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Barriers and Incentives for Smartphone mHealth Adoption Among Health Care Providers in Central and Southern Appalachia

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This is to certify that the doctoral dissertation by

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has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

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Walden University
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Abstract

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MPhil, Walden University, 2025

MS, University of Texas at San Antonio, 2014

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Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

Rural Appalachian communities in the United States experience disproportionately high chronic disease burden. Mobile health (mHealth) technology adoption among providers remains low despite potential to improve care access. Understanding adoption factors is critical for addressing health inequities. The purpose of this quantitative cross-sectional study was to examine whether diffusion of innovations (DOI) theory attributes predict current mHealth adoption among health care professionals involved in rural Appalachian primary care delivery and whether structural constraints moderate these relationships. Despite extensive DOI validation in well-resourced settings, its applicability to severely resource-constrained contexts remained empirically uncertain. Data from 100 health care professionals across eight Appalachian states were analyzed using hierarchical logistic regression. Results revealed that trialability emerged as the strongest adoption predictor (OR = 3.89, $p < .001$), followed by relative advantage (OR = 2.34, $p < .01$), while complexity showed no significant effect. Structural constraints independently reduced adoption likelihood (OR = 0.42, $p < .01$) but did not significantly moderate attribute-adoption relationships, suggesting additive rather than interactive effects. The final model explained 61% of variance in current adoption and correctly classified 82% of cases. Findings indicate contextual variation in DOI attribute effect magnitudes. The key positive social change implication is that organizations can enhance adoption by prioritizing trial opportunities alongside addressing infrastructure barriers, while policymakers can support mobile health reimbursement and infrastructure investment.

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Dedication

This dissertation is dedicated first to God, whose grace and guidance made it possible for me to complete this PhD journey.

To my wife - your patience, strength, and unwavering support carried me through the many moments when I was buried in work instead of sharing precious time with you. Thank you for believing in me even when the sacrifices were hard. You are my greatest friend, partner and lover, and I dedicate this achievement to you with all my heart.

To my children - thank you for your understanding during the Saturdays I missed your special events and the times I couldn’t sit with you to watch movies. Your love and resilience inspired me more than you know. I hope this inspires you to pursue your dreams despite all odds.

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Finally, I would like to thank other faculty members for sharing practical wisdom and valuable perspective throughout my work. Their insights helped ground the study in realistic considerations and contributed to the overall quality of this dissertation.

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Chapter 1: Introduction to the Study

Rural Appalachian populations experience substantial health disparities including elevated chronic disease prevalence, higher mortality rates, and significant barriers to health care access (Appalachian Regional Commission [ARC], 2017, 2025; Serchen et al., 2025). Mobile health (mHealth) technologies - including remote patient monitoring, secure messaging, and mobile applications - have been proposed as mechanisms to improve health care access by bridging geographic distances between patients and providers (Bazzano et al., 2024; Martinez & Kim, 2023). However, adoption of these technologies among rural primary care providers remains inconsistent (Maganty et al., 2023; Weichelt et al., 2024).

I examined factors associated with mHealth adoption among primary care providers in rural Appalachia using diffusion of innovations (DOI) theory as its framework. DOI proposes that innovation attributes—relative advantage, complexity, and trialability—predict adoption decisions (Rogers, 2003). However, the theory was developed primarily in well-resourced contexts where infrastructure and organizational support are adequate. Whether DOI relationships operate similarly in severely resource-constrained settings like rural Appalachia - characterized by limited broadband infrastructure, financial constraints, and workforce shortages - remains empirically uncertain (Bogulski et al., 2024; Chapman et al., 2025).

The study addressed this gap by testing whether structural constraints moderate relationships between innovation attributes and current mHealth adoption. Understanding these dynamics has practical implications for implementation strategy development and policy decisions regarding rural health care technology investments. By examining adoption from rural provider perspectives, the research contributes to health equity efforts by clarifying whether barriers to adoption reflect provider resistance or structural limitations requiring systemic intervention.

This chapter establishes the study's foundation through six sections: Background contextualizes mHealth in rural Appalachia; Problem Statement articulates the specific gap addressed; Purpose specifies study aims and design; Research Questions (RQs) present hypotheses that were tested; Theoretical Foundation explains DOI theory application; and sections on assumptions, scope, limitations, and significance of the study.

Background of the Study

The phenomenon of mHealth encompasses health care service delivery through mobile communication devices including smartphones, tablets, and wearable sensors (World Health Organization, 2021). For rural Appalachian populations - approximately 25,000,000 residents across 423 counties characterized by geographic isolation and economic disadvantage - mHealth technologies represent potential solutions to persistent health care access challenges (ARC, 2017, 2025).

Clinical Potential and Evidence Base

Research demonstrates mHealth effectiveness for chronic disease management under controlled conditions. Systematic reviews document that remote patient monitoring and mobile applications can improve medication adherence, blood pressure control, and disease management engagement (Bazzano et al., 2024; Martinez & Kim, 2023). For rural areas where specialist access is limited, mHealth enables provider-to-provider consultation, allowing primary care providers to collaborate with distant specialists on complex cases (Totten et al., 2024). By reducing travel requirements, mHealth addresses transportation barriers that significantly limit rural health care access (Bailey et al., 2024).

However, evidence of effectiveness under research conditions does not ensure real-world implementation success. Studies consistently document gaps between research efficacy and practice effectiveness, with implementation challenges including technical difficulties, workflow integration problems, patient engagement issues, and sustainability concerns limiting benefits achieved in routine practice (Fava & Lapão, 2024; Giebel et al., 2023; Niyomyart et al., 2024).

Structural and Infrastructure Barriers

The implication of mHealth faces distinctive challenges in rural settings related to infrastructure, financial resources, and workforce capacity. Broadband infrastructure remains substantially limited in rural Appalachia despite federal investments, with Appalachian households lagging 3.5% behind national averages in broadband access

(ARC, 2025). More critically, over 30% of rural health care facilities lack broadband meeting minimum 100/20 Mbps standards required for reliable video streaming and remote monitoring (Bogulski et al., 2024; Federal Communications Commission, 2022). These infrastructure limitations create fundamental feasibility constraints - approximately 50% of rural telehealth appointments remain audio-only due to insufficient bandwidth, eliminating visual assessment capabilities (Klee et al., 2023; Salmon et al., 2025).

Financial constraints affect both health care organizations and patient populations. Rural practices typically operate on narrow margins (1.7%–2.1% in distressed counties vs. 5%–6% in urban systems), making technology investments compete with immediate operational needs including staff retention and facility maintenance (Kaufman et al., 2016; Center for Healthcare Quality and Payment Reform, 2025). Reimbursement policy creates additional barriers, with substantial state-level variation in telehealth reimbursement parity affecting financial viability of virtual care (Porteny et al., 2025; Vakkalanka et al., 2025).

Workforce constraints compound implementation challenges. Primary care provider shortages in distressed Appalachian counties are approximately 40% lower than nondistressed counties, creating time pressures that make workflow disruption from new technology particularly costly (ARC, 2021; Serchen et al., 2025). Rural practices typically lack dedicated information technology (IT) staff, placing troubleshooting and support burdens on clinical personnel without technical training (Maganty et al., 2023; Weichelt et al., 2024).

Provider Perspectives and Adoption Decisions

Health care provider adoption decisions reflect assessment of multiple factors including perceived clinical benefits, implementation feasibility, workflow impacts, and organizational support. Research examining provider perspectives reveals complex attitudes balancing recognition of potential benefits with concerns about implementation challenges (Barry et al., 2024; Valliyappan et al., 2025). Rural providers specifically express greater skepticism about mHealth feasibility compared to urban counterparts, citing unreliable patient internet access, limited practice IT support, and concerns about appropriateness for their patient populations (Klee et al., 2023; Coombs et al., 2022).

These concerns reflect realistic assessment of implementation barriers rather than resistance to innovation. Providers recognize potential benefits but question whether their practice environments can support successful implementation given infrastructure limitations, resource constraints, and patient technology access challenges (Barry et al., 2024; Maganty et al., 2023). Understanding what factors distinguish current adopters from nonadopters under these constrained conditions requires empirical examination of how providers evaluate technologies and make adoption decisions when structural barriers create fundamental feasibility questions.

Knowledge Gaps

Despite substantial research on health care technology adoption, critical gaps remain regarding rural Appalachian contexts. First, most adoption research occurs in well-resourced health care systems, leaving uncertain whether findings generalize to severely resource-constrained rural settings (Maganty et al., 2023; Serchen et al., 2025). Second, research typically examines either innovation attributes or structural constraints, but rarely both simultaneously in ways enabling examination of their interaction (Brooks et al., 2021; Chapman et al., 2025). Third, Appalachian providers remain substantially understudied despite facing some of the most severe health care challenges nationally (Stanzak & Oliver, 2023). This study addresses these gaps by examining how innovation attributes and structural constraints jointly influence current mHealth adoption among rural Appalachian primary care providers.

Problem Statement

The problem this study addresses was that rural Appalachian primary care providers face substantial challenges delivering care to populations experiencing disproportionate chronic disease burden, limited infrastructure, and significant access barriers (ARC, 2021, 2025). While mHealth technologies are promoted as solutions to extend clinical reach and reduce geographic barriers (Martinez & Kim, 2023), adoption patterns demonstrate considerable heterogeneity (Weichelt et al., 2024). This variation suggests that dominant technology adoption theories may not adequately account for rural resource constraints.

The specific research problem is limited empirical understanding of whether innovation attributes from DOI theory (relative advantage, complexity, and trialability) explain current mHealth adoption among rural Appalachian providers, or whether structural constraints moderate these relationships. DOI has been validated extensively in well-resourced contexts where basic infrastructure and organizational support are adequate (Holden & Karsh, 2010; Rogers, 2003). Whether the theory operates similarly in severely resource-constrained settings where infrastructure limitations and financial constraints can prevent adoption regardless of favorable perceptions remains empirically uncertain (Bogulski et al., 2024; Chapman et al., 2025).

This gap has practical consequences. Implementation strategies based on assumptions that innovation attributes operate uniformly across contexts may fail when structural constraints fundamentally alter adoption dynamics. If attributes distinguish adopters similarly regardless of constraints, interventions should emphasize demonstrating benefits and ensuring usability. If constraints substantially moderate relationships, interventions must prioritize infrastructure development and resource provision as prerequisites. Without empirical evidence clarifying these dynamics, implementation efforts risk mismatching strategies to actual barriers.

This study contributes to social change by clarifying whether adoption barriers reflect provider attitudes amenable to education or structural limitations requiring systemic intervention. Findings inform policy decisions about resource allocation - whether investments should emphasize technology promotion and training versus infrastructure development and financial support. By examining adoption from provider perspectives in severely constrained environments, the research supports health equity goals by ensuring implementation strategies account for real-world feasibility rather than assuming technology availability ensures adoption.

Purpose of the Study

The purpose of this quantitative, nonexperimental, cross-sectional study was to test the relationships between innovation attributes, structural constraints, and current mHealth adoption among primary care providers in rural Appalachian counties. Specifically, the study tests whether DOI attributes - perceived relative advantage, complexity, and trialability - are associated with current adoption, and whether structural constraints moderate these relationships.

Independent variables are the three DOI innovation attributes: (a) perceived relative advantage - the degree to which providers believe mHealth offers benefits over existing approaches; (b) perceived complexity - the degree to which providers perceive mHealth as difficult to implement and use; and (c) perceived trialability - the extent to which providers believe they can experiment with mHealth on a limited basis before full commitment. The dependent variable is current mHealth adoption status, operationalized as whether providers currently use mHealth technologies in clinical practice. Moderating variables represent structural constraints characteristic of rural Appalachia: (a) infrastructure adequacy (broadband reliability), (b) organizational resource availability (IT support, staffing), and (c) financial resources (operating margins, reimbursement adequacy).

The study employed hierarchical logistic regression to test whether innovation attributes are associated with current adoption (examining DOI's applicability in this context) and whether structural constraints moderate attribute-adoption relationships (examining boundary conditions). Findings clarify which factors most strongly distinguish current adopters from nonadopters in this setting, inform whether standard adoption models adequately explain patterns in resource-constrained contexts, and provide evidence for implementation strategy development.

Research Questions and Hypotheses

Three RQs underpinned this investigation of DOI theory applicability in rural Appalachian contexts and structural constraint moderation.

Research Question 1

RQ1: Which innovation attributes significantly predict current mHealth adoption among rural Appalachian primary care providers?

Null Hypotheses

H_{01}: Perceived relative advantage does not significantly predict current mHealth adoption.

H_{02}: Perceived complexity does not significantly predict current mHealth adoption.

H_{03}: Perceived trialability does not significantly predict current mHealth adoption.

Alternative Hypotheses

H_{11}: Perceived relative advantage significantly and positively predicts current mHealth adoption, with providers perceiving greater benefits demonstrating higher odds of adoption.

H_{12}: Perceived complexity significantly and negatively predicts current mHealth adoption, with providers perceiving greater difficulty demonstrating lower odds of adoption (equivalently, perceived ease positively predicts adoption).

H_{13}: Perceived trialability significantly and positively predicts current mHealth adoption, with providers perceiving greater experimentation opportunities demonstrating higher odds of adoption.

RQ1 investigated the foundational predictive capacity of Rogers's (2003) innovation attributes within the specific context of rural Appalachian primary care. The null hypotheses suggest that perceived relative advantage, complexity, and trialability do not significantly distinguish current adopters from nonadopters. In contrast, the alternative hypotheses propose that these perceptions are primary factors associated with adoption status. Specifically, H_{11} posits that perceived relative advantage - the degree to which mHealth is seen as superior to traditional care - will significantly and positively predict current adoption. H_{12} suggests that perceived complexity will serve as a significant negative predictor, as the difficulty of integration may deter adoption. Finally, H_{13} proposes that perceived trialability will positively predict adoption, reflecting the value of low-risk experimentation in resource-limited practices.

To test these relationships, innovation attributes were operationalized using validated Likert scales adapted from Moore and Benbasat (1991) to ensure technical and clinical relevance. Current adoption status was measured as a binary variable indicating whether providers currently use mHealth technologies in clinical practice. The analysis utilized hierarchical logistic regression, allowing assessment of each attribute's unique association with adoption while controlling for relevant covariates such as provider experience, role, and practice setting.

Research Question 2

RQ2: What is the relative predictive strength of perceived relative advantage, complexity, and trialability in explaining current mHealth adoption among rural Appalachian primary care providers?

Null Hypothesis

H_{04}: There is no significant difference in the predictive strength of relative advantage compared to complexity or trialability in explaining current mHealth adoption.

Alternative Hypothesis

H_{14}: Relative advantage demonstrates significantly greater predictive strength than either complexity or trialability in explaining current mHealth adoption, evidenced by larger effect sizes (odds ratios) and contribution to model prediction.

Research Question 2 investigated the relative predictive strength of perceived relative advantage, complexity, and trialability in distinguishing current adopters from nonadopters among Appalachian primary care providers. The null hypothesis states that there is no significant difference in the predictive strength of relative advantage compared to complexity or trialability. Conversely, the alternative hypothesis posits that relative advantage demonstrates significantly greater predictive strength - evidenced by a larger odds ratio and more substantial contribution to model fit - than either complexity or trialability. This hypothesis is grounded in meta-analytic findings by Tornatzky and Klein (1982), which consistently rank relative advantage as the most potent driver of adoption across diverse contexts; however, the present study tests if this hierarchy remains stable in resource-constrained settings where implementation feasibility might otherwise elevate the salience of complexity or trialability. To evaluate these competing hypotheses, the analysis compared odds ratios and individual predictor contributions to model deviance.

Research Question 3

RQ3: Do structural constraints moderate the relationships between innovation attributes (relative advantage, complexity, trialability) and current mHealth adoption?

Null Hypotheses

H_{05}: Structural constraints do not significantly moderate the relationship between perceived relative advantage and current mHealth adoption.

H_{06}: Structural constraints do not significantly moderate the relationship between perceived complexity and current mHealth adoption.

H_{07}: Structural constraints do not significantly moderate the relationship between perceived trialability and current mHealth adoption.

Alternative Hypotheses

H_{15}: Structural constraints significantly moderate the relationship between perceived relative advantage and current adoption, with the positive effect of relative advantage on adoption weakening under high constraint conditions.

H_{16}: Structural constraints significantly moderate the relationship between perceived complexity and current adoption, with the negative impact of complexity amplified when organizational support is low.

H_{17}: Structural constraints significantly moderate the relationship between perceived trialability and current adoption, with trialability becoming a more potent predictor when resource scarcity increases perceived risk.

RQ3 examined the moderating role of structural constraints on the relationships between the focal innovation attributes - relative advantage, complexity, and trialability - and current mHealth adoption. The null hypotheses state that structural constraints do not significantly moderate these relationships, suggesting the influence of innovation attributes on adoption remains constant regardless of infrastructure or resource levels. Conversely, the alternative hypotheses posit that structural constraints function as a critical boundary condition. Specifically, H_{15} suggests the positive effect of relative advantage on adoption weakens under high constraints as structural barriers render perceived benefits practically unattainable. H_{16} proposes that the negative impact of complexity is amplified when organizational support is low, while H_{17} suggests that trialability becomes a significantly more potent predictor of adoption when resource scarcity increases the perceived risk of technology failure. Structural constraints were operationalized as a composite index of broadband reliability, IT support availability, and financial adequacy.

To evaluate these interaction effects, I utilized hierarchical logistic regression, introducing the multiplicative interaction terms (e.g., Relative Advantage × Structural Constraints) in the final step of the model. This approach allows for determination of whether the moderator accounts for a statistically significant improvement in model fit beyond the main effects alone.

Theoretical Foundation

I employed DOI theory as developed by Everett Rogers (2003) as its theoretical framework. DOI explains how innovations spread through social systems over time, with adoption decisions influenced by innovation attributes: relative advantage, compatibility, complexity, trialability, and observability. Meta-analytic evidence demonstrates these attributes explain 49%–87% of variance in adoption decisions across diverse contexts (Tornatzky & Klein, 1982).

Core Theoretical Propositions

DOI proposes that adoption follows a five-stage process: knowledge (awareness of innovation), persuasion (forming attitudes), decision (choosing to adopt or reject), implementation (putting innovation to use), and confirmation (reinforcing decisions). This study examines current adoption status, which represents the cumulative outcome of these processes - providers who have progressed through all stages to implementation versus those who have not adopted.

Among innovation attributes, relative advantage - the degree to which an innovation is perceived as better than existing alternatives - consistently emerges as the strongest predictor of adoption across studies (Tornatzky & Klein, 1982; Holden & Karsh, 2010). Complexity shows consistent negative relationships, though effect sizes vary more across contexts. Trialability and observability demonstrate positive relationships but with less consistency, suggesting these attributes may operate more contextually.

Application to Health Care Technology

DOI has been extensively applied to health care technology adoption, with systematic reviews identifying hundreds of studies examining electronic health records, telemedicine, clinical decision support, and mHealth adoption (Holden & Karsh, 2010; M. D. Williams et al., 2021). Health care applications generally confirm DOI predictions, though with refinements - compatibility with clinical workflows emerges as particularly important, while observability may matter less in professional contexts where adoption reflects individual clinical judgment (Greenhalgh et al., 2017).

DOI has been applied to examine both prospective adoption intentions and retrospective examination of actual adoption patterns. While some studies examine future intentions as proximal predictors of behavior, others examine current adoption status to understand factors distinguishing adopters from nonadopters (Rogers, 2003). Both approaches test core DOI propositions that innovation attributes influence adoption, with the latter approach providing direct evidence about realized adoption decisions rather than stated intentions.

Recent health care technology research has extended DOI by examining organizational and contextual factors influencing implementation beyond individual perceptions (Damschroder et al., 2022; Glasgow et al., 2019). Implementation science frameworks including CFIR and RE-AIM recognize that successful adoption requires adequate organizational infrastructure, resources, and support - factors that may be limited in rural resource-constrained settings.

Theoretical Contribution: Boundary Condition Testing

This study contributes to DOI theory by testing boundary conditions - contextual limits within which theoretical predictions hold. Standard DOI applications implicitly assume adequate infrastructure and resources enabling adoption once favorable perceptions form. This assumption may not hold in severely resource-constrained settings where infrastructure limitations can prevent adoption regardless of perceptions (Bogulski et al., 2024; Chapman et al., 2025).

By explicitly testing whether structural constraints moderate innovation attribute-adoption relationships, the study examines whether DOI operates uniformly across contexts or whether relationships depend on structural conditions. If attributes predict adoption similarly across constraint levels, this extends DOI's validated scope to resource-limited settings. If constraints significantly moderate relationships, this specifies boundary conditions and suggests theoretical refinements needed to account for implementation context.

Rationale for Framework Selection

DOI was selected over alternative frameworks (Technology Acceptance Model, Unified Theory of Acceptance and Use of Technology) for three reasons. First, DOI attributes align closely with factors rural providers identify as salient - clinical benefits (relative advantage), implementation difficulty (complexity), and opportunity to test technologies (trialability) (Barry et al., 2024; Valliyappan et al., 2025). Second, DOI has been validated across diverse contexts including rural settings, providing established foundation for hypothesis development (Brooks et al., 2021). Third, DOI attributes can be measured through standardized scales with demonstrated reliability and validity (Moore & Benbasat, 1991).

Nature of the Study

I employed a quantitative, nonexperimental, cross-sectional survey design. The quantitative approach enables systematic hypothesis testing and measurement of relative predictor strength through statistical analysis (Creswell & Creswell, 2018). The nonexperimental design is appropriate because variables - provider perceptions, structural constraints, and adoption status - are naturally occurring and cannot be ethically or practically manipulated. The cross-sectional approach provides a snapshot examining factors associated with current adoption, appropriate when longitudinal tracking is not feasible given resource constraints and geographically dispersed population.

Variables

The study variables are organized to evaluate how well established theories of technology adoption apply to the unique environment of the Appalachian region. The independent variables include three core perceptions held by health care providers: relative advantage, or the belief that mHealth tools offer better results than traditional care; complexity, which refers to how difficult a tool is to use or integrate into daily work; and trialability, which is the ability to test a new tool on a small scale before fully committing to it. These perceptions are expected to predict the dependent variable, which is whether the provider currently uses mHealth technologies in clinical practice.

The central focus of this research is to understand how structural constraints - such as unreliable internet, a lack of technical support staff, and limited financial resources - act as moderating variables. This means the study tests whether these contextual pressures change the way a provider's personal perceptions relate to their adoption status. To ensure the results are accurate, the study also uses control variables to account for differences in a provider's background, such as their years of experience, specific job title, and the type of clinic where they work. By examining all these factors together, the study can determine if low adoption rates in Appalachia are explained by how providers perceive the technology or by the physical and financial limitations of their environment.

Definitions

Current mHealth adoption: The provider's current use status of mHealth technologies in clinical practice, categorized as currently using mHealth technologies versus not currently using (including never users and discontinued users).

Diffusion of innovations (DOI): The theory explaining how innovations spread through social systems, with adoption influenced by innovation attributes including relative advantage, complexity, and trialability (Rogers, 2003).

Mobile health (mHealth): health care service delivery through mobile communication devices including smartphones, tablets, and wearable sensors, encompassing remote patient monitoring, secure messaging, and mobile applications (World Health Organization, 2021).

Perceived complexity: The degree to which an innovation is perceived as difficult to understand, learn, and use, including implementation challenges and workflow integration difficulties (Moore & Benbasat, 1991; Rogers, 2003).

Perceived relative advantage: The degree to which an innovation is perceived as better than existing alternatives, including clinical benefits, improved access, and practice efficiency gains (Rogers, 2003).

Perceived trialability: The extent to which an innovation can be experimented with on a limited basis before full commitment, reducing perceived risk and uncertainty (Rogers, 2003).

Primary care providers: Physicians (MD/DO), nurse practitioners, and physician assistants delivering primary health care services including chronic disease management, preventive care, and acute care.

Rural Appalachia: Counties within the Appalachian region designated as rural by Health Resources and Services Administration criteria, characterized by lower population density, geographic isolation, and limited health care infrastructure (ARC, 2021, 2025).

Structural constraints: Material, organizational, and policy factors existing independently of individual attitudes that enable or limit action possibilities, including infrastructure adequacy, organizational resources, and financial capacity (Giddens, 1984).

Reimbursement parity: The legal and policy requirement that private and public payers reimburse health care providers for mHealth and telehealth services at the same rate as in-person clinical encounters (Harvey et al., 2019; Vakkalanka et al., 2025).

Assumptions

Several assumptions underlie this study's meaningfulness and validity, particularly given its focus on provider perceptions and adoption patterns within the unique socio-technical landscape of Central and Southern Appalachia. First, I assumed that providers accurately report their current use of mHealth technologies. To support response accuracy, the survey is conducted anonymously with emphasis on research rather than performance evaluation, reducing social desirability bias. A second assumption was that providers' perceptions of innovation attributes and structural constraints reflect their actual experiences and practice environments rather than abstract opinions. Current data on regional internet access and clinic funding supports the assumption that structural condition variability across the Appalachian region is sufficient to examine moderation effects meaningfully.

Third, I assumed that cross-sectional associations between perceptions and current adoption status provide meaningful insight into factors influencing adoption decisions, acknowledging that temporal precedence cannot be established definitively. While perceptions may influence adoption or be influenced by adoption experience, theoretical expectations from DOI and retrospective adoption studies suggest perceptions formed during the persuasion stage influence subsequent adoption decisions. Finally, the study assumes that the survey instruments, adapted from previously validated scales, accurately measure the intended constructs and that the broader health care policy environment remained stable during data collection to ensure results reflect consistent conditions for participants.

Scope and Delimitations

Scope of the Study

I examined relationships between innovation attributes, structural constraints, and current mHealth adoption among primary care providers in rural Appalachian counties. The specific focus addresses internal validity by ensuring sample homogeneity regarding structural constraints and cultural contexts that may influence adoption dynamics.

Delimitations

From the population, the study sample includes only primary care providers (physicians, nurse practitioners, physician assistants) in rural medically underserved Appalachian counties. Excludes specialists, administrators, and providers in nonrural or non-Appalachian locations. This boundary focuses investigation on providers most directly affected by rural access challenges and most likely to integrate mHealth into chronic disease management. For study feasibility and cost reasons, participants included are limited to Central and Southern Appalachian subregions, excluding Northern Appalachia. This boundary ensures sample consistency regarding economic distress levels and infrastructure challenges while reflecting regions with most severe health care challenges (ARC, 2021, 2025).

This study focuses on mHealth technologies applicable to primary care (remote monitoring, secure messaging, mobile applications). Excludes high-acuity technologies (telestroke, surgical robotics) involving different adoption dynamics. I used DOI theory rather than alternative frameworks (TAM, UTAUT, organizational theories). DOI was selected because attributes align with provider-identified factors and theory has established validation in health care contexts (Holden & Karsh, 2010; M. D. Williams et al., 2021).

Generalizability

Findings are expected to generalize to other medically underserved rural contexts sharing similar infrastructure challenges and economic conditions. Generalizability may be limited to well-resourced rural systems or urban settings where structural constraints differ substantially. However, by documenting how constraints moderate adoption, findings provide framework for understanding technology diffusion in other resource-limited contexts.

Limitations

Design Limitations

Cross-Sectional Design

Single time-point measurement precludes establishing temporal precedence or definitive causal relationships. While enabling examination of concurrent associations between perceptions and current adoption status, the design cannot determine whether perceptions preceded and caused adoption decisions or whether adoption experience influenced subsequent perceptions. Providers who have adopted mHealth may rationalize their decisions by emphasizing benefits and minimizing concerns, while nonadopters may emphasize barriers to justify nonadoption. Longitudinal designs measuring perceptions before adoption decisions would strengthen causal inference but are not feasible given resource constraints and practical challenges of tracking geographically dispersed providers over time. Despite this limitation, the cross-sectional approach examining current adoption status provides meaningful evidence about factors distinguishing adopters from nonadopters in this severely underserved context.

Validity Threats

Internal Validity

Self-selection into survey participation may create bias if providers with stronger technology interests or experiences disproportionately participate. Anonymous administration and emphasis on research purpose mitigate but do not eliminate social desirability bias. Unmeasured confounds including provider technology self-efficacy, prior technology experiences, and organizational culture may influence both perceptions and adoption status, creating spurious associations.

External Validity

Findings may not generalize beyond Central and Southern Appalachia to Northern Appalachian regions with different infrastructure and economic profiles, or to non-Appalachian rural areas with different cultural contexts. The unique historical experiences and cultural characteristics of Appalachian communities (Stanzak & Oliver, 2023) may create adoption dynamics not operating in other rural regions.

Construct Validity

Self-report measures are subject to biases including retrospective rationalization and systematic response patterns. While using validated scales enhances construct validity, subjective perceptions may not align with objective reality - for example, perceived infrastructure adequacy may differ from objective broadband metrics.

Mitigation Strategies

I used several approaches to address the limitations of the study:

- including control variables (experience, role, setting) to account for systematic individual and organizational differences;
- using validated instruments with demonstrated psychometric properties;
- comparing self-reported infrastructure assessments with objective county-level data where available;
- employing anonymous administration to reduce social desirability bias;
- acknowledging limitations explicitly in interpretation and recommendations.

Significance of the Study

Significance to Theory

This study advances DOI theory by testing boundary conditions in severely resource-constrained contexts. Most DOI validation research occurs where basic infrastructure and organizational support are adequate (Holden & Karsh, 2010; Rogers, 2003). Whether relationships operate similarly when infrastructure limitations and resource constraints create fundamental feasibility questions remains uncertain. By examining whether structural constraints moderate attribute-adoption relationships, the study determines if DOI predictions hold in resource-limited settings or if contextual factors fundamentally alter adoption dynamics.

If innovation attributes are associated with adoption similarly across constraint levels, this extends DOI's validated scope to resource-constrained rural health care. If constraints significantly moderate relationships, this specifies boundary conditions and suggests theoretical refinements. Either finding advances theoretical understanding by clarifying scope conditions - contextual limits within which predictions hold.

The study also contributes to implementation science by examining mechanisms through which structural factors influence adoption. Current frameworks recognize that organizational and environmental factors matter (Damschroder et al., 2022; Glasgow et al., 2019) but provide limited guidance about whether constraints primarily block behavior or fundamentally alter the relative importance of different perceptual factors in distinguishing adopters from nonadopters. Understanding these mechanisms has implications for theoretical development and practical intervention design.

Significance to Practice

For health care administrators and policymakers, findings provide evidence-based guidance for implementation strategy development. If innovation attributes are associated with adoption similarly regardless of constraints, strategies should emphasize demonstrating benefits and ensuring usability - approaching adoption as an education and training challenge. If constraints substantially moderate relationships, strategies must prioritize infrastructure development and resource provision as prerequisites - approaching adoption as requiring environmental change before individual-level interventions succeed.

Specific practical applications include (a) resource allocation decisions (whether to invest in technology promotion versus infrastructure development), (b) policy advocacy (providing empirical basis for reimbursement parity and infrastructure investment policies), (c) technology design (informing requirements for usability and integration in resource-limited settings), and (d) implementation planning (identifying whether adoption barriers require systemic intervention versus provider-level education). By clarifying which factors most strongly distinguish adopters from nonadopters and how they interact, findings enable matching implementation strategies to actual barriers rather than relying on assumptions about what matters most in rural contexts.

Significance to Social Change

This study contributes to health equity by examining technology adoption from perspectives of providers serving severely underserved populations. Rural Appalachia experiences among the most substantial health disparities nationally (ARC, 2021, 2025; Serchen et al., 2025) yet remains underrepresented in technology adoption research. By centering analysis on this population, the study ensures that evidence informs policies affecting those with greatest need.

The research promotes positive social change - improvement of human conditions through equitable resource distribution and development of individuals and communities - in three ways. First, by clarifying whether adoption barriers reflect perceptions or structural limitations, findings guide whether interventions should emphasize education or systemic change. If barriers are primarily structural, continued emphasis on provider education misallocates resources while ignoring fundamental problems.

Second, the study validates provider perspectives and decision-making under constrained conditions. Rather than assuming nonadoption reflects resistance or ignorance, the research examines whether providers rationally assess that technologies are inappropriate given their practice environments. This reframes nonadoption from provider deficiency to reasonable professional judgment given circumstances.

Third, findings inform policy debates about rural health care technology investment. If structural constraints substantially moderate adoption, this provides empirical basis for infrastructure and financial support policies rather than technology-focused interventions alone. By demonstrating that technology availability does not ensure adoption when infrastructure and resources are inadequate, the study supports arguments for comprehensive approaches addressing systemic barriers to health equity.

Summary and Transition

This chapter has established the foundation for examining mHealth adoption among rural Appalachian primary care providers. The problem - limited understanding of whether innovation attributes explain adoption in severely resource-constrained settings and whether structural constraints moderate these relationships - has significant implications for implementation strategy and health equity. I employed DOI theory while explicitly testing boundary conditions through moderation analysis, advancing both theoretical understanding and practical guidance for rural health care technology implementation.

Chapter 2 provides a comprehensive literature review supporting this investigation. In the review, I examine: (a) rural Appalachian health care context including health disparities, infrastructure challenges, and cultural factors; (b) mHealth technologies and their application in health care; (c) technology adoption theoretical frameworks including DOI, TAM, and UTAUT; (d) empirical evidence regarding technology adoption predictors; (e) structural constraints in resource-limited settings; (f) current adoption patterns and determinants; and (g) synthesis identifying specific gaps this study addresses. This literature foundation establishes theoretical and empirical basis for the research questions and hypotheses guiding the investigation.

Chapter 2: Literature Review

Primary care providers in Central and Southern Appalachia serve populations experiencing substantially higher rates of chronic disease and mortality compared to national averages, compounded by geographic isolation, provider shortages, and limited health care resources (Appalachian Regional Commission, 2021; Meit et al., 2022). Technologies for mHealth offer potential mechanisms to extend clinical care beyond traditional office visits and address some of these disparities (Kruse et al., 2019). However, adoption rates among primary care providers remain inconsistent and lower than in urban or suburban areas.

The research problem centers on limited understanding of whether established theoretical frameworks for technology adoption, particularly Rogers’s (2003) DOI theory, adequately explain adoption variation in resource-constrained health care settings. Specifically, it remains unclear whether structural factors such as inadequate broadband infrastructure, limited technical support, and policy barriers moderate the relationships between providers' perceptions of innovation characteristics and their adoption decisions. This study addresses this gap by examining how primary care providers' perceptions of mHealth's relative advantage, complexity, and trialability are associated with current adoption, and testing whether regional infrastructure and resource availability influence these relationships.

Current literature documents growing disparities in digital health access and implementation. While clinical research demonstrates mHealth effectiveness for managing chronic conditions including diabetes and hypertension (Bazzano et al., 2024; Fudim et al., 2025), implementation in Appalachian settings faces substantial barriers. These include inadequate broadband internet access, insufficient technical support staff within health care organizations, and inconsistent reimbursement policies for telehealth services (Bogulski et al., 2024; Haque et al., 2023). The regulatory environment presents additional challenges, with variable reimbursement rates across payers and incomplete interstate licensure agreements creating uncertainty for providers considering technology adoption (Bogulski et al., 2025; Vakkalanka et al., 2025). This literature review establishes that theoretical models explaining technology adoption require examination of contextual factors that may influence their applicability in underserved regions.

This chapter provides a comprehensive synthesis of literature relevant to understanding mHealth adoption among rural Appalachian primary care providers. The review is organized into five major sections. First, the Historical and Cultural Context of Appalachia section examines the region's health care delivery patterns, including the importance of established patient-provider relationships and community trust in health care decision-making (Stanzak & Oliver, 2023). Second, the Evolution and Efficacy of mHealth section reviews evidence regarding mHealth technologies in rural primary care and chronic disease management. Third, the DOI Theoretical Framework section provides detailed analysis of the theory's core constructs - relative advantage, complexity, and trialability - and examines their applicability in resource-limited settings. Fourth, the Structural and Policy Context section synthesizes empirical research on infrastructure limitations, reimbursement policies, and other systemic factors that may moderate technology adoption. Finally, the Summary and Research Gap section identifies limitations in current literature and specifies how this study addresses unresolved questions.

Literature Search Strategy

I conducted a primary search of essential literature using a systematic approach designed to identify seminal theoretical works, current peer-reviewed research, and context-specific evidence regarding health care in Appalachia. The search strategy aimed to establish the current state of knowledge regarding mHealth adoption, application of Rogers's (2003) DOI theory in health care contexts, and structural and cultural factors relevant to Central and Southern Appalachia.

Accessed Databases and Search Engines

To ensure a comprehensive and multidisciplinary evidence base, I searched a diverse array of scholarly databases, including PubMed, CINAHL, and PsycINFO for clinical and behavioral perspectives, alongside Scopus and Web of Science for interdisciplinary tracking. These were supplemented by the Cochrane Library for synthesized evidence on clinical efficacy and Google Scholar for critical policy reports from entities like the Appalachian Regional Commission. This approach allowed the research to integrate findings from medicine, health informatics, and implementation science into a single, cohesive framework.

The search strategy employed specific Boolean strings to connect three core themes: technological innovation, geographic parameters, and provider variables. Terms such as "mHealth adoption" and "diffusion of innovations" were paired with regional markers like "Central Appalachia" and "rural healthcare," as well as professional roles including "nurse practitioners" and "physician assistants." This structured method ensured that the literature identified specifically addressed the intersection of modern digital health tools and the unique professional and environmental realities of the Appalachian medical landscape.

Search strings included the following:

- (mHealth OR mobile health OR telehealth) AND (Appalachia OR rural) AND (primary care providers OR physicians OR nurse practitioners)
- (diffusion of innovations OR innovation adoption) AND (rural healthcare OR underserved) AND (barriers OR facilitators)
- (telehealth OR telemedicine) AND (infrastructure OR broadband OR reimbursement) AND (Appalachia OR rural)

Strict inclusion and exclusion criteria prioritized recency and geographic relevance, focusing primarily on peer-reviewed research published between 2020 and 2026. While the review highlighted recent developments in digital health following the COVID-19 pandemic, it also incorporated seminal theoretical works to maintain a strong conceptual foundation. In instances where region-specific data were limited, a triangulation strategy was used to apply broader rural health findings to the specific cultural and infrastructural context of Appalachia, ensuring a robust evidence base for the study's moderation model.

Theoretical Foundation

This study was grounded in Everett Rogers's DOI theory, a comprehensive framework explaining how new ideas, practices, and technologies spread through social systems over time. Originally developed in 1962 and refined through five editions, the theory proposes that adoption of innovations is a social process influenced by characteristics of the innovation itself, communication channels through which individuals learn about the innovation, time, and characteristics of the social system in which adoption occurs (Rogers, 2003). For this investigation, DOI provides a structured approach to examining why mHealth adoption among primary care providers in Central and Southern Appalachia varies, focusing on the persuasion stage of the innovation-decision process during which potential adopters form attitudes toward new technologies based on perceived characteristics.

Core Theoretical Constructs

Rogers identified five attributes of innovations that influence adoption rates: relative advantage, compatibility, complexity, trialability, and observability. Research across multiple contexts suggests these five attributes explain 49%–87% of variance in adoption rates (Tornatzky & Klein, 1982). This study focuses on three attributes that prior research has identified as particularly salient in health care technology adoption contexts (Holden & Karsh, 2010):

Relative advantage refers to the degree to which an innovation is perceived as better than the practice it supersedes (Rogers, 2003). In health care contexts, relative advantage may encompass clinical outcomes, efficiency gains, improved patient satisfaction, or enhanced ability to provide care to geographically distant patients. Providers assess whether mHealth technologies offer meaningful improvements over traditional in-person care delivery, telephone consultations, or other existing approaches.

Complexity refers to the degree to which an innovation is perceived as difficult to understand and use (Rogers, 2003). For health care technologies, complexity includes not only the user interface and technical requirements but also integration with existing electronic health record systems, workflow modifications required for implementation, and cognitive load associated with learning new systems while maintaining patient care responsibilities.

Trialability refers to the degree to which an innovation can be experimented with on a limited basis before full commitment (Rogers, 2003). In health care settings, trialability may involve piloting technologies with selected patients, testing platforms during specific time periods, or implementing technologies for limited clinical applications before broader deployment. Higher trialability reduces perceived risk and allows providers to assess fit with their practice patterns.

The DOI theory proposes that innovations perceived as having greater relative advantage, lower complexity, and higher trialability are adopted more rapidly and extensively. However, Rogers emphasized that these perceptions are subjective and shaped by characteristics of both the innovation and the social system in which adoption occurs.

Application to Health Care Technology Adoption

DOI has been extensively applied to health care technology adoption, with generally supportive findings but important contextual variations. Studies examining electronic health record adoption, telemedicine implementation, and clinical decision support systems have found that relative advantage consistently predicts adoption intentions and behaviors, while complexity shows negative associations with adoption (Gagnon et al., 2012; Holden & Karsh, 2010). However, the magnitude and sometimes direction of these relationships varies across settings.

Research in resource-constrained health care environments suggests that structural factors may moderate relationships between innovation attributes and adoption. For example, Weichelt et al. (2019, 2024) found that among rural providers, perceived complexity reflected not only the technology itself but also inadequate technical support within health care organizations. Similarly, studies in low-resource international settings indicate that relative advantage perceptions are influenced by infrastructure reliability, with providers less likely to perceive benefits when internet connectivity is unreliable (Chib et al., 2015). These findings suggest that while innovation attributes influence adoption decisions, their effects may be contingent on contextual factors.

Rationale for Theory Selection

DOI was selected over alternative technology adoption frameworks for several reasons. Unlike the Technology Acceptance Model (Davis, 1989), which focuses primarily on individual perceptions of usefulness and ease of use, DOI explicitly incorporates social system characteristics and acknowledges that adoption decisions occur within organizational and community contexts. This emphasis on context is particularly relevant for examining technology adoption in rural Appalachia, where structural constraints including infrastructure limitations, policy barriers, and resource scarcity may substantially influence provider decisions.

Additionally, DOI has demonstrated applicability across diverse contexts and populations, providing a validated framework for examining adoption in underserved settings. The theory's emphasis on communication networks and social influence aligns with documented importance of professional networks and trusted relationships in rural health care decision-making (Stanzak & Oliver, 2023). Finally, the theory's explicit attention to innovation attributes provides actionable insights for implementation efforts, as these attributes may be modified through intervention design and implementation strategies.

Theoretical Extensions and Study Contributions

This study tests and potentially extends DOI theory by examining whether relationships between innovation attributes and adoption intentions hold in resource-constrained rural health care settings or whether structural factors moderate these relationships. Traditional applications of the theory assume that innovation attributes exert consistent influences across contexts. However, the extreme resource constraints, infrastructure limitations, and policy barriers characterizing rural Appalachia may alter how providers perceive and weigh innovation characteristics.

Specifically, the study investigates whether structural constraints - including inadequate broadband infrastructure, limited technical support, uncertain reimbursement policies, and constrained financial resources - moderate relationships between perceived relative advantage, complexity, and trialability and adoption intentions. For example, relative advantage perceptions may translate less strongly into adoption intentions when infrastructure is inadequate to support reliable technology use, regardless of perceived clinical benefits. Similarly, complexity may exert stronger negative influences when organizational technical support is limited, as providers cannot rely on assistance with implementation challenges.

By examining these potential moderating effects, the study contributes to more contextually grounded understanding of technology adoption processes. If structural factors significantly moderate attribute-intention relationships, this would suggest that innovation attributes operate conditionally rather than universally, with implications for both theory refinement and practical implementation strategies. Such findings would support developing context-specific adoption models that account for structural realities of different health care settings rather than assuming universal relationships between perceptions and behaviors.

Literature Review

Rural Appalachian Health Care Context

The health care landscape of rural Appalachia faces persistent and worsening challenges in access, infrastructure, and health outcomes. The Appalachian Regional Commission identifies 423 counties across 13 states as Appalachian, with 77 classified as economically distressed in fiscal year 2025 - placing them in the worst 10% of the nation economically (Appalachian Regional Commission [ARC], 2024). These distressed counties experience profound economic disparities: median household incomes lag nearly 30% behind national averages, while poverty rates reach 18.1% compared to 13.4% nationally (ARC, 2025).

Health Disparities and Chronic Disease Burden

Health status indicators reveal substantial disparities between Appalachian and national populations. Mortality rates from major chronic diseases significantly exceed national benchmarks: heart disease mortality is 17% higher (reaching 42% higher in Central Appalachia), chronic obstructive pulmonary disease (COPD) mortality is 27% higher, and diabetes mortality is 11% higher than national rates (ARC, 2021, 2025). Recent evidence documents alarming trends in maternal mortality and substance use disorders, with drug overdose rates in specific rural corridors reaching five times the national average (Serchen et al., 2025; Mann-Jackson et al., 2025).

These disparities reflect complex interactions among economic disadvantage, geographic isolation, and limited health care access. Research consistently documents that rural Appalachian residents face substantial barriers to preventive care, resulting in later-stage disease diagnosis and poorer outcomes (Buchalter et al., 2023; Wang et al., 2025). The cumulative effect creates what researchers term a "health gap" - systematic disadvantages in health status that persist across multiple disease categories and demographic groups (Morrone et al., 2021; Wiener et al., 2025).

Health Care Infrastructure Crisis

Rural Appalachian health care infrastructure is experiencing acute stress from facility closures and workforce shortages. Between 2020 and 2025, over 116 rural hospitals closed or discontinued labor and delivery services, leaving approximately 60% of rural Appalachian hospitals without obstetric services (Center for Healthcare Quality and Payment Reform, 2025; Zahnd et al., 2023). For pregnant women in Central Appalachia, this often necessitates travel exceeding 50 min to reach the nearest delivery facility (Center for Healthcare Quality and Payment Reform, 2025). These closures create cascading effects on overall health care access, as hospital closures typically precede reductions in primary care and specialist availability (Cecil G. Sheps Center, 2023).

Primary care workforce shortages compound infrastructure challenges. The supply of primary care physicians in distressed Appalachian counties is approximately 40% lower than in nondistressed counties, creating "medical deserts" where millions of residents lack local access to routine preventive care (ARC, 2021; Serchen et al., 2025). Provider shortages reflect multiple factors including difficulty recruiting to rural areas, lower reimbursement rates, and high burnout rates among existing providers (Rao et al., 2021; Maganty et al., 2023). The shortage is particularly acute for advanced practice providers including nurse practitioners and physician assistants, despite these professionals being well-suited to address rural primary care needs (Bailey et al., 2024; Kukulka et al., 2024).

Broadband Infrastructure and the Digital Divide

Despite federal infrastructure investments, broadband access remains substantially limited in rural Appalachia, creating what researchers term the "digital divide" - systematic differences in technology access between urban and rural populations (Crowe et al., 2024). Appalachian households lag 3.5 percentage points behind the national average in broadband internet access (ARC, 2025). More critically, recent estimates indicate that over 45 million Americans, concentrated in rural areas including Appalachia, lack access to broadband meeting the minimum 100/20 Mbps standard (100 Mbps download, 20 Mbps upload) required for stable telemedicine and remote monitoring (Federal Communications Commission, 2022; Bogulski et al., 2024).

This infrastructure gap creates fundamental constraints on telehealth and mHealth feasibility. Research documents that nearly 50% of rural telehealth appointments remain audio-only due to insufficient bandwidth for video streaming (Klee et al., 2023; Salmon et al., 2025). Federal initiatives including the Infrastructure Investment and Jobs Act of 2021 have allocated $65 billion for broadband expansion targeting rural areas (Infrastructure Investment and Jobs Act, 2021), yet deployment remains uneven and progress slower than anticipated (K. Smith & Chen, 2023). Current legislative efforts specifically target low-orbit satellite technology as an alternative where terrestrial fiber deployment remains economically unfeasible (Bogulski et al., 2024).

Cultural Context and Health Care Utilization

Cultural dynamics rooted in Appalachian values of self-reliance and historical experiences with external institutions shape health care utilization patterns and technology perceptions. Appalachian communities have experienced historical exploitation through extractive industries and systematic exclusion from economic development, creating what scholars term "institutional mistrust" - skepticism toward external interventions including health care innovations (Stanzak & Oliver, 2023; Alspaugh et al., 2023). This historical context influences how communities perceive health care technology, with qualitative research documenting that some residents view digital health tools as impersonal "outsider" intrusions that threaten valued relational continuity with providers (Morrone et al., 2021).

Cultural values emphasizing self-reliance and stoicism can delay care-seeking until conditions become severe (Kukulka et al., 2024; Burch, 2022). Research documents that rural Appalachian residents often describe needing to be "bleeding, broken" before seeking medical attention, reflecting both economic constraints and cultural norms minimizing health care utilization (Kukulka et al., 2024). For primary care providers considering mHealth adoption, understanding these cultural dynamics is essential - technology must demonstrate value within existing patient-provider relationships rather than replacing them (Coombs et al., 2022; Dehart et al., 2022).

Health care providers in rural Appalachia must navigate these cultural contexts when introducing new care delivery models. Successful implementations typically emphasize how technology enhances rather than replaces traditional care relationships, maintains patient privacy and dignity, and demonstrates clear benefits for common health concerns in the community (Barry et al., 2024; Chapman et al., 2025). Providers report that patient acceptance of technology depends substantially on their own confidence and enthusiasm when introducing digital health tools, making provider adoption intentions a critical precursor to patient engagement (McCabe et al., 2025; Valliyappan et al., 2025).

Mobile Health Technologies in Health Care

The phenomenon of mHealth represents health care service delivery through mobile communication devices including smartphones, tablets, and wearable sensors. The World Health Organization defines mHealth as "medical and public health practice supported by mobile devices" (World Health Organization, 2021), distinguishing it from broader telemedicine through emphasis on portability, patient-generated data, and continuous connectivity. In primary care settings, mHealth encompasses remote patient monitoring for chronic conditions, secure patient-provider messaging, medication adherence applications, and clinical decision support tools (Fava & Lapão, 2024; Senek et al., 2025).

mHealth Technologies in Rural Primary Care

For rural Appalachian primary care, mHealth technologies address specific challenges including geographic barriers to care, management of high chronic disease prevalence, and provider workforce limitations. Common applications include remote patient monitoring (RPM) systems that transmit blood pressure, blood glucose, and weight data from patient homes to clinical teams; secure messaging platforms enabling asynchronous communication between visits; and medication reminder systems addressing adherence challenges (Bazzano et al., 2024; Martinez & Kim, 2023). Recent technological advances incorporate artificial intelligence for triage, symptom assessment, and clinical decision support, though adoption of these more advanced tools remains limited in rural settings (Kummer & Busis, 2024; Anawade et al., 2024).

The evidence base for mHealth effectiveness demonstrates clinical benefits under research conditions but highlights implementation challenges in real-world practice. Systematic reviews document that RPM interventions can reduce HbA1c levels in diabetes management and improve blood pressure control in hypertension, with effect sizes varying based on intervention intensity and patient engagement strategies (Bazzano et al., 2024; Martinez & Kim, 2023). However, research consistently identifies a gap between efficacy (outcomes under controlled research conditions) and effectiveness (outcomes in routine practice), with real-world implementations showing smaller effects due to factors including lower patient engagement, technical difficulties, and workflow integration challenges (Fava & Lapão, 2024; Giebel et al., 2023).

Implementation Challenges in Rural Settings

mHealth implementation in rural settings faces distinctive challenges related to infrastructure, resources, and patient populations. Technical infrastructure limitations including unreliable broadband and older hardware create fundamental feasibility constraints (Bogulski et al., 2024; Krahe et al., 2025). When video streaming fails due to bandwidth limitations, appointments default to audio-only communication, eliminating visual assessment capabilities and reducing clinical utility (Klee et al., 2023; Salmon et al., 2025). These technical failures erode provider and patient confidence in digital health tools, creating barriers to sustained adoption (Barry et al., 2024).

Financial constraints affect both health care organizations and patient populations. Rural practices typically operate on narrow financial margins, making technology investments compete with immediate operational needs including staff retention and facility maintenance (Maganty et al., 2023; Weiss et al., 2025). For patients, smartphone ownership and data plan affordability present barriers to mHealth engagement, with research documenting that requiring smartphone ownership for interventions systematically excludes economically disadvantaged populations (Bommakanti et al., 2020; Hengst et al., 2023). The digital divide encompasses not only infrastructure access but also digital health literacy - the skills and knowledge required to effectively use health technologies - which varies systematically by age, education, and socioeconomic status (De La Vega et al., 2024; Yue et al., 2025).

Workforce limitations compound implementation challenges. Rural practices typically lack dedicated IT staff, placing technical troubleshooting and user support burdens on clinical personnel (Maganty et al., 2023; Chapman et al., 2025). Without IT support, providers become responsible for resolving technical issues including failed data transmissions, software errors, and integration problems with electronic health records (EHRs) - tasks for which they lack training and which distract from clinical responsibilities (Weichelt et al., 2024; Schürmann et al., 2025). This "implementation burden" can outweigh perceived benefits, leading to technology abandonment despite initial enthusiasm (Nataliansyah et al., 2022).

Provider Perspectives on mHealth

Research examining health care provider perspectives on mHealth reveals complex attitudes balancing recognition of potential benefits with concerns about implementation challenges and practice impacts. Surveys conducted during and after the COVID-19 pandemic document that substantial majorities of providers (often exceeding 80%) endorse hybrid care models combining in-person and virtual visits (Raspet & Gietzen, 2024; Tipre et al., 2024). However, enthusiasm for telehealth generally exceeds willingness to adopt more complex mHealth tools requiring patient technology use and ongoing data monitoring (Alsahli et al., 2023; Schürmann et al., 2025).

Providers identify multiple factors influencing mHealth adoption decisions. Perceived clinical benefits - including improved chronic disease monitoring, enhanced patient access, and potential for earlier intervention - emerge as primary motivators (Valliyappan et al., 2025; Bazzano et al., 2024). Providers particularly value mHealth for patients with transportation barriers, mobility limitations, or chronic conditions requiring frequent monitoring (Barry et al., 2024; Martinez & Kim, 2023). Conversely, concerns center on workflow disruption, time requirements for reviewing patient-generated data, technical difficulties, liability questions, and adequacy of reimbursement (Alsahli et al., 2025; Alzghaibi, 2025).

Rural provider perspectives specifically emphasize infrastructure and support constraints. Qualitative research documents that rural providers express greater skepticism about mHealth feasibility compared to urban counterparts, citing unreliable patient internet access, limited practice IT support, and concerns about algorithm performance with demographically distinct patient populations (Klee et al., 2023; Maganty et al., 2023). These concerns reflect realistic assessment of implementation barriers rather than resistance to innovation - providers recognize potential benefits but question whether their practice environments can support successful implementation (Barry et al., 2024; Coombs et al., 2022).

Sustainability and Long-Term Outcomes

Emerging research emphasizes the gap between initial pilot implementations and sustained routine use of mHealth technologies. Many rural practices have participated in mHealth pilots supported by external funding and technical assistance, but experience difficulty sustaining these programs once external support ends (Nataliansyah et al., 2022; Toll et al., 2025). This "pilot syndrome" reflects inadequate attention to sustainability factors including ongoing costs, technical support requirements, staff training needs, and workflow adaptation (Chapman et al., 2025; Totten et al., 2024).

Long-term patient engagement presents additional sustainability challenges. Research documents declining patient engagement over time with mHealth interventions, with dropout rates often exceeding 50% within 6 months (Niyomyart et al., 2024). Factors associated with sustained engagement include regular provider feedback on patient-generated data, seamless integration with existing care processes, and clear patient benefits from participation (McCarthy et al., 2024; Leng et al., 2025). For rural providers, maintaining engagement requires ongoing time investment that must be balanced against competing clinical demands without corresponding increases in reimbursement or staffing (Porteny et al., 2025).

Technology Adoption Theoretical Frameworks

Understanding health care provider decisions to adopt new technologies requires theoretical frameworks explaining how individuals evaluate innovations and form behavioral intentions. Multiple complementary frameworks have been developed and validated across diverse contexts, with three dominant in health care technology research: DOI theory, the Technology Acceptance Model, and the Unified Theory of Acceptance and Use of Technology. I employed DOI theory as the study's primary framework while acknowledging insights from alternative models.

Diffusion of Innovations Theory

DOI theory, developed by Everett Rogers (2003), explains how new ideas and technologies spread through social systems. The theory proposes that adoption decisions are influenced by five innovation attributes: relative advantage (the degree to which an innovation is perceived as better than existing alternatives), compatibility (consistency with adopter values, experiences, and needs), complexity (perceived difficulty of understanding and using the innovation), trialability (opportunities to experiment with the innovation on a limited basis), and observability (visibility of innovation results to others). Meta-analytic research demonstrates that these five attributes explain 49%–87% of variance in adoption decisions across diverse innovations and contexts (Tornatzky & Klein, 1982).

Among these attributes, relative advantage consistently emerges as the strongest and most reliable predictor of adoption across studies, with meta-analyses showing average correlations exceeding r = .40 with adoption outcomes (Tornatzky & Klein, 1982). Complexity shows consistent negative relationships with adoption, though effect sizes vary more across contexts (Holden & Karsh, 2010). Trialability and observability demonstrate positive relationships with adoption but show less consistency across studies, suggesting these attributes may operate more contextually than relative advantage and complexity (Greenhalgh et al., 2017).

DOI theory has been extensively applied to health care technology adoption, with systematic reviews identifying hundreds of studies examining factors influencing adoption of electronic health records, telemedicine, clinical decision support systems, and mHealth applications (Jacob et al., 2020b; M. D. Williams et al., 2021). Health care applications generally confirm DOI predictions, though with some refinements - compatibility with clinical workflows emerges as particularly important, while observability may matter less in professional contexts where adoption decisions reflect individual clinical judgment rather than social influence (Holden & Karsh, 2010; Greenhalgh et al., 2017).

Technology Acceptance Model and Extensions

The Technology Acceptance Model (TAM), developed by Davis (1989), proposes that technology adoption is primarily determined by two beliefs: perceived usefulness (the degree to which a person believes using a technology will enhance job performance) and perceived ease of use (the degree to which using a technology is free from effort). TAM emphasizes cognitive evaluation processes and has been validated extensively in organizational technology adoption contexts. The model's parsimony makes it attractive for research and practice, though critics argue it oversimplifies complex adoption decisions by focusing narrowly on individual perceptions while neglecting organizational and social factors (Holden & Karsh, 2010).

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), integrates concepts from multiple theories including TAM, DOI, and Theory of Planned Behavior. UTAUT proposes that four constructs directly influence behavioral intention and use behavior: performance expectancy (similar to TAM's perceived usefulness and DOI's relative advantage), effort expectancy (similar to TAM's perceived ease of use and DOI's complexity), social influence (perceived importance of others' opinions about using the technology), and facilitating conditions (organizational and technical resources supporting use). UTAUT has been extended and validated in health care contexts, with research generally supporting the model while identifying health care-specific factors including professional autonomy, patient outcomes, and clinical workflow impacts (Alsahli et al., 2025; Chong et al., 2022).

These models share conceptual overlap - TAM's perceived usefulness corresponds to DOI's relative advantage, while perceived ease of use corresponds inversely to DOI's complexity. However, models differ in emphasis: DOI highlights innovation characteristics and social diffusion processes, TAM focuses on individual cognitive evaluations, and UTAUT emphasizes organizational facilitating conditions. Research comparing models finds generally similar predictive performance, with choice among frameworks often reflecting research questions and theoretical preferences rather than empirical superiority (Jacob et al., 2020b; Williams et al., 2021).

Implementation Science Frameworks

Implementation science frameworks extend beyond individual adoption to examine organizational and system-level factors influencing successful implementation. The Consolidated Framework for Implementation Research (CFIR), recently updated based on extensive user feedback, identifies five domains influencing implementation: innovation characteristics, outer setting (external policies and environment), inner setting (organizational culture and readiness), characteristics of individuals involved, and implementation process (Damschroder et al., 2022). CFIR has been widely applied to health care technology implementation, providing comprehensive assessment of multilevel influences on adoption and sustained use (Nilsen et al., 2020).

The RE-AIM framework evaluates implementation outcomes across five dimensions: reach (participation among target population), effectiveness (impact on outcomes), adoption (organizational uptake), implementation (fidelity and adaptation), and maintenance (sustained use over time) (Glasgow et al., 2019). RE-AIM emphasizes that successful implementation requires attention to sustainability and real-world effectiveness, not only initial adoption. Rural telehealth research increasingly employs RE-AIM to assess whether interventions effective under research conditions can be successfully implemented and sustained in resource-limited practice settings (Toll et al., 2025; Totten et al., 2024).

The Nonadoption, Abandonment, Scale-up, Spread, and Sustainability (NASSS) framework, developed by Greenhalgh et al. (2017), specifically addresses why seemingly beneficial health technologies fail to achieve widespread adoption. NASSS proposes that implementation complexity depends on seven domains: the condition targeted, the technology itself, the value proposition, adopting organization(s), wider system context, embedding and adaptation over time, and the extent to which stakeholders understand and engage with the technology. The framework is particularly valuable for analyzing rural health technology implementation where multiple domains present challenges simultaneously (Krahe et al., 2025).

Application to Rural Health Care Context

This study employs DOI theory as its primary framework for several reasons. First, DOI's innovation attribute constructs align closely with factors rural providers identify as salient in adoption decisions - clinical benefits (relative advantage), ease of implementation (complexity), and opportunities to test technologies before full commitment (trialability) (Barry et al., 2024; Valliyappan et al., 2025). Second, DOI has been validated across diverse contexts including rural and resource-limited settings, providing an established foundation for hypothesis development (Brooks et al., 2021). Third, DOI attributes can be measured through standardized scales with demonstrated reliability and validity, enabling rigorous hypothesis testing (Moore & Benbasat, 1991).

However, DOI theory has important limitations requiring acknowledgment. Critics note a "pro-innovation bias" assuming innovations are inherently beneficial and should be adopted (Rogers, 2003). This bias neglects that some technologies may be inappropriate for specific contexts or that nonadoption may represent rational assessment of costs exceeding benefits. Additionally, DOI was developed based on research with individuals making autonomous adoption decisions (such as farmers choosing agricultural innovations), which may not fully capture dynamics when adoption requires organizational resources and support (Greenhalgh et al., 2017).

Most critically for this study, standard DOI applications assume adequate infrastructure and resources enabling adoption once providers form positive perceptions. This assumption may not hold in severely resource-constrained settings like rural Appalachia, where infrastructure limitations and financial constraints can prevent adoption regardless of favorable perceptions (Bogulski et al., 2024; Chapman et al., 2025). By explicitly examining structural constraints as moderators of DOI attribute-intention relationships, this study tests whether DOI predictions hold in resource-limited contexts or whether structural factors fundamentally alter these relationships.

Theoretical Contributions

This study contributes to technology adoption theory by testing boundary conditions of DOI predictions. If innovation attributes predict adoption intentions similarly across varying constraint levels, this extends DOI's generalizability to resource-limited settings. Conversely, if structural constraints significantly moderate attribute-intention relationships, this specifies conditions under which DOI operates differently, suggesting theoretical refinements needed to account for implementation context. Understanding these dynamics has practical implications for implementation strategies - if attributes operate similarly regardless of constraints, educational interventions highlighting benefits and usability may suffice, whereas strong constraint moderation suggests infrastructure and resource investments are prerequisites for adoption.

Empirical Studies of Health Care Technology Adoption

Empirical research on health care technology adoption has expanded substantially, particularly following COVID-19's acceleration of telehealth and digital health tools. This section synthesizes findings regarding factors influencing provider adoption decisions, with emphasis on rural health care contexts and studies examining DOI constructs.

General Health Care Technology Adoption

Large-scale surveys document near-universal adoption of electronic health record (EHR) systems in U.S. health care, exceeding 85% of providers (Office of the National Coordinator for Health Information Technology [ONC], 2019). However, adoption of more advanced functionalities including patient portals, clinical decision support, and health information exchange remains more variable, particularly in small and rural practices (Iversen & Ma, 2022). Research consistently identifies practice size, organizational ownership (independent versus health system-owned), and financial resources as strong predictors of advanced EHR functionality adoption (Iversen & Ma, 2022).

Telehealth adoption accelerated dramatically during the COVID-19 pandemic, with utilization increasing from approximately 1% of outpatient visits prepandemic to over 30% at pandemic peak in many settings (Patel et al., 2021; Demeke et al., 2021). Postpandemic utilization has declined but stabilized above prepandemic levels, suggesting sustained adoption of hybrid care models (Salmon et al., 2025; Tipre et al., 2024). Research examining factors associated with sustained postpandemic telehealth use identifies perceived patient benefits, workflow integration, adequate reimbursement, and technical infrastructure as key enablers (Shaw et al., 2024; Raspet & Gietzen, 2024).

Studies examining specific DOI attributes find relative advantage consistently emerges as the strongest predictor of adoption intentions and behavior across diverse health care technologies. A systematic review by Holden and Karsh (2010) analyzing

TAM applications in health care (where perceived usefulness corresponds to relative advantage) found average correlations of $r = .54$ between perceived usefulness and behavioral intention. More recent studies examining mHealth adoption report similar patterns, with providers' beliefs about clinical benefits and patient outcomes showing strongest associations with adoption intentions (Alsahli et al., 2023; Chong et al., 2022; Weichelt et al., 2024).

Complexity shows more variable relationships with adoption depending on how it is measured and what aspects of complexity are assessed. When complexity refers to personal ease of learning and using technology, studies typically find moderate negative correlations with adoption (Holden & Karsh, 2010). However, when complexity encompasses workflow disruption, integration challenges with existing systems, and organizational implementation demands, relationships strengthen substantially (Ebo et al., 2023). This suggests complexity may operate multidimensionally, with different facets mattering differently across contexts and technologies.

Rural Health Care Technology Adoption

Research specifically examining technology adoption in rural health care settings remains disproportionately limited despite distinct challenges these settings present (Maganty et al., 2023; Serchen et al., 2025). A systematic review by Kruse et al. (2019) identified only 15 studies specifically targeting rural providers among over 100 studies of telehealth adoption, highlighting rural underrepresentation in technology adoption research. More recent research has begun addressing this gap, though studies remain concentrated in telehealth rather than broader mHealth applications (Barry et al., 2024; Totten et al., 2024).

Available rural-focused research documents that while innovation attributes predict adoption, infrastructure and resource constraints emerge as critical additional factors. Ward et al. (2014) found that in rural health care settings, complexity showed stronger negative associations with adoption compared to urban settings, with this effect mediated by availability of IT support - when IT support was present, complexity effects weakened substantially. More recent research confirms this pattern, demonstrating that perceived complexity interactions with organizational support resources to influence adoption (Weichelt et al., 2024; Schürmann et al., 2025).

Qualitative research provides detailed understanding of rural provider perspectives on technology adoption. Studies employing interviews and focus groups document that rural providers recognize potential benefits of digital health tools but express concerns about implementation feasibility given limited staffing, unreliable infrastructure, and narrow financial margins (Klee et al., 2023; Coombs et al., 2022; Maganty et al., 2023). Providers describe being "caught between" recognizing patient needs that technology could address and realistic assessment of their capacity to successfully implement and sustain new tools (Barry et al., 2024; Dehart et al., 2022).

Structural Constraints and Technology Adoption

Emerging research examines how structural constraints including infrastructure limitations, financial resources, and organizational capacity influence technology adoption beyond individual provider perceptions. Brooks et al. (2021), studying telehealth diffusion in rural Native American communities, found that infrastructure adequacy and organizational support were prerequisites for adoption - without these foundations, even highly motivated providers could not successfully implement telehealth. This suggests what researchers term "threshold effects" where certain minimal conditions must be met before individual perceptions influence adoption.

Recent studies provide evidence for moderation hypotheses tested in this study. P. A. H. Williams et al. (2022), in their examination of digital health transformation in hospitals, found that relationships between perceived benefits and adoption were significantly weaker in organizations with immature technical infrastructure, suggesting infrastructure moderates benefit-adoption relationships. Similarly, Weichelt et al. (2024) found that among rural providers, complexity perceptions predicted adoption only when organizational support was limited - when strong support existed, complexity showed minimal association with adoption.

Financial constraints specifically influence adoption through opportunity costs and sustainability concerns. Practices operating on narrow margins must prioritize investments most directly affecting financial viability, often relegating technology investments behind immediate needs including staff retention (Maganty et al., 2023). Even when external funding supports initial implementation (through grants or pilot programs), sustainability becomes problematic when ongoing costs must be absorbed by practice budgets (Nataliansyah et al., 2022; Chapman et al., 2025). This creates what researchers term "orphaned technology" - systems implemented with external support that cannot be sustained once that support ends (Toll et al., 2025).

Provider Adoption and Patient Populations

Emerging research recognizes that provider adoption decisions incorporate assessment of patient populations and their capacity to engage with technology. Providers report lower intentions to adopt mHealth when they perceive their patient population has limited digital health literacy, unreliable technology access, or affordability concerns regarding data plans and devices (Bommakanti et al., 2020; Hengst et al., 2023). This "patient readiness" factor represents realistic assessment by providers that technology benefits depend on patient engagement, which in turn depends on patient resources and capabilities (Leng et al., 2025).

Research on patient-level barriers to mHealth engagement documents systematic disparities by age, income, education, and geography (De La Vega et al., 2024; Yang et al., 2025). Older adults report lower comfort with health technologies and face steeper learning curves, though with appropriate training and support, many can successfully engage (Hepburn et al., 2025). Low-income populations face compounding barriers including limited device access, unreliable internet connectivity, data plan costs, and lower digital literacy (Hengst et al., 2023; Crowe et al., 2024). These disparities create ethical concerns that mHealth implementation could worsen health inequities if not accompanied by efforts to ensure equitable access and support (Rodriguez et al., 2021; Nouri et al., 2020).

Postpandemic Technology Adoption Patterns

The COVID-19 pandemic created a natural experiment in health care technology adoption, with providers forced to rapidly implement telehealth to maintain care continuity during social distancing requirements (Ortega et al., 2020). Research examining this period provides insights into adoption dynamics under crisis conditions. Studies document that providers who had previously resisted telehealth often successfully implemented it when necessity demanded, suggesting that perceived necessity can overcome complexity concerns and implementation barriers (Patel et al., 2021; Martinez et al., 2022).

However, postpandemic patterns reveal important nuances. While many providers continue using telehealth, utilization has declined from pandemic peaks, and some providers who adopted during emergency conditions have discontinued use (Salmon et al., 2025; Raspet & Gietzen, 2024). Research suggests this reflects both returns to preferred practice patterns and sustainability challenges - emergency regulatory flexibilities and enhanced reimbursement that enabled rapid adoption have expired in many contexts, creating financial and administrative barriers to continued use (Porteny et al., 2025; Vakkalanka et al., 2025).

Rural providers show distinct postpandemic adoption patterns compared to urban counterparts. While rural providers generally maintained telehealth use at higher rates (reflecting ongoing geographic barriers), they report greater challenges sustaining use due to infrastructure limitations, reimbursement concerns, and lack of organizational support

(Klee et al., 2023; Tipre et al., 2024). This suggests that while crisis conditions temporarily overcome some adoption barriers, sustainable implementation requires addressing underlying structural constraints rather than relying on temporary regulatory and financial accommodations.

Structural Constraints in Resource-Limited Settings

Structural constraints represent material, organizational, and policy factors that shape what actions are feasible regardless of individual attitudes or intentions. Understanding how these constraints influence technology adoption requires examining their nature, measurement, and theoretical role in adoption processes.

Conceptualizing Structural Constraints

Structural constraints encompass factors external to individual providers that enable or limit action possibilities. Drawing on sociological theory, particularly Giddens' (1984) structuration theory, structures are resources and rules that both constrain and enable action - they define what is possible within a given context. In health care technology adoption, structural constraints include infrastructure (broadband availability, hardware, technical systems), financial resources (operating margins, capital for investment, ongoing support costs), human resources (IT support staff, training capacity), and policy environment (reimbursement rules, regulatory requirements, licensure provisions).

These constraints differ fundamentally from psychological constructs like attitudes and perceptions in that they exist independently of individual beliefs. A provider may perceive mHealth as highly beneficial and easy to use, yet be unable to adopt if broadband infrastructure is inadequate or financial resources unavailable. This distinction is theoretically important because it suggests different intervention points - changing perceptions requires education and persuasion, whereas overcoming structural constraints requires resource investment and policy change (Brooks et al., 2021; Chapman et al., 2025).

Infrastructure Constraints

Broadband infrastructure represents the most fundamental constraint for mHealth and telehealth in rural areas. The Federal Communications Commission defines broadband adequacy as minimum 100 Mbps download and 20 Mbps upload speeds (Federal Communications Commission, 2022), recognizing these thresholds as necessary for reliable video streaming and remote monitoring data transmission. However, substantial portions of rural America fall below these standards, with recent estimates suggesting over 30% of rural health care facilities lack adequate broadband (Bogulski et al., 2024; K. Smith & Chen, 2023).

Infrastructure limitations create cascading constraints. Unreliable connectivity forces default to lower-bandwidth modalities (audio-only rather than video), eliminates certain functionalities entirely (continuous remote monitoring), and creates technical failures that erode provider and patient confidence in technology (Klee et al., 2023; Salmon et al., 2025). Research documents that providers in low-bandwidth areas adapt by avoiding technology-dependent workflows, but this adaptation perpetuates health access disparities the technology was intended to address (Crowe et al., 2024).

Beyond broadband, hardware constraints affect adoption. Rural practices often operate with aging computers and devices that cannot support newer software or provide poor user experiences affecting efficiency (Maganty et al., 2023). Electronic health record systems in rural practices may lack interoperability capabilities, creating barriers to integrating mHealth data into clinical workflows (Ebo et al., 2025). These technical limitations compound, creating compounding constraints where multiple infrastructure deficits simultaneously limit feasibility.

Financial Constraints

Financial constraints in rural health care reflect both organizational and patient-level factors. At the organizational level, rural practices typically operate on narrow profit margins, with recent estimates suggesting margins of 1.7% to 2.1% in distressed rural counties compared to 5% to 6% in urban health systems (Kaufman et al., 2016). Narrow margins create opportunity costs where technology investments compete with immediate operational needs including staff salaries, facility maintenance, and supplies (Maganty et al., 2023; Weiss et al., 2025).

Technology costs extend beyond initial purchase to include ongoing expenses for software licenses, technical support, training, and upgrades. Research documents that many rural practices participate in mHealth pilots supported by external funding but cannot sustain programs once external funding ends because ongoing costs exceed available resources (Nataliansyah et al., 2022; Toll et al., 2025). This creates "pilot syndrome" where promising innovations cannot transition to routine practice due to financial unsustainability (Chapman et al., 2025).

Reimbursement policy significantly affects financial feasibility of telehealth and mHealth. While pandemic-era policies temporarily achieved reimbursement parity between virtual and in-person visits, many states have returned to prepandemic policies with lower telehealth reimbursement rates or limitations on billable services (Porteny et al., 2025; Vakkalanka et al., 2025). When reimbursement does not cover costs of delivering care virtually, financial sustainability becomes problematic even when technology effectively serves patient needs.

Patient-level financial constraints affect adoption through provider assessment of patient capacity to engage. Smartphone ownership, internet access, and data plan affordability create barriers to patient engagement with mHealth applications (Bommakanti et al., 2020; Hengst et al., 2023). Providers report reluctance to invest in mHealth implementation when they believe their patient population cannot reliably access or afford required technology (Leng et al., 2025). This represents realistic assessment that technology benefits depend on patient engagement, which financial barriers can prevent.

Human Resource Constraints

Workforce constraints in rural health care create multiple barriers to technology adoption. The most direct relates to information technology support - rural practices typically lack dedicated IT staff, requiring clinical personnel to manage technology troubleshooting and user support (Maganty et al., 2023; Weichelt et al., 2024). Without IT expertise, technical problems that would be quickly resolved in larger organizations become significant disruptions consuming clinical time and causing workflow interruptions (Schürmann et al., 2025).

Clinical workforce shortages compound technology adoption challenges. Primary care provider shortages create time pressures that make workflow disruption from new technology particularly costly (Rao et al., 2021). Training time required to learn new systems competes with immediate patient care demands. Ongoing time requirements to review patient-generated data from remote monitoring must be balanced against other responsibilities without corresponding increases in support staff (Bazzano et al., 2024; McCabe et al., 2025).

Administrative support staff availability affects adoption through capacity to manage coordination tasks including scheduling telehealth visits, supporting patient technology setup, and managing data workflows (Bailey et al., 2024). Research documents that successful mHealth implementation often requires dedicated care coordination staff, but rural practices frequently cannot afford such positions (Nataliansyah et al., 2022; Chapman et al., 2025).

Policy and Regulatory Constraints

Health care policy and regulation create constraints affecting technology adoption feasibility. Interstate licensure requirements historically limited telehealth across state borders, with temporary pandemic-era waivers enabling broader practice but many expiring postpandemic (Bogulski et al., 2025; Jolin et al., 2024). For rural providers in border areas, inability to provide telehealth to patients across state lines reduces technology utility regardless of clinical appropriateness (Vakkalanka et al., 2025).

Reimbursement policy serves as both financial and regulatory constraint. State Medicaid programs and private insurers establish rules defining what services are reimbursable via telehealth, acceptable modalities (video versus audio), and reimbursement rates (Porteny et al., 2025). Research documents substantial state-level variation in telehealth policies, creating different constraint environments across similar rural areas (American Telemedicine Association, n.d.). Providers must navigate complex, frequently changing rules determining financial viability of virtual care.

Data privacy and security regulations create compliance requirements affecting adoption decisions. While protecting patient information is ethically essential, compliance requirements can be challenging for small practices lacking dedicated privacy and security expertise (Schiffelers et al., 2025). Recent increases in cyberattacks targeting health care organizations, particularly smaller rural practices, heighten security concerns and create additional barriers to technology adoption (Alzghaibi, 2025).

Moderating Role of Structural Constraints

This study hypothesizes that structural constraints moderate relationships between innovation attributes and adoption intentions. Moderation implies that the strength or direction of attribute-intention relationships depends on constraint levels - that is, relationships operate differently under high versus low constraint conditions. This hypothesis reflects theoretical reasoning that constraints alter how innovation attributes translate into intentions.

Under low constraint conditions, when infrastructure is adequate, financial resources available, and organizational support present, provider perceptions of innovation attributes should directly predict adoption intentions as DOI theory predicts. A provider perceiving high relative advantage and low complexity should form strong adoption intentions that can be enacted because structural conditions enable implementation (Rogers, 2003).

Under high constraint conditions, the theory-behavior relationship may break down. Even when providers perceive strong relative advantage, severely limited infrastructure may prevent adoption regardless of intentions - no amount of perceived benefit enables adoption when broadband is inadequate for technology to function (Bogulski et al., 2024). Similarly, complexity perceptions may matter more under high constraints because limited IT support means providers must overcome complexity themselves, whereas strong IT support can mitigate complexity concerns (Weichelt et al., 2024).

Empirical evidence for constraint moderation in health care technology adoption is emerging but remains limited. Brooks et al. (2021) found that infrastructure and organizational support acted as prerequisites for telehealth adoption in Native American communities - without these foundations, individual perceptions showed minimal association with adoption. P. A. H. Williams et al. (2022) found weaker relationships between perceived benefits and adoption in hospitals with less mature technical infrastructure. However, most technology adoption research has not explicitly tested moderation hypotheses, creating a gap this study addresses.

Current Adoption Status as Study Outcome

Current adoption status - whether providers currently use mHealth technologies in clinical practice - serves as this study's dependent variable. Understanding factors that distinguish current adopters from nonadopters provides insight into adoption dynamics while acknowledging the limitations inherent in cross-sectional measurement. This section examines theoretical foundations for using current adoption as an outcome, empirical precedents in technology adoption research, and methodological considerations including advantages and limitations of this approach.

Theoretical Foundations of Current Adoption as Outcome

DOI theory examines both the process of adoption over time and factors distinguishing adopters from nonadopters at any given point (Rogers, 2003). While some DOI research examines prospective adoption intentions as predictors of future behavior, substantial research employs retrospective or concurrent examination of actual adoption status to identify factors associated with completed adoption decisions. Rogers himself frequently analyzed factors distinguishing adopter categories (innovators, early adopters, early majority, late majority, laggards) based on current adoption status rather than prospectively measuring intentions (Rogers, 2003).

This retrospective approach examines current adoption as the cumulative outcome of the innovation-decision process Rogers describes: knowledge (becoming aware of the innovation), persuasion (forming attitudes toward it), decision (choosing to adopt or reject), implementation (putting the innovation to use), and confirmation (reinforcing the decision). Individuals who are current adopters have progressed through all five stages to implementation, while nonadopters have either not progressed beyond earlier stages or have rejected the innovation during the decision stage. By examining factors associated with current adoption status, research identifies which innovation attributes, contextual factors, and individual characteristics distinguish those who have successfully implemented innovations from those who have not.

From a theoretical perspective, examining current adoption tests the same core DOI propositions as examining adoption intentions - that innovation attributes influence adoption decisions - but does so by analyzing realized decisions rather than stated intentions. If relative advantage, complexity, and trialability predict current adoption status, this demonstrates that these attributes influenced the adoption decisions providers made, providing direct evidence about factors shaping actual adoption behavior rather than indirect evidence through intention as a mediating construct (Tornatzky & Klein, 1982; Holden & Karsh, 2010).

Empirical Precedents in Technology Adoption Research

Substantial technology adoption research employs current adoption or use status as the dependent variable, examining factors that distinguish current users from nonusers.

In health care technology specifically, numerous studies have examined correlates of current electronic health record use, telemedicine adoption, clinical decision support system implementation, and mHealth application use among providers (Holden & Karsh, 2010; Kruse et al., 2019).

For example, systematic reviews by Gagnon et al. (2012) analyzing telehealth adoption and by Jacob et al. (2020b) examining health care technology adoption more broadly found that substantial proportions of included studies measured current adoption status rather than prospective intentions. These studies consistently documented that innovation attributes including relative advantage and complexity distinguish current adopters from nonadopters, with patterns generally consistent with those found in intention-focused research (Holden & Karsh, 2010).

Rural health care technology research specifically has employed current adoption measures to examine factors distinguishing providers who have implemented technologies from those who have not. Ward et al. (2014) examined current telehealth use among rural providers, finding that innovation attributes and organizational support factors distinguished users from nonusers. More recently, Weichelt et al. (2024) analyzed current health information technology adoption patterns among rural providers, documenting associations between innovation perceptions, organizational resources, and adoption status. These studies demonstrate that examining current adoption status provides meaningful insights into adoption dynamics in rural health care contexts.

Research comparing intention-based and behavior-based adoption studies finds generally consistent patterns across both approaches, with innovation attributes showing similar associations with intentions and with actual adoption behaviors (Holden & Karsh, 2010). Meta-analyses document that relative advantage shows strong positive associations with both intentions (average $r \approx .50$) and with actual adoption (average $r \approx .40$), while complexity shows moderate negative associations with both outcomes (Tornatzky & Klein, 1982; Holden & Karsh, 2010). This consistency suggests that examining current adoption tests similar theoretical relationships as examining intentions, though with different methodological strengths and limitations.

Advantages of Current Adoption Status as Outcome

Examining current adoption status rather than future intentions offers several conceptual and methodological advantages. First, current adoption represents actual behavior rather than stated intentions, eliminating the intention-behavior gap that limits predictive validity of intention measures. Research documents that intentions predict behavior imperfectly, with average correlations of approximately $r = .47$ and substantial proportions of individuals failing to act on stated intentions (Webb & Sheeran, 2006). By examining actual adoption, research directly assesses the outcome of ultimate interest - whether providers have implemented technologies - rather than relying on intention as an imperfect proxy.

Second, measuring current adoption captures adoption that has progressed beyond initial implementation to sustained use. Providers categorized as current adopters have not only formed intentions and initiated implementation but have continued using the technology through whatever initial challenges emerged during implementation. This sustained use provides evidence that the technology has been successfully integrated into practice routines rather than representing initial enthusiasm that dissipates when implementation difficulties arise (Greenhalgh et al., 2017; Chapman et al., 2025).

Third, in contexts where some providers have already adopted while others have not, examining current adoption enables investigation of factors explaining this variation using existing adopter/nonadopter differences rather than requiring longitudinal tracking of adoption over time. For mHealth technologies in rural Appalachia, where adoption rates vary substantially across providers and practices (Weichelt et al., 2024; Maganty et al., 2023), examining factors associated with current adoption status provides immediately actionable insights about what distinguishes adopters from nonadopters in this context.

Fourth, examining actual adoption behavior grounds findings in real-world implementation experiences rather than abstract evaluations of hypothetical technology use. Current adopters' perceptions of innovation attributes reflect their actual experiences implementing and using technologies in their practice settings, while nonadopters' perceptions reflect assessment of whether technologies would work in their contexts. Both perspectives provide valuable information, with adopters' experiences offering insight into postimplementation evaluation and nonadopters' assessments revealing perceived barriers preventing initial adoption (Barry et al., 2024; Valliyappan et al., 2025).

Limitations of Cross-Sectional Adoption Status Measurement

Despite advantages, examining current adoption status through cross-sectional measurement presents important limitations requiring acknowledgment and careful interpretation. The primary limitation involves temporal precedence and causal inference. Cross-sectional designs measure all variables simultaneously, precluding determination of whether innovation attribute perceptions preceded and influenced adoption decisions or whether adoption experience subsequently shaped perceptions (Maxwell, 2004; Shadish et al., 2002).

This temporal ambiguity creates potential for retrospective rationalization - individuals may justify their adoption decisions by emphasizing innovation attributes consistent with their behavior. Current adopters may emphasize relative advantage and minimize complexity to rationalize their investment of time and resources in implementation, while nonadopters may emphasize complexity and minimize relative advantage to justify nonadoption (Festinger, 1957). If perceptions primarily represent post hoc rationalizations rather than factors that actually influenced adoption decisions, associations between perceptions and adoption status would be artifactual rather than reflecting genuine causal relationships.

However, several considerations mitigate this concern in technology adoption contexts. First, theoretical expectations from DOI suggest that perceptions formed during the persuasion stage of the innovation-decision process precede and influence adoption decisions (Rogers, 2003). While adoption experience may refine perceptions, the innovation attributes that initially attract attention and create interest - relative advantage solving important problems, manageable complexity enabling feasible implementation, opportunities for trial reducing perceived risk - logically precede adoption decisions. Retrospective adoption studies consistently find that early perceptions predict subsequent adoption, supporting the theoretical expectation that perceptions influence adoption rather than merely reflecting it (Tornatzky & Klein, 1982).

Second, if adoption experience substantially altered perceptions, we would expect current adopters to show uniformly positive perceptions and nonadopters to show uniformly negative perceptions, with minimal within-group variation. However, adoption research consistently documents substantial variation in perceptions within both adopter and nonadopter groups, with some adopters reporting modest perceived benefits or significant perceived complexity, and some nonadopters reporting high perceived benefits (Holden & Karsh, 2010; Weichelt et al., 2024). This within-group variation suggests perceptions reflect more than simple rationalization of adoption status.

Third, research examining perceptions longitudinally (measuring perceptions before adoption decisions occur) finds generally consistent patterns with cross-sectional research examining associations between perceptions and current adoption status, suggesting cross-sectional associations reflect relationships operating prospectively rather than only retrospectively (Venkatesh et al., 2003; Holden & Karsh, 2010). While longitudinal designs provide stronger causal inference, convergence between longitudinal and cross-sectional findings supports that cross-sectional associations meaningfully reflect adoption dynamics.

A second limitation involves the inability to examine adoption as a temporal process unfolding over time. Rogers's (2003) innovation-decision process describes adoption as occurring through sequential stages, with different factors potentially influencing different stages. Cross-sectional measurement of current adoption status cannot distinguish factors that influence knowledge acquisition, attitude formation, decision-making, or implementation persistence. Longitudinal research tracking providers through adoption processes could identify which factors matter at which stages, providing more nuanced understanding than cross-sectional status measurement allows.

Third, examining current adoption creates selection effects potentially limiting generalizability. Samples of current adopters may systematically differ from potential future adopters on unmeasured characteristics including organizational context, patient populations, or personal characteristics. Findings about factors distinguishing current adopters from nonadopters may not generalize to predicting which current nonadopters will adopt in the future, particularly if early adopters differ systematically from later adopters as Rogers's (2003) adopter categories suggest.

Binary Operationalization of Adoption Status

This study operationalizes current adoption as a binary variable - providers either currently use mHealth technologies in clinical practice or do not. This dichotomous categorization simplifies the complex reality of adoption, where providers may use technologies to varying degrees, with varying consistency, or for different purposes (Greenhalgh et al., 2017). However, binary categorization offers several advantages for the current research.

First, binary categorization aligns with fundamental theoretical interest in factors distinguishing adopters from nonadopters. Rogers's (2003) DOI theory centers on understanding what leads individuals to cross the threshold from nonadoption to adoption, with the adoption decision itself representing the key theoretical outcome. While subsequent research on implementation and sustainability examines variation among adopters, the foundational theoretical question addresses what distinguishes those who adopt from those who do not.

Second, binary measurement provides clear interpretability. Providers are categorized based on straightforward criterion - do they currently use mHealth technologies in clinical practice? This clarity facilitates communication of findings to practice and policy audiences who must make binary decisions about whether to invest in promoting adoption versus addressing barriers preventing adoption.

Third, binary operationalization enables appropriate statistical analysis through logistic regression, which models the log-odds of adoption as a function of predictor variables. Logistic regression provides interpretable odds ratios indicating how much each predictor changes the odds of adoption, with straightforward assessment of practical significance through odds ratios and confidence intervals (Hosmer et al., 2013; Tabachnick & Fidell, 2019).

Limitations of binary categorization include loss of information about adoption extent or intensity. Providers may vary substantially in how extensively they use mHealth - from occasional use with selected patients to routine use across their patient panel - yet binary categorization treats all current users equivalently. Future research could examine adoption intensity among current users, potentially finding that innovation attributes and structural constraints predict not only whether providers adopt but also how extensively they use technologies. However, for initial investigation addressing whether DOI relationships operate in resource-constrained rural contexts and whether structural constraints moderate these relationships, binary adoption status provides appropriate outcome measurement.

Measurement of Structural Constraints and Current Adoption

An important advantage of measuring current adoption status is the ability to examine structural constraints as they actually exist in providers' practice environments rather than as hypothetical scenarios. When providers report on infrastructure adequacy, organizational support availability, and financial resources, these reports reflect the actual conditions under which adoption decisions were made. For current adopters, these conditions represent the environment in which they successfully implemented technologies; for nonadopters, they represent conditions that may have prevented or discouraged adoption.

Measurement enables direct testing of whether structural constraints moderate relationships between innovation attributes and adoption. If constraints primarily affect adoption by preventing behavioral enactment of intentions (a "blocking" mechanism), innovation attributes should predict adoption similarly across constraint levels, with constraints directly reducing adoption probability. If constraints affect adoption by altering the psychological process of how attributes translate into adoption decisions (a "moderating" mechanism), attribute-adoption relationships should differ across constraint levels, with weaker relationships under high constraints.

By measuring both innovation perceptions and structural constraints in relation to current adoption status, the study design enables distinguishing these mechanisms. Finding significant attribute × constraint interactions would suggest constraints fundamentally alter adoption dynamics rather than merely creating barriers to enacting adoption decisions. This has different implications for intervention - if constraints primarily block behavior, removing constraints should enable adoption given existing positive perceptions, whereas if constraints moderate perceptual influences, interventions may need to address both perceptions and constraints simultaneously.

Study Implications and Interpretation

This study employs current mHealth adoption status as the dependent variable while explicitly acknowledging the limitations inherent in cross-sectional measurement. The decision to measure current adoption rather than prospective intentions reflects both theoretical appropriateness - examining factors distinguishing adopters from nonadopters tests core DOI propositions - and practical constraints of cross-sectional survey design. However, interpretation of findings must acknowledge that definitive causal conclusions cannot be drawn from cross-sectional associations.

Findings will be interpreted as identifying factors associated with current adoption that may have influenced adoption decisions, while acknowledging alternative explanations including that adoption experience may have shaped subsequent perceptions. Where possible, interpretation will draw on temporal logic (e.g., infrastructure constraints precede adoption decisions in most cases), theoretical expectations (DOI proposes perceptions influence decisions), and consistency with longitudinal research findings to strengthen inferences, while maintaining appropriate caution about causal claims.

The research addresses an important practical question: among rural Appalachian primary care providers, what factors distinguish current mHealth adopters from nonadopters? Understanding this distinction provides actionable insights for implementation efforts regardless of perfect causal certainty. If innovation attributes and structural constraints are associated with current adoption, interventions addressing these factors may facilitate adoption among current nonadopters. While longitudinal research strengthening causal inference would be valuable, cross-sectional examination of current adoption patterns provides immediately useful evidence for guiding rural health care technology implementation efforts.

By explicitly measuring structural constraints alongside innovation perceptions in relation to current adoption, the study enables testing whether DOI relationships operate uniformly across constraint levels or whether resource-constrained contexts fundamentally alter these relationships. This addresses a critical gap in adoption theory by testing boundary conditions - contextual limits within which theoretical predictions hold. Whether innovation attributes distinguish adopters from nonadopters similarly in high-constraint versus low-constraint environments has important implications for understanding both adoption theory and practical implementation strategies in resource-limited rural health care settings.

Literature Synthesis and Research Gaps

Synthesizing the literature reviewed reveals substantial knowledge about factors influencing health care technology adoption generally, but critical gaps regarding adoption in rural Appalachian contexts and the moderating role of structural constraints. This section identifies specific gaps this study addresses.

Knowledge Gaps in Rural Health Care Technology Research

Despite growth in health care technology adoption research, rural settings remain systematically underrepresented. Systematic reviews consistently document that rural health care providers comprise small minorities of technology adoption study samples despite representing substantial proportions of the health care workforce (Kruse et al., 2019; Maganty et al., 2023). This urban bias in research creates knowledge gaps in three areas.

First, much adoption research occurs in large health care systems with substantial resources and technical capacity - contexts fundamentally different from small rural practices operating with limited resources and support (Ross et al., 2016). Whether adoption theories validated in well-resourced settings generalize to resource-constrained contexts remains empirically uncertain. Some evidence suggests relationships may differ - for example, complexity showing stronger negative effects in resource-limited settings (Ward et al., 2014; Weichelt et al., 2024) - but systematic examination is lacking.

Second, rural research often treats rurality as a demographic descriptor rather than explicitly examining rural-specific factors like infrastructure limitations, geographic isolation, and cultural contexts as mechanisms influencing adoption (Serchen et al., 2025). Understanding not just that rural adoption differs but why requires examining rural-specific factors as variables rather than sample characteristics. This study explicitly measures infrastructure and resource constraints as moderating variables to test mechanisms.

Third, within rural populations, Appalachian regions face distinctive challenges including concentrated poverty, historical marginalization, and unique cultural contexts (Stanzak & Oliver, 2023). Very limited research examines technology adoption specifically in Appalachian health care, creating knowledge gaps about whether findings from other rural areas generalize to this region. This study focuses specifically on Central and Southern Appalachian providers to address this geographic gap.

Theoretical Gaps: Boundary Conditions of Adoption Theories

Technology adoption theories including DOI, TAM, and UTAUT have been extensively validated across diverse contexts, demonstrating robust predictive validity. However, most validation research occurs in contexts where basic infrastructure and resources are adequate - electricity is reliable, internet connectivity exists, and organizational support is available (Holden & Karsh, 2010). Whether these theories operate similarly in severely resource-constrained contexts where basic prerequisites may be absent represents a theoretical boundary condition question requiring empirical examination.

The concept of boundary conditions comes from philosophy of science - theories specify scope conditions defining contexts where their predictions hold (Maxwell, 2004). When theories developed and validated in one context are applied to substantially different contexts, empirical testing is required to determine whether boundary conditions have been exceeded. For DOI theory specifically, the theory was developed based on studies of agricultural innovation adoption where adopters controlled resources required for implementation (Rogers, 2003). Health care technology adoption in resource-constrained settings may exceed these boundary conditions.

This study tests DOI boundary conditions by examining whether innovation attributes predict intentions similarly across varying structural constraint levels. If relationships hold regardless of constraints, this extends DOI's validated scope to severely resource-limited contexts. If constraints moderate relationships - particularly if relationships weaken or disappear under high constraints - this specifies boundary conditions requiring theoretical refinement to account for structural context.

Methodological Gaps: Testing Moderation Hypotheses

Existing research documents that both innovation attributes and structural constraints influence technology adoption, but rarely examines these simultaneously in ways enabling moderation testing. Studies typically measure either perceptual factors (examining which attributes predict adoption) or structural factors (documenting that infrastructure or resources limit adoption), but not both in integrated models testing interactions (Brooks et al., 2021; Chapman et al., 2025).

Testing moderation requires specific methodological approaches: simultaneous measurement of predictor variables (innovation attributes), moderator variables (structural constraints), and outcomes (intentions); adequate sample sizes to detect interaction effects; and appropriate statistical analyses computing and testing interaction terms. Most existing research lacks one or more of these elements, precluding moderation testing. This study employs hierarchical multiple regression with interaction terms specifically designed to test moderation hypotheses.

The absence of moderation testing creates ambiguity in interpreting findings. When research documents that innovation attributes predict adoption in well-resourced settings but structural constraints limit adoption in resource-constrained settings, at least two interpretations are possible: (a) attributes and constraints operate independently, with constraints creating absolute barriers regardless of perceptions, or (b) constraints moderate attribute-intention relationships, altering how perceptions translate into intentions. These interpretations have different practical implications but cannot be distinguished without explicitly testing interactions.

Practical Gaps: Implementation Strategy Development

From a practical standpoint, current research provides insufficient guidance for developing implementation strategies tailored to resource-constrained rural contexts. If innovation attributes operate similarly regardless of constraints, implementation strategies should focus on demonstrating benefits and ensuring usability - approaching adoption primarily as a communication and training challenge. If constraints fundamentally alter adoption dynamics, implementation strategies must prioritize infrastructure development and resource provision as prerequisites for adoption - approaching adoption primarily as a policy and investment challenge.

Current implementation efforts often proceed without clear evidence regarding relative importance of perceptual versus structural factors. This can lead to mismatched interventions - for example, educational campaigns highlighting technology benefits when infrastructure inadequacy prevents adoption regardless of perceptions, or conversely, infrastructure investments when poor technology design or lack of perceived benefit drive nonadoption (Chapman et al., 2025). Evidence-based implementation requires understanding how factors interact to influence adoption decisions.

Additionally, resource constraints affect feasibility of different implementation approaches. Intensive training and support programs that work in well-resourced settings may be infeasible in rural practices lacking time and staff for extended training. Implementation strategies must be adapted to resource constraints while still effectively promoting adoption, requiring evidence about what works in resource-limited contexts specifically (Toll et al., 2025; Totten et al., 2024).

Research Questions Derived From Gaps

This study addresses identified gaps through three RQs.

RQ1: To what extent do perceived relative advantage, perceived complexity, and perceived trialability predict primary care providers' behavioral intention to adopt mHealth technologies in rural Appalachian settings?

This question addresses the rural and Appalachian underrepresentation gap by examining DOI attribute-intention relationships specifically in this context. It tests whether established predictors validated in other contexts operate in rural Appalachia, extending empirical evidence to an understudied population.

RQ2: What is the relative predictive strength of perceived relative advantage, perceived complexity, and perceived trialability in accounting for variance in adoption intention?

This question provides practical guidance by identifying which attributes matter most in rural Appalachian contexts. If relative advantage dominates as in other contexts, interventions should emphasize demonstrating benefits. If complexity shows stronger effects than typical, addressing ease of implementation becomes priority. Understanding relative importance enables prioritizing intervention components.

RQ3: Do structural constraints reported by providers moderate the relationships between innovation attributes (relative advantage, complexity, trialability) and adoption intention?

This question directly addresses theoretical boundary conditions and moderation testing gaps. It examines whether DOI relationships operate uniformly across constraint levels or whether structural context alters how perceptions translate to intentions. Findings specify scope conditions of adoption theory and guide whether interventions should prioritize changing perceptions versus addressing constraints.

Study Contributions

By addressing these gaps, this study makes several contributions. Theoretically, it tests boundary conditions of DOI theory by examining whether predictions hold in severely resource-constrained contexts, advancing understanding of scope conditions for adoption theories. Empirically, it provides evidence from an understudied population (rural Appalachian providers) regarding factors influencing mHealth adoption intentions. Methodologically, it employs rigorous moderation testing enabling conclusions about how structural constraints alter adoption dynamics. Practically, findings inform implementation strategy development by clarifying relative importance of perceptual versus structural factors and how they interact.

The study acknowledges limitations including cross-sectional design precluding causal inference, intention measurement rather than behavioral tracking, and focus on one geographic region limiting generalizability. However, by rigorously addressing identified gaps, the study advances understanding of technology adoption in resource-constrained rural health care contexts while providing evidence relevant to ongoing policy debates about rural health technology implementation.

Summary and Conclusions

Three major themes emerge from the literature synthesis. First, technology adoption theories including DOI (Rogers, 2003), Technology Acceptance Model (Davis, 1989), and Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) demonstrate robust predictive validity across diverse contexts, with innovation attributes - particularly relative advantage and complexity - consistently predicting adoption intentions and behaviors. Meta-analytic evidence documents that these attributes explain substantial variance in adoption decisions, with relative advantage typically emerging as the strongest predictor (Tornatzky & Klein, 1982; Holden & Karsh, 2010). Recent health care applications continue to support these theoretical predictions, though with increasing recognition that organizational and contextual factors significantly influence adoption processes (Alsahli et al., 2025; Chong et al., 2022; Greenhalgh et al., 2017;).

Second, rural health care faces distinctive challenges that differentiate technology adoption dynamics from urban and suburban settings. Infrastructure limitations including inadequate broadband, financial constraints reflected in narrow operating margins, workforce shortages limiting both clinical and technical support capacity, and patient populations with lower technology access collectively create a more constrained environment for technology implementation (Bogulski et al., 2024; Maganty et al., 2023;

K. Smith & Chen, 2023). Research documents that rural providers recognize potential benefits of mHealth technologies but express substantial concerns about implementation feasibility given these constraints (Barry et al., 2024; Klee et al., 2023; Coombs et al., 2022). The digital divide in rural areas encompasses both infrastructure access and digital health literacy, creating compounding barriers to effective mHealth deployment (Crowe et al., 2024; Hengst et al., 2023).

Third, rural Appalachia experiences particularly severe challenges reflecting concentrated economic disadvantage, health disparities exceeding national averages across multiple disease categories, accelerating health care infrastructure erosion through hospital and clinic closures, and cultural contexts shaped by historical experiences with external institutions (ARC, 2021, 2025; Stanzak & Oliver, 2023; Serchen et al., 2025). These factors create what researchers characterize as a "medical desert" - regions where millions of residents lack adequate access to primary health care services (Bailey et al., 2024; Kukulka et al., 2024). While mHealth technologies represent potential mechanisms to improve health care access in these underserved areas, their adoption requires navigating the complex interplay of provider perceptions, patient capabilities, and structural constraints that characterize the Appalachian health care environment.

Evidence establishes that mHealth interventions can improve clinical outcomes for chronic diseases including diabetes, hypertension, and cardiovascular disease - conditions disproportionately affecting rural Appalachian populations (Bazzano et al., 2024; Martinez & Kim, 2023). Remote patient monitoring, secure messaging, and medication adherence applications demonstrate efficacy in research contexts, with effect sizes suggesting meaningful clinical benefits when successfully implemented. However, research also documents substantial challenges in translating research efficacy to real-world effectiveness, with implementation barriers including technical difficulties, workflow integration challenges, patient engagement issues, and sustainability concerns frequently limiting the benefits achieved in routine practice settings (Fava & Lapão, 2024; Giebel et al., 2023; Niyomyart et al., 2024).

This study addresses a critical gap in health informatics by investigating the intersection of psychological predictors and structural constraints in mHealth adoption, a relationship that has historically been examined in isolation rather than through simultaneous interaction (Brooks et al., 2021; Chapman et al., 2025). By focusing on independent primary care providers in the understudied and resource-limited context of Central and Southern Appalachia, the research tests the boundary conditions of DOI theory to determine if environmental scarcities fundamentally alter the psychological process of intention formation (Rogers, 2003; Serchen et al., 2025). Methodologically, the study employs rigorous moderation testing via hierarchical multiple regression to quantify how factors like broadband and financial capacity moderate the influence of perceived technology attributes (Hayes, 2022). Ultimately, these findings contribute to both theoretical generalizability and practical implementation science by clarifying whether digital health interventions in underserved regions should prioritize provider education to change perceptions or infrastructure development to resolve structural impossibilities.

The literature synthesis reveals substantial knowledge about factors influencing health care technology adoption generally, but critical gaps regarding adoption in rural Appalachian contexts and mechanisms through which structural constraints influence adoption processes. Addressing these gaps requires rigorous empirical investigation employing appropriate sampling, measurement, and analytical approaches.

In Chapter 3, I present the research methodology designed to test the hypotheses derived from literature review. The chapter details the quantitative, nonexperimental, cross-sectional survey design employed; the target population of primary care physicians, nurse practitioners, and physician assistants practicing in rural Appalachian counties; the sampling strategy using proportional stratified random selection from state medical board licensure registries to ensure geographic representation; instrumentation including validated scales for measuring DOI constructs, structural constraints, and behavioral intentions; data collection procedures; and analytical approach employing hierarchical multiple regression to test main effects of innovation attributes and moderation effects of structural constraints.

Chapter 3: Research Method

The primary purpose of this quantitative, nonexperimental, cross-sectional study is to examine whether innovation attributes from DOI theory - specifically perceived relative advantage, complexity, and trialability - predict current mHealth adoption among primary care providers practicing in rural Appalachian settings, and whether structural constraints characteristic of resource-limited rural health care environments moderate these relationships. This investigation addresses a critical gap in technology adoption research: while DOI has been extensively validated in well-resourced contexts (Holden & Karsh, 2010; Tornatzky & Klein, 1982), its applicability to severely resource-constrained settings remains theoretically and empirically underexamined, particularly in the post-COVID-19 health care landscape where telehealth adoption patterns have fundamentally shifted (Ortega et al., 2020; Patel et al., 2021). The study tests boundary conditions of DOI predictions by examining whether innovation attribute-adoption relationships operate uniformly across contexts or are contingent upon structural factors - infrastructure adequacy, technical support availability, financial resources, and organizational capacity - that may fundamentally alter how providers translate perceptions into adoption decisions (Brooks et al., 2021; P. A. H. Williams et al., 2022).

This chapter details the research methodology employed to examine relationships between innovation attributes, structural constraints, and mHealth adoption intentions among rural Appalachian primary care providers. The chapter specifies population, sampling procedures, data collection methods, instrumentation, analytical approaches, validity considerations, and ethical protocols to ensure scientific rigor and replicability.

Research Design and Rationale

I employed a quantitative, nonexperimental, cross-sectional survey design to test hypothesized relationships between innovation attributes, structural constraints, and mHealth adoption intentions. The quantitative approach enables systematic hypothesis testing of DOI theoretical propositions using standardized measurement and statistical inference (Creswell & Creswell, 2018). The design is nonexperimental because variables - provider perceptions and structural constraints - are naturally occurring and cannot be ethically or practically manipulated. The cross-sectional approach captures all variables at a single time point, providing temporal snapshot appropriate when longitudinal tracking is not feasible given resource constraints and geographically dispersed population.

The study's three RQs informed design decisions:

RQ1: To what extent do perceived relative advantage, complexity, and trialability predict current mHealth adoption among rural Appalachian primary care providers?

RQ2: What is the relative predictive strength of these innovation attributes in explaining current mHealth adoption?

RQ3: Do structural constraints moderate relationships between innovation attributes and current mHealth adoption?

These questions require simultaneous measurement of multiple predictors, moderator, and outcome to enable regression analysis testing main effects (RQ1, RQ2) and interaction effects (RQ3). Cross-sectional survey design provides this capability while remaining feasible for studying geographically dispersed rural providers.

The quantitative cross-sectional design directly aligns with the study's research questions, each requiring distinct analytical capabilities this design provides. Research Question 1 necessitates measurement of multiple predictor-outcome relationships simultaneously while controlling for covariates, a task optimally accomplished through logistic regression analysis of cross-sectional data examining binary outcomes (Hosmer et al., 2013; Tabachnick & Fidell, 2019). Research Question 2 requires comparison of effect sizes (odds ratios) from simultaneous entry of all attributes into a logistic regression model, enabling direct quantitative comparison of which attributes most strongly distinguish current adopters from nonadopters. Research Question 3 tests whether the strength of predictor-outcome relationships depends on constraint levels, requiring statistical interaction testing through hierarchical moderated logistic regression with interaction terms (Jaccard, 2001). The cross-sectional design's collection of all variables at one time point enables examination of factors associated with current adoption status while acknowledging that temporal precedence cannot be established definitively.

Study Variables

I operationalized constructs derived from DOI theory (Rogers, 2003) and contemporary organizational adoption frameworks (Venkatesh et al., 2003; M. D. Williams et al., 2021).

Independent Variables

Three of the innovation attributes theorized by DOI as primary adoption predictors: (a) Perceived Relative Advantage - the degree to which providers believe mHealth offers benefits over existing practice approaches, including improved patient outcomes, enhanced care access particularly for chronic disease management, and practice efficiency gains (Rogers, 2003). In the current context, relative advantage perceptions are shaped by pandemic-era experiences with remote care delivery and recognition of persistent rural access barriers (Johnson et al., 2022; Martinez et al., 2023); (b) Perceived Complexity - the degree to which providers perceive mHealth as difficult to understand, learn, or integrate into existing workflows, with higher complexity expected to inhibit adoption (Moore & Benbasat, 1991). Recent research suggests complexity perceptions in health care increasingly focus on system integration challenges (EHR interoperability, workflow disruption) rather than personal learning difficulty (Ebo et al., 2025); and (c) Perceived Trialability - the extent to which providers believe they can experiment with mHealth on a limited basis before full commitment, reducing adoption risk and uncertainty (Rogers, 2003). Contemporary understanding recognizes that trialability in health care contexts often depends on organizational support for piloting technologies rather than individual experimentation (Greenhalgh et al., 2017; Shaw et al., 2024). These attributes represent cognitive-perceptual factors theorized as proximal determinants of adoption decisions.

Dependent Variable

Current mHealth Adoption Status - providers' current use of mHealth technologies in clinical practice, operationalized as a binary variable indicating whether providers currently use mHealth technologies (coded 1) versus do not currently use mHealth (coded 0, combining providers who have never used mHealth with those who used previously but discontinued). Current adoption status is assessed through a single item: "Which statement best describes your current use of mobile health (mHealth) technologies?" with response options: (a) Currently use mHealth technologies, (b) Used in past but discontinued, and (c) Never used.

Current adoption status serves as the dependent variable rather than prospective behavioral intentions because it represents actual realized adoption decisions rather than stated future plans, providing direct evidence about factors distinguishing adopters from nonadopters in this severely underserved context (Rogers, 2003). While cross-sectional measurement precludes establishing temporal precedence - whether perceptions preceded adoption or adoption experience shaped subsequent perceptions - examining current adoption addresses the fundamental theoretical question of whether DOI relationships operate in resource-constrained rural settings (Brooks et al., 2021; Weichelt et al., 2024). The binary operationalization aligns with DOI theory's foundational focus on what distinguishes those who adopt from those who do not, enables appropriate logistic regression analysis, and provides clear interpretability for implementation strategy development. Meta-analyses demonstrate that innovation attributes show similar associations with adoption intentions and actual adoption behaviors (Tornatzky & Klein, 1982; Holden & Karsh, 2010), supporting that examining current adoption tests core DOI propositions while providing more direct behavioral evidence than intention measures.

The study acknowledges that combining discontinued users with never users into a single "nonadopter" category may obscure meaningful differences between those who tried and rejected mHealth versus those who never adopted. However, preliminary analysis indicated relatively few discontinued users (15% of sample), insufficient for three-category multinomial logistic regression with adequate statistical power. The primary theoretical interest centers on current adoption status - whether providers have successfully implemented and sustained mHealth use - making the binary categorization theoretically appropriate while acknowledging this analytical decision in interpretation and limitations.

Moderating Variables

Structural Constraints - organizational and environmental factors external to individual provider perceptions that may limit adoption feasibility, measured as a composite of four dimensions reflecting current rural health care realities: (a) broadband infrastructure adequacy, operationalized in light of recent federal infrastructure investments targeting rural connectivity (Infrastructure Investment and Jobs Act, 2021; Federal Communications Commission, 2022); (b) availability of technical support for implementation and troubleshooting, recognized as critical for sustained adoption in resource-limited settings (Brooks et al., 2021; Warren et al., 2023); (c) financial resources for technology acquisition and maintenance, particularly relevant given ongoing rural hospital financial distress and closure trends (Cecil G. Sheps Center, 2023); and (d) organizational leadership support for mHealth adoption, identified in recent implementation science research as essential facilitating condition (Damschroder et al., 2022; Nilsen et al., 2020). These constraints represent the resource context within which perceptions translate (or fail to translate) into intentions, with the moderation hypothesis positing that innovation attribute effects on current adoption depend on constraint levels - favorable perceptions may predict higher adoption probability when constraints are minimal but show attenuated effects when constraints are severe, a pattern supported by emerging research on technology adoption in resource-constrained settings (Chong et al., 2022; Williams et al., 2022).

Control Variables

Provider demographic and practice characteristics known from prior research to influence technology adoption, including years in clinical practice (experience level), professional role (physician versus advanced practice provider), practice setting (independent practice, hospital-owned clinic, Federally Qualified Health Center/Rural Health Center, other), current mHealth use status (currently using, previously discontinued, never used), and estimated percentage of patients with reliable smartphone and internet access (Chau & Hu, 2002a; Holden & Karsh, 2010). Recent research suggests that postpandemic provider characteristics may relate to adoption differently than prepandemic patterns, with current use status particularly relevant given that many providers were forced to adopt telehealth during COVID-19 emergency declarations and must now decide whether to sustain these practices under normal operating conditions (Gajarawala & Pelkowski, 2021; A. C. Smith et al., 2022). These covariates are included to isolate innovation attribute and structural constraint effects on current adoption status from confounding influences of demographic and contextual factors.

Design Constraints and Rationale

The cross-sectional design was selected after careful consideration of feasible alternatives given practical, methodological, and theoretical constraints inherent in studying rural primary care providers. Longitudinal designs, while theoretically ideal for establishing temporal precedence and examining intention-behavior relationships over time, present prohibitive challenges for this population and research context. Rural providers experience high turnover rates due to burnout and recruitment to urban settings, with workforce instability intensifying postpandemic (MacDowell et al., 2010; Rao et al., 2021; Sharma et al., 2023), creating substantial attrition risk that would undermine statistical power and introduce systematic bias if those who remain differ from those who leave. Moreover, the 12–24-month observation period required for behavioral follow-up would position data collection across rapidly evolving postpandemic policy landscapes including ongoing revisions to telehealth reimbursement rules, state licensure reciprocity laws, and federal broadband infrastructure deployment (American Telemedicine Association, n.d.; Federal Communications Commission, 2022), introducing temporal confounds that would complicate interpretation of whether changes reflect individual adoption trajectories or environmental shifts affecting the entire population. Finally, longitudinal designs require substantially larger initial samples to accommodate expected attrition (typically 30%–50% over 12 months in health care provider studies), exceeding resources available for a doctoral dissertation while providing diminishing marginal returns for answering research questions focused on current perceptions and their moderators rather than behavioral trajectories over time.

Experimental designs involving manipulation of innovation attributes or structural constraints are ethically and practically infeasible. Innovation attribute perceptions reflect providers' authentic professional judgments developed through clinical experience and cannot be experimentally manipulated without deception, which would violate research ethics principles (American Psychological Association, 2020). Structural constraints (infrastructure adequacy, resource availability, organizational support) are fixed environmental realities that cannot be experimentally assigned - researchers cannot randomly provide some providers with adequate broadband infrastructure while denying it to others, nor can they manipulate practice-level resources without engaging in complex organizational interventions beyond dissertation scope. Moreover, the research questions concern *naturally occurring variation* in perceptions and constraints within the real-world context of rural Appalachian health care; experimental manipulation would create artificial conditions undermining external validity and policy relevance of findings (Shadish et al., 2002). Recent debates in implementation science emphasize the value of observational research for understanding how interventions perform in authentic practice contexts rather than controlled experimental conditions (Glasgow et al., 2019; Patsopoulos, 2011), supporting this study's naturalistic observational approach.

The cross-sectional survey design represents the optimal methodological approach for this study's theoretical goals and practical constraints. It enables (a) systematic measurement of all constructs using validated psychometric scales ensuring construct validity, with items adapted to reflect current technological capabilities and policy contexts (Marikyan et al., 2023); (b) adequate statistical power with achievable sample sizes ($N = 100$) to detect hypothesized effects of medium magnitude, validated through a priori power analysis using contemporary standards (Faul et al., 2009; Lakens, 2022); (c) rigorous hypothesis testing through hierarchical multiple regression and interaction analysis following current methodological best practices (Hayes, 2022); (d) completion within doctoral dissertation timeframe while maintaining scientific rigor; and (e) examination of perceptions and constraints as they currently exist in authentic rural health care contexts, maximizing ecological validity and policy relevance for understanding postpandemic adoption dynamics (Ortega et al., 2020).

While acknowledging that cross-sectional designs preclude definitive causal inference due to temporal ambiguity and cannot address the intention-behavior gap documented in meta-analytic research (Webb & Sheeran, 2006), the design provides essential evidence regarding whether and how DOI relationships explain current adoption patterns in rural contexts - evidence currently absent from the literature despite the explosion of telehealth research during COVID-19 (Johnson et al., 2021; Martinez et al.,

2022) and necessary before investing resources in more resource-intensive longitudinal or intervention research. Recent methodological literature emphasizes that all research designs involve tradeoffs and that cross-sectional designs remain valuable for theory testing when research questions focus on relationships among variables at a single time point rather than temporal dynamics (Spector, 2019; Maxwell, 2004).By examining factors associated with current adoption status, the study provides actionable insights about what distinguishes adopters from nonadopters, informing targeted implementation strategies for rural health care technology adoption.

This methodological choice aligns with contemporary philosophy of science emphasizing that research designs should match research questions and theoretical goals rather than adhering to rigid methodological hierarchies that privilege experimental or longitudinal designs regardless of appropriateness (Maxwell, 2004; Shadish et al., 2002). The study's contribution lies not in definitively proving causality or predicting behavior, but in testing boundary conditions of established theory - determining whether relationships documented in well-resourced contexts hold in resource-constrained settings, and whether structural factors create contingencies requiring theoretical refinement. Cross-sectional analysis of concurrent perceptions, constraints, and intentions provides precisely the evidence needed to address these theoretical questions while remaining feasible within practical constraints. Moreover, by positioning findings explicitly as tests of theoretical generalizability rather than causal proofs, the study appropriately communicates inferential limitations while advancing knowledge regarding how technology adoption processes operate across diverse contexts - a critical question for implementation science (Damschroder et al., 2022; Nilsen et al., 2020), health equity research examining digital divide implications (Nouri et al., 2020; Rodriguez et al., 2021), and global health technology initiatives targeting resource-limited settings worldwide (Labrique et al., 2018; Naslund et al., 2019).

Methodology

Population

The target population comprises primary care providers - physicians (MD/DO), nurse practitioners (NP), and physician assistants (PA) - currently practicing in rural counties within Central and Southern Appalachian subregions. Rural designation follows Health Resources and Services Administration (HRSA) criteria identifying counties as rural based on population density and urbanization measures. Central and Southern Appalachia includes portions of Kentucky, Tennessee, West Virginia, Virginia, North Carolina, South Carolina, Georgia, Alabama, and Mississippi as defined by the Appalachian Regional Commission (ARC, 2021, 2025).

The population is defined by three inclusion criteria: (a) professional role as primary care provider (physician, nurse practitioner, physician assistant) currently providing direct patient care; (b) practice location in HRSA-designated rural county within Central or Southern Appalachian subregions; and (c) active clinical practice delivering primary care services including chronic disease management. Providers are excluded if they practice exclusively in specialties (cardiology, surgery, psychiatry), hold only administrative positions without clinical responsibilities, or practice in urban counties or Northern Appalachian subregions.

Population size estimation presents challenges due to lack of comprehensive registries cross-referencing provider type, specialty, and practice location. State medical board data indicate approximately 45,000 physicians practice in Appalachian states, with approximately 30% in primary care and 40% in rural areas, suggesting approximately 5,400 rural Appalachian primary care physicians. Similar calculations for nurse practitioners (~3,200) and physician assistants (~1,800) yield estimated target population of approximately 10,000-12,000 providers. This estimate acknowledges uncertainty due to provider mobility, incomplete specialty coding, and rural-urban boundary imprecision.

Sampling and Sampling Procedures

Sampling Strategy

I employed stratified random sampling with proportional allocation across Central and Southern Appalachian subregions and provider types. Stratification ensures adequate representation of geographic areas with distinct economic and infrastructure characteristics (ARC, 2021, 2025) and professional roles with potentially different adoption patterns (Weichelt et al., 2024). Random selection within strata ensures each eligible provider has known probability of selection, supporting generalizability to the target population.

Sampling frames are state medical board and nursing board licensure databases for Kentucky, Tennessee, West Virginia, Virginia, North Carolina, South Carolina, Georgia, Alabama, and Mississippi. These databases provide provider names, credentials, practice addresses, and specialty designations. Geographic information systems (GIS) software cross-references practice addresses with HRSA rural designation and ARC county classifications to identify eligible providers.

Sample Size Determination

Sample size was determined through *a priori* power analysis using G*Power 3.1.9.7 (Faul et al., 2009). For multiple regression with up to 12 predictors (3 innovation attributes, 3 interaction terms, 6 covariates), detecting medium effect size ($f^2 = .15$, approximately $R^2 = .13$), with $\alpha = .05$ (two-tailed) and power = .80, minimum required sample size is N = 98. This effect size is consistent with technology adoption meta-analyses showing innovation attributes explain substantial variance (Tornatzky & Klein, 1982) while being conservative enough to detect meaningful relationships.

For interaction effects specifically, moderation analysis with 3 predictors, 1 moderator, and 3 interactions requires N = 77 to detect medium effect size ($f^2 = .15$) with power = .80 and $\alpha = .05$. The target sample of N = 100 provides adequate power for both main effects and interaction testing while accommodating potential incomplete responses requiring listwise deletion.

While the target sample of N=100 provides adequate power for detecting medium effect sizes, logistic regression also requires consideration of events per variable (EPV) - the number of cases in the smaller outcome category divided by the number of predictors. With approximately 37 current adopters (events) and 12 predictors in the full model, EPV

= 3.08, which falls below the recommended minimum of 10 EPV for stable coefficient estimation (Peduzzi et al., 1996). This limitation is acknowledged and addressed through (a) parsimonious modeling emphasizing theoretically essential predictors; (b) sensitivity analyses with reduced covariate sets; and (c) clear acknowledgment in interpretation that coefficients may be less stable than optimal, requiring replication. Alternative approaches including penalized maximum likelihood (Firth's correction) may be employed if standard maximum likelihood estimation shows convergence issues or extreme standard errors.

Sampling Procedures

Sampling proceeded in four steps:

1. Frame construction. State licensure databases are obtained for nine Appalachian states. Practice addresses are geocoded and cross-referenced with HRSA rural designation and ARC county classifications. Providers are classified by subregion (Central Appalachia: Kentucky, Tennessee, West Virginia; Southern Appalachia: Virginia, North Carolina, South Carolina, Georgia, Alabama, Mississippi) and role (physician, nurse practitioner, physician assistant).
2. Proportional allocation. Sample allocation follows population proportions: Central Appalachia (approximately 40%) and Southern Appalachia (approximately 60%), with physician (approximately 55%), nurse practitioner (approximately 30%), and physician assistant (approximately 15%)

distributions. Target sample of N = 100 allocates approximately: Central Appalachia physicians (n=22), NPs (n=12), PAs (n=6); Southern Appalachia physicians (n=33), NPs (n=18), PAs (n=9).

3. Random selection. Within each stratum, simple random sampling identifies providers to contact. Oversampling factor of 7:1 (700 providers contacted to yield 100 responses) accounts for estimated 14% response rate based on similar health care provider surveys (Weichelt et al., 2024).
4. Replacement. If target sample size is not achieved after initial contact and two reminder waves, additional randomly selected providers from the same strata are contacted until target is reached or sampling frame is exhausted.

Procedures for Recruitment, Participation, and Data Collection

Recruitment

Recruitment involved email invitation with survey link distributed to randomly selected providers. I obtained email addresses from licensure databases where available or through internet search of practice websites. The invitation email described the study purpose (examining factors influencing mHealth adoption), eligibility criteria, voluntary nature, anonymity protections, estimated completion time (10–15 min), and survey link. The recruitment strategy follows modified Dillman method (Dillman et al., 2014, as cited in contemporary survey methodology research): initial email invitation, followed by reminder emails at 1 week (first reminder), 2 weeks (second reminder), and 3 weeks (final reminder) to nonresponders. Each contact emphasizes voluntary participation, anonymity, and study importance for rural health care improvement.

Informed Consent

I employed an anonymous design with implied consent through survey completion, approved by Walden University Institutional Review Board (no. 08-28-25-1124176). The first survey page presents information typically included in consent forms: study purpose, procedures, voluntary nature, right to withdraw, anonymity protections, potential risks and benefits, researcher contact information, and IRB contact information. Participants indicate informed consent by clicking "Continue to Survey"; clicking "Exit Survey" terminates participation without data collection. This approach was appropriate because (a) the research presents minimal risk to participants; (b) signed consent would be the only record linking participants to the research, potentially compromising anonymity; and (c) completion of an anonymous survey reasonably indicates consent to participate (see American Psychological Association, 2020).

Data Collection

Data collection occurred through a web-based survey administered via SurveyMonkey platform with HIPAA-compliant configuration. The platform enables (a) anonymous response collection without tracking IP addresses or other identifiers, (b) SSL encryption for data transmission, (c) password-protected researcher access, and (d) automated skip logic for efficient survey flow. The survey included six sections: (a) eligibility screening (professional role, practice location, clinical activity status), (b) demographic and practice characteristics (experience, setting, current technology use), (c) innovation attribute scales (relative advantage, complexity, trialability), (d) structural constraint scales (infrastructure, resources, support), (e) behavioral intention scales, and (f) optional comments. Estimated completion time is 10–15 min based on pilot testing. Survey data are exported to SPSS format for analysis. Data security follows university requirements: password-protected devices, encrypted storage, limited access (researcher and faculty advisor only), and retention for minimum 5 years per university policy followed by secure deletion.

Participant Exit and Follow-up

Participants may exit the survey at any time by closing their browser without consequence. Partial responses are retained only if participants complete at least 80% of substantive items (innovation attributes, structural constraints, intentions), enabling meaningful analysis with minimal missing data. No follow-up contact occurs due to anonymous design precluding participant identification. No debriefing is necessary given minimal risk nature of the research. Study results will be published in Walden University ScholarWorks upon completion, with findings potentially shared through rural health care conferences and journals to inform practice and policy.

Instrumentation and Operationalization of Constructs

Innovation Attribute Scales

Innovation attributes (relative advantage, complexity, trialability) are measured using scales adapted from Moore and Benbasat's (1991) instrument for measuring perceptions of adopting information technology innovations. The original instrument operationalizes Rogers's (2003) DOI constructs for information technology contexts and has been extensively validated in health care technology research (Holden & Karsh, 2010; Chong et al., 2022; Zhang et al., 2017).

Perceived relative advantage was measured with six items assessing the degree to which providers believe mHealth improves patient care quality, access, and practice efficiency compared to traditional approaches. Example items include "Using mHealth would improve quality of care for chronic disease patients" and "Using mHealth would enable more efficient clinical task completion." Items use 5-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*), with scores averaged to create composite scale (range 1–5, higher scores indicating greater perceived advantage). Moore and Benbasat (1991) reported Cronbach's α = .90 for relative advantage. Recent health care applications report α = .85-.92 (Alsahli et al., 2025; Chong et al., 2022).

Perceived complexity was measured with seven items assessing difficulty of understanding, learning, and using mHealth, including workflow integration challenges. Example items include "Overall, I would find mHealth technologies easy to use" (reverse coded) and "Integrating mHealth with our EHR would be difficult." Four items assessing implementation difficulty are reverse-coded so that higher scores consistently indicate lower perceived complexity (greater ease). Items use 5-point Likert scale with scores averaged for composite (range 1-5, higher scores indicating lower complexity). Moore and Benbasat (1991) reported α = .85. Recent health care applications report α = .81-.88

Perceived trialability was measured with five items assessing opportunities to experiment with mHealth on limited basis before full commitment. Example items include "It would be easy to test mHealth with a small number of patients first" and "My practice could pilot mHealth without major financial commitment." Items use 5-point Likert scale with scores averaged for composite (range 1-5, higher scores indicating greater trialability). Moore and Benbasat (1991) reported $\alpha = .71$. Recent applications report $\alpha = .76\text{-}.82$ (Alsahli et al., 2025).

Appropriateness and Adaptation. The Moore and Benbasat (1991) scales are appropriate because they operationalize DOI constructs central to this study and have established validity in health care contexts. Adaptations for this study included (a) replacing generic "innovation" references with specific "mHealth" terminology, (b) adding items addressing rural-specific concerns (patient technology access, infrastructure reliability), and (c) ensuring language appropriate for diverse provider roles (physicians, nurse practitioners, physician assistants). Adapted items maintain construct definitions while enhancing relevance to the study context.

Permission. The Moore and Benbasat (1991) scales are published and widely used in academic research. While formal permission is not required for use in dissertation research, appropriate citation acknowledges the source.

Reliability and Validity in Current Study. Internal consistency reliability (Cronbach's α) will be calculated for each scale using the study sample. Acceptable reliability threshold is $\alpha \geq .70$ for research purposes. Construct validity in this study was supported by (a) established validity of source instrument across diverse contexts, (b) factorial validity demonstrated in prior health care applications, and (c) convergent validity with theoretically related constructs (correlations among innovation attributes and with intentions should follow expected patterns).

Structural Constraint Scale

Structural constraints are measured using a 4-item scale assessing infrastructure, organizational resources, and financial factors limiting mHealth implementation feasibility. Items are based on Weichelt et al.'s (2019) mHealth readiness assessment and recent rural telehealth research identifying critical constraints (Bogulski et al., 2024; Chapman et al., 2025). Items assess: (a) practice financial resources for technology implementation, (b) practice leadership support for mHealth adoption, (c) technical support availability, and (d) internet/mobile infrastructure adequacy in the practice area.

Items use 5-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*) with reverse coding so that higher scores indicate greater constraints (fewer resources). Example item: "My practice has financial resources to implement mHealth" (reverse coded so agreement indicates low financial constraints). Scores are averaged to create composite scale (range 1-5, higher scores indicating greater constraints).

Appropriateness. This scale is appropriate because it operationalizes structural factors identified in rural health care technology literature as critical implementation barriers (Bogulski et al., 2024; Maganty et al., 2023; Chapman et al., 2025). The scale captures multiple constraint dimensions (infrastructure, financial, organizational) while remaining brief enough to minimize respondent burden.

Development Basis. Items were developed based on (a) systematic review of rural telehealth barrier literature, (b) Weichelt et al.'s (2019) mHealth readiness framework, and (c) recent empirical studies identifying specific rural constraints (Bogulski et al., 2024; K. Smith & Chen, 2023). Item wording was refined through expert review (3 rural health care researchers) and pilot testing with 10 rural providers.

Reliability Evidence. Internal consistency will be assessed through Cronbach's α with target threshold $\alpha \geq .70$. Item-total correlations will identify poorly performing items ($r < .30$) for potential exclusion.

Validity Evidence. Content validity is supported by systematic derivation from empirical literature and expert review confirming items represent construct domain. Construct validity will be assessed through (a) correlational patterns with innovation attributes (constraints should show negative correlations with relative advantage and trialability, positive with complexity), (b) predictive validity (constraints should predict lower intentions), and (c) moderation effects (constraints should interact with innovation attributes to predict intentions).

Current mHealth Adoption Status

Current mHealth adoption status is assessed through a single item asking: "Which statement best describes your current use of mobile health (mHealth) technologies?" with three response options: (a) "Currently use mHealth technologies," (b) "Used in past but discontinued," and (c) "Never used." The item is accompanied by a brief definition: "mHealth technologies include smartphone apps, text messaging, remote monitoring devices, and other mobile tools for patient care."

For analysis purposes, responses are recoded into a binary variable with current users coded as 1 (adopted) and nonusers coded as 0 (not adopted). Nonusers combine both providers who have never used mHealth and those who used previously but discontinued, reflecting the primary theoretical interest in sustained current adoption versus any form of nonadoption. This categorization enables binary logistic regression analysis testing which factors distinguish current adopters - providers who have successfully implemented and sustained mHealth use - from nonadopters.

Appropriateness. Single-item measurement of adoption status is standard in technology diffusion research (Rogers, 2003) and health care technology adoption studies (Holden & Karsh, 2010; Weichelt et al., 2024). Unlike psychological constructs requiring multi-item scales, adoption status is a concrete behavioral fact appropriately assessed through direct self-report. The item's clarity and face validity make multi-item measurement unnecessary and potentially burdensome.

Validity. Self-reported current use has been validated in health care technology research through comparison with administrative data (e.g., EHR access logs, billing records), showing strong concordance ($r > .80$) between self-report and objective measures (Iversen & Ma, 2022). The anonymous survey design reduces social desirability bias that might inflate self-reported adoption. The inclusion of "used in past but discontinued" response option provides socially acceptable alternative to "never used," further reducing bias toward over-reporting current use.

Binary Operationalization Rationale. The binary categorization (current users vs. nonusers) aligns with DOI theory's foundational question - what distinguishes adopters from nonadopters (Rogers, 2003). While adoption intensity could be examined among current users, the threshold question of whether adoption occurs at all is theoretically and practically primary. Binary measurement enables logistic regression, providing interpretable odds ratios showing how each predictor affects adoption probability. The decision to combine discontinued users with never users reflects both statistical necessity (insufficient discontinued users for three-category analysis) and theoretical focus on sustained adoption as the outcome of interest.

Control Variables

Demographic and practice characteristics serving as control variables are measured through single items or brief scales:

- Years in practice: Continuous variable (number of years since licensure)
- Professional role: Categorical variable (physician, nurse practitioner, physician assistant)
- Practice setting: Categorical variable (independent/small group practice, Federally Qualified Health Center/rural health clinic, hospital-owned clinic, other)

- Current mHealth use: Categorical variable (currently use mHealth technologies, used in past but discontinued, never used)
- Patient technology access: Continuous variable (estimated percentage of patients with reliable smartphone and internet access, 0%–100%)
- Geographic subregion: Categorical variable (Central Appalachia, Southern Appalachia) derived from practice location

I selected these variables based on prior research documenting relationships with technology adoption (Holden & Karsh, 2010; Iversen & Ma, 2022; Weichelt et al., 2024) and serve to isolate innovation attribute and structural constraint effects from demographic and contextual confounds.

Sufficiency of Instrumentation

The instrumentation was sufficient to answer the RQs because (a) innovation attribute scales directly measure the independent variables (RQ1, RQ2), (b) structural constraint scale measures the moderator variable (RQ3), (c) intention scale measures the dependent variable for all research questions, (d) control variables account for known confounds, and (e) all constructs are measured with established or newly developed scales with planned reliability and validity assessment. The complete instrument (see Appendix A) provides comprehensive measurement of all constructs specified in the theoretical model while remaining brief enough (approximately 40 items, 10–15-min completion time) to minimize respondent burden and maximize response rates.

Data Analysis Plan

Software

To analyze the data, I used IBM SPSS Statistics Version 30.0. I selected this software for its comprehensive regression analysis capabilities, user-friendly interface for computing and probing interactions, and wide acceptance in technology adoption research (Hayes, 2022).

Data Screening and Preparation

Data Cleaning. Survey responses will be screened for completeness, accuracy, and response patterns indicating insufficient effort (straight-lining, completing in implausibly short time). Responses completing fewer than 80% of substantive items will be excluded from analysis. Responses showing identical responses across all items regardless of content will be flagged for review and potential exclusion.

Missing Data Analysis. Patterns and extent of missing data will be examined for all variables. Little's Missing Completely at Random (MCAR) test will assess whether missing data are random or systematic. If missing data are MCAR and minimal ($< 5\%$ per variable), listwise deletion will be employed. If missing data patterns are systematic or exceed 5%, multiple imputation with 20 imputations will be considered, though given survey design encouraging completion, substantial missing data are not anticipated.

Outlier Detection. Univariate outliers will be identified through standardized scores ($|z| > 3.29$). Multivariate outliers will be identified through Mahalanobis distance (χ^2 critical value, $p < .001$). Influential cases will be identified through Cook's distance (D

$> 4/n$) and leverage ($h > 2k/n$). Outliers will be examined for data entry errors or meaningful extreme values. Analyses will be conducted with and without outliers to assess influence on results.

Outcome Distribution Check. The distribution of the binary outcome variable will be examined. Logistic regression performs best when neither outcome category is extremely rare (general guideline: both categories should represent at least 10% of sample). With 37% current adopters anticipated based on pilot data, distribution is adequate. If outcome distribution is severely imbalanced (< 10% in either category), rare events logistic regression methods may be considered.

Assumption Testing. Multiple regression assumptions will be assessed:

Linearity of the logit. Box-Tidwell test will examine whether continuous predictors show linear relationships with the log-odds of adoption by testing interaction terms between each predictor and its natural logarithm.

Independence. Durbin-Watson statistic will assess independence of residuals (acceptable range 1.5-2.5).

Normality of Predictors. Distribution of continuous predictors will be assessed via skewness and kurtosis statistics (acceptable ranges: $|\text{skewness}| < 2$, $|\text{kurtosis}| < 7$).

Perfect Separation. Models will be examined for perfect separation (complete prediction of outcome) through assessment of convergence, standard errors, and predicted probabilities.

Multicollinearity. Variance inflation factors (VIF < 5, conservatively < 10), tolerance (> .20), and correlations ($r < .80$) will assess multicollinearity.

If assumptions are violated, appropriate remedies will be applied: transformations for nonnormality or nonlinearity, heteroscedasticity-consistent standard errors for heteroscedasticity, examination of correlated predictors for multicollinearity.

Variable Preparation

Composite Scales. Innovation attribute, structural constraint, and intention scales will be created by averaging items after reverse coding negatively worded items. Cronbach's α will be calculated to assess internal consistency.

Centering for Interactions. Continuous variables involved in interactions (innovation attributes, structural constraints) will be mean-centered by subtracting sample mean from each observation. This reduces multicollinearity between main effects and interactions while preserving interpretability (Aiken & West, 1991; Hayes, 2022). Interaction terms will be computed as products of centered variables. For logistic regression, predictors should be standardized (z-scores) rather than only mean-centered when computing interaction terms. This facilitates interpretation of odds ratios and reduces multicollinearity. Standardized predictors enable reporting of odds ratios for one standard deviation change, a meaningful effect size metric. Interaction terms will be computed as products of standardized variables.

Dummy Coding. Categorical control variables will be dummy coded with appropriate reference categories (hospital-owned clinic for practice setting, physician for role). Appendix B contains the variable coding and scale scoring procedures.

Research Questions and Hypotheses

RQ1: To what extent do perceived relative advantage, complexity, and trialability predict current mHealth adoption among rural Appalachian primary care providers?

H_1: Perceived relative advantage significantly and positively predicts current mHealth adoption, with higher perceived advantage associated with greater odds of being a current adopter.

H_2: Perceived complexity significantly and negatively predicts current mHealth adoption, with higher perceived complexity associated with lower odds of adoption (equivalently, perceived ease positively predicts adoption).

H_3: Perceived trialability significantly and positively predicts current mHealth adoption, with higher perceived trialability associated with greater odds of being a current adopter.

RQ2: What is the relative predictive strength of perceived relative advantage, complexity, and trialability in explaining current mHealth adoption?

H_4: Relative advantage demonstrates significantly greater predictive strength than complexity or trialability, evidenced by larger odds ratios and greater contribution to model fit.

RQ3: Do structural constraints moderate relationships between innovation attributes and current mHealth adoption?

H_5a: Structural constraints significantly moderate the relative advantage-adoption relationship, with the positive effect of relative advantage on adoption weakening under high constraint conditions.

H_5b: Structural constraints significantly moderate the complexity-adoption relationship, with the negative impact of complexity amplified when organizational support is low.

H_5c: Structural constraints significantly moderate the trialability-adoption relationship, with trialability becoming a more potent predictor when resource scarcity increases perceived risk.

Statistical Analysis Plan

Descriptive Statistics

Means, standard deviations, ranges, skewness, and kurtosis will be calculated for all continuous variables. Frequencies and percentages will be calculated for categorical variables, including the dependent variable (current adoption: % currently using vs. % not currently using). These descriptives characterize the sample and assess distributional assumptions.

Bivariate Associations

For continuous predictors and binary outcome, point-biserial correlations will examine zero-order relationships between each innovation attribute, structural constraints, and current adoption status. For categorical predictors, chi-square tests of independence will examine associations with adoption status. These preliminary analyses provide initial hypothesis tests and inform subsequent multivariate modeling.

Hierarchical Binary Logistic Regression

Four sequential models will be tested to examine main effects and interactions:

Model 1 (Controls): Current adoption status regressed on control variables (years in practice, professional role, practice setting, patient technology access) to establish baseline prediction from demographic and practice factors. Model fit assessed through -2 Log Likelihood (-2LL), Nagelkerke R^2, and classification accuracy (percentage correctly classified as adopters vs. nonadopters).

Model 2 (Innovation Attributes): Control variables plus innovation attributes (relative advantage, complexity, trialability) entered to test RQ1 hypotheses (H_1-H_3). Model comparison tests whether adding innovation attributes significantly improves fit beyond controls (likelihood ratio test: $\chi^2 = -2LL_1 - (-2LL_2)$, df = 3, $p < .05$). Individual predictor significance assessed through Wald χ^2 tests ($p < .05$) with odds ratios (OR) and 95% confidence intervals. Odds ratios indicate multiplicative change in odds of adoption for each standard deviation increase in predictor:

- OR > 1: Predictor increases odds of adoption
- OR = 1: No effect on odds
- OR < 1: Predictor decreases odds of adoption

For example, OR = 2.50 for relative advantage indicates that each SD increase in perceived relative advantage increases odds of current adoption by 150% (odds multiply by 2.50).

Model 3 (Structural Constraints): Control variables, innovation attributes, plus structural constraints entered to test constraints main effect. Likelihood ratio test (df = 1) assesses whether constraints significantly improve prediction beyond innovation attributes alone.

Model 4 (Interactions): Control variables, innovation attributes, structural constraints, plus three interaction terms (Relative Advantage × Constraints, Complexity × Constraints, Trialability × Constraints) entered to test RQ3 hypotheses (H_5a-H_5c). Likelihood ratio test (df = 3) assesses whether interactions significantly improve fit beyond main effects model. Individual interaction significance (Wald χ^2, $p < .05$) tests specific moderation hypotheses. Significant interactions indicate that attribute-adoption relationships differ across constraint levels.

Model Comparison: Each model evaluated for:

- Overall fit: Model χ^2 (improvement over null model), $p < .05$
- Pseudo R^2: Nagelkerke R^2 indicating variance explained (analogous to R^2 in OLS regression)
- Classification accuracy: Percentage correctly classified, sensitivity (% adopters correctly identified), specificity (% nonadopters correctly identified)

- Incremental fit: Likelihood ratio test comparing nested models (ΔLL, Δdf, $p < .05$)

Interaction Probing: For significant interactions, predicted probabilities of adoption will be calculated at three constraint levels: low (-1 SD), mean, and high (+1 SD), across the range of each innovation attribute. Simple slopes analysis tests whether the effect of each attribute on log-odds of adoption differs significantly from zero at each constraint level. Interaction plots display predicted probability of adoption across attribute values at each constraint level, visually illustrating moderation patterns.

Effect Size Interpretation:

- Odds Ratios: OR = 1.50 (small), OR = 2.50 (medium), OR = 4.00 (large) following Cohen's d conversions to OR
- Nagelkerke R^2: .02 (small), .13 (medium), .26 (large) following Cohen (1988)

Addressing RQ2 (Relative Importance): Odds ratios from Model 2 will be compared to determine relative importance of innovation attributes. Standardized odds ratios (computed using standardized predictors) enable direct comparison. Wald χ^2 statistics provide test of each predictor's unique contribution controlling for others. While no definitive test compares dependent ORs statistically, confidence interval overlap and relative Wald χ^2 magnitudes inform relative importance assessment.

Statistical Significance: Two-tailed Wald tests with $\alpha = .05$. Confidence intervals and effect sizes (ORs) emphasized alongside significance tests. Results approaching significance ($p = .05$-$.10$) noted as trends requiring replication.

Sensitivity Analyses:

1. Models reestimated excluding influential cases (standardized residuals $|z| > 2.5$, leverage $> 2k/n$, or Cook's distance > 1)
2. Three-category outcome (current users, discontinued users, never users) examined via multinomial logistic regression if discontinued user sample size permits ($n > 30$)
3. Alternative constraint level specifications (tertiles, median split) examined to verify interaction robustness

Logistic Regression Assumptions

Binary logistic regression makes different assumptions than OLS regression. The following will be assessed:

- Linearity of Logit: The relationship between continuous predictors and the log-odds of adoption must be linear. This will be assessed by creating interaction terms between each continuous predictor and its natural logarithm, entering these into the model, and testing significance (Box-Tidwell test). Nonsignificant interactions ($p > .05$) support linearity assumption.
- Independence of Observations: Each provider contributes one observation. Survey design ensures independence. Durbin-Watson statistic will assess independence, though this is primarily a concern for time-series data.

- Absence of Multicollinearity: Same assessment as OLS: VIF < 5, tolerance > .20, correlations r < .80. Multicollinearity inflates standard errors, making coefficients unstable.
- No Perfect Separation: The outcome cannot be perfectly predicted by any predictor or combination of predictors. This will be assessed through examination of extremely large standard errors (SE > 2) or failure of model convergence. If perfect or quasi-perfect separation is detected, the offending predictor(s) will be examined and potentially excluded or collapsed into broader categories.
- Adequate Sample Size: Minimum 10 events per predictor variable (EPV) recommended for stable coefficient estimation (Peduzzi et al., 1996). With approximately 37 current adopters (*N* = 100) and maximum 12 predictors in full model, EPV = 37/12 = 3.08, below the recommended threshold. This will be addressed by (a) parsimonious modeling using only theoretically essential predictors; (b) sensitivity analysis with reduced covariate sets; and (c) acknowledgement that coefficient estimates may be less stable than desired, requiring replication with larger samples.

If assumptions are violated:

- Nonlinearity: Transform predictors (log, square root, polynomial) or use categorical predictor representation
- Multicollinearity: Remove or combine highly correlated predictors

- Separation: Remove problematic predictor or collapse categories
- Small sample: Penalized maximum likelihood estimation (Firth's correction) or exact logistic regression

Model Diagnostics for Logistic Regression

Model Diagnostics

- Residual Analysis: Standardized residuals will identify poorly predicted cases ($|z| > 2.5$ suggests poor fit)
- Influential Cases: Cook's distance ($D > 1$), leverage values ($h > 2k/n$), and DFBetas ($|DFBETA| > 2/\sqrt{n}$) will identify influential observations
- Goodness of Fit: Hosmer-Lemeshow test will assess overall model calibration (nonsignificant $p > .05$ supports adequate fit), though this test has low power with small samples
- Classification Table: Sensitivity (% adopters correctly classified), specificity (% nonadopters correctly classified), and overall accuracy will evaluate predictive performance
- ROC Curve: Area under the ROC curve (AUC) will quantify discriminative ability (.50 = chance, .70 = acceptable, .80 = excellent, .90 = outstanding)

Treatment of Multiple Comparisons

The analysis involves testing multiple hypotheses, raising concerns about Type I error inflation. However, formal adjustment for multiple comparisons (e.g., Bonferroni correction) is not employed for three reasons: (a) hypotheses are theoretically motivated rather than exploratory, with specific predictions about direction and magnitude; (b) hypotheses are tested within coherent theoretical framework rather than independent tests; and (c) overly conservative adjustments risk Type II errors where theoretically important relationships go undetected. This approach follows recommendations for confirmatory hypothesis testing (Rothman, 1990, as cited in epidemiological and social science methodology literature). Results will be interpreted with appropriate caution, with replication recommended for borderline significant findings.

Covariates and Confounding Variables

Control variables (years in practice, role, setting, current use, patient access) are included as covariates based on prior research documenting relationships with technology adoption (Holden & Karsh, 2010; Weichelt et al., 2024). Including these variables as covariates in regression models statistically controls for their influence, isolating innovation attribute and structural constraint effects. If covariates show nonsignificant relationships with intentions, simplified models without those covariates may be examined as sensitivity analyses. However, primary analyses will include all planned covariates to ensure conservative testing of focal predictors.

Potential unmeasured confounds include provider technology self-efficacy, organizational culture, and prior technology implementation experiences. While these cannot be directly controlled, their influence is partially accounted for through (a) current mHealth use status covariate capturing technology experience, (b) practice setting covariate capturing organizational context, and (c) structural constraint measure capturing organizational resources and support.

Threats to Validity

External Validity

External validity concerns whether findings generalize beyond the study sample to other populations, settings, and times. Several threats warrant consideration.

Population Specificity

The study focuses specifically on rural Appalachian primary care providers, raising questions about generalization to non-Appalachian rural providers, suburban or urban providers, or providers in other countries. However, this geographic specificity is deliberate - the study tests DOI boundary conditions in this underserved context rather than claiming universal applicability. Findings should generalize to other severely resource-constrained rural settings in the United States sharing similar infrastructure and economic characteristics (Brooks et al., 2021; Serchen et al., 2025), but may not generalize to well-resourced settings where structural constraints are minimal.

Temporal Specificity

Data collection occurs at a specific time point in the post-COVID-19 health care landscape when telehealth policies, reimbursement rules, and technology capabilities are evolving (Shaw et al., 2024; Vakkalanka et al., 2025). Findings reflect adoption intentions under current conditions and may not generalize to substantially different policy or technological environments. However, this temporal specificity provides value by documenting current dynamics relevant to immediate implementation decisions.

Interaction of Selection and Treatment

Self-selection into survey participation may limit generalization if respondents differ systematically from nonrespondents. Providers with stronger technology interests or more extreme adoption positions may be more motivated to participate, creating range restriction or biased parameter estimates. Anonymous survey design and emphasis on research rather than advocacy purposes help mitigate but do not eliminate this threat. Response rate monitoring and demographic comparison of respondents to population characteristics (where available) will enable assessment of selection bias magnitude.

Internal Validity

Internal validity concerns whether observed relationships reflect causal connections rather than spurious associations. Several threats require acknowledgment.

Cross-Sectional Design Limitation

The most significant internal validity threat is that cross-sectional design measuring all variables simultaneously cannot establish temporal precedence - whether perceptions cause intentions, intentions influence perceptions through rationalization, or third variables cause both (Spector, 2019). The study examines associations consistent with theoretical predictions but cannot definitively establish causal direction. This limitation is inherent in feasible designs for studying geographically dispersed populations and is acknowledged in interpretation. Theoretical arguments and prior longitudinal research support the hypothesized causal direction (perceptions→intentions), though reciprocal relationships cannot be ruled out.

Temporal Precedence in Current Adoption

A specific concern with examining current adoption is that perceptions may represent post hoc rationalizations of adoption decisions rather than factors that preceded and influenced those decisions. Current adopters may emphasize relative advantage and minimize complexity to justify their investment, while nonadopters may emphasize complexity and minimize benefits to rationalize nonadoption. However, several factors mitigate this concern: (a) theoretical expectations from DOI suggest perceptions form during the persuasion stage preceding adoption decisions; (b) substantial within-group variation in perceptions (both adopters and nonadopters show varied perceptions) argues against simple rationalization patterns; (c) longitudinal research finds similar attribute-adoption associations when perceptions are measured before adoption occurs, supporting that cross-sectional associations reflect prospective relationships; and (d) current adoption represents sustained implementation rather than only initial decisions, suggesting perceptions reflect genuine implementation experiences. While temporal ambiguity remains a limitation of cross-sectional design, these factors support that findings meaningfully reflect adoption dynamics rather than only retrospective justification.

Common Method Variance

Measuring all variables through self-report at one time point creates potential for common method variance inflating relationships (Spector, 2019). Several procedural remedies address this threat: (a) anonymous survey reducing social desirability bias, (b) counterbalancing question order, (c) using validated scales with demonstrated discriminant validity, and (d) including objective county-level broadband data (where available) to complement self-reported infrastructure assessments. Statistical remedies including Harman's single-factor test will assess common method variance magnitude.

Maturation

Provider perceptions and intentions may change over time due to maturation (gaining experience, changing attitudes) unrelated to study variables. However, maturation is primarily a threat for longitudinal designs; in cross-sectional research, different providers at different experience levels are compared rather than tracking individuals over time.

Selection

Selection bias is addressed through random sampling from comprehensive sampling frame (licensure databases), reducing systematic selection of particular provider types. However, self-selection into participation (response bias) remains a threat as discussed under external validity.

Confounding Variables

Unmeasured variables potentially related to both predictors and outcome create spurious relationship risk. Control variables account for known confounds, but unmeasured organizational, cultural, or personal factors may remain. Including multiple control variables and testing alternative model specifications as sensitivity analyses helps assess confound influence.

Construct Validity

Construct validity concerns whether measures accurately represent intended theoretical constructs. Several considerations apply.

Measurement Error

All measures contain random error reducing reliability and potentially attenuating relationships. Using validated multi-item scales rather than single items improves reliability. Internal consistency assessment (Cronbach's α) will quantify measurement precision. Reliability coefficients can inform correction for attenuation in effect size interpretation.

Construct Representation

Innovation attribute scales adapted from Moore and Benbasat (1991) have established construct validity in health care contexts (Holden & Karsh, 2010), supporting that they measure intended constructs rather than other factors. However, adaptation for mHealth and rural contexts requires validation in the current sample. Factor analysis could assess whether items load on expected constructs, though sample size may limit this analysis.

Mono-Operation Bias

Measuring each construct with one scale type (Likert items) creates potential for method-specific variance. However, using established scales with demonstrated validity across contexts suggests measures capture constructs rather than just method variance.

Current Adoption as Behavioral Outcome

Measuring current adoption status rather than behavioral intentions provides direct behavioral evidence, eliminating the intention-behavior gap that limits validity of intention-based research. However, current adoption represents a single time point snapshot and does not capture adoption as a temporal process. Providers categorized as current adopters may vary substantially in adoption extent, consistency, and duration, yet binary categorization treats all adopters equivalently. Future research could examine adoption intensity, consistency, and sustainability among current users to provide more nuanced understanding. For initial investigation testing whether DOI relationships operate in resource-constrained contexts, binary adoption status provides appropriate outcome measurement while acknowledging this limitation in interpretation.

Social Desirability

Providers may report socially desirable intentions (appearing progressive, technology-friendly) rather than actual intentions. Anonymous survey design and emphasis on research purpose reduce but do not eliminate social desirability influence.

The pattern of results (including reports of concerns and barriers) will be examined for social desirability indicators.

Ethical Procedures

Institutional Permissions and Institutional Review Board Approval

I received study approval from Walden University Institutional Review Board (approval no. 08-28-25-1124176) prior to data collection. The IRB review process assessed potential risks to participants, adequacy of informed consent procedures, protection of confidential data, and compliance with ethical research standards. All study procedures described in this chapter were reviewed and approved. No additional institutional permissions are required because recruitment occurs through publicly available licensure databases rather than through health care organizations, and no patient data or organizational records are accessed. Providers participate as individual professionals rather than as employees of specific institutions.

Recruitment Ethics

Recruitment materials (email invitation, consent information) were reviewed and approved by IRB to ensure appropriate description of study purpose, procedures, voluntary nature, and participant rights. Potential concerns and mitigation strategies include the following:

- Coercion: Email recruitment could create perception of obligation if providers believe researchers have authority over them. The invitation explicitly states participation is voluntary, anonymous, and will not affect licensure or employment. No compensation is offered, eliminating undue inducement concerns.

- Privacy: Contact information obtained from public licensure databases and practice websites raises no privacy concerns as this information is publicly available. Email addresses are not retained after recruitment is complete, ensuring participant privacy.
- Deception: No deception is involved; study purpose and procedures are transparently described.

Data Collection Ethics

Informed Consent. I employed implied consent through survey completion following presentation of consent information. This approach is ethically appropriate for anonymous, minimal risk survey research (American Psychological Association, 2020).

Right to Withdraw. Participants may exit the survey at any time without consequence by closing their browser. This right is clearly stated in consent information.

Participant Burden. Survey length (10–15 min) is minimized while ensuring adequate construct measurement. Pilot testing confirmed feasibility and acceptability of completion time.

Adverse Events. No adverse events are anticipated given the study involves only completion of questionnaire about professional opinions. If participants experience distress related to survey content, researcher contact information is provided for questions or concerns.

Data Quality. Anonymous design precludes follow-up to clarify responses or verify data accuracy. However, attention check items and completion time monitoring enable identification of low-quality responses for exclusion.

Data Protection

Anonymity Versus Confidentiality. I employed anonymous data collection. No identifying information were collected, eliminating ability to link responses to individuals. Anonymity provides stronger protection than confidentiality because even the researcher cannot identify participants. Survey platform is configured to not collect IP addresses, email addresses, or other potentially identifying information.

Data Storage. Survey data are stored on password-protected, encrypted devices accessible only to the researcher and faculty advisor. SurveyMonkey platform employs HIPAA-compliant security procedures including SSL encryption for data transmission and secure server storage. Downloaded data files are stored on university-approved cloud storage (OneDrive) with encryption and access controls.

Data Retention and Destruction. Per Walden University requirements, data will be retained for minimum 5 years following study completion in secure storage. After 5 years, data will be permanently deleted through secure deletion procedures preventing data recovery.

Data Sharing. No individually identifiable data will be shared. Aggregate findings may be shared through publications and presentations, but no individual responses or combinations of responses enabling identification will be disclosed. If data sharing for verification purposes is requested, only de-identified aggregate data will be provided.

Summary

In this chapter, I detailed the research methodology for examining relationships between innovation attributes, structural constraints, and mHealth adoption intentions among rural Appalachian primary care providers. The quantitative, cross-sectional survey design enables systematic hypothesis testing while remaining feasible for studying geographically dispersed providers. Stratified random sampling ensures adequate representation across geographic subregions and provider types. Validated instrumentation measures theoretical constructs with established reliability and validity. Hierarchical multiple regression analysis tests main effects and interactions addressing each research question. Threats to validity are acknowledged and addressed where possible. Ethical procedures protect participant rights and data integrity while enabling meaningful research contribution.

Chapter 4 will present study results including: sample characteristics, descriptive statistics, assumption testing results, bivariate association analyses (point-biserial correlations, chi-square tests), and hierarchical logistic regression findings testing each hypothesis. Results will be presented systematically corresponding to each research question, with tables presenting odds ratios, confidence intervals, and model fit statistics, and figures illustrating interaction patterns if significant moderating effects are found.

Chapter 4: Results

This chapter presents findings from quantitative analysis examining relationships between innovation attributes, structural constraints, and current mHealth adoption among rural Appalachian primary care providers. The study tested whether DOI theory attributes - perceived relative advantage, complexity, and trialability - are associated with current adoption in resource-constrained rural health care contexts, which attributes demonstrate greatest predictive strength, and whether structural constraints moderate attribute-adoption relationships.

Three research questions underpinned the investigation. RQ 1 examined whether DOI innovation attributes significantly predict current mHealth adoption among rural Appalachian providers, testing theory applicability in this underserved context. RQ2 assessed relative predictive strength of innovation attributes to inform implementation strategy prioritization. RQ3 tested whether structural constraints moderate innovation attribute-adoption relationships, examining boundary conditions where DOI predictions may be attenuated or amplified by environmental factors.

Based on these research questions, four hypotheses were tested. H_1 predicted that perceived relative advantage would significantly and positively predict current adoption. H_2 predicted that perceived complexity would significantly and negatively predict adoption (equivalently, perceived ease would positively predict adoption). H_3 predicted that perceived trialability would significantly and positively predict adoption. H_4

predicted that structural constraints would significantly moderate innovation attribute-adoption relationships, with relationships attenuated under high constraint conditions.

The chapter is organized into three major sections. First, Data Collection describes recruitment procedures, response rates, sample characteristics, and representativeness assessment. Second, Preliminary Analyses reports descriptive statistics, scale reliabilities, bivariate associations, and logistic regression assumption testing. Third, Primary Analyses presents hierarchical logistic regression findings testing each hypothesis, including main effects of innovation attributes and moderation effects of structural constraints. The chapter concludes with summary of key findings and transition to Chapter 5 discussion of theoretical and practical implications.

Data Collection

Recruitment and Response

Data collection occurred between September and December 2025 following Walden University Institutional Review Board approval. Email invitations with survey links were distributed to 784 primary care providers (physicians, nurse practitioners, physician assistants) practicing in rural counties within Central and Southern Appalachian subregions, randomly selected from state medical board licensure registries for eight states (Kentucky, Tennessee, West Virginia, Virginia, North Carolina, South Carolina, Georgia, Alabama). The surveys for this study were completed via SurveyMonkey, which is a secure website specializing in survey software that helps researchers distribute questionnaires, collect data in real time, analyze survey responses, and allows researchers to export the data into other statistical analysis software programs.

The recruitment strategy followed modified Dillman method with initial invitation followed by three reminder emails at weekly intervals to nonresponders (Dillman et al., 2014, as referenced in contemporary survey methodology literature). Of 784 providers contacted, 128 initiated the survey (16.3% initiation rate). Among those initiating, 100 completed all substantive items enabling analysis (78.1% completion rate among initiators, 12.8% overall response rate).

The 12.8% response rate is lower than the 20%–30% rates typical for physician surveys (Cunningham et al., 2015) but consistent with declining response rates documented for health care provider surveys in recent years, particularly web-based surveys without incentives (Cho et al., 2013 VanGeest et al., 2007). Several factors likely contributed to lower response: (a) no monetary compensation offered, (b) email-only recruitment without mail follow-up, (c) survey length (10–15 min) potentially deterring time-pressured providers; and (d) survey topic potentially less salient for providers not currently considering mHealth adoption. Comparison of early versus late responders on demographic variables and key study variables revealed no significant differences (all $p > .20$), suggesting limited nonresponse bias though this test has limited power.

Sample Characteristics

Table 1 presents demographic and practice characteristics of the analytic sample (N=100). The sample included physicians (MD/DO, 11%), nurse practitioners (28%), physician assistants (14%), and other health care professionals (47%). The substantial proportion of respondents in the "other healthcare professionals" category requires acknowledgment, as this represents a departure from the originally specified target population of physicians, nurse practitioners, and physician assistants.

Respondents selecting "other healthcare professional" and providing role specifications included pharmacists, psychologists (PhD), licensed practical nurses, medical assistants, nurse technicians, social workers (LCSW), therapists, certified surgical technologists, and various clinical and administrative support staff. This heterogeneous composition reflects the interprofessional nature of primary care delivery in rural settings, where diverse health care professionals contribute to patient care and participate in practice-level technology adoption decisions. However, it differs from the physician and advanced practice provider population originally defined in the study design.

This sample composition affects interpretation of findings in several ways. First, the sample provides insight into mHealth adoption perspectives across the interprofessional care team rather than exclusively among independent practitioners with prescribing authority. Second, generalizability claims are appropriately limited to health care professionals involved in primary care delivery in rural Appalachian settings, rather than to physicians and advanced practice providers specifically. Third, the diversity of professional roles introduces additional variance in technology experience, clinical autonomy, and organizational influence that may affect adoption perceptions and current adoption status.

The demographic profile of respondents otherwise aligned with population parameters for rural primary care settings. Providers reported mean 17.3 years in practice (SD=15.3, range=0-50), with substantial variance reflecting representation across career stages. Practice settings included hospital-owned clinics (39%), independent/small group practices (25%), Federally Qualified Health Centers or Rural Health Clinics (14%), and other settings (22%). Current mHealth use status showed 37% currently using mHealth technologies (n=37), 15% having discontinued after prior use (n=15), and 48% never having used mHealth (n=48) - indicating substantial variance in technology experience consistent with adoption research objectives.

Table 1

*Characteristics of Participants (*N *= 100)*	*n*	%
Professional role		
Physician (MD/DO)	11	11.0
Nurse practitioner	28	28.0
Physician assistant	14	14.0
Other health care professional	47	47.0
Years in practice		
M (*SD*)	17.3 (15.3)	
Range	0–50	
Practice setting		
Hospital-owned clinic	39	39.0
Independent/small group	25	25.0
FQHC/rural health clinic	14	14.0
Other	22	22.0
Current mHealth use status		
Currently using	37	37.0
Used in past, discontinued	15	15.0
Never used	48	48.0
Geographic region		
North Carolina	28	28.0
Virginia	17	17.0
Georgia	16	16.0
South Carolina	10	10.0
Kentucky	9	9.0
Tennessee	7	7.0
West Virginia	4	4.0
Not specified/border	9	9.0
Patient technology access		

M% (*SD*)	60.7 (28.8)
Range	0%–100%

Note. Sample composition includes substantial proportion (47%) of health care professionals in roles other than physician, nurse practitioner, or physician assistant. This reflects interprofessional primary care team composition but represents departure from originally specified target population. Current mHealth use status serves as the study's dependent variable, operationalized as binary outcome (currently using vs. not currently using). FQHC = federally qualified health center.

Geographic distribution showed 20% practicing in Central Appalachia (Kentucky, Tennessee, West Virginia), 71% in Southern Appalachia (Virginia, North Carolina, South Carolina, Georgia, Alabama), and 9% not specifying state or practicing in border counties. Specific state representation included North Carolina (28%), Virginia (17%), Georgia (16%), South Carolina (10%), Kentucky (9%), Tennessee (7%), and West Virginia (4%). This distribution slightly underrepresents Central Appalachia relative to its proportion of the rural Appalachian primary care workforce (approximately 30%), potentially limiting generalizability to the most economically distressed Appalachian subregion.

Providers estimated that mean 60.7% of their patients (SD=28.8%, range=0-100%) had reliable smartphone and internet access, with substantial variance reflecting heterogeneous patient populations. This patient technology access estimate is consistent with regional data showing rural Appalachian household broadband access lagging national averages (ARC, 2025).

Missing Data Analysis

Among the 100 respondents who completed substantive survey items, there was zero item-level missing data. All participants provided responses to all 37 study variables, enabling complete case analysis without missing data bias or need for imputation. Missing data occurred at the survey level (28 of 128 initiators did not complete, 21.9% partial completion rate) rather than through item-level nonresponse, a pattern typical of web-based surveys with item-level validation.

Representativeness Assessment

The sample's demographic characteristics show both alignment with and departure from rural Appalachian primary care population parameters. Geographic distribution slightly underrepresents Central Appalachia (20% of sample vs. approximately 30% of population), potentially limiting generalizability to the most economically distressed Appalachian subregion. Practice setting distribution approximates population parameters for rural Appalachia, with appropriate representation of hospital-owned clinics, independent practices, and Federally Qualified Health Centers.

The sample's professional composition requires specific acknowledgment. While physicians comprised 11% of the sample, the 47% "other healthcare professionals" category substantially exceeds the originally intended population of physicians, nurse practitioners, and physician assistants. This composition reflects recruitment challenges inherent in surveying rural health care providers, including limited sampling frame accuracy for advanced practice providers and potential self-selection among interprofessional team members interested in health care technology.

The inclusion of diverse health care professionals provides both opportunities and limitations for interpretation. The sample offers insight into technology adoption perspectives across the care team, potentially reflecting adoption decision-making processes in real-world rural practice settings where multiple professional roles contribute to implementation success. However, findings cannot be generalized specifically to physicians or advanced practice providers as independent decision-makers. Results are appropriately interpreted as representing perspectives of health care professionals involved in primary care delivery in rural Appalachian settings, acknowledging the heterogeneity in clinical roles, autonomy, and organizational influence within this population.

The 37% current mHealth use rate exceeds population estimates of 20% to 25% for rural primary care settings (Weichelt et al., 2024), suggesting potential response bias favoring technology-experienced respondents. This could influence adoption estimates and relationships if current users differ systematically from nonusers. However, the sample includes substantial proportions of discontinued users (15%) and never users (48%), providing variance in technology experience supporting meaningful analysis. Years in practice (M=17.3) and estimated patient technology access (M=60.7%) align with workforce and regional infrastructure data, supporting sample representativeness on these dimensions.

Covariate Justification

Control variables were selected based on prior research documenting relationships with technology adoption (Holden & Karsh, 2010). Bivariate analyses confirmed their relevance. Current mHealth use showed the binary outcome (37% current users vs. 63% nonusers) serving as the dependent variable. Patient technology access showed weak negative association with current adoption ($r_{pb} = -.15$, $p = .13$), but was retained based on theoretical rationale that provider adoption may depend on patient capacity to use technologies. Years in practice showed weak positive association ($r_{pb} = .06$, $p = .54$), included to control for potential experience effects. Provider role and practice setting showed relationships with adoption in chi-square tests, justifying inclusion as categorical covariates.

Study Results

Descriptive Statistics

Table 2 presents descriptive statistics for study variables. Innovation attribute perceptions showed moderate means with substantial variance. Perceived relative advantage averaged $M=3.72$ ($SD=0.68$, range=2.57-5.00) on the 5-point scale, indicating generally favorable perceptions of mHealth benefits with considerable individual variation. The composite scale demonstrated excellent internal consistency (Cronbach's $\alpha=.90$), with all items showing strong item-total correlations.

Perceived complexity reverse-coded for ease averaged M=3.13 (SD=0.55, range=1.29-5.00), indicating moderate perceived ease with substantial variance. Internal consistency was minimally acceptable (α=.68), with item-total correlations ranging from .28 to .62. The lower reliability likely reflects heterogeneity in the complexity construct, with some items assessing personal ease of learning and use while others assess organizational implementation complexity such as EHR integration and workflow incorporation. This distinction between individual-level and organizational-level complexity has been noted in prior health IT adoption research (Holden & Karsh, 2010) and may indicate that "complexity" is better conceptualized as a multidimensional rather than unidimensional construct in health care settings.

Perceived trialability averaged M=3.47 (SD=0.72, range=1.20-5.00), indicating moderate perceived trial opportunities. Internal consistency was good (α=.82), with item-total correlations ranging from .54 to .74. The range extending to 1.20 indicates some respondents perceived minimal trial opportunities, while others perceived substantial opportunities to test mHealth on a small scale before full implementation.

Structural constraints averaged M=2.48 (SD=0.75, range=1.00-5.00), indicating low-to-moderate perceived constraints with considerable variance. Note that this scale was reverse-coded such that higher scores indicate greater constraints (fewer resources). Internal consistency was good (α=.79), with item-total correlations ranging from .48 to .68. The mean of 2.48 indicates that on average, providers perceived relatively adequate resources, though with substantial individual variation. Individual constraint domains showed similar means, indicating constraints span multiple domains rather than concentrating in single areas.

Table 2

*Descriptive Statistics and Reliabilities for Study Variables (*N *= 100)*

Variable	*M*	*SD*	Range	Skewness	Kurtosis	α
Dependent						
Current mHealth adoption	0.37	0.49	0-1	0.53	-1.76	-
Independent						
Relative advantage	3.72	0.68	2.57-5.00	0.25	-0.89	0.90
Complexity/ease	3.13	0.55	1.29-5.00	-0.32	0.74	0.68
Trialability	3.47	0.72	1.20-5.00	-0.18	-0.24	0.82
Moderator						
Structural constraints	2.48	0.75	1.00-5.00	0.42	-0.33	0.79
Control						
Years in practice	17.3	15.3	0-50	0.56	-1.01	-
Patient tech access (%)	60.7	28.8	0-100	-0.48	-0.76	-

Note. Current mHealth adoption is binary outcome (0 = not currently using, 1 = currently using); statistics shown are for binary variable. Complexity reverse-coded such that higher scores indicate lower complexity (greater ease). Structural Constraints reverse-coded such that higher scores indicate greater perceived constraints (fewer resources). All continuous scales use 1-5 metric. All distributions approximate normality with skewness and kurtosis within acceptable ranges (|skewness| < 2, |kurtosis| < 7).

All distributions for continuous variables approximated normality with skewness and kurtosis values within acceptable ranges (|skewness|<2, |kurtosis|<7; Curran et al., 1996), supporting appropriateness for parametric analyses. Scale reliabilities ranged from minimally acceptable to excellent (α=.68-.90). While the Complexity/Ease reliability of .68 falls slightly below the preferred .70 threshold, it remains within the acceptable range for research purposes (Nunnally & Bernstein, 1994) and the construct demonstrates adequate validity through expected relationships with other variables.

Variable Operationalization: Behavioral Intention

The dependent variable, current mHealth adoption status, was operationalized using a single survey item asking: "Which statement best describes your current use of mobile health (mHealth) technologies?" with three response options: (a) "Currently use mHealth technologies," (b) "Used in past, discontinued," and (c) "Never used." The item was accompanied by a brief definition: "mHealth technologies include smartphone apps, text messaging, remote monitoring devices, and other mobile tools for patient care."

For analysis purposes, responses were recoded into a binary variable with current users coded as 1 (adopted, n = 37, 37%) and nonusers coded as 0 (not adopted, n = 63, 63%). Nonusers combined both providers who have never used mHealth (n=48) and those who used previously but discontinued (n=15), reflecting the primary theoretical interest in sustained current adoption versus any form of nonadoption. This categorization enables binary logistic regression analysis testing which factors distinguish current adopters - providers who have successfully implemented and sustained mHealth use - from nonadopters.

This operationalization aligns with DOI research examining factors distinguishing adopters from nonadopters (Rogers, 2003). The binary classification provides clear, interpretable categories for logistic regression while acknowledging that adoption represents sustained implementation rather than only initial uptake. The 37%/63% split provides adequate distribution for stable parameter estimation in logistic regression (both categories exceed the recommended minimum 10% threshold).

Bivariate Correlations

Table 3 presents associations between study variables and current adoption status. For continuous predictors, point-biserial correlations (r_pb) assess relationships with the binary outcome. All three innovation attributes showed significant associations with current adoption: relative advantage (r_pb = .37, p < .001), complexity/ease (r_pb = .07, p = .47, not significant), and trialability (r_pb = .55, p < .001). Trialability demonstrated the largest bivariate association (r_pb = .55, large effect), followed by relative advantage (r_pb = .37, medium-to-large effect). Complexity/ease showed weak nonsignificant association, suggesting ease perceptions may not distinguish adopters from nonadopters at the bivariate level, though multivariate analysis may reveal conditional effects.

Structural constraints showed significant negative association with current adoption (r_pb = -.46, p < .001), indicating that providers reporting greater resource constraints were substantially less likely to be current adopters. This large effect (r_pb =

-.46) suggests structural factors play a meaningful role in distinguishing adopters from nonadopters.

Control variables showed expected patterns. Years in practice showed weak nonsignificant positive association (r_pb = .06, p = .54). Patient technology access showed weak negative association approaching significance (r_pb = -.15, p = .13), suggesting that paradoxically, providers estimating lower patient technology access were slightly more likely to be current adopters, though this relationship was not statistically significant.

Table 3

*Point-Biserial Correlations Between Continuous Variables and Current mHealth Adoption (*N *= 100)*

Variable	r_pb	*p*
Independent variable		
Relative advantage	.367***	<.001
Complexity/ease	0.073	0.467
Trialability	.547***	<.001
Moderator		
Structural constraints	-.455***	<.001
Control		
Years in practice	0.062	0.543
Patient tech access	-0.153	0.129

Note. r_pb = point-biserial correlation coefficient. Current adoption coded as 1 = currently using, 0 = not currently using. Positive correlations indicate higher values associated with greater likelihood of current adoption. ***p < .001 (two-tailed).

Table 4 presents comparison of means between current users and nonusers. Current users reported significantly higher perceived relative advantage (M=4.05 vs. M=3.53, t=3.90, p<.001), substantially higher perceived trialability (M=3.98 vs. M=3.17, t=6.47, p<.001), and significantly lower structural constraints (M=2.03 vs. M=2.74, t=-5.06, p<.001). These large differences (Cohen's d ranging from 0.73 to 1.13) indicate that current adopters perceive markedly greater benefits, more trial opportunities, and fewer structural barriers than nonadopters.

Complexity/ease showed no significant difference between groups (M=3.19 vs. M=3.10, t=0.73, p=.47), suggesting that perceived ease may not be a primary distinguishing factor at the bivariate level. Years in practice and patient technology access also showed no significant differences between adopters and nonadopters.

Table 4

Comparison of Study Variables by Current mHealth Adoption Status

Variable	Current users (n = 37) M (SD)	Nonusers (n = 63) M (SD)	t	p	Cohen's d
Relative advantage	4.05 (0.62)	3.53 (0.66)	3.90	<.001***	0.81
Complexity/ease	3.19 (0.53)	3.10 (0.56)	0.73	0.467	0.16
Trialability	3.98 (0.52)	3.17 (0.67)	6.47	<.001***	1.35
Structural constraints	2.03 (0.60)	2.74 (0.74)	-5.06	<.001***	-1.05
Years in practice	18.5 (14.3)	16.6 (15.9)	0.61	0.543	0.13
Patient tech access (%)	55.0 (27.8)	64.1 (29.1)	-1.53	0.129	-0.32

Note. $^{***}p < .001$ (two-tailed). Cohen's d effect sizes: 0.2 = small, 0.5 = medium, 0.8 = large. Negative d values indicate nonusers scored higher. Current users show significantly higher relative advantage and trialability perceptions, and significantly lower structural constraints.

Chi-square analyses examined associations between categorical variables and adoption status. Professional role showed significant association ($\chi^2(3)=14.2$, $p=.003$), with nurse practitioners showing higher adoption rates (61% adopters) compared to other roles. Practice setting showed significant association ($\chi^2(3)=12.8$, $p=.005$), with FQHC/ Rural Health Clinic settings showing higher adoption rates (57% adopters) compared to other settings. Geographic region (state) showed no significant association with adoption ($\chi^2(7)=5.8$, $p=.56$).

Assumption Testing

Binary logistic regression makes specific assumptions requiring assessment. Linearity of the logit was assessed using Box-Tidwell test, examining whether continuous predictors show linear relationships with the log-odds of adoption. Interaction terms between each predictor and its natural logarithm were nonsignificant (all $p > .15$), supporting linearity assumption. Independence of observations was confirmed by study design (each provider contributes one observation) and Durbin-Watson statistic of 1.89 (acceptable range 1.5-2.5), indicating no substantial autocorrelation.

I confirmed the absence of multicollinearity through variance inflation factors (VIF) ranging from 1.08 to 2.84 for main effects, all well below threshold of 10 indicating problematic multicollinearity (Hair et al., 2010). Tolerance values ranged from .35 to .92, all above the .10 threshold. Correlations among predictors were all below .65, confirming adequate independence.

Perfect separation (complete prediction of outcome by predictors) was assessed and not detected - no predictors or combinations showed perfect prediction, and all models converged normally with stable standard errors (all $SE < 1.5$). Sample size adequacy was assessed through events per variable (EPV) calculation. With 37 current adopters (events) and maximum 12 predictors in full model, EPV = 3.08, which falls below the recommended minimum of 10 EPV for stable coefficient estimation (Peduzzi et al., 1996). This limitation is acknowledged and addressed through (a) parsimonious modeling emphasizing theoretically essential predictors, (b) sensitivity analyses, and (c) conservative interpretation acknowledging that coefficients may be less stable than optimal. Model fit diagnostics identified four cases with standardized residuals between 2.0 and 2.5, but these represented meaningful variation rather than errors and were retained. No cases showed Cook's distance > 1 or extreme leverage, indicating no overly influential observations.

Primary Analyses

Research Questions 1 and 2: Innovation Attribute Main Effects

Hierarchical binary logistic regression tested whether innovation attributes predict current adoption (RQ1) and their relative predictive strength (RQ2). Table 5 presents results for four sequential models. Model 1 included control variables only, establishing baseline prediction. Model 2 added innovation attributes. Model 3 added structural constraints main effect. Model 4 added interaction terms testing moderation.

Model 1 (Control Variables) achieved marginal significance, $\chi^2(5, N=100) = 10.13$, $p = .072$, Nagelkerke $R^2 = .13$. The model correctly classified 65.0% of cases. Current adoption rates varied by professional role and practice setting, though individual predictors did not achieve statistical significance at $p < .05$ level. Years in practice (OR = 1.01, 95% CI [0.98, 1.04], $p = .52$) and patient technology access (OR = 0.99, 95% CI [0.98, 1.01], $p = .35$) showed minimal associations with adoption.

Model 2 (Innovation Attributes) showed substantial improvement, $\chi^2(8, N=100) = 52.74$, $p < .001$, Nagelkerke $R^2 = .55$. The model correctly classified 80.0% of cases. Addition of innovation attributes produced highly significant improvement over controls,

$\Delta\chi^2(3) = 42.61$, $p < .001$, indicating that innovation attributes contribute meaningfully beyond demographic and practice characteristics.

H_1 (Relative Advantage) was supported. Relative advantage showed significant positive relationship with current adoption (OR = 2.85, 95% CI [1.42, 5.72], $p = .003$). For each standard deviation increase in perceived relative advantage, the odds of being a current adopter increased by 185% (odds multiplied by 2.85). The confidence interval excludes 1.0 with substantial margin, providing strong evidence for population effect. Relative advantage demonstrated medium-to-large effect size.

H_2 (Complexity/Ease) was not supported. Complexity reverse-coded as ease showed nonsignificant relationship with adoption (OR = 1.24, 95% CI [0.65, 2.35], $p = .52$). The confidence interval spans 1.0, indicating insufficient evidence that perceived ease distinguishes current adopters from nonadopters after controlling for other innovation attributes. This suggests that while providers generally perceive mHealth as moderately easy to use, ease perceptions do not independently predict current adoption status.

H_3 (Trialability) was strongly supported. Trialability showed highly significant positive relationship with adoption (OR = 4.67, 95% CI [2.28, 9.55], $p < .001$). For each standard deviation increase in perceived trialability, the odds of being a current adopter increased by 367% (odds multiplied by 4.67). This represents a large effect and emerged as the strongest predictor among innovation attributes. The large odds ratio indicates that providers who perceive greater opportunities to trial mHealth are substantially more likely to be current adopters.

Model 3 (Structural Constraints) further improved fit, $\chi^2(9, N=100) = 60.28$, $p < .001$, Nagelkerke $R^2 = .61$. Addition of structural constraints produced significant improvement, $\Delta\chi^2(1) = 7.54$, $p = .006$, indicating constraints predict adoption beyond innovation attributes. Structural constraints showed significant negative relationship with adoption (OR = 0.42, 95% CI [0.23, 0.77], $p = .005$). For each standard deviation increase in structural constraints, the odds of being a current adopter decreased by 58% (odds multiplied by 0.42). This large effect indicates that resource constraints substantially reduce adoption likelihood even after accounting for innovation perceptions.

Model 4 (Interactions) achieved marginal additional improvement, $\chi^2(12, N=100) = 64.82$, $p < .001$, Nagelkerke $R^2 = .64$. Addition of interactions produced borderline significant improvement, $\Delta\chi^2(3) = 4.54$, $p = .21$, indicating limited evidence for moderation effects.

Table 5
Hierarchical Logistic Regression: Innovation Attributes and Structural Constraints Predicting Current mHealth Adoption (N = 100)

Predictor	Model 1 *OR* [95% CI]	Model 2 *OR* [95% CI]	Model 3 *OR* [95% CI]	Model 4 *OR* [95% CI]
Control variables				
Years in practice	1.01 [0.98, 1.04]	1.00 [0.96, 1.03]	0.99 [0.95, 1.03]	0.98 [0.94, 1.03]
Patient tech access	0.99 [0.98, 1.01]	1.00 [0.98, 1.02]	1.00 [0.98, 1.02]	1.00 [0.98, 1.02]
Role: nurse practitioner	2.45 [0.71, 8.48]	3.12 [0.68, 14.3]	3.45 [0.71, 16.8]	4.22 [0.79, 22.5]
Role: physician assistant	1.68 [0.42, 6.71]	2.13 [0.41, 11.1]	2.45 [0.44, 13.6]	2.89 [0.48, 17.4]
Role: other	0.35 [0.10, 1.19]	0.42 [0.09, 1.94]	0.48 [0.10, 2.35]	0.54 [0.10, 2.89]
Innovation attributes				
Relative advantage	-	2.85** [1.42, 5.72]	2.34* [1.10, 4.98]	2.45* [1.12, 5.36]
Complexity/ease	-	1.24 [0.65, 2.35]	1.18 [0.60, 2.32]	1.22 [0.60, 2.48]
Trialability	-	4.67*** [2.28, 9.55]	3.89*** [1.81, 8.36]	4.12*** [1.88, 9.03]
Structural Constraints				
Structural constraints	-	-	0.42** [0.23, 0.77]	0.38** [0.20, 0.74]
Interactions				
RA × Constraints	-	-	-	0.72 [0.38, 1.36]
Complexity × Constraints	-	-	-	0.85 [0.45, 1.60]
Trialability × Constraints	-	-	-	0.68 [0.35, 1.32]
Model fit statistics				
Model χ^2	10.13	52.74***	60.28***	64.82***
df	5	8	9	12
Nagelkerke R^2	0.13	0.55	0.61	0.64

Classification accuracy	65.0%	80.0%	82.0%	83.0%
$\Delta\chi^2$ from previous model	-	42.61***	7.54**	4.54

Note. OR = odds ratio; CI = confidence interval. Reference categories: role = physician (MD/DO); practice setting = hospital-owned clinic (not shown for space). All continuous predictors standardized ($M = 0$, $SD = 1$) before analysis. Interaction terms computed from standardized variables. *$p < .05$, **$p < .01$, ***$p < .001$ (two-tailed).

Addressing RQ2 (Relative Predictive Strength): Comparison of odds ratios from Model 3 revealed clear hierarchy. Trialability demonstrated greatest predictive strength (OR = 3.89), followed by relative advantage (OR = 2.34) and complexity/ease (OR = 1.18, not significant). Trialability's odds ratio indicates that providers perceiving high trial opportunities (+ 1 SD) have nearly 4 times the odds of being current adopters compared to those perceiving low trial opportunities (- 1 SD), holding other factors constant. Relative advantage showed substantial but weaker effect, with high benefit perceptions more than doubling adoption odds. Complexity/ease showed minimal effect.

This hierarchy differs somewhat from typical DOI findings where relative advantage usually emerges as strongest predictor (Tornatzky & Klein, 1982). In this rural Appalachian context, opportunities to trial mHealth on a limited basis emerged as the dominant predictor, suggesting that risk reduction through experimentation may be particularly important in resource-constrained settings where failed implementations carry higher costs. Relative advantage remains important but secondary to trialability. Complexity/ease showed minimal independent contribution, possibly because most mHealth technologies are now designed with user-friendly interfaces making ease less of a differentiating factor.

Research Question 3: Structural Constraint Moderation

Model 4 tested whether structural constraints moderate innovation attribute-adoption relationships (RQ3, H_4). The full model with interactions remained significant, $\chi^2(12, N=100) = 64.82$, $p < .001$, Nagelkerke $R^2 = .64$, correctly classifying 83.0% of cases. However, addition of interaction terms produced only marginal improvement over Model 3, $\Delta\chi^2(3) = 4.54$, $p = .21$, indicating limited overall evidence for moderation.

H_4a (Relative Advantage × Constraints) was not supported. The interaction was not statistically significant (OR = 0.72, 95% CI [0.38, 1.36], $p = .31$). The confidence interval spans 1.0, indicating insufficient evidence that structural constraints moderate relative advantage effects on adoption. Simple slopes analysis at low (-1 SD), mean, and high (+1 SD) constraint levels showed relatively consistent patterns: at low constraints OR = 3.42 ($p < .001$); at mean constraints OR = 2.34 ($p = .02$); at high constraints OR = 1.60 ($p = .18$). While numerical weakening occurred under high constraints, the interaction did not achieve statistical significance.

H_4b (Complexity × Constraints) was not supported. The interaction was not statistically significant (OR = 0.85, 95% CI [0.45, 1.60], $p = .61$). Given that complexity/

ease showed no main effect, testing moderation was less meaningful. Simple slopes revealed consistently nonsignificant complexity effects across all constraint levels.

$H_{4}c$ (Trialability × Constraints) was not supported. The interaction was not statistically significant (OR = 0.68, 95% CI [0.35, 1.32], $p = .25$). Simple slopes analysis showed: at low constraints OR = 6.05 ($p < .001$); at mean constraints OR = 3.89 ($p < .001$); at high constraints OR = 2.50 ($p = .02$). While trialability effects were numerically weaker under high constraints, the interaction did not achieve statistical significance, indicating insufficient evidence for moderation.

The lack of significant moderation effects suggests that innovation attributes - particularly trialability and relative advantage - predict current adoption similarly across varying resource constraint levels. This indicates that perceptions of trial opportunities and benefits matter for distinguishing adopters from nonadopters regardless of structural context, though constraints exert independent negative effects on adoption likelihood (as shown by significant main effect in Model 3).

Model Diagnostics and Sensitivity Analyses

Classification accuracy improved across models, from 65.0% (Model 1) to 83.0% (Model 4). Sensitivity (correctly identifying current adopters) reached 78.4% in final model, while specificity (correctly identifying nonadopters) reached 85.7%. These metrics indicate strong discriminative ability.

Hosmer-Lemeshow goodness-of-fit test for Model 3 was nonsignificant ($\chi^2(8) = 9.32$, $p = .32$), indicating adequate model calibration. ROC curve analysis showed area under curve (AUC) = .87 for Model 3, indicating excellent discriminative ability (.80-.90 range).

Influential case analysis identified 3 cases with standardized residuals > 2.0 and 2 cases with Cook's distance > 0.15. Models were reestimated excluding these cases; results remained substantively identical with all significant effects maintaining significance and odds ratios changing by < 15%, confirming robustness.

Alternative specifications were tested:

1. Three-category outcome (current users vs. discontinued users vs. never users) via multinomial logistic regression: Results showed discontinued users resembled never users more closely than current users, supporting binary categorization decision.

2. Reduced covariate model (removing nonsignificant controls): Innovation attribute effects remained virtually identical, confirming focal relationships are not artifacts of covariate inclusion.

3. Constraint tertiles (low/medium/high groups instead of continuous): Pattern of results remained consistent.

Summary of Findings

All three hypotheses regarding innovation attribute main effects received mixed support. H_1 (Relative Advantage) was supported: perceived benefits significantly predicted current adoption with medium-to-large effect (OR = 2.34). H_2 (Complexity/Ease) was not supported: perceived ease did not significantly distinguish adopters from nonadopters (OR = 1.18, p = .52). H_3 (Trialability) was strongly supported: perceived trial opportunities powerfully predicted current adoption with large effect (OR = 3.89), emerging as the strongest innovation attribute predictor.

Together, innovation attributes explained substantial variance beyond controls (Nagelkerke $\Delta R^2 = .42$ from Model 1 to Model 2), representing a very large effect. The final model explained 61% of variance in current adoption (Model 3 Nagelkerke $R^2 = .61$) and correctly classified 82% of cases, indicating strong predictive validity.

Structural constraints independently predicted adoption (OR = 0.42, $p = .005$), with higher constraints associated with substantially lower odds of current adoption even after controlling for innovation perceptions. This demonstrates that resource context operates partially independently of individual perceptions in shaping adoption outcomes.

Moderation hypotheses (H_4) were not supported: interactions between innovation attributes and structural constraints did not achieve statistical significance (Model 4 $\Delta\chi^2(3) = 4.54$, $p = .21$). While numerical trends suggested possible attenuation of innovation attribute effects under high constraints, evidence was insufficient to conclude significant moderation. This indicates that innovation attributes - particularly trialability - predict current adoption relatively consistently across varying constraint levels, though constraints exert independent negative main effects.

The hierarchy of predictors revealed trialability as most important (OR = 3.89), followed by relative advantage (OR = 2.34) and structural constraints (OR = 0.42 for inverse relationship). Complexity/ease showed minimal effect (OR = 1.18, not significant). This pattern suggests that in rural Appalachian contexts, adoption is most strongly associated with opportunities for low-risk experimentation, followed by perceived benefits and available resources. Ease of use appears less critical, possibly because modern mHealth technologies are generally designed for user-friendliness.

Summary

This chapter presented findings from quantitative analysis examining innovation attributes, structural constraints, and current mHealth adoption among 100 rural Appalachian health care professionals. Data collection yielded 12.8% response rate, with final sample comprising physicians (11%), nurse practitioners (28%), physician assistants (14%), and other health care professionals (47%) from diverse practice settings across Central and Southern Appalachia. Current adoption rate was 37% (n = 37 current users, n= 63 nonusers).

Preliminary analyses confirmed adequate scale reliabilities (α=.68-.90), satisfaction of logistic regression assumptions, and expected bivariate associations. Hierarchical logistic regression revealed that two of three DOI innovation attributes significantly predicted current adoption: trialability demonstrated greatest predictive strength (OR = 3.89), followed by relative advantage (OR = 2.34). Complexity/ease did not significantly predict adoption (OR = 1.18, p = .52). Structural constraints independently predicted lower adoption likelihood (OR = 0.42). However, constraints did not significantly moderate innovation attribute effects, indicating relatively consistent relationships across resource contexts.

The final model (Model 3) explained 61% of variance in current adoption (Nagelkerke $R^2 = .61$) and correctly classified 82% of cases. Innovation attributes contributed 42% incremental variance beyond control variables. These findings support DOI theory applicability in resource-constrained rural settings while highlighting that opportunities for trial emerge as the dominant predictor, followed by perceived benefits and resource availability.

The primacy of trialability suggests that in severely resource-constrained contexts, providers' adoption decisions are most strongly associated with opportunities to experiment with technologies on a limited basis before full commitment. This may reflect risk-averse decision-making under resource scarcity, where the costs of failed implementations are particularly high. Demonstrating clear benefits remains important (relative advantage OR = 2.34) but secondary to trial opportunities. Ease of use appears less critical, potentially because contemporary mHealth technologies are generally designed with user-friendly interfaces.

Structural constraints' independent negative effect (OR = 0.42) confirms that resource limitations reduce adoption likelihood beyond their influence on innovation perceptions. However, the absence of significant interactions indicates that innovation attributes - particularly trialability - matter for adoption relatively consistently whether resources are scarce or adequate, suggesting that addressing perceptions and addressing structural barriers may both be necessary for promoting adoption. In Chapter 5, I interpret these findings in relation to existing theory and research, examine theoretical and practical implications, acknowledge study limitations, and propose directions for future research addressing questions this study could not resolve.

Chapter 5: Discussion, Conclusions, and Recommendations

In this quantitative, cross-sectional study, I examined whether DOI theory attributes—perceived relative advantage, complexity, and trialability—predict current mHealth adoption among rural Appalachian health care professionals involved in primary care delivery, and whether structural constraints moderate these relationships. The study addressed a critical gap in technology adoption research: while DOI has been extensively validated in well-resourced contexts, its applicability to severely resource-constrained settings remained empirically uncertain. Understanding adoption dynamics in rural Appalachia has practical implications for implementation strategy development and empirical implications for understanding contextual variation in adoption processes.

I collected data from 100 health care professionals practicing in rural counties across Central and Southern Appalachia. Hierarchical logistic regression tested relationships between innovation attributes and current adoption status (currently using mHealth vs. not currently using), with structural constraints examined as both predictor and potential moderator. The final model explained 61% of variance in current adoption (Nagelkerke $R^2 = .61$) and correctly classified 82% of cases.

Key findings revealed that trialability emerged as the strongest predictor of current adoption ($OR = 3.89$, $p < .001$), followed by relative advantage ($OR = 2.34$, $p < .01$). Complexity/ease did not significantly distinguish adopters from nonadopters ($OR = 1.18$, $p = .52$). Structural constraints independently predicted lower adoption likelihood ($OR = 0.42$, $p < .01$) but did not significantly moderate innovation attribute effects. These findings support DOI theory applicability in resource-constrained settings while revealing that the relative magnitude of innovation attribute effects varies across this context compared to typical research settings. The greater magnitude of trialability's effect compared to relative advantage suggests that in severely resource-constrained environments, opportunities for low-risk experimentation may be particularly salient, potentially consistent with risk-averse decision-making when implementation failures carry high costs, though risk propensity was not directly measured. In this chapter, I interpret the findings in relation to existing theory and research, examine limitations, propose recommendations for future research, discuss implications for practice and policy, and present conclusions regarding mHealth adoption in rural health care contexts.

Interpretation of the Findings

Overview of Key Results

Three major findings emerged from this investigation. First, innovation attributes from DOI theory significantly predicted current mHealth adoption among rural Appalachian health care professionals, with the model explaining substantial variance (Nagelkerke $R^2 = .55$ for innovation attributes beyond controls). Second, the hierarchy of attribute effect magnitudes differed from typical DOI findings: trialability demonstrated greatest predictive strength ($OR = 3.89$), followed by relative advantage ($OR = 2.34$), while complexity showed no significant effect ($OR = 1.18$, $p = .52$). Third, structural constraints exerted independent negative effects on adoption ($OR = 0.42$) but did not significantly moderate innovation attribute relationships, suggesting that perceptions and resources operate through additive rather than interactive mechanisms in shaping adoption outcomes.

These findings both confirm and extend existing knowledge. They confirm DOI theory's applicability to resource-constrained rural health care by demonstrating that innovation attributes meaningfully distinguish current adopters from nonadopters. However, they reveal contextual variation in relative effect magnitudes: trialability's larger effect compared to relative advantage differs from the typical hierarchy found in urban health care settings and suggests that the salience of risk-reduction mechanisms may be elevated under resource scarcity. The absence of significant moderation effects, while failing to confirm hypothesized interactions, provides important information about how structural factors influence adoption—primarily through direct additive effects rather than by altering perceptual processes.

Trialability as Dominant Predictor: Theoretical Interpretation

The finding that trialability emerged as the strongest predictor (OR = 3.89) diverges from meta-analytic evidence consistently identifying relative advantage as the most powerful DOI attribute (Tornatzky & Klein, 1982; Holden & Karsh, 2010). In typical health care technology adoption research, relative advantage shows correlations with adoption averaging $r = .50$-$.60$, while trialability shows weaker relationships (Holden & Karsh, 2010). This study's findings show a different pattern, with trialability showing the largest point-biserial correlation with current adoption ($r_{pb} = .55$) compared to relative advantage ($r_{pb} = .37$).

Important Methodological Note on Trialability Measurement

It is important to acknowledge that while trialability was operationalized using items grounded in Rogers's (2003) definition—focusing on opportunities to experiment with mHealth on a limited basis before full commitment—some measurement elements may also reflect aspects of observability (seeing peer use, accessing demonstrations) and compatibility (pilot feasibility within practice constraints). However, these elements align with trialability's core function in health care contexts: reducing implementation uncertainty through experiential exposure. Thus, trialability in this study is best interpreted as a contextualized, practice-based trial construct emphasizing hands-on experimentation rather than a narrow technical definition isolated from related innovation characteristics. This overlap is consistent with Rogers's acknowledgment that innovation attributes often interrelate in practice, though future research employing refined measurement distinguishing trial opportunities from observation opportunities could clarify the unique contributions of each construct.

This pattern of effect magnitudes suggests contextual variation in DOI attribute salience. Rogers (2003) originally conceptualized trialability as reducing perceived risk by enabling experimentation before full commitment. In well-resourced urban health care systems with robust IT support and adequate financial margins, the risks of technology adoption may be manageable even without extensive trial opportunities—organizations can absorb the costs of failed implementations and providers have support systems mitigating implementation challenges. Under these conditions, whether technologies are triable may matter less than whether they offer clear benefits.

In contrast, severely resource-constrained rural settings face different adoption dynamics. Rural practices operating on narrow financial margins (1.7%–2.1% in distressed counties; Kaufman et al., 2016) cannot easily absorb costs of failed implementations. Limited IT support staff means technical problems become crises rather than minor inconveniences. Workforce shortages create time pressures making any workflow disruption costly. Under these conditions, the ability to test technologies on a small scale before committing may become critically important—providers can assess actual feasibility given their specific constraints before risking resources on full implementation.

This interpretation is consistent with decision-making research documenting behavioral changes under resource scarcity. Behavioral economics literature indicates that scarcity creates cognitive and behavioral shifts including heightened risk aversion, increased focus on immediate costs over future benefits, and preference for reversible over irreversible decisions (Shah et al., 2012). Trialability provides precisely this reversibility—providers can experiment, evaluate, and discontinue without major commitment. The large odds ratio (OR = 3.89) suggests that providers perceiving high trial opportunities have nearly four times the odds of current adoption compared to those perceiving low trial opportunities, controlling for other factors. This substantial effect indicates trialability is not merely helpful but potentially decisive in adoption decisions under resource constraints.

However, it is important to note that risk aversion was not directly measured in this study, and remains an inferred mechanism rather than empirically demonstrated. The pattern of findings is consistent with risk-averse decision-making under resource scarcity, but alternative explanations warrant consideration. For example, trialability's dominance might reflect practical feasibility assessment (can this work in my practice?) rather than risk psychology per se, or might indicate that trial opportunities provide social validation through peer observation rather than primarily reducing individual risk perceptions. Future research directly measuring risk propensity, risk perceptions, and their relationships with adoption would strengthen causal claims about psychological mechanisms.

Recent health care technology research provides converging evidence for the importance of trial opportunities in rural contexts. Weichelt et al. (2024) found that among rural providers, implementation concerns and feasibility assessments dominated benefit considerations when evaluating technology adoption. Barry et al. (2024) documented that rural providers emphasized "seeing it work in a place like ours" as critical for adoption confidence. These qualitative findings align with this study's quantitative evidence that trial opportunities—enabling providers to verify feasibility in their specific contexts—emerged as a strong adoption predictor.

Relative Advantage: Persistent but Secondary Importance

While relative advantage demonstrated significant positive association with current adoption (OR = 2.34, $p < .01$), its effect magnitude was smaller than trialability's. Providers perceiving high mHealth benefits had more than double the odds of being current adopters compared to those perceiving low benefits, holding other factors constant. This represents a meaningful effect consistent with DOI theory's proposition that perceived benefits drive adoption.

However, the magnitude (OR = 2.34) was both smaller than trialability's effect (OR = 3.89) and smaller than typical relative advantage effects found in urban health care settings, where odds ratios often exceed 3.0-4.0 (Holden & Karsh, 2010). This relative attenuation may reflect conditional benefit perceptions under resource constraints. Even when providers recognize mHealth's potential benefits—improved chronic disease monitoring, enhanced access for geographically distant patients, more efficient care delivery—these benefits may seem hypothetical or unattainable when infrastructure, resources, and support are inadequate to support successful implementation.

The mean relative advantage score ($M = 3.72$, $SD = 0.68$) indicates that on average, providers recognized mHealth benefits. Current adopters reported significantly higher benefit perceptions ($M = 4.05$) than nonadopters ($M = 3.53$, $t = 3.90$, $p < .001$), confirming that benefit perceptions distinguish these groups. However, the fact that even nonadopters averaged above the scale midpoint ($M = 3.53$ on 5-point scale) suggests that many health care professionals who are not currently adopting nonetheless recognize potential benefits. This pattern implies that recognizing benefits may be necessary but insufficient for adoption—unless accompanied by trial opportunities enabling feasibility assessment and confidence building.

This interpretation aligns with implementation science frameworks emphasizing that innovations must be not only efficacious but also feasible and appropriate for specific contexts (Damschroder et al., 2022; Glasgow et al., 2019). Rural providers may perceive mHealth's efficacy (clinical benefits) while questioning its feasibility (whether it will work given their constraints) and appropriateness (whether it fits their specific patient populations and practice characteristics). Trialability addresses feasibility and appropriateness questions through direct experience, potentially explaining its prominence relative to benefit perceptions alone.

Complexity/Ease: Nonsignificant Effects and Interpretation

Contrary to hypothesis, perceived complexity (reverse-coded as ease) did not significantly distinguish current adopters from nonadopters ($OR = 1.18$, 95% CI [0.60, 2.32], $p = .52$). Current users and nonusers reported similar ease perceptions ($M = 3.19$ vs. $M = 3.10$, $t = 0.73$, $p = .47$), both averaging above scale midpoint, indicating that health care professionals generally perceive contemporary mHealth technologies as moderately easy to use.

This null finding diverges from typical DOI results where complexity shows significant negative relationships with adoption (Holden & Karsh, 2010; Tornatzky & Klein, 1982). Several explanations warrant consideration. First, technological maturation may have reduced ease-of-use concerns. Many current mHealth applications employ consumer-grade interfaces designed for intuitive use, potentially making personal ease of learning and use less of a differentiating factor than in earlier technology generations. If most mHealth options are now sufficiently user-friendly, ease perceptions may no longer discriminate between adopters and nonadopters.

Second, measurement limitations likely attenuated the complexity effect. The complexity scale showed marginal reliability ($\alpha = .68$), falling below the preferred .70 threshold. More importantly, the scale conflated personal ease (learning to use the interface) with organizational implementation complexity (EHR integration, workflow incorporation, staff training requirements). Recent research distinguishes between personal ease and organizational complexity, finding that organizational factors often matter more for adoption decisions than personal ease (Chen et al., 2024). This study's scale combined both dimensions, potentially obscuring distinct effects. While technological maturation may partially explain the nonsignificant complexity effect, the marginal reliability of the complexity scale ($\alpha = .68$) and its conflation of personal ease and organizational implementation difficulty likely attenuated its predictive power. Future research should disaggregate these dimensions using separate validated scales to clarify which aspects of complexity influence adoption under different conditions.

Third, in severely resource-constrained contexts, ease concerns may be overshadowed by more fundamental questions about infrastructure adequacy, financial feasibility, and organizational support. Providers facing unreliable broadband, limited IT support, and narrow operating margins may view technology ease as secondary to whether basic implementation prerequisites exist. If fundamental feasibility questions dominate decision-making, personal ease of use becomes less salient.

Structural Constraints: Additive Effects Without Moderation

Structural constraints showed significant independent association with current adoption (OR = 0.42, 95% CI [0.23, 0.77], $p < .01$), indicating that health care professionals reporting greater resource limitations had substantially lower odds of being current adopters even after controlling for innovation perceptions. For each standard deviation increase in structural constraints, adoption odds decreased by 58%. Current adopters reported significantly lower constraints ($M = 2.03$) than nonadopters ($M = 2.74$, $t = -5.06$, $p < .001$), confirming that resource context distinguishes these groups.

This finding validates the study's premise that structural factors meaningfully influence adoption in resource-constrained settings. The effect size (OR = 0.42) is substantial, indicating that resource availability operates as a significant adoption barrier independent of individual perceptions. This supports implementation science frameworks emphasizing that organizational and environmental factors—not only individual attitudes—shape implementation success (Damschroder et al., 2022; Nilsen et al., 2020).

However, contrary to hypotheses, structural constraints did not significantly moderate innovation attribute-adoption relationships. The interaction terms testing whether constraints moderated relative advantage, complexity, or trialability effects were all nonsignificant (Model 4 $\Delta\chi^2(3) = 4.54$, $p = .21$). While simple slopes analyses showed numerical patterns suggesting possible attenuation of innovation attribute effects under high constraints, these trends did not achieve statistical significance with adequate confidence.

The absence of significant moderation has important theoretical implications. Rather than demonstrating that structural factors create boundary conditions altering how innovation attributes operate—as hypothesized—the findings suggest that innovation attributes and structural constraints operate through parallel, additive mechanisms. Favorable perceptions of trial opportunities and benefits predict higher adoption likelihood regardless of resource context, while resource constraints directly reduce adoption likelihood across all perception levels. This pattern indicates that constraints primarily exert main effects (reducing adoption probability overall) rather than moderating effects (changing how perceptions translate into adoption). While contextual patterns observed in effect magnitudes (trialability's prominence) indicate variation in attribute salience across contexts, these results should be interpreted as contextual differences in effect strength rather than formal confirmation of boundary conditions requiring interaction effects.

Several considerations inform this interpretation. First, the additive effects model may better represent adoption dynamics in this context than the hypothesized interactive model. Rather than constraints weakening the perception-adoption relationship, perceptions and constraints both contribute independently to adoption decisions. Health care professionals weigh both considerations—"Do I see value and trial opportunities?"

and "Do I have adequate resources?"—with both influencing adoption but through separate mechanisms. This has different implications for intervention than an interactive model would: parallel strategies can address perceptions (demonstrate benefits, create trial opportunities) and constraints (improve infrastructure, provide resources) somewhat independently rather than requiring integrated approaches.

Second, statistical power limitations may have constrained ability to detect interactions. With 37 current adopters (events) and 12 predictors in the full model, the events-per-variable ratio (EPV = 3.08) fell below recommended thresholds (EPV ≥ 10), potentially limiting power to detect interaction effects which typically require larger samples than main effects (Peduzzi et al., 1996). Simple slopes patterns showing numerical weakening of effects under high constraints suggest that true moderation may exist but was undetectable given sample constraints. Future research with larger samples achieving adequate EPV ratios could reexamine moderation hypotheses with sufficient statistical power.

Third, the range of constraints in this sample may have been insufficient to reveal moderation. The constraint scale mean (M = 2.48, SD = 0.75) indicated relatively low-to-moderate perceived constraints on average, with full range 1-5 but limited cases at the extreme high end. If moderation effects manifest primarily under severe constraint conditions, the sample may not have included sufficient health care professionals experiencing extreme constraints to detect these effects. Future research in even more severely constrained settings (e.g., frontier rural areas, low-resource international contexts) might reveal moderation patterns not observable in this sample.

Comparison to Prior Research: Confirming and Extending Findings

These findings can be situated within existing literature to identify points of confirmation, contradiction, and extension.

Confirmation of Prior Research

This study validates that DOI innovation attributes meaningfully predict technology adoption in rural health care contexts, consistent with systematic reviews documenting DOI's broad applicability (Holden & Karsh, 2010; M. D. Williams et al., 2021). The substantial variance explained by innovation attributes (Nagelkerke $\Delta R^2 = .42$ beyond controls) confirms that perceptual factors are powerful adoption determinants even under resource constraints.

The finding that structural constraints independently predict adoption confirms research documenting that organizational and environmental factors shape implementation success beyond individual attitudes (Brooks et al., 2021; Chapman et al., 2025; Weichelt et al., 2024). Specifically, this finding supports Brooks et al.'s (2021) conclusion from studying Native American rural communities that infrastructure and organizational resources serve as adoption prerequisites that cannot be overcome by favorable perceptions alone.

Revelation of Contextual Variation

The greater magnitude of trialability's effect compared to relative advantage diverges from typical DOI findings and meta-analytic evidence identifying relative advantage as the dominant predictor (Tornatzky & Klein, 1982). This pattern suggests contextual variation in attribute salience. While relative advantage typically shows the largest effects in well-resourced settings, trialability may show amplified effects in severely constrained contexts where risk reduction and feasibility demonstration become paramount. This contextual variation in effect magnitude represents an important empirical observation, though formal boundary condition confirmation would require significant interaction effects that were not observed in this study. Future research systematically comparing attribute effects across contexts varying in resource levels could clarify whether this pattern represents reliable contextual variation.

The null finding for complexity effects contradicts studies typically showing complexity as a significant adoption barrier (Holden & Karsh, 2010). However, it aligns with recent research suggesting that user interface improvements have reduced ease-of-use concerns for many contemporary technologies (Hussain et al., 2025). This may reflect technological evolution—as interfaces become more intuitive, personal ease of use becomes less differentiating, though organizational implementation complexity may remain important.

Extension of Prior Research

This study provides evidence about adoption dynamics among health care professionals involved in interprofessional primary care delivery in Appalachian contexts, an understudied population despite facing among the most severe rural health challenges nationally (Stanzak & Oliver, 2023; Serchen et al., 2025). The specific pattern of findings—trialability's prominence, constraints' additive effects, complexity nonsignificance—may characterize adoption in severely resource-constrained settings more broadly. This suggests that implementation strategies developed for well-resourced settings may require adaptation for resource-limited contexts, with greater emphasis on creating trial opportunities and addressing structural barriers.

The study also extends methodology by explicitly testing moderation hypotheses often assumed but rarely examined in adoption research (Brooks et al., 2021). While hypothesized interactions were not supported, this null finding is informative—it suggests constraints affect adoption through direct mechanisms rather than by changing perceptual processes. This distinction has practical implications: interventions may be able to target perceptions and constraints through parallel strategies rather than requiring integrated approaches that simultaneously address both.

Implications for Diffusions of Innovation Theory: Contextual Variation and Theoretical Refinement

These findings inform DOI theory by documenting contextual variation in attribute effect magnitudes and clarifying relationships between perceptual and structural factors. Standard DOI applications implicitly assume adequate resources enabling adoption once favorable perceptions form. This assumption may hold in well-resourced settings but may not fully characterize adoption processes in severely constrained contexts.

The study suggests three theoretical considerations. First, attribute effect magnitudes vary across contexts. The typical relative advantage > complexity > trialability hierarchy in effect sizes (Tornatzky & Klein, 1982) may shift under resource scarcity, with trialability showing amplified effects. This suggests DOI applications should assess which attributes show largest effects in specific settings rather than assuming universal hierarchies. Resource scarcity may elevate salience of risk-reduction attributes (trialability) while technological evolution reduces relevance of personal ease concerns (complexity). However, without significant interaction effects confirming formal boundary conditions, these observations represent contextual patterns requiring replication and further investigation rather than definitive theoretical refinements.

Second, structural context operates additively rather than interactively with perceptions. Rather than constraints moderating perception-adoption relationships (interactive model), constraints appear to exert independent effects alongside perceptions (additive model). Both favorable perceptions and adequate resources are needed, but they contribute through parallel mechanisms rather than perceptions requiring resources to translate into adoption. This suggests DOI applications should incorporate structural factors as parallel predictors rather than only as contextual moderators, recognizing that adoption requires both psychological willingness (perceptions) and structural capability (resources) operating through distinct pathways.

Third, contextual factors warrant explicit consideration in DOI applications. Current DOI theory focuses primarily on innovation attributes and communication networks, treating organizational and environmental factors as implementation context. However, this study's findings suggest structural factors meaningfully influence adoption, justifying explicit measurement and analysis. Comprehensive adoption models should recognize both perceptual evaluation and feasibility assessment as important processes, even if operating somewhat independently.

These considerations do not invalidate DOI but rather inform context-sensitive application. DOI remains valuable for understanding how innovation characteristics shape adoption, but effective application requires assessing which attributes show largest effects in specific settings and explicitly incorporating structural feasibility alongside perceptual favorability. This moves toward adoption frameworks recognizing both psychological and structural determinants.

Limitations of the Study

This study has several limitations affecting interpretation and generalizability. Understanding these limitations enables appropriate conclusions while identifying directions for future research addressing unresolved questions.

Design and Measurement Limitations

Cross-sectional design represents the primary limitation. Measuring all variables at a single time point precludes establishing temporal precedence - whether innovation perceptions preceded and influenced adoption decisions or whether adoption experience shaped subsequent perceptions. Providers who have adopted mHealth may emphasize benefits and trial opportunities retrospectively to justify their decisions, while nonadopters may emphasize barriers. While theoretical expectations suggest perceptions precede adoption and within-group variance argues against simple rationalization, the possibility of reciprocal or reverse causation cannot be ruled out. Longitudinal designs measuring perceptions before adoption decisions would strengthen causal inference but were not feasible given resource constraints and practical challenges of tracking geographically dispersed providers.

Current adoption status as outcome provides direct behavioral evidence, eliminating intention-behavior gaps that limit intention-based research. However, it creates different limitations. Current adopters represent a heterogeneous group - some may have recently adopted while others have used mHealth for years, some may use technologies extensively while others use minimally. The binary categorization (currently using vs. not currently using) treats all adopters equivalently despite likely varying in adoption extent, consistency, and duration. More nuanced measurement of adoption intensity, sustainability, and integration depth could reveal relationships not apparent with binary classification. However, for initial investigation testing whether DOI relationships operate in this context, binary classification provides appropriate outcome measurement addressing the fundamental question of what distinguishes adopters from nonadopters.

Sample size and statistical power constrained analyses, particularly for detecting interaction effects. With 37 current adopters and 12 predictors in the full model, the events-per-variable ratio (EPV = 3.08) fell below recommended minimum (EPV $\geq$ 10). This may have limited power to detect interactions, which typically require larger samples than main effects. The nonsignificant moderation findings should be interpreted cautiously - true interactions may exist but were undetectable given sample constraints. However, main effect results showed adequate power, with large effect sizes and narrow confidence intervals indicating stable estimates. Future research with larger samples could reexamine moderation hypotheses with greater power.

Scale reliability issues affect the complexity/ease scale (α = .68), which fell slightly below the preferred .70 threshold. While within acceptable range for research purposes, this marginal reliability may have attenuated complexity-adoption relationships, potentially contributing to null findings. The scale's conceptual heterogeneity - mixing personal ease items with organizational implementation complexity items - suggests construct measurement issues. Future research should employ scales separately measuring personal ease versus organizational complexity to clarify which aspects influence adoption.

Sample Composition Limitations

The sample's professional composition requires specific acknowledgment and affects generalizability. While targeting physicians, nurse practitioners, and physician assistants, the final sample included 47% "other healthcare professionals" encompassing diverse roles (pharmacists, social workers, medical assistants, various support staff). This composition reflects interprofessional primary care team realities but limits generalizability to physicians and advanced practice providers as independent prescribers making autonomous adoption decisions.

Findings should be interpreted as reflecting adoption dynamics across interprofessional primary care teams rather than independent prescriber decision-making alone. The diversity provides insight into technology adoption perspectives across the care team, potentially reflecting adoption processes in real-world rural practice settings where multiple professional roles contribute to implementation success. However, results cannot be generalized specifically to physicians or advanced practice providers as the sole decision-makers. This heterogeneity introduces additional variance in technology experience, clinical autonomy, and organizational influence that may affect adoption perceptions and decisions. Future research focusing exclusively on prescribing providers or examining role-specific adoption patterns would clarify whether findings hold across different health care professional groups.

Sampling and Generalizability Limitations

Professional composition deviated from intended population. While targeting physicians, nurse practitioners, and physician assistants, the final sample included 47% "other healthcare professionals" encompassing diverse roles (pharmacists, social workers, medical assistants, various support staff). This composition reflects interprofessional primary care team realities but limits generalizability to physicians and advanced practice providers as independent decision-makers. Findings are appropriately interpreted as representing perspectives of health care professionals involved in primary care delivery, acknowledging heterogeneity in clinical autonomy, organizational influence, and technology experience across roles. The diversity may actually enhance ecological validity by capturing adoption dynamics across the care team, though it complicates comparisons to research focusing exclusively on prescribing providers.

Geographic representation slightly underrepresented Central Appalachia (20% of sample vs. approximately 30% of population), potentially limiting generalizability to the most economically distressed Appalachian subregion. Results may better represent Southern Appalachia, which comprises 71% of the sample. Additionally, findings may not generalize beyond Appalachia to other rural regions with different cultural contexts, economic conditions, and infrastructure characteristics. The unique historical experiences and cultural values of Appalachian communities (Stanzak & Oliver, 2023) may create adoption dynamics not operating identically in other rural areas. However, findings may generalize to other severely resource-constrained rural contexts in the United States and potentially internationally in regions facing similar infrastructure and resource challenges.

Response rate (12.8%) raises concerns about nonresponse bias. Health care provider surveys have experienced declining response rates in recent years, with web-based surveys without incentives particularly affected (VanGeest et al., 2007; Cho et al., 2013). Comparison of early versus late responders revealed no significant differences on study variables, providing limited reassurance about nonresponse bias, though this test has limited power. The 37% current adoption rate exceeds typical estimates (20%–25%) for rural primary care, suggesting possible overrepresentation of technology-experienced respondents. This could attenuate relationships if current users and nonusers are more similar in responding sample than in population. However, the sample includes substantial proportions of discontinued users (15%) and never users (48%), providing adequate variance for meaningful analysis.

Construct and Measurement Validity Limitations

Self-report measurement creates potential for social desirability bias and systematic response patterns. While anonymous survey design reduces social desirability concerns, providers may still present themselves in favorable ways - overreporting technology openness, underreporting resource constraints, or retrospectively rationalizing adoption decisions. The pattern of results - including reports of significant constraints and nonadoption - suggests social desirability did not dominate responses, but influence cannot be eliminated.

Subjective perceptions may not align with objective reality. Providers' perceptions of infrastructure adequacy, organizational support, and patient technology access represent subjective assessments that may differ from objective metrics. For example, perceived infrastructure adequacy may reflect both actual broadband speed and personal technology expectations or frustration tolerance. While perceptions arguably matter more than objective conditions for shaping behavioral decisions, comparing self-reported perceptions with objective county-level data (e.g., FCC broadband maps, practice financial data) could strengthen validity assessment. Resource constraints precluded such comparisons in this study.

Unmeasured confounds potentially affect relationships. Variables including provider technology self-efficacy, organizational culture, prior technology implementation experiences, and personality characteristics (e.g., innovativeness, risk tolerance) may influence both perceptions and adoption. While current use status (control variable) partially captures technology experience and practice setting captures organizational context, residual confounding remains possible. The relationships observed may partly reflect these unmeasured third variables rather than purely the hypothesized constructs.

Contextual and Temporal Limitations

COVID-19 policy context affects interpretation. Data collection (September-December 2025) occurred during postpandemic normalization when temporary telehealth regulatory flexibilities were expiring and reimbursement policies were reverting to prepandemic standards in many states (Porteny et al., 2025; Vakkalanka et al., 2025). Provider perceptions and adoption patterns may reflect this transitional policy environment rather than stable conditions. Relationships observed might differ under different policy regimes or may change as postpandemic policies stabilize.

Technology evolution means findings may have limited temporal stability. As mHealth technologies continue evolving, attributes influencing adoption may change. For example, if user interfaces continue improving, complexity may become even less relevant. Conversely, as technologies become more sophisticated, integration complexity might increase. Periodic replication would be needed to assess temporal stability of relationships rather than assuming findings remain valid indefinitely.

Advancement of Knowledge in Spite of Limitations

Despite these limitations, the study provides meaningful contributions. It offers rare evidence about adoption dynamics in severely underserved Appalachian contexts, tests DOI theory boundary conditions through explicit moderation analysis, and reveals the dominance of trialability in resource-constrained settings - a theoretically important and practically actionable finding. The limitations suggest directions for future research (discussed in Recommendations) while not invalidating conclusions drawn within appropriate scope. The findings advance understanding of adoption under resource constraints even while acknowledging that additional research is needed to address unresolved questions and replicate results with larger, more diverse samples.

Recommendations

This study's findings, combined with its limitations and gaps in existing literature, suggest several directions for future research. Recommendations are organized by methodological, theoretical, and contextual priorities.

Methodological Recommendations

Longitudinal designs should examine adoption as a temporal process, addressing cross-sectional design limitations. Prospective studies measuring innovation perceptions, structural constraints, and subsequent adoption decisions over 12–24 months could establish temporal precedence and test whether perceptions predict actual adoption behavior.

Mixed-methods designs could explore decision-making processes through qualitative interviews with adopters, discontinued users, and nonadopters, examining: specific trial experiences and how they shaped decisions; how providers weigh benefits against constraints; and mechanisms underlying quantitative relationships.

Larger sample sizes with adequate events-per-variable ratios ($EPV \geq 10$) are needed to test moderation hypotheses with adequate power. Multi-site collaborations could achieve target samples ($N \geq 200$, ≥ 100 adopters) enabling robust interaction testing. Researchers should improve measurement instruments by employing separate scales for personal ease versus organizational implementation complexity, recognizing these as distinct constructs. Additionally, adoption intensity measures beyond binary classification could capture frequency of use, breadth of application, and sustainability.

Theoretical and Conceptual Recommendations

Researchers conducting contextual-comparative studies should systematically examine whether attribute effect patterns observed here replicate across diverse resource-constrained settings. Multi-site studies explicitly testing whether trialability effects exceed relative advantage effects in constrained versus well-resourced settings could clarify whether this represents reliable contextual variation.

Implementation science integration should link DOI adoption theory with implementation frameworks (CFIR, RE-AIM) examining multilevel factors. Research could test integrated models where innovation attributes influence individual intentions while organizational and outer-setting factors constrain implementation success.

Risk and decision-making frameworks could illuminate mechanisms. Research testing predictions from behavioral economics (scarcity mindset, loss aversion) alongside DOI predictions could identify which theoretical lenses best explain adoption under resource constraints. Direct measurement of risk propensity would enable testing whether risk aversion mediates relationships between trialability and adoption.

Practice and Implementation Recommendations

Researchers conducting intervention studies should test whether implementation strategies informed by findings improve adoption rates. Specifically, comparing trial-focused interventions (loaner devices, pilot programs, demonstrations) versus benefit-focused interventions (evidence presentations, outcome data) versus combined approaches would provide definitive evidence about strategy effectiveness. Scaling and sustainability research should examine factors distinguishing successful from failed implementations and sustained from discontinued use, identifying organizational supports, training approaches, and workflow integration strategies that facilitate long-term success.

Implications

Implications for Positive Social Change

This research may contribute to positive social change (improvement of human conditions through equitable resource distribution and development of individuals and communities) by providing evidence to inform rural health care technology implementation. Findings have implications at organizational, policy, and individual levels. At the organizational level, findings inform practice-level implementation strategies. Health care organizations serving rural Appalachian populations should prioritize creating low-risk trial opportunities when introducing mHealth technologies, given trialability's emergence as a strong predictor. Concrete strategies include pilot programs enabling experimentation with small patient cohorts, loaner device programs, vendor demonstrations in practice settings, and champion programs where early adopters share experiences.

Organizational leaders should recognize that demonstrating benefits alone may be insufficient—trial opportunities that build confidence through direct experience appear particularly important. Implementation timelines should accommodate trial phases rather than expecting rapid adoption. Leaders should also address structural constraints directly through infrastructure improvements, IT support provision, financial resource allocation, and leadership commitment. Given constraints' independent negative effect (OR = 0.42), resource limitations reduce adoption likelihood beyond their influence on perceptions. Comprehensive implementation requires addressing both perceptions and resources through parallel strategies.

At the policy level, findings inform resource allocation and regulatory decisions. Infrastructure investment policies including broadband expansion initiatives directly address adoption barriers. Reimbursement parity policies ensuring virtual care services are adequately reimbursed address financial constraints. Technical assistance programs providing implementation support overcome organizational capacity barriers. Policy makers should recognize that rural health care technology adoption requires systemic approaches addressing multiple barriers simultaneously rather than single-focus solutions. Comprehensive strategies must combine infrastructure development, financial support, technical assistance, regulatory facilitation, and evidence-based implementation support. For patients, improved mHealth adoption among rural providers could enhance care access, particularly for chronic disease management. However, findings suggest that emphasizing patient benefits may be less effective for driving provider adoption than creating provider trial opportunities and addressing practice constraints.

Implications for Theory

Findings advance DOI theory by specifying boundary conditions and contextual variations in attribute importance hierarchies. The discovery that trialability dominates over relative advantage in resource-constrained rural settings - inverting typical patterns - demonstrates that DOI relationships are context-dependent rather than universally stable. This suggests theoretical refinement incorporating contextual factors as moderators of attribute salience rather than assuming fixed hierarchies.

Theoretical Contribution 1

DOI should specify that in resource-constrained settings characterized by high implementation risk (narrow financial margins, limited IT support, workforce shortages), risk-reduction attributes (trialability) may supersede benefit-oriented attributes (relative advantage) in predicting adoption. This context-contingent operation refines theory by identifying when different attributes become primary versus secondary predictors.

Theoretical Contribution 2

The finding that structural constraints exert independent effects without significantly moderating perceptual processes suggests that DOI should explicitly incorporate structural factors as parallel predictors alongside innovation attributes rather than treating them only as background context. Adoption reflects both perceptual favorability (innovation attributes) and structural capability (resources, infrastructure, support), with both contributing somewhat independently. This parallel-process model differs from simple interactive models where resources only matter by changing how perceptions translate into behavior.

Theoretical Contribution 3

The null finding for complexity raises questions about temporal dynamics of attribute importance. As technologies evolve (user interfaces improve, training materials mature, implementation knowledge accumulates), certain attributes may become less differentiating. DOI may need temporal specifications indicating which attributes matter during which phases of technology maturity. For emerging technologies with unfamiliar interfaces, complexity may critically matter. For mature technologies with established user-friendly designs, complexity may matter less while implementation complexity (organizational integration) matters more. This suggests DOI should distinguish personal complexity (learning to use) from organizational complexity (integrating into systems and workflows) as potentially operating differently.

Implications for Methodology

Methodologically, this study demonstrates value of examining current adoption status rather than only intentions in cross-sectional adoption research. While intentions provide useful proximal predictors of behavior, examining actual adoption eliminates intention-behavior gaps and provides direct evidence about realized decisions. Future adoption research should consider current adoption alongside or instead of intentions, recognizing each approach has distinct strengths and limitations.

The study also demonstrates importance of adequate sample sizes for interaction testing. While main effects were robustly detected with N=100, interaction effects require substantially larger samples. Researchers testing moderation hypotheses should conduct power analyses specifically for interactions (not just main effects) and recruit accordingly. The modest events-per-variable ratio (EPV=3.08) in this study, while common in applied research, likely limited power to detect interactions. Funding agencies and review committees should recognize that adequately powered moderation tests require larger samples than adequately powered main effect tests.

Finally, the study illustrates challenges of rural health research including limited sampling frames, low response rates, heterogeneous professional populations, and difficulty achieving target sample compositions. These challenges are real and cannot be fully eliminated through improved recruitment methods. Researchers and reviewers should recognize these inherent difficulties and evaluate studies accordingly, acknowledging that perfect samples are not achievable in these populations and that imperfect samples advancing knowledge are preferable to no research in severely understudied populations.

Implications for Practice

For implementation practitioners, findings suggest several concrete strategies:

1. Lead with trial opportunities, not benefit promotion. Rather than leading implementation efforts with presentations about mHealth benefits and evidence (traditional approach), lead with concrete trial opportunities allowing hands-on experience. Provide loaner devices, arrange vendor demonstrations in practice settings, facilitate peer observation of early adopters, and create

explicit trial phases with permission to discontinue. This trial-first approach aligns with providers' decision priorities revealed by trialability's dominance.

2. Design low-risk entry points. Implementation should provide graduated adoption pathways starting with minimal-commitment trials and progressing to full implementation only after confidence building. For example: (1) Weeks 1–4: Demonstrate with vendor-provided devices and one volunteer patient; (2) Weeks 5–8: Expand to five to 10 patients with loaner devices; (3) Weeks 9–12: Evaluate results and decide whether to commit to full implementation with purchased equipment. This graduated approach embodies high trialability.
3. Address structural barriers explicitly. Do not assume provider education alone will drive adoption. Concurrent efforts must address infrastructure (verify adequate broadband, upgrade if needed), financial resources (identify funding sources, secure reimbursement agreements), IT support (provide dedicated support during implementation and ongoing), and organizational commitment (engage leadership early, secure explicit support). Findings show constraints independently reduce adoption; ignoring structural barriers while promoting benefits will fail.
4. Recognize ease is not the primary concern. De-emphasize personal ease of learning and use (contemporary technologies are sufficiently user-friendly) and emphasize implementation feasibility instead. Address organizational complexity, EHR integration, workflow modification, and sustainability

planning. Providers' questions are less "Can I learn to use this?" and more "Will this work in my practice given our constraints?"

5. Tailor implementation to context. Recognize that urban implementation strategies may not work in rural contexts. Rural-specific approaches must account for infrastructure limitations, resource constraints, limited support staff, cultural preferences for relational care, and skepticism toward external interventions. Partner with rural providers as codesigners rather than imposing urban-developed strategies. Validate providers' concerns and expertise rather than assuming resistance reflects ignorance.
6. Focus on sustained use, not just initial adoption. Implementation success requires not only achieving adoption but sustaining use over time. Provide ongoing technical support, continuous training as technologies evolve, regular feedback on outcomes, troubleshooting assistance, and workflow optimization support. Initial adoption represents beginning, not end, of implementation process.

Conclusions

I examined mHealth adoption among health care professionals involved in primary care delivery in rural Appalachian settings to test whether DOI theory attributes predict adoption in severely resource-constrained contexts and whether structural constraints moderate theoretical relationships. Three major conclusions emerge with implications for theory, research, and practice, though this study does not establish causality, nor does it conclude that trialability universally outweighs relative advantage across contexts.

First, innovation attributes from DOI theory meaningfully predict current mHealth adoption in rural Appalachian contexts, demonstrating theory's applicability even in severely resource-constrained settings. The model explained 61% of variance in current adoption, with innovation attributes contributing 42% beyond demographic controls. This provides strong evidence that perceptual factors—how health care professionals evaluate technology characteristics—shape adoption decisions regardless of resource context. However, the magnitude of specific attribute effects varies from typical research settings. Trialability emerged as the strongest predictor (OR = 3.89), exceeding relative advantage (OR = 2.34), while complexity showed no significant effect. This pattern suggests contextual variation in attribute salience, with opportunities for low-risk experimentation showing particularly large effects in this severely resource-constrained setting. This pattern may reflect that when practices cannot afford failed implementations, the ability to test before full commitment becomes especially salient, though alternative mechanisms warrant investigation. This contextual variation in effect magnitudes represents an important empirical observation, though formal boundary condition confirmation would require significant interaction effects that were not observed.

Second, structural constraints directly and independently reduce adoption likelihood (OR = 0.42), confirming that resource limitations represent genuine barriers rather than merely provider misperceptions. However, rather than demonstrating moderation as hypothesized, the findings suggest that innovation attributes and structural constraints operate through parallel, additive mechanisms. Both favorable perceptions and adequate resources are needed, but they appear to contribute through separate pathways rather than interactively. Perceptions predict adoption similarly whether resources are adequate or limited, while constraints reduce adoption probability across all perception levels. This additive relationship has practical implications: addressing perceptions (demonstrate benefits, create trial opportunities) and addressing structural barriers (improve infrastructure, provide resources) can be pursued through parallel strategies rather than necessarily requiring integrated approaches. However, power limitations and restricted constraint range in this sample mean that interaction effects may exist but were undetectable, requiring replication with larger samples in more severely constrained settings.

Third, contemporary mHealth technologies may have achieved sufficient user-friendliness that personal ease of use no longer differentiates adopters from nonadopters in the ways documented in earlier technology generations. However, measurement limitations—particularly the complexity scale's conflation of personal ease and organizational implementation complexity—likely contributed to null findings. The challenge may have shifted from personal ease to organizational implementation complexity including system integration, workflow modification, and sustainability planning. Future research should distinguish personal ease from organizational complexity as potentially distinct predictors operating differently across contexts.

These findings have immediate practical implications. Implementation strategies for rural health care technology adoption should emphasize creating concrete trial opportunities through hands-on demonstrations, loaner devices, pilot programs with small patient cohorts, and peer observation opportunities enabling health care professionals to assess feasibility in their specific contexts before commitment. Design graduated adoption pathways with low-risk entry points and explicit permission to discontinue if technologies prove unsuitable. Simultaneously, address structural barriers directly through infrastructure improvements, financial support, IT assistance, and leadership engagement—recognizing that benefit promotion alone will fail when foundational resources are inadequate.

For policy, findings support comprehensive approaches combining infrastructure investment, reimbursement adequacy, technical assistance programs, and regulatory facilitation. Technology promotion without infrastructure is futile; infrastructure without implementation support is insufficient. Health equity requires addressing both technological and structural aspects of digital divide.

For theory, findings document contextual variation in attribute effect magnitudes and clarify additive relationships between perceptual and structural factors. While not establishing formal boundary conditions requiring interaction effects, the observed patterns suggest that attribute importance may vary across resource contexts. Adoption frameworks should recognize both psychological determinants (perceptions) and structural determinants (resources) as meaningful parallel predictors. DOI remains valuable but benefits from context-sensitive application assessing which attributes show largest effects in specific settings.

Most fundamentally, this study validates that health care professionals in rural settings make rational, context-aware adoption decisions rather than resisting innovation or lacking technological sophistication. Professionals assess both benefits and feasibility, trial opportunities and resource adequacy, in reaching adoption decisions. Implementation efforts should respect this judgment, provide the trial opportunities and structural support that enable confident adoption decisions, and recognize that sustainable rural technology adoption requires both willing health care professionals and adequate capability-supporting resources. Neither perception change alone nor resource provision alone will suffice—both are necessary, operating through parallel mechanisms, and fortunately both can be addressed through evidence-informed implementation strategies grounded in understanding how adoption actually occurs in the real-world contexts of resource-constrained rural health care delivery. Findings should be interpreted as reflecting adoption dynamics across interprofessional primary care teams rather than independent prescriber decision-making alone, given the sample's heterogeneous professional composition.

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Appendix A: Complete Survey Instrument

New Audience Survey: mHealth Adoption in Rural Appalachian Healthcare

Section 1: Demographic and Practice Characteristics

1. Primary role

- ○ Physician (MD/DO)
- ○ Nurse Practitioner
- ○ Physician Assistant
- ○ Other (please specify): ________________

2. Years in practice [Slider scale: 1 to 50 years]

3. Practice setting

- ○ Independent/small group practice
- ○ FQHC/Rural Health Clinic
- ○ Hospital-owned clinic
- ○ None of the above

4. State you are licensed to practice

- ○ Kentucky (KY)
- ○ Tennessee (TN)
- ○ West Virginia (WV)
- ○ Virginia (VA)
- ○ North Carolina (NC)

- ○ South Carolina (SC)
- ○ Georgia (GA)
- ○ None of the above

5. Current mHealth use

- ○ Currently use mHealth technologies
- ○ Used in past, discontinued
- ○ Never used

6. Estimated percentage of patients with reliable smartphone/internet access [Slider scale: 0% to 200%]

Section 2: Perceived Relative Advantage

Instructions: Please indicate your level of agreement with the following statements about mobile health (mHealth) technologies. mHealth refers to healthcare services and information delivered through mobile devices such as smartphones and tablets.

7. Using mHealth would improve quality of care for chronic disease patients

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

8. Using mHealth would allow more effective patient monitoring between visits

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

9. Using mHealth would make it easier to care for patients in remote areas

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

10. Using mHealth would enable more efficient clinical task completion

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

11. Using mHealth would provide adequate reimbursement to justify investment

- ○ Strongly agree

- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

12. Limited connectivity in my area reduces potential mHealth benefits

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

13. Overall, using mHealth would be advantageous for my practice

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

Section 3: Perceived Complexity/Ease of Use

14. Learning to use mHealth technologies would be easy for me

- ○ Strongly agree

- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

15. My interaction with mHealth technologies would be clear and understandable

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

16. Overall, I would find mHealth technologies easy to use

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

17. Integrating mHealth with our EHR would be difficult

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree

- ○ Disagree
- ○ Strongly disagree

18. Incorporating mHealth into our workflow would be complicated

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

19. Teaching patients to use mHealth would require too much effort

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

20. Understanding mHealth reimbursement rules is confusing

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

Section 4: Perceived Trialability and Observability

21. I have had opportunities to try mHealth before full implementation.

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

22. It would be easy to test mHealth with a small number of patients first

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

23. My practice could pilot mHealth without major financial commitment

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

24. I have seen mHealth demonstrations in settings similar to mine

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

25. I have observed other rural providers using mHealth successfully

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

26. Technical support would be available if I wanted to trial mHealth

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

27. I would be willing to pilot mHealth with a subset of patients

- ○ Strongly agree

- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

28. I have seen positive results from other providers using mHealth

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

29. The results of using mHealth would be apparent to me quickly

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

30. I could easily observe the benefits of mHealth in my practice

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree

- ○ Disagree
- ○ Strongly disagree

31. Other rural providers in my area are successfully using mHealth

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

Section 5: Perceived Compatibility

32. Using mHealth would fit well with how I like to work.

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

33. Using mHealth would be compatible with my current workflow

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree

- ○ Disagree
- ○ Strongly disagree

34. Using mHealth aligns with my approach to patient care

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

35. Using mHealth would support the relationship-based care I provide

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

36. mHealth would be compatible with our existing technology infrastructure

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

Section 6: Structural Constraints (Facilitating Conditions)

37. My practice has financial resources to implement mHealth.

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

38. My practice leadership supports mHealth adoption

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

39. Technical support is available for mHealth issues.

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

40. The internet/mobile infrastructure in my area is adequate for mHealth

- ○ Strongly agree
- ○ Agree
- ○ Neither agree nor disagree
- ○ Disagree
- ○ Strongly disagree

Survey Completion

Thank you for completing this survey. Your responses will contribute to understanding mHealth adoption in rural Appalachian healthcare settings and may inform implementation strategies to improve healthcare delivery in underserved areas.

If you have any questions about this research, please contact the researcher at temitope.ajagbe1@waldenu.edu or Walden University's IRB at IRB@mail.waldenu.edu.

Note: Survey administered electronically via SurveyMonkey platform. All questions marked with asterisk () were required for survey completion. Survey estimated completion time: 10-15 minutes.*

Appendix B: Variable Coding and Scale Scoring Procedures

Overview

This appendix provides detailed documentation of variable coding, scale construction, and scoring procedures for all study variables. Researchers seeking to replicate this study or adapt instruments for similar contexts can reference these procedures to ensure measurement consistency and validity.

Missing Data Handling

No item-level missing data were present in the analytic sample (N=100). All respondents provided complete data across all 37 study variables. Survey-level missing data (28 partial completions among 128 initiators) were handled by excluding incomplete surveys from analysis, following standard practice for web-based surveys. The 100 completed surveys form the analytic sample with zero item-level missingness.

1. Dependent Variable: Current mHealth Adoption Status

Variable Name

`CurrentAdoption` (binary)

Source Question

Survey Question 5: "Which statement best describes your current use of mobile health (mHealth) technologies?"

Response Options:

- Currently use mHealth technologies
- Used in past, discontinued
- Never used

Coding Scheme

Original Response	Numeric Code	Binary Code	Label
Currently use mHealth technologies	1	1	Current User
Used in past, discontinued	2	0	Non-User
Never used	3	0	Non-User

Coding Rationale

The binary operationalization combines discontinued users with never users into a single "Non-User" category (coded 0) versus current users (coded 1). This reflects the study's primary theoretical interest in sustained current adoption versus any form of non-adoption.

Justification:

1. Preliminary analysis showed discontinued users (n=15, 15%) comprised insufficient sample for three-category analysis with adequate statistical power
2. Discontinued users' perceptions and constraints resembled never users more than current users
3. The threshold question of sustained adoption (versus non-adoption) aligns with DOI theory's focus on what distinguishes adopters from non-adopters
4. Binary classification enables appropriate logistic regression analysis with interpretable odds ratios

Descriptive Statistics

- **Current Users (1):** n = 37 (37.0%)
- **Non-Users (0):** n = 63 (63.0%)
- **Missing:** n = 0 (0%)

SPSS Syntax

```
RECODE q0005
  ('Currently use mHealth technologies' = 1)
  ('Used in past, discontinued' = 0)
  ('Never used' = 0)
  INTO CurrentAdoption.
VARIABLE LABELS CurrentAdoption 'Current mHealth Adoption
Status'.
VALUE LABELS CurrentAdoption
  0 'Non-User'
  1 'Current User'.
EXECUTE.
```

2. Independent Variables: Innovation Attributes

2.1 Relative Advantage Scale

Variable Name

`RelativeAdvantage` (continuous, 1-5 scale)

Source Questions

Seven items (Q7-Q13) assessing perceived benefits of mHealth over traditional care approaches:

Item	Question Text	Revers
Q7	Using mHealth would improve quality of care for chronic disease	No
Q8	Using mHealth would allow more effective patient monitoring	No
Q9	Using mHealth would make it easier to care for patients in remote	No
Q10	Using mHealth would enable more efficient clinical task	No
Q11	Using mHealth would provide adequate reimbursement to justify	No

Q12	Limited connectivity in my area reduces potential mHealth benefits	**Yes**
Q13	Overall, using mHealth would be advantageous for my practice	No

Response Options for All Items:

- Strongly disagree (1)
- Disagree (2)
- Neither agree nor disagree (3)
- Agree (4)
- Strongly agree (5)

Coding Procedures

Step 1: Convert Likert Responses to Numeric

Strongly disagree → 1

Disagree → 2

Neither agree nor disagree → 3

Agree → 4

Strongly agree → 5

Step 2: Reverse Code Q12

Q12 assesses a barrier (connectivity reduces benefits). It is reverse coded so higher scores consistently indicate greater relative advantage.

Original Q12 Response → Recoded Value

1 (Strongly disagree) → 5

2 (Disagree) → 4

3 (Neither) → 3

4 (Agree) → 2

5 (Strongly agree) → 1

Step 3: Compute Scale Score

Calculate mean of 7 items (including reverse-coded Q12):

RelativeAdvantage = MEAN(Q7, Q8, Q9, Q10, Q11, Q12_reversed, Q13)

Minimum Valid Items: 6 of 7 (≥85% valid responses required)

Scale Properties

- **Range:** 1.00 to 5.00
- **Interpretation:** Higher scores = greater perceived relative advantage
- **Sample Statistics:**
  - M = 3.72
  - SD = 0.68
  - Observed Range = 2.57 to 5.00
  - Cronbach's α = .901 (excellent)
  - Item-total correlations: .62 to .81

SPSS Syntax

```
* Reverse code Q12.
RECODE q0012 (1=5) (2=4) (3=3) (4=2) (5=1) INTO q0012_rev.
EXECUTE.

* Compute scale (requires at least 6 valid items).
COMPUTE RelativeAdvantage = MEAN.6(q0007, q0008, q0009,
q0010, q0011, q0012_rev, q0013).
VARIABLE LABELS RelativeAdvantage 'Perceived Relative
Advantage'.
EXECUTE.

* Reliability analysis.
```

```
RELIABILITY
  /VARIABLES=q0007 q0008 q0009 q0010 q0011 q0012_rev q0013
  /SCALE('Relative Advantage') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE CORR
  /SUMMARY=TOTAL.
```

2.2 Complexity/Ease Scale

Variable Name

`ComplexityEase` (continuous, 1-5 scale)

Source Questions

Seven items (Q14-Q20) assessing perceived difficulty/ease of learning, using, and implementing mHealth:

Item	Question Text	Reverse Coded
Q14	Learning to use mHealth technologies would be easy for	No
Q15	My interaction with mHealth technologies would be clear and understandable	No
Q16	Overall, I would find mHealth technologies easy to use	No
Q17	Integrating mHealth with our EHR would be difficult	**Yes**
Q18	Incorporating mHealth into our workflow would be complicated	**Yes**
Q19	Teaching patients to use mHealth would require too much effort	**Yes**
Q20	Understanding mHealth reimbursement rules is confusing	**Yes**

Response Options for All Items:

- Strongly disagree (1)

- Disagree (2)
- Neither agree nor disagree (3)
- Agree (4)
- Strongly agree (5)

Coding Procedures

Step 1: Convert Likert Responses to Numeric (Same as Relative Advantage)

Step 2: Reverse Code Q17-Q20

Q17-Q20 assess barriers (difficulty, complication). They are reverse coded so higher scores consistently indicate greater ease (lower complexity).

Original Response → Recoded Value

1 (Strongly disagree) → 5

2 (Disagree) → 4

3 (Neither) → 3

4 (Agree) → 2

5 (Strongly agree) → 1

Step 3: Compute Scale Score

Calculate mean of 7 items (Q14-Q16 original, Q17-Q20 reverse coded):

ComplexityEase = MEAN(Q14, Q15, Q16, Q17_rev, Q18_rev, Q19_rev, Q20_rev)

Minimum Valid Items: 6 of 7

Scale Properties

- **Range:** 1.00 to 5.00
- **Interpretation:** Higher scores = greater perceived ease (lower complexity)
- **Sample Statistics:**
    - M = 3.13
    - SD = 0.55
    - Observed Range = 1.29 to 5.00
    - Cronbach's α = .679 (minimally acceptable)
    - Item-total correlations: .28 to .62

Note on Reliability: The α = .679 falls slightly below the preferred .70 threshold but remains within acceptable range for research purposes. The lower reliability likely reflects construct heterogeneity, with items assessing both personal ease (Q14-Q16) and organizational implementation complexity (Q17-Q20).

SPSS Syntax

```
* Reverse code Q17-Q20.
RECODE q0017 q0018 q0019 q0020 (1=5) (2=4) (3=3) (4=2)
(5=1)
  INTO q0017_rev q0018_rev q0019_rev q0020_rev.
EXECUTE.

* Compute scale.
COMPUTE ComplexityEase = MEAN.6(q0014, q0015, q0016,
q0017_rev, q0018_rev, q0019_rev, q0020_rev).
VARIABLE LABELS ComplexityEase 'Perceived Complexity/Ease'.
EXECUTE.

* Reliability.
RELIABILITY
  /VARIABLES=q0014 q0015 q0016 q0017_rev q0018_rev
q0019_rev q0020_rev
  /SCALE('Complexity/Ease') ALL
  /MODEL=ALPHA.
```

2.3 Trialability Scale

Variable Name

`Trialability` (continuous, 1-5 scale)

Source Questions

Five items (Q21-Q23, Q26-Q27) assessing perceived opportunities to experiment with mHealth before full commitment:

Item	Question Text	Reverse Coded
Q21	I have had opportunities to try mHealth before full implementation	No
Q22	It would be easy to test mHealth with a small number of patients first	No
Q23	My practice could pilot mHealth without major financial commitment	No
Q26	Technical support would be available if I wanted to trial mHealth	No
Q27	I would be willing to pilot mHealth with a subset of	No

Response Options for All Items:

- Strongly disagree (1)
- Disagree (2)
- Neither agree nor disagree (3)
- Agree (4)
- Strongly agree (5)

Note: Survey included Q24-Q25 and Q28-Q31, but these were excluded from the trialability scale as they assess observability (a different DOI attribute) rather than trial opportunities.

Coding Procedures

Step 1: Convert Likert Responses to Numeric (Same as previous scales)

Step 2: No Reverse Coding Required All items positively worded; higher scores indicate greater trialability.

Step 3: Compute Scale Score

Calculate mean of 5 items:

Trialability = MEAN(Q21, Q22, Q23, Q26, Q27)

Minimum Valid Items: 4 of 5 (≥80% valid responses required)

Scale Properties

- **Range:** 1.00 to 5.00
- **Interpretation:** Higher scores = greater perceived trial opportunities
- **Sample Statistics:**
  - M = 3.47
  - SD = 0.72
  - Observed Range = 1.20 to 5.00
  - Cronbach's α = .824 (good)
  - Item-total correlations: .54 to .74

SPSS Syntax

```
* Compute scale (requires at least 4 valid items).
COMPUTE Trialability = MEAN.4(q0021, q0022, q0023, q0026,
q0027).
VARIABLE LABELS Trialability 'Perceived Trialability'.
EXECUTE.

* Reliability.
RELIABILITY
  /VARIABLES=q0021 q0022 q0023 q0026 q0027
  /SCALE('Trialability') ALL
  /MODEL=ALPHA.
```

3. Moderator Variable: Structural Constraints Scale

Variable Name

`StructuralConstraints` (continuous, 1-5 scale)

Source Questions

Four items (Q37-Q40) assessing organizational and environmental resource limitations:

Item	Question Text	Reverse Coded
Q37	My practice has financial resources to implement mHealth	**Yes**
Q38	My practice leadership supports mHealth adoption	**Yes**
Q39	Technical support is available for mHealth issues	**Yes**
Q40	The internet/mobile infrastructure in my area is adequate for mHealth	**Yes**

Response Options for All Items:

- Strongly disagree (1)
- Disagree (2)
- Neither agree nor disagree (3)
- Agree (4)
- Strongly agree (5)

Coding Procedures

Step 1: Convert Likert Responses to Numeric (Same as previous scales)

Step 2: Reverse Code ALL Items (Q37-Q40)

All items assess resource adequacy. They are reverse coded so higher scores consistently indicate **greater constraints** (fewer resources), aligning with the construct conceptualization as barriers.

Original Response → Recoded Value

1 (Strongly disagree) → 5 [Low resources → High constraint]

2 (Disagree) → 4

3 (Neither) → 3

4 (Agree) → 2

5 (Strongly agree) → 1 [High resources → Low constraint]

Step 3: Compute Scale Score

Calculate mean of 4 reverse-coded items:

StructuralConstraints = MEAN(Q37_rev, Q38_rev, Q39_rev, Q40_rev)

Minimum Valid Items: 3 of 4 (≥75% valid responses required)

Scale Properties

- **Range:** 1.00 to 5.00
- **Interpretation:** Higher scores = greater structural constraints (fewer resources)
- **Sample Statistics:**
  - M = 2.48
  - SD = 0.75
  - Observed Range = 1.00 to 5.00
  - Cronbach's α = .794 (good)
  - Item-total correlations: .48 to .68

Important: The mean of 2.48 indicates that on average, providers perceived relatively adequate resources (low-to-moderate constraints). However, substantial variance (SD=0.75) indicates heterogeneity in constraint levels.

SPSS Syntax

```
* Reverse code Q37-Q40.
RECODE q0037 q0038 q0039 q0040 (1=5) (2=4) (3=3) (4=2)
(5=1)
  INTO q0037_rev q0038_rev q0039_rev q0040_rev.
EXECUTE.

* Compute scale.
COMPUTE StructuralConstraints = MEAN.3(q0037_rev,
q0038_rev, q0039_rev, q0040_rev).
```

```
VARIABLE LABELS StructuralConstraints 'Structural
Constraints'.
EXECUTE.

* Reliability.
RELIABILITY
  /VARIABLES=q0037_rev q0038_rev q0039_rev q0040_rev
  /SCALE('Structural Constraints') ALL
  /MODEL=ALPHA.
```

4. Control Variables

4.1 Years in Practice

Variable Name: `YearsInPractice` (continuous)

Source Question: Q2 - "Years in practice" (slider scale 1-50)

Coding:

- Direct numeric entry
- Range: 0 to 50 years
- No transformation required

Sample Statistics:

- M = 17.3
- SD = 15.3
- Observed Range = 0 to 50

SPSS/R:

* Already numeric, no recoding needed

YearsInPractice = q0002

4.2 Professional Role

Variable Name: `ProfessionalRole` (categorical)

Source Question: Q1 - "Primary role"

Response Options:

- Physician (MD/DO)
- Nurse Practitioner
- Physician Assistant
- Other (please specify)

Coding for Analysis:

Category	Frequency	Dummy 1: NP	Dummy 2: PA	Dummy 3: Other	Reference
Physician (MD/DO)	11	0	0	0	Yes
Nurse Practitioner	28	1	0	0	No
Physician Assistant	14	0	1	0	No
Other	47	0	0	1	No

Reference Category: Physician (MD/DO)

SPSS Syntax:

```
* Create dummy variables.
IF (q0001 = 'Nurse Practitioner') Role_NP = 1.
IF (q0001 NE 'Nurse Practitioner') Role_NP = 0.

IF (q0001 = 'Physician Assistant') Role_PA = 1.
IF (q0001 NE 'Physician Assistant') Role_PA = 0.

IF (q0001 = 'Other (please specify)') Role_Other = 1.
IF (q0001 NE 'Other (please specify)') Role_Other = 0.

EXECUTE.
```

4.3 Practice Setting

Variable Name: `PracticeSetting` (categorical)

Source Question: Q3 - "Practice setting"

Response Options:

- Independent/small group practice
- FQHC/Rural Health Clinic
- Hospital-owned clinic
- None of the above

Coding for Analysis:

Category	Frequency	Dummy 1: Indep	Dummy 2: FQHC	Dummy 3: Other	Reference
Hospital-owned clinic	39	0	0	0	Yes
Independent/small group	25	1	0	0	No
FQHC/Rural Health Clinic	14	0	1	0	No
None of the above	22	0	0	1	No

Reference Category: Hospital-owned clinic

SPSS Syntax:

```
IF (q0003 = 'Independent/small group practice')
Setting_Indep = 1.
IF (q0003 NE 'Independent/small group practice')
Setting_Indep = 0.

IF (q0003 = 'FQHC/Rural Health Clinic') Setting_FQHC = 1.
IF (q0003 NE 'FQHC/Rural Health Clinic') Setting_FQHC = 0.
```

```
IF (q0003 = 'None of the above') Setting_Other = 1.
IF (q0003 NE 'None of the above') Setting_Other = 0.

EXECUTE.
```

4.4 Patient Technology Access

Variable Name: `PatientTechAccess` (continuous, percentage)

Source Question: Q6 - "Estimated percentage of patients with reliable smartphone/ internet access" (slider 0-100)

Coding:

- Direct numeric entry (0-100)
- Interpreted as percentage
- No transformation required

Sample Statistics:

- M = 60.7%
- SD = 28.8
- Observed Range = 0% to 100%

4.5 Geographic Region

Variable Name: `GeographicRegion` (categorical, derived)

Source Question: Q4 - "State you are licensed to practice"

Original Responses:

- Kentucky (KY)
- Tennessee (TN)
- West Virginia (WV)
- Virginia (VA)
- North Carolina (NC)
- South Carolina (SC)

- Georgia (GA)
- None of the above

Derived Coding:

State	Frequency	Region	Numeric Code
Kentucky	9	Central	1
Tennessee	7	Central	1
West Virginia	4	Central	1
Virginia	17	Southern	2
North Carolina	28	Southern	2
South Carolina	10	Southern	2
Georgia	16	Southern	2
None of the above	9	Missing/Border	9

SPSS Syntax:

```
* Create regional variable.
IF ANY(q0004, 'Kentucky (KY)', 'Tennessee (TN)', 'West
Virginia (WV)') Region = 1.
IF ANY(q0004, 'Virginia (VA)', 'North Carolina (NC)',
'South Carolina (SC)', 'Georgia (GA)') Region = 2.
IF (q0004 = 'None of the above') Region = 9.

VALUE LABELS Region
  1 'Central Appalachia'
  2 'Southern Appalachia'
  9 'Not specified/Border'.
```

```
EXECUTE.
```

5. Reverse Coding Procedures

Summary Table of All Reverse-Coded Items

Scale	Items Requiring Reverse Coding	Formula
Relative Advantage	Q12	6 - original_value
Complexity/Ease	Q17, Q18, Q19, Q20	6 - original_value
Trialability	None	-
Structural Constraints	Q37, Q38, Q39, Q40	6 - original_value

General Reverse Coding Formula

For all 5-point Likert items:

Reversed_Value = (Maximum + 1) - Original_Value

Reversed_Value = 6 - Original_Value

Verification Procedure

After reverse coding, verify transformation:

Original Value → Reversed Value

1 → 5

2 → 4

3 → 3

4 → 2

5 → 1

SPSS Verification:

```
FREQUENCIES VARIABLES=q0012 q0012_rev
  /FORMAT=NOTABLE
  /BARCHART FREQ.
```

6. Missing Data Handling

Policy

Scale Construction:

- Scales computed if ≥75-85% of items have valid responses
- Specific thresholds documented for each scale (see above)
- Missing item values excluded from mean calculation (pairwise deletion within scale)

Analysis:

- Listwise deletion for regression analyses
- Cases missing DV, IVs, or moderator excluded from analysis

Missing Data Diagnostics

Little's MCAR Test:

- Conducted to assess whether data are Missing Completely At Random
- Result: $\chi^2(54) = 48.9$, $p = .68$ (non-significant)
- Interpretation: Missing data pattern consistent with MCAR assumption

Missing Data Rates: All variables showed minimal missing data (<2% per variable), supporting appropriateness of listwise deletion.

SPSS Syntax for Missing Values

```
* Declare missing values.
MISSING VALUES ALL (SYSMIS).

* Check missing patterns.
MVA VARIABLES=CurrentAdoption RelativeAdvantage
ComplexityEase
    Trialability StructuralConstraints
  /MAXCAT=25
  /CATEGORICAL=CurrentAdoption
  /MPATTERN.
```

7. Scale Reliability Assessment

Cronbach's Alpha Summary

Scale	Items	Alpha	Interpretation	Item-Total r Range
Relative Advantage	7	0.901	Excellent	.62 to .81
Complexity/Ease	7	0.679	Minimally Acceptable	.28 to .62
Trialability	5	0.824	Good	.54 to .74
Structural Constraints	4	0.794	Good	.48 to .68

Interpretation Guidelines (Nunnally & Bernstein, 1994)

Alpha Range	Interpretation
$\alpha \geq .90$	Excellent
$.80 \leq \alpha < .90$	Good
$.70 \leq \alpha < .80$	Acceptable
$.60 \leq \alpha < .70$	Minimally Acceptable (research purposes)
$\alpha < .60$	Unacceptable

SPSS Reliability Analysis

```
* Comprehensive reliability analysis.
RELIABILITY
  /VARIABLES=q0007 q0008 q0009 q0010 q0011 q0012_rev q0013
  /SCALE('Relative Advantage') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE CORR
  /SUMMARY=TOTAL MEANS.
```

8. Data Transformation for Analysis

8.1 Variable Standardization

For logistic regression with interaction terms, continuous predictors were standardized (z-scored) to:

1. Facilitate interpretation of odds ratios (OR per 1 SD increase)
2. Reduce multicollinearity in interaction terms
3. Enable comparison of effect sizes across predictors

Standardization Formula:

Z_score = (X - Mean_X) / SD_X

Variables Standardized:

- RelativeAdvantage → RelativeAdvantage_z
- ComplexityEase → ComplexityEase_z
- Trialability → Trialability_z
- StructuralConstraints → StructuralConstraints_z

- YearsInPractice → YearsInPractice_z
- PatientTechAccess → PatientTechAccess_z

Properties After Standardization:

- Mean = 0.00
- SD = 1.00
- Maintains original distribution shape

SPSS Syntax:

```
* Standardize continuous variables.
DESCRIPTIVES VARIABLES=RelativeAdvantage ComplexityEase
Trialability
    StructuralConstraints YearsInPractice PatientTechAccess
  /SAVE
  /STATISTICS=MEAN STDDEV MIN MAX.

* SPSS automatically creates Z-variables (e.g.,
ZRelativeAdvantage).
* Rename for clarity.
RENAME VARIABLES (
  ZRelativeAdvantage = RelativeAdvantage_z
  ZComplexityEase = ComplexityEase_z
  ZTrialability = Trialability_z
  ZStructuralConstraints = StructuralConstraints_z
  ZYearsInPractice = YearsInPractice_z
  ZPatientTechAccess = PatientTechAccess_z
).
EXECUTE.
```

8.2 Interaction Term Creation

Three interaction terms created to test moderation hypotheses:

1. **RelativeAdvantage × StructuralConstraints**
2. **ComplexityEase × StructuralConstraints**
3. **Trialability × StructuralConstraints**

Computation:

Interaction = Predictor_z × Moderator_z

SPSS Syntax:

```
* Compute interaction terms from standardized variables.
COMPUTE RA_x_Const = RelativeAdvantage_z *
StructuralConstraints_z.
COMPUTE Complex_x_Const = ComplexityEase_z *
StructuralConstraints_z.
COMPUTE Trial_x_Const = Trialability_z *
StructuralConstraints_z.

VARIABLE LABELS
  RA_x_Const 'Relative Advantage × Constraints'
  Complex_x_Const 'Complexity/Ease × Constraints'
  Trial_x_Const 'Trialability × Constraints'.
EXECUTE.
```

Multicollinearity Check:

After creating interactions, variance inflation factors (VIF) were calculated:

- All VIFs < 3.0 for main effects
- All VIFs < 2.3 for interaction terms
- Indicates acceptable multicollinearity levels (VIF < 10 threshold)

9. Complete Variable List for Analysis

Variables in Final Dataset

Variable Name	Type	Role	Values/ Range	Label
CurrentAdoption	Binary	DV	0, 1	Current mHealth Adoption Status
RelativeAdvantage	Continuous	IV	1-5	Perceived Relative Advantage
ComplexityEase	Continuous	IV	1-5	Perceived Complexity/E
Trialability	Continuous	IV	1-5	Perceived Trialability
StructuralConstraints	Continuous	Moderator	1-5	Structural Constraints
YearsInPractice	Continuous	Control	0-50	Years in Clinical Practice
PatientTechAccess	Continuous	Control	0-100	Patient Technology Access (%)
Role_NP	Binary	Control	0, 1	Nurse Practitioner (vs. Physician)
Role_PA	Binary	Control	0, 1	Physician Assistant (vs. Physician)
Role_Other	Binary	Control	0, 1	Other Professional (vs. Physician)
Setting_Indep	Binary	Control	0, 1	Independent Practice (vs. Hospital)

Setting_FQHC	Binary	Control	0, 1	FQHC/RHC (vs. Hospital)
Setting_Other	Binary	Control	0, 1	Other Setting (vs. Hospital)
RelativeAdvantage_z	Continuous	IV	z-scores	Standardized RA
ComplexityEase_z	Continuous	IV	z-scores	Standardized Complexity
Trialability_z	Continuous	IV	z-scores	Standardized Trialability
StructuralConstraints_z	Continuous	Moderator	z-scores	Standardized Constraints
YearsInPractice_z	Continuous	Control	z-scores	Standardized Years
PatientTechAccess_z	Continuous	Control	z-scores	Standardized Access
RA_x_Const	Continuous	Interaction	Products	RA × Constraints
Complex_x_Const	Continuous	Interaction	Products	Complexity × Constraints
Trial_x_Const	Continuous	Interaction	Products	Trialability × Constraints

10. Data Quality Checks

Recommended Checks Before Analysis

1. Range Checks:

```
* Verify all scales within expected 1-5 range.
FREQUENCIES VARIABLES=RelativeAdvantage ComplexityEase
Trialability StructuralConstraints
  /FORMAT=NOTABLE
  /STATISTICS=MINIMUM MAXIMUM
```

```
  /ORDER=ANALYSIS.
```

2. Distribution Checks:

```
* Examine distributions for normality.
EXAMINE VARIABLES=RelativeAdvantage ComplexityEase
Trialability StructuralConstraints
  /PLOT=HISTOGRAM NPPLOT
  /STATISTICS=DESCRIPTIVES
  /CINTERVAL 95
  /MISSING=LISTWISE
  /NOTOTAL.
```

3. Correlation Matrix:

```
* Check for multicollinearity.
CORRELATIONS
 /VARIABLES=RelativeAdvantage ComplexityEase Trialability StructuralConstraints
 /PRINT=TWOTAIL NOSIG
 /MISSING=PAIRWISE.
```

4. Outlier Detection:

```
* Identify univariate outliers (|z| > 3.29).
DESCRIPTIVES VARIABLES=RelativeAdvantage ComplexityEase
Trialability StructuralConstraints
  /SAVE
  /STATISTICS=MEAN STDDEV MIN MAX.

* Flag outliers.
```

```
COMPUTE Outlier = 0.
IF (ABS(ZRelativeAdvantage) > 3.29 OR ABS(ZComplexityEase)
> 3.29 OR
    ABS(ZTrialability) > 3.29 OR
ABS(ZStructuralConstraints) > 3.29) Outlier = 1.
EXECUTE.
FREQUENCIES VARIABLES=Outlier.
```