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Data-Driven Service Flexibility in Mobile Health Platforms: Demographic and Behavioural Drivers of Consultation Engagement in the MENA Region

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ORIGINAL RESEARCH

Data-Driven Service Flexibility in Mobile Health Platforms: Demographic and Behavioural Drivers of Consultation Engagement in the MENA Region

Abstract *Retaining users beyond their first consultation is a central management challenge for mobile health (mHealth) platforms. Drawing on flexible systems management, the resource-based view and dynamic capabilities, this study examines which user attributes are associated with consultation engagement on a multi-country teleconsultation platform and translates the evidence into service-flexibility levers. Anonymised records of 5,399 millennial users of Altibbi in Jordan, Egypt and Saudi Arabia were analysed with a hurdle model separating repeat use from consultation intensity, a fractional-logit model of channel preference, seven machine-learning classifiers under nested cross-validation with SHAP explanations, and k-prototypes segmentation. The number of dependents linked to an account was the strongest correlate of both repeat use (OR = 2.74 per log unit) and intensity (IRR = 2.37). Users in Jordan and Egypt engaged more than those in Saudi Arabia, and single users were more likely to return. Gender and age were unrelated to engagement but shaped channel choice: women relied more on chat and older users more on voice calls. Predictive performance was moderate (best AUC = 0.67), and complex learners offered no significant gain over logistic regression. Four user segments emerged, including a family-account core (17% of users) with 95% repeat use. The study contributes a view of engagement as two distinct decisions and a flexibility levers matrix covering market, offer, channel, retention and capacity flexibility for digital health providers.*

Keywords Service flexibility · Flexible systems management · Mobile health · User engagement · Machine learning · Middle East and North Africa

Introduction

Digital consultation was once a thing used on the outside of providing medical services. This was increased due to the pandemic of COVID-19. Studies have shown across different countries in Europe and Asia that performance expectancy and desire to avoid getting infected was what caused patients to adopt teleconsultation (Baudier et al., 2021). Perceived risk was found to be an inhibitor. Peixoto et al (2022) also found similar results when studying adoption in Brazil. With trust in technology affecting the perceived usefulness. Telemedicine was made available in France through their public health law back in 2009 but did not become popular until the pandemic allowed it to become the front line of allowing patients to continue receiving care (Sebai et al., 2025). Across the European Union, online consultations and prescriptions increased markedly, but the patterns of use differed between countries according to socioeconomic and geographical conditions (Davidescu et al., 2024).

Adoption, however, is only the first step. The commercial and clinical value of a consultation platform depends on whether users come back after their first consultation. Attrition has long been recognised as a defining feature of digital health: Eysenbach (2005) described a "law of attrition" whereby a substantial share of users stop using eHealth applications, and a meta-analysis of app-based interventions for chronic disease reported a pooled dropout rate of 43% (Meyerowitz-Katz et al., 2020). After pandemic restrictions were lifted, it was unclear whether new users would continue to consult online. Among new users in the United Kingdom, continued use depended on confirmed expectations, system and information quality, and users' self-efficacy (Chen et al., 2024). Even where apps exist and patients express interest, actual use often stays low and concentrates on a few platforms (Grijalvo et al., 2026). On the supply side, the need for physical examination, concerns about physicians' remuneration and gaps in training continue to slow the long-term institutionalisation of teleconsultation (Rodrigues et al., 2026). For a subscription-based platform, the step from a first to a second consultation is therefore the decisive point at which a trial becomes a relationship.

Most of the literature has explained this behaviour through users' perceptions and intentions. Studies based on the technology acceptance model and its extensions have identified trust, ease of use, privacy, perceived usefulness, affordability and accessibility as drivers of the intention to use teleconsultation (Ekaimi et al., 2024; Kulkarni et al., 2025; Lu et al., 2024). Other studies have examined satisfaction, showing that technical quality, functional quality, cost and patient cognition shape how patients evaluate teleconsultation (Lu et al., 2021). More recent work has reframed teleconsultation as a platform governance and design problem, showing that some platform attributes act as necessary conditions for patients to recommend a service (Galegale et al., 2026). A systematic review in operations management concluded that patient engagement in remote consultation is multidimensional and cyclical, and is shaped by nine categories of contextual factors across the stages before, during and after the service (Liu et al., 2024). Yet these studies rely mostly on surveys of stated intentions. Studies that use platforms' behavioural records remain fewer, and

most of them draw on Chinese online health platforms and focus on physicians' behaviour rather than on patients' return (Chen et al., 2025; Hu et al., 2026; Liu et al., 2025).

The evidence gap is wider in the Middle East and North Africa (MENA). Regional studies have documented awareness, attitudes and intention to use telemedicine in Jordan (Murshidi et al., 2022), compared public use of telemedicine in Egypt and Saudi Arabia (Hussein & Refaie, 2023), examined satisfaction and barriers in Jeddah (Albaghdadi & Al Daajani, 2023) and reviewed the factors behind telehealth adoption in Saudi Arabia (Alamri & Alshagrawi, 2024). To our knowledge, however, no study has examined the actual consultation records of a private platform operating across several MENA markets, which leaves open whether attitude-based findings translate into repeat use.

The gap matters for management as much as for health research. Healthcare organisations increasingly need flexible service management, defined as the ability to adapt to continuously changing patient demands and resource availability (Hossain et al., 2026). The flexible systems management literature has shown that flexibility is linked to adaptability and performance across sectors. Dynamic capabilities support organisational agility partly through IT capabilities (Awwad et al., 2022). Organisational flexibility improves innovation performance when management support is present (De la Gala-Velásquez et al., 2023). Flexibility and resilience can be built into corporate decision-making under uncertainty (Settembre-Blundo et al., 2021). In healthcare, Kumar et al. (2018) proposed a framework of auxiliary flexibility in healthcare delivery systems. Data analytics is widely seen as an enabler of such adaptability: analytics capabilities create value in healthcare organisations (Wang & Hajli, 2017), and digital capabilities help hospital departments sense and respond to patient needs (van de Wetering, 2021). Little research, however, connects user-level behavioural analytics on a digital health platform to concrete flexibility decisions about which markets, offers, channels and user groups the provider should adapt to.

A methodological gap compounds the substantive one. Users of teleconsultation are heterogeneous: Spanish users fall into distinct latent classes shaped more by their digital lifestyles than by socio-demographic characteristics (Gaitán et al., 2026), and EU citizens' attitudes to teleconsultation form clusters that differ by country (Davidescu et al., 2024). Count outcomes such as the number of consultations are skewed and over-dispersed, and studies of online health engagement have turned to count models to analyse them (Zhang et al., 2025). Few studies, however, combine count models suited to the structure of consultation data with cross-validated machine learning, explainability and segmentation on the same platform records.

This study addresses these gaps using anonymised records of 5,399 millennial users of Altibbi, a teleconsultation platform operating in Jordan, Egypt and Saudi Arabia. It asks three questions:

RQ1. Which demographic and behavioural user attributes are associated with (a) repeat use and (b) consultation intensity on a multi-country mHealth platform?

RQ2. To what extent can these attributes predict repeat use, and which attributes contribute most?

RQ3. What distinct user segments emerge, and which service-flexibility levers do they imply?

The study makes four contributions.

1. *Engagement as two decisions.* It separates retaining a user after the first consultation from deepening use among those retained, using a hurdle model. This shows that the drivers of the two decisions overlap only partly.
2. *Behavioural evidence from MENA.* It provides platform-record evidence from three MENA markets, complementing a regional literature that relies mainly on attitude and intention surveys.
3. *Explanation alongside prediction.* It combines the statistical model with cross-validated machine learning, explainability and segmentation, and reports honestly how much the available attributes can predict.
4. *From evidence to flexibility levers.* It translates the evidence into a matrix of service-flexibility levers for digital health providers, linking behavioural analytics to the flexible systems management literature.

The remainder of the paper is organised as follows. The next section reviews the literature and develops the hypotheses. The methodology section then describes the data and methods, and the results section reports the findings. The discussion section considers the findings and their implications, followed by the limitations and the conclusion.

Literature Review and Hypotheses Development

This section reviews six strands of prior research: the move from teleconsultation adoption to sustained use, the conceptualisation and measurement of engagement, user heterogeneity and segmentation, consultation channels, analytics in digital health management, and flexibility in organisations and healthcare. It then sets out the theoretical lens, summarises the research gaps and develops the hypotheses.

From teleconsultation adoption to sustained use

Research on teleconsultation has been dominated by adoption models. During the pandemic, a cross-national study of 386 respondents in Europe and Asia extended UTAUT2

with personal traits, availability, perceived risk and a new construct of contamination avoidance. It found that performance expectancy and contamination avoidance increased acceptance, whereas perceived risk reduced it (Baudier et al., 2021). In Brazil, a survey of 415 consumers showed that perceived usefulness, itself driven by trust and technology readiness, was central to teleconsultation adoption (Peixoto et al., 2022). A study of 100 teleconsultation users using the technology acceptance model found that trust, ease of use and privacy influenced intention and actual use, while usefulness did not, and that trust was the dominant factor (Ekaimi et al., 2024).

Later studies broadened these models. With 979 respondents, Kulkarni et al. (2025) showed that perceived accessibility benefits and perceived economic benefits mediate the effect of perceived usefulness on the intention to use teleconsultation. They concluded that affordability and accessibility, together with usefulness, best explain adoption. Combining structural equation modelling with fuzzy-set qualitative comparative analysis, Lu et al. (2024) found that perceived usefulness, trust, social influence, economic benefits and perceived severity drove the intention to use telemedicine, and they identified five alternative pathways to adoption behaviour. Satisfaction has been studied as a related outcome: among 459 paying teleconsultation patients, technical quality, functional quality, medical expenses and patient cognition all contributed to satisfaction (Lu et al., 2021).

There are also researches looking at what occurs after adoption. One research from France used mixed methods on 2511 users and hundreds of professionals to determine people's perceptions and their satisfaction with telemedicine post initial lockdown (Sebai et al., 2025). Research done on new users in the UK found that expectation confirmation, system quality and information quality increased self-efficacy and lead to the continuance usage of online consultation. With the user's perception of health risk as a moderating variable (Chen et al., 2024). Galegale et al. (2026) shifted the lens from users to the telemedicine platform. Finding that aspects of the platform that fall under governance affected their intention to use and recommend the teleconsultation platform. Such as whether it was diverse on the platform side and if there are ways to make money from it. They found some factors that where a prerequisite for continuing to use the platform. Healthcare professionals can be resistant to teleconsultations as well. Interviews with health care regulators found that having the ability to physically examine patients was required, lack of compensation and training inhibited them from using teleconsultation on a grander scale in the near future. (Rodrigues et al., 2026).

Similar findings have been found in other areas of teleconsultation. Apps created for patients with multiple sclerosis were studied in spain. They discovered that most of these apps only offered common functionality and are underutilized. Adoption is found in only certain applications (Grijalvo et al., 2026). There should be an awareness of the patient's attitude towards these eHealth apps when doing a usability evaluation as found during the pandemic. Including lifestyle and behaviors and even the patient's knowledge and abilities (Althani, 2021). As discussed before drop off rates continue to be an issue with technology (Eysenbach, 2005; Meyerowitz-Katz et al., 2020).

Studies within the MENA area follow in the lines of adoption. Surveying individuals across Jordan found that ⅔ would be interested in using telemedicine. If they believed they had the knowledge to use electronic devices (Murshidi et al., 2022). Another study correlated people's interest in tele medicine services and their belief that the healthcare was of good quality (Hussein & Refaie, 2023). Tele medicine services have shown high satisfaction from those who used them in Jeddah. Patients ages and how familiar they were with the telemedicine service played a factor in satisfaction (Albaghdadi & Al Daajani, 2023). It was also found in studies within Saudi Arabia that the use of tele health has increased since the pandemic. Factors that led to people continuing to use telehealth was based on infrastructure, policy and culture (Alamri & Alshagrawi, 2024). There is more research that needs to be conducted on the continuance of these platforms.

Conceptualizing and measuring engagement on consultation platforms

Engagement is a broader construct than adoption. In their review of digital behavior change interventions, Perski et al. (2017) conceptualized engagement as having both experiential and behavioural aspects. In their framework, engagement is influenced by the intervention's content and delivery, by the context of use, including the population using it, and by the target behaviour. In healthcare operations management, a systematic review of 63 articles defined patient engagement in remote consultation along dimensions, process, and antecedents and consequences. It identified nine contextual categories that influence engagement and proposed metrics for the stages before, during and after the service, adopting a cyclical view of engagement (Liu et al., 2024).

When engagement is measured as behaviour, platform records become the natural data source. Several recent studies use such records, mostly from Chinese online health platforms. Liu et al. (2025) built an index of doctors' proactive behaviour from consultation rate, number of consultations and response speed, and found an optimal, moderate level of proactivity for online consultation volume. Using

longitudinal data on 2,423 physicians and a difference-in-differences design, Hu et al. (2026) showed that patients were more likely to seek online consultations from physicians who took part in paid knowledge activities. Zhang et al. (2025) modelled patient engagement with doctors' live-streamed content using negative binomial regression, reflecting the count nature of engagement data. Chen et al. (2025) used a 51-month panel to show that physicians' omnichannel integration strongly affected whether new patients chose them for paid online consultations, but had a much weaker effect for existing patients.

Two features of this literature are relevant here. First, the behavioural studies focus mainly on the physician or content side of the platform rather than on the patient's decision to return. Second, they show that new and existing users can respond very differently to the same platform features (Chen et al., 2025). This supports treating the first return as a separate decision from later use.

Evaluation frameworks reach the same conclusion from a different direction. Katsaliaki et al. (2025) adapted the health technology assessment framework to mHealth apps using app-store information and analytics on 172 mental health apps, linking user preferences and app features to engagement. A systematic review of 59 stated-preference studies found that patients prefer health information technologies that are convenient and lower in cost without sacrificing quality, and that preferences vary with demographic features such as age and with the type of health information involved (Crossnohere et al., 2021).

User heterogeneity and segmentation

If preferences differ across users, a single average model of engagement will hide important differences. Several studies have therefore segmented users of digital health services.

- *Lifestyle classes.* In a survey of 1,412 Spanish teleconsultation users, latent class analysis identified eight user profiles, grouped into pro-internet, neutral and anti-internet types. Teleconsultation use was associated more closely with digital lifestyles than with socio-demographic factors alone (Gaitán et al., 2026).
- *Country clusters.* Using Eurofound survey data, hierarchical and k-means clustering revealed different patterns of teleconsultation use across EU countries, shaped by socioeconomic and geographical factors. The authors stressed the need to tailor strategies to each country's needs and digital capabilities (Davidescu et al., 2024).
- *Customer segments.* In health insurance, cluster analysis of users' attitudes led to recommendations to add telemedicine and other features and to offer customisation to prevent switching (Dutta & Singh, 2021).
- *Behavioural segmentation in policy.* Behavioural segmentation, nudges and omnichannel communication have been proposed as tools to engage diverse and marginalised groups in digitally enabled health systems (Abdulwahab, 2026).

Individual differences also moderate how users respond to digital service designs. In two experiments on medical chatbots, the effect of the chatbot's tone of voice on patients' intention to use depended on perceived warmth and competence and was moderated by patients' need for emotional receptivity (Sestino et al., 2025). Household context is a further source of heterogeneity that this literature has rarely examined. Studies of patient portals show that family caregivers often access digital health services on behalf of the people they care for, sometimes by sharing login credentials rather than through formal proxy accounts (Latulipe et al., 2018). For a consultation platform whose accounts can cover several family members, the household may therefore shape engagement as much as the individual user.

Consultation channels and service design

Channel choice is part of how users engage. In a simulation study, Jahan et al. (2025) applied causal forests in a double machine learning setting to compare video, telephone and chatbot consultations, and found better recovery outcomes for video than for telephone calls. Chen et al. (2025) showed that omnichannel integration, the synergistic use of online and offline channels, matters for patients' choice of physicians on a telemedicine platform. Service models can also extend the channel mix beyond the home: an Italian case study showed how real-time teleconsultation delivered through pharmacies changed the pharmacies' role and supported new care models when backed by appropriate organisational design (Musso et al., 2022).

Design choices within a channel also matter. Chatbot features such as tone of voice change patients' intentions (Sestino et al., 2025), and platform governance and design shape willingness to use and recommend (Galegale et al., 2026). For a platform that offers both chat and voice consultations, as Altibbi does, which users prefer which channel is a direct input to service design.

Analytics and machine learning in digital health management

Analytics is increasingly treated as a management capability in healthcare. Gensinger et al. (2021) provide an introduction to the use of analytics in healthcare organisations. Using resource-based theory and a capability-building view, Wang and Hajli (2017) analysed 109 case descriptions from 63 healthcare organisations and traced the paths from

analytics capabilities to business value. In hospital departments, a digital dynamic capability supported the ability to sense and respond to patients, which in turn improved patient service performance (van de Wetering, 2021). In Ugandan health facilities, digital transformation affected patient experience and engagement mainly through a patient-centred strategy rather than directly (Businge et al., 2026). At the organisational level, telehealth adoption has been associated with financial performance: among 1,530 US hospitals observed over 2009–2019, persistent telehealth adopters showed higher operating and total margins (Karim et al., 2025). The data infrastructure behind such analytics, notably cloud computing, also raises security concerns that healthcare organisations must manage (Yin & Rana, 2024).

Some areas that machine learning has been used for within telemedicine is analyzing patients' sentiment towards telemedicine applications during the pandemic. (M & S, 2024) They used support vector machines and a naive Bayes classifier. There have also been studies that look at what type of consultation modality's using causal machine learning (Jahan et al., 2025). Long-term scenario planning has been used to examine how digital tools may support chronic care management in primary healthcare (Peyroteo & Lapão, 2025). What is less common is the use of explainable machine learning on a platform's own user records to inform service decisions, combined with statistical models that respect the structure of consultation counts.

Flexibility in organizations and in healthcare delivery

The flexible systems management literature treats flexibility as an organisation's capacity to adapt to change while preserving what should remain stable. Sushil's (2013) flowing stream strategy frames this as managing continuity and change together rather than as opposites. Edited collections examine flexibility across strategy, organisation, information systems, operations and value chains (Sushil & Stohr, 2014; Sushil & Chroust, 2015). Methodological work in this tradition has proposed structured literature reviews with total interpretive structural modelling (TISM) to build argument-based conceptual models (Sushil & Dinesh, 2022).

Empirical studies in the Global Journal of Flexible Systems Management link flexibility to performance in many settings.

- *IT and agility.* In the Jordanian IT sector, IT capabilities mediated the association between dynamic capabilities and organisational agility (Awwad et al., 2022).
- *Innovation.* Organisational flexibility was associated with innovation performance, with management support acting as a moderator (De la Gala-Velásquez et al., 2023).
- *Decision-making under uncertainty.* Flexibility and resilience have been integrated into a sustainability-based risk management system for corporate decision-making in uncertain times (Settembre-Blundo et al., 2021).
- *Sectors and supply chains.* Studies have examined automotive flexibility in supporting sustainable mobility initiatives through stakeholder attitudes (D'Adamo et al., 2023), the critical success factors of sustainable supply chain flexibility (Chirra & Raut, 2025), and flexibility as a route to resilience against pandemic disruption in textile and clothing supply chains, analysed with the SAP–LAP framework (Majumdar & Srivastava, 2025).
- *People.* At the individual level, a detachment–flexibility–innovation mechanism has been examined in IT workplaces (Panda & T.N.V.R.L, 2025).

In healthcare, Kumar et al. (2018) proposed an integrative framework of auxiliary flexibility in healthcare delivery systems. Hossain et al. (2026) defined flexible healthcare management as the system's ability to adapt to continuously changing patient demands and resource availability, and argued that digital technologies help organisations achieve and sustain it.

Building on this literature, we focus on five forms of flexibility that a multi-country teleconsultation platform can act on directly:

- **Market flexibility:** adapting targets, offers and messaging to each country.
- **Offer flexibility:** adapting the product to the household, for example plans that cover family members.
- **Channel flexibility:** offering and promoting chat or voice consultations to the users who prefer them.
- **Retention flexibility:** adapting follow-up after a first consultation to the users most at risk of not returning.
- **Capacity flexibility:** adjusting physician supply to the demand of the heaviest users.

These categories are the authors' operationalisation for this setting, not an established typology. They are derived from the general flexibility literature cited above.

Theoretical lens: analytics as a sensing capability

The resource-based view holds that firms gain sustained advantage from resources that are valuable, rare, inimitable and non-substitutable (Barney, 1991). The dynamic capabilities view adds that advantage in changing environments depends on the ability to integrate, build and reconfigure competences (Teece et al., 1997). A platform's records of its own users are a resource of this kind. They become a capability only when they are analysed and used to adjust the service, as studies of analytics capabilities in healthcare suggest (Wang & Hajli, 2017; van de Wetering, 2021). Evidence

from the Jordanian IT sector that IT capabilities carry dynamic capabilities into organisational agility (Awwad et al., 2022) points the same way.

We treat the analyses in this study as an instance of this sensing step. They identify which user characteristics are associated with returning and with intensive use, and they turn those associations into flexibility levers (Fig. 1).

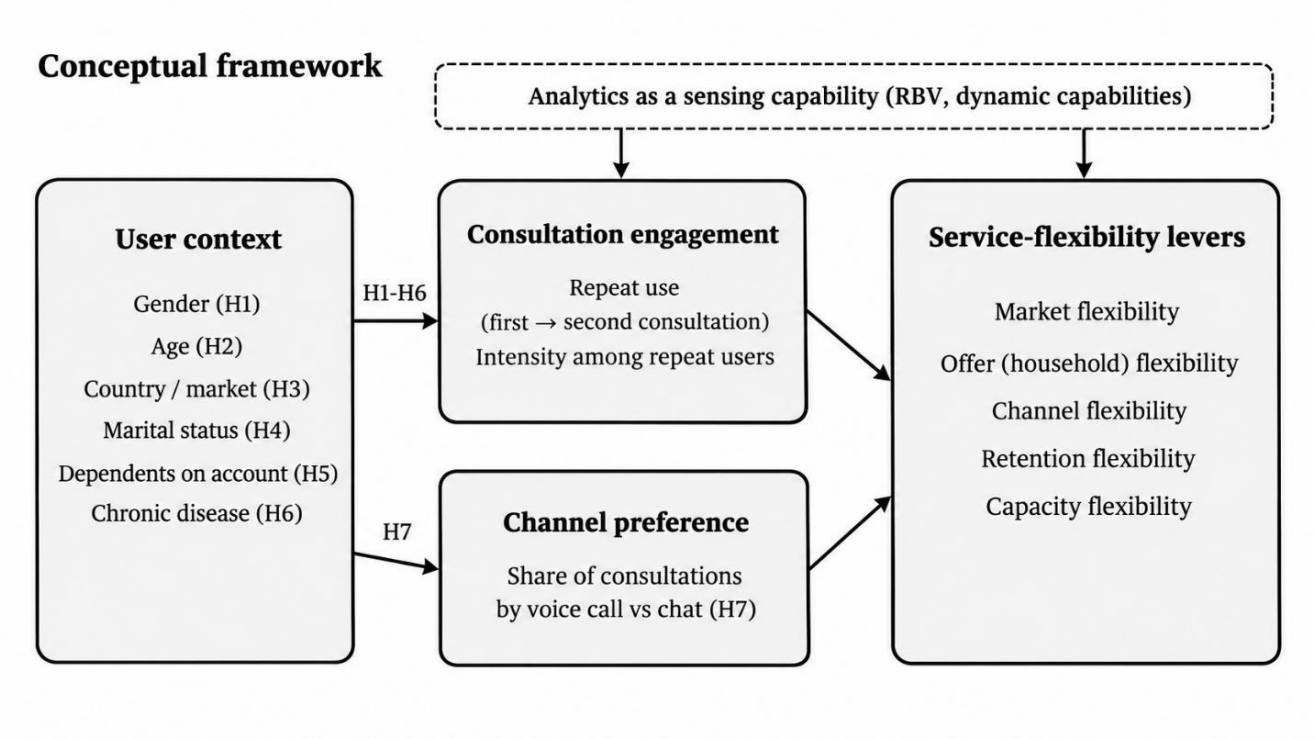

Fig. 1 Conceptual framework of the study

Research gaps

Although research on mobile health (mHealth) platforms and teleconsultation services has expanded considerably, several theoretical, empirical, contextual, and managerial limitations remain unresolved. A substantial proportion of existing research has concentrated on technology acceptance, behavioural intentions, perceived usefulness, and satisfaction rather than actual and sustained engagement with digital healthcare platforms. For example, Baudier et al. (2021), Kulkarni et al. (2025), and Lu et al. (2024) examined factors influencing teleconsultation acceptance and intended utilisation. Although more recent studies have incorporated objective behavioural records, their analytical emphasis has largely concerned physicians' activities and consultation-related performance rather than patients' decisions to return for additional consultations (Hu et al., 2026; Liu et al., 2025). Consequently, limited attention has been devoted to distinguishing between the likelihood of repeat consultation and the intensity of subsequent service utilisation. This distinction is particularly relevant for understanding different stages of patient engagement and identifying opportunities for adaptive service management.

A second important limitation concerns the geographical concentration and contextual relevance of existing evidence. Within the Middle East and North Africa (MENA) region, empirical investigations have primarily employed cross-sectional surveys and literature reviews to understand telemedicine adoption, perceived barriers, and public attitudes (Alamri & Alshagrawi, 2024; Murshidi et al., 2022). However, comparatively little evidence is available from actual consultation records collected across multiple national markets within a single healthcare platform. Furthermore, research investigating user heterogeneity has typically focused on digital lifestyles, socioeconomic characteristics, and national differences (Davidescu et al., 2024; Gaitán et al., 2026). The influence of household-linked accounts, dependents, and consultation channel preferences remains insufficiently explored, despite the potential importance of these characteristics for explaining differences in service demand, repeat utilisation, and user preferences.

A third limitation relates to the connection between behavioural analytics and organisational flexibility. Previous studies have established the significance of dynamic capabilities, information technology capabilities, and organisational flexibility in supporting adaptability and performance (Awwad et al., 2022; De la Gala-Velásquez et al., 2023).

Nevertheless, the application of these theoretical perspectives to user-level behavioural data from digital healthcare platforms remains relatively underdeveloped. In particular, limited research has examined how patterns of consultation engagement can inform specific managerial decisions regarding market differentiation, household-oriented service offerings, communication channels, retention strategies, and resource capacity. Moreover, although quantitative modelling and machine-learning approaches are increasingly employed in healthcare analytics, their integration with interpretable statistical models and user segmentation for the explicit purpose of informing service-flexibility decisions remains insufficiently established in the literature reviewed. To synthesise these limitations, Table 1 identifies the principal research gaps, the supporting literature, and the corresponding contributions of the present study.

Table 1 Summary of identified research gaps and contributions of the present study

Research dimension	Existing literature	Identified research gap	Contribution of the present study
Gap 1: Behavioural engagement	Baudier et al. (2021); Lu et al. (2024); Kulkarni et al. (2025); Hu et al. (2026); Liu et al. (2025)	Limited evidence on actual patient repeat use and subsequent consultation intensity, compared with intentions and physician-focused behaviours.	Examines actual platform records and distinguishes repeat consultation from intensity of use among returning users.
Gap 2: MENA regional context	Murshidi et al. (2022); Alamri & Alshagrawi (2024); Davidescu et al. (2024)	Insufficient multi-country behavioural evidence from mHealth platforms operating within the MENA region.	Investigates consultation engagement across Jordan, Egypt, and Saudi Arabia using 5,399 unique user records.
Gap 3: Household and channel heterogeneity	Latulipe et al. (2018); Davidescu et al. (2024); Gaitán et al. (2026); Sestino et al. (2025)	Limited understanding of how household-linked dependents and user characteristics relate to actual consultation-channel preferences.	Incorporates marital status, dependents, and chronic disease into engagement models and analyses voice-call versus chat utilisation.
Gap 4: Analytics-driven service flexibility	Awwad et al. (2022); De la Gala-Velásquez et al. (2023); Wang & Hajli (2017); van de Wetering (2021)	Limited translation of user-level behavioural analytics into explicit, actionable service-flexibility decisions.	Connects behavioural findings to five proposed flexibility levers: market, offer, channel, retention, and capacity flexibility.
Gap 5: Integrated analytical methodology	Liu et al. (2024); Zhang et al. (2025); Gaitán et al. (2026)	Limited integration of engagement-specific statistical models, explainable predictive analytics, and behavioural segmentation within one analytical framework.	Combines hurdle modelling, fractional-logit regression, cross-validated machine learning, SHAP explanations, and k-prototypes clustering.

Collectively, these research gaps establish the need for an integrated analytical framework that moves beyond explaining telemedicine adoption towards understanding sustained consultation behaviour and translating behavioural evidence into managerial flexibility. Accordingly, the present study draws on the resource-based view and dynamic capabilities perspective to conceptualise analytics as an organisational sensing capability. Using anonymised consultation records from the Altibbi platform in Jordan, Egypt, and Saudi Arabia, the study investigates the demographic, household, geographical, and health-related determinants of engagement while examining the predictive value of these attributes and identifying distinct user segments. Its contribution lies not only in generating empirical evidence from a relatively underexplored regional setting but also in connecting user-level behavioural insights to specific opportunities for adapting digital healthcare services. This integration extends the discussion of flexible systems management into the context of multi-country mHealth platforms.

Hypotheses development

This study looks at consultation engagement using the definition of digital engagement created by Perski et al. (2017) and uses concepts from Liu et al. (2024) about what leads patients to engage. Using these we can look at how users and the service may affect someone engaging in consultations. We measure if a user will engage by measuring repeat usage and intensity of consultation. We measure repeat usage by seeing if someone comes back for another consultation and if they do how many more will they have. We believe that the behaviour of someone returning to use a service and using it more frequently may be driven by different things. The following hypothesis's try to predict whether someone will be more likely to engage with consultations based on their gender, age, country, married and if they have family and if they have a chronic disease. We will also see how each attribute relates to someone using a certain consultation channel. If there is not enough evidence in our review to assume that a behaviour will go up or down we will create non directional hypothesis.

Gender and Consultation Engagement

It can also be assumed that gender could play a role as people may use healthcare services differently due to various factors such as behaviour towards illness and their ability to communicate and navigate technology based health services. It has been found that there are many factors that can effect if a person will use telemedicine and if they are happy with the service provided (Baudier et al., 2021; Lu et al., 2024). In the model proposed by Perski et al (2017) user engagement can be affected by the population who use a digital intervention which can also include characteristics about them. Therefore gender could have an effect on how people use digital consults but this may vary depending on the service being offered.

However there is not enough evidence to say that gender alone can explain why a person may or may not re-consult. Gaitán et al. (2026) found that there are factors relating to ones digital life that may help predict why a person used a teleconsult instead of traditional demographics. It is possible that gender could have similarities with having family and living area so we will look into this when analysing if users engage. As there is no sufficient evidence to show if gender does or doesn't affect user engagement we propose the following hypothesis:

H1. Consultation engagement differs between female and male users.

Age and Consultation Engagement

Age can be considered an important demographic variable when studying eHealth due to it being associated with how much someone knows about technology and what type of care they require and want to have easy access to. Age has been linked to an individuals preference when using technology in the health field. Crossnohere et al. (2021) concluded that people of different ages had varying levels of desire for these types of services. Therefore there may be value placed on these aspects of eHealth when using these platforms at different ages. Age was also found to be associated with satisfaction when patients used telemedicine in Jeddah. (Albaghdadi & Al Daajani 2023). All these show that age could have some factor when using a teleconsultation service and if they continue to use the platform or not.

Although age may have some associations with satisfaction and preferences towards technology. It doesn't necessarily mean that age will affect the amount of times a person consults. A study done by Gaitán et al. (2026) stated that having a digital lifestyle had more to do with teleconsultation then socio-demographics. Therefore questioning if age alone would affect the behaviour of consultation. For our sample we have many people that are in their millennial years so the ages we will see vary isn't as great. Someone of each age may have a need for care and responsibility's which could affect them to re-consult and amount of consultations. A non-directional hypothesis will be made:

H2. Consultation engagement varies with user age.

Country and Consultation Engagement

Due to differences in each country we can expect there to be some variations in user usage of a digital health solution. Each country will have different health care needs, ease of use and views on tele health solutions. There are multiple studies that have looked into users views of tele medicine, utilization and variables within different countries such as Jordan (Murshidi et al., 2022) Egypt (Hussein & Refaie, 2023) and Saudi Arabia (Alamri & Alshagrawi, 2024). These countries have different attributes that may affect users perception on usefulness and accessibility to teleconsultations. By looking at users who use an mhealth platform in different countries we can see that the variables within each country could play a role on a users usage and intention to come back.

Other research has shown similar results with users in different geographical areas. Research has shown that there were variations between teleconsultations across europe which correlated to users socio-demographic background (Davidescu et al., 2024). As well as other variables that affected users intention to use teleconsultations by looking at ease of access and monetary gains (Kulkarni et al., 2025). So when using teleconsultation through the same platform we can see there may be variations when using it in different countries. This variable may also allow for flexibility in the markets:

H3. Consultation engagement differs across Jordan, Egypt, and Saudi Arabia.

Marital Status and Consultation Engagement

It could also be argued that marital status can affect how much people use healthcare. Depending on your marital status there could be different levels of responsibility for ensuring family members have healthcare needs met and organising these for them. Latulipe et al. (2018) found that many family care givers used digital health services on behalf of others. Which can lead us to believe that marital status can play a role in household usage of digital health. As someone on that household may also be using that healthcare.

However there could be factors that play a opposite role on usage. Those that are married could have family members that require the use of digital health and therefore may use it. Those that are single may use healthcare on their own

that allows them to use digital health or if they were previously married may use it for different reasons. There is no correlation that was shown in the studies that related marital status to actually using healthcare again. So we cannot predict which direction marital status will have on usage. With this in mind we will see if there is any difference in usage with those who have different marital statuses but allow for other variables that effect households.

H4. Consultation engagement differs by marital status.

Number of Dependents and Consultation Engagement

Number of dependents could be considered as one variable that relates to the number of individuals within a household. There could be a reason that a household would use more consultations if they have more people under their digital account. In typical research regarding utilization people look at the usage from one person. With subscription-based teleconsultations users have the ability to consult for their entire family. Studies have shown that there are individuals that will consult for others using their digital account. It is possible that some households may have multiple health issues that need attention. Therefore, allowing for more usage of consultations if there are more people under their account. As discussed, earlier number of dependents could also relate to offer flexibility. Because if there are many people under one account there is more likelihood that more consultations will be used. We believe that number of dependents is related to how much care someone would need but we are considering this as an account feature not someone who requires care. With this assumption we will predict that number of dependents is positively correlated with utilization.

H5. The number of dependents linked to an account is positively associated with consultation engagement.

Chronic Disease and Consultation Engagement

As health may play a role in usage because people who suffer from health problems need to see doctors more frequently and may need to ask medical related questions or require consistent care. Telehealth could benefit these types of users as they will be able to consult doctors without traveling and will have easier access to healthcare. Chen et al. (2025) used omnichannel telemedicine for chronic patients and showed that there is value in using multiple digital channels to provide healthcare to users. It can be assumed that if someone has a chronic health condition they will use a teleconsultation more because they may have issues that require more than one visit.

Although some people with health conditions may need to consult doctors regularly there isn't a guarantee they will continue using digital health platforms. Meyerowitz-Katz et al. (2020) found high drop off rates with app based chronic health conditions. Meaning continuous use of digital services may be hard to keep users engaged. There are many factors that could play into why users want to stop using teleconsultation services. They may require an in person visit for more serious health issues or could stop using teleconsultations for a variety of other reasons. So we cannot conclude that health conditions will lead to an increase or decrease in teleconsultations usage. Given these competing considerations, the study adopts a non-directional hypothesis:

H6. Consultation engagement differs between users with and without a chronic disease.

User Characteristics and Consultation Channel Preference

Preference on consultation channel is another behaviour when it comes to using digital health services and something that could be useful when offering flexibility with your service. Many online consultation services offer different forms of communication to patients such as chatting, calling and video calling. Research has shown that the mode of consultation can have an effect on health (Jahan et al., 2025). It has also been found that different characteristics will cause a person to act differently when offered certain digital service designs (Sestino et al., 2025). As people may need different things when consulting remotely there may be differences in how each group utilise their chosen channel.

On Altibbi we offer consultations through chatting and calling so we are able to see which channel our users are utilising. There may be certain users who use more voice calls than others depending on factors such as age, nationality or even if they have children at home. Maybe they like talking on the phone as its quicker to ask and receive information or maybe they enjoy typing out their questions and concerns. Finding out why our users may use one channel over the other could allow us to become more flexible with what communication channels we offer and where we can invest our resources. We do not have enough information from current research to conclude if someone is more likely to use voice calls. Therefore, the present study proposes the following hypothesis:

H7. The share of consultations delivered by voice call rather than chat varies with user characteristics.

Methodology

Research setting and data

The study uses secondary, user-level data from Altibbi, a subscription-based mHealth platform that offers on-demand

chat and voice-call consultations with physicians in Jordan, Egypt and Saudi Arabia. The data were provided by the platform for the dissertation from which this article is derived, under a written permission letter, and were anonymised before release; no direct identifiers were available to the researchers. The records cover millennial users (aged 27–45) who had an active account during 2022–2024 and had completed at least one doctor consultation.

The file received from the platform contained 26,995 rows. An integrity audit showed that every user identifier appeared exactly five times as an identical record, leaving 5,399 unique users after removing 21,596 exact duplicates. All analyses use this deduplicated sample: Egypt (n = 1,998; 37.0%), Saudi Arabia (n = 1,742; 32.3%) and Jordan (n = 1,659; 30.7%). One user's total consultations (190) exceeded the sum of chat and call consultations (187); the reported total was retained. No values were missing. Fig. 2 summarises the analytical workflow, from the data audit to the service-flexibility levers derived in the Discussion section.

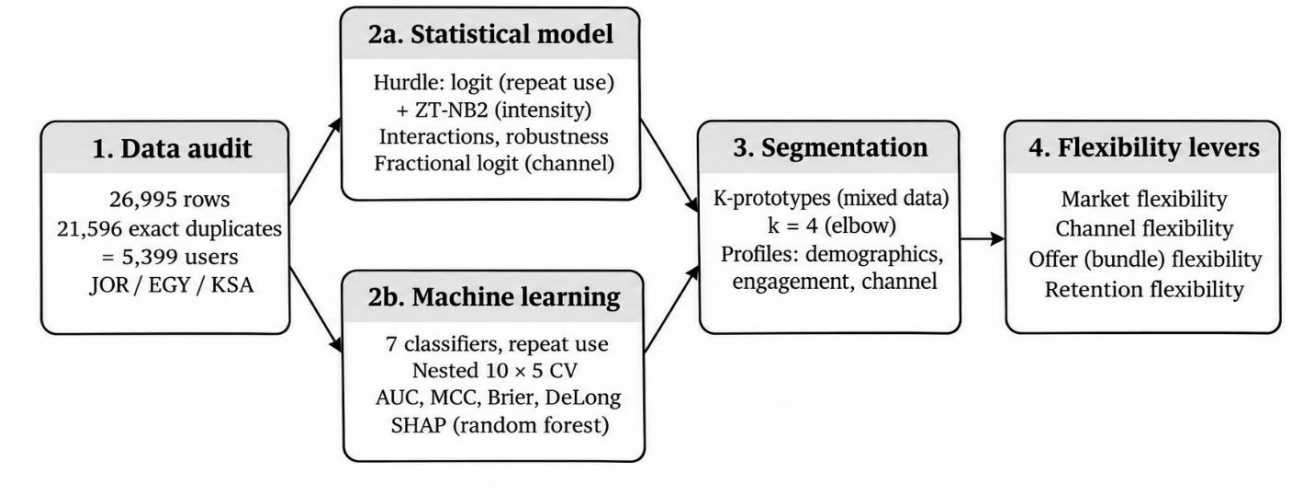

Fig. 2 Analytical workflow of the study

Measures

Consultation engagement was measured by taking the amount of consultations each user completed and ranged from 1-190 consultations with a median of 2. It was heavily overdispersed with a mean of 3.67 and a variance of 62.2. As everyone that completed at least one consultation was in our data we decided to split consultation engagement into two different concepts. First, repeat use. If the user completed 2 or more consultations they would be labelled as a repeat user. The second was how many consultations they completed after their first. By operationalising consultation engagement in this manner we can look at if the user came back to the platform and how much they used it.

There are six demographic/geographical/household/health factors that we will use to see what factors play a role in consultation engagement. Gender was categorised as female and male. Age was measured in years and mean centred then divided by 5 to allow the coefficients to have an understandable interpretation. There were three countries in our dataset Saudi Arabia, Egypt and Jordan. We used Saudi Arabia as our base for country. Married status was measured as married, single or divorced/widowed. We used married as our base and grouped divorced and widowed together due to low number of respondents in those categories (n=112 and n=87 respectively). Number of dependents was measured by the number of dependents a user had on their profile it ranged from 1-73 so we took a natural log to prevent extreme numbers from affecting our data. Since they all had at least one dependent we assumed this was the number of family profiles on their account. This needs to be verified with the company. Last we used if the user had a chronic disease or not (n=37). All these variables will help us identify why users come back to the platform and how much they use it once they return.

Channel preference was also operationalised to see why users may choose to use voice calls over chatting when completing consultations on the platform. Channel preference was calculated by taking a users number of voice call consultations divided by their total number of voice call and chat consultations. Allowing us to see how often users use the voice call function compared to chat. Like consultation engagement we will look at what demographic/geographical/household/health factors can affect a users choice of channel.

Statistical modelling

Non-parametric bivariate tests were used to assess if user attributes were associated with the number of consultations received. A Mann–Whitney U test with rank biserial

correlation was conducted when appropriate, the Kruskal–Wallis H test with Epsilon squared (ε2) and the Spearman's Rho (ρ) correlation coefficient were used where fitting. Pairwise comparisons were made for country and marital status and corrected for p-value via the Holm correction (Holm, 1979). We examined which model would be most suitable for our data and estimated four different types of count models. Zero truncated poisson, zero truncated negative binomial (NB2), negative binomial modelled on the count shifted down by one (y -1) and the hurdle model (Mullahy, 1986; Cameron & Trivedi, 2013). It was found that the hurdle model provided the best fit to the data with an AIC of 20,292.9 and BIC of 20,418.2 compared to a AIC of 20,435.8 and BIC of 20,501.8 for the zero truncated NB2 model. AIC of 20,519.4 and BIC of 20,585.4 for the negative binomial on shifted counts model. The zero truncated NB2 model had a unstable dispersion estimate.

The hurdle model consisted of a logistic regression predicting if a user would return to use the service. Results were reported as odds ratios (OR). And a zero truncated NB2 model predicting how many more times those who returned came back to receive consultations (n = 3,022). Results were reported as incidence rate ratios (IRR). Both parts of the model had robust standard errors to correct for heteroskedasticity and multicollinearity was not of concern (VIF < 1.53). Interaction terms of country and gender and country and marital status were tested and the Holm correction was made to the p value from the likelihood-ratio test. We estimated probabilities of returning to use the service, number of consultations and expected counts using average adjusted predicted values. We tested the robustness of the model by binning the number of dependents into 1, 2 and > 3. We also removed the highest 1% of people that used the service and those with more than 10 dependents. And finally we removed the variable for having a chronic disease. Fractional-logit was used to see if the preferred method of receiving consultations was associated with any user characteristics. Number of consultations was used to weight each observation and all variables as well as the log of the total number of consultations were included in this model. Pearson's Scaled Dispersion was reported along with robust standard errors.

Machine learning

Machine learning methods were applied to predict which demographics would return to consult again (56.0%). Variables of interest were as follows; female, age, number of dependents, chronic disease and if they live in Egypt or Jordan as well as marital status (single, divorced and widow). As there were different channels they could use we omitted consultation channel total to not have the outcome variable. Machine learning methods used were logistic regression, decision tree, K-Nearest Neighbours, SVM radial, Random forest, XGBOOST and Lightgbm. Using nested cross validation we assessed how well these methods predicted who would use more than once. A 10 fold outer cross validation and 5 fold inner cross validation was used (Varma & Simon, 2006). Each model except SVM radial had 20 attempts to find the optimal set of parameters with 8 being used for SVM.

We looked at how each method performed at predicting users. Using AUC, precision recall AUC, accuracy, balanced accuracy, F1 score, Matthes correlation coefficient and brier score with cutoff values of 0.5 (Chicco & Jurman, 2020). DeLong's test was used to determine if any method performed better than the top classifier. We also assessed calibration of models by predicted probability groups of 10%. The best classifier was refit on all the data with the mode of the best parameters found during parameter search. Number of trees was set to 300 with max depth of 6. Each split used 50% of features and at least 100 observations per terminal node. We then assessed what features were contributing to our model using SHAP values.

User segmentation

Users were segmented into different clusters using k-prototypes as there were both numeric and categorical variables used. These variables consisted of Age, log of number of dependents, log of number of consultations taken and ratio of consultations that were voice-calls which were all standardised. The variables Gender, Country and Marital Status were also included as they were categorical. The clustering process used Cao's method of initialisation and 2 initializations for each solution (Cao et al., 2009). Solutions with 2-7 clusters were examined and an elbow criterion was used to decide how many clusters should be created.

A total of 4 clusters were created as the difference between cost from cluster 2 to 3 decreased by 20.6% and 3 to 4 decreased by 15.6%. Whereas from cluster 4 to 5 the difference was only 8.4%. All clusters were then looked at in terms of their demographics and consultations they took out to find differences that could help offer flexible services. Python version 3.13 was used to complete these analyses. Statsmodels 0.15.0, Sklearn 1.9.1, XGboost 3.4.1, LightGBM 4.7.0, Shap 0.54.1 and Kmodes 0.12.2 were used. The zero truncated NB2 was found by directly estimating the likelihood function using Scipy 1.18.1. Code can be obtained from the authors.

Results

Descriptive profile

Engagement was concentrated in a minority of users. Across the 5,399 users, the median number of consultations was 2 and the mean 3.67 (SD 7.89); 44.0% consulted only once (Table 2). Unadjusted engagement was highest in Jordan (mean 5.36; 69.1% repeat users) and lowest in Saudi Arabia (2.50; 44.6%). It rose steeply with the number of dependents, from 47.7% repeat users among users with one dependent to 81.2% among those with three or more. Fig. 3 shows the long right tail of the distribution, which is heaviest in Jordan.

Table 2 Sample profile and unadjusted consultation engagement (n = 5,399)

Variable	Level	n	%	Mean (SD)	Median (IQR)	Repeat users (%)
All users	—	5,399	100.0	3.67 (7.89)	2 (1–3)	56.0
Gender	Female	2,682	49.7	3.88 (9.14)	2 (1–3)	56.5
	Male	2,717	50.3	3.47 (6.40)	2 (1–3)	55.4
Country	Saudi Arabia	1,742	32.3	2.50 (3.85)	1 (1–3)	44.6
	Egypt	1,998	37.0	3.30 (5.29)	2 (1–3)	55.0
	Jordan	1,659	30.7	5.36 (12.20)	2 (1–5)	69.1
Marital status	Single	2,687	49.8	4.40 (8.53)	2 (1–4)	62.4
	Married	2,513	46.5	2.77 (5.46)	1 (1–3)	49.2
	Divorced	112	2.1	1.88 (1.25)	1 (1–2)	42.9
	Widowed	87	1.6	9.84 (25.96)	2 (1–7)	70.1
Dependents	1	3,778	70.0	2.57 (4.28)	1 (1–3)	47.7
	2	872	16.2	4.26 (8.19)	2 (1–5)	70.3
	3 or more	749	13.9	8.56 (15.73)	4 (2–9)	81.2
Chronic disease	No	5,362	99.3	3.64 (7.49)	2 (1–3)	56.0
	Yes	37	0.7	7.97 (30.93)	1 (1–2)	48.6
Age (years)	27–29	1,562	28.9	3.52 (5.85)	2 (1–3)	54.6
	30–34	1,872	34.7	3.97 (9.65)	2 (1–4)	58.5
	35–39	1,183	21.9	3.87 (8.75)	2 (1–4)	55.5
	40–45	782	14.5	2.97 (4.62)	2 (1–3)	53.3

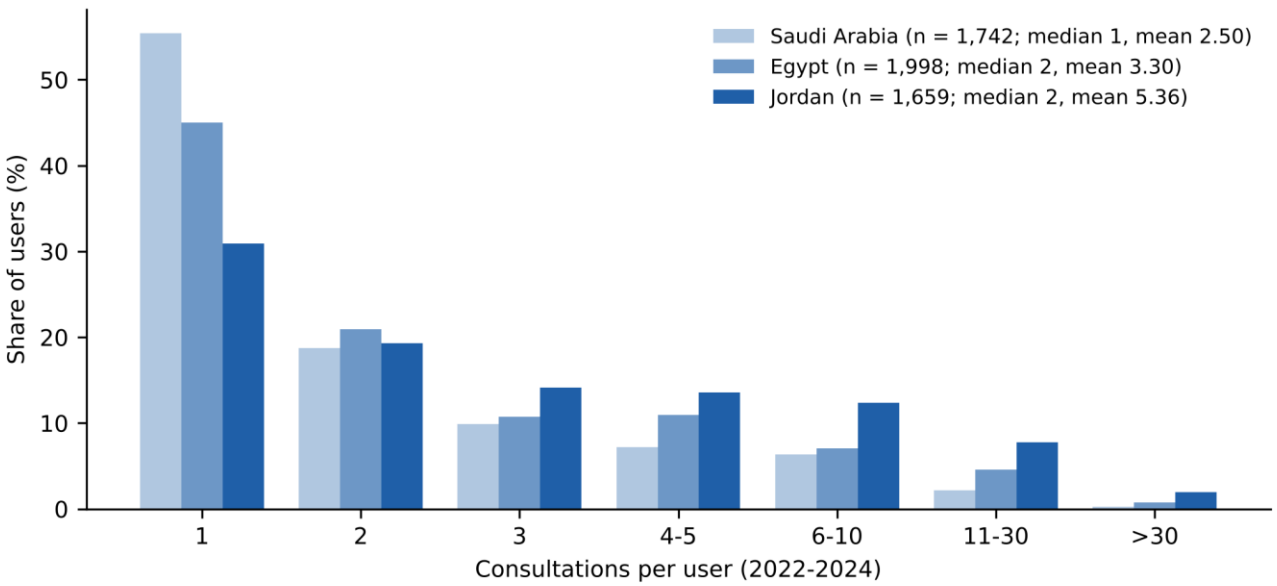

Fig. 3 Distribution of consultations per user by country

In the bivariate tests (Supplementary Tables S1–S2), country ($H = 276.76$, $\varepsilon^2 = 0.051$), marital status ($H = 164.20$, $\varepsilon^2 = 0.030$) and dependents ($\rho = 0.342$) were associated with consultation counts (all Holm-adjusted $p < 0.001$). Gender ($r = 0.008$), age ($\rho = -0.014$) and chronic disease ($r = 0.114$) were not (Holm-adjusted $p = 0.626$). All three pairwise country contrasts were significant; Saudi Arabia versus Jordan showed the largest effect ($r = 0.309$).

Drivers of repeat use and consultation intensity

According to the results in Table 3 number of dependents, country and marital status were key correlates of consultation utilization. Number of dependents was the highest predictor of consultation usage within the first hurdle model (n=5399 users) (OR = 2.74, 95%CI = [2.37, 3.16] p<0.001). Meaning if a users number of dependents increased by one unit (log transformed) they would have 2.74x the odds of coming back for an additional consultation. There were also differences based on country with Egypt having 1.44 times greater odds of using again (p<0.001) and Jordan 1.91 times greater odds of using again (p<0.001). Than those that resided in Saudi Arabia. Those who were single had a higher chance of coming back compared to married users (OR = 1.18, p=0.008). While there was no significance difference between previously married and married users (p=0.430). No other variables were statistically significant (p>0.05).

Within our second hurdle model we evaluated how many consultations repeat users (n=3022) would return with. Once again the number of dependents was our highest predictor (IRR = 2.37, 95% CI = [2.07, 2.71], p<0.001) so having an account that links to your family members may increase chance of coming back to the platform and utilizing it more. Differences were also found in country where Egypt (IRR = 1.33, p=0.020) and Jordan (IRR = 1.52, p=0.002) used the service more than those from Saudi Arabia. When looking at marital status differences were less prominent with those that were single having no significant difference than married users (IRR = 1.14, p=0.236). Previously married showed a slightly decrease in amount of consultations used (IRR = 0.72, p=0.056). Again no other variables were found to be statistically significant. Having a higher number of dependents and residing in different countries may correlate to amount of consultations used.

Figure 4 shows the averages that can be predicted using our hurdle model. If a user increased their dependents from 1 to 2 they had a higher chance of coming back to use the service going from 49.5% to 66.1% and will come back to use the service an average of 2.63 to 4.15 times. Once the number of dependents reach 3 the chance of coming back increased to 74.4% and with 5 dependents they will have a 82.9% chance of using again. The number of times they will use the service will also increase from 4.15 to 5.48 with three dependents and 7.80 with 5 dependents. As shown above when using country as a predictor those from Saudi Arabia are predicted to come back 2.91 times, Egypt 3.64 and Jordan 4.15. Gender made very little difference in number of times the service was used males averaging 3.56 and females 3.71 times. We see similar trends as our models above when trying to predict the amount someone will use the service number of dependents and country play a bigger role then gender.

Table 3 Hurdle model of consultation engagement

Predictor	Part 1: Repeat use, OR [95% CI]	p	Part 2: Intensity, IRR [95% CI]	p
Country: Egypt (ref. Saudi Arabia)	1.44 [1.25, 1.65]	< 0.001	1.33 [1.05, 1.70]	0.020
Country: Jordan (ref. Saudi Arabia)	1.91 [1.65, 2.22]	< 0.001	1.52 [1.17, 1.96]	0.002
Single (ref. married)	1.18 [1.05, 1.33]	0.008	1.14 [0.92, 1.43]	0.236
Previously married (ref. married)	0.88 [0.64, 1.21]	0.430	0.72 [0.51, 1.01]	0.056
Female (ref. male)	1.05 [0.93, 1.18]	0.443	1.06 [0.88, 1.28]	0.511
Age (per 5 years)	0.98 [0.92, 1.04]	0.474	0.93 [0.85, 1.02]	0.110
Dependents (log)	2.74 [2.37, 3.16]	< 0.001	2.37 [2.07, 2.71]	< 0.001
Chronic disease	0.69 [0.34, 1.43]	0.320	3.58 [0.60, 21.29]	0.161
n	5,399		3,022	
Fit	McFadden $R^2 = 0.067$		$\alpha = 15.89$	

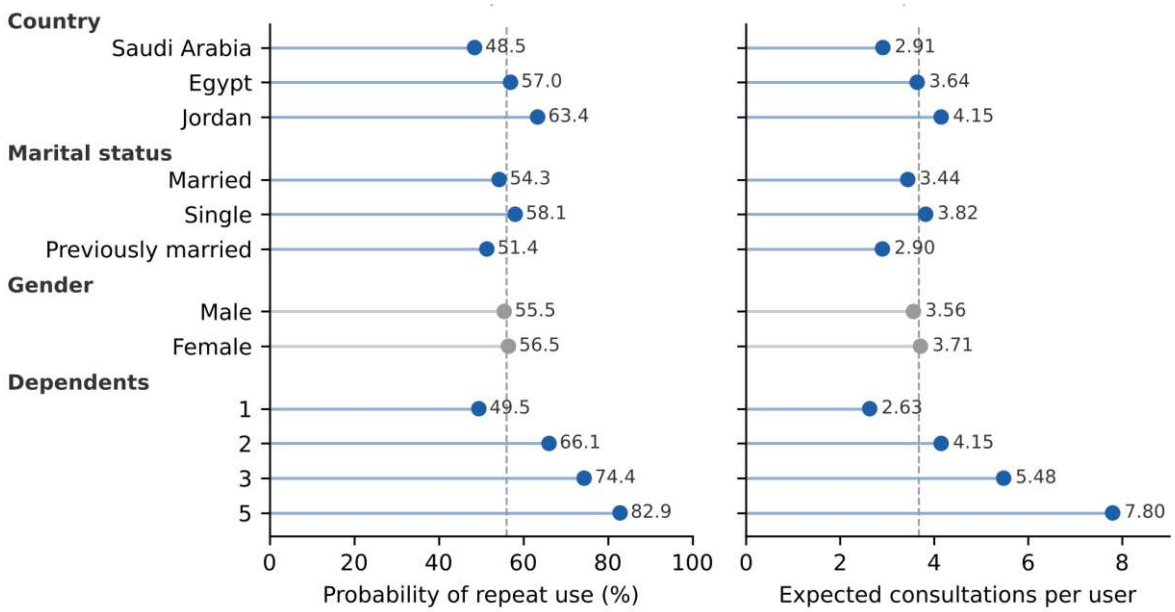

Fig. 4 Average adjusted predictions of repeat use and expected consultations, by attribute

The interaction analysis revealed that neither country × gender nor country × marital status significantly improved model fit after Holm adjustment (Supplementary Table S3). Specifically, country × gender interactions were non-significant for both repeat use ($\chi^2(2) = 2.95$, $p = 0.229$) and consultation intensity ($\chi^2(2) = 1.46$, $p = 0.482$), as were country × marital status interactions ($\chi^2(4) = 7.33$, $p = 0.119$; $\chi^2(4) = 1.76$, $p = 0.779$, respectively). These findings suggest that country-related differences in engagement were broadly consistent across gender and marital-status groups. Furthermore, robustness analyses confirmed the stability of the main findings across four alternative specifications (Supplementary Table S4), with country and number of dependents retaining their direction and statistical significance throughout. When dependents were categorised, users with two dependents (OR = 2.25) and three or more dependents (OR = 3.62) demonstrated higher odds of repeat use than those with one dependent. The association between single marital status and repeat use also remained consistent (OR = 1.18–1.19). However, excluding the top 1% of users by consultation frequency revealed a small negative association between age and consultation intensity (IRR = 0.92 per five years, $p = 0.027$), while previously married users exhibited significantly lower consultation intensity in two alternative specifications (IRR = 0.67–0.69, $p < 0.05$). Overall, these results support the robustness of the primary findings while highlighting limited sensitivity in selected demographic associations.

Channel preference

Chat was the most commonly used consultation channel in all three countries. 60.4% of users used only chat and 20.4% used only voice-calls. There was a difference between the countries when looking at channel utilisation ($\chi 2$ (4)=81.62, $p < 0.001$). Users using chat and voice-calls was highest in Jordan at 26.0%. Then Egypt at 18.2% and lastly Saudi Arabia at 14.0%. The above shows that there are significant differences across each country regarding consultation-channels. This can be taken into account when providing a more flexible consultation channel through a digital health platform.

As shown in Table 4 gender, age, country and if you have a chronic disease were all associated with using voice-calls. Females were less likely to use voice-calls compared to chat than males (OR=0.68, 95% CI [0.58-0.79], p<0.001). Age was also associated with voice-call utilisation (OR=1.22, for every increase of 5 years, 95% CI [1.12-1.33], p<0.001). Egypt (OR=0.77, p=0.014) and Jordan (OR=0.66, p<0.001) had lower shares of voice-calls when compared to Saudi Arabia. If you had a chronic disease, you were more likely to use voice-calls (OR=23.96, p=0.003). Though this estimate should be interpreted with caution due to small sample size n=37 and large CI (95% CI [2.92-196.67]). You were also more likely to use voice-calls the more consultations you did (OR=1.10, p=0.039). Marital status and how many people you depended on were not associated with voice-call utilisation (p>0.05). This shows that different demographics have a higher chance of using certain channels over others.

Table 4 Fractional-logit model of the share of consultations delivered by voice call

Predictor	OR [95% CI]	p
Country: Egypt (ref. Saudi Arabia)	0.77 [0.63, 0.95]	0.014
Country: Jordan (ref. Saudi Arabia)	0.66 [0.53, 0.82]	< 0.001
Single (ref. married)	0.94 [0.78, 1.13]	0.493
Previously married (ref. married)	1.08 [0.74, 1.59]	0.682
Female (ref. male)	0.68 [0.58, 0.79]	< 0.001
Age (per 5 years)	1.22 [1.12, 1.33]	< 0.001
Dependents (log)	1.07 [0.92, 1.24]	0.394
Chronic disease	23.96 [2.92, 196.67]	0.003
Total consultations (log)	1.10 [1.01, 1.21]	0.039

Note. Binomial GLM of the call share, weighted by each user's consultations, with Pearson-scaled dispersion and robust 95% CIs (n = 5,399).

Predictive performance and explainability

The machine-learning results presented in Table 5 indicate moderate predictive performance in identifying repeat consultation users based on demographic, geographical, and household characteristics. Random forest achieved the highest discriminative performance (AUC = 0.670, SD = 0.023), followed closely by XGBoost (AUC = 0.669) and logistic regression (AUC = 0.666). However, DeLong's tests revealed no statistically significant differences between random forest and XGBoost (Holm-adjusted p = 0.290) or logistic regression (p = 0.158), suggesting that more complex algorithms provided limited predictive improvement over conventional regression. Random forest nevertheless significantly outperformed LightGBM (p = 0.027), decision tree, support vector machine, and k-nearest neighbours (all p < 0.001). Balanced accuracy among the best-performing models ranged from 0.616 to 0.628, while random forest achieved an accuracy of 0.630, F1-score of 0.661, and Matthews correlation coefficient of 0.256, compared with a majority-class baseline accuracy of 0.560. Furthermore, random forest demonstrated satisfactory probability calibration (Brier score = 0.225), with observed repeat-use rates deviating from predicted probabilities by no more than 3.3 percentage points across probability deciles ranging from 0.39 to 0.80. Overall, these findings indicate that the available user characteristics offer useful but limited predictive information, while more computationally complex models do not necessarily yield meaningful improvements in repeat-use prediction.

The SHAP analysis presented in Fig. 5 provides further insight into the relative contributions of individual predictors and supports the findings of the hurdle regression model. The number of dependents emerged as the most influential feature, accounting for 47.3% of the total mean absolute SHAP contribution, followed by Jordanian market membership (25.0%), single marital status (12.2%), Egyptian market membership (9.0%), age (4.6%), and female gender (2.0%). In contrast, chronic-disease status and the divorced and widowed indicators showed negligible contributions. The relationship between dependents and predicted repeat use was nonlinear, with users having one dependent exhibiting a negative mean SHAP value (−0.067), compared with a positive contribution among users with two dependents (+0.129). The effect increased further before stabilising at approximately +0.18 for users with four or more dependents, indicating that the transition from one to two dependents contributed more substantially to repeat-use predictions than subsequent increases. These findings reinforce the importance of household-linked characteristics and geographical context in explaining consultation engagement, while highlighting the potential of explainable machine learning to inform targeted retention strategies and data-driven service-flexibility decisions.

Table 5 Nested cross-validated performance in predicting repeat use (10 outer folds; mean, with SD for AUC)

Model	AUC (SD)	PR-AUC	Accuracy	Balanced accuracy	F1	MCC	Brier	DeLong p vs RF (Holm)
Random forest	0.670 (0.023)	0.720	0.630	0.628	0.661	0.256	0.225	—
XGBoost	0.669 (0.021)	0.716	0.626	0.627	0.649	0.253	0.226	0.290
Logistic regression	0.666 (0.020)	0.720	0.624	0.616	0.671	0.234	0.227	0.158
LightGBM	0.665 (0.020)	0.714	0.626	0.622	0.663	0.245	0.227	0.027
Decision tree	0.664 (0.023)	0.700	0.632	0.627	0.670	0.256	0.227	< 0.001
SVM (RBF)	0.648 (0.019)	0.696	0.619	0.608	0.671	0.220	0.232	< 0.001
k-nearest neighbours	0.641 (0.026)	0.692	0.602	0.597	0.642	0.194	0.232	< 0.001

Note. Majority-class baseline accuracy = 0.560. DeLong tests use pooled out-of-fold predictions. RF = random forest; MCC = Matthews correlation coefficient.

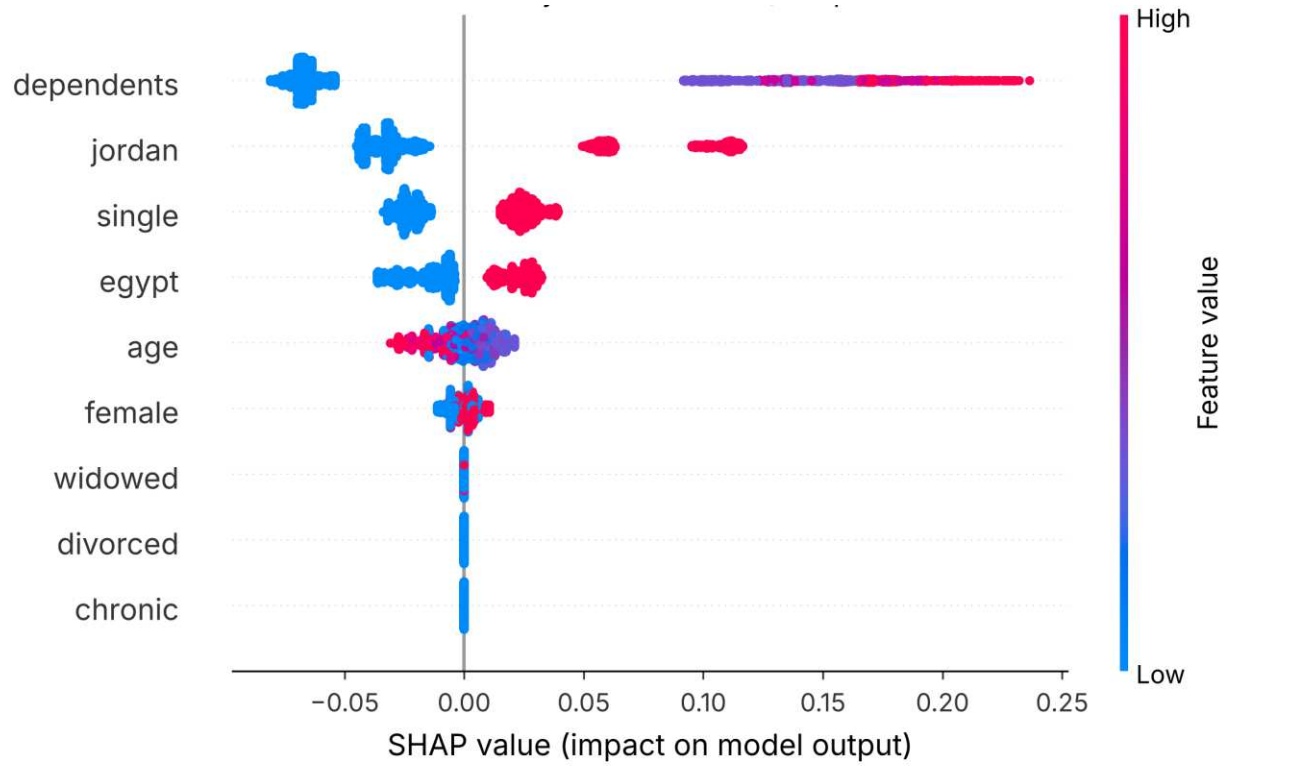

Fig. 5 SHAP summary of the random-forest model of repeat use

User segments

The k-prototypes clustering analysis identified four distinct user segments characterised primarily by differences in household dependents, consultation engagement, and channel preferences (Table 6; Fig. 6). Segment S2 (17.3%) represented the platform's most engaged user group, with 95.4% returning for additional consultations, an average of 10.85 consultations per user, and 4.13 dependents per account. This segment consisted predominantly of Jordanian users (62.7%) and single individuals (78.8%) and exhibited the most diversified utilisation of chat and voice-call services. In contrast, Segment S3 (24.1%) was characterised by a strong preference for voice consultations, which accounted for 88.8% of its total consultations, with no users relying exclusively on chat. This group demonstrated moderate engagement, with 58.3% completing repeat consultations.

Segments S1 (22.3%) and S4 (36.4%) represented lower-engagement groups, with approximately 90% of users in each segment relying exclusively on chat consultations. Their repeat-use rates were 40.4% and 45.3%, respectively. However, these segments differed considerably in demographic and geographical composition. S1 comprised relatively older users (mean age = 38.5 years) and was

predominantly associated with Saudi Arabia, whereas S4 consisted of younger users (mean age = 29.6 years) and was mainly concentrated in Egypt. Overall, the segmentation findings reveal substantial heterogeneity in consultation behaviour, highlighting the importance of household composition, geographical context, and communication preferences. These distinctions provide an empirical basis for developing differentiated retention strategies, household-oriented service offerings, channel flexibility, and market-specific service management approaches.

Table 6 Profile of the four user segments (k-prototypes)

Attribute	S1 Older one-time chat users	S2 Family-account heavy users	S3 Call-first users	S4 Young chat trial-lists
Users, n (%)	1,202 (22.3)	932 (17.3)	1,299 (24.1)	1,966 (36.4)
Mean age (years)	38.5	33.3	34.0	29.6
Female (%)	57.5	57.6	43.0	45.6
Main country (%)	Saudi Arabia (47.9)	Jordan (62.7)	Egypt (39.5)	Egypt (48.4)
Single (%)	24.5	78.8	44.5	54.9
Mean dependents	1.18	4.13	1.28	1.16
Mean consultations (median)	1.75 (1)	10.85 (6)	2.76 (2)	2.06 (1)
Repeat users (%)	40.4	95.4	58.3	45.3
Call share of consultations (%)	6.7	30.7	88.8	6.6
Chat-only users (%)	90.6	43.5	0.0	89.8

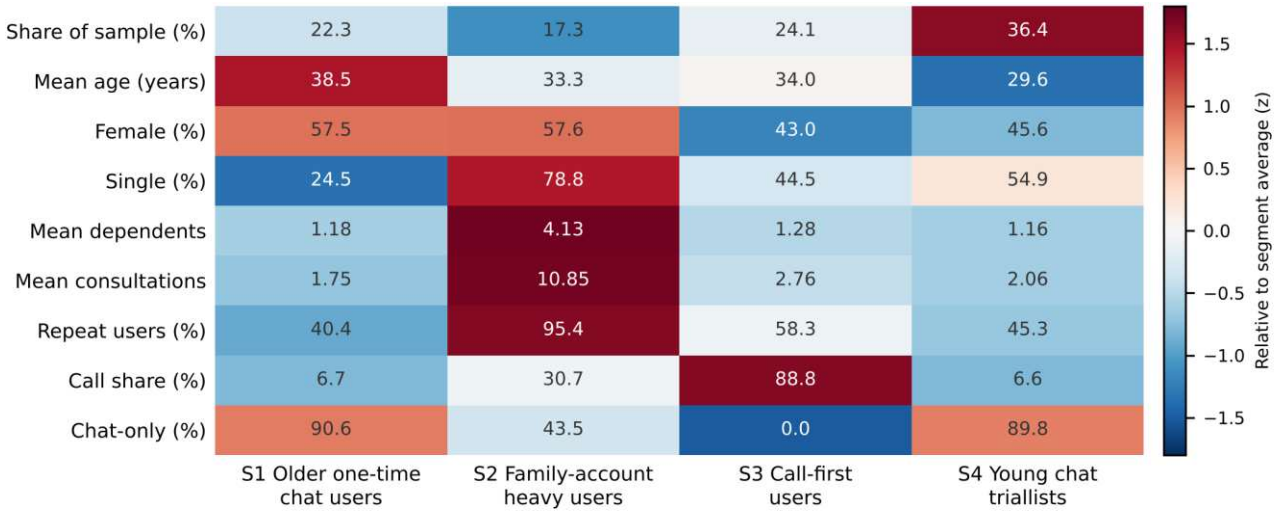

Fig. 6 Segment profiles relative to the average across segments

Summary of hypothesis tests

When testing our hypotheses we found that people who used our consultations were more likely to have a relationship with their country of residence and the amount of people in their household. When we tested if a person was more likely to be a repeat user or increase the number of times they consult based on their country. We found that H3 was true. Jordanians were more likely to be a repeat user and had higher amounts of consultations compared to users from Egypt and Saudi Arabia. We also found that H5 was true when looking at number of dependents a person has. This had a strong correlation with being a repeat user and number of consultations a person uses. When looking at H1 and H2 we were unable to find any evidence that gender or age had a relationship to being a repeat user or having an increased number of consultations. H4 was half true we found that users who are single had a greater chance of being a repeat user than users who were married. But marital status did not show that a person will have more consultations. We also found that H6 was false users with a chronic disease had no greater chance of being a repeat user or consulting more often. It should be noted that we only had 37 users with a chronic disease which may affect these findings.

We also tested if there was a relationship between the number of times someone used the voice channel over chat and gender age and country. We found that H7 was true.

Females had less voice usage then males. When we looked at age, we found that as users got older, they preferred using the voice channel. We also found a difference when looking at each country users in Saudi Arabia used more of the voice channel compared to Egypt and Jordan. From our findings we can conclude that there are different factors that lead a person to use our service more or become a repeat user. The number of dependents someone has in their household and what country they live in had a greater effect on whether a person would use our service more or be a repeat user. But when it came to which channel someone used, they were affected by their gender and age. These results give us insight on why we should offer flexibility in our service and tailor our offering to different markets, households and channels.

Table 7 Summary of hypothesis tests

Hypothesis	Repeat use (Part 1)	Intensity (Part 2)	Verdict
H1 Gender	n.s.	n.s.	Not supported
H2 Age	n.s.	n.s.	Not supported
H3 Country	Jordan > Egypt > Saudi Arabia	Jordan, Egypt > Saudi Arabia	Supported
H4 Marital status	Single > married	n.s.	Partly supported (repeat use only)
H5 Dependents	Positive	Positive	Supported (strongest effect)
H6 Chronic disease	n.s.	n.s.	Not supported (n = 37; underpowered)
H7 Channel preference	—	—	Supported: gender, age and country predict call share

Discussion

This study set out to identify which user attributes are associated with returning to, and intensively using, a multi-country mHealth consultation platform, and to translate the evidence into service-flexibility levers. Five findings stand out. Each is discussed below against the literature reviewed earlier.

The number of dependents linked to an account predicted both whether a user returned (OR = 2.74 per log unit) and how much they used the service (IRR = 2.37), and it carried almost half of the random forest's explanatory weight. This is consistent with evidence that digital health services are often used on behalf of family members, sometimes through shared credentials rather than formal proxy accounts (Latulipe et al., 2018). It also extends the literature on user heterogeneity: earlier studies segmented users by digital lifestyle (Gaitán et al., 2026) or by country (Davidescu et al., 2024), whereas our results point to the household linked to an account as a distinct and powerful source of heterogeneity. Two features of the result matter for interpretation.

- *The step, not the count.* The step from one to two dependents changed predicted repeat use (49.5% to 66.1%) more than any later increase, and the SHAP contribution levelled off from about four dependents onward. The first additional family member is therefore the critical threshold.
- *A partly mechanical effect.* Accounts that cover more people should generate more consultations simply because more people can fall ill. The data record consultations per account, not per person, so this study cannot separate more people from more use per person.

Engagement followed a stable gradient, Jordan > Egypt > Saudi Arabia, in both repeat use and intensity. Because none of the country interactions was significant, the gap is a market-level difference rather than a difference in how particular groups behave within a market. This pattern mirrors the cross-country variation in teleconsultation use reported in the European Union (Davidescu et al., 2024) and the differences in public use of telemedicine between Egypt and Saudi Arabia (Hussein & Refaie, 2023). The data cannot identify its causes. Several explanations are consistent with the literature: differences in affordability and accessibility (Kulkarni et al., 2025), in the cost and quality of the service as perceived by patients (Lu et al., 2021), in competing public and private telehealth provision (Alamri & Alshagrawi, 2024), and in platform governance and pricing logic (Galegale et al., 2026). Testing these explanations requires market-level data on prices, competition and plans.

After adjustment, neither gender nor age was associated with engagement, and the small unadjusted gender difference disappeared once household and market were controlled. Both were, however, associated with channel choice: women used chat more and calls less, and the call share rose with age. This pattern agrees with the systematic finding that preferences for health information technologies vary with demographic features such as age (Crossnohere et al., 2021). It also qualifies adoption studies that place demographics alongside perceptions (Albaghdadi & Al Daajani, 2023; Murshidi et al., 2022): in behavioural data, demographics may matter less for whether people use a service than for the form in which they use it. The reasons for the gender difference in channel choice, such as privacy, convenience or the type of health concern, cannot be tested with

these data. Experimental evidence that individual differences moderate responses to service design (Sestino et al., 2025) suggests that such differences deserve direct study.

Single users were more likely to return than married users (OR = 1.18) but did not consult more intensively once they had returned. This asymmetry supports the decision to model engagement as two parts: the two decisions do not share all their drivers, which is consistent with the finding that new and existing platform users respond differently to the same features (Chen et al., 2025). No effect of chronic disease could be established. With only 37 such users, the test had little power, so the result says nothing about the role of chronic conditions, which the literature treats as central to digital health (Chen et al., 2025; Meyerowitz-Katz et al., 2020).

The six attributes predicted repeat use with an AUC of about 0.67, and flexible machine-learning models did no better than logistic regression. This is a substantive result, not only a technical one. It agrees with the view that engagement depends on the service and the context of use, not only on who the user is (Liu et al., 2024; Perski et al., 2017), and with evidence that digital lifestyles explain teleconsultation use better than socio-demographics (Gaitán et al., 2026). It also shows why the analysis of duplicated records matters (Online Resource 1, Table S5): apparent predictive performance can be inflated when the same users appear in both training and test data, a risk that nested cross-validation on deduplicated records avoids (Varma & Simon, 2006). Demographic records alone are therefore a weak basis for targeting individual users, but they remain informative about where, and for which groups, the service should adapt.

Theoretical implications

The study makes four contributions to theory. First, it shows the value of treating engagement as two decisions. The hurdle model fitted better than single-equation count models, and its two parts had partly different drivers: single status mattered for returning but not for intensity. This refines cyclical and stage-based views of patient engagement in remote consultation (Liu et al., 2024) by showing empirically that the transition from first to second consultation is a distinct stage with its own correlates. For the flexibility literature, it means that the point of adaptation, whether before or after the first return, should be specified when flexibility is linked to service outcomes.

Second, the study illustrates how analytics works as a sensing capability in the sense of the dynamic capabilities view (Teece et al., 1997). It also shows the limits of that capability. User-level analytics revealed stable, actionable differences between markets, households and channels, consistent with the view that analytics capabilities create value when they inform decisions (Wang & Hajli, 2017; van de Wetering, 2021). Its predictive reach, however, was bounded by what the platform records. The capability therefore rests on the data asset (Barney, 1991) as much as on the analytical method. This adds a qualification to studies linking IT and dynamic capabilities to agility (Awwad et al., 2022): sensing is only as good as the data that the organisation chooses to capture.

Third, the study extends flexible systems management to digital health platforms. Prior work has linked flexibility to innovation performance (De la Gala-Velásquez et al., 2023), to resilience in decision-making and supply chains (Majumdar & Srivastava, 2025; Settembre-Blundo et al., 2021) and to healthcare delivery (Hossain et al., 2026; Kumar et al., 2018). Our results suggest that on a consultation platform, flexibility is needed at several distinct points: the market, the household offer, the channel, retention after the first consultation and capacity for heavy users. In the language of flowing stream strategy (Sushil, 2013), the core consultation service provides continuity, while these five levers are where change should be concentrated.

Fourth, the study contributes behavioural evidence from three MENA markets to a literature that has relied mainly on attitude and intention surveys in the region (Alamri & Alshagrawi, 2024; Hussein & Refaie, 2023; Murshidi et al., 2022). It shows that stated receptiveness to teleconsultation coexists with substantial one-time use: 44% of users in the sample consulted only once.

Managerial implications

Table 8 translates the findings into service-flexibility levers. Each lever is tied to the evidence that supports it, the users it targets and an indicator the provider can monitor. The levers are proposals derived from associations in the data. They should be tested, for example through controlled pilots, before being adopted at scale.

Table 8 Flexibility levers matrix for a multi-country mHealth consultation platform

Flexibility type	Evidence from this study	Proposed lever	Target users	Indicator to monitor
Market	Stable country gradient (Jordan > Egypt > Saudi Arabia) in both parts; no country interactions	Market-specific targets for second-consultation conversion; market-level review of pricing and plans	Saudi users (48.5% predicted repeat use)	Repeat-use rate by country
Offer (household)	Dependents strongest driver; largest gain from 1 to 2 dependents	Household plans and simple onboarding to add a family profile	Single-profile accounts (70.0% of users)	Share of accounts with 2 or more profiles; their repeat-use rate
Channel	Women prefer chat; call share rises with age; mixed use most common in Jordan	Let users switch channel within a consultation; default channel by user preference	All users, especially chat-only (60.4%)	Channel switching; share of mixed-channel users
Retention	S1 and S4 together hold 58.7% of users, mostly chat-only, 40–45% repeat use	Structured follow-up after the first consultation; trial of the alternative channel	S1 older one-time chat users; S4 young chat trial-lists	Return within a fixed window after first consultation
Capacity	S2 (17.3% of users) averages 10.85 consultations	Physician scheduling and service levels sized to household demand peaks	S2 family-account heavy users	Waiting time; churn among heavy users
Sensing (analytics)	Demographics predict repeat use only moderately (AUC about 0.67)	Record consultation timing, duration, rating and reason, and link consultations to the person treated	Platform data function	Predictive performance on richer data

Limitations and Future Research

Despite its theoretical and empirical contributions, this study has several limitations that should be considered when interpreting the findings. First, the cross-sectional and aggregated nature of the consultation records prevents the examination of longitudinal engagement patterns, temporal changes, and causal relationships. Consequently, the identified relationships should be interpreted as associations rather than causal effects. Second, the dataset lacks important service-related information, including consultation dates, durations, patient satisfaction ratings, and service quality indicators, limiting the analysis of operational factors potentially influencing engagement. Third, the interpretation of the number of dependents depends on the platform's operational definition, which requires confirmation from the data provider. Moreover, because individual consultations cannot be linked to specific household members, the observed association between dependents and engagement cannot distinguish between increased utilisation arising from a larger number of service users and more frequent consultations per individual. Fourth, the small number of users with recorded chronic diseases (n = 37) limits statistical power and makes the corresponding estimates, particularly those related to channel preference, unreliable for substantive interpretation. Fifth, the sample was restricted to millennial users aged 27–45 years from a single mHealth platform operating in Jordan, Egypt, and Saudi Arabia, potentially limiting the generalisability of the findings to other age groups, digital healthcare providers, and regional markets.

Additionally, divorced and widowed users were combined into a single category because of their limited sample sizes, potentially concealing differences between these groups. The moderate predictive performance of the machine-learning models also suggests that the available demographic and household characteristics are insufficient for reliable individual-level targeting. Furthermore, the four-cluster segmentation solution remains exploratory and requires external validation before operational implementation. Finally, this article re-analyses data originally collected for a doctoral dissertation, following the identification and removal of duplicated records. Consequently, some descriptive statistics differ from those previously reported, with the present findings based exclusively on the deduplicated dataset.

Future research should address these limitations by incorporating longitudinal, consultation-level data that include timestamps, service duration, patient feedback, healthcare outcomes, and the identity of the household member receiving care. Such information would enable more advanced analytical approaches, including survival analysis to examine time to repeat consultation and longitudinal models to investigate changes in engagement. Expanding the sample to include additional age groups, healthcare platforms, and MENA countries would improve external validity and facilitate broader comparisons of digital healthcare utilisation. Future studies should also examine chronic-disease populations using sufficiently large samples, investigate marital-status categories separately, and incorporate service-quality and behavioural variables to strengthen predictive performance. Moreover, the identified user segments should be validated using independent datasets, while the proposed service-flexibility strategies could be evaluated through controlled field experiments or pilot interventions to assess

their effectiveness in improving retention, channel utilisation, and operational performance. Finally, interpretive approaches established within flexible systems management, including the Situation–Actor–Process–Learning–Action–Performance (SAP–LAP) framework (Majumdar & Srivastava, 2025) and Total Interpretive Structural Modelling (TISM) (Sushil & Dinesh, 2022), could be employed alongside interviews with platform managers to examine the implementation priorities, interdependencies, and organisational requirements associated with the proposed flexibility levers.

Conclusion

This study examined which user attributes are associated with returning to, and intensively using, a multi-country mHealth consultation platform in the MENA region. Engagement was driven mainly by the household and the market. Accounts covering more dependents, and users in Jordan and Egypt, returned more often and consulted more. Gender and age mattered for the choice of channel rather than for the level of use.

The available attributes predicted repeat use only moderately. Their main value lies in pointing to where the service should adapt, not in targeting individual users. For digital health providers, the results point to five flexibility levers: market-specific conversion targets, household-based offers, flexible channels, structured follow-up after the first consultation, and capacity planning for heavy family users. A sixth priority is richer data capture to strengthen the platform's sensing capability. Framed this way, user-level analytics becomes a practical route from data to flexible service management.

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Data Availability The data are proprietary to Altibbi and are not publicly available. They may be available from the corresponding author on reasonable request with the permission of Altibbi.

Code Availability Analysis scripts (Python) are available from the corresponding author on request.

Declaration

Conflict of interest The authors declare that they have no conflict of interest.

Ethics Approval The study used secondary, anonymised platform records released by Altibbi under a written permission letter; no identifiable personal data were accessed.

Consent to Participate Not applicable (secondary analysis of anonymised records).

Supplementary Information Supplementary Tables S1–S6 are provided in Online Resource 1.

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