Research Project Logbook

AI in Agriculture: Accessibility and Sustainability Analysis

Project Overview

Research Question: Is the adoption of AI in agriculture sustainable for the long term and accessible for those who need it most?

Phase 1: Getting Started

Coming Up with the Research Question

At first, I knew I wanted to research something about AI and agriculture, but I wasn't sure exactly what angle to take. After reading through a bunch of articles and sources online, I noticed something interesting. Everyone was talking about how amazing AI is for farming and all the productivity gains, but hardly anyone mentioned whether small farms could actually use this technology. That seemed like a pretty big gap.

I found out that small farms produce 80% of the world's food, which was honestly surprising to me. If these farms can't access AI technology, then what's the point of all this innovation? That's when I settled on my research question: Is AI adoption in agriculture actually sustainable and accessible for the people who need it most?

Reading and Background Research

I spent a lot of time going through different sources - Forbes articles, McKinsey reports, stuff from the FAO, and company websites like Bayer and Syngenta. Here's what I learned:

- The AI agriculture market is expected to grow by $3 billion from 2023 to 2028 (that's 275% growth, which is huge)

- We need to produce 60% more food by 2050 because the population is growing to 9.3 billion people
- AI can do things like precision farming, monitor crops, remove weeds and pests, and run automated machinery
- The potential benefits are real - like 25-32% better crop yields and cutting advisory costs by 99%

The more I read, the more I realized this was going to be an important question to answer.

Figuring Out My Approach

I decided to use quantitative analysis because I wanted actual numbers to back up my arguments. I chose to use open-source tools and datasets for two reasons: first, it matched my whole point about accessibility, and second, I wanted anyone to be able to check my work.

Tools I picked:

- Python 3.x for analyzing data
- Pandas for handling the data
- Matplotlib for making graphs
- Visual Studio Code because it's free and works well

I got my data from the World Bank's agricultural indicators database since it's publicly available and reliable.

Phase 2: Collecting and Preparing Data

Finding the Right Data

I focused on the World Bank's data about irrigated agricultural land as a percentage of total farmland. I picked four countries to compare: Afghanistan, Cyprus, Azerbaijan, and Albania. These countries were good choices because they show different levels of development and infrastructure investment.

The data covered 60 years, from 1960 to 2020, which gave me a solid long-term view.

Problems I Ran Into

The data wasn't perfect. There were missing values, especially for Afghanistan in the earlier years. I also couldn't find direct data on AI adoption rates, so I had to pull information from different industry reports and piece it together. I made sure to note these limitations in my paper because being honest about data quality is important.

Working with the Data

Using Pandas made this part pretty straightforward. I loaded the CSV file, filtered it by country, pulled out the year columns, and converted everything to numbers. I kept my code clean and added comments so someone else could understand what I did.

Phase 3: Analyzing Data and Making Graphs

Creating the Figures

Figure 1: Irrigation Over Time

This was my first real visualization. I wanted to show how different countries' irrigation infrastructure has developed over 60 years. The contrast was striking - Cyprus hit 40% while Afghanistan stayed under 5%. This really drove home the infrastructure gap I was trying to highlight.

Figure 2: Farm Size and AI Adoption

This figure was probably the most important one for my argument. When I saw that only 8% of small farms use AI compared to 67% of large farms, it was like "wow, that's an eight times difference." And remember, small farms produce most of the world's food. This chart basically visualized the core problem.

Figure 3: Market Growth

I made this one to show that there's real money and confidence behind agricultural AI. The growth from $1 billion to $4 billion is impressive. But when I dug into where this investment was going, I found something I didn't expect - it's almost all concentrated in North America and Europe. That was actually more extreme than I thought it would be.

Figure 4: AI Applications

I wanted to see which AI tools farmers are actually using. Crop monitoring and yield optimization were most popular, which makes sense. The lower adoption of automated machinery (45%) told me that even farmers using AI still face cost barriers for the expensive stuff.

Figure 5: Yield Improvements

This figure shows that AI really does work - 32% better corn yields, 30% for soybeans. These are legitimate improvements. But I had to be careful here because most of this data comes from big commercial farms in ideal conditions. Would small farms see the same results? I don't know, and I made sure to say that.

Figure 6: Infrastructure Gaps

This chart pulled everything together. The differences between developed and developing regions were huge across every category - internet (85% vs 25%), electricity (95% vs 45%), training (60% vs 20%). I was even surprised that technical training was only at 60% in developed regions.

Making My Code Better

At first, I was just copying and pasting code for each figure, which was messy. I cleaned it up by:

- Setting global style parameters at the top
- Creating a helper function to save figures
- Using dictionaries instead of separate lists
- Making everything more consistent

This cut my code by about 30% and made it way easier to read.

Phase 4: Writing Everything Up

The Abstract

Writing the abstract was harder than I expected. I had to fit everything important into a short summary - what I studied, how I studied it, what I found, and why it matters. It took several tries to get it concise enough.

Introduction

My first draft was pretty basic. I improved it by:

- Adding details about my specific methods
- Making it flow better into the other sections
- Sounding more professional without being stuffy
- Adding all the LaTeX formatting (%, $)

The final version was about 350 words.

Methods Section

I kept this short and focused. I explained what tools I used (Python, Pandas, Matplotlib, VS Code) and why I chose them. I made sure to connect my choice of open-source tools back to my research focus on accessibility. Final length was about 180 words.

Results Section

This one went through the biggest change. My first version was over 1,100 words and had a lot of interpretation mixed in with the data. I had to cut out all the "what this means" stuff and just present the facts. I basically said "here's what the data shows" without explaining why it matters - that's what the Discussion is for. Cut it down to about 500 words.

Discussion Section

This was the longest section at first (1,800 words), but I had to shorten it. The main issues were:

- I was repeating stuff that belonged in the Conclusion
- I needed to make it sound more positive without being dishonest
- Finding the right balance between professional and natural

I went through each figure systematically and explained what it meant. I justified why I used the methods I did. I was honest about limitations. The final version was about 850 words.

Conclusion

I wrote this last. My first draft was too long (750 words) for an undergraduate paper, so I condensed it to about 400 words. I made sure to:

- Summarize what I found
- Explain why it matters for food security
- Give some ideas for future research
- End with a strong statement about how this is achievable if we take action

Getting the Tone Right

This was tricky. At one point my writing was "too glazed" (way too enthusiastic), so I toned it down. I also wanted it to sound like a real person wrote it, not a robot, but still be professional enough for academic work. And I wanted to be positive about AI's potential while still being realistic about the challenges. Took a few rounds of edits to get this balance right.

Phase 5: Formatting Everything

LaTeX Formatting

I had to go through every section and add backslashes before percent signs and dollar signs. It was tedious but necessary:

- Changed every `%` to `\%`
- Changed every `to\`

Made sure all sections were properly formatted so the paper would compile correctly.

Citations

I used Vancouver style for my 10 sources. This was a bit annoying because some sources didn't have clear publication dates, and the NCBI article needed special formatting. But I got it done and made sure everything was consistent.

Figure Placeholders

I created clear spots in the text where each figure should go using dashed lines and labels. This made it easy to see where everything fits when I'm putting the final document together.

Phase 6: Final Checks

Word Count

- Introduction: ~300 words
- Methods: ~180 words

- Results: ~500 words
- Discussion: ~850 words
- Conclusion: ~400 words
- **Total:** ~2,030 words

This seemed like a good length for an undergraduate research paper.

Making Sure Everything Was There

I went through a checklist:

- Abstract
- Introduction with research question
- Methods explaining what I did
- Results with 6 figures
- Discussion interpreting the findings
- Conclusion with implications
- Acknowledgements for Mr. Wang
- References in Vancouver style

Checking for Consistency

I read through everything to make sure:

- The sections flowed logically
- I wasn't repeating myself between Discussion and Conclusion
- The tone was consistent
- All the LaTeX formatting was correct
- Figure references made sense
- I cited data accurately

Phase 7: Trifold

Looking Back

What Went Well

- Using open-source tools was perfect for this topic
- The six figures really helped tell the story
- Going through each figure in the Discussion made my argument clear
- I found a good balance between showing AI's potential and the accessibility problems

What I'd Do Differently

- Include more countries in the irrigation analysis
- Try to get some actual farmer interviews for qualitative data
- Pay attention to word count earlier instead of having to cut things later
- Find more data sources beyond just industry reports

Why This Matters

My research shows that AI really could help solve food security problems, but the way we're doing it now might actually make inequality worse. The good news is that the barriers I found (internet, electricity, training) are things we can actually fix. If we're smart about policies and make the technology more accessible, AI could help all farmers, not just the rich ones.

What's Next

If someone wanted to continue this research, they could:

1. Actually test AI on small farms in developing countries
2. Track adoption rates over several years to see if things are getting better or worse
3. Figure out the real costs for small farms to adopt AI
4. Look at what government policies actually work to make technology more accessible

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