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ANALYSIS OF GUI TESTING AND E-RECRUITMENT SITE PERFORMANCE USING KATALON STUDIO AND JMETER WITH TWO WAY ANOVA METHOD

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ABSTRACT

A Graphical User Interface (GUI) is a method of interaction between users and software that displays a graphical interface easily understood by users when operating a system. It can measure the quality of a site. However, in addition to the GUI that can affect the quality of a website, performance can also affect the quality of a website. Performance is a process carried out to evaluate the performance of a website when the traffic load is high. This study aims to analyze the differences in GUI quality and performance on five e-recruitment platforms, namely Jobstreet, LinkedIn, Karir.com, Glints, and Kalibrr, using the Two-Way ANOVA method. GUI testing with Katalon Studio showed that JobStreet and Karir.com had high response times on the Login and Profile features due to difficulty in recognizing complex elements. Glints failed on the second and third tests in the Sign Up feature, while LinkedIn showed a high response time due to difficulty in recognizing attributes in the Search for Jobs feature, and Kalibrr appeared stable. Performance testing with JMeter, Jobstreet, Karir.com, and Kalibrr showed stable performance with low response time, stable throughput, and a 0% error rate. Glints experienced a 100% error rate because access was denied with a 403 code of “Forbidden”, while LinkedIn showed a spike in error rate as the number of threads increased. Two-way ANOVA analysis showed that in GUI testing, there were significant differences in response time and success rate based on application and feature. In performance testing, response time and error rate also showed significant differences, but throughput did not show significant differences by application and feature.

Keyword: Analysis, GUI Testing, Performance Testing, E-Recruitment, Two Way Anova, Katalon Studio, JMeter.

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1. INTRODUCTION

The development of technology and communication (ICT) has changed the way we interact, work, shop, and communicate with the world around us. One of the main impacts of technological developments is on the human resource management (HRM) sector. The innovation that has been applied to the human resource management (HR) sector is e-recruitment. E-recruitment is an innovation that facilitates job seekers and companies through the internet.

According to Jakpat's survey results, the most widely used job vacancy platform by job seekers is Jombstreet with a percentage of 51.4%, LinkedIn ranks second as the most widely used job search platform with a percentage of 38%, then as many as 22.9% of respondents use karir.com.

As many as 10.7% of respondents use Glints to find job vacancies. While the last place is Kalibrr, which is used by 9.2 respondents [1] This popularity is also influenced by the quality of the system offered, including the ease of the graphical interface (GUI) and optimal application performance. System quality can be measured by measuring tools considered to design user satisfaction through system convenience, access speed, system reliability, flexibility, and system security [2].

Graphical User Interface (GUI) is a way of interacting between users and software, which displays a graphical interface that is easily understood by users when operating a system. GUI testing aims to measure the functional capabilities of GUI widgets and affects the quality of the system [3]. However, in addition to the GUI, which can affect the quality of the website, performance can also affect the quality of the web. Performance is a process carried out to evaluate the performance of a website under high traffic loads. It aims to ensure that the website can provide fast response and optimal performance under high load to users [4].

GUI testing uses the Katalon Studio testing tool, which is an automated testing tool that supports a variety of platforms. The output generated in GUI testing is the response time and success status of the test case execution on each feature. Meanwhile, performance testing uses the Apache JMeter testing tool, which is an application to simulate user loads and also measure application responses. The output generated in performance testing is performance response time, throughput, and error rate. This study aims to determine the differences in GUI and performance using the Katalon Studio and Apache JMeter testing tools between platforms using the Two-Way ANOVA hypothesis test.

2. METHODS

2.1. Problem Identification and Literature Study

Problem identification is done through observations on Jobstreet, Glints, LinkedIn, Kalibrr, and Karir.com job vacancy sites to understand their performance and functionality in providing the best experience for users. Literature study was also conducted by reviewing previous research as a theoretical basis and reference in GUI and performance testing.

2.2. Pemilihan Objek Penelitian

In this study, the object of testing was chosen based on the results of the JakPat survey on the websites most used by job seekers in Indonesia. Therefore, this research has chosen the E-Recruitment website as the object of research. Among them are:

a. Jobstreet
b. Linkedin
c. Karir.com
d. Glints
e. Kalibrr

2.3. Testing

In this study, using the Software Testing Life Cycle (STLC) method, which is a series of systematically planned activities carried out during the software testing process to ensure that the software is fulfilled [5]. The following are the stages of STLC:

2.3.1 Requirement Analysis

This stage is the initial stage of the software testing life cycle (STLC) process. In this process, we analyze the requirements such as the software to be tested using the Katalon Studio tool, application features, and system requirements and specifications. The features tested are login, register, job search, and profile features.

2.3.2 Test Planning

Test planning is the stage of testing that has been prepared by testers so that the system to be tested can meet certain standards and can function properly [6]. In GUI testing using the Katalon Studio tool, which includes the success status of the test case (passed or failed) and also the response time (seconds). Meanwhile, performance testing uses Apache JMeter tools, which include performance response time (seconds), Throughput (seconds), and error rate (percent).

2.3.3 Test Case Development

Test case development is the stage where the tester or tester will perform actions on the system, input data on the system to be tested, and then compare the results provided by the system with the expected results.

a. GUI Testing

This GUI testing aims to ensure that each feature in the application functions according to predetermined specifications. The indicator used is the result of a successful or failed test case.

Table 1 GUI Testing Scenario

Test Case ID	Fitur	Test Type	Test Case Descriptioi	Expected Result	Status
TC_01	Login	Valid	User enters account data correctly	User can login with the entered account data	Passed/Failed
TC_05	Register	Invalid	User enters registered email address	The user cannot create an account and the system will display a notification	Passed/Failed
TC_07	Search Job	Valid	User enters keyword correctly	The system can display data according to the keywords entered by the user	Passed/Failed
TC_11	Profile	Invalid	User enters education data correctly	The system can add data that has been inputted	Passed/Failed

b. Performance Testing

This performance testing refers to the methodology used in the journal by Harijanto and Ariyanto (2021)[7], which tests application performance using Apache JMeter with various load scenarios. Meanwhile, the parameters used refer to the methodology used in the journal Suwarsono et al. (2022) [8] are response time, concurrent users, throughput, and error rate. It aims to provide the best service for users to feel satisfied and not experience interruptions such as errors or slow access services. The following are the performance testing parameters of the websites: jobstreet, linkedin, karir.com, kalibrr, glints.

Table 2 Performance Testing Parameters

Scenario	Number of Users	Ramp-up period (s)
1st measurement	200	200
2nd measurement	600	200
3rd measurement	1000	200

2.3.4 Test Environment Setup

At this stage are the requirements needed to run GUI testing using Katalon Studio and performance testing using Apache JMeter are listed. The following are the hardware and software specifications needed:

a. Hardware

1) Laptop LOQ 15IRH8
2) Processor Intel I7 gen 13 i7-13620, Computer Core 16 @2.4Ghz
3) Installed RAM 8.00 GB
4) 64-bit operating system, x64-based processor

b. Software

1) System Operation Windows 11
2) Katalon Studio & Katalon TestOps (GUI)
3) Browser Google Chrome
4) Java 19
5) Apache JMeter version 5.6.3 (Performance)
6) SPSS (Statistical Package for the Social Sciences)
7) Website Jobstreet, LinkedIn, Kalibrr, Karir.com, dan Glints

2.3.5 Test Execution

At this test execution stage, the tester or tester will run tests that have been made previously using the Katalon Studio tool for GUI testing and the Apache JMeter tool for performance testing.

2.3.6 Test Closure

In test closure, researchers will analyze the test results on jobstreet, LinkedIn, glints, kalibrr, and karir.com sites using Katalon Studio and Apache JMeter tools. The results of data analysis include a comparison of GUI response time and performance, successful execution of scenarios, throughput, and error rate from testing each application.

2.4. Hypothesis Testing

In testing this hypothesis, a sample of users from the five websites, jobstreet, linkedin, karir.com, kalibrr, and glints was taken. In the analysis using the two-way anova method, which is a statistical test used to analyze the difference between the means in more than two groups [9]. Therefore, this hypothesis testing tests the dependent variable.

2.4.1 GUI Hypothesis Testing

In testing the GUI hypothesis, the variables used are two independent variables and two dependent variables. The following are the dependent variables used.

a. Dependent Variable: Response Time

Response time is the time it takes for the system to respond to user actions, with output measured in milliseconds (ms). The independent variables in this study are applications and features, where applications are the object of GUI performance testing, and features include main functions such as login, register, search for vacancies, and profile. The statistical hypothesis for testing the dependent variable GUI response time is:

H0: There is no significant difference in GUI response time based on the websites and features of the five websites.

H1: There is a significant difference in GUI response time based on the websites and features of the five websites.

b. Dependent Variable: Success Status

Success status is a variable that shows whether a test case in the GUI test is successfully executed according to the scenario (passed) or not (failed). Application variables are used as GUI performance test objects, while features include login, register, vacancy search, and profile to see differences in GUI consistency between websites. The statistical hypothesis for testing the dependent variable of success status is:

H0: There is no significant difference in success status based on the websites and features of the five websites.

H1: There is a significant difference in success status based on the website and features of the five websites.

2.4.2 Performance Hypothesis Testing

In testing the performance hypothesis, the variables used are two independent variables and three dependent variables.

a. Dependent Variable: Response Time

Response time in performance testing is the time it takes for the system to respond to a user request, calculated from the time the request is sent until the response is received, and measured in milliseconds (ms). In this research, response time is used to see if the system remains stable and fast even if the user load increases. The independent variables used are the application as the test object and the main features such as login, register, vacancy search, and profile. The statistical hypothesis for testing the dependent variable response time is:

H0: There is no significant difference in response time based on the website and features of the five websites.

H1: There is a significant difference in response time based on the website and features of the five websites.

b. Dependent Variable: Throughput

Throughput is the number of requests the system can process per second (rps) or per byte (bps), and will increase with load until it reaches the maximum capacity of the network or server. The independent variables in this study are applications and features. The application is used as the object of performance testing, while the features include the main functions such as login, register, search for vacancies, and profile to see the difference in performance. The statistical hypothesis used in testing the dependent variable throughput is:

H0: There is no significant difference in throughput based on the website and features of the five websites

H1: There is a significant difference in throughput based on the website and features of the five websites.

c. Dependent Variable: Error Rate

Error rate indicates the system's ability to handle requests without failing, calculated as the ratio of failed requests to total requests, in percent. A high error rate indicates problems such as bottlenecks, crashes, or processing errors. The independent variables in this study are applications and features. The application is used as the object of performance testing, while the features include the main functions such as login, register, search for vacancies, and profile to see the difference in performance. The statistical hypothesis for testing the dependent variable error rate is:

H0: There is no significant difference in error rate based on the website and features of the five websites.

H1: There is a significant difference in error rate based on the websites and features of the five websites.

3. RESULTS AND DISCUSSION

3.1. GUI Test Execution Results

3.1.1. GUI Testing of E-Recruitment Website Jobstreet

Table 3 Jobstreet Website GUI Testing Results

Features	1st Testing		2nd Testing		3rd Testing	
	Response Time	Success Rate	Response Time	Success Rate	Response Time	Success Rate
Login	833 sec	3/3 (100%)	837 sec	3/3 (100%)	839 sec	3/3 (100%)
Register	826 sec	3/3 (100%)	817 sec	3/3 (100%)	817 sec	3/3 (100%)
Search	18 sec	2/2 (100%)	16 sec	2/2 (100%)	32 sec	2/2 (100%)
Profile	2631 sec	6/6 (100%)	2760 sec	6/6 (100%)	2618 sec	6/6 (100%)

Feature testing on the Jobstreet site showed significant variations in execution time. Login and Register features recorded an average of 836 seconds, and Profile averaged 2669 seconds, which was affected by OTP constraints and page elements that were difficult to recognize by Katalon Studio. In contrast, the Search feature showed the best performance with an average of 22 seconds. Despite the technical obstacles, all features were successfully run with a 100% success rate.

3.1.2. GUI Testing of E-Recruitment Website Glints

Table 4 Glints Website GUI Testing Results

Features	1st Testing		2nd Testing		3rd Testing	
	Response Time	Success Rate	Response Time	Success Rate	Response Time	Success Rate
Login	247 sec	3/3 (100%)	247 sec	3/3 (100%)	248 sec	3/3 (100%)
Register	203 sec	3/3 (100%)	204 sec	2/3 (66.67%)	211 sec	2/3 (66.67%)
Search	53 sec	2/2 (100%)	51 sec	2/2 (100%)	47 sec	2/2 (100%)
Profile	203 sec	6/6 (100%)	204 sec	6/6 (100%)	211 sec	6/6 (100%)

Testing the Login feature on the Glints website showed fast and consistent execution times (247-248 seconds) with a 100% success rate. The register feature was also efficient (203-211 seconds), but the success rate dropped to 66.67% due to the use of the same email in the second and third tests. Search feature recorded fast times (47-53 seconds) with 100% success, while the Profile feature performed well (203-211 seconds) with a full success rate in all six test cases.

3.1.3. GUI Testing of E-Recruitment Website LinkedIn

Table 5 LinkedIn Website GUI Testing Results

Features	1st Testing		2nd Testing		3rd Testing	
	Response Time	Success Rate	Response Time	Success Rate	Response Time	Success Rate
Login	35 detik	3/3 (100%)	40 detik	3/3 (100%)	35 detik	3/3 (100%)
Daftar	205 detik	3/3 (100%)	213 detik	3/3 (100%)	208 detik	3/3 (100%)
Search	663 detik	2/2 (100%)	664 detik	2/2 (100%)	666 detik	2/2 (100%)
Profile	205 detik	6/6 (100%)	213 detik	6/6 (100%)	208 detik	6/6 (100%)

Testing the Login feature on LinkedIn showed short and consistent execution times (35-40 seconds) with 100% success. The Sign Up feature was stable (205-213 seconds) with no failures. The search feature had a longer execution time (663-666 seconds) due to interface complexity, initial login requirements, and element detection constraints, but still ran successfully. The Profile feature also performed well with consistent response time (205-213 seconds) and 100% success rate.

3.1.4. GUI Testing of E-Recruitment Website Karir.com

Table 6 Karir.com Website GUI Testing Results

Features	Pengujian ke-1		Pengujian ke-2		Pengujian ke-3	
	Response Time	Success Rate	Response Time	Success Rate	Response Time	Success Rate
Login	15 sec	3/3 (100%)	15 sec	3/3 (100%)	15 sec	3/3 (100%)
Daftar	375 sec	3/3 (100%)	313 sec	3/3 (100%)	378 sec	3/3 (100%)
Search	14 sec	2/2 (100%)	30 sec	2/2 (100%)	16 sec	2/2 (100%)
Profile	757 sec	6/6 (100%)	1098 sec	6/6 (100%)	742 sec	6/6 (100%)

On the Karir.com site, the Login feature performed best with the fastest and most stable execution time (15 seconds) and 100% success. The Register feature was also fully successful despite using OTP, with a time of 313-378 seconds, and was considered superior to Jobstreet in handling OTP. Search feature recorded a fast and stable time (14-30 seconds) with 100% success. Meanwhile, the Profile feature showed full success, but the execution time was quite high, at 742-1,098 seconds.

3.1.5. GUI Testing of E-Recruitment Website Kalibrr

Table 7 Kalibrr Website GUI Testing Results

Features	Pengujian ke-1		Pengujian ke-2		Pengujian ke-3	
	Response Time	Success Rate	Response Time	Success Rate	Response Time	Success Rate
Login	247 sec	3/3 (100%)	247 sec	3/3 (100%)	247 detik	3/3 (100%)
Daftar	317 sec	3/3 (100%)	314 sec	3/3 (100%)	263 detik	3/3 (100%)
Search	49 sec	2/2 (100%)	38 sec	2/2 (100%)	43 detik	2/2 (100%)
Profile	424 sec	6/6 (100%)	315 sec	6/6 (100%)	320 detik	6/6 (100%)

The Register feature on Kalibrr showed stable execution times (263-317 seconds) with 100% success. Overall, Kalibrr performed well with a response time of 315-424 seconds. In comparison, the Profile feature on Karir.com showed unstable execution duration, ranging from 742 to 1,098 seconds.

3.2. Performance Test Execution Results

3.2.1. Performance Testing of E-Recruitment Website Jobstreet

Table 8 Jobstreet Website Performance Testing Results

Features	Scenario	Response Time	Throughput	Error Rate (%)
	200 Threads	0.619	1.0/detik	0%
Login	600 Threads	0.555	3.0/detik	0%
	1000 Threads	0.548	5.0/detik	0%
	200 Threads	0.427	1.0/detik	0%
Daftar	600 Threads	0.393	3.0/detik	0%
	1000 Threads	0.390	5.0/detik	0%
	200 Threads	0.924	1.0/detik	0%
Search	600 Threads	0.853	3.0/detik	0%
	1000 Threads	0.809	5.0/detik	0%
	200 Threads	0.273	1.0/detik	0%
Profile	600 Threads	0.255	3.0/detik	0%
	1000 Threads	0.241	5.0/detik	0%

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The results of performance testing with Apache JMeter show that all pages (login, register, vacancy search, and profile) can handle up to 1000 users without error (error rate 0%). Response time tends to decrease as load increases, while throughput increases. The login page dropped from 0.619 seconds to 0.548 seconds, the register page from 0.427 to 0.390 seconds, and the vacancy search from 0.924 to 0.809 seconds. The profile page recorded the fastest response time, from 0.273 to 0.241 seconds. These results prove the system remains stable under high load.

3.2.2. Performance Testing of E-Recruitment Website LinkedIn

Table 9 LinkedIn Website Performance Testing Results

Features	Scenario	Response Time	Throughput	Error Rate (%)
	200 Threads	0.474	1.0/detik	0%
Login	600 Threads	0.508	3.0/detik	0%
	1000 Threads	0.535	5.0/detik	0%
	200 Threads	0.361	1.0/detik	0.50%
Daftar	600 Threads	0.441	3.0/detik	6.33%
	1000 Threads	0.372	5.0/detik	44.80%
	200 Threads	0.481	1.0/detik	0%
Search	600 Threads	0.497	3.0/detik	28.67%
	1000 Threads	0.310	5.0/detik	79.50%
	200 Threads	0.723	1.0/detik	100%
Profile	600 Threads	0.232	3.0/detik	100%
	1000 Threads	0.235	5.0/detik	100%

Performance testing shows that the login page can handle up to 1000 users without error, with a response time of 0.474-0.535 seconds and increased throughput. However, the listing and job search pages experienced significant spikes in error rate-up to 44.80% and 79.50%-although response times remained good. The profile page failed completely with an error rate of 100% and the appearance of error 429, indicating a request restriction by the server. This suggests that some features, especially the profile and vacancy search, are not optimized to handle high loads.

3.2.3. Performance Testing of E-Recruitment Website Karir.com

Table 10 Karir.com Website Performance Testing Results

Fitur	Scenario	Response Time	Throughput	Error Rate (%)
	200 Threads	0.202	0,97/detik	0%
Login	600 Threads	0.051	3.0/detik	0%
	1000 Threads	0.185	4.7/detik	0%
	200 Threads	0.053	0,97/detik	0%
Daftar	600 Threads	0.051	3.0/detik	0%
	1000 Threads	0.050	4.7/detik	0%
	200 Threads	0.026	0,97/detik	0%
Search	600 Threads	0.026	3.0/detik	0%
	1000 Threads	0.026	4.7/detik	0%
	200 Threads	0.064	0,97/detik	0%
Profile	600 Threads	0.026	3.0/detik	0%
	1000 Threads	0.062	4.7/detik	0%

Performance testing results show that the site can handle up to 1000 users without error (0% error rate) on all pages. Login response times ranged from 0.051-0.202 seconds, with throughput increasing significantly. The listing and profile pages showed fast and stable performance, while the vacancy search was the fastest, with a response time of 0.026 seconds. Overall, the system performed very well and consistently under high load.

3.2.4. Performance Testing of E-Recruitment Website Kalibrr

Table 11 Kalibrr Website Performance Testing Results

Features	Scenario	Response Time	Throughput	Error Rate (%)
	200 Threads	0.514	0.833/detik	0%
Login	600 Threads	1.034	2.3/detik	0%
	1000 Threads	0.520	4.0/detik	0%
	200 Threads	1.120	0.983/detik	0%
Daftar	600 Threads	0.948	3.0/detik	0%
	1000 Threads	0.933	5.0/detik	0%
	200 Threads	0.951	1.0/detik	0%
Search	600 Threads	0.855	3.0/detik	0%
	1000 Threads	0.801	5.0/detik	0%
	200 Threads	0.992	1.0/detik	0%
Profile	600 Threads	0.844	3.0/detik	0%
	1000 Threads	0.811	5.0/detik	0%

Performance testing shows that all web pages can handle up to 1000 users without error (0% error rate). The login response time ranged from 0.514 to 1.034 seconds, and the listing page showed stable performance in the range of 0.933 to 1.120 seconds. The vacancy and profile searches showed improved performance with response time decreasing to 0.801 seconds and throughput increasing. These results prove that the site remains stable and responsive despite the significant increase in user load.

3.2.5. Performance Testing of E-Recruitment Website Glints

Table 12 Glints Website Performance Testing Results

Fitur	Scenario	Response Time	Throughput	Error Rate (%)
	200 Threads	0.121	1.0/detik	100%
Login	600 Threads	0.238	3.0/detik	100%
	1000 Threads	0.127	5.0/detik	100%
	200 Threads	0.110	1.0/detik	100%
Daftar	600 Threads	0.173	3.0/detik	100%
	1000 Threads	0.121	5.0/detik	100%
	200 Threads	0.109	1.0/detik	100%
Search	600 Threads	0.174	3.0/detik	100%
	1000 Threads	0.120	5.0/detik	100%
	200 Threads	0.112	1.0/detik	100%
Profile	600 Threads	0.192	3.0/detik	100%
	1000 Threads	0.120	5.0/detik	100%

Performance testing on the Glints site showed a 100% error rate across all features and test scenarios (200, 600, 1000 users), despite fast response times (0.109-0.238 seconds) and increased throughput. All requests failed with a 403 Forbidden response, indicating that the Glints server was blocking access from automated test tools such as JMeter.

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3.3. GUI Testing Normality Test

3.3.1. Normality Test of Dependent Variable Response Time

The normality test is carried out to determine whether the data obtained is normally distributed or not. If the significance value (Sig) > 0.05, then the data is considered normally distributed. The hypotheses used in this test are:

H_0: Response time data is normally distributed

H_a: Response time data is not normally distributed

One-Sample Kolmogorov-Smirnov Test

			ResponseTime
N			60
Normal Parameters[a,b]	Mean		746.80
	Std. Deviation		956.560
Most Extreme Differences	Absolute		.246
	Positive		.246
	Negative		-.222
Test Statistic			.246
Asymp. Sig. (2-tailed)[c]			<,001
Monte Carlo Sig. (2-tailed)[d]	Sig.		.000
	99% Confidence Interval	Lower Bound	.000
		Upper Bound	.000

Figure 1 Normality Test Results for GUI Response Time Data

Based on Figure 1, the results of the response time normality test using the Kolmogorov-Smirnov method show a significance value (Sig) <0.05. Thus, H_0 is rejected, and the data are not normally distributed. Therefore, the data does not qualify for the Two-Way ANOVA test, so Friedman's non-parametric Two-Way ANOVA test is used as an alternative.

3.3.2. Normality Test of Dependent Variable Success Rate

The normality test is carried out to determine whether the data obtained is normally distributed or not. If the significance value (Sig) > 0.05, then the data is considered normally distributed. The hypotheses used in this test are:

H_0: Success rate data is normally distributed

H_a: The success rate data is not normally distributed

One-Sample Kolmogorov-Smirnov Test

			Tingkat Keberhasilan
N			60
Normal Parameters[a,b]	Mean		.98890
	Std. Deviation		.060280
Most Extreme Differences	Absolute		.540
	Positive		.427
	Negative		-.540
Test Statistic			.540
Asymp. Sig. (2-tailed)[c]			<,001
Monte Carlo Sig. (2-tailed)[d]	Sig.		.000
	99% Confidence Interval	Lower Bound	.000
		Upper Bound	.000

Figure 2 Normality Test Results for GUI Success Rate Data

Based on Figure 2, the results of the normality test of the success rate using the Kolmogorov-Smirnov method show a significance value (Sig) <0.05. Thus, H_0 is rejected, and the data are not normally distributed. Therefore, the data did not qualify for the Two-Way ANOVA test, and Friedman's non-parametric Two-Way ANOVA test was used as an alternative.

3.4. Normality Test of Performance Testing

3.4.1. Normality Test of Dependent Variable Response Time

The normality test is carried out to determine whether the data obtained is normally distributed or not. If the significance value (Sig) > 0.05, then the data is considered normally distributed. The hypotheses used in this test are:

H_0: Response time data is normally distributed

H_a: Response time data is not normally distributed

One-Sample Kolmogorov-Smirnov Test

			ResponseTime
N			60
Normal Parameters[a,b]	Mean		.40530
	Std. Deviation		.321946
Most Extreme Differences	Absolute		.146
	Positive		.146
	Negative		-.119
Test Statistic			.146
Asymp. Sig. (2-tailed)[c]			.003
Monte Carlo Sig. (2-tailed)[d]	Sig.		.003
	99% Confidence Interval	Lower Bound	.001
		Upper Bound	.004

Figure 3 Normality Test Results for Performance Response Time Data

Based on Figure 3, the results of the normality test for response time performance using the Kolmogorov-Smirnov method show a significance value (Sig) <0.05. Thus, H_0 is rejected, and the data are not normally distributed. Therefore, the data did not qualify for the Two-Way ANOVA test, so Friedman's non-parametric Two-Way ANOVA test was used as an alternative.

3.4.2. Normality Test of Dependent Variable Throughput

The normality test is carried out to determine whether the data obtained is normally distributed or not. If the significance value (Sig) > 0.05, then the data is considered normally distributed. The hypotheses used in this test are:

H_0: Throughput data is normally distributed

H_a: Throughput data is not normally distributed

One-Sample Kolmogorov-Smirnov Test

			Throughput
N			60
Normal Parameters[a,b]	Mean		2.9466
	Std. Deviation		1.61627
Most Extreme Differences	Absolute		.219
	Positive		.219
	Negative		-.178
Test Statistic			.219
Asymp. Sig. (2-tailed)[c]			<,001
Monte Carlo Sig. (2-tailed)[d]	Sig.		.000
	99% Confidence Interval	Lower Bound	.000
		Upper Bound	.000

Figure 4 Normality Test Results for Performance Throughput Data

Based on Figure 4, the results of the normality test of throughput performance using the Kolmogorov-Smirnov method show a significance value (Sig) <0.05. Thus, H_0 is rejected, and the data are not normally distributed. Therefore, the data does not qualify for the Two-Way ANOVA test, so Friedman's non-parametric Two-Way ANOVA test is used as an alternative.

3.4.3. Normality Test of Dependent Variable Error Rate

The normality test is carried out to determine whether the data obtained is normally distributed or not. If the significance value (Sig) > 0.05, then the data is considered normally distributed. The hypotheses used in this test are:

H_0: Error rate data is normally distributed

H_a: Error rate data is not normally distributed

One-Sample Kolmogorov-Smirnov Test

			Error_Rate
N			60
Normal Parameters[a,b]	Mean		27.6633
	Std. Deviation		43.81664
Most Extreme Differences	Absolute		.416
	Positive		.416
	Negative		-.264
Test Statistic			.416
Asymp. Sig. (2-tailed)[c]			<,001
Monte Carlo Sig. (2-tailed)[d]	Sig.		.000
	99% Confidence Interval	Lower Bound	.000
		Upper Bound	.000

Figure 5 Normality Test Results for Performance Error Rate Data

Based on Figure 5, the results of the normality test of the performance error rate using the Kolmogorov-Smirnov method show a significance value (Sig) <0.05. This means that H_0 is rejected and the data is not normally distributed. Thus, the data does not qualify for the Two-Way ANOVA test, so Friedman's non-parametric Two-Way ANOVA test is used as an alternative.

3.5. Friedman GUI Two-Way Anova Hypothesis Test

After conducting GUI testing on five e-recruitment sites using Katalon Studio, hypothesis testing was conducted using the Two-Way ANOVA test. However, the Friedman test is used when the assumptions of parametric statistics are not met, namely when the data is not normally distributed [10]. Based on the results of the previous normality test, the response time data were not normally distributed, so the main requirement for using Two-Way ANOVA was not met. Therefore, hypothesis testing in this study continued using non-parametric analysis, namely Friedman's Two-Way ANOVA.

a. Two-Way Anova Friedman Test Response Time Data

After conducting a normality test on the GUI response time variable, a significance value (Sig) <0.05 was obtained, indicating that the data was not normally distributed. Thus, the Two-Way ANOVA test cannot be used. As an alternative, hypothesis testing was conducted using Friedman's Two-Way ANOVA non-parametric analysis.

Test Statistics[a]

N	60
Chi-Square	96.000
df	2
Asymp. Sig.	<,001

Figure 6 Friedman's Two-Way Anova Results Response Time GUI

Based on Figure 6, the significance result of Friedman's Two-Way ANOVA analysis using SPSS software shows a value of <0.001. Since the value is ≤ 0.05, H_0 is rejected and H_1 is accepted. Thus, it can be concluded that there is a significant difference in GUI response time based on the website and features of the five e-recruitment sites tested.

b. Two-Way Anova Friedman Test Success Rate Data

After conducting a normality test on the GUI success rate variable, a significance value (Sig) <0.05 was obtained, indicating that the data was not normally distributed. Thus, the Two-Way ANOVA test cannot be used. As an alternative, hypothesis testing was conducted using Friedman's Two-Way ANOVA non-parametric analysis.

Test Statistics[a]

N	60
Chi-Square	67.364
df	2
Asymp. Sig.	<,001

Figure 7 Friedman's Two-Way Anova Results Success Rate GUI

Based on Figure 7, the significance result of Friedman's Two-Way ANOVA analysis using SPSS software shows a value of <0.001. Since the value is ≤ 0.05, H_0 is rejected and H_1 is accepted. Thus, it can be concluded that there is a significant difference in the success rate of GUIs based on the website and features of the five e-recruitment sites tested.

3.6. Friedman Performance Two-Way Anova Hypothesis Test

After conducting performance testing on five e-recruitment sites using Katalon Studio, hypothesis testing was conducted using the Two-Way ANOVA test. However, the Friedman test is used when the assumptions of parametric statistics are not met, namely when the data is not normally distributed [10]. Based on the results of the previous normality test, the response time data were not normally distributed, so the main requirement for using Two-Way ANOVA was not met. Therefore, hypothesis testing in this study continued using non-parametric analysis, namely Friedman's Two-Way ANOVA.

a. Two-Way Anova Friedman Test Response Time Data

After performing the normality test on the performance response time variable, the significance value (Sig) <0.05 was obtained, indicating that the data was not normally distributed. Thus, the Two-Way ANOVA test cannot be used. As an alternative, hypothesis testing was conducted using Friedman's Two-Way ANOVA non-parametric analysis.

Test Statistics[a]

N	60
Chi-Square	14.000
df	2
Asymp. Sig.	<,001

Figure 8 Friedman's Two-Way Anova Results Response Time Performance

Based on Figure 8, the significance result of Friedman's Two-Way ANOVA analysis using SPSS software shows a value of <0.001. Since the value is ≤ 0.05, H_0 is rejected and H_1 is accepted. Thus, it can be concluded that there is a significant difference in response time performance based on the website and features of the five e-recruitment sites tested.

b. Two-Way Anova Friedman Test Throughput Data

After performing the normality test on the performance throughput variable, the significance value (Sig) <0.05 is obtained, which indicates that the data is not normally distributed. Thus, the Two-Way ANOVA test cannot be used. As an alternative, hypothesis testing was carried out using Friedman's Two-Way ANOVA non-parametric analysis.

Test Statistics[a]

N	60
Chi-Square	3.015
df	2
Asymp. Sig.	.222

Figure 9 Friedman's Two-Way Anova Results Throughput Performance

Based on Figure 9, the significance result of Friedman's Two-Way ANOVA analysis using SPSS software shows a value of 0.222. Since the value is ≥ 0.05, H_1 is rejected and H_0 is accepted. Thus, it can be concluded that there is no significant difference in throughput performance based on the website and features of the five e-recruitment sites tested.

c. Two-Way Anova Friedman Test Error Rate Data

After performing the normality test on the performance error rate variable, the significance value (Sig) <0.05 was obtained, indicating that the data was not normally distributed. Thus, the Two-Way ANOVA test cannot be used. As an alternative, hypothesis testing was conducted using Friedman's non-parametric Two-Way ANOVA analysis.

Test Statistics[a]

N	60
Chi-Square	93.088
df	2
Asymp. Sig.	<,001

Figure 10 Friedman's Two-Way Anova Results Error Rate Performance

Based on Figure 10, the significance result of Friedman's Two-Way ANOVA analysis using SPSS software shows a value of <0.001. Since the value is ≤ 0.05, H_0 is rejected and H_1 is accepted. Thus, it can be concluded that there is a significant difference in performance error rate based on the website and features of the five e-recruitment sites tested.

CONCLUSION

Based on the results of research entitled GUI and Performance Testing Analysis on Jobstreet, LinkedIn, Karir.com, Kalibrr, and Glints Sites Using Katalon Studio and JMeter with the Two-Way ANOVA Method, it can be concluded as follows:

1. GUI testing showed that Jobstreet had high response times on Login and Profile features due to OTP constraints, while Glints had a failure on the Listings feature with a 66.7% success rate. LinkedIn was slow on Job Search, Karir.com was slow on Sign Up and Profile, while Kalibrr showed the most stable and consistent GUI performance.
2. Performance testing showed that Jobstreet, Karir.com, and Kalibrr had low response time, stable throughput, and 0% error rate. Glints failed with a 100% error rate due to server rejection (403 Forbidden). LinkedIn shows error spikes in some features when the load increases.
3. The results of SPSS analysis show that there are significant differences in the variables of response time and GUI success status, and performance response time and error rate. However, there is no significant difference in the throughput variable.

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REFERENCES

[1] C. M. Annur, “6 Platform Lowongan Kerja Paling Banyak Digunakan di Indonesia,” https://databoks.katadata.co.id/tenaga-kerja/statistik/dd6adbdcb128ea1/6-platform-lowongan-kerja-paling-banyak-digunakan-di-indonesia.

[2] S. F. Abdinnour-Helm, B. S. Chaparro, and S. M. Farmer, “Using the End-User Computing Satisfaction (EUCS) Instrument to Measure Satisfaction with a Web Site,” 2005. [Online]. Available: www.landsend.com

[3] F. S. Nurcahyani, “ANALISA PENGUJIAN GUI PADA WEBSITE ONLINE COURSE RUANGGURU & ZENIUS DENGAN MENGGUNAKAN KATALON STUDIO,” *JEISBI*, vol. 4, no. 4, 2023.

[4] P. Memon, A. Dewani, S. Bhatti, and T. Hafiz, “Meneliti pengujian beban otomatis melalui blazmeter, apache jmeter, dan hp loadrunner,” *Jurnal Internasional Studi Lanjutan dalam Komputer, Sains dan Teknik*, vol. 7, no. 3, pp. 35–42, 2018.

[5] Manday Dani, Turnip Mardi, and Sinurat Stiven, *Modul Pengajaran Testing Dan Implementasi*. 2023.

[6] A. Rodrigues, J. Vilela, and C. Silva, “A Systematic Mapping Study on Techniques for Generating Test Cases from Requirements,” *IoTBDS*, pp. 141–148, 2024.

[7] B. Harijanto and Y. Ariyanto, “PENGUJIAN KINERJA WEB SERVER POLINEMA MENGGUNAKAN ALAT UJI JMETER,” 2021. [Online]. Available: http://polinema.ac.id.

[8] L. W. Suwarsono, A. N. Aisha, and F. N. Nugraha, “The Role of E-Learning Readiness on Workload: Perspective Engineering and non-Engineering Students,” *International Journal of Innovation in Enterprise System*, vol. 6, no. 01, pp. 85–94, Jan. 2022, doi: 10.25124/ijies.v6i01.165.

[9] R. Bevans, “Two-Way ANOVA | Examples & When To Use It.”

[10] Sugiyono, “Statistika Untuk Penelitian,” 2007.