Factors Affecting the Adoption of Digital Health Technologies

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1. Introduction
1.1 Project Background
This study aims to investigate the adoption of digital health technologies and the factors that influence its implementation. Specifically, we will explore how the implementation technologies like electronic prescribing (eRx) and electronic health records are influenced by time, geography, and if there is a difference in usage amongst different medical professionals. Additionally, we will analyze prescription trends over time, and inspect how they compare to eRx adoption trends. Through data-driven analysis, this study seeks to provide valuable insights in order to guide policies about the use of these technologies, and to integrate them into standard practice as needed.

1.2 Research Questions
We are going to explore the effectiveness of these technologies, specifically through asking:

1. *How does eRx adoption differ between urban and rural counties within a state?*
   This question allows for the exploration of geographical discrepancies in eRx adoption, which is crucial for identifying potential gaps in digital healthcare access between urban and rural communities.

2. *How has the number of prescriptions varied across regions, and how does it compare to eRx adoption trends?*
   This question helps in checking whether eRx is being adopted proportionally according to prescription activity, offering insights into whether eRx adoption is driven by demand, or other external factors.

3. *How does the percentage of eRx compare between nurse practitioners and physician assistants across states?*
   This question examines how eRx adoption varies between different roles in healthcare, which is important for targeting support and funding to provider groups that may benefit most from additional resources or training.

1.3 Impact of Knowing this Information
Through this research, variation in eRx adoption and prescriptions across regions and provider roles can be identified. Recognizing these patterns is paramount for establishing healthcare policy and improving system efficiency in the United States. The insights gained from this research can guide funding efforts, address regional disparities in technological infrastructure, and streamline provider workflows, which can ultimately contribute to a more efficient and connected healthcare system in the United States [Gabriel et al., 2013]. Furthermore, eRx adoption has been proven to be a key strategy in reducing medication errors [Institute of Medicine, 2007], so by identifying and addressing gaps in adoption, this study can also contribute to better safety outcomes and improved quality of care.

2. Related Work

2.1 Prior Research Motivation

Prior research of electronic prescribing (eRx) systems has uncovered the inconsistencies in its adoption across provider types and geographic regions. These inconsistencies underline the importance of recognizing such patterns of variation, in order to inform more effective policies and support strategies. Differences in eRx adoption, especially between urban and rural regions, and even amongst different healthcare roles have been shown to have major implications on patient safety and logistics. As the importance of such issues has been emphasized through prior work, addressing these issues in this study remains a critical research focus for improving healthcare delivery.

2.2 Existing Projects and Studies

This section highlights key studies that have explored disparities referenced in the previous section, forming the foundations that inform this research. They are as follows:

- "*Emerging and Encouraging Trends in E-Prescribing Adoption Among Providers and Pharmacies*"
  [Gabriel et al., 2013]
  This study utilized nationwide data to track trends in eRx adoption across provider types and rural/urban regions. The research in this study addressed the disparity between urban and rural eRx adoption, while also emphasizing the narrowing of the gap over time, directly supporting the first research question.

- "*Electronic Prescribing at the Point of Care: A Time-Motion Study in the Primary Care Setting*"
  [Devine et al., 2010]
  A time-motion approach was used in this study to examine how the implementation of eRx influences healthcare efficiency. The results indicated an increase in time allocated for prescribing, however, a reduction in time for other administrative tasks was also present. This is related to the second research question, addressing how eRx adoption would be related to prescription volume.

- "*Electronic Prescribing Improves Medication Safety in Community-Based Office Practices*"
  [Kaushal et al., 2010]
  This study assessed how eRx affects medication safety in ambulatory settings, and found that electronic prescribing, along with clinical decision support significantly improves medication safety. In the context of the third research question which investigates differences in eRx adoption among provider types, this study is highly important. By identifying the scenarios in which eRx improves medication safety, we can better promote its adoption across the board.

3. Data

3.1 Datasets Used

1. *State Drug Utilization Data 2013*
2. *Electronic Prescribing Adoption and Use by County*
3. *Electronic Prescribing Adoption and Use by State*
4. *Rural-Urban Continuum Codes*

3.2 Justification for Dataset Choice

To investigate patterns in electronic prescribing (eRx) across U.S. counties and states, this study utilizes four high-quality, nationally representative datasets. These datasets were selected based on their relevance, granularity, nationwide coverage, data quality, and ability to address the research questions, particularly regarding geographical variation and urban-rural disparities in eRx adoption.

- CMS Medicaid State Drug Utilization Data: Provides detailed Medicaid claims at the state and county levels, offering insights into prescription volume and trends. This comprehensive dataset supports modeling of healthcare usage and e-prescription activity.

- Electronic Prescribing Adoption and Use by County: Contains granular, county-level data on provider eRx adoption rates. Selected for its completeness and ability to facilitate local-level spatial analysis and policy comparison.

- Electronic Prescribing Adoption and Use by State: Offers a macro-level perspective on state-wide adoption trends, enabling comparative analysis between states and enhancing the robustness of policy impact assessments.

- Rural-Urban Continuum Codes (RUCC): Categorizes U.S. counties by urbanity and population size. This dataset is key for evaluating disparities in eRx adoption between rural and urban areas—central to the first research question.

Together, these datasets allow for a comprehensive, multi-scale analysis of e-prescription trends and access, enabling both fine-grained geographic insights and broad policy-level evaluations.

3.3 Data Cleaning Steps

3.3.1 Initial Data Inspection

Using .info() and .describe(), we did a high-level examination of the dataset, by looking at column types, missing values, and data distribution as a whole. Additionally, for the purpose of this research, we have decided to only look at data from the year 2013, in lieu of analyzing multiple years of data. This has been done to maintain consistency and reduce potential variability over time.

3.3.2 Handling Missing Data/Removing Duplicates

Missing values were identified using .isnull().sum().

For the dataset containing the State-Level eRx Data by Surescripts, we performed group-wise imputation, wherein the missing data was replaced based on group aggregates. We applied this approach to the variables required. However, the 'pct_new_renewal_e_Rx' variable still had missing values across entire regions, rendering the imputation ineffective. Since it was not useful for our analysis, we dropped this column.

For the dataset containing the Drug Utilization Data by Medicaid, we decided to drop the columns with large amounts of missing values, like ‘Units Reimbursed’, ‘No. of Prescriptions’, ‘Total Amount Reimbursed’, ‘Medicaid Amount Reimbursed’, and ‘Non-Medicaid Amount Reimbursed’, since they were not to be used in the analysis at all. Additionally, duplicates were identified using .duplicated().sum(), and none were found, so no further action was required.

Given the large number of columns that are not relevant enough for our research currently, only the key columns were selected for our research.

3.4 EDA

To explore trends and patterns in electronic prescribing (eRx) adoption and prescription behavior, we conducted a series of visualizations and summary analyses. These visualizations provide an early indication of potential disparities across regions and provider types, guiding our further statistical testing and policy recommendations.

3.4.1 eRx Adoption by County Classification (Urban vs. Rural)

We visualized total eRx adoption counts by county classification using RUCC codes.

Findings:

- Urban counties consistently showed higher eRx adoption rates than rural counties.
- Although rural counties are greater in number, their eRx participation is significantly lower.
- States like California and New York had a large number of participating urban counties, while rural counties lagged behind in these areas.

Implications: This supports our **first research question** and indicates a clear urban-rural gap in technology access and implementation, likely driven by disparities in digital infrastructure, healthcare funding, and provider resources.

3.4.2 Prescription Volume vs. eRx Usage (State-Level)

We plotted the total number of prescriptions (bar chart) alongside eRx prescriptions (line plot) across all states.

Findings:

- States with higher overall prescription volumes (e.g., CA, NY, TX) also tended to have higher eRx counts, though not always proportionally.
- Some smaller states (e.g., Vermont, Alaska) exhibited high variability between total prescriptions and eRx use.

Implications: This directly relates to **Research Question 2**, and suggests that eRx adoption is influenced by more than just volume. Policy mandates and infrastructure likely play a significant role in whether a state shifts from paper to digital prescriptions.

3.4.3 Distribution of Urban vs. Rural Counties by State

We used a stacked bar chart to represent the number of urban and rural counties within each state.

Findings:

- Some states (e.g., Texas, Georgia) have a dominant number of rural counties.
- Others (e.g., New Jersey, Massachusetts) are urban-heavy, which likely affects their healthcare technology adoption strategies.

Implications: This provides further support for urban-rural breakdowns and helps contextualize the results found in **Research Question 1**. States must adopt tailored strategies to ensure technology reaches rural providers.

3.4.4 eRx Adoption by Provider Type (NPs vs. PAs)

We constructed a grouped bar plot to show the proportion of eRx prescriptions submitted by nurse practitioners (NPs) and physician assistants (PAs) per state.

Findings:

- States like Mississippi had a high percentage of NPs but very low PA presence.
- California and New York showed balanced but lower NP proportions.
- eRx adoption was often higher among PAs in urban states, whereas NPs showed stronger presence in rural states.

Implications: This links to **Research Question 3**, indicating that eRx training and support needs to be tailored depending on the dominant provider types in a state. States with more NPs might need specialized strategies to support their digital transition.

Impact on Future Direction

The EDA process has provided critical insights that shape the direction of this study:

We will conduct t-tests to quantify the significance of urban-rural eRx adoption differences.
We will explore correlations between prescription volume and eRx adoption at the state level.
Workforce distribution will be further analyzed in context with regulatory environments and state healthcare policies.
Together, these analyses validate our hypotheses and provide meaningful direction for in-depth statistical exploration.

3.5 Data Considerations

3.5.1 Dataset Size

The dataset containing the Drug Utilization Data by Medicaid, contains around 3.67 million entries. Since this dataset is too large for efficient processing, we will use a stratified sample of n=100,000, instead of using the full dataset, using 'State Code' as the stratum. This ensures that our sample is representative of different states, while making the analysis more manageable.

We selected n=100,000 as the sample size, since it struck a perfect balance between maintaining interpretability and preserving data integrity.

For the rest of the datasets, we kept all entries, since their sizes were already manageable, and missing values were handled accordingly.

3.5.2 Outliers

After performing the initial analysis, we determined that there were no significant outliers in the dataset. As a result, no outlier removals were required for this EDA.

3.5.3 Merging Logic and Classification

Since multiple datasets were merged, we chose FIPS codes as the primary key to link county-level data across the datasets. The RUCC dataset contains FIPS codes, which allow us to classify all of the counties as either urban or rural. After linking, each county is assigned its respective urban or rural classification, based on RUCC codes.

Metro counties (urban) have codes 1-3, while non-metro (rural) counties have codes 4-9.

4. Methodology

4.1 Approach

This research utilizes a quantitative approach, presenting descriptive statistics to examine patterns in eRx adoption across regions, providers, and overall prescription volume. The aim of this study was to extract and summarize crucial insights from well-sourced datasets, in order to highlight disparities and guide practical decision-making. Key components of the approach include:

- Data aggregation by geographic units: Data is grouped at county/state levels, in order to aid in the assessment of variation of eRx adoption across regions. Geographical trends can be easily identified, specifically the differences between urban and rural regions.

- Calculation of provider-level eRx adoption rates: eRx adoption percentages were computed per provider type, which will help evaluate role-specific disparities in eRx usage.

- Visualization of adoption patterns: Bar charts and line plots were used to visualize trends in eRx adoption geographically, according to provider type, and also to compare prescription volume with adoption rates by region.

- Statistical testing:
  - Correlation analysis: A Pearson correlation coefficient was calculated in order to evaluate the strength and direction of the relationship between eRx adoption and the number of prescriptions.
  - t-tests for comparison: Two-sample t-tests were performed to test for statistically significant differences in eRx adoption between rural/urban counties, and NPs and PAs.

The statistical testing was carried out to confirm that the observed differences in eRx adoption between groups were not due to random variation.

4.2 Justification
This approach was chosen due to its clarity and efficiency to decision-making. Through the usage of descriptive statistics, visualizations, and statistical tests, meaningful differences in eRx usage were able to be underlined easier, without the use of complex statistical modeling.

Specifically, visualizations allow for easier interpretation of results by stakeholders that need to make timely and important policy adjustments. The t-tests allow us to determine whether the observed differences are statistically significant, warranting change in policy and resource allocation. The Pearson correlation coefficient quantifies the strength of the linear relationship between the eRx adoption rates and the volume of prescriptions; a strong positive relationship indicates that the adoption of eRx is beneficial, warranting new technology rollout strategies.

However, there are limitations to this approach. The descriptive nature of the analysis may mask underlying patterns that were not studied, and could be captured through more advanced modeling. Additionally, the t-tests cannot account for any potential confounding variables, while correlation tests cannot confirm any causation, and therefore any direct influence.

5. Results and Discussion
5.1 Overview of Results
Research Question 1
The analysis identified 1,797 rural and 1,137 urban counties across the United States, confirming that rural regions outnumber urban ones geographically. However, patterns in electronic prescribing (eRx) adoption varied significantly by state and locality.

For instance, Alaska (AK) reported minimal adoption, with only 9 rural and 3 urban counties using eRx systems. In contrast, California (CA) demonstrated extensive adoption, with 20 rural and 37 urban counties participating in e-prescribing. States such as Texas (TX), Georgia (GA), and Florida (FL) also exhibited strong rural adoption, with 141, 80, and 44 rural counties respectively reporting eRx use.

Despite a larger number of rural counties overall, urban regions appeared to demonstrate higher eRx adoption rates. This likely reflects disparities in healthcare infrastructure, technical capacity, and policy enforcement between rural and urban areas. Urban counties may benefit from more robust provider networks and greater access to digital tools, contributing to higher uptake.

Research Question 2
When examining prescription volumes, California (CA) emerged as the national leader with approximately 2.85 million total prescriptions, of which 1.8 million were electronic. New York (NY) followed closely, with 3.2 million total prescriptions and 1.5 million delivered electronically. These figures highlight strong eRx penetration, particularly in states with large urban populations and mature healthcare systems.

In contrast, smaller states such as Vermont (VT) recorded much lower totals, with only 53,000 eRx prescriptions and around 40,000 total prescriptions. Alaska (AK) and Wyoming (WY) also showed limited adoption, likely due to their smaller populations and more isolated healthcare delivery models. These trends suggest that state-level population size, funding, and infrastructure quality strongly influence eRx adoption.

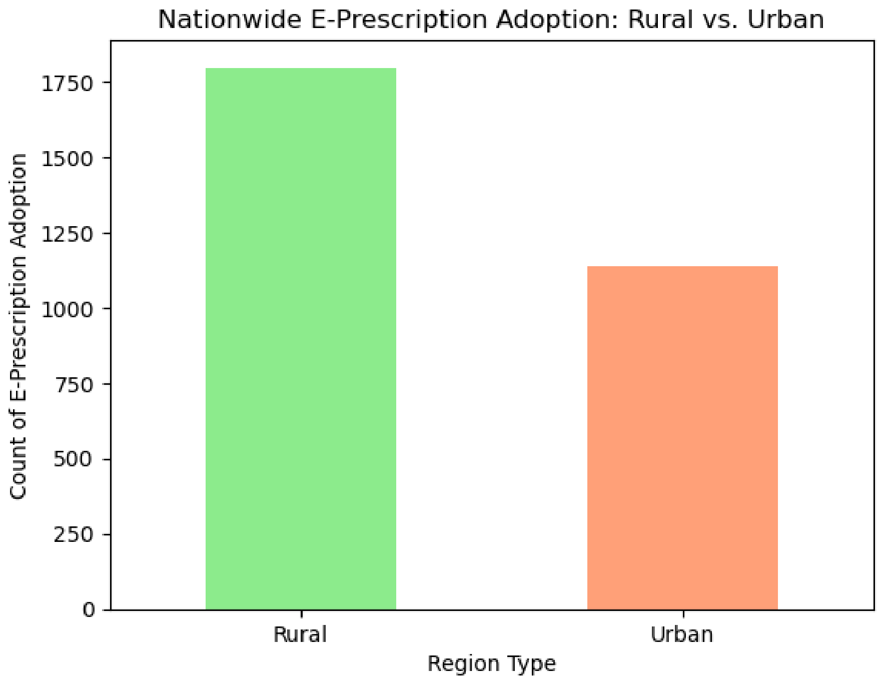
Research Question 3

Workforce composition also varied notably across states. In Alaska (AK), nurse practitioners (NPs) made up 17.76% of the provider population, while physician assistants (PAs) comprised 11.26%. These high percentages likely reflect a reliance on non-physician providers in rural and remote communities.

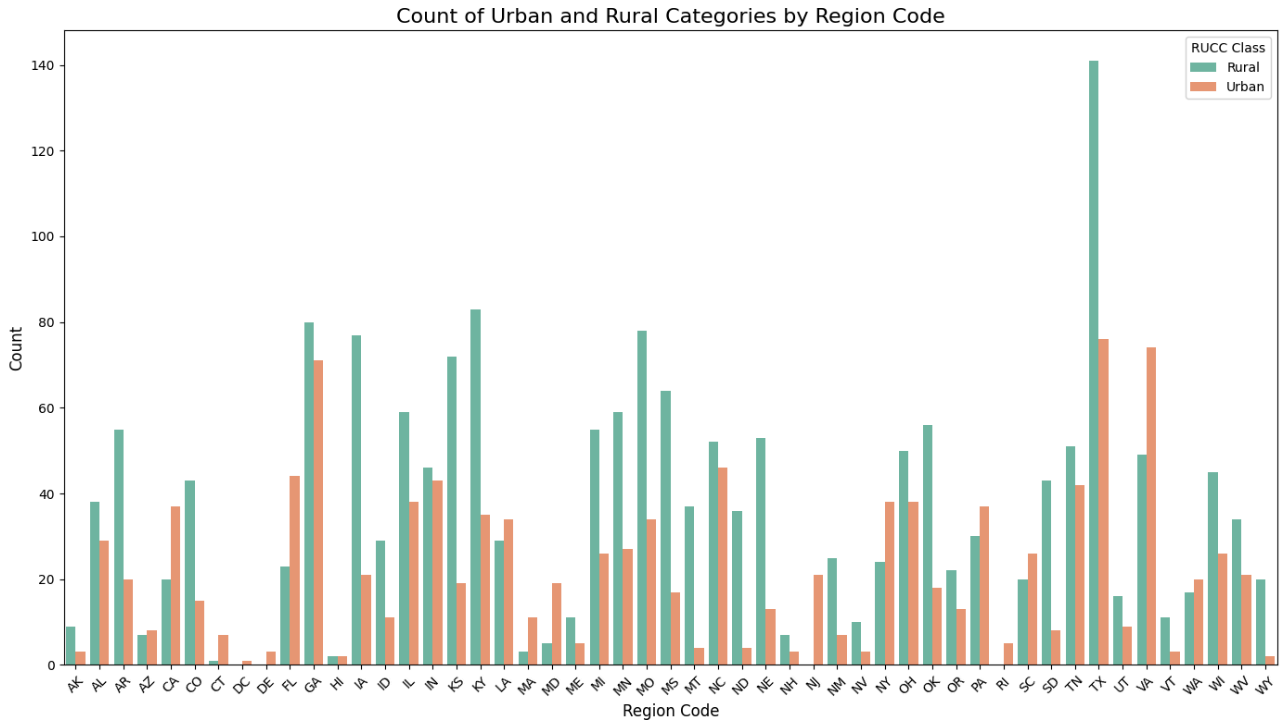
Mississippi (MS) reported the highest NP percentage at 21.1%, but a low PA presence at just 0.81%, suggesting state-specific regulatory environments or healthcare delivery preferences. On the other hand, states like California (CA) and New York (NY) exhibited lower NP representation (around 7-8%) but higher PA percentages (between 6-8%), reflecting a different approach to team-based care.

These workforce variations may directly affect how states adopt and implement eRx systems. Regions with higher concentrations of NPs and PAs might face different training, support, and regulatory challenges, potentially influencing adoption rates and effectiveness.

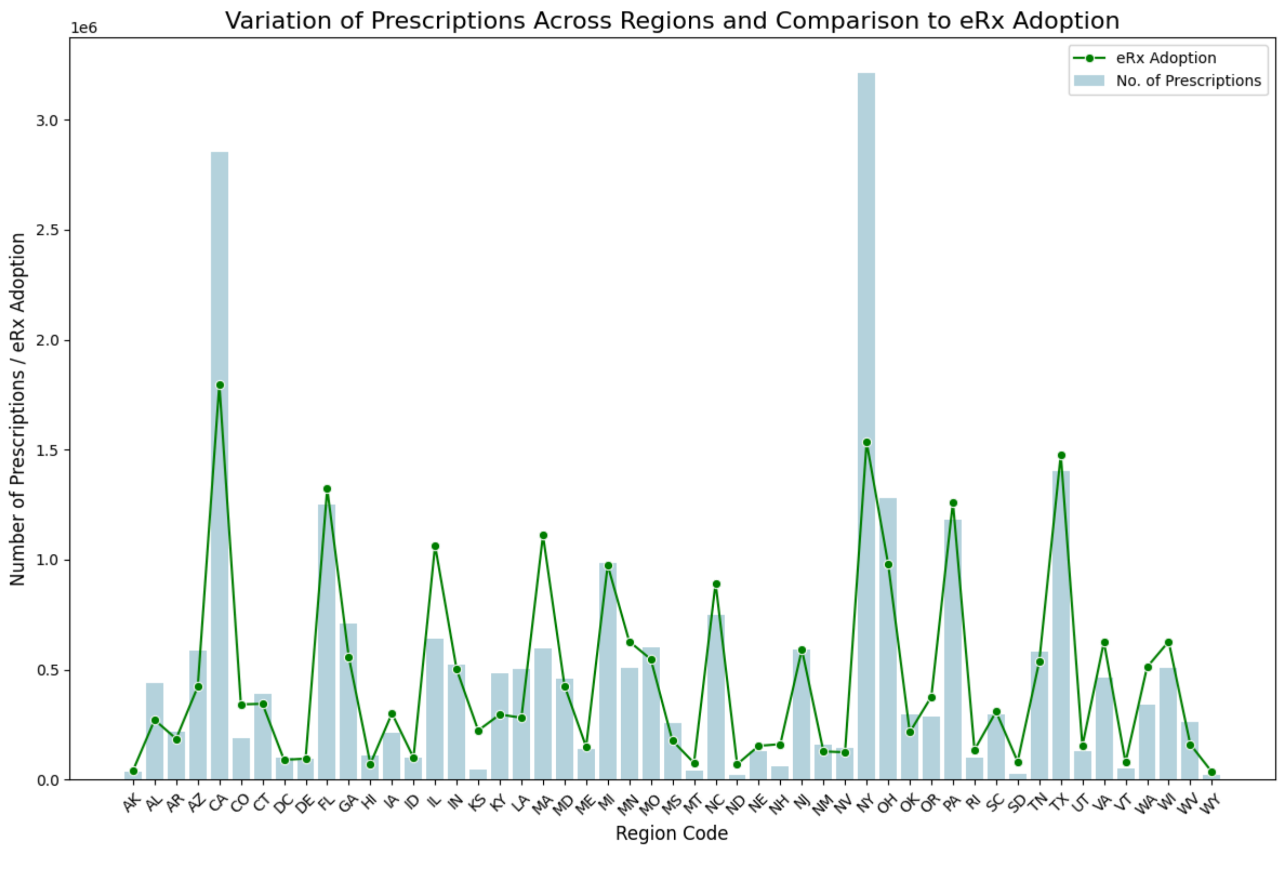
5.2 Graphs and Key Findings



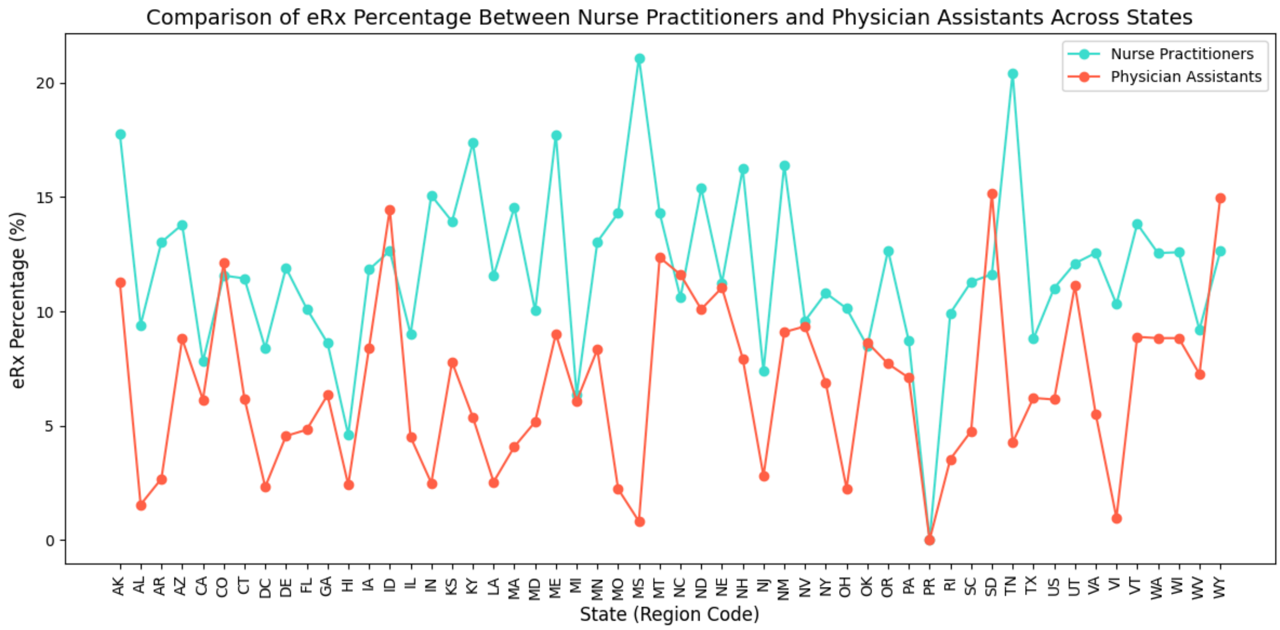
This bar plot compares the total counts of e-prescription adoption in rural versus urban regions across the U.S.



This chart categorizes each region's counties into urban and rural classifications. This is to investigate how the proportion of urban and rural areas within a state affect the trends in eRx adoption.



This chart compares the number of prescriptions in each region (represented as bars) with eRx adoption rates (represented as a line graph). This chart helps identify patterns in how prescriptions and eRx adoption vary by state.



This chart provides a comparison of eRx percentages and nurse practitioners and physician assistants across different states. This is to observe how the quantity of nurse practitioners/ physician assistants could affect eRx adoption rates.

5.3 Internal Validity

The internal validity of this study is strong because the data directly supports the research questions. Each variable—whether it's the count of eRx prescriptions, the rural or urban classification of counties, or the percentages of nurse practitioners and physician assistants—is clearly defined and appropriately measured. For example, rural and urban comparisons rely on official RUCC codes, which are standardized and widely used in geographic analyses. This ensures that the observed differences in eRx adoption are genuinely reflective of geographic disparities rather than classification errors. Moreover, prescription data and provider statistics come from reputable sources and represent real-world patterns of healthcare usage. These factors together support the reliability of the results and increase confidence that the analysis measures what it intends to measure.

5.4 External Validity

The findings also demonstrate strong external validity, as they reflect real-world trends that can be observed beyond this dataset. For instance, states like California and New York (larger populations and more developed healthcare systems) show higher eRx adoption, which aligns with what we would expect based on their infrastructure and access to digital tools. Similarly, the provider workforce composition in states like Alaska and Mississippi matches known rural healthcare strategies, where nurse practitioners often take on greater roles due to physician shortages. Because these trends are consistent with broader national patterns, the study's insights can be reasonably generalized to other regions and healthcare settings, making the results both relevant and applicable in practice.

6. Interpretation and Limitations

6.1 Contextual Interpretation

Research Question 1

The difference between eRx adoption in urban and rural counties is highly significant according to statistical testing. Specifically, the independent t-test returned a t-statistic of 6.40 and a p-value of $1.76e^{-10}$, which is well below the typical cutoff of 0.05. This confirms that urban counties have much different eRx adoption rates than rural counties, and supports the visual trends noted in the data.

The difference in eRx use in urban and rural counties appears to reflect systemic limitations around healthcare access. Rural populations generally experience more barriers when it comes to accessing healthcare. In this case, the lower eRx utilization in rural areas reflects limitations in the digital, policy and implementation capabilities of healthcare providers in rural counties.

Healthcare policymakers and technology implementers should take action from this analysis to develop eHealth strategies that will intentionally support implementation of digital health technologies in rural counties. Without intentionally investing into rural digital infrastructure and training, the benefits of digital health technologies, especially eRx, such as decreased prescription errors and increasing administrative efficiency may not reach all parts of the country equitably.

Research Question 2

Our results revealed a significant, positive correlation ($r = 0.8852$) between the total number of prescriptions across states and the corresponding eRx adoption. This strong correlation indicates that where the state is prescribing more medications, a higher percentage of those prescriptions are being filled electronically.

This correlation implies some level of alignment between prescriber behaviors and electronic uptake, but correlation does not explicitly mean causation. The relationship identified is likely a function of shared underlying factors such as states with higher volumes of prescriptions coupled with more mature healthcare systems, making them more prepared to adopt new digital tools, such as eRx. Therefore, it is not merely the volume of prescriptions that drives adoption, but the readiness of the healthcare system in the particular region. For example, a state with low prescription volume may also have low eRx usage, but it is not sufficient to determine whether this was due to either a lack of need or possibly structural causes.

This finding is important for administrators and policymakers in healthcare. It suggests that the volume of prescriptions can be a useful but incomplete measure of eRx readiness as other factors may play bigger roles as well. High volume states could already realize some of the digital efficiencies, meaning lower volume states may still need to receive intentional policy and resource support from policymakers or the government to drive adoption of eRx.

Research Question 3

The independent t-test examining the proportion of nurse practitioners and physician assistants within states alone generated a t-statistic of 7.12 and a p-value of $1.35e^{-10}$, suggesting a significant difference in the distribution of these two providers across the country. The workforce differences matter because eRx adoption does not happen without regard to who is authorized and trained to perform the tasks needed to successfully implement the technology.

This information is useful for health system designers and policy makers as it demonstrates that eRx implementation should consider the composition of provider workforce in each state. Implementation may vary by whether NPs and PAs are given resources and supported to adopt a digital tool such as eRx than a “one size fits all” implementation approach. Being able to distinguish and acknowledge those differences is essential to equally and effectively denoting eRx adoption in different healthcare systems.

6.2 Other Limitations

A major limitation of this research is its narrow timeline as only the data for year 2013 has been taken into consideration. Although utilising one year allows for uniformity, it prohibits longitudinal analysis that could track shifting trends, variation with respect to newly implemented digital health policies or recent developments in technology. The findings are reflective of a moment in time as opposed to including current trends as well.

Additionally, while the study demonstrates variation in eRx usage based on location and quantity of healthcare providers, direct measures of policy enforcement, digital training, or infrastructure were not considered characteristics. These additional characteristics could have helped in producing more helpful findings.

7. Future Work

7.1 Application of Findings

The findings from this research can help future digital health strategies to be more thoughtful in their overall implications for future integration into various types of healthcare organizations in the US. Policymakers and other healthcare organization leaders could use the current analysis to identify areas of the country or types of providers or organizations that may require additional assistance integrating eRx. Instead of relying upon generic strategies, stakeholders should implement eRx strategy based upon the local reality in which they work, specifically with regard to their local infrastructure, workforce, and digital advancement readiness.

For those areas with limited digital infrastructure, especially in underserved or rural areas, investment in the area of connectivity, technical assistance, and workforce training will likely be required for successful adoption of digital work processes. On the flip-side, for nurses or physician assistants that account for a larger portion of the workforce, the implementation strategy should take into consideration their unique role and service structure. Providing a tool, training, and access to a new system will help ensure they do not lag behind in the migration to digital workflows.

These findings can also be useful for technology vendors, public health agencies, and health care organizations in improving the design and implementation of e-prescribing platforms. Knowing where there are gaps in adoption can inform more effective outreach, onboarding, and resource allocation. Decision-makers can help facilitate a more equitable and efficient distribution of digital health systems by aligning eRx strategies to structural conditions and workforce realities. This approach provides better care coordination, improved medication safety, and ultimately improves the ways that patients access and benefit from prescription services across the nation.

7.2 Opportunities for Further Research

Future studies could advance the work provided they apply additional years of data to look at the trends in eRx uptake over time, which may assist in identifying if any legislation changes or infrastructure added momentum to this uptake over time and whether it stuck. If the study extended to include state level policies like the presence of e-prescribing requirements or financial incentives, more information could be used to identify external influences on the uptake of the eRx system.

Incorporating a more provider-level data could add more granularity to the findings because individual behaviors, training, and organizational factors influence eRx use. More advanced analytic approaches such as causal models could also identify which of the previous interventions were most effective. All of these additional analyses would continue to strengthen the evidence base as well as institute a more effective decision making process in constructing nationwide or state-wide digital health policy.

Declaration of AI Tool Usage

During the creation of this research paper, our group utilized the generative AI tool 'ChatGPT' to check for and to correct minor grammatical errors.
https://chatgpt.com/c/67f5f6b9-b3f4-8008-baf8-52e2dd822be7

References

Anon. https://www.ajmc.com/view/emerging-and-encouraging-trends-in-e-prescribing-adoption-among-providers-and-pharmacies

CMS Medicaid Data. https://data.medicaid.gov/dataset/6a91f80f-e2fd-5f43-8e38-afcebebb8387/data

Electronic prescribing adoption and use by county. https://www.healthit.gov/data/datasets/electronic-prescribing-adoption-and-use-county

Electronic prescribing adoption and use by State. https://www.healthit.gov/data/datasets/electronic-prescribing-adoption-and-use-state

Emily Beth Devine et al. 2010. *Electronic prescribing at the point of care*: A Time-motion study in the Primary Care Setting. (February 2010). https://pmc.ncbi.nlm.nih.gov/articles/PMC2813442/

Institute of Medicine; Board on Health Care Services; Committee on Identifying and Preventing Medication Errors; Philip Aspden. 2006. *Preventing medication errors*. (July 2006). https://nap.nationalacademies.org/catalog/11623/preventing-medication-errors

Rainu Kaushal, Lisa M. Kern, Yolanda Barr, Jill Quaresimo, and Erika L. Abramson. 2010. *Electronic prescribing improves medication safety in community-based office practices* - Journal of General Internal Medicine. (February 2010). https://link.springer.com/article/10.1007/s11606-009-1238-8

Rural-urban continuum codes. https://www.ers.usda.gov/data-products/rural-urban-continuum-codes

README file

- List of all of the external libraries that need to be installed in order to run the project code
- Each of the project files and a brief description of its purpose
- The location of the SQL queries that are used to help answer each of your research questions. (Line numbers)