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Application of Machine Learning Techniques to Predict Perceived Usability of Mobile Banking Apps in Türkiye

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ABSTRACT

Purpose – Mobile banking applications have revolutionized the way individuals manage their finances, offering convenient access to banking services at any time and place. These apps have become indispensable for banks seeking to remain competitive, address their customers' changing needs, and gather valuable data on consumer behavior. Ensuring optimal system usability is vital for the success of such technologies, as it significantly influences user experience and adoption rates. This research investigates the perceived system usability scores of private and public banks in Türkiye.

Design/Methodology/Approach – This study employs machine learning techniques to predict perceived system usability scores of mobile banking apps. The System Usability Scale (SUS) has been utilized to evaluate the perceived system usability. Factors considered in the prediction model include demographic data, system usage data, and device technical specifications.

Findings - The research demonstrates that machine learning techniques can effectively predict the perceived usability of both public and private bank mobile apps. Key predictors of perceived usability included demographic details, mobile app usage experience, and technical specifications of the devices used. Factors such as age, gender, education, occupation, screen size, mobile operating system, mobile app usage frequency, and previous app experience significantly influence perceived usability.

Discussion - The study highlights the potential of machine learning as a powerful tool in social science research, offering valuable insights into complex data sets and patterns. The findings of this research can offer valuable insights to system interface designers and human-computer interaction researchers examining system usability challenges.

1. Introduction

A mobile banking app is a software application designed to allow customers to perform various banking functions using their mobile devices, such as smartphones or tablets (Alavi and Ahujai, 2016; Wazid et al., 2019). These apps enable customers to access their bank accounts, view account balances, transfer funds, pay bills, deposit checks, and perform other banking transactions through a secure and mobile-friendly interface (Wazid et al., 2019). The development of mobile banking apps has revolutionized the way people manage their finances, providing customers with convenient access to banking services anytime and anywhere, as long as they have an internet connection. Similarly, mobile banking apps have become an essential tool for banks, providing them with a competitive advantage and helping them to meet the evolving needs and expectations of their customers (Shahid et al., 2022). Mobile banking apps provide banks with valuable data on their customers' spending habits and preferences. This data help to develop more targeted marketing campaigns and to improve the overall customer experience. By prioritizing system usability in their app development, banks can gain a competitive advantage, increase customer satisfaction, and ultimately, drive growth and success for their business.

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System usability encompasses the ease-of-use, effectiveness, and satisfaction of a system or technology from the user's perspective (Nielsen and Loranger, 2006; Koohjani et al., 2019; Gronier and Baudet, 2021; Vlachogianni and Tselios, 2022; Almasi et al., 2023). It evaluates the user experience with the system, considering factors such as learnability, efficiency, error rate, and satisfaction. The importance of system usability lies in its direct impact on the user experience, which can ultimately determine the success or failure of a system or technology. If a system is difficult to use, inefficient, or frustrating, it can decrease productivity, increase errors, and result in user dissatisfaction. Negative user perceptions can lead to decreased adoption or even abandonment of the system. Conversely, if a system is easy to use, efficient, and satisfying, it can increase productivity, reduce errors, and result in positive user perceptions. This can lead to increased adoption, satisfaction, and loyalty towards the system, resulting in better overall outcomes for both the user and the organization (Vlachogianni and Tselios, 2022; Setiyawati and Bangkalang, 2022). Therefore, it is crucial to measure and improve system usability to ensure the success of any system or technology.

This research is about calculating the perceived system usability scores of private and public banks in Türkiye and predicting the system usability scores with machine learning algorithms. More specifically, this study tries to answer the research questions of whether the perceived system usability scores of private or public banks are higher and whether the system usability scores of banks can be predicted with machine learning algorithms, taking into account demographic information, system usage experience, and technical specifications of the devices used. Standardized questionnaires and surveys are used to measure system usability and provide an overall assessment of the user's perception of the system's usability. In this study System Usability Scale (SUS) of Brooke (1996) was chosen to assess the usability of mobile banking applications because of its versatility, ease of administration, and comparative value.

This study provides important information for system interface design experts developing mobile banking applications and researchers in human-computer interaction studying system usability issues.

2. User Experience and Usability

The term "user experience" encompasses all aspects of a user's interaction with a product, service, environment, or facility, according to the ISO (2010). It focuses on the emotions, enjoyment, and contentment that individuals experience when interacting with, observing, handling, opening, or closing a product. It is important to emphasize that a positive user experience cannot be explicitly designed; instead, the design should be aimed at fostering a favorable user experience. That is, one can create the design features that can evoke good user experience. Designing interactive end-user products requires consideration of various dimensions within the user experience. Key dimensions include usability, functionality, aesthetics, content, look and feel, and emotional appeal. Fun, health, social capital (e.g., shared values, goals, and norms), and cultural identity (e.g., age, ethnicity, race, occupation, and education) are other user experience dimensions highlighted by Carroll (2004). In order to form good user experience product or system must be useful (content should be original and fulfill a need), usable (easy to use), desirable (evoke emotion and appreciation), findable (navigable and locatable content), accessible (accessible to people with disabilities), and credible (leaving reliable and trustworthy impression).

Usability falls within the realm of user experience design. Defining usability is challenging due to its complexity, and there isn't a universally accepted definition (Lewis, 2014). The Cambridge dictionary defines "usability" as the ease with which something can be used or the degree to which it is user-friendly. Selected definitions from researchers and institutions include Nielsen and Loranger (2006), who describe usability as a quality attribute related to how easy something is to use. According to ISO (2010), usability is the extent to which a product or system can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a defined context of use. Some definitions highlight that usability is not a single, one-dimensional property but encompasses various aspects of a product, system, or user interface.

According to these definitions, usability is a blend of various elements. For instance, Rogers et al. (2023) assert that usability ensures interactive products are easy to learn, effective to use, and enjoyable, optimizing interactions for work, school, and daily activities. Rogers et al. (2023) identify effectiveness, efficiency, safety, utility, learnability, and memorability as six dimensions of usability. Intuitive design, ease of learning, efficiency of use, memorability, error frequency and severity, and subjective satisfaction are other possible dimensions of usability. From these definitions, it's clear that a design is not inherently usable; its features, along with the user's context, determine its level of usability.

Usability is a crucial aspect of the user experience that demands careful attention during the design and implementation of interactive products or systems. The success of these products or systems is heavily influenced by their usability. If users perceive a lack of usability, there is a high likelihood that they will discontinue using the product or system (Liu and Pu, 2023; Lei and Lee, 2020; Hadi et al., 2022).

Numerous questionnaires are available to assess the usability of interactive end-user systems. Some well-known examples include the After Scenario Questionnaire (Lewis, 1991), the Post-Scenario System Usability Questionnaire (Lewis, 1992), the Computer Software Usability Questionnaire (Lewis, 1995), the Software User Measurement Inventory (Kirakowski, 1995), and the System Usability Scale (SUS) (Brooke, 1996). Among these, the SUS is particularly notable for its widespread adoption as a standardized tool for evaluating perceived system usability. Developed by John Brooke at Digital Equipment Corporation in the UK in 1986, the SUS was initially intended for the usability engineering of electronic office systems. This straightforward, ten-item Likert scale provides a comprehensive overview of subjective usability assessments.

The calculation of the SUS score is a simple process. Subtract 1 from the score for each odd-numbered item and subtract the value of each even-numbered item from 5. The sum of these adjusted scores is then calculated and multiplied by 2.5. The resulting value after this multiplication is the standard SUS score.

SUS has been translated to numerous languages and validated in diverse cultural contexts such as Turkish (Demirkol and Şeneler, 2018), German (Rummel, 2015), Polish (Borkowska and Jach, 2017), Chinese (Wang et al., 2020), Slovene (Blažica and Lewis, 2015), Indonesian (Sharfina and Santoso, 2016), etc. A great deal of studies utilized SUS in the assessment of usability of diverse type of products and interactive end user systems. Systems assessed through SUS include mobile applications (Kortum and Sorber, 2015), voting system (Byrne et al., 2007), mHealth systems (Hsieh et al., 2019), safety signs (Ng et al., 2012), traffic signs (Saremi et al., 2018), e-government systems (Hassan Basri et al., 2019), learning software (Tsai et al., 2018), and websites (Phillips and Chaparro, 2009).

By using more than 5000 individual SUS responses from 446 different studies Sauro and Lewis (Sauro and Lewis, 2012; Sauro and Lewis, 2016) created the curved grading scale (SL-CGS) shown in Table 1. The SL-CGS provides an empirically grounded approach to the interpretation of mean SUS scores.

Table 1. SUS percentile ranks and grades (Sauro and Lewis, 2012; Sauro and Lewis, 2016)

SUS Score Range	Grade	Percentile range
84.1 – 100.0	A+	96-100
80.8 – 84.0	A	90-95
78.9 – 80.7	A-	85-89
77.2 – 78.8	B+	80-84
74.1 – 77.1	B	70-79
72.6 – 74.0	B-	65-69
71.1 – 72.5	C+	60-64
65.0 – 71.0	C	41-59
62.7 – 64.9	C-	35-40
51.7 – 62.6	D	15-34
0.0 – 51.6	F	0-14

3. Methodology

In investigating the problem statement, this study employs a correlational predictive research technique. This method involves the application of statistical tools like regression analysis and correlation analysis to determine the strength and direction of relationships between variables. Analyzing these relationships enables researchers to predict future outcomes and devise strategies for enhancing those outcomes.

3.1. Instruments

The SUS developed by Brooke (1996) was used to evaluate system usability. It is a widely adopted and standardized questionnaire that assesses perceived system usability. The SUS is in the form of a Likert scale. Typically, Likert-type scales include five to seven items. In this study, the Likert-type scale measurement ranged from 1 (strongly disagree) to 5 (strongly agree). Participants rated each questionnaire item based on their level of agreement, using a scale of 1 to 5. Along with the SUS questionnaire, demographic and system usage data were collected in the form of categorical and continuous variables.

3.2. Sampling

Convenience sampling technique was utilized in this study, which is a type of non-probability sampling method that involves selecting participants who are easy to contact or reach. A total of 452 volunteers completed the study survey, with 61 percent being university students and 39 percent professionals from diverse fields including marketing, finance, aviation, health, education, and telecommunications.

3.3. Procedures

Ethical approval for the research survey has been obtained from the Gebze Technical University Human Research Ethics Committee (Decision No: 05-03, Dated April 5, 2023). Individuals in this study volunteered to participate by completing a survey. The study questionnaire, available in both printed hard copy and digital formats, was distributed to participants. Students filled out the questionnaire during their classes, while non-student participants completed it at their workplaces. Over a six-month period, the study collected 452 usable responses from participants.

3.4. Statistical Techniques

In this research, scikit-learn (commonly referred to as sklearn) was employed. Sklearn is a widely used open-source Python library designed for constructing machine learning models. It provides a diverse set of both supervised and unsupervised machine learning algorithms to facilitate advanced data analysis. This study specifically utilized supervised algorithms, which involve input and output variables and aim to learn the mapping function from input to output. The main goal of these algorithms is to create a model capable of accurately predicting the output variable for new input data.

In this study, the Linear Regression model from scikit-learn was used to build predictive models. Linear regression is a widely used and straightforward technique that offers a clear interpretation of the relationship between independent variables and the target variable. It is computationally efficient and works well with small to moderately large datasets. Additionally, linear regression's simplicity makes it easy to implement and understand, facilitating the communication of results to non-technical stakeholders. This technique's transparency and ease of interpretation are particularly beneficial for explaining model predictions and making data-driven decisions.

4. Data Analysis

The demographic distribution of the volunteer participants who participated in this research is given in Table 2. The majority of the participants (53.0%) are male. Looking at the age distribution, it is seen that the majority (63.0%) are between the ages of 18 and 25. 61.0% of the participants are students and 39.0% are employees in different sectors. It appears that the operating system used by the participants for mobile banking transactions is primarily (51.3%) iOS.

Table 2. Demographics details of participants.

Gender		**Frequency**	**Percentage**
	Male	240	53.0
	Female	212	47.0
Age			
	18-25	285	63.0
	26-33	91	20.1
	34-41	50	11.1

	42 and above	26	5.8
Occupation			
	Students	274	61.0
	Non-students	178	39.0
Mobile OS			
	Android	220	48.7
	iOS	232	51.3

Various statistics regarding the use of mobile banking are given in Table 3. The average screen size of the device used by the participants for mobile banking transactions is 5.61 inches. Participants reported using the mobile banking application approximately 8 times a week on average. They also reported conducting about 7-8 different activities within the mobile banking application. Participants reported using 2-3 different mobile banking applications before.

Table 3. Mobile banking usage details of participants

Technology Usage Detail	Response
Average Screen Size of the Device Used in Mobile Banking (inches)	5.61
Average Mobile Banking App Visit Frequency (Weekly)	8.30
Average Number of Activities Performed in the Mobile Banking App	7.60
Average Number of Mobile Banking App Used Before	2.40

Table 4 shows the average SUS scores of banks. SUS scores range from an average of 67.61 (B-) to 86.58 (A-). The average SUS score for public banks is 71.1 (C+), and the average for private banks is 78.43 (B+). PR3, a private bank, has been found to have the best mobile banking application with an SUS score of 86.58 (A+). PB1, a public bank, has been identified as having the lowest-rated mobile banking application with an SUS score of 67.61 (C).

Table 4. Average SUS scores of public and private banks in Türkiye

#	Bank Name	% of participant	SUS Scores	Grade [40][41]	Status [43]
1	PR1	20.1	75.03	B	Acceptable (Good)
3	PR2	10.8	86.58	A+	Acceptable (Best Imaginable)
4	PR3	33.2	77.23	B+	Acceptable (Good)
6	PR4	28.8	77.04	B+	Acceptable (Good)
11	PR5	32.3	76.27	B	Acceptable (Good)
12	PB1	10.2	67.61	C	Marginal (OK)
13	PB2	14.8	71.72	C+	Acceptable (Good)
14	PB3	53.3	73.97	B-	Acceptable (Good)

In this study, data augmentation techniques were employed to enhance the research outcomes and improve the predictive performance of the machine learning algorithms. Data augmentation refers to the process of generating additional training data by applying various transformations to the existing dataset (Shorten and Khoshgoftaar, 2019). The specific techniques used included:

- **Noise Injection:** Adding random noise to the data to make the model more robust to variations.
- **Synthetic Data Generation:** Creating new data points based on the existing data distribution.
- **Resampling:** Randomly oversampling the minority class and undersampling the majority class to address class imbalance.

These techniques helped to increase the diversity and size of the dataset, reducing overfitting and improving the generalizability of the model. The 5x dataset increase achieved through these transformations improved model generalization and prediction accuracy, resulting in user-friendly and efficient mobile banking apps catering to diverse customer needs.

In this study, feature selection techniques were employed to identify the most important features that enhance the predictive power of the regression models while eliminating irrelevant, redundant, or noisy features that could decrease model accuracy. Several methods were used to determine pertinent features for the regression models. These methods included examining the correlation coefficients between multiple variables, employing univariate feature selection, and assessing feature importance scores. Univariate feature selection involved evaluating each feature individually to determine its relevance to the target variable using statistical tests such as chi-square or ANOVA. Assessing feature importance scores involved using algorithms like random forests or gradient boosting to rank features based on their contribution to the model's predictive performance. Additionally, the study utilized backward elimination technique, where all initial features are included and iteratively the least significant features are removed based on statistical criteria (e.g., p-values), aiming to simplify the model while maintaining predictive accuracy. These combined approaches ensured that the most informative features were retained, leading to more accurate and robust regression models. Features included in predictive regression models of public and private banks are given in Table 5. In all regression models, all included features have been found to be statistically significant predictors of the SUS score.

Table 5. Features selected for predictive regression models for public and private banks

Features	PR1	PR2	PR3	PR4	PR5	PB1	PB2	PB3
Age	0.491***	0.791***	0.794***	0.691***	0.482***	0.397***	0.472***	0.693***
Gender	2.439***	2.941**	4.429***	3.183***	2.473**	5.391***	6.483***	4.732***
Education	1.693**	1.943**	0.483**	2.583***	3.743***	2.693***	3.684***	3.794***
Occupation	-4.622**	-3.912**	-4.183*	3.129**	3.451**	-2.194*	-1.943**	-1.848**
Screen Size of the Device Used in Mobile Banking	1.396**	1.639**	4.932***	1.730**	1.548**	0.596***	0.971***	0.754**
Mobile OS	2.186*	2.643*	1.782**	2.394***	1.482***	1.945**	2.854***	3.179**
Mobile Banking App Usage Frequency (Weekly)	3.629***	3.891**	5.492***	3.912***	5.184***	3.945***	4.731***	4.549***
Number of Activities Performed in the Mobile Banking App	6.291***	5.431***	4.391***	5.381***	3.749***	4.282***	3.891***	3.731***
Number of Mobile Banking App Used Before	3.463***	3.925***	4.583***	3.894***	4.943**	2.694**	1.745***	2.390***

Note: *p<0.1; **p<0.05; ***p<0.01, PR1 to PR5 represent private banks and PB1 to PB3 represent public banks.

To assess the effectiveness of the constructed regression models, commonly used metrics such as MAE, MSE, RMSE, and R-squared were employed (see Table 6). Mean Absolute Error (MAE) calculates the average of the absolute differences between predicted and actual values, measuring the average magnitude of errors without considering their direction. The Mean Squared Error (MSE) calculates the average of the squared differences between predicted values and actual values. By measuring the average squared difference, MSE penalizes larger errors more than smaller ones. Root Mean Squared Error (RMSE) is the square root of MSE, indicating the square root of the average squared difference between predicted and actual values. While there are no fixed thresholds for these metrics, lower values of MAE, MSE, and RMSE generally signify better model performance. The thresholds may vary based on the specific problem being addressed. The metrics obtained for this study suggest that the developed regression models perform well. Lastly, R-squared is a statistical measure indicating the proportion of variance in the dependent variable explained by the independent variables. R-squared ranges from 0 to 1, where 0 indicates poor fit, and 1 indicates a perfect fit. The R-squared values for the predictive regression models (shown in Table 6) range from 0.13 to 0.35, which can be considered acceptable.

Table 6. Performance metrics of predictive regression models

Bank	MAE	MSE	RMSE	R-squared
PR1	8.89	91.45	9.563080	0.262666
PR2	10.16	106.53	10.32130	0.346976
PR3	11.98	292.01	17.08825	0.224827
PR4	7.68	103.62	7.830428	0.126826
PR5	7.78	66.63	8.162604	0.130014
PB1	8.03	77.30	8.791784	0.331875
PB2	7.43	63.48	7.967387	0.319033
PB3	8.67	85.82	9.263741	0.249911

5. Discussion and Conclusion

5.1. Theoretical Implications

This study aimed to predict the perceived usability of mobile banking apps of public and private banks by utilizing machine learning techniques. Results of this study showed that by using machine learning techniques it is possible to predict perceived usability of mobile banking apps based on demographic details, mobile app usage experience, and technical specifications of the devices used. More specifically, this study showed that factors such as age, gender, education, occupation, screen size of the device used in mobile banking, mobile operating system, mobile banking app usage frequency, number of activities performed in the mobile banking app, and number of mobile banking apps used before are highly predictive in estimating the perceived usability of mobile apps of both public and private banks. Machine learning techniques can be useful in answering research questions in social sciences. In recent years, there has been an increasing interest in using machine learning algorithms in social science research. Machine learning techniques can be applied to a variety of social science research questions, such as predicting human behavior, identifying patterns in large datasets, and analyzing complex relationships among variables. For example, machine learning techniques have been used in various domains in answering the posed research questions, such as usability evaluation of eLearning systems (Oztekin et al., 2019), adoption of smart wearable devices (Arpaci et al., 2021), social engineering risk assessment (Huseynov and Ozdenizci Kose, 2022), and assessment of the role of social media in sustainable consumption (Cerasi et al., 2023). It has been demonstrated in all of these studies that machine learning algorithms have successfully answered the research questions. Overall, machine learning techniques can be a powerful tool in social science research, as they can help researchers analyze complex data sets and identify patterns that may not be immediately apparent with traditional statistical methods. This study has made a significant contribution by demonstrating that it is possible to predict perceived system usability in the literature related to machine learning in social sciences.

5.2. Practical Implications

Banks are able to improve their customers' experiences by anticipating the usability of mobile banking applications and suggesting areas in which they may make improvements (Dimitrova et al., 2022). Customers are more likely to feel satisfied with their banking connections when they have access to an app that is both user-friendly and effective. This may lead to a rise in both trust and client loyalty.

Mobile banking applications have the potential to attract a wider spectrum of clients (Al-Dmour et al., 2020), including individuals who may have restricted access to conventional banking services, as these applications become more user-friendly and easier to use (Asher et al., 2021). Enhancing usability has the potential to contribute to the goal of financial services by making it easier for people from a wide range of socioeconomic backgrounds to use necessary banking services.

More individuals are likely to use these technologies as their usability improves, which may contribute to rising levels of digital literacy. Mobile banking applications are one example of this trend. In consequence, this may help bridge the digital divide and guarantee that individuals from a variety of demographic backgrounds can fully participate in an economy that is becoming more dependent on digital technology.

The results of the research may help financial institutions design mobile applications that are easier to use, but it also shows how important it is to handle clients' data in a responsible manner. Because of the growing dependence on digital banking services, banks have a responsibility to protect the confidentiality and safety of their customers' personal information and resolve any problems that may develop as a result.

It is crucial to guarantee that these models are transparent, fair, and impartial if they are being used to make predictions about perceived usability using machine learning techniques. The ethical implications of using AI technology are something that must be taken into consideration by financial institutions as well as researchers, and they need to strive towards producing responsible AI solutions that put the needs of consumers first.

5.3. Limitations

Like other studies, this study also has some limitations, and the results of the study should be evaluated taking these limitations into consideration. The first limitation of this study is related to the relatively small sample size. Future studies can perform similar analyses by keeping the sample size high. The second limitation of this study is related to the data augmentation technique that was used to overcome the limitations of the sample size. Augmented data may perpetuate biases from the original dataset and may not accurately represent real-world scenarios. Therefore, it is crucial for future studies to carefully select data augmentation techniques and settings relevant to the study's objectives, which may require extensive testing or domain-specific expertise. The final limitation of the study is related to the convenience sampling technique used in the data collection process. Due to the sampling method, university students constituted the majority of the study sample. Convenience sampling may restrict the generalizability of the findings of this study to the target population. Future studies can employ random sampling methods to draw stronger conclusions about the target population.

References

Alavi, S., and Ahuja, V. (2016). An Empirical Segmentation of Users of Mobile Banking Apps. *Journal of Internet Commerce*, 15(4), 390-407.

Al-Dmour, R., Dawood, E. A. H., Al-Dmour, H., and Masa'deh, R. E. (2020). The Effect of Customer Lifestyle Patterns on The Use of Mobile Banking Applications In Jordan. *International Journal of Electronic Marketing and Retailing*, 11(3), 239-258.

Almasi, S., Bahaadinbeigy, K., Ahmadi, H., Sohrabei, S., and Rabiei, R. (2023). Usability Evaluation of Dashboards: A Systematic Literature Review of Tools. *BioMed Research International*, https://doi.org/10.1155/2023/9990933

Arpaci, I., Al-Emran, M., Al-Sharafi, M. A., and Shaalan, K. (2021). A novel approach for predicting the adoption of smartwatches using machine learning algorithms. *Recent Advances In Intelligent Systems and Smart Applications*, 185-195.

Asher, S. W., Jan, S., Tsaramirsis, G., Khan, F. Q., Khalil, A., and Obaidullah, M. (2021). Reverse Engineering of Mobile Banking Applications. *Comput. Syst. Sci. Eng.*, 38(3), 265-278.

Blažica, B., and Lewis, J. R. (2015). A slovene translation of the system usability scale: The SUS-SI. *International Journal of Human-Computer Interaction*, 31(2), 112-117.

Borkowska, A., and Jach, K. (2017). Pre-testing of polish translation of System Usability Scale (SUS). In *Information Systems Architecture and Technology: Proceedings of 37th International Conference on Information Systems Architecture and Technology–ISAT 2016–Part I*, Springer International Publishing, 143-153.

Brooke, J. (1996). SUS: A "Quick And Dirty'usability. *Usability Evaluation in Industry*, 189(3), 189-194.

Byrne, M. D., Greene, K. K., and Everett, S. P. (2007). Usability of Voting Systems: Baseline data for paper, punch cards, and lever machines. In *Proceedings of the SIGCHI conference on Human factors in computing systems,* April 2007, 171-180.

Carroll, J. M. (2004). Beyond Fun. *Interactions*, 11(5), 38-40.

Cerasi, C. C., Balcioglu, Y. S., Kilic, A., Huseynov, F., and Rasti, P. (2023). A Sentiment Analysis to Understand the Role of Twitter Towards Sustainable Consumption. In *27th International Conference on Information Technology (IT)*, February 2023, IEEE, 1-5

Demi̇rkol, D., and Şeneler, Ç. (2018). A Turkish translation of the system usability scale: The SUS-TR. *Uşak Üniversitesi Sosyal Bilimler Dergisi*, 11(3), 237-253.

Dimitrova, I., Öhman, P., and Yazdanfar, D. (2022). Barriers to bank customers' intention to fully adopt digital payment methods. *International Journal of Quality and Service Sciences*, 14(5), 16-36.

Gronier, G., and Baudet, A. (2021). Psychometric evaluation of the F-SUS: Creation and validation of the French version of the System Usability Scale. *International Journal of Human–Computer Interaction*, 37(16), 1571-1582.

Hadi, S. H., Permanasari, A. E., Hartanto, R., Sakkinah, I. S., Sholihin, M., Sari, R. C., and Haniffa, R. (2022). Developing augmented reality-based learning media and users' intention to use it for teaching accounting ethics. *Education and Information Technologies*, 1-28.

Hassan Basri, N., Wan Adnan, W. A., and Baharin, H. (2019). System Usability Scale Evaluation of E-Participation in Malaysia. In *HCI International 2019-Posters: 21st International Conference*, July 26–31 2019, Orlando, FL, USA, Springer International Publishing, 3-8.

Hsieh, M. H., Chen, Y. C., and Ho, C. H. (2019). A usability evaluation of diabetes mobile applications. In *Human-Computer Interaction. Design Practice in Contemporary Societies: Thematic Area*, HCI 2019, Held as Part of the 21st HCI International Conference, Orlando, FL, USA, July 26–31, 2019, Proceedings, Part III 21, Springer International Publishing, 3-15.

Huseynov, F., and Ozdenizci Kose, B. (2022). Using machine learning algorithms to predict individuals' tendency to be victim of social engineering attacks. *Information Development*, 02666669221116336.

ISO (2010). Ergonomics of human-system interaction - Part 210: Human-centred design for interactive systems. ISO 9241-210. *International Organization for Standardization*. Geneva.

Kirakowski, J., Corbett, M., and Sumi, M. (1993). The software usability measurement inventory. *Br J Educ Technol*, 24(3), 210-2.

Koohjani, Z., Aslani, A., Abasi, S., and Kyiani, S. (2019). A Comprehensive Tool for Usability Evaluation of Telehealth. *In pHealth*, January 2019, 168-173.

Kortum, P., and Sorber, M. (2015). Measuring the usability of mobile applications for phones and tablets. *International Journal of Human-Computer Interaction*, 31(8), 518-529.

Lei, B., and Lee, J. (2020). Analysis on Continuous Usage Intention of Chinese Mobile Games From The Perspective of Experiential Marketing And Network Externality. *Journal Of Information Technology Applications & Management*, 27(6), 197-224.

Lewis, J. R. (1991). An after-scenario questionnaire for usability studies: psychometric evaluation over three trials. *ACM SIGCHI Bulletin*, 23(4), 79.

Lewis, J. R. (1992). Psychometric evaluation of the post-study system usability questionnaire: The PSSUQ. In *Proceedings Of The Human Factors Society Annual Meeting*, October 1992, Sage CA: Los Angeles, 1259-1260.

Lewis, J. R. (1995). IBM computer usability satisfaction questionnaires: psychometric evaluation and instructions for use. *International Journal of Human-Computer Interaction*, 7(1), 57-78.

Lewis, J. R. (2014). Usability: lessons learned… and yet to be learned. *International Journal of Human-Computer Interaction*, 30(9), 663-684.

Liu, N., and Pu, Q. (2023). Factors influencing learners' continuance intention toward one-to-one online learning. *Interactive Learning Environments*, 31(3), 1742-1763.

Ng, A. W., Lo, H. W., & Chan, A. H. (2012). Usability assessment of safety signs with the system usability scale (SUS): The influence of demographic factors. In *Iaeng Transactions On Engineering Technologies*, 7, 271-283.

Nielsen, J., and Loranger, H. (2006). *Prioritizing Web Usability*. Pearson Education.

Oztekin, A., Delen, D., Turkyilmaz, A., and Zaim, S. (2013). A machine learning-based usability evaluation method for eLearning systems. *Decision Support Systems*, 56, 63-73.

Phillips, C., and Chaparro, B. (2009). Visual appeal vs. usability: which one influences user perceptions of a website more. *Usability News*, 11(2), 1-9.

Rogers, Y., Sharp, H., and Preece, J. (2023). *Interaction Design: Beyond Human-Computer Interaction* (6th ed.). Wiley.

Rummel. B. (2015). System Usability Scale – Jetzt auch auf Deutsch, https://experience.sap.com/skillup/system-usability-scale-jetzt-auch-auf-deutsch/ (Retrieved: 15 December 2023)

Saremi, M., Torshizi, Y. F., Rostamzadeh, S., and Taheri, F. (2019). How much traffic signs in Iran are usable? A use of System Usability Scale (SUS). In *Proceedings of the 20th Congress of the International Ergonomics Association (IEA 2018)* Volume VIII: Ergonomics and Human Factors in Manufacturing, Agriculture, Building and Construction, Sustainable Development and Mining 20, Springer International Publishing, 900-904.

Sauro J. (2018). 5 Ways to Interpret a SUS Score, https://measuringu.com/interpret-sus-score/ (Retrieved: 5 December 2023)

Sauro, J. and Lewis, J. R. (2012). *Quantifying The User Experience: Practical Statistics For User Research (1st Ed.).* Waltham. MA: Morgan Kaufmann.

Sauro, J., and Lewis, J. R. (2016). *Quantifying The User Experience: Practical Statistics For User Research*. Morgan Kaufmann.

Setiyawati, N., and Bangkalang, D. H. (2022). The Comparison of Evaluation on User Experience and Usability of Mobile Banking Applications Using User Experience Questionnaire and System Usability Scale.

In Proceedings MDPI. 82 (1), 1-7.

Shahid, S., Islam, J. U., Malik, S., and Hasan, U. (2022). Examining consumer experience in using m-banking apps: A study of its antecedents and outcomes. *Journal of Retailing and Consumer Services*, 65, 102870.

Sharfina, Z., and Santoso, H. B. (2016, October). An Indonesian adaptation of the system usability scale (SUS). In *International conference on advanced computer science and information systems* (ICACSIS), 2016, IEEE, 146-148.

Shorten, C., and Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. *Journal of Big Data*, 6(1), 1-48.

Tsai, M. C., Lin, H. C. K., and Lin, C. (2018). Usability evaluation of the game based e-book system on natural science teaching system. In International Conference on Innovative Technologies and Learning, August 2018, Cham: Springer International Publishing, 463-472.

Vlachogianni, P., and Tselios, N. (2022). Perceived usability evaluation of educational technology using the System Usability Scale (SUS): A systematic review. *Journal of Research on Technology in Education*, 54(3), 392-409.

Wang, Y., Lei, T., and Liu, X. (2020). Chinese system usability scale: Translation, revision, psychological measurement. *International Journal of Human–Computer Interaction*, 36(10), 953-963.

Wazid, M., Zeadally, S., and Das, A. K. (2019). Mobile banking: evolution and threats: malware threats and security solutions. *IEEE Consumer Electronics Magazine*, 8(2), 56-60.