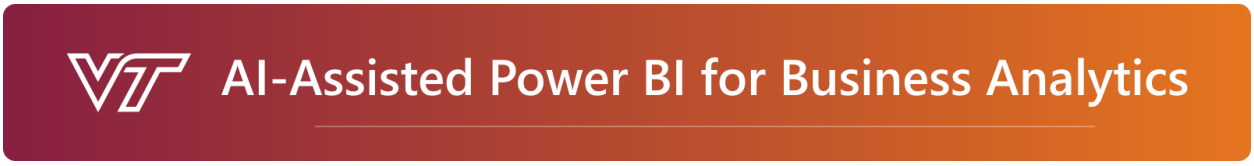

Figure 1: AI-Assisted Power BI for Business Analytics

Lab AIRS-02: AI Readiness Growth Analysis

Module 6: Real-World Deployment

Duration: 45 minutes **Platform**: airs.correax.com + Power BI **Deliverable**: Growth reflection + cohort analysis

Learning Objectives

By the end of this lab, you will be able to:

- Complete a post-course assessment and measure personal growth
- Apply Power BI skills to analyze real psychometric data
- Calculate and interpret effect sizes (Cohen's d)
- Visualize pre-post changes across multiple dimensions
- Draw evidence-based conclusions about learning effectiveness

Part 1: Post-Course Assessment (15 min)

Step 1: Retake the AIRS-16 (5 min)

1. Navigate to airs.correax.com/assessment
2. Log in with your **same @vt.edu email** from Module 1
3. Complete the 16-item assessment again
4. Answer based on how you feel **now**, after completing the course

Step 2: Personal Growth Comparison (5 min)

The platform shows your pre-post comparison. Record in your Prompting Journal:

Construct	Pre (T1)	Post (T2)	Change
Performance Expectancy (PE)			
Effort Expectancy (EE)			
Social Influence (SI)			
Facilitating Conditions (FC)			
Hedonic Motivation (HM)			
Price Value (PV)			
Habit (HB)			
Trust in AI (TR)			

Step 3: Reflection on Growth (5 min)

Answer in your Prompting Journal:

1. **Largest increase**: Which construct grew most? What course experience drove this?
2. **Unexpected finding**: Did any score decrease or stay flat? Why?

3. **Goal check**: Review your Module 1 goal. Did you achieve it?
4. **Most valuable lesson**: What single insight from this course most changed your view of AI?

Part 2: Cohort Data Analysis (30 min)

Now apply your Power BI skills to analyze anonymized class data.

The Datasets

Your instructor will provide **two CSV files** via Canvas:

File 1: `AIRS_VT_Cohort_Anonymized.csv` — Raw participant data

Column	Description
`participant_id`	Anonymous identifier
`PE_pre`, `PE_post`	Performance Expectancy scores
`EE_pre`, `EE_post`	Effort Expectancy scores
`SI_pre`, `SI_post`	Social Influence scores
`FC_pre`, `FC_post`	Facilitating Conditions scores
`HM_pre`, `HM_post`	Hedonic Motivation scores
`PV_pre`, `PV_post`	Price Value scores
`HB_pre`, `HB_post`	Habit scores
`TR_pre`, `TR_post`	Trust in AI scores
`BI_pre`, `BI_post`	Behavioral Intention (mean of 4 items, 1-5)

File 2: `AIRS_Analysis_Results.csv` — Pre-computed statistics

Column	Description
`Construct`	Construct code (PE, EE, etc.)
`Pre Mean`, `Post Mean`	Average scores
`Change`	Mean difference
`Cohen's d`	Effect size
`Effect`	Interpretation (Small/Medium/Large)
`Significant`	Stars indicating $p < .05/.01/.001$

> **Why two files?** Statistical tests (t-tests, p-values) require Python or R, which aren't fully supported in Power BI Online. The instructor pre-computed these so you can focus on visualization.

Exercise 1: Calculate Change Scores

Create calculated columns for each construct:

```
PE_change = PE_post - PE_pre
EE_change = EE_post - EE_pre
... (repeat for all 8 constructs)

// AIRS Score (sum of 8 construct means, range 8-40)
AIRS_pre = PE_pre + EE_pre + SI_pre + FC_pre + HM_pre + PV_pre + HB_pre + TR_pre
AIRS_post = PE_post + EE_post + SI_post + FC_post + HM_post + PV_post + HB_post + TR_post
AIRS_change = AIRS_post - AIRS_pre

// Behavioral Intention change
BI_change = BI_post - BI_pre
```

Questions: 1. What is the average AIRS change across all students? 2. What percentage of students showed positive BI change?

Exercise 2: Visualize Pre-Post Comparison

Create a **clustered bar chart** showing: - X-axis: 8 constructs - Y-axis: Average score - Two bars per construct: Pre (blue) and Post (green)

Question: Which constructs show the largest visual difference?

Exercise 3: Calculate Effect Sizes

Cohen's d measures practical significance:

`d = (Mean_post - Mean_pre) / SD_pooled`

Where pooled SD average of pre and post standard deviations.

Use DAX measures:

```
PE_Cohen_d =
VAR mean_diff = AVERAGE(AIRS[PE_post]) - AVERAGE(AIRS[PE_pre])
VAR sd_pre = STDEV.P(AIRS[PE_pre])
VAR sd_post = STDEV.P(AIRS[PE_post])
VAR sd_pooled = (sd_pre + sd_post) / 2
RETURN DIVIDE(mean_diff, sd_pooled)
```

Interpretation Guide: | Cohen's d | Effect Size | |———–|————-| | 0.2 | Small | | 0.5 | Medium | | 0.8 | Large |

Question: Which constructs have medium or large effect sizes?

Exercise 4: Individual Growth Classification

Create a measure to categorize students:

```
Growth_Category =
VAR AIRS_change = [AIRS_post] - [AIRS_pre]
RETURN
    SWITCH(TRUE(),
        AIRS_change >= 6, "High Growth",
        AIRS_change >= 2, "Moderate Growth",
        AIRS_change >= -2, "Stable",
        "Declined"
    )
```

Create a **pie chart** showing distribution of growth categories.

Question: What percentage of students showed "High Growth"?

Exercise 5: Statistical Summary Table

Load `AIRS_Analysis_Results.csv` and create a **table visual** showing:

Construct	Pre Mean	Post Mean	Cohen's d	Effect	Significant

Format the table: - Center-align numeric columns - Add conditional formatting: green for Large effects, yellow for Medium - Sort by Cohen's d descending

Question: Which constructs showed the largest effect sizes? Were all changes statistically significant?

Exercise 6: Correlation Insight (Bonus)

Using the cohort data, create a **scatter plot**: - X-axis: `AIRS_change` (sum of all change scores) - Y-axis: `BI_post` (Behavioral Intention at course end)

Add a trendline.

Question: Is there a relationship between AI readiness growth and intent to adopt AI tools?

Expected Analysis Output

The visualization below shows what a complete analysis should look like. Your Power BI report should produce similar insights:

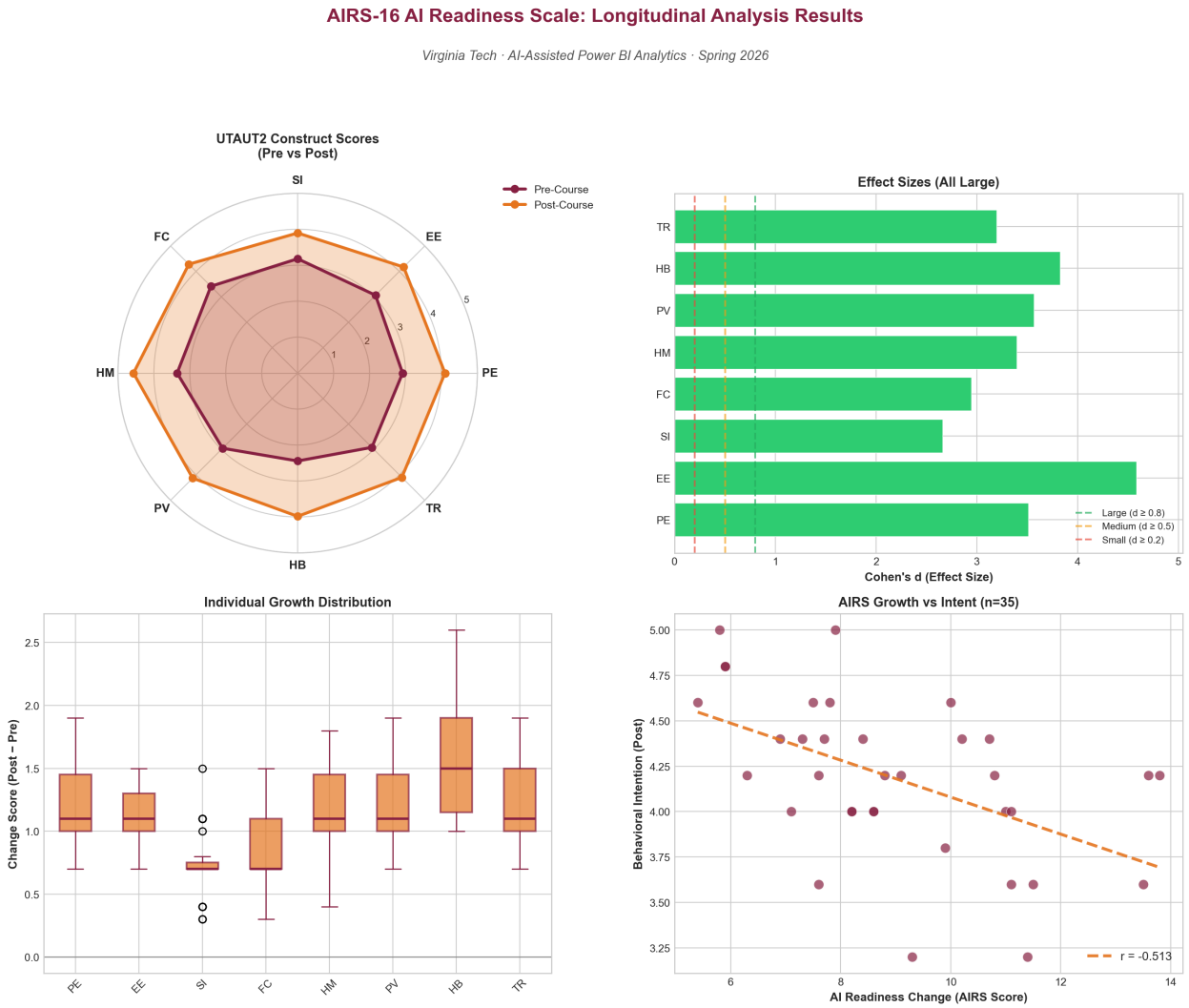

Figure 2: AIRS-16 Longitudinal Analysis Results

Panel Interpretation:

Panel	What It Shows	Key Insight
Top-Left (Radar)	Pre/post scores across all 8 UTAUT2 constructs	The orange polygon (post) should expand beyond the maroon polygon (pre), indicating growth across all dimensions
Top-Right (Effect Sizes)	Cohen's d values with threshold lines	All bars exceeding the green dashed line (d 0.8) indicate practically significant Large effects
Bottom-Left (Box Plots)	Distribution of change scores per construct	Positive medians confirm consistent growth; narrow boxes indicate uniform learning outcomes
Bottom-Right (Scatter)	Relationship between AIRS change and Behavioral Intention	A positive correlation indicates students who improved on AIRS show stronger intent to adopt AI tools

> **Note**: Your individual Power BI visualizations may use different chart types (clustered bars, tables) but should reveal similar patterns.

Deliverable: Analysis Summary

Create a one-page **Executive Summary** (use the template from Lab 5):

Sections: 1. **Headline Finding**: Most impactful result in one sentence 2. **Pre-Post Comparison**: Bar chart visual 3. **Effect Sizes**: Table with Cohen's d values 4. **Key Insight**: What does this tell us about AI education effectiveness? 5. **Limitations**: Sample size, self-report bias, no control group

Completion Checklist

- ☐ Completed post-course AIRS-16 assessment
- ☐ Recorded personal pre-post scores in Prompting Journal
- ☐ Loaded anonymized cohort data into Power BI
- ☐ Created change score columns for all 8 constructs
- ☐ Built pre-post comparison visualization
- ☐ Calculated Cohen's d effect sizes
- ☐ Created growth category classification
- ☐ Wrote executive summary (1 page)

Research Contribution

Your analysis contributes to understanding how structured AI coursework impacts readiness. Findings may inform:

- Future course design improvements
- Research publication on AI education effectiveness
- Evidence base for AI training programs in organizations

Thank you for participating in this research study.

Further Reading

- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum.
- Lakens, D. (2013). Calculating and reporting effect sizes to facilitate cumulative science. *Frontiers in Psychology*, 4, 863.
- Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology. *MIS Quarterly*, 36(1), 157-178.

This lab completes the longitudinal research component of the course. Your growth demonstrates the value of hands-on AI learning.