Learning Based Recognition: User Acceptance Test

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Abstract: Long distance learning is very popular these days, especially after the pandemic, as learning systems are no longer limited by space and time. Nowadays, human achievement is valuable because everything needs proof or evidence. A web-based application was then made that combines these two main features. Learning Based Recognition Platform (LBRP) is an e-learning platform for university or institutional users that enables users' past achievements to be recognized as passing course subjects in university curriculum. This platform will be evaluated using the waterfall method which user acceptance test (UAT) is conducted to know its eligibility whether can be implemented into the society. This study is using neuro research for the research method. The result of UAT is some improvement was made. They are involved in speed of performance, rate of error, and retention over time.

1 INTRODUCTION

The concept of long-distance education has been founded way back, starting from the 19th century. Long- distance learning refers to educational programs, starting from a single course and even to entire degree programs, that are delivered through the internet as the media (Nicholson, 2007). Nowadays, online education can also be known as e- learning, has become increasingly popular accepted in recent years due to the convenience that e-learning offers (Nortvig et al., 2018). Through e-learning, learners can have access to course materials suited to their needs and wants, complete their assignments, and even participate in discussions using internet, enabling learners to have their education wherever they are and whenever they could (Huba and Kozák, 2016).

E-learning is well-accepted as a learning style implemented in many organizations and even institutions (Sari and Oktaviani, 2016). It is especially true because e-learning can be as effective as traditional training with much cheaper cost and that is because organizations and institutions only require fees for technical assistance, web servers, etc. Rather than spending for renting a building to have classes, fee for educators, etc. (Gillett-Swan, 2017; Da et al., 2020). Overall, e-learning can be an alternative as opposed to traditional education, as e-learning can be a good option for learners with limitation due to their geographical location, their schedule or commitments, and other reasons, thus they need the flexibility that are offered by e-learning (Siahaan et al., 2020). However, although e-learning has many potential benefits, it also presents several challenges and limitations. Not every learner has equal access to the internet and technology to participate in e- learning, this limitation makes it difficult for the learners (Gillett-Swan, 2017). Other than that, e-learning may also make it more difficult for learners to have feedback on their work, as it is harder for instructors to monitor the progress of the learners (Markova et al., 2017). Learners with visual impairment would experience several accessibility barriers (Mateus et al., 2021). Thus, it is also important to consider the potential disadvantages and limitations presented by e-learning.

As of recent months, a website application for e-learning platform namely Learning Based Recognition Platform (LBRP) is developed (Liu, 2017). Users can have an online education wherever and whenever they are, regardless of their geographical limitation (Cui, 2021). The Learning Based Recognition system is designed to facilitate the process of delivering education online (HALIM, 2020). LBRP also has another main feature where users can upload their past

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achievement and then get their achievement recognized and accepted for the course topic in a curriculum of an institution. The success of a website application is directly proportional to meeting the expectations and the needs of their user. Thus, one crucial step in ensuring this is through the collection and incorporation of user feedback before the website application is publicized for society use (Sudrajat et al., 2019; Carroll and Hertzum, 2020; Rupere and Jakovljevic, 2021). This evaluation step match with waterfall method that LBRP used where user testing is required after the application is developed, thus a User Acceptance Testing (UAT) needs to be conducted (Salnikov, 2021; Suhirman et al., 2021; Aldi, 2022).

This research paper will explore the importance of UAT in the development and implementation of a website application. This paper will examine current methods and techniques for conducting UAT and present a case study of a website application that has been developed and is ready for implementation but has undergone UAT before its launch. Additionally, this paper will review the related literature on UAT, including studies that have been conducted on the effectiveness of UAT in website application development and implementation. Through this research, we aim to demonstrate the value of UAT in ensuring the success and acceptance of a website application among its users, and to contribute to the body of literature on the topic of UAT in website application development.

2 LITERATURE REVIEW

User Acceptance Testing (UAT) is the final stage of the software testing process after completing unit testing, functional testing, and integration testing. The purpose of this process is to gather feedback from users using the application before it is applied to society. The results of user testing feedback are important and a major component of producing high-quality applications. In addition, UAT is to ensure that the application meets the customer's needs (Sudrajat et al., 2019; Mohamad and Yassin, 2016; Poston et al., 2014). Meanwhile, the UAT is based on Shneiderman's five measurable human factors that comprises of learnability, efficiency, memorability, errors, and satisfaction (Shneiderman and Plaisant, 2010). After some consideration, this paper uses all five factors as the criteria for the UAT process. Table 1 provides the criteria of each factor.

Table 1: Five measurable human factors according to Shneiderman.

Factor	Criteria
Learnability	User's ability to understand how the application works
Efficiency	User's ability to complete certain set of tasks more quickly
Errors	Minimalized error rate of user's action during application usage
Memorability	User's experience to how memorable the flow of a certain set of tasks
Satisfaction	User's satisfaction and comfortability regarding the application

The first factor is time to learn, which is measured by how long it takes for typical members of the target community to learn how to use the task relevant set of commands. Less time required means that the application flow is clearer, so users can easily understand how to complete tasks in the web application. The second factor is speed of performance, which is measured by how long it takes to carry out the benchmark set of tasks. The faster users can complete tasks, the better the speed of performance. The third factor is the rate of errors, which is measured by how many and what kind of errors are made in carrying out the benchmark set of tasks. Although time to make and correct errors might be incorporated into the speed of performance, error making is such a critical component of system usage that it deserves extensive study. This factor is important because making mistakes is a common things users can do and must have solutions such as update. The fourth factor is retention over time. How well do users maintain their knowledge after an hour, days, or even weeks. Retention may be closely linked to ease of learning; frequency of use plays an important role. It is important for the user to remember the knowledge of how to use the application so that the user does not have to learn it from scratch again after a long period of inactivity with the application. The last factor is subjective satisfaction, which is measured by how well users like used aspects of the system. This can be ascertained by interviews or written surveys which include satisfaction scales and space for free form comments. This can be summed up as the most important factor because the purpose of UAT is to know user satisfaction with the application (Shneiderman and Plaisant, 2010). Since the LBRP web-based application is about to be released, user testing feedback is needed. A common approach to UAT is to provide software demos to customers. In the study, users were given a manual book and a tutorial video guide on how to use the application before they are using the app and providing feedback (Harte et al., 2017). The flow of UAT process picture can be seen on Figure 1.

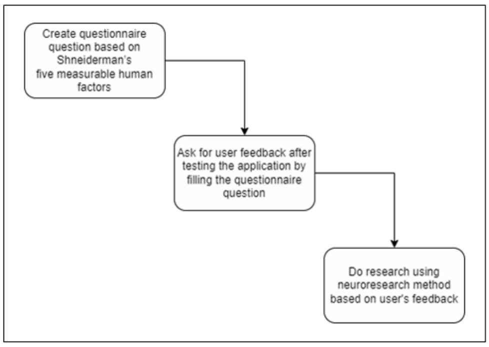

Figure 1: Flow of UAT.

3 RESEARCH METHOD

The research method for this paper was using the Neuroresearch method. Neuroresearch is a term to describe the interlinked and complex hooks of a study that are not merely through qualitative-quantitative research methods that are often called mixed-methods, but more than that is through qualitative-qualitative-calibration research in quantitative-quantitative calibration pattern that is then called Neuroresearch. In Neuroresearch, the qualitative process aims to develop a theoretical basis as a construct of specialization, while the quantitative process aims to validate the instrument to be used as a basis for system development. The quantitative process involves explanatory and confirmatory stages. Using the Neuroresearch, it allows for more comprehensive results in uncovering research problems because researchers have the freedom to use all methods to obtain the various types of data needed (Sasmoko et al., 2018).

For the explanatory stage of this paper, a survey using questionnaire was used for the data collection to obtain practical information and feedback from various users. The survey was conducted with 54 users and 15 questions. All these questions are grouped into five measurable human factors based on Shneiderman's (Shneiderman and Plaisant, 2010).

Based on Figure 2 above, the number of respondents by age is dominated by the age 21-30 with 88.9% of the chart, about 7.4% of the respondents by the age under 20, then 1.9% by the age 41-50, and the rest 1.9% by the age above 50. Meanwhile for the gender, 64.8% of the number of respondents are males and the rest 35.2% are females.

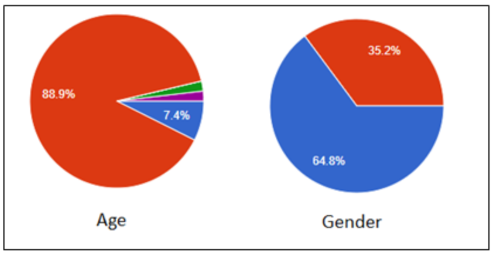

Figure 2: Percentage of respondent by age and gender.

4 RESULT AND DISCUSSION

4.1 Calibration of User Acceptance Test (UAT) Instruments from the Learning Based Recognition Platform (LBRP)

The validity of UAT from LBRP uses 2 (two) approaches, namely (1) Nearest Neighbor Analysis approach and (2) Two-Step Cluster.

First, nearest neighbor analysis is an analytical method for determining the distribution pattern of indicators and items, whether they are uniform or random or cluster. In this study, analysts considered the aspects of distance and the number of points of spread of indicators and items. The results of the analysis are in the form of the Nearest Neighbor index, the value is between 0 to 2.15 whose results are as shown in Figures 3 and 4.

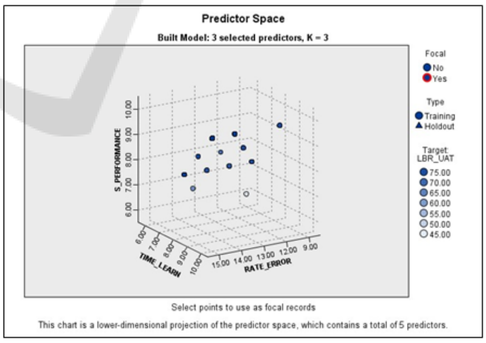

Figure 3: Nearest Neighbor Index Based on Indicator Spread Pattern.

Figures 3 and 4 can be explained that overall, the UAT instruments of LBRP have a spread pattern that tends to be randomly patterned. This means that the distance between the indicator and item spread points to the user does not have the same distance.

Second, because the UAT of LBRP aims to measure objects that have mixed, continuous and category variables, it is first analyzed with a Two-Step Cluster

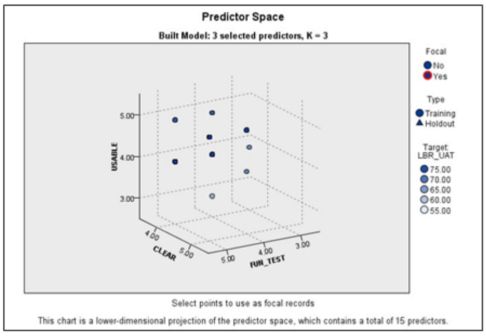

Figure 4: Nearest Neighbor Index Based on Item Deployment Pattern.

between UAT against its 5 (five) indicators and UAT against its 15 items. This analysis is to see the equivalence of distance and UAT balance of LBRP with each indicator and each item as a cluster. The results are like the following Figures 5 and 6.

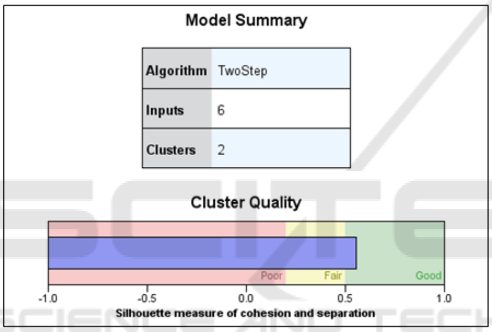

Figure 5: Analysis of Two-Step Cluster UAT from LBRP against Indicators as Clusters.

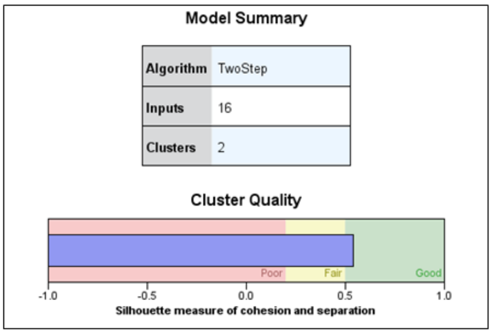

Figure 6: Analysis of Two-Step Cluster UAT from LBRP against Items as Clusters.

Based on Figures 5 and 6, it can be explained that each optimal cluster is 2 pieces that have an above-average contribution margin. Clustering testing was carried out using the Silhouette Method and showed that the quality of the resulting cluster had a large Silhouette value of ± 0.7 (Good). This proves that the clusters in the UAT of the formed LBRP have been well clustered. So UAT from LBRP can be recommended for use to measure UAT from LBRP in the next platform performance improvement effort.

The results of the two validity approaches above have a Reliability Index UAT of LBRP calculated by the Cronbach Alpha Formula of 0.934. That is, with 15 valid items and a sample of 54 users, in measuring UAT from LBRP has very high accuracy based on the range of values between 0 to 1.

4.2 Answer to the First Problem Formulation: What is the General Trend of User Acceptance Conditions Towards LBRP

To prove the tendency of user acceptance of LBRP, it was analyzed with a confidence interval at a significance level of $\alpha < 0.05$. The category of tendency conclusions is set in 3 categories, namely: (1) Do not accept, (2) Doubtful, and (3) Accept. Final calculation for μ interval could be calculated by using figure 7 formula. μ formula used to get the user perception value category (Widhoyoko et al., 2018). The result is in the following Table 2.

$$\bar{X} - t_p \frac{s}{\sqrt{n}} < \mu < \bar{X} + t_p \frac{s}{\sqrt{n}} \quad (1)$$

Table 2: General Trend of User Acceptance of LBRP as a Whole.

Variable/Indicator	μ = Lower Upper Bound	Conclusion $\alpha < 0.05$
LBRP'S UAT Variable	67.6471-71.0936	Accept
Time to Learn Indicator	8.9605-9.5210	Accept
Speed of Performance Indicator	8.9605-9.5210	Accept
Rate of Errors by Users Indicator	13.7337-14.4885	Accept
Retention Over Time Indicator	4.5076-4.8257	Doubtful
Subjective Satisfaction Indicator	27.0831-28.4725	Accept

Based on Table 2, it can be explained that the overall population of the population whose variance is unknown has been shown to have received 4 indicators, namely Time to Learn, Speed of Performance, Rate of Errors by Users, and Subjective Satisfaction. Then the results of the analysis generally recommend that LBRP improvements be made, especially on the Retention Over Time indicator, namely that the results are significantly doubtful at $\alpha < 0.05$.

4.3 Answer to the Second Problem Formulation: The Most Dominant Indicator Determines the UAT of LBRP

The analysis was carried out using binary segmentation approaches called Classification and Regression Trees. In this analysis, researchers set Depth Pruning at 2, Parent Pruning at 2, and Child Pruning at 1, with a significance level of $\alpha < 0.05$. Results such as Figure 7.

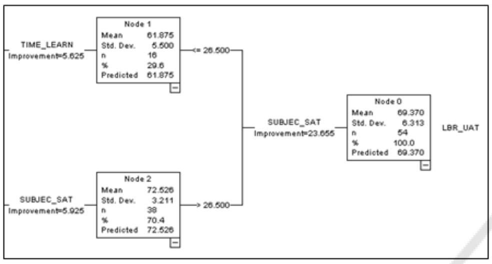

Figure 7: The most dominant indicator that determine LBRP eligibility.

Based on Figure 8 above, it can prove that Subjective Satisfaction (SUBJECT_SAT) is the most dominant indicator of determining good acceptance of LBRP to have a high performance. Recommendations on how to improve the Subjective Satisfaction (SUBJECT_SAT) Indicator are by improving the time to learn (TIME_LEARN) of the platform. Improvement to Subjective Satisfaction (SUBJECT_SAT) is predicted to be able to improve platform performance by 29.58 times the current LBRP performance. Based on the analysis above, the LBRP that must be improved are 3 indicators, namely indicators: (1) Speed of Performance, (2) Rate of Errors by Users, and (3) Retention Over Time.

4.4 Answer to Third Problem Formulation: Improved Form (1) Speed of Performance, (2) Rate of Errors by Users, and (3) Retention Over Time on LBRP

Online learning platform application improvement scenarios refer to scenarios where the system can propose and execute certain tasks according to user needs (Ho et al., 2008). The standard of fast in the speed of performance indicator is obtained from interviewing 20 people as Table 3.

The data of the questionnaire feedback for the speed of performance indicator can be seen as depicted in Figure 8. The x axis (horizontal) describes the satisfaction of the user which described in Table 3. The y axis (vertical) describes the number of respondents.

Table 3: Standard of fast in the speed of performance indicator.

Score	Speed
1	>60 seconds
2	51 – 60 seconds
3	41 – 50 seconds
4	31 – 40 seconds
5	<20 seconds

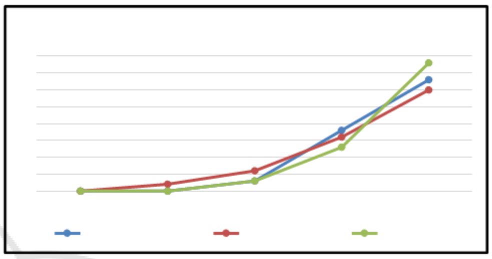

Figure 8: Speed of Performance Result.

Improvements to the features mentioned have been made is the system will not check whether the same document exists or not, which can be seen in Figures 9 and 10. These improvements reduce the time needed to upload documents.

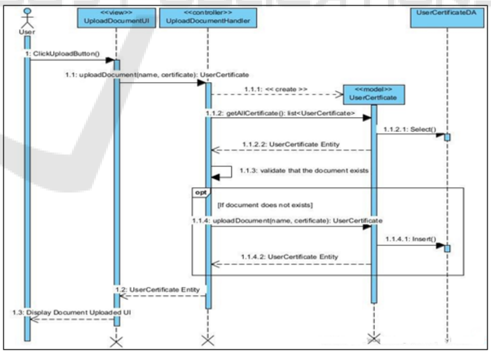

Figure 9: Sequence diagram representing the flow of document upload feature before improvement.

Next regarding the indicator rate of errors by users, where respondent feels that the system can't minimize the rate of human errors created by the user, this happened on some features such as the add to cart system. The data of the questionnaire feedback for the rate of errors by user's indicator can be seen as depicted in Figure 11. The x axis (horizontal) describes the satisfaction of the user which described in Table 3 above. The y axis (vertical) describes the number of

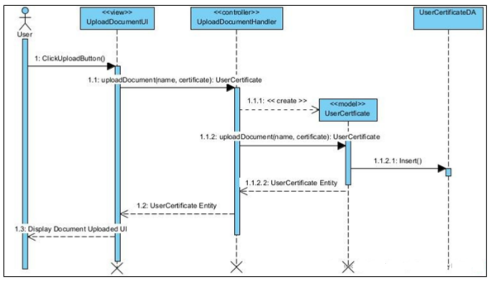

Figure 10: Sequence diagram representing the flow of document upload feature after improvement.

respondents.

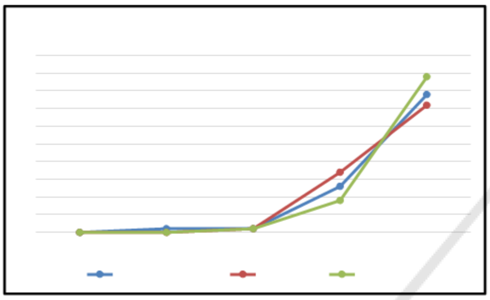

Figure 11: Rate of Errors by Users Result.

Improvements have been made where the previous system could insert duplicate topic data bought by users and will continue without error message. It was solved by creating one more validation within the system which if user click add to cart a topic within the website, the system will validate the topic whether the topic is already bought by the user or already added to cart before or even the topic is not active from the database.

The last indicator about the retention overtime indicators. On this indicator the respondent forgotten compared to here are features that are quite easily forgotten than the others. The data of the questionnaire feedback for the retention over time indicator can be seen as depicted in Figure 12. The x axis (horizontal) describes the satisfaction of the user which described in Table 3. The y axis (vertical) describes the number of respondents.

Improvements to the website has been made where the main color of the website and all interactable component or the components that LBRP wants the user to notice has been synchronized to orange, so that the user can know that the orange component indicates that the component can interact with the user. In addition, the menu contained in the header of the website has also undergone improvements so that the main menus of the website have been grouped to make it easier to access and use by users. For improvement, see Figure 13.

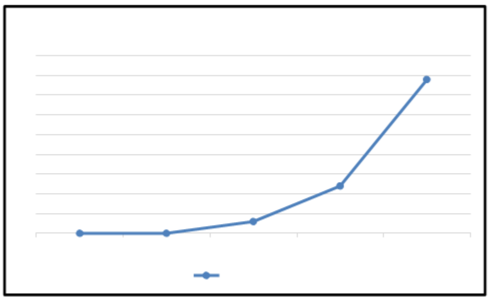

Figure 12: Retention Over Time Result.

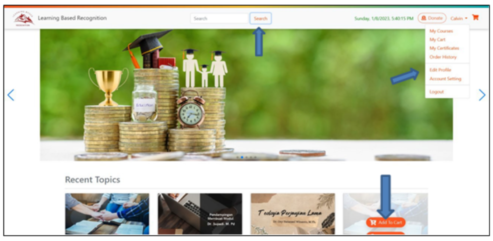

Figure 13: LBRP Home Page.

5 CONCLUSIONS

User Acceptance Testing (UAT) is a crucial step in developing a website application. Because no matter how good and how high technology a website is, it will fail if the user does not feel comfortable when using it. In Learning Based Recognition (LBR) website application, 5 factors of UAT have been measured by users' feedback, there are: time to learn, speed of performance, rate of user error, retention over time, and user's satisfaction. According to 15 questionnaire questions that were filled in by 54 respondents who have been using the application, this website has been improved as in analyzes result and discussion section.

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REFERENCES

Aldi, F. (2022). Web-based new student admission information system using waterfall method. *Sinkron*, 7(1):111–119.

Carroll, J. M. and Hertzum, M. (2020). Usability testing a practitioner's guide to evaluating the user experience.

Cui, Y. (2021). Self-efficacy for self-regulated learning and chinese students' intention to use online learning in covid-19: A moderated mediation model. *International Journal of Information and Education Technology*, 11(11):532–537.

Da, S., He, Y., and Zhang, X. (2020). Effectiveness of psychological capital intervention and its influence on work-related attitudes: Daily online self-learning method and randomized controlled trial design. *International Journal of Environmental Research and Public Health*, 17(23):1–19.

Gillett-Swan, J. (2017). The challenges of online learning supporting and engaging the isolated learner (journal of learning design gillett-swan) 10.

HALIM, M. (2020). Web services composition in e-learning platform (international journal of emerging trends in engineering research.

Harte, R., Glynn, L., Rodríguez-Molinero, A., Baker, P. M., Scharf, T., Quinlan, L. R., and ÓLaighin, G. (2017). A human-centered design methodology to enhance the usability, human factors, and user experience of connected health systems. A Three-Phase Methodology (JMIR Human Factors) 4 (1.

Ho, H., Fong, S., and Yan, Z. (2008). In *User Acceptance Testing of Mobile Payment in Various Scenarios (IEEE International Conference on E-Business Engineering, ICEBE'08 - Workshops: AiR'08*, volume EM2I'08, SOAIC'08, SOKM'08, BIMA'08, DKEEE'08, page 341–348.

Huba, M. and Kozák, S. (2016). From e-learning to industry 4.0.

Liu, K. (2017). Design and application of an online english self-learning platform. International Journal of Emerging Technologies in Learning.

Markova, T., Glazkova, I., and Zaborova, E. (2017). Quality issues of online distance learning (procedia - social and behavioral sciences.

Mateus, D. A., Silva, C. A., Oliveira, A. F., Costa, H., and Freire, A. P. (2021). A systematic mapping of accessibility problems encountered on websites and mobile apps: A comparison between automated tests. *Manual Inspections and User Evaluations (Journal on Interactive Systems*, 12(1):145–171.

Mohamad, R. and Yassin, N. M. (2016). Comparative evaluation of automated user acceptance testing tool for web based application development of dengue-entomological surveillance system view project sbse, meta-heuristic search algorithms and artificial immune system view project.

Nicholson, P. (2007). A history of e-learning echoes of the pioneers.

Nortvig, A., Petersen, A., and Balle, S. (2018). A literature review of the factors influencing e-learning and blended learning in relation to learning outcome. *Student Satisfaction and Engagement*, 16(1):46–55.

Poston, R., Sajja, K., and Calvert, A. (2014). Lncs 8527 - managing user acceptance testing of business applications.

Rupere, T. and Jakovljevic, M. (2021). Usability and user evaluation of an integrated multimedia e-learning management system. Knowledge Management and E-Learning.

Salnikov, N. (2021). How software development methodologies affect dynamic capabilities under extreme contexts: a covid-19 study on agile and waterfall methodologies subject strategic management.

Sari, F. M. and Oktaviani, L. (2016). Undergraduate students' views on the use of online learning platform during covid-19 pandemic.

Sasmoko, Y. I., Karsidi, R., Wuisan, D., and Ruliana, P. (2018). *Neuroresearch: Another Form of Mixed Method (International Journal of Engineering and Technology (UAE*, 7(2):134–138.

Shneiderman, B. and Plaisant, C. (2010). Designing the user interface: Strategies for effective human-computer interaction. Ed.) United States of America: Pearson Education Inc.

Siahaan, A. U., Aji, S. B., Antoni, C., and Handayani, Y. (2020). Online social learning platform vs e-learning for higher vocational education in purpose to english test preparation.

Sudrajat, D., Achdisty, M., Kurniasih, N., Roslina, P., Mulyati, S., Purnomo, A., and Sallu, S. (2019). In *The Implementation of Innovation in Educational Technology to Improve the Quality of Website Learning in Industrial Revolution Era 4.0 Using Waterfall Method (Journal of Physics: Conference Series) 1364*.

Suhirman, S., Hidayat, A. T., Saputra, W. A., and Saifullah, S. (2021). Website-based e-pharmacy application development to improve sales services using waterfall method. *International Journal of Advances in Data and Information Systems*, 2(2):114–129.

Widhoyoko, S. A., Sasmoko, L. A. N., Manalu, S. R., and Indrianti, Y. (2018). W.a.w (we are watching) smart app: Accommodating social perception towards public officers. In *Performance (Journal of Physics: Conference Series*, page 978.