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The effect of interface quality, system quality, and perceived usefulness of an automated pronunciation scoring system on student satisfaction

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A B S T R A C T

Presently, the utilization of an automated pronunciation scoring system holds significant importance in the endeavor to enhance the pronunciation skills of non-native learners. A plethora of research endeavors have been dedicated to exploring the various factors that contribute to students' satisfaction with this technology. This particular investigation, however, narrows its focus to examine the influence of interface quality, system quality, and perceived usefulness of the automated pronunciation scoring system on students' levels of satisfaction. The approach employed in this study is quantitative, employing a cross-sectional design, and data was gathered through a survey questionnaire administered to a sample of 250 students from two universities in Malaysia. The collected data were subjected to analysis utilizing Structural Equation Modelling Partial Least Square (SEM-PLS), complemented by SmartPLS3.3 software. The outcomes of this analysis unequivocally indicate that both system quality and the perceived usefulness of the automated pronunciation scoring system significantly and positively impact students' satisfaction. However, it was found that the interface quality does not wield a significant influence on students' overall satisfaction. In conclusion, this investigation has successfully identified and explored the critical factors that contribute to students' satisfaction when utilizing an automated pronunciation scoring system. Moreover, the study establishes a strong correlation between the implementation of such a system and heightened levels of student satisfaction. These findings underscore the importance of diligently attending to interface quality, system quality, and perceived usefulness to optimize the effectiveness of an automated pronunciation scoring system. It is crucial for instructors to play an active role in ensuring that users are adept at navigating and interacting with the system, fostering a positive and fruitful learning experience.

1. Introduction

An automated pronunciation scoring system holds the potential to be a valuable tool for enhancing the pronunciation skills of non-native learners. Nevertheless, the level of user satisfaction with this system is influenced by several factors, namely interface quality, system quality, and perceived usefulness, warranting further investigation. The extent to which an automated pronunciation scoring system contributes to the efficacy of pronunciation learning can be ascertained through an examination of learner satisfaction perceptions. Consequently, research focusing on user satisfaction with the implementation of such a system is imperative.

Practical experience has indicated that a successful and effective system is often synonymous with a satisfying user experience. Therefore, it becomes crucial to explore the dimensions related to user satisfaction with the recommended automated pronunciation scoring system. By gaining insights into user satisfaction, significant implications can be

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derived. The implications arising from the satisfaction model can be classified into three categories. Firstly, the users' perception of interface quality emerges as a pivotal aspect, as it directly impacts their satisfaction with the system (Gaona-García et al., 2017). The user-friendly interface of the system certainly increases the satisfaction levels of the learners, and they will be attracted to continue using the system. Secondly, system quality is also affected (Schön et al., 2017). An agile system quality fulfills the users' requirements and needs to use the system to support their learning actively. At the same time, perceived system quality will affect the so-called loyalty and support to a system the learners found supportive (Wijaksono and Ali, 2019). Lastly, the effect of perceived usefulness plays an important role (Indarsin and Ali, 2017). Perceived usefulness determines the attitudes towards present use as well as future use of the system in supporting the learners' acquisition of language skills. Overall, the objective of the study is to examine the effect of interface quality, system quality, and perceived usefulness of automated pronunciation scoring systems on students' satisfaction.

2. Literature review

The use of any automated pronunciation scoring system must bring about satisfaction to the users. However, users' satisfaction is always affected by the factors such as interface quality, system quality, and perceived usefulness.

2.1. Satisfaction

User satisfaction is considered an important aspect of information system success. Assessing learners' satisfaction with the recommended learning system is essential (Elia et al., 2019). There are many determinants of satisfaction (Costa et al., 2016). Among them are interface quality, system quality, perceived usefulness, etc. There is a need to examine user satisfaction to recommend any system to support learning (Xu and Du, 2019). The experience of using any system that brings about satisfaction will drive the users to continue using the system (Forster et al., 2020). Several widely accepted user satisfaction models are considered and compared in this direction. The purpose is to increase learning performance when user satisfaction is taken care of, and the usage will certainly follow (Isaac et al., 2016). For this study, a model of satisfaction of an automated pronunciation scoring system was developed and explored by integrating the three dimensions discussed below.

2.2. Interface quality

Interface quality and perceived usefulness are two characteristics that relate to satisfaction (Wang, 2016). Relationships between interface quality and perceived usefulness on satisfaction have been noticed (Noh and Lee, 2016). Interface quality is typically associated with usability evaluation with heuristics (Granollers, 2018). Interface with high quality brings about high usability and thus encourages frequent use of the system. In order to make sure that the users are satisfied with the online system, which includes an automated pronunciation scoring system, web accessibility also reflects interface quality (Daoust, 2018; Song et al., 2018). Users must find out that accessibility will become an issue. Developers of any online learning system should adhere to the guidelines in ensuring interface quality that brings about accessibility. Instructors who attend to use any online system in supplementing the teaching and learning process must assist students in tackling any interface problems to enable students to access the system without facing any hindrances and predicaments.

Besides, relevant interface quality criteria and indicators must be established and evaluated (Sun et al., 2019). Users' feedbacks are essential. Allam et al. (2017) mentioned interface quality is the marker that affects user perception. Once the users are satisfied with the interface quality, there isn't any reason that hinders them from using any viable system that can support their learning.

2.3. System quality

Tian and Xu (2017) have stressed that system quality and perceived usefulness significantly impact satisfaction, students must be confident that the system quality is adhered to what they want. They might find assistance as well as support for their learning. System quality must be undergone continuous improvement. One way is to obtain the user's feedback. Developers of the system, instructors, and users are improving together in the whole process (Adkins et al., 2017; Smith et al., 2017). Developers will explore areas of improvement for their system quality (Szczepańska-Woszczyna and Gatnar, 2022). At the same time, instructors will improve their ways of instruction in assisting the students in maximizing the use of the use, and the learners will improve their skills and technique on the proper use of the system to gain maximum benefits. System quality might be due to racial or ethnic disparities (Dong et al., 2018).

Perception discrepancies occur due to different needs and expectations of the system. Especially when it comes to language use and support in the system itself, individual-level cultural values on system quality must be examined (Tarhini et al., 2017). Non-native learners might have different demands on system quality in supporting their learning. As Young et al. (2017) discussed, measuring is the key to improvement. It is possible to improve the system quality when efforts in measuring have been added. Constant checks on system quality before, during and after use are essential. These will explain the effective use of any system recommended for students in supporting learning.

2.4. Perceived usefulness

Perceived usefulness is part of the Technology Acceptance Model (Davis, 1989). Some researchers conclude that perceived ease of use in technology will build the perception of perceived usefulness (Davis, 1989; Ibrahim et al., 2017; Wu and Chen, 2017). Continuance intention to use a system is therefore highly associated with perceived usefulness. Technology acceptance which contains the element of perceived usefulness led to task technology fit, which means the task based on the system will be carried out actively once the students' perceived usefulness levels are high. As Ouyang et al., 2017 emphasized, expectations of perceived usefulness will eventually lead to confirmation of use. Perceived usefulness is also strongly related to the lead to the intention of use (Alrajawy et al., 2016; Chang et al., 2017; Hussein, 2017).

An effective learning environment in integrating system use can be actualized when perceived usefulness is taken care of Cabada et al. (2018). Perceived usefulness is thus a commonly studied variable (Abdullah et al., 2016). Perceived usefulness adds value to the satisfaction of use and brings about loyalty in use (El-Adly and Eid, 2016). Therefore, the critical factors that affect perceived usefulness related to satisfaction must be explored (Keržič et al., 2019). The determinants of perceived usefulness must be studied (Aristovnik et al., 2016). Investigating students' perceived usefulness of the system recommended by the instructors should not be ignored (Song and Kong, 2017). User-perceived usefulness should be constantly monitored (Veral and Macías, 2019). Benchmarking should be developed and explored through studies. A learning approach that integrates system support of learning should take advantage of implementing the recommendations based on the findings of these studies.

Besides, studies on perceived usefulness can always be linked to perceived system quality (Isaac et al., 2016). The reason is that perceived system quality is typically associated with perceived compatibility. A system with high perceived quality should also consider compatibility across various platforms to suit users of different types of devices in accessing the system. Thus, the current study adopts the three dimensions, interface quality, system quality, and perceived usefulness, in developing the satisfaction model of an automated pronunciation scoring system used for pronunciation improvement. Furthermore, a conceptual framework will be developed since the current study focuses on the selected three dimensions. The conceptual framework of this study is depicted in Fig. 1. There are three hypotheses proposed for this study, namely:

Hypothesis 1: Interface quality has a significant positive effect on students' satisfaction.
Hypothesis 2: System quality has a significant positive effect on students' satisfaction.
Hypothesis 3: Perceived usefulness has a significant positive effect on students' satisfaction.

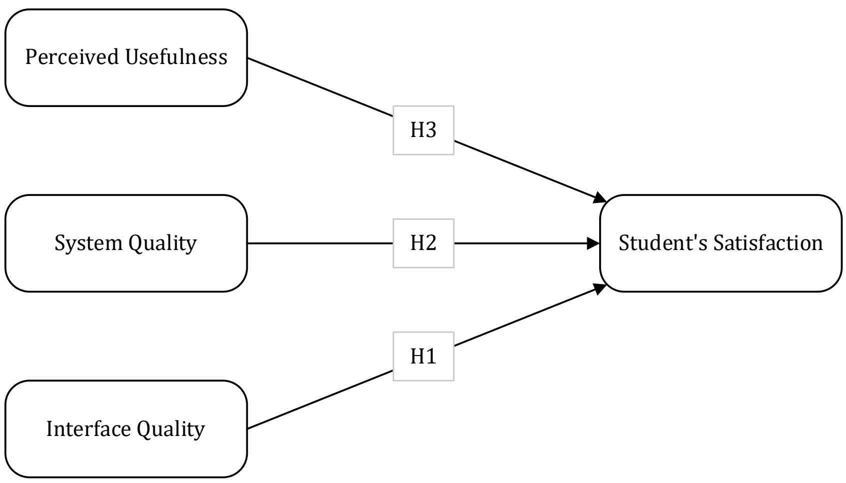

Fig. 1: Research framework

3. Methodology

The research focuses on gathering students' satisfaction with using an automated pronunciation scoring system to support their pronunciation learning. This study is a quantitative study using the PLS-SEM approach for data analysis. Researchers using PLS-SEM routinely stress the predictive nature of their analyses. Model evaluation relies exclusively on metrics designed to assess the path model's explanatory power (Shmueli et al., 2019). This study uses PLS-SEM to explore the relationships among the three dimensions of satisfaction perceptions. It was a non-random sampling study. A purposive sampling technique was employed to engage those students who have used this automated pronunciation scoring system for pronunciation learning for the whole semester. This study was conducted at two universities in Malaysia. They were UiTM and UMT.

They were 250 students in total. The students involved were non-native learners of Chinese as a foreign language. There were 156 diploma students and 94 bachelor's students involved in this study. The diploma students had 4 hours per week for non-native Chinese learning, while the degree students only had 2 hours per week for their non-native Chinese courses.

Before the questionnaire distribution to gauge the students' satisfaction and three dimensions, the students were taught how to use an automated pronunciation scoring system to improve their pronunciation. They were briefed on how to use the system at the beginning of the semester. Before students used the system to support their pronunciation learning, any technical issues were attended. Questions pertaining to the use were settled through WhatsApp to ensure that the students might not have any problems using an automated pronunciation scoring system. The selection of phrases and sentences for automated pronunciation scoring was based on the syllabus. The contents were basically based on those phrases or sentences with which students typically faced problems. By using this automated pronunciation scoring system, students could get immediate feedback on how well they had mastered those phrases and sentences, thus enhancing their pronunciation. The procedure for using an automated pronunciation scoring system is shown in Table 1.

Students accessed the system for a semester to improve their pronunciation by using the phrases and sentences recommended by their instructors. At the end of the semester, these students were asked to answer the online questionnaire at https://form.jotform.com/211652095859060.

Table 1: Procedures for using an automated pronunciation scoring system

Process	Note
Key in sentences for self-testing	Generate voice for testing
Simple scoring is given	Incorrect pronunciation is highlighted and detected in red

3.1. Research instruments

Previous research confirmed that the questionnaire mode is the most popular way to collect data on system usability (Al-Badi et al., 2013). Furthermore, questionnaires can be used to rate users' satisfaction and are one of the most effective ways to gather users' opinions about systems. The questionnaire used in this study is adapted based on System Usability Questionnaire (SUQ) developed by IBM to evaluate system usability. Moreover, this questionnaire consists of 23 questions (adapted from IBM system usability satisfaction) (Lewis, 1995). Each question was rated from one to five and the scale ranged from "strongly disagree" to "strongly agree" and a "neutral" option is present.

The questionnaire is categorized into four key factors: System usefulness (questions 1 to 8), system quality (questions 9 to 17), interface quality (18 to 20), and satisfaction (questions 21 to 23). The contents of the questionnaire are shown in Table 2 below. The PLS-SEM approach is a viable research method to determine the impact of various aspects affecting satisfaction (Farooq et al., 2018). Hence, PLS-SEM is employed for data analysis in this study.

Table 2: Definition of operational variables, instruments, and sources

Constructs	Definition of operational variable	Item	Source
Perceived usefulness	Students believe that the use of an automated pronunciation scoring system is very useful in improving their pronunciation	1. I am satisfied with how easy it is to use this system 2. It is simple to use this system 3. I can effectively evaluate my pronunciation using this system 4. I am able to obtain feedback on the accuracy of my pronunciation quickly using this system 5. I am able to detect where my mistakes are in my pronunciation using this system 6. I feel comfortable using this system 7. It is easy to learn to use this system 8. I believe I am able to improve my pronunciation using this system	Lewis (1995)
System quality	Students are willing to use this automated pronunciation scoring system as the system is high quality and beneficial to their pronunciation learning	9. The system gives messages that clearly tell me how to follow the instructions. 10. The system gives messages that clearly tell me how to fix problems I faced. 11. I easily discover each time a mistake is made using this system. 12. The information (such as online help, on-screen messages, and other documentation) provided in this system is clear 13. It is easy to follow the instructions given by the system 14. The instructions given in this system are easy to understand 15. The instructions given are effective in helping me to complete the tasks of doing self-automated pronunciation scoring 16. The organization of instructions on the system screens is clear 17. The organization of instructions on the system screens is easy to follow	Lewis (1995)
Interface quality	Students believe that the system's interface is easy to use and high quality	18. The interface of this system is pleasant 19. I like using the interface of this system 20. This system has all the functions I expect it to have	Lewis (1995)
Students' satisfaction	Students believe that this automated pronunciation scoring system brings subjective satisfying feelings in supporting their pronunciations learning	21. I am satisfied with the system as it is easy to use 22. I am satisfied with the system as it can help me to improve my pronunciation 23. As a whole, I am satisfied with this system	Lewis (1995)

3.2. Data analysis

In the present study, the Partial Least Squares-Structural Equation Modelling (PLS-SEM) using SmartPLS 3 is used for the statistical analysis (Sarstedt et al., 2019). Besides, since this study is an exploratory based-research, PLS-SEM is considered the suitable approach for such studies (Hair et al., 2017, 2021). In terms of the measurement model, Hair et al. (2017, 2021) suggested that scholars should consider the outer loadings of the items and the average variance extracted (AVE) to establish convergent validity. In addition, they have also suggested a measure for establishing a discriminant validity: Cross loading, which was used in this study. Moreover, Henseler et al. (2014, 2015) have suggested examining the Heterotrait-Monotrait (HTMT) as another criterion for assessing the discriminant validity. Regarding the structural model, the path coefficients and the coefficient of determination (Q2) were measured (Hair et al., 2017; 2021). Accordingly, all the criteria were applied to assess the measurement and structural models.

4. Results

A lack of careful consideration of common method effects in empirical research can lead to several negative consequences for interpreting research outcomes. Table 3 shows the full collinearity testing of the 4 constructs in this study. The purpose is to eliminate common method bias in this study. As stated by Kock (2015) and Kock and Lynn (2012), VAF values are less than 5. VAF for interface quality (3.439), satisfaction (3.625), system quality (4.227), and usefulness (4.890) are all acceptable. It is a preliminary step of PLS-SEM analysis. Hence, it is ready for measurement model assessment in the following subsection.

Table 3: Result of collinearity testing

Interface quality	Satisfaction	System quality	Usefulness
3.439	3.625	4.227	4.890

4.1. Measurement model

Before initiating the PLSpredict procedure, researchers should ensure that all the constructs' measurement models meet the relevant quality standards. In other words, reflectively specified measurement models must exhibit sufficient levels of reliability and convergent validity (Franke and Sarstedt, 2019; Hair et al., 2017, 2021; Henseler et al. 2015). When running PLSpredict, researchers need to make a series of choices. Most importantly, they need to select a key target to construct in the PLS path model for which they want to assess the model's predictive relevance. This construct usually has a reflectively specified measurement model to support the prediction of its items, even though PLS-SEM technically also allows for assessing the prediction of a target construct's formative specified items (Shmueli et al., 2019).

The examination of the measurement model in this study includes reflective metrics. Loadings greater than .50 show that the construct accounts for more than half of the variation in the indicator (Md Noor et al., 2019). Reliability ratings of .70–.95 are considered "acceptable to good" (Hair et al., 2019). Construct reliability (C.R) ratings of .70–.95 are considered appropriate (Shmueli et al., 2019). The items' average variance extracted (AVE) linked with a specific construct is used to measure convergent validity. The AVE must be .500 or greater to be considered acceptable (Ogbeibu et al., 2021), accounting for (more than) 50% of the variation in its components on average. As shown in Table 4 below, all the loadings, AVE and C.R. are in acceptable ranges. Hence the measurement model is apt for hypothesis testing in the next section. This measurement model is depicted as well in Fig. 2. Item SQ13, SQ15, SQ16, and SQ17 were deleted due to cross-loading issues.

The measurement model must exhibit sufficient levels of discriminant validity (Franke and Sarstedt, 2019; Hair et al., 2017; 2021; Henseler et al., 2015). On top of these, Table 5 shows the discriminant validity values of all four constructs. Discriminant validity is the final stage (Palos-Sanchez et al., 2019) that demonstrates how empirically different a concept is from others. In PLS-SEM, discriminant validity is determined by examining the Heterotrait–Monotrait ratio of correlations. If the route model includes variables defined as conceptually and extremely similar, a value of .900 is proposed as a threshold. In PLS-SEM, the Heterotrait–Monotrait ratio criterion is a novel requirement for assessing discriminant validity that outperforms the Fornell–Larcker criterion and cross-loading assessments (Hair et al., 2019). As stated by Henseler et al. (2015), and Franke and Sarstedt (2019), the values should be below 0.90. In this study, HTMT values of interface quality-satisfaction (0.782), interface quality-system quality (0.893), interface quality-usefulness (0.860), satisfaction–system quality (0.844), satisfaction–usefulness (0.870), and system quality-usefulness (0.853) were all above 0.90. Therefore, the findings are considered acceptable for hypothesis testing in the next subsection.

4.2. Hypotheses testing

As shown in Table 6, H1 is rejected (p value>.0000). For both H2 and H3, they are accepted with p values=.000. The results showed that for H1, interface quality did not significantly influence satisfaction (β=0.037, t=0.684). However, for H2, system quality affected satisfaction significantly (β=0.078, t=4.456), and for H3, usefulness affected satisfaction significantly (β=0.574, t=10.466); thus, supporting hypotheses H2 and H3, respectively. Therefore, the discussion on the structural model is worth noticing.

Table 4: Result of construct validity and reliability

Constructs	Items	Loadings	AVE	CR
Interface quality	IQ18	0.883	0.922	0.798
	IQ19	0.885		
	IQ20	0.912		
Satisfaction	S21	0.883	0.945	0.852
	S22	0.954		
	S23	0.932		
System quality	SQ09	0.920	0.952	0.797
	SQ10	0.860		
	SQ11	0.880		
	SQ12	0.909		
	SQ14	0.894		
Usefulness	U1	0.883	0.980	0.857
	U2	0.912		
	U3	0.939		
	U4	0.960		
	U5	0.959		
	U6	0.951		
	U7	0.976		
	U8	0.816		

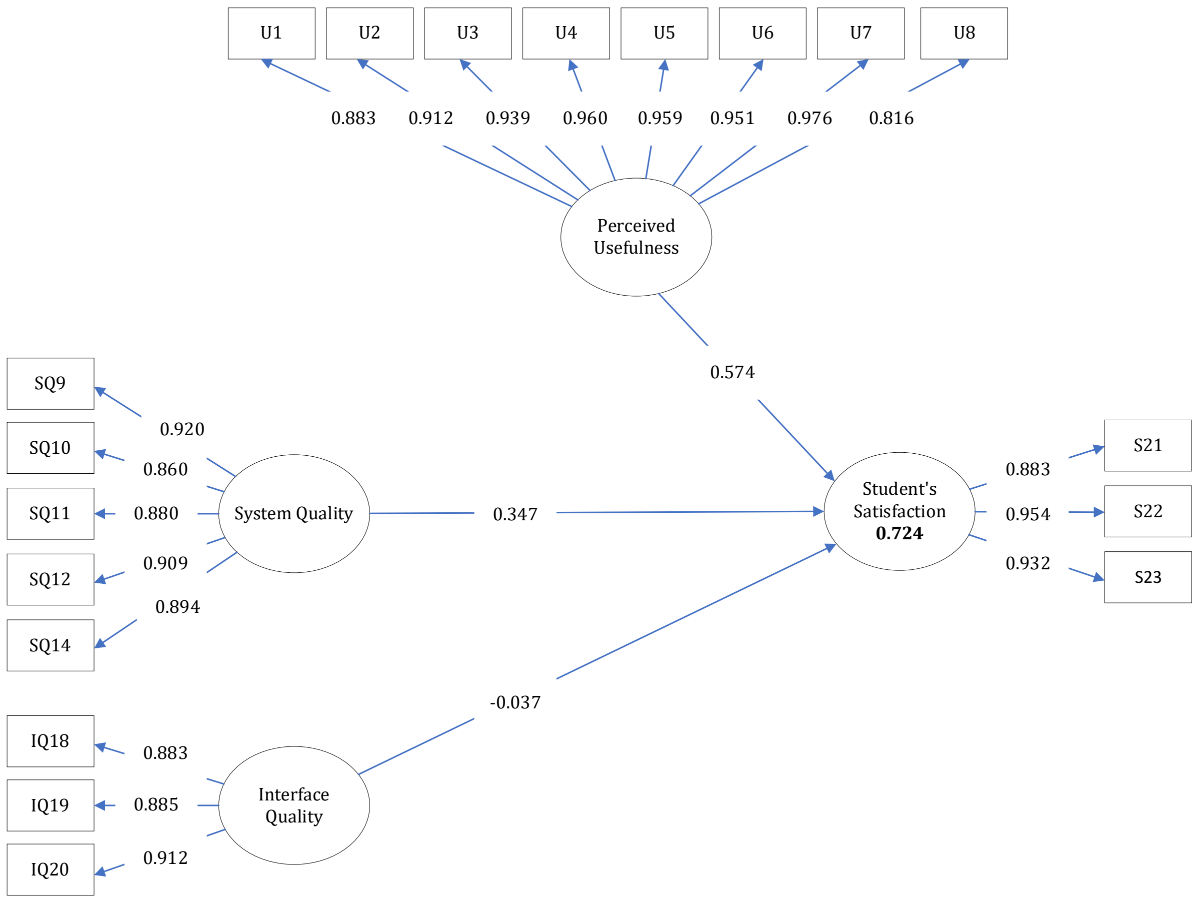

Fig. 2: Result of the PLS algorithm

Table 5: Discriminant validity (HTMT)

Variable	1	2	3	4
Interface quality	1.000			
Student's satisfaction	0.782	1.000		
System quality	0.892	0.844	1.000	
Perceived usefulness	0.860	0.870	0.853	1.000

Table 6: Result of hypothesis testing

Path	Std. beta	Std. error	t-stat	LL	UL	VIF
Interface quality → Satisfaction	-0.037	0.055	0.684	-0.132	0.049	3.433
System quality → Satisfaction	0.347	0.078	4.456	0.214	0.472	3.789
Usefulness → Satisfaction	0.574	0.055	10.466	0.485	0.665	3.692

4.3. Structural model

Researchers e.g., Henseler et al. (2014) and Ringle et al. (2020) recommend looking at measures like R2, f2, Q2, model fit, and statistical significance to assess the structural model. For a given endogenous component, Q2 values larger than zero indicate a reasonable degree of prediction accuracy (Hair et al., 2014; Ringle et al., 2020). To test for statistical significance, Hair et al. (2019) recommend a minimum t-value of 1.65 at p<.05. The structural model was estimated using the consistent PLS bootstrapping option with 5,000 subsamples in this investigation (Lowry and Gaskin, 2014). Table 7 shows the PLS prediction findings. As stated by Shmueli et al. (2019), Q square>0.35 is with large predictive relevance. Therefore, this model is of high predictive relevance. Fig. 3 shows the structural model of this study.

Table 7: PLS-predict

Item	PLS-RMSE	LM-RMSE	PLS-LM	Q^2_predict
S21	0.630	0.279	0.351	0.589
S22	0.699	0.254	0.445	0.629
S23	0.787	0.190	0.597	0.605

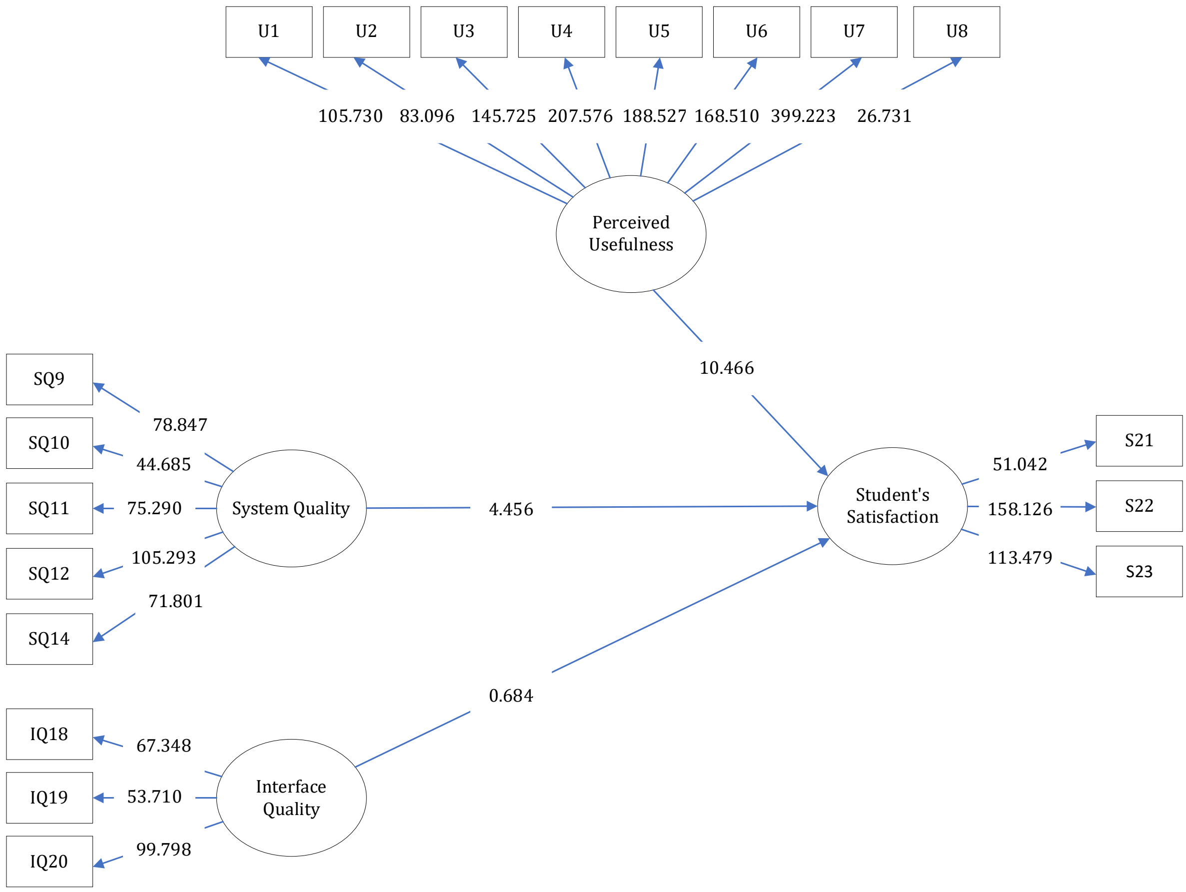

Fig. 3: Result of PLS bootstrapping

5. Conclusion

This research study has undertaken the validation of three key variables that influence students' satisfaction when utilizing an automated pronunciation scoring system to improve their pronunciation learning. The findings of this study have substantiated the positive impact of both system quality and perceived usefulness on students' satisfaction. However, the study did not conclusively establish a significant relationship between interface quality and student satisfaction. Nevertheless, this investigation contributes valuable insights into the examination of the three factors that affect students' satisfaction with the use of an automated pronunciation scoring system for pronunciation learning enhancement.

The integration of an automated pronunciation scoring system exhibits a strong correlation with student satisfaction. Consequently, these findings underscore the need for a thorough consideration of interface quality, system quality, and perceived usefulness. It is crucial for instructors to play an active role in ensuring that users are at ease and proficient in their interaction with the system. Furthermore, system developers must ensure that the provided interface aligns with technological knowledge and incorporates features that facilitate ease of use, including system requirements, language support, and resolution of technical issues, among others. Continued satisfaction is vital in fostering sustained utilization of an automated pronunciation scoring system to support pronunciation learning.

Despite the contributions of this study, certain limitations warrant attention in future research. The current model, focusing on three dimensions of satisfaction, may benefit from additional empirical testing with the inclusion of further factors and subsequent discussion of the results. Exploring other determinants that contribute to the influence of satisfaction dimensions should also be pursued in future studies. Understanding good teaching from the students' perspective necessitates the consideration of more critical factors or variables, and this aspect merits further investigation. Additionally, the incorporation of moderators, mediators, and other individual differences variables in satisfaction measurement could yield valuable insights in future research. For example, investigating variables such as task support, technical support, instructors' support, and facilities support would enhance our understanding of satisfaction dynamics in the context of automated pronunciation scoring systems. Therefore, future research endeavors should take these aspects into account to deepen our comprehension of student satisfaction and system utilization for pronunciation learning support.

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Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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