modelling binary outcomes as a linear combination of the constituent factors. The results are displayed in Table VII.

The use of portal communication increases significantly as the length of time on service increases (Odds Ratio (OR) = 1.047, 95% Confidence Interval (CI) [1.047, 1.048], $p < 0.0001$), the use of calls decreases significantly as LOS increases (OR = 0.954, 95% CI [0.954, 0.955], $p < 0.0001$), and the use of emails decreases significantly as LOS increases (OR = 0.533, 95% CI [0.513, 0.B554]).

D. Discussion

For each additional month a patient is on service, their likelihood of using portal to confirm their deliveries increases by 4.7%. Likewise, their likelihood of medication delivery confirmation via calls decreases by 4.6% and with email by 46.7%. The increased use of successful portal delivery confirmations as LOS increases is a positive finding, highlighting an increased willingness to engage in digital health over time. Additionally, this CoC requires a higher level of proactivity from the patient than phone calls, as the patient is required to actively log on to a service to confirm their delivery, rather than passively receive a phone call. The increasing use of the portal is therefore indicative of increasing patient engagement as length of time on service increases. Some potential reasons for this could be increased habituation to the service, although further data analysis would be required to substantiate this. The decrease in confirmed deliveries via calls, as LOS increases, is also a reassuring finding as it showcases a willingness from patients to pivot to more active treatment management channels. Additionally, within our sample, calls are prioritized by the Clinical Homecare provider when a medication delivery is at risk of being overdue because it requires the least effort from the patient to confirm their delivery. The decreasing frequency in the use of calls to confirm medication delivery as LOS increases could also be an indication of habituation to service or the establishment of effective equilibrium between the patient and the provider.

Finally, the use of emails as a means of medication delivery confirmation suffers a large reduction as LOS increases. In this sample, no patients have ever been shown to utilize email more than once in successfully confirming their medication delivery, over their entire service-duration. These

TABLE VII. MIXED-EFFECTS LOGISTIC REGRESSION – PATIENT COMMUNICATION PREFERENCES OVER TIME

Communication Type	**Odds ratio⁺ (Std. error)**	**Z-value**	**Chi^2 ($p > chi2$)**
Portal	1.047*** (0.000326)	148.60	22082.50 (0.000)
Call	0.954*** (0.000236)	-188.52	35538.97 (0.000)
Email	0.533*** (0.0106)	-31.70	1004.76 (0.000)

Note. Three mixed-effects logistic regression models were run to ascertain these results. Communication type is recorded every month, with a maximum of one communication type per month. This communication type corresponds to the generation of a successful delivery. (*** p<0.01, **p<0.05, *p<0.1).⁺ (OR) observations suggest that emails are used by some patients to confirm deliveries at the beginning of their service due to uncertainty or unfamiliarity with the other CoCs, or in specific situations which require the provision of more information to the service provider. On some occasions, it could also result from a patient being referred to the service from a center which did not provide the patient's contact number, but this is infrequent. Emails are not used by patients consistently, which should be considered by healthcare providers with several channels of communication available.

RQ3: Does inconsistency in patient communication preference influence adherence?

- H_0 Inconsistency in communication preference does not affect adherence.
- H_1 Inconsistency in communication preference affects adherence.

To answer RQ3, both pooled and panel analysis is required. The reasoning behind both approaches is to assess how patient adherence is predicted to change over the duration of their time on service, and in any given month.

E. Pooled Analysis Results

Initially, we performed pooled analysis using aggregated adherence data, in the same manner as previous analysis. To establish whether patients' stated preference at the beginning of their Clinical Homecare service are consistent with their revealed communication behavior through the course of their time on the service, we compare all patient's stated preferences with their modal CoC and introduced it as a binary variable. For 53.1% of the patients in the sample, there was a match between their stated and revealed preferences. The results of the Linear Probability Model (LPM) assessing the effect of preference consistency on PDC are displayed in Table VIII.

In LPM 1, the coefficient for consistent preferences is $\beta = 0.0118$, with a standard error of 0.00220. This effect is highly significant at the $p < 0.01$ level. In LPM 2, the effect size increases to $\beta = 0.0202$, with a standard error of 0.00237, which is also significant at the $p < 0.01$ level. This is indicative that people who have consistent preferences are more likely to adhere to their medication – these findings are even more robust with the inclusion of demographic and diagnosis covariates.

F. Pooled Analysis Discussion

Consistency in the CoC preference results in a 1.2% to 2.0% higher PDC across the service-life of a patient. Simply put, if a patient's modal CoC is the same as their stated communication preference at the onset of the service, their adherence will be 1.2% to 2.0% greater than patients with inconsistent preferences. Whilst the findings of overall consistent preferences are useful, it is vital to have a sense of how inconsistent these preferences can be. To ascertain this, we generated a categorical variable which captured how often the patient's Stated preferences matched their Revealed (SR Percentage), using monthly data. The results of the LPM are detailed in Table IX.

TABLE VIII. LPM: PREFERENCE CONSISTENCY AND ADHERENCE - DIRECT EFFECTS

Variable	LPM 1		LPM 2	
	Coefficient	**Std. Error**	**Coefficient**	**Std. Error**
Consistent Preferences	0.0118***	0.00220	0.0202***	0.00237
Gender			0.00496**	0.00235
Age			0.000218**	0.0000731
IMD			0.0000916*	0.0000477
PES			-0.00350	0.00248
Hidradenitis Suppurativa			-0.0640***	0.0119
Juvenile Arthritis			-0.0453***	0.0170
Psoriasis			0.000268	0.00383
Crohn's Disease			-0.0192***	0.00486
Eosionophilic Eosophagitis			0.0249	0.0479
IBD			0.0404	0.0253
Ulcerative Colitis			0.0119	0.00732
Uveitis			-0.0164	0.0139
Severe Asthma			0.0631***	0.00315
Axial Spondyloarthritis			-0.0120**	0.00595
Rheumatoid Arthritis			-0.0206***	0.00458
F-stat	28.72		55.60	
$p > F$	0.0000		0.0000	
# Observations	29,499		24,730	

Note: Linear probability regression models. Outcome variable: PDC (100% days covered=1, 0% days covered=0). LPM 1 regresses only preference consistency (consistent=1, inconsistent=0) and LPM 2 includes covariates age (in years), gender (Female=omitted category), IMD (index of multiple deprivation in percentiles), PES (tailored interventions (with homecare provider interactions at pre-determined intervals) designed to improve treatment adherence/compliance), and diagnosis (Atopic Dermatitis=omitted category) (*** p<0.01, **p<0.05, *p<0.1).

In LPM 3, the coefficient for the proportion of communications which match the stated preference is $\beta = -0.0235$, with a standard error of 0.00669 and high significance at the $p < 0.01$ level. However, post the inclusion of demographic and diagnosis covariates in LPM 4, the finding loses significance as the coefficient decreases to $\beta = -0.00487$ with a standard error of 0.00723. The variation within LPM 3 caused by the consistency percentage can be attributed to demographic and condition-specific variation. This finding is reassuring, as it demonstrated that preference consistency, with respect to which CoC is used by the patient, has a positive effect on PDC, which is not affected by the degree of this consistency. The takeaway is that patients may use non-preferred communication methods for a host of reasons, and if their modal communication method matches their stated preferred, adherence is not affected.

TABLE IX. LPM: PREFERENCE CONSISTENCY % AND ADHERENCE - DIRECT EFFECTS

Variable	LPM 3		LPM 4	
	Coefficient	Std. Error	Coefficient	Std. Error
Consistent Preferences	0.0233***	0.00381	0.0225***	0.00399
SR Percentage	-0.0235***	0.00669	-0.00487	0.00723
Gender			0.00498**	0.00235
Age			0.000214***	0.0000736
IMD			0.0000913*	0.0000477
PES			-0.00361	0.00249
Hidradenitis Suppurativa			-0.0640***	0.0119
Juvenile Arthritis			-0.0455***	0.0170
Psoriasis			0.000293	0.00383
Crohn's Disease			-0.0192***	0.00486
Eosionophilic Eosophagitis			0.0246	0.0483
IBD			0.0402	0.0253
Ulcerative Colitis			0.0119	0.00731
Uveitis			-0.0164	0.0139
Severe Asthma			0.0632***	0.00317
Axial Spondyloarthritis			-0.0119**	0.00595
Rheumatoid Arthritis			-0.0205**	0.00458
F-stat	22.12		52.29	
$p > F$	0.0000		0.0000	
# Observations	29,499		24,730	

Note: Linear probability regression models. Outcome variable: PDC (100% days covered=1, 0% days covered=0). LPM 3 regresses preference consistency (consistent=1, inconsistent=0) and preference percentage (modal CoC and total communications are equal=1, modal CoC and total communications are unequal=0) and LPM 4 includes covariates age (in years), gender (Female=omitted category), IMD (index of multiple deprivation in percentiles), PES (tailored interventions (with homecare provider interactions at pre-determined intervals) designed to improve treatment adherence/compliance), and diagnosis (Atopic Dermatitis=omitted category) (*** p<0.01, **p<0.05, *p<0.1).

G. Panel Analysis Results

Whilst the pooled analysis helps to reveal overall trends within our patient population, month-by-month data gives greater granularity about patient adherence behaviors and its drivers, as well as tangible effects which could be expected in a shorter, more defined timespan.

It is important for us to validate the use of a random effects model over a fixed effects model for our panel analysis. Many of the independent variables utilized in this study are time-invariant. As a result, the use of a fixed effects model is inappropriate. Fixed effect modelling establishes how much of the variation in independent variables stems from a time-only relationship. In essence, how much the independent variables change because of time. In this scenario, where the independent variables do not change over time, this leads to an almost-entirely omitted panel regression model. However, this is not enough to validate the use of a random effects model. By running the Breusch and Pagan Lagrangian multiplier test (BPLM), we can ascertain that random effects are present in our model, assuring that panel regression with random effects is a superior model to pooled Ordinary Least Squares (OLS) regression for our sample. The results of the BPLM are shown in Table X.

The BPLM evidences a significant presence of random effects in the model, which means the variation in adherence across patients is significant and should be accounted for in the regression model.

The panel data model with random effects estimates the effect of preference consistency on monthly adherence and is detailed in Table XI.

In Panel 3, the coefficient for consistent preferences is $\beta = 0.0611$, with a standard error of 0.00118. This effect is highly significant at the $p < 0.01$ level. In Panel 4, the effect size increases to $\beta = 0.0632$, with a standard error of 0.00130, which is also significant at the $p < 0.01$ level.

Thus, the results of this analysis are indicative that people who have consistent preferences are more likely to adhere to their medication in any given month and is robust to the inclusion of demographic and diagnosis covariates.

H. Panel Analysis Discussion

Our panel analysis has shown that dynamic communication preferences have a statistically significant effect on adherence. When a patient uses a CoC that was their initial preference, in any given month, their PDC is predicted to be 6.1% to 6.3% greater than those displaying inconsistent preferences in that month. Thus, a patient who is inconsistent in their choice of CoC is likely to have a lower PDC than those who are consistent. These findings are positive, as it allows Clinical Homecare providers to utilize knowledge of a patient's consistency (or lack of it) with respect to their CoC preference over time, to tailor support that is provided to the patient in order to foster better adherence.

TABLE X. BREUSCH AND PAGAN LAGRANGIAN MULTIPLIER TEST (BPLM): VALIDATING A RANDOM EFFECTS MODEL

	Variance	Standard Deviation
PDC this month	0.104	0.322
e	0.0725	0.269
u	0.0243	0.156
Test: Var(u) = 0		
	Chi^2	770,000
	$p > chi2$	0.0000

Note. The BPLM test for the presence of random effects. e represents the idiosyncratic error term, the part of the error term which varies between patients and over time. u represents the random effects, the part of the error term that varies between patients but is constant over time for each patient.

TABLE XI. PANEL DATA MODEL: PREFERENCE CONSISTENCY AND ADHERENCE - DIRECT EFFECTS (PANEL SAMPLE)

Variable	Panel 3		Panel 4	
	Coefficient	**Std. Error**	**Coefficient**	**Std. Error**
Consistent Preferences	0.0611***	0.00118	0.0632***	0.00130
Gender			-0.00335**	0.00168
Age			0.000636***	0.0000505
IMD			0.0000356	0.0000344
PES			0.00296*	0.00179
Hidradenitis Suppurativa			-0.0155**	0.00716
Juvenile Arthritis			-0.0455	0.0170
Psoriasis			-0.0150***	0.00309
Crohn's Disease			-0.00816**	0.00341
Eosionophilic Eosophagitis			0.0147	0.0128
IBD			0.0431**	0.0184
Ulcerative Colitis			0.0199***	0.00495
Uveitis			-0.0126	0.0116
Severe Asthma			0.0404***	0.00222
Axial Spondyloarthritis			-0.00834*	0.00452
Rheumatoid Arthritis			-0.0202***	0.00338
Chi^2	2688.50		3286.03	
$p > chi2$	0.0000		0.0000	
# Observations	285,621		230,687	
# Patients	28,311		23,820	

Note: Panel regression models with random effects. Outcome variable: Monthly PDC (100% days covered=1, 0% days covered=0). Panel 3 regresses monthly preference consistency (consistent=1, inconsistent=0) and Panel 4 includes covariates age (in years), gender (Female=omitted category), IMD (Index of Multiple Deprivation in percentiles), PES (tailored interventions (with homecare provider interactions at pre-determined intervals) designed to improve treatment adherence/compliance), and diagnosis (Atopic Dermatitis=omitted category) (*** p<0.01, **p<0.05, *p<0.1)..

VI. CONCLUSION

Across the studied research questions many valuable insights have been uncovered, which can be used by Health service providers to maximize a patient's engagement with their diagnosis management and thus improve adherence. It was found that patients who exhibit consistent CoCs for their medication delivery confirmations have a 1.2%-2.0% higher PDC than patients exhibiting relatively more inconsistency with their CoC use. This insight can be used to provide additional support or communication with patients who are observed to have such inconsistencies. Furthermore, this insight also facilitates a more efficient and informed use of resources in a bid to drive better patient engagement.

It was observed that patients gravitate towards the use of a web portal as their service-duration increases, with a 4.7% increase month on month. Whilst the use of phone calls exhibits a reduction of 4.6% month on month. This is a finding that validates the use of digital forms of communication in healthcare and is also indicative of increasing levels of engagement from patients over time (as the use of a web portal requires more initiative from the patient to confirm a delivery than receiving a phone call does). Additionally, it was shown that users who confirm their medication deliveries via portal have a PDC 6.67%-6.80% greater than those that use phone calls for such delivery confirmation – providing further support for the validity of digital healthcare and its benefit for users.

Through these observations, we aim to improve patient satisfaction and adherence through greater understanding of when they are at increased risk of not engaging with their treatment/communication with their health service provider. These insights can have utility in optimizing resource management to patients most in need and improving treatment outcomes.

However, the research conducted is not exhaustive and there are other areas that can be the focus of future research. For instance, it is likely that there is a relationship between demographic and diagnosis-specific data with adherence, and a further understanding of this would provide additional benefit to the insights uncovered in this work. Likewise, the behaviors that are exhibited through patient stockpiling of medication, and the dynamics between this and other patient behaviors, such as adherence and communications, could uncover further utility.

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