**Unit 8 – Inference and Hypothesis Testing**

**Objective**

This unit introduced the logical and mathematical foundations of statistical inference—the process of drawing conclusions about a population from sample data.  
The exercise explored the four stages of hypothesis testing:

1. Stating hypotheses (H₀ and H₁)
2. Setting the level of significance (α)
3. Computing the test statistic
4. Making the decision and interpreting results

Through this structured framework, I learned how to make data-driven judgments while controlling for potential error, a crucial practice for any research involving quantitative analysis—particularly when assessing information system adoption patterns among SMEs.

**Step 1 – Stating the Hypotheses**

In hypothesis testing, we start with a null hypothesis (H₀), which represents the assumption of no effect or difference. For example:

*H₀: The population mean daily TV viewing time for children is 3 hours.*

The alternative hypothesis (H₁) reflects what the researcher suspects might be true:

*H₁: The mean daily TV viewing time differs from 3 hours (μ ≠ 3).*

This step mirrors the “presumption of innocence” principle—H₀ is assumed true until sufficient evidence suggests otherwise.

In my future project, this principle applies when evaluating SME behaviour:

*H₀: Digital adoption has no significant effect on SME productivity.*  
*H₁: Digital adoption increases SME productivity.*

**Step 2 – Setting the Criteria for the Decision**

The level of significance (α) defines how much evidence we require to reject H₀.  
Common thresholds include α = 0.05 (5%) for behavioural studies and α = 0.01 (1%) for medical or high-risk research.

If the computed p-value is lower than α, we reject H₀.  
This means that the observed data are unlikely if the null hypothesis were true.

| Decision Rule | Interpretation |
| --- | --- |
| p ≤ α | Reject H₀ (evidence supports H₁) |
| p > α | Fail to reject H₀ (insufficient evidence) |

In practical terms, α defines the tolerance for Type I error—wrongly rejecting a true null hypothesis.

**Step 3 – Computing the Test Statistic**

The test statistic measures how far the sample mean is from the hypothesised population mean in standard error units.

This provides a standardised metric to assess whether the observed difference is large enough to be considered statistically significant, given the variability in the data.

In Excel, this is operationalised using functions like T.TEST() or via the Data Analysis Toolpak, as practiced in Unit 7.

For example, if children’s mean TV time is 4 hours (vs. hypothesised 3), a large t-statistic indicates the difference is unlikely due to random sampling.

**Step 4 – Making a Decision**

Based on the computed p-value, we decide:

* Reject H₀: Evidence suggests the sample mean is significantly different.
* Fail to reject H₀: Evidence is insufficient; sample results could occur by chance.

This decision-making process parallels real-world policy or managerial choices based on statistical evidence.

For instance, in my SME IS study, I might test:

*H₀: There is no difference in productivity between SMEs using digital tools and those not using them.*  
*Decision:* If p < 0.05, reject H₀ → infer that digital tools significantly improve productivity.

**Type I and Type II Errors**

The framework acknowledges two possible decision errors:

| Reality | Decision: Accept H₀ | Decision: Reject H₀ |
| --- | --- | --- |
| H₀ is true | Correct | Type I error (α) |
| H₀ is false | Type II error (β) | Correct |

* Type I error (α): Concluding a difference exists when it doesn’t (false positive).
* Type II error (β): Failing to detect a real difference (false negative).

The power of a test (1 − β) reflects the likelihood of correctly rejecting a false null hypothesis—improving with larger sample sizes and lower variance.

**Ethical and Practical Considerations**

The worksheet also emphasised research integrity:

* Hypotheses must be pre-registered before data inspection to prevent bias.
* Choosing a one-tailed test *after* viewing results is statistically dishonest, as it inflates the apparent significance (effectively doubling α).
* Statistical testing does not “prove” or “disprove” a hypothesis; it only quantifies uncertainty.

These cautions directly relate to ethical reporting, as discussed in Unit 7’s Abi case. Data analysts must avoid misusing tests to “find significance” or to confirm pre-existing beliefs.

**Reflection**

This unit clarified that hypothesis testing is not about *proving truths*, but about managing uncertainty through structured reasoning.  
I realised how inference connects technical analysis to decision-making ethics—each p-value represents a judgment about evidence strength, not absolute truth.

For my future project, I will:

* Clearly state null and alternative hypotheses before analysis.
* Choose significance levels consistent with research risk.
* Report both p-values and effect sizes transparently.
* Interpret outcomes conservatively, acknowledging limitations.

**Skills Developed**

| Skill | Description |
| --- | --- |
| Hypothesis formulation | Defining clear, testable research questions |
| Critical statistical reasoning | Understanding probability, errors, and significance |
| Ethical analysis | Avoiding bias in statistical decision-making |
| Application of Excel tools | Using Data Analysis Toolpak for inferential testing |
| Research transparency | Aligning quantitative methods with professional integrity |

**Conclusion**

Through this inference exercise, I developed a conceptual foundation for evidence-based research.

It bridged the gap between numerical computation and ethical interpretation, reinforcing that data analytics is not merely about numbers, but about trust, integrity, and informed decision-making.