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MACHINE LEARNING APPROACHES TO FORECAST HOUSEHOLD TELEHEALTH ADOPTION: A DATA GROUNDED FRAMEWORK

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Abstract

Household telehealth adoption remains uneven, particularly in communities facing limited broadband access and low levels of digital readiness. Traditional analytic approaches often describe adoption patterns retrospectively and frequently overlook the structural conditions that shape who is able to engage with telehealth services. In the absence of theory-driven, data-grounded frameworks, planners, organizations, and public agencies lack effective tools to support outreach strategies, infrastructure investment, and equitable resource allocation. As telehealth becomes an increasingly essential component of healthcare access, understanding the conditions that shape household-level adoption is critical for ensuring equitable service delivery. This study adopts a data-grounded, theory-guided design to examine household telehealth adoption, with an emphasis on feasibility assessment and framework development rather than fitted model performance. Guided ex ante by the Unified Theory of Acceptance and Use of Technology (UTAUT), the study specifies how facilitating conditions, effort expectancy, social influence, and performance expectancy can be operationalized using observable indicators related to broadband access, digital readiness, demographic context, and health needs. The analysis draws on empirically observed distributions from community-based survey data and supporting public-sector information, supplemented by qualitative insights that contextualize barriers to telehealth use. This paper contributes a theory-constrained, data-grounded framework that integrates technology adoption theory with exploratory analytic techniques to structure empirical signals related to access, digital readiness, and perceived usefulness at the household level. Rather than training or validating supervised learning models, the study evaluates whether the available data exhibit sufficient structure to support the future application of supervised machine learning within a theory-constrained analytic space. Observed patterns are interpreted at the level of UTAUT constructs to inform scenario-based reasoning about adoption readiness, rather than to generate population-level predictions. The resulting framework provides a transparent and policy-relevant foundation for targeted planning, guiding future data collection efforts and supporting equitable telehealth strategies in underserved communities. In addition, the framework contributes to engineering education by providing a transparent, theory-driven example of how data, machine learning concepts, and equity considerations can be integrated and taught in applied, data-constrained contexts.

Keywords: Planning and Policy, Telehealth, Data-grounded frameworks, Digital divide.

Introduction

Background of Study

Telehealth has become an increasingly important component of healthcare delivery in the United States, offering new ways to improve access to care, reduce travel burdens, and support continuity for individuals managing chronic or ongoing health conditions. The expansion of telehealth during and after the COVID19 pandemic accelerated the integration of virtual care across health systems and demonstrated its potential to support primary care, behavioral health, and chronic disease management when appropriate technological and organizational conditions are in place [1]. As telehealth becomes more embedded in routine healthcare delivery, understanding the factors that shape household-level adoption has become an important area of inquiry.

Despite its potential, telehealth adoption has not occurred evenly across households or communities. Barriers related to broadband availability, device access, digital skills, affordability, and language continue to influence who is able to engage with telehealth services and who is not. These challenges are often concentrated among older adults, low-income households, rural populations, and racially marginalized communities, raising concerns that telehealth expansion may unintentionally reinforce existing health inequities [2]. For policymakers, broadband authorities, and healthcare organizations, the ability to reason systematically about where telehealth adoption readiness may vary and where additional support may be required is essential for effective planning, targeted intervention, and equitable allocation of resources.

Much of the existing research on telehealth adoption has focused on retrospective analyses of utilization patterns, patient satisfaction, or provider-level implementation. While this work has generated valuable insights into how telehealth is used once adopted, it offers limited guidance for forward-looking decision-making. In particular, there is a lack of analytic approaches that support theory-guided, scenario-based reasoning about household-level telehealth adoption using integrated information on connectivity, digital readiness, demographic characteristics, and health needs. This limitation is especially evident in community-based and policy-driven contexts, where access to respondent-level microdata is often constrained, and planning decisions must still be made in the absence of validated predictive tools [3].

From an engineering education and workforce development perspective, telehealth adoption analysis also represents a learning and data literacy challenge. Engineers, planners, and public-sector professionals increasingly must learn to reason with incomplete, heterogeneous data, apply theory to real-world decision contexts, and use analytic tools responsibly under constraints rather than relying on optimized predictive models. Developing and teaching frameworks that make analytic reasoning, theory integration, and equity considerations explicit is therefore an important educational objective. Within this context, telehealth adoption provides a concrete, socially relevant domain through which applied data literacy, theory-driven analysis, and responsible use of machine learning can be examined and learned.

To address this gap, this study presents a theory-driven, data-grounded framework for examining household telehealth adoption in underserved community contexts. Rather than proposing or validating a predictive model, the paper contributes a planning-oriented framework informed by exploratory analytic techniques that integrates the Unified Theory of Acceptance and Use of

Technology (UTAUT) to structure and interpret empirical signals from a small, cross-sectional dataset. In this context, forecasting is defined not as population-level prediction or causal inference, but as scenario-based reasoning about adoption readiness under varying conditions of access, digital skills, social context, and perceived usefulness. UTAUT is applied ex ante to constrain variable selection, feature grouping, and interpretation, while machine learning is used supportively to assist in pattern structuring within the theory-defined space. Accordingly, the study does not claim generalizability, causal effects, or high predictive accuracy; instead, it offers a transparent methodological approach for translating limited public-sector data into actionable insight for planning and decision-making.

Research Questions.

In response to these challenges, this study focuses on the development of a data-grounded, theory-guided framework for examining household telehealth adoption. The analysis is guided by the following research questions:

1. What connectivity, digital readiness, demographic, and health-related factors should be incorporated into a data-grounded framework for examining household telehealth adoption within a UTAUT-guided structure?
2. Do empirically observed community-level distributions of telehealth use and related indicators exhibit sufficient variation and structure to support the future application of supervised learning approaches in planning-oriented telehealth analyses?

Addressing these research questions supports engineering education and workforce learning by making explicit how theory-guided frameworks can be constructed and evaluated using imperfect, real-world data. In particular, the questions are designed to illuminate how learners and practitioners reason analytically about adoption readiness, data limitations, and methodological appropriateness when predictive modeling is not feasible.

Objective of Study.

The overall objective of this study is to develop a theory-driven, data-grounded framework for examining household telehealth adoption that can support policy and planning decisions in contexts where respondent-level microdata may be limited.

Specifically, the study seeks to:

1. Identify and define key connectivity, digital readiness, demographic, and health-related factors relevant to household telehealth adoption using empirically observed community-level data.
2. Operationalize constructs from the Unified Theory of Acceptance and Use of Technology into measurable indicators that can inform the design of a planning-oriented, machine learning– supported framework.
3. Assess whether available community-level data exhibit sufficient variation and structure to support future supervised machine learning applications, without training or validating predictive models in the present study.

Framework and Data Context

All constructs, indicators, and analytic groupings are specified before empirical analysis based on the Unified Theory of Acceptance and Use of Technology, ensuring that theory-constrained analytic choices are applied rather than being applied retrospectively. Guided by UTAUT, this study conceptualizes household telehealth adoption as the result of facilitating conditions, effort expectancy, social influence, and performance expectancy [4]. Empirically observed distributions from the Health and Broadband Connectivity Needs Survey are used to ground the selection of variables related to broadband access, device availability, digital readiness, demographic characteristics, and health status. Qualitative insights from community focus groups are incorporated to contextualize access barriers and lived experiences associated with telehealth use. Rather than estimating model performance, the study evaluates analytic readiness and specifies a transparent framework that can inform future machine learning applications in telehealth and broadband planning. In addition, the framework is intentionally designed to be instructionally usable, providing a concrete example for teaching responsible analytic reasoning, theory-guided modeling, and decision-making under uncertainty in data-constrained, real-world contexts.

Literature Review

Telehealth Adoption, Use, and Equity.

Existing literature consistently shows that telehealth adoption and use remain uneven across populations, with disparities shaped by race, age, socioeconomic status, and geographic context. Studies examining telehealth use in mental health and chronic care settings demonstrate that while telehealth can improve access and outcomes, uptake varies substantially based on household and community conditions rather than clinical need alone. Analyses of national- and program-level data further indicate that telehealth utilization differs across demographic groups, with socioeconomic context and home environments playing a central role in shaping observed patterns of use [5]. Research examining race-specific outcomes in telehealth-supported care highlights persistent inequities in access and downstream outcomes, reinforcing the need to examine adoption through an equity-focused and planning-oriented lens rather than assuming uniform benefits across populations [6].

Broadband Access, Digital Readiness, and Structural Barriers.

A closely related body of work emphasizes broadband access, digital readiness, and structural barriers as foundational conditions shaping telehealth adoption. Research focused on rural and underserved communities consistently identifies limited broadband availability, low digital literacy, language barriers, and infrastructure gaps as persistent constraints on effective telehealth engagement [7]. Policy-oriented studies further demonstrate that access to technology alone is insufficient, as households must also possess the skills, confidence, and institutional support needed to meaningfully engage with digital health services [8]. Language access and culturally responsive systems have likewise been identified as critical components of equitable telehealth delivery, particularly for populations with limited English proficiency [9]. Collectively, this literature underscores that telehealth adoption is shaped by broader digital and social conditions that vary across communities and must be accounted for in planning-oriented analytic frameworks.

Predictive Analytics and Machine Learning in Telehealth and Health Planning.

More recent literature has explored the use of predictive analytics and machine learning to support telehealth planning and evaluation. Studies applying machine learning techniques to large-scale health and telehealth datasets illustrate how data-driven approaches can be used to structure patterns of use, examine associations, and inform resource allocation under conditions of rich and linked data availability [5]. Predictive modeling has also been applied to explore cost implications and differential impacts across demographic groups, suggesting potential value for targeted planning when analytic assumptions and data requirements are met [6]. At the same time, researchers consistently note that many public-sector and community-based contexts face substantial limitations related to data availability, quality, and linkage, which constrain the direct application of fully trained predictive models [7]. This body of work points to the need for data-grounded, theory-guided frameworks that align analytic methods with real-world data constraints while still supporting forward-looking, planning-oriented decision making in telehealth and digital equity initiatives.

Technology Adoption Theory and UTAUT

To complement empirical and analytic perspectives on telehealth adoption, a growing body of literature emphasizes the role of technology adoption theory in structuring analyses of why individuals and households choose to engage with digital health tools. Technology acceptance models, including the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology (UTAUT), provide conceptually grounded frameworks for organizing how perceptions of usefulness, ease of use, social context, and facilitating conditions relate to adoption behavior [10]. In healthcare contexts, these models have been used to move beyond descriptive measures of access or utilization and instead structure analyses around readiness, perceived value, and contextual constraints, which are particularly relevant in voluntary, non-organizational settings such as household telehealth use.

Recent studies applying UTAUT to telehealth adoption further demonstrate its relevance for understanding disparities in use. Qualitative and mixed-methods research examining older adults' engagement with telehealth indicates that facilitating conditions, digital confidence, and perceived effort shape willingness to engage with virtual care even when services are available [11]. These findings align with broader evidence that adoption is influenced not only by infrastructure, but also by individual perceptions and capabilities.

Extensions of UTAUT that incorporate digital literacy and lifespan perspectives provide additional support for its use in telehealth planning contexts. Research extending UTAUT to eHealth literacy demonstrates how technology adoption constructs can be operationalized using measurable indicators related to skills, confidence, and prior experience, particularly in populations facing structural disadvantage [12]. Together, this literature supports the use of UTAUT as a conceptual constraint for framework development, enabling theory-guided operationalization and interpretation without requiring predictive model validation.

Policy Context and Public Sector Data Constraints

While predictive analytics and theory-driven frameworks offer promise for improving telehealth planning, a growing body of literature highlights the practical constraints that shape how these approaches can be applied in public-sector and community-based settings. Policy-focused studies emphasize that agencies responsible for broadband expansion, digital equity initiatives, and telehealth planning often operate with fragmented, aggregated, or incomplete data, limiting the feasibility of fully trained predictive models [13]. These constraints reflect structural considerations related to data governance, privacy requirements, and resource capacity across jurisdictions.

Research examining digital equity and artificial intelligence in public-sector contexts further underscores the importance of aligning analytic approaches with local capacity and data realities. Studies focused on reducing the digital divide argue that responsible use of advanced analytics requires frameworks that prioritize transparency, interpretability, and scalability, particularly when serving underserved or marginalized populations [14]. In telehealth and digital health planning, this has contributed to increased emphasis on framework-based approaches that support decision-making in the absence of respondent-level microdata. Policy analyses addressing language access, rural connectivity, and underserved communities further reinforce the need for planning tools that account for structural barriers beyond healthcare delivery systems [15]. Collectively, this literature supports the development of data-grounded, planning-oriented frameworks that integrate equity considerations and data constraints without relying on model-driven prediction alone.

Methodology

Study Design

This study adopts a theory-driven, framework-development design grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT serves as the primary theoretical foundation and is applied ex ante to constrain variable selection, feature grouping, analytic interpretation, and framework construction before any empirical analysis. The study is explicitly oriented toward feasibility assessment and framework development, rather than predictive model training or validation.

UTAUT explains technology adoption through four core constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions, with use behavior as the outcome of interest [4]. The application of UTAUT in this study reflects extensions of the theory beyond organizational information systems to consumer and voluntary technology use contexts, including healthcare and telehealth

applications [16]. Applying UTAUT as a design constraint ensures that analytic choices remain theoretically grounded and prevents post hoc fitting of theory to observed empirical patterns.

In this study, analytic readiness is defined as the extent to which available data exhibit sufficient variation, internal structure, and alignment with theory-defined constructs to support responsible, planning-oriented analytic use, independent of predictive model performance. Establishing analytic readiness is therefore a prerequisite for framework validity, as it determines whether empirical signals can be meaningfully interpreted within the proposed theory-guided structure.

Theoretical Framework: Unified Theory of Acceptance and Use of Technology (UTAUT)

Building on UTAUT, the study specifies a UTAUT-guided conceptual framework tailored to household telehealth adoption in Northeastern region, Maryland. The conceptual framework does not introduce a new theory. Rather, it represents a contextual instantiation of UTAUT that reflects how adoption processes unfold in an underserved, non-organizational community setting.

Within this framework, facilitating conditions such as broadband access and device availability shape effort expectancy by influencing perceived ease of use. Effort expectancy and social influence interact with health-related needs to inform performance expectancy, which in turn influences telehealth use behavior. Prior qualitative research applying UTAUT to telehealth adoption among older adults supports this interpretation of construct interaction in voluntary and non-organizational contexts [9].

Figure 1 presents the UTAUT-based conceptual framework for household telehealth adoption, illustrating how performance expectancy, effort expectancy, social influence, and facilitating conditions are operationalized using observable indicators relevant to underserved community contexts. An exploratory machine learning layer is depicted as a supporting analytic component that structures and interprets theory-guided variables but does not function as a causal or predictive mechanism.

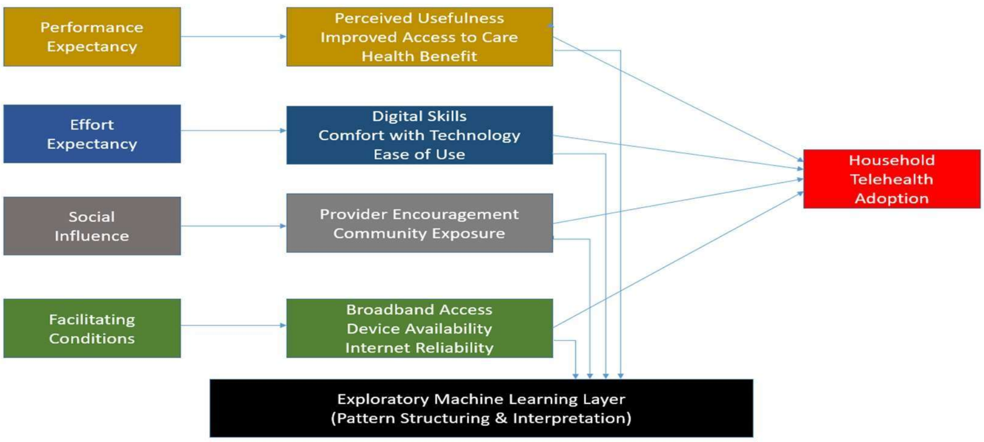

Figure 1: UTAUT-Based Conceptual Framework for Household Telehealth Adoption

UTAUT is particularly well-suited to planning-oriented, household-level analysis because it foregrounds facilitating conditions and perceived effort alongside expected benefits, allowing infrastructure readiness and digital capacity to be examined as integral components of adoption rather than as background variables.

Operationalization of UTAUT Constructs

To ensure that UTAUT constrained the analysis ex ante, observable and context-specific indicators were created from the abstract theoretical constructs of UTAUT using the data available from the household survey and qualitative materials. Instead of assuming survey items as separate explanatory variables, the survey items were categorized according to their association with performance expectancy, effort expectancy, social influence, and facilitating conditions constructs.

The purpose of such an approach to operationalizing constructs in theory-led research was to preserve interpretability and avoid construct drift in the small-n and public-sector data context. The operationalization of UTAUT constructs is shown in Table 1, which highlights how theoretical frameworks informed the choice and arrangement of variables before performing exploratory analysis.

As several UTAUT constructs had more than one survey item (e.g., the digital confidence indicators for effort expectancy), the construct coherence was examined descriptively in order to ensure that survey items had consistent direction and construct alignment within each construct group. Due to the exploratory nature and framework development, the sample size was small (n=50).

Table 1: Operationalization of UTAUT Constructs for Household Telehealth Adoption

UTAUT Construct	Conceptual Definition (UTAUT)	Operational Indicators (Observed / Derived)	Data Source
Performance Expectancy	The degree to which telehealth is perceived to provide benefits in accessing healthcare or improving health outcomes.	Perceived usefulness of telehealth services; perceived improvement in access to care; perceived health benefit of telehealth use	Household survey responses; qualitative focus group themes
Effort Expectancy	The degree of ease associated with learning and using telehealth technologies	Self-reported digital skills; comfort with technology use; perceived ease of using digital devices and online platforms	Household survey responses
Social Influence	The degree to which individuals perceive that important others believe they should use telehealth	Provider encouragement to use telehealth; community exposure to telehealth services; normative perceptions derived from community engagement	Household survey responses; community focus group discussions
Facilitating Conditions	The degree to which individuals believe that organizational and technical infrastructure exists to support telehealth use	Broadband access, availability of internet-enabled devices, and reliability of internet connectivity	Household survey responses; broadband assessment documentation
Use Behavior (Outcome)	Actual use of telehealth services	Reported household use of telehealth services	Household survey responses

Data Source and Study Population

The framework is grounded in a small-n (n = 50), cross-sectional household survey administered in a Northeastern region of the United States as part of a community needs assessment focused on broadband access and telehealth readiness. Participation was voluntary and distributed through local outreach channels, resulting in a convenience sample of 50 households. Surveys were collected electronically and included structured, closed-ended questions with optional open-text responses.

The unit of analysis is the household, reflecting the level at which broadband access, device availability, digital skills, and health-related needs intersect in telehealth adoption decisions. The survey captured information on broadband availability and reliability, access to internet-enabled devices, self-reported digital confidence, health status, and prior telehealth use.

Ex ante, survey items were mapped to constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT). Access to broadband and devices was categorized under facilitating conditions; confidence in digital tasks (e.g., making video calls, troubleshooting technology, connecting with providers remotely) was categorized under effort expectancy; provider encouragement and community exposure were categorized under social influence; and perceived usefulness and satisfaction with telehealth were categorized under performance expectancy.

Missing values were minimal and handled using listwise exclusion at the construct level to preserve interpretability within the small-n dataset. Although demographic characteristics such as gender, age, race, insurance status, and language-related barriers were captured descriptively, no formal sampling frame or stratified sampling design was employed. Accordingly, findings are interpreted as exploratory and context-specific rather than representative of the broader population.

Qualitative materials from community engagement activities were incorporated to contextualize survey findings and provide insight into lived experiences and access barriers associated with telehealth use. The dataset reflects typical public-sector planning conditions, where respondent-level microdata and longitudinal observations are often unavailable.

Outcome Variable Definition

Household telehealth adoption is defined as observed use behavior, operationalized through survey responses indicating whether telehealth services have been used. This definition aligns directly with UTAUT's emphasis on use behavior as the outcome of acceptance processes [4], [9]. Measures related to interest in telehealth or training are treated as contextual indicators rather than substitutes for adoption.

Data Preparation and Feature Structuring

Data preparation is guided by theory rather than algorithmic convenience. Variables are grouped by UTAUT construct before analysis, and dimensionality is deliberately constrained to preserve interpretability and analytic stability. This approach differs from conventional machine learning pipelines that emphasize feature expansion and automated selection and is consistent with the study's framework development orientation.

Before conducting analysis, the variables were first standardized in order to maintain consistency among indicators belonging to a construct. Categorical variables were transformed into codes that were compatible with the definition of the construct, while missing data were addressed using listwise deletion at the construct level.

Machine Learning Approach

Machine learning techniques are employed in an exploratory and supportive capacity. Low-complexity, interpretable model classes are used to examine construct-level patterns and interactions within the UTAUT-guided structure. The models are not treated as predictive engines, but as analytic instruments that support framework development. This positioning aligns with calls for explainable and responsible use of machine learning in health-related and public-sector domains [12], [16].

Interpretation of the exploratory analysis outputs was done at the construct level and not at the variable level. Cluster analysis outputs, for instance, helped understand how different households clustered with respect to the combination of their facilitating conditions and effort expectancy, while the decision tree provided an Framework Interpretation understanding of how the particular indicators helped differentiate constructs. Interpretation of these outputs was informed by the UTAUT constructs to ensure that theory constraining was still achieved.

Since the UTAUT framework aggregates several indicators into the constructs, there is no readiness configuration in relation to any one indicator from the survey. There was no sensitivity testing done due to the exploratory nature of the study and small sample size (n = 50). However, this logic of aggregating reduces the chances of sensitivity to specifications.

Model Evaluation Philosophy

Model evaluation emphasizes interpretability, internal consistency, and coherence with theoretical expectations rather than numerical optimization. Performance metrics are treated cautiously and are not used to support claims of predictive accuracy, causal inference, or generalizability.

Framework Construction Process

Theory, data, and analytic techniques were integrated to develop the proposed framework. The methodological workflow is made explicit through both a figure and a table. Figure 2 visually summarizes the sequential stages of the analysis, beginning with UTAUT-based theory specification and proceeding through data alignment, construct operationalization, exploratory machine learning analysis, and synthesis into a scenario-based planning framework.

Complementing the workflow diagram, Table 2 provides a structured account of each analytic stage by documenting the inputs, analytic purpose, and outputs associated with that stage. Together, Figure 2 and Table 2 ensure transparency in the framework construction process by making the analytic logic traceable and auditable.

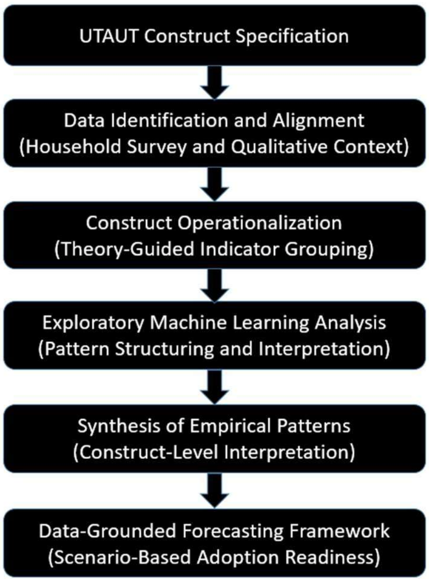

Figure 2: Analytic Workflow for Developing a Data-Grounded Framework for Household Telehealth Adoption,

Table 2: Analytic Stages in Framework Development,

Analytic Stage	Inputs	Analytic Purpose	Outputs
Theory Specification	UTAUT literature	Define adoption constructs and constrain analytic scope	UTAUT-based construct framework
Data Identification and Alignment	Household survey data; qualitative context	Identify observable indicators relevant to UTAUT constructs	Theory-aligned data inputs
Construct Operationalization	Survey indicators; qualitative themes	Translate abstract constructs into observable measures	Operationalized UTAUT constructs (Table 1)
Exploratory Machine Learning Analysis	Operationalized constructs	Examine construct-level patterns and interactions	Structured empirical insights
Synthesis and Interpretation	Empirical patterns; theoretical expectations	Integrate theory and data without overclaiming	Interpretable construct relationships
Framework Construction	Synthesized insights	Develop scenario-based forecasting logic	Data-grounded telehealth adoption framework

Ethical, Equity, and Methodological Considerations

All analyses are conducted using aggregated, de-identified data to protect confidentiality. Equity considerations are embedded throughout the framework through explicit attention to broadband access, digital readiness, and health-related needs. Responsible analytic use is emphasized to avoid reinforcing existing disparities, consistent with broader scholarship on equity-aware, accountable, and fairness-oriented data practices [14], [15], [16].

Results

Collectively, these results are presented not only to ground the proposed framework empirically, but also to illustrate how theory-guided analytic reasoning can be applied in practice when working with limited, imperfect data.

Sample Characteristics and Data Coverage

These findings were obtained using a small-n (n = 50), cross-sectional survey of households conducted within an underserved community setting. Home broadband was used by 52% of surveyed households, 19% of which utilized mobile only, and 10% indicated a lack of home internet. While smartphone ownership was common (85%), 43% of households reported owning no personal computers, such as laptops or desktops.

Utilization of telehealth services occurred among 62% of households, whereas 38% had no experience with telehealth services. Of those who had experience, 73% of households found them very satisfactory, and 88% showed interest in taking a free training class for learning to navigate telehealth services. The sample consisted mainly of Black or African Americans (69%) and women (61%). Age-wise, the sample included 33% aged between 25 and 34 years old.
While the sample is not meant to represent anything, the above shows variability in the distribution of access, readiness, context, and use of telemedicine at the household level. The variability is important because it allows for analysis of how access, readiness, and context interact. Information gathered from qualitative means through community outreach activities helps us interpret the empirical findings without making inferences outside the data.

The variability is important in our framework because it provides us with evidence that there is enough variety in access, readiness, and health-related issues to warrant a scenario planning approach to adoption rather than a threshold approach.

Observed Patterns in UTAUT Constructs

Empirical patterns are organized by the UTAUT construct to maintain theoretical alignment and interpretability. Patterns associated with facilitating conditions indicate heterogeneity in broadband access, device availability, and perceived reliability of internet service, suggesting that foundational infrastructure and technical support conditions vary meaningfully within the community. These differences are salient for understanding downstream perceptions of feasibility and ease of engagement with telehealth services.

Effort expectancy–related indicators reflect variation in digital skills, comfort with technology, and perceived ease of navigating online platforms. Households reporting greater digital confidence generally described fewer perceived barriers to engaging with telehealth, whereas limited skills or unfamiliarity were associated with hesitation or reliance on external support. Performance expectancy patterns highlight differences in perceived usefulness of telehealth, often linked to specific use cases such as follow-up care or management of ongoing health needs rather than to generalized endorsement of virtual care. Social influence indicators capture variability in external encouragement and normative exposure, including provider recommendations and community awareness of telehealth services, which appeared to shape perceptions of legitimacy and appropriateness of use, particularly among households with limited prior experience.

A construct-level synthesis of these observed patterns is presented in Table 3, which consolidates empirical signals across facilitating conditions, effort expectancy, performance expectancy, and social influence. The table provides a structured overview of how theory-defined constructs manifest in the data and serves as a conceptual reference point for subsequent framework development.

This pattern informs the framework by reinforcing the need to treat facilitating conditions, effort expectancy, performance expectancy, and social influence as interacting readiness dimensions that jointly shape household telehealth adoption, rather than as independent or sequential predictors.

Table 3: Summary of Observed UTAUT Construct-Level Patterns Relevant to Household Telehealth Adoption

UTAUT Construct	Observed Empirical Patterns	Planning-Relevant Interpretation
Facilitating Conditions	Households exhibited heterogeneity in broadband availability, device access, and perceived reliability of internet service. Some households reported stable access and adequate devices, while others described intermittent connectivity or shared device constraints.	Variation in foundational access conditions suggests that infrastructure and technical support remain uneven within the community, highlighting the need for differentiated planning approaches that address both connectivity gaps and reliability challenges.
Effort Expectancy	Differences were observed in digital skills, comfort with technology use, and perceived ease of navigating online platforms. Higher digital confidence was often associated with fewer perceived barriers, whereas limited skills corresponded with hesitation or reliance on external assistance.	Digital readiness emerges as a critical readiness dimension, indicating that training, technical assistance, and user-centered design may be as important as infrastructure investments in supporting telehealth adoption.

Performance Expectancy	Perceived usefulness of telehealth varied across households and was frequently tied to specific use cases, such as follow-up appointments or management of ongoing health needs, rather than to generalized endorsement of virtual care.	Adoption readiness appears context dependent, suggesting that planning efforts should align telehealth services with concrete household needs rather than assuming uniform perceived benefit.
Social Influence	External encouragement, including provider recommendations and community exposure to telehealth services, varied across households. Social norms and trusted intermediaries appeared to shape perceptions of legitimacy and appropriateness, particularly among those with limited prior experience.	Social context and trusted messengers may play an enabling role in adoption, indicating that outreach and communication strategies can complement infrastructure and skillsbased interventions.
Use Behavior (Outcome)	Reported telehealth use was observed across households with differing access and readiness profiles, indicating that adoption does not follow a single pathway and may occur under varying combinations of conditions.	The presence of multiple adoption pathways reinforces the value of a flexible, scenariobased forecasting framework rather than a single predictive threshold.

Exploratory Machine Learning–Supported Pattern Structuring

Exploratory, interpretable machine learning techniques were applied to support pattern structuring within the UTAUT-guided construct space. These techniques were used to examine whether construct-level indicators exhibited coherent relationships and separations that could inform framework development, rather than to generate predictions or optimized classifications. At this level, the analyses suggested that households tended to align along dimensions associated with access and readiness, with facilitating conditions and effort expectancy frequently emerging as prominent organizing factors.

The purpose of these exploratory analyses was to aid interpretation by revealing tendencies in how theory-defined constructs co-occur, not to infer causal relationships or predictive strength. Figure 3 illustrates how households occupy different regions of the construct space based on observed indicators. The visualization supports conceptual understanding of readiness configurations and complements the tabular summaries by making construct-level structure more accessible to planners and stakeholders.

This pattern informs the framework by demonstrating how exploratory analytics can be used to surface interpretable readiness configurations within a theory-constrained space without invoking predictive classification or model optimization.

Figure 3 represents an empirical visualization derived from observed construct-level patterns, simplified for interpretability. It is not a predictive model output but a conceptual representation grounded in empirical distributions.

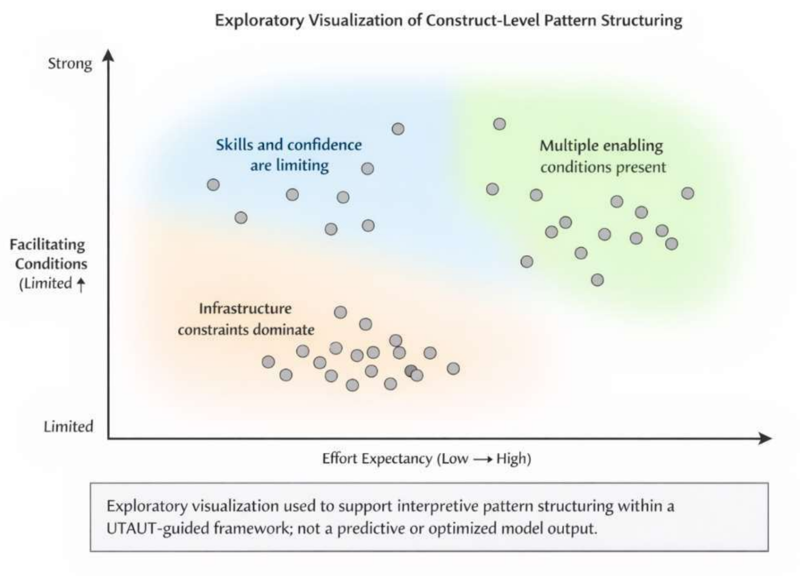

Figure 3. Exploratory Visualization of Household-Level Readiness Configurations within a UTAUT-Guided Framework

Indicators of Forecasting Feasibility

Taken together, the observed distributions and construct-level patterns indicate that the dataset exhibits meaningful variation and internal structure relevant to planning-oriented forecasting efforts. Variation across facilitating conditions, digital readiness, and perceived usefulness suggests that adoption-related signals are not uniformly distributed, a necessary condition for future scenario-based forecasting. In addition, the alignment of observed patterns with UTAUT expectations supports the use of theory as an organizing constraint for structuring limited data in public-sector contexts.

These findings are interpreted as indicators of readiness for future forecasting rather than as evidence of forecasting itself. The results demonstrate that, even under small-n and cross-sectional constraints, theory-guided organization can surface empirically grounded structure that is relevant for planning and resource allocation decisions.

This pattern informs the framework by establishing analytic readiness as a criterion for responsible application, clarifying when available data can meaningfully support planning-oriented forecasting without overextending empirical claims.

Integration of Quantitative and Qualitative Signals

Qualitative data collected from the community engagement process through structured dialogue among local people and other relevant stakeholders were used for contextualizing the quantitative trends found in the survey results. The dialogue involved [insert number] people and concentrated on the experiences of the respondents with regard to their connectivity issues, digital competency, and access to healthcare facilities. The notes taken during these sessions were coded using the UTAUT model, such that the topics of interest were categorized as per the model's constructs and dimensions.

In some instances, qualitative data explained how seemingly equal levels of access had resulted in different telehealth utilization among household members. Qualitative findings were used to provide meaning to quantitative findings, but were not independently used to validate the results. Qualitative signals functioned as interpretive scaffolding that grounded construct-level patterns in lived experience. This integration reinforces the planning-oriented focus of the framework by linking observed empirical variation to practical barriers and enabling conditions that are salient to community stakeholders and public-sector decision-makers, while remaining consistent with the study's methodological constraints.

This pattern informs the framework by ensuring that construct-level readiness assessments remain grounded in lived experience, supporting planning decisions that account for both measurable conditions and contextual realities.

Discussion

From an engineering education and workforce learning perspective, this framework supports learners in developing the ability to reason analytically with incomplete, heterogeneous data while remaining grounded in theory rather than defaulting to purely data-driven or performance-optimized approaches. By making construct selection, analytic grouping, and interpretive logic explicit, the framework helps learners avoid common analytic pitfalls such as post hoc theory fitting, over interpretation of small-n results, and inappropriate reliance on predictive metrics when data constraints preclude valid modeling. The educational benefits extend to students learning applied data science concepts, trainees developing professional judgment in public-sector or health-related contexts, and practitioners seeking transparent, responsible ways to integrate theory, data, and exploratory analytics into planning and decision-making under uncertainty.

Interpreting Household Telehealth Adoption through a Theory-Guided Lens

This study set out to develop a data-grounded, theory-driven framework for examining household telehealth adoption under real-world public-sector data constraints. The results underscore the value of applying the Unified Theory of Acceptance and Use of Technology (UTAUT) as an ex ante organizing structure for interpreting empirical signals related to access, readiness, and perceived usefulness. Rather than treating telehealth adoption as a single outcome driven by isolated predictors, the findings highlight how facilitating conditions, effort expectancy, performance expectancy, and social influence co-occur at the household level to shape adoption readiness.

Observed heterogeneity across these constructs reinforces the relevance of UTAUT for non-organizational and community-based contexts, extending prior applications of the theory beyond individual workplace settings into household decision environments [4], [11]. In particular, the configurational patterns observed in the Results section suggest that adoption readiness emerges from the interaction of structural access conditions and perceived ease of use, rather than from infrastructure or skills alone. This interpretation aligns with prior qualitative work applying UTAUT to telehealth among older adults, which emphasizes the role of confidence, support, and context in shaping willingness to engage with virtual care [9].

Implications for Planning-Oriented Forecasting

A central contribution of this paper is the reframing of forecasting as a scenario-based, readiness-oriented activity rather than as population-level prediction. The empirical patterns observed across households indicate that telehealth adoption does not follow a single pathway and that similar levels of access may lead to different outcomes depending on digital confidence, health needs, and social context. This finding has important implications for planners, broadband authorities, and healthcare organizations seeking to anticipate where telehealth services are likely to be feasible and where targeted support may be required.

By demonstrating that small-n, cross-sectional data can still exhibit meaningful construct-level structure when organized theoretically, the framework provides a practical alternative to predictive modeling approaches that are often infeasible in public-sector contexts due to data limitations [3]. Rather than attempting to optimize model performance, the framework supports strategic reasoning about different household readiness configurations, enabling decision-makers to align interventions such as infrastructure investment, digital skills training, or provider outreach with observed conditions on the ground.

Role of Exploratory Machine Learning in Framework Development

The exploratory use of machine learning in this study illustrates how analytic techniques can support framework development without displacing theory or overstating empirical claims. By using interpretable, low-complexity methods to assist in pattern structuring, the analysis made construct-level relationships more visible while remaining consistent with UTAUT-defined boundaries. Importantly, machine learning was not used to generate predictions, rank households, or estimate adoption probabilities, but rather to support sense-making within a theory-guided space.

This positioning responds to growing concerns about the responsible use of advanced analytics in health and public-sector domains, where opacity and overreach can undermine trust and exacerbate inequities [12], [16]. By explicitly subordinating machine learning to theory and planning objectives, the framework demonstrates a pathway for integrating data-driven tools in ways that remain transparent, interpretable, and aligned with equity goals.

Equity Considerations and Household-Level Readiness

The discussion of household-level readiness configurations highlights the importance of addressing digital equity as an integral component of telehealth planning. The results indicate that facilitating conditions such as broadband reliability and device availability remain uneven, even within a single community, and that digital skills and confidence can act as independent constraints on adoption. These findings reinforce broader scholarship emphasizing that access to technology alone is insufficient to ensure equitable engagement with digital health services [3], [7], [15].

By centering the household as the unit of analysis, the framework captures how resources, skills, and support are distributed within living environments, offering a more nuanced view of readiness than individual-level measures alone. This perspective is particularly relevant for underserved communities, where household composition, shared devices, and informal support networks play a critical role in shaping technology use. The framework thus provides a foundation for equity-aware planning that moves beyond one-size-fits-all assumptions and instead accounts for differentiated needs and capacities.

Limitations and Scope of Interpretation

Several limitations should be acknowledged when interpreting the findings. First, the analysis is based on a small-n, cross-sectional dataset from a single community and is not intended to support generalizable conclusions or causal inference. The framework is designed to be transferable in logic rather than in results, offering a methodological approach that can be adapted to other contexts with appropriate local data.

Second, the exploratory machine learning analyses are used solely to support interpretive pattern structuring and do not provide evidence of predictive performance. As such, the framework should not be interpreted as a validated forecasting model, but rather as a preparatory step that clarifies data requirements, construct alignment, and readiness signals for future work.

Finally, qualitative insights are used to contextualize and interpret observed patterns, not to validate or triangulate quantitative findings. This integration reflects the study's planning-oriented focus and respects the limitations of the available data.

Transferability of the Framework to Other Contexts

While the empirical findings of this study are context-specific and not intended to be generalizable, the analytic logic underlying the framework is designed to be transferable across communities. To support application in other settings, the framework can be implemented through the following sequence:

1. Define theoretical constructs ex ante using an appropriate technology adoption or behavioral framework (e.g., UTAUT).
2. Identify locally available data sources relevant to these constructs, including survey data, administrative records, or qualitative inputs.
3. Operationalize constructs into observable indicators that reflect local conditions such as infrastructure, digital readiness, and health-related needs.
4. Assess analytic readiness by evaluating whether the available data exhibit sufficient variation, internal structure, and alignment with theory-defined constructs.
5. Apply exploratory, interpretable analytic techniques to examine construct-level patterns without relying on predictive model performance.

6. Synthesize findings into a scenario-based framework that supports planning and decision-making rather than population-level prediction.

This structured process enables adaptation of the framework to different geographic and institutional contexts while maintaining alignment between theory, data, and analytic scope.

Readiness Typology for Planning

Based on construct-level patterns observed in the data, the framework supports a typology of household telehealth readiness configurations:

Infrastructure-Constrained Households: - Limited broadband and device access → Intervention: infrastructure investment

Digitally Constrained Households: - Adequate access but low digital skills → Intervention: digital literacy support

Conditionally Ready Households: - Moderate access and readiness, variable perceived usefulness→ Intervention: targeted outreach

Fully Ready Households: - Strong access, skills, and perceived benefit → Intervention: service optimization

This typology translates construct-level patterns into actionable planning categories aligned with observed conditions.

To illustrate how the framework functions in practice, consider households reporting no home internet access (10%) or limited access to computing devices (43% reporting no personal laptop or desktop computer). Within the proposed framework, such households would be interpreted as infrastructure-constrained, even when interest in telehealth services is present. In this scenario, prioritizing infrastructure development and device access would be more appropriate than outreach activities alone.

Several considerations temper the interpretation of the framework outputs. The small sample size (n = 50) may amplify instability in construct-level groupings, and convenience sampling may introduce selection bias if households with greater digital engagement were more likely to participate. Because the data are cross-sectional, observed readiness configurations reflect conditions at a single point in time and cannot capture temporal shifts in access, skills, or perceived usefulness. Accordingly, the framework is intended to support planning reflection rather than to produce definitive or predictive classifications.

Conclusion

This work contributes to a shift in how engineering education approaches machine learning and forecasting, emphasizing theory-guided, equity-aware analytic reasoning and demonstrating how responsible use of data-driven methods can be taught and applied in planning contexts characterized by uncertainty and constraint.

It presents a theory-driven, data-grounded framework for examining and forecasting household telehealth adoption in underserved community contexts. Guided ex ante by the Unified Theory of Acceptance and Use of Technology (UTAUT), the study demonstrated how limited, cross-sectional public-sector data can be systematically organized to support planning-oriented reasoning about telehealth readiness without relying on predictive modeling or claims of generalizability. By centering the household as the unit of analysis and foregrounding facilitating conditions, effort expectancy, performance expectancy, and social influence, the framework offers a structured approach for interpreting adoption-related signals under real-world data constraints.

A key contribution of this work lies in its reframing of forecasting as a scenario-based, readiness-oriented activity rather than as population-level prediction. The empirical patterns observed across UTAUT constructs indicate that household telehealth adoption is shaped by configurational interactions among access, digital skills, and perceived value, rather than by any single factor in isolation. This finding reinforces prior work emphasizing that equitable telehealth expansion depends on addressing both structural and perceptual barriers simultaneously, particularly in communities facing persistent digital inequities [2], [3], [9].

The study also illustrates how exploratory machine learning techniques can be incorporated responsibly into framework development. By using interpretable, low-complexity analytic tools to support pattern structuring within a theory-defined space, the analysis avoided overreach while enhancing transparency and interpretability. This approach aligns with broader calls for explainable and equity-aware uses of data-driven methods in health and public-sector contexts, where analytic opacity and optimization-focused models may be inappropriate or infeasible [12], [16].

Several limitations necessarily shape the scope of the framework. The analysis draws on a small-n dataset from a single community and does not support causal inference, statistical generalization, or predictive accuracy claims. The framework is intended to be transferable in logic rather than in empirical results, offering a methodological template that can be adapted to other settings as data availability, governance structures, and planning needs evolve. Future work may build on this foundation by applying the framework to larger or longitudinal datasets, integrating additional contextual variables, or evaluating how readiness configurations change over time as infrastructure and digital skills interventions are implemented.

From an engineering education and ASEE perspective, this study contributes a concrete example of how theory-driven frameworks and applied data science methods can be used to address complex socio-technical challenges in equitable and responsible ways. By prioritizing conceptual clarity, transparency, and alignment between data, theory, and claims, the framework demonstrates how machine learning can be positioned as a supportive analytic tool rather than an end in itself. As telehealth and digital infrastructure continue to expand, such approaches will be increasingly important for informing policy, guiding resource allocation, and preparing engineers and planners to engage thoughtfully with data-limited, equity-sensitive environments [14].

In summary, this paper advances a planning-oriented framework that bridges technology adoption theory, empirical observation, and responsible analytics. By doing so, it provides a practical and theoretically grounded foundation for future telehealth planning efforts and contributes to ongoing conversations within ASEE and related fields about how data, theory, and equity can be integrated in meaningful and methodologically disciplined ways.

Looking forward, the framework offers a transferable instructional model for engineering education and workforce development, enabling future curricula and training programs to engage learners in theory-guided, equity-aware analytic reasoning using realistic, data-constrained scenarios. As machine learning and forecasting become increasingly embedded in public-sector and health-related decision-making, this work illustrates how education can move beyond performance optimization to emphasize responsible analytic judgment, transparency, and contextual awareness.

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