Optimising Defence Testing Efficiency: A Risk-Adapted Approach Using Sequential Testing, Bayesian Inference, and AI Integration

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INTRODUCTION

This presentation explores advanced statistical methodologies in Defence T&E, focusing on optimising resources and decision-making.

Defence testing challenges.

•The need for adaptive methods.

•Future-facing methodologies: Bayesian Inference, AI, Sequential Testing.

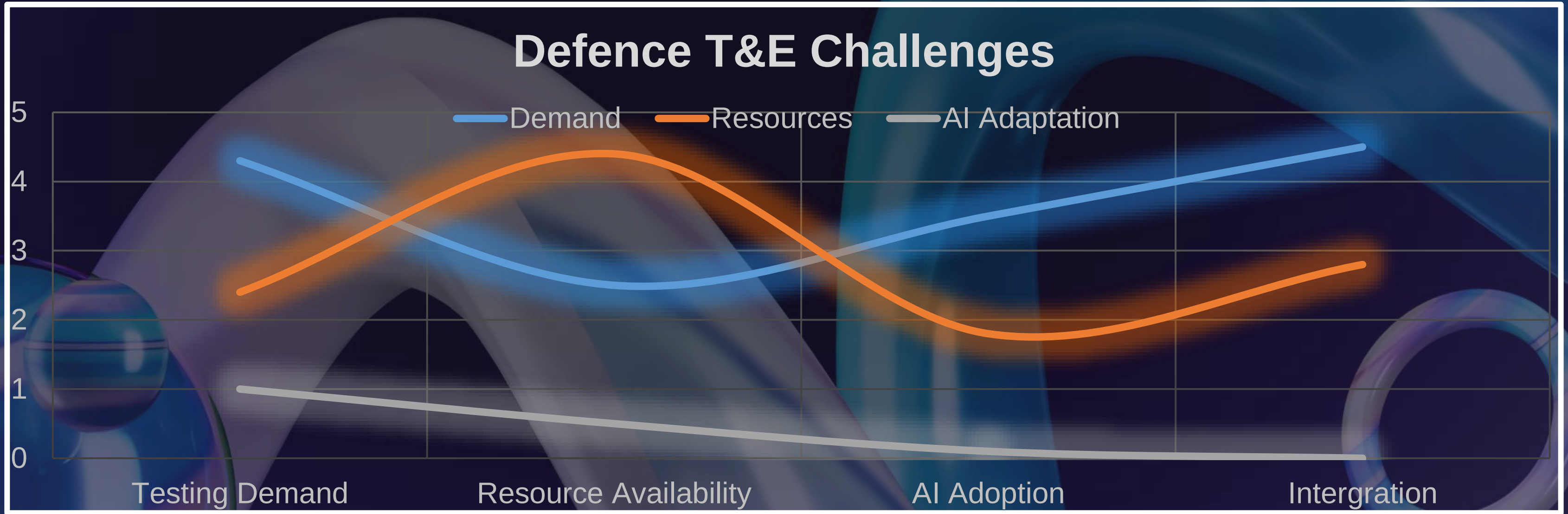
Challenges in Modern Defence T&E

Excessive Testing Demand

Resource Constraints and Backlogs

Traditional Methods Vs Progressive Innovation

Slow Adaptation to AI and Modern Techniques



Adaptive Statistical Frameworks

BINOMIAL SAMPLING

Strengths and weaknesses in defect detection.

BAYESIAN INFERENCE

Updating probabilities as new data is gathered.

STRATIFIED SAMPLING with FPC

The benefit of dividing populations into subgroups for improved precision.

SEQUENTIAL TESTING

Iterative testing to reduce sample size and testing time

BINOMIAL SAMPLING

Binary outcomes: Pass or Fail.

$$n = \frac{Z^2\, p\,(1 - p)}{E^2}$$

$$n_{adj} = n \frac{n}{1 + \frac{n-1}{N}}$$

Sample Size Determined → Test Each Item → Pass or Fail

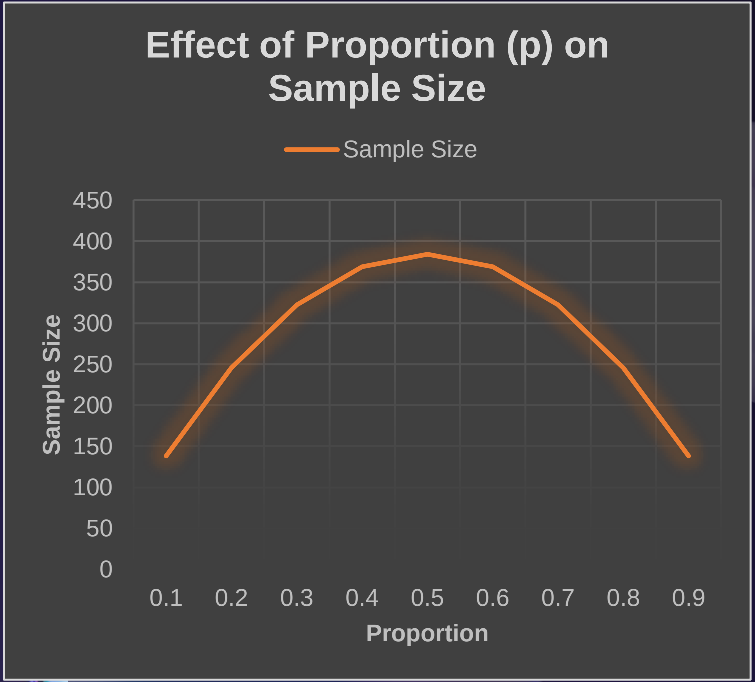
BINOMIAL SAMPLING

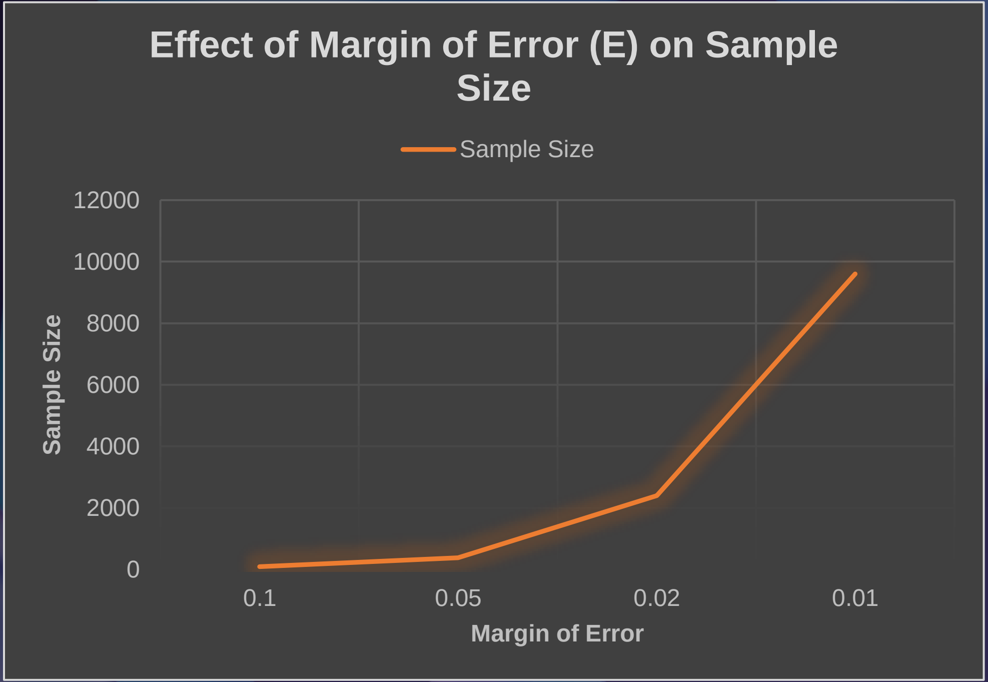
$$n = \frac{Z^2 p(1-p)}{E^2}$$

n =	384.16
Z = Z-Value	1.96
p =	0.50
E =	0.05

Binomial sampling Single LOT

LOT/Serial Number	Stock Balance	Binomial Sampling (Rounded)
Mech Parts 1	1600	384.16
Population N total	**1600**	





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ADVANCED BINOMIAL SAMPLING: INTEGRATING STRATIFIED SAMPLING WITH FPC

LOT/Serial Number	Stock Balance	Binomial Sampling (Rounded)	Binomial Proportion Adjusted (FPC)
Mech Parts 1	1600	78	74
Mech Parts 2	1323	64	61
Mech Parts 3	1188	58	55
Mech Parts 4	385	19	18
Mech Parts 5	1123	55	52
Mech Parts 6	265	13	12
Mech Parts 7	923	45	43
Mech Parts 8	301	15	14
Mech Parts 9	759	37	35
Mech Parts 10	31	2	1
Population N total	**7898**	**386**	**365**

$$n_{adj}^{i} = \frac{n\,\frac{N_i}{N_{total}}}{1 + \frac{n\,\frac{N_i}{N_{total}} - 1}{N_i}}$$

What is Acceptance Quality Level (AQL)

Definition

AQL defines the maximum percentage of defective items acceptable in a batch.

Key Use

Ensures quality control without testing 100% of items.

Why It Matters

Balances quality with efficient resource use.

Mechanics of AQL in Testing

LOT/Serial Number	Stock Balance	AQL (%)	AQL-based binomial sampling	Allowable Defects
Mech Parts 1	1600	**1.5**	23	0
Mech Parts 2	1323	**2.0**	30	1
Mech Parts 3	1188	**1.8**	27	0
Mech Parts 4	385	**1.6**	24	0
Mech Parts 5	1123	**1.5**	23	0
Mech Parts 6	265	**2.0**	30	1
Mech Parts 7	923	**1.7**	26	0
Mech Parts 8	301	**1.5**	23	0
Mech Parts 9	759	**1.5**	23	0
Mech Parts 10	31	**2.0**	30	0
Population N total	**7898**		**259**	

n = 384.16

n_adj = 365.00

AQL = 259

Advanced AQL Mechanics: Incorporating Stratified Sampling

Sampling Plan:

LOT/Serial Number	Stock Balance	AQL (%)	AQL-based binomial sampling	FPC Adjusted	Stratified Adjusted	Defects Allowed
Mech Parts 1	1600	**1.5**	23	23	5	0
Mech Parts 2	1323	**2.0**	30	29	5	1
Mech Parts 3	1188	**1.8**	27	26	4	0
Mech Parts 4	385	**1.6**	24	23	1	0
Mech Parts 5	1123	**1.5**	23	23	3	0
Mech Parts 6	265	**2.0**	30	27	1	1
Mech Parts 7	923	**1.7**	26	25	3	0
Mech Parts 8	301	**1.5**	23	21	1	0
Mech Parts 9	759	**1.5**	23	22	2	0
Mech Parts 10	31	**2.0**	30	16	0	1
Population N total	**7898**		**259**	**235**	**25**	

BAYESIAN INFERENCE
AND
SEQUENTIAL SAMPLING

$$P(H|E) = \frac{P(E|H)\,P(H)}{P(E)}$$

$$\Lambda_n = \frac{P(data\ collected\ so\ far|H_1)}{P(data\ collected\ so\ far|H_0)}$$

WHAT IS BAYESIAN INFERENCE

Bayesian inference updates probabilities based on new data.

$$P(H|E) = \frac{P(E|H)\,P(H)}{P(E)}$$

P(H|E): Posterior Probability (updated belief)

P(E|H): Likelihood (evidence given the hypothesis)

P(H): Prior Probability (initial belief)

P(E): is the marginal likelihood, the total probability of the evidence.

Impact of Prior Probabilities on Bayesian Updates

Stock Balance	Prior Probability	Fail	Log - Likelihood	Posterior Probability
1600	0.50	2	-23.4803396618	3.17386E-11
1323	0.50	2	-19.2659197225	2.14727E-09
1188	0.50	3	-17.4597397485	1.30708E-08
385	0.50	0	-5.7195699176	0.001640561

Stock Balance	Prior Probability	Fail	Log - Likelihood	Posterior Probability
1600	0.10	2	-5.4775692826	0.000417948
1323	0.10	2	-4.8369644148	0.000793109
1188	0.10	3	-5.5166619808	0.000401924
385	0.10	0	-0.8693923207	0.041920621

Sequential Testing in Practical Applications

$$\Lambda_n = \frac{P(data\ collected\ so\ far|H_1)}{P(data\ collected\ so\ far|H_0)}$$

Sequential testing allows us to make real-time decisions with fewer samples, enhancing efficiency and saving resources..

Likelihood: The probability of observing the test results under a specific hypothesis.

Cumulative Failures: Total failures observed during the testing process.

Cumulative Likelihood: Sum of probabilities indicating the progression towards a decision.

Decision Threshold: Predefined criteria that determine when the testing stops.

Sequential Testing in Practical Applications

Likelihood	Test Stage	Sequential Testing Cumulative Failures	Cumulative Likelihood	Decision Threshold
0.009999679	1.010049843	2	0.009999679	Continue
0.029344459	1.029779251	2	0.039344138	Continue
0.093902606	1.098452758	3	0.133246744	Continue
0.135085172	1.144634271	0	0.268331916	Continue
0.018597656	1.018771669	1	0.286929571	Continue
0.254186583	1.289412364	0	0.541116154	Continue
0.008727964	1.008766163	0	0.549844118	Continue
0.343151887	1.409382812	1	0.892996005	Continue
0.083355078	1.086927684	1	0.976351083	Stop
0.81	2.247907987	0	1.786351083	Stop

AI-Enhanced Sampling - Modern Approach (General Overview)

- Optimisation of Sample Size
- Real-time Bayesian Updating
- AI-Assisted Stratified Sampling
- Pattern Recognition in Defect Detection
- Predictive Modelling for Defect Rates
- AI-Driven Sequential Testing
- Digital Twins and Simulation

AI-Enhanced Sampling - Modern Approach (Key Benefits)

- AI integrates automation and predictive analytics into sampling strategies.
- Optimises test plans based on real-time data patterns and risk profiles.
- Enables dynamic adaptation to changing testing conditions.

Key Benefits:

- Reduces manual intervention and accelerates decision-making.
- Predicts failure patterns and prioritises critical areas for testing.

CONCLUSION

Traditional methods like Binomial Sampling are resource-intensive for complex systems.

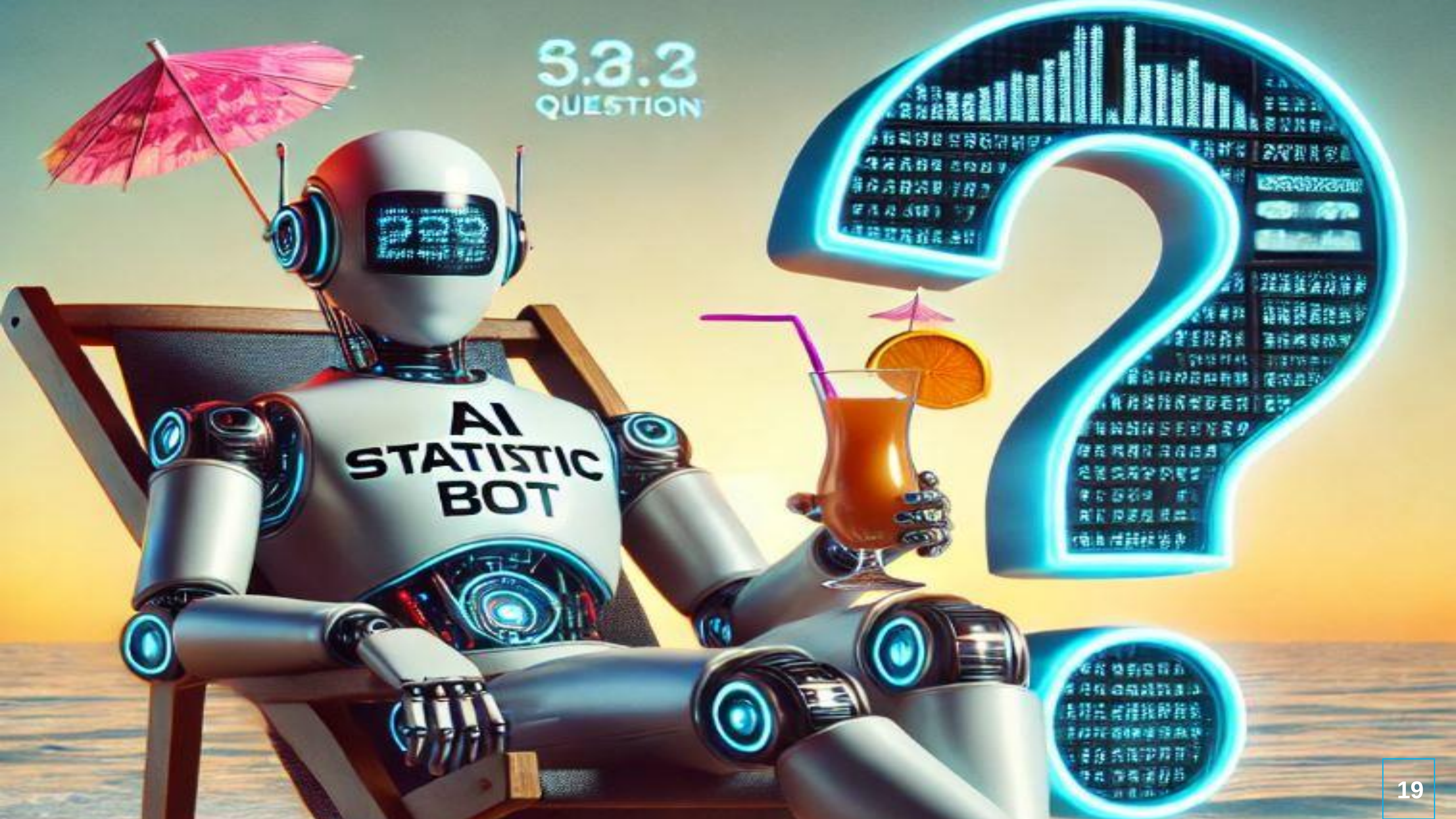
Adaptive methodologies (Bayesian, Sequential) reduce sample sizes and improve efficiency.

AI-Enhanced Strategies provide a flexible, data-driven approach for Defence T&E.

Recommendations:

- Implement a hybrid framework combining Bayesian and AI methodologies.
- Use Sequential Testing for high-risk, resource-sensitive environments.

Sampling Method	Sample Size	Decision Time	Resource Intensity	Key Strengths	Key Limitations
Binomial Sampling	Large (proportional to population size)	Fixed, all samples must be tested	High (particularly for destructive testing)	Straightforward, well-established methodology	Resource-intensive, not suitable for small populations or destructive testing
Bayesian Inference	Adaptive, can start with a smaller sample and adjust as data is collected	Continuous, decisions can be made as more data comes in	Lower	Incorporates prior knowledge and real-time updates	May require more computational effort (if done manually)
Sequential Testing (SPRT)	Minimal, testing stops as soon as criteria are met	Early, testing stops when pass/fail criteria are met	Lower	Early decision-making, fewer samples required	More complex to set up and interpret
AI-Enhanced Sampling	Optimised in real-time based on predictive analytics	Dynamic, highly efficient	Very Low (automation reduces human intervention)	Predicts failure patterns and adapts to changing conditions	Initial setup for AI might require investment


QUESTION
AI
STATISTIC
BOT