Al and Testing

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Goals



UNDERSTAND AI'S ROLE IN SOFTWARE TESTING



DISCUSSION AND EXPLORE
AI'S CAPABILITIES AND
LIMITATIONS



ENGAGE IN HANDS-ON LEARNING

Why This Is a Hot Topic?

- 1. Rising Complexity of Software
 - Manual testing is time consuming
- Growing Use of Large Language Models Engineering
 - Test case generation
 - Bug localization
 - Debugging (LLM-driven testing process)

But AI Is Not Perfect! (YET?)

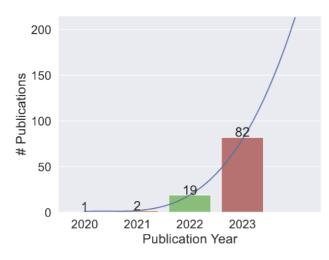


Fig. 3: Trend in the number of papers with year

[&]quot;Software testing with large language models: Survey, landscape, and vision." *IEEE Transactions on Software Engineering* (2024).

[&]quot;Evaluating large language models for software testing." Computer Standards & Interfaces 93 (2025): 103942.

Discussion

- •How was your experience using AI for test generation?
- •What were the strengths and weaknesses of Al-generated tests?
- •Did AI identify edge cases correctly?
- •Did Al generate any incorrect tests?
- •What improvements/points would you suggest to consider for better result?

Al in Software Testing – Capabilities

1. Higher Readability & Usability

Developers found Al-generated tests easier to understand.

2. Decent Code Coverage

- Al-generated unit tests achieved comparable test coverage to manually written tests.
- Effectively complement manual testing by detecting additional errors.

3. Possible Improvements

 With iterative refinement (e.g., ChatTester), AI-generated tests improved compilability by 34.3% and assertion correctness by 18.7%.

Al can significantly improve test automation but still needs human verification.

[&]quot;No more manual tests? evaluating and improving chatgpt for unit test generation." arXiv preprint arXiv:2305.04207 (2023).

Al in Software Testing – Limitations

1. Correctness Issues

- 24.8% of AI-generated tests failed execution due to syntax or assertion errors.
- Al sometimes generated invalid assertions that didn't match program logic.

2. Security Risks and Mocking Issues

- AI fails at generating security tests like SQL injection detection, Mock when needed, unless explicitly trained.
- Misses edge cases that are critical in penetration testing.

TABLE 3: Performance of unit test case generation

Dataset	Correctness	Coverage	LLM	Paper
5 Java projects from Defects4J	16.21%	5%-13% (line coverage)	BART	[26]
10 Jave projects	40%	89% (line coverage), 90% (branch coverage)	ChatGPT	[36]
CodeSearchNet	41%	N/A	ChatGPT	[7]
HumanEval	78%	87% (line coverage), 92% (branch coverage)	Codex	[39]
SF110	2%	2% (line coverage), 1% (branch coverage)	Codex	[39]

Note that, [39] experiments with Codex, CodeGen, and ChatGPT, and the best performance was achieved by Codex.

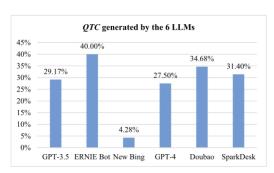


Fig. 2. Quality of test cases (QTC) generated by the six large language models

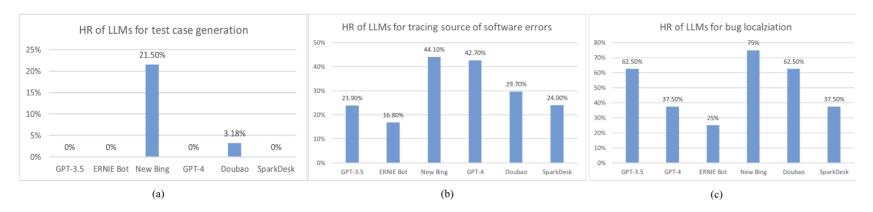
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Al in Software Testing – Limitations

1. Contextual Understanding is Limited

- Al often misinterprets business logic, leading to functionally useless test cases.
- Al is prone to hallucinations!



Al-generated tests are not always reliable—human oversight is needed to correct and refine them.

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Class Activity- Al-Based Testing for Authentication Service

Similar to HW3, maybe a bit complex code to practice mocking ©

You will test a simplified Authentication Service that includes:

- AuthService: Handles login, signup, and session management.
- User: Represents individual user accounts.
- UserStorage: Handles database queries. (Which needs to be mocked)

Steps for the Activity

- 1. Review and Understand Code
- 2. Generate Al-Based Test Cases
- 3. Run & Evaluate the Tests

Comparison of Als

ChatGPT-4o

8 test cases, 5 failed

Name	Stmts	Miss	Cover	Missing
auth_service.py	49	32	35%	13-14, 18-20, 24-26, 30-39, 42-57, 60-61
user.py	62	25	60%	35-42, 50-53, 56-61, 64-70, 73-76
TOTAL	170	79	54%	

ChatGPT

16 test cases, 3 failed

Name	Stmts	Miss	Cover	Missing
auth_service.py	49	9	82%	 24-26, 32, 34, 36, 50-52
user.py	62	25	60%	35-42, 50-53, 56-61, 64-70, 73-76
TOTAL	215	53	75%	

Copilot

8 test cases, all pass

Name	Stmts	Miss	Cover	Missing
auth_service.py	49	8	84%	32, 34, 36, 44, 47, 50-52
user.py	62	35	44%	10-11, 14-32, 35-42, 45-53, 56-61, 64-70, 73-76
TOTAL	172	44	74%	

projector

desk

