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Measurement of Attitude in Language Learning with AI (MALL:AI)

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In the novel context of human and artificial intelligence (AI) connection, people seem to be getting more affiliated to AI nowadays in everyday life, which is also valid for education and language learning (LL) processes. Language learners' attitudes towards AI mostly play a crucial role in their acceptance of AI initially as they embrace new technologic advances with a positive attitude. The goal of this study was to develop an instrument to measure the attitudes toward AI in LL process which is MALL:AI (attitude scale in LL with AI) of language learners. The participants were 174 university students from different regions of Türkiye as they are dominant using the new generation technologic tools such as digital educational tools or mobile applications based on AI. The MALL:AI scale was found to be valid and reliable with three factors such as communicative, behavioural, and cognitive skills, as a result of the data analysing. Three sub-factors captured different aspects of the items in line with their valence. Few existing scales for measurement the attitudes toward AI in education are different from the current one as the items were, specifically, grounded according to the LL process. The study suggested that language learners were highly satisfied and preferred to use AI in their LL process.

Introduction

The use of Artificial Intelligence (AI) is raising its popularity in every area of business and education (Olhede & Wolfe, 2018). The importance of AI can be measured by its acceptance by means of the people's perceptions and apprehension. The attitudes of the language learners toward AI, as a teaching material, play crucial role to explore its conceptuality and practicality.

General attitudes toward AI took place in literature from different perspectives such as a dominance of negative views, in which narratives featuring unreal contemplation of AI's future effect (Cave, Coughlan, & Dihan, 2019) in contrast with the study of Fast and Horvitz (2017) which demonstrated that a general increase in optimism to AI was marked. On the other hand, in regarding with the personal concerns or choice restrictions, there is still preoccupation for them, but also, attitudes through applications like Siri, people seem to agree to support AI overwhelmingly (Zhang & Dafoe, 2019). Some of the ethical issues triggered

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the people's perception on AI such as the replacement of robots to human workforce negatively (Granulo, Fuchs, & Puntoni, 2019; Lacity & Willcocks, 2017) while AI can unveil new job opportunities (Wilson, Daugherty & Morini-Bianzino, 2017). The benefit of AI is not ignored in daily life including safe driving or medical care (Hamet & Tremblay (2017) as well as in education (Seldon & Abidoye, 2018). As suggested by Loeckx (2016), AI could be used as an efficient learning tool that lightens the teachers' and the sudents' stress. However, some people have issues in acknowledging such novel tools, human thoughts toward technologies tend to be very polarized (Joinson, 2004).

Unmatched with traditional education types, in relation to the contemporary digitalization of education resources, there are many chances for the improvement of AI applications. The adaptation of these applications has been parlayed for building an appropriate individual learning tool by atoning for decreasing the relationship between students and the classical learning environment. Some of the previous studies (i.e., Boulay, 2016) found out that AI digital learning tools are beneficial regarding monitoring the student's input, delivering appropriate tasks, providing effective feedback, and applying interfaces for human-computer communication. Therefore, it becomes crucial that the advancement of AI in education challenges the role of teachers (Fenwick, 2018).

AI in LL & Teaching in Literature

AI has a profound impact on all walks of life, especially in the field of LL. For instance, AI can mine substantial data by analysing the total data of a student's learning from different aspects of various disciplines according to the data of the previous years and can effectively exhibit the causes of the learning problems and compatible suggestions. Language teaching and learning activity is a complex process including many undetermined factors such as level of professionalism, the problems of infrastructure (i.e., internet, software, hardware etc.), individual differences, learning and teaching styles, environment, cognitive readiness etc. The advantage of AI emerges as it can simulate the teachers' role, reduce the duration of solution, suggest the most appropriate need, exhibit the most unique performance to specify and support the individual learning and teaching strategies since the definition of AI includes its role as the emulation of the behaviour of a language teacher or a learner (Matthews, 1993). As Bull (1997) stated, whether AI has the knowledge of teaching methodology, it emulates the behaviour of the teacher, and whether it has the knowledge of learning methodology, it emulates the behaviour of the student. With the continuous improvement of AI in language learning, it becomes compulsory to stipulate AI in curriculum and syllabus (Somasundaram, Palani & Pandian, 2020). Also, students that are driven and skilled may profit from AI technologies. It's important to comprehend the teacher's role in facilitating and promoting learning with AI technology in the classroom. Self-determination theory served as the foundation for the study by Chiu, Moorhouse, Chai, and Ismailov (2023), which looked at how teacher assistance influences how well students met their needs and how intrinsically motivated they were to learn using AI technology. It is obvious, in contrast to friendship and amusement, that the functional usefulness and dynamic control had a beneficial relationship to users' happiness (Shao & Kwon, 2021). It was also investigated how social presence affected user satisfaction. The moderated analyses revealed that for the users who experienced low levels of functional utility and dynamic control, social presence not only had a primary effect but also significantly contributed to enhancing pleasure. Thus, LL has new demands and higher requirements in technology supported learning environment such as AI with language learners. It is indispensable to use AI in smartphones, computers, cars, houses or schools for entertainment, education, communication and work (Klimova & Poulova, 2015).

The study of Lou, Lin, Chen and Fang (2015) shows that language learners' time is mostly dedicated to smart devices which should be taken into consideration when mentioning language learning. Thus, the innovation in AI cannot be ignored behind modern LL flow as well as the language teaching methods should keep pace with these improvements in order not to be tested by competitive LL world. The utility of AI can be thought as an essential stone to build a considerable and responsible LL process (Mehdipour & Zerehkafi, 2013). Since the Language learner was born just before-after 2000, they have availed different tools for emphasizing their skills and competencies (Sung, Chang, & Liu, 2016; Muhammed, 2014). Moreover, in order to take these learners' attention, AI based methodology is growing to provide the best teaching (Tratnik, Urh & Jereb, 2019).

It seems that in LL and teaching, the term AI assisted LL reaches a wide range of meaning in its usage when integrated (Kite-Powell, 2017). It has been proved that AI enables to the practitioners native-like learning environment as optimizing LL horizons (Wei, 2018). AI offers a new developed platform for the installation of an intelligent and individualized teaching environment. Furthermore, whether gender difference has any effect on the perception of AI is also related, since previously, males mostly incline positively (Cai, Fan & Du, 2017).Furthermore, among the other headings, one of the key elements that affects cooperative learning with AI, is group size, although there is disagreement in the research regarding the ideal number of students to put in each group when working on a task. Zhan, He, Li, He and Xiang (2022) found out that the group size affected student learning motivation and the standard of cooperative problem-solving in the AI module.

AI informs and promotes an LL system without judgement. Thus, the aim should be mainly focused on global interconnection and accessibility of the classrooms in means of multimedia and network technology usage not only in classrooms but also in personalized learning environment. Named as computer network teaching system (CNTS) have been realigned for language teaching methods (Jin, 2014). In spite of the fact that language teaching, sometimes, has hard-shell characteristics, the use of AI in four skills of LL becomes increasingly necessary. There are previous studies which investigate AI from different perspectives such as; learner errors (e.g. Heift, 2003; Tschichold, 1999), speeding up learning process (Kite-Powell, 2017), Siri as AI from an operating system of iOS developed by Apple so as to improve the students' listening and pronunciation skills in English (Goksel-Canberk & Mutlu, 2016), being effective on self-efficacy positively (Shin, 2018), enabling human to talk to another human through AI (Daniels, 2015), to turn the practice into understanding and training deep thinking and methods of learning (Ruecker & Ives, 2015). Artificially intelligent instructional assistants and their function in presenting flexible learning possibilities in light of learners' varied personal learning prerequisites in the area of motivation and emotion (Lazarides & Chevalère, 2021).

Most language teachers are aware of unconventionality of being teacher-centred since it cannot address the current condition of technology, so AI can be a turning point in this respect. The collaboration of teachers and AI can be an important challenge in creativity of the awareness for the learners. Teachers should be capable of ensuring rich input and reinforcing self-learn (Nieto, Garcia-Diaz, Montenegro, González & González, 2019). From this point of view, the findings of the current study are expected to draw attention because of demonstrating the perceptions of language learners who are the essence, toward AI.

The Significance of the Study

The significance of an article that produces a new scale to measure the perception of language learners toward AI integrated in LL process is that it provides a way to systematically and quantitatively measure the attitudes and beliefs of language learners towards AI. This can help researchers and educators to better understand the impact of AI on LL and to develop effective strategies for integrating AI into LL environments. By providing a reliable and valid measure of learners' perception, this scale can also help to identify potential barriers or challenges to the adaption of AI in language learning, and to develop interventions to address these issues. Overall, the development of a new scale for measuring learners' perceptions of AI in LL is an important step towards improving our understanding of this rapidly evolving field and maximizing the benefits of AI for language learners.

The perception of language learners toward AI play an essential role in influencing LL achievement, making the relationship among teacher, learner and AI increasingly important area in language education. To better understand the necessity of AI, researchers need data instruments designed to exhibit how these attitudes or perceptions associated with each other.

If teaching toward AI is considered to be an example of new generation technology trend, then the learners might well have negative or positive attitudes in LL process. For instance, the study of Kanda, Ishiguro, Ima and Ono (2003) measured the impression of people of a communicative robot. Also, the matching hypothesis was presented to explore that friendlier appearance of a robot affects the relationship between human and robot positively (Goetz, Kiesler & Powers, 2003). Previous studies have examined the anxiety, negative attitudes, and communication avoidance behaviour toward robots (i.e., negative attitudes toward robots' scale (NARS) and robot anxiety scale (RAS).

Measuring mentioned constructs in one instrument might have an insight into whether the language learners' have negative or positive attitude toward AI. When the literature is examined, as aforementioned, there is not many of the instruments measuring the perceptions toward LL with AI. Thus, the present study aimed to develop a new and comprehensive, but not boring, questionnaire and provide its validity and reliability for language learner to make contributions, backwardly, to educators and policymakers.

Introducing a measurement tool such as a questionnaire being reliable and valid to put forward the perception of the young language learners is the goal of the current study to enable future research about human–AI communication or interaction in terms of language learning. Although some research has been carried out for human-robot interaction in general meaning of daily life, there have been few investigations about perception of AI in LL environments due to the novelty of the topic.

Methodology

Process Design and Pilot Survey

To determine the candidate items for a questionnaire, a pilot survey has been carried out by collecting opinions toward AI integrated LL process from November 2022 to February 2023. This survey was based on a writing sessions which included the opinions of the 30 Turkish language learners about the effect of AI in LL process. The data collected, were analysed by three academicians who had doctorate studies in the fields of language education programs and two experts of AI assessment. The data were transformed into attitude sentences together. The participants of the pilot study responded to the following questions without any time pressure or subject frame:

(1) "What do you think about LL with AI?"
(2) "What are the differences or similarities when you are taught language by AI from the perspectives of learning environment, classical learning tools?"
(3) "Can AI replace teachers and why?"
(4) "If you faced AI in LL lessons, what do you feel about it? Do you feel more comfortable or more stressed? Please answer freely."

The frequencies of the resulted sentences were calculated, and the expressions were ordered from the most repeated to the least repeated. In this way, 20 attitude items consisting of positive and negative sentences were designated by the consensus of the academicians and the experts after modifying expressions of the answers from the participants of the plot survey. The resulting items were examined by an academician from the field of Turkish education and language editing was done properly. The scale, which was prepared in 3 point-Likert type, was transformed into a 3-grade form based on expert opinions, taking into account the age and grade levels of the students. These degrees are "strongly agree", "partially agree" and "strongly disagree". Positive items were scored as 3, 2, 1 starting from the "strongly agree" option, while negative items were scored as 1, 2, 3, operating in the opposite direction. The reason why the answers given to the positive and negative attitude items are evaluated with a different scoring is because the attitudes are calculated by the sum of the scores given to the items in the Likert-type attitude scales.

The Participants

The participants of the study were drawn from universities. The prototype of the attitude scale of LL with AI (MALL:AI) including of the questionnaire items extracted in the pilot survey was applied during English lessons. A total of 174 university students participated voluntarily. Gender and age information of the participants can be seen in Table 1.

Table 1. Gender and Ages of the Participants

Variable	Options	n	Mean %
Gender	Male	75	43,1
	Female	99	56,8
Age	18	16	9,1
	19	53	30,4
	20	42	24,1
	21	27	15,5
	22	22	12,6
	23	7	4,0
	24	6	3,4

According to the Table 1, 99 female and 75 male students participated, and their ages varied between 18 and 24 (most of them are at the age of 19 & 20). Furthermore, two more specific questions were added in the information form such as; "what applications you use while learning language", and "how much time you spend in the LL applications in a day".

Table 2. Information about the Applications & Web 2.0 Tools and Time

Variable	Options	n	Mean %
Applications	Duolingo	35	20,1
	Udemy	5	2,8
	Translater&Dictionary	17	9,7
	Cambly	9	5,1
	Youtube	12	6,8
	ChatGPT	15	8,6
	Quizlet	4	2,2
Time (daily)	1-3 hours	141	81,0
	3-5 hours	33	18,9
	5-7 hours	none	

As can be understood from the Table 2, most of the participants prefer to utilize some of the applications such as Duolingo, translaters (google, yandex) or dictionary (tureng, cambridge) and ChatGPT (AI based). Furthermore, most of the students (%81) spend 1-3 hours in using applications for LL in a day.

Data Collection Tools

Attitude scale which was developed by the researcher in order to determine the attitudes, perception and opinion toward AI in language learning. Developing items and the data processing were explained detailed in the previous section.

The Findings

The steps of scale development indicated by DeVellis (2017) were followed in the development stages of the scale. After the determining of the items and obtaining expert opinions, the items were individually analysed in terms of reliability. DeVellis (2017) stated that a preliminary analysis of item performance should be conducted and that item-total correlations, item variances, and item means should be considered in this stage. Before starting the preliminary evaluation of the items, the negative items (5, 6, 13, and 14) were reverse coded. As a result of the first analysis, the Cronbach's alpha reliability coefficient of the 20-item scale (Appendix 1) was calculated as 0.831. It was observed that item-total correlations of the items varied between -.269 and .632. Many researchers have stated that items with item-total correlations below .30 measure a different structure than the whole scale (Field, 2013; Pallant, 2016). In the analyses conducted within the scope of the study, it was observed that there were five items with item-total correlations below .30 (M5=.219; M6=.171; M13=-.269; M14=.261; M20=.255). It was also seen that the reliability coefficient of the scale would increase when these items were removed. Considering all these findings, it was deemed appropriate to remove these five items from the scale's preliminary analysis on item performance in accordance with the relevant literature (DeVellis, 2017; Field, 2013; Pallant, 2016).

As a result of the analysis conducted on the item performance of the remaining 15 items (Appendix 2), it was seen that the reliability coefficient of the 15-item scale was .873, which was classified as very good by DeVellis (2017). Item-total correlations ranged from .345 to .641, indicating that this range showed that all correlation coefficients were above the reference value of .30. The item-total correlation coefficients, means, and standard deviation values of the items are given in Table 3.

Table 3. Mean, Standard Deviation and Item-Total Correlation Coefficients for Items

	Item-total correlation	Mean	Standard deviation
1	.345	1.93	.264
2	.492	1.78	.418
3	.492	2.18	.932
4	.424	2.39	.851
7	.587	2.37	.876
8	.568	2.23	.915
9	.603	1.96	.814
10	.590	2.18	.925
11	.520	2.48	.845
12	.457	2.70	.638
15	.640	2.40	.859
16	.518	2.29	.905
17	.520	1.87	.887
18	.641	2.02	.850
19	.534	2.42	.841

The mean of item variances was calculated as .657. The mean of item variance is quite high and it clear that the items have the desired high variance (DeVellis, 2017). It is also known that the mean of items being close to the middle value of 2 and the absence of items very close to the extreme values increase the reliability of the scale (DeVellis, 2017). When the values in Table 1 are examined, it is seen that there is not any mean of the items that is very close to 1 and 3, which are the extreme values of the measurement tool developed within the scope of this research. When the item-total correlations, item variances and the mean of the items are examined, it is seen that the remaining 15 items have the desired reference values, and it was found appropriate to perform an exploratory factor analysis with these items in the next step.

Before performing the exploratory factor analysis (EFA), it was examined whether the sample size was sufficient or not. There are opinions in the literature that a sample size of ten (Watkins, 2021) or seven times the number of items (Mundfrom, Shaw, & Ke, 2005) would be sufficient to perform EFA. Within the scope of the study, there is a sample group of 174 people without missing data and a measurement tool consisting of 15 items. These values meet both reference values mentioned above. In addition, the Kaiser-Meyer-Olkin (KMO) values of the whole scale and the items were individually examined to determine whether the sample size was sufficient.

Within the scope of the study, the KMO value was calculated as .889. It is desired that the KMO value would be greater than .6 (Kaiser, 1974). In addition, the closeness this value to 1 indicates the adequacy of the sample size (Field, 2013). Also, it is seen that the KMO value of each item in the anti-image matrix varies between .763-.954, which shows the adequacy of the sample size. In addition to the calculated KMO values, the result of the Barlett test being significant (p<.0001) shows that the sample size is sufficient for EFA.

After determining that the sample size was sufficient, the correlation matrix was handled to examine whether the data were suitable for factor analysis. When the correlation matrix was examined, it was seen that most of the correlation coefficients were greater than .30 and none of the correlation coefficients were above .90. The determinant coefficient (.007) was calculated as greater than the reference value .00001. All these measurements show that the data are suitable for EFA (Field, 2013; Pallant, 2016; Tabachnick & Fidell, 2019; Watkins, 2021).

In order to determine the number of factors in EFA, it is recommended to look at the factors with an eigenvalue greater than 1 as a result of the principal components analysis, to examine the line graph of the eigenvalues and to perform a parallel analysis (Watkins, 2021). As a result of the EFA performed using principal component analysis, it was seen that there were three factors whose eigenvalues are greater than 1. Figure 1 shows the line graph of the eigenvalues and the number of factors obtained as a result of the principal component analysis.

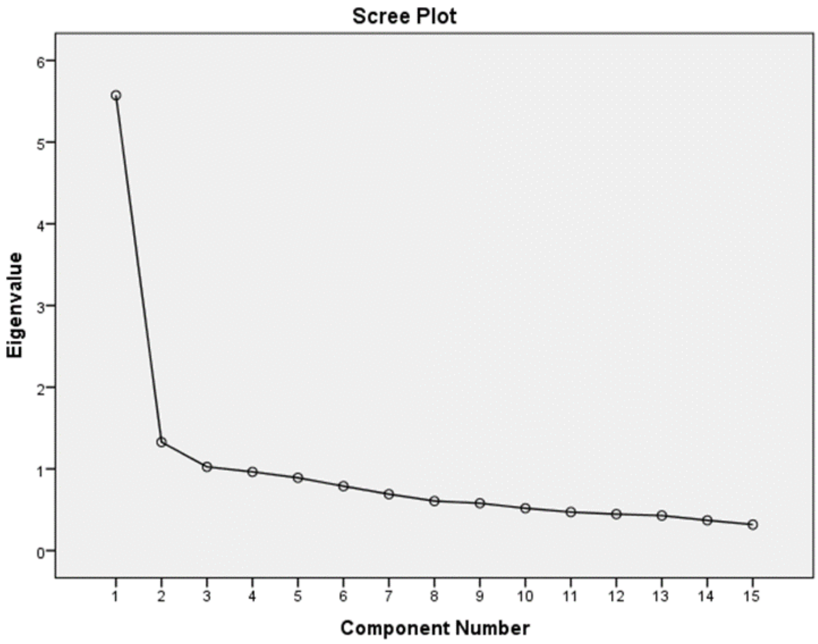

Figure 1. Eigenvalues of the Factors

As can be seen in Figure 1, the graph becomes horizontal starting from the third factor and when a horizontal line is drawn, two factors remain above this line. The line chart proposes a two-factor model. Finally, the number of factors that should be included in the scale was tried to be determined by parallel analysis. An application named Monte Carlo PCA was used for parallel analysis. In this application, random eigenvalues are calculated for a certain number of samples and variables. The eigenvalues calculated with SPSS are compared with the eigenvalues calculated with this application, and it is decided to keep the factors with values greater than the eigenvalues calculated with the application (Pallant, 2016). The eigenvalues and actual eigenvalues calculated by Monte Carlo PCA are given in Table 4.

Table 4. Principal Components and Eigenvalues Obtained as a Result of Parallel Analysis

Number of the Factors	Eigenvalues obtained from principal components	Eigenvalues obtained from parallel analysis
1	1.529	5.574
2	1.413	1.328
3	1.326	1.025

As can be seen from Table 4, only the eigenvalue of the first factor is greater than the eigenvalue obtained as a result of the parallel analysis. In other words, as a result of parallel analysis, it is concluded that a one-factor model would be more appropriate. Since each criterion considered to decide on the number of factors suggests a different number of factors, it was decided to evaluate all three models and choose the most suitable one (Watkins, 2021). Evaluating the models and choosing the appropriate model for the results are also included in similar studies (Smith & Zelkowski, 2022).

After the three-factor model obtained by oblimin rotation, the number of factors was determined as one and two, respectively, and two more factor analysis were performed. The KMO values, mean variances, internal consistency coefficients, eigenvalues of each factor and variance explained and model fit indices for these three models are given in Table 5.

Table 5. EFA and CFA Statistics for Comparing One-, Two-, And Three-Factor Models

	One-factor model	Two-factors model		Three-factors model		
	Factor 1	Factor 1	Factor 2	Factor 1	Factor 2	Factor 3
KMO-Barlett	.889*	.889*		.889*		
Mean of shared value variances	.372	.460		.529		
Cronbach's alpha	.873	.865	.556	.830	.590	.725
Factor eigenvalues	5.574	5.574	1.328	5.574	1.328	1.025
Total Variance Explained by Factor (Cumulative)	37.16%	37.16%	8.86% (46.02%)	37.16%	8.86% (46.02%)	6.83% (52.85%)
χ^2/df	2.00	1.67		1.50		
CFI	.881	.922		.943		
TLI	.861	.908		.931		
SRMR	.065	.064		.057		
RMSEA	.076	.062		.054		

When the values in Table 5 are examined, it is seen that the three-factor model explains more variance and the items have the highest mean of common variance values. In EFA, it is aimed to select a small number of factors to explain as much variance as possible (Field, 2013). In addition, $\chi2$/df, CFI, TLI, SRMR and RMSEA values were decided to examine the compatibility of three different models, which were determined to be evaluated as a result of EFA, with the research data. Collier (2020) states that if the $\chi2$/df value is less than three, the CFI and TLI values are less than .90, and the SRMR and RMSEA values are less than .08, it means that the model and the data have an acceptable fit. It was decided that the three-factor model is more compatible with the data collected within the scope of the research, and this model should be used because the EFA result has the most explained variance and average common variance values, and the model fit indices give better results than other models. Table 6 shows the factor loadings of the items in each factor.

Table 6. Factor Loadings for Each Item

Number of the items	Factor 1	Factor 2	Factor 3	Shared Value Variances
1		.909		.786
2		.755		.696
3			.382	.340
4			.723	.506
5			.507	.504
6			.584	.500
7	.621			.506
8	.518			.458
9			.729	.545
10		.452		.463
11	.631			.558
12	.626			.436
13	.833			.589
14	.814			.654
15	.396			.384
Eigenvalues	5.574	1.328	1.025	
Explained variance	37.16%	8.86%	6.83%	
Cronbach's alpha	.830	.590	.725	
Cronbach's alpha for the whole scale	.873			

There are seven items in total in the first factor, and the factor loadings of these items vary between .396-.833. The majority of the items are close to the upper value of this range, and the internal consistency coefficient for this factor was calculated as .830. This factor is named "communicative" because it bounds the communicative part of the LL with AI. There are three items in the second factor, and many researchers stated that there should be at least three items in a factor (Field, 2013; Tabachnick & Fidell, 2019; Watkins, 2021). The factor loadings of the items in this factor were calculated as .909, .755 and .452, respectively. The reliability coefficient of this factor was calculated as .590. The items in this factor the behaviour of the language learners is more relevant to AI, thus, the factor was named "behavioural". Finally, in the third factor, there are five items with factor loadings ranging from .382 729, and the internal consistency coefficient of this factor is .725. This factor, on the other hand, was named "cognitive", considering that the items under it were more about the improvement of the LL process cognitively with AI. Thanks to all these findings, it can be said that the three-factor model gives reliable results (Field, 2013; Watkins, 2021). Confirmatory Factor Analysis (CFA) was performed to confirm the compatibility of the three-factor model obtained in the last step of the scale adaptation phase with the research data and to verify this model.

For confirmatory factor analysis, it is recommended that the sample size be 20 times greater than the number of variables. It has been stated that a sample size of 10 times greater than the number of variables is acceptable, and samples with a ratio of less than 10:1 will reduce the reliability of the results (Kline, 2016). From this point of view, it is possible to say that a sample of 174 people for 15 variables within the scope of the research will obtain reliable results as a result of CFA. After the sample size for CFA, it was examined whether the data showed a normal distribution. While the lowest skewness value for the items was calculated as -2.963, the highest value was calculated as .263. It was observed that the kurtosis values of the items were in the range of -1.753 to 8.749. These ranges, which include the skewness and kurtosis values of the items, are recommended for these values, respectively |3| and |10|. It is apparent that the data provides the assumption of normal distribution because it is within the ranges of the data (Byrne, 2016; Kline, 2016). After providing the assumption of normal distribution, DFA was performed to verify the three-factor model obtained by using the maximum likelihood method and the model showing the standardized values is given in Figure 2.

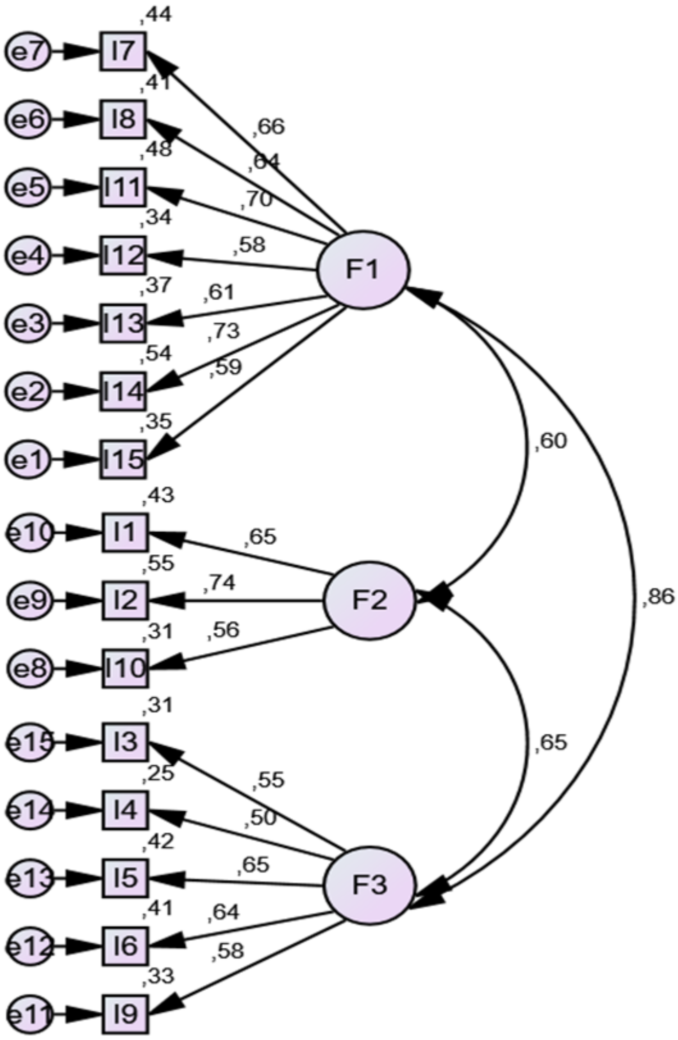

Figure 2. Standardized Resolution Values for The Model

The factor loading values of the items in the first factor ranged between .58-.73, the factor loading values of the items in the second factor ranged between .56-.74 and the factor loading values of the items in the third factor ranged between .50-.65. These values are greater than .5, which is the reference value for DFA (Kline, 2011). Composite Reliability Index (CRI) was calculated for each factor to examine to what extent the items under each factor measure the same structure. The CRI values were calculated as .833 for the first factor, .689 for the second factor and .722 for the third factor, which show that the items under each factor measure the same structure. At the same time, it is possible to say that the internal validity of the scale tool is provided. When the relations between the factors were examined, it was found that the correlation coefficient of the first and second factors was .60, the correlation coefficient of the second and third factors was .65, and the correlation coefficient of the first and third factors was .86. These values show that each factor is closely related to each other. The fact that the correlation coefficients are not excessively high indicates that although each factor is closely related to each other, they do not measure the same structure, which supports external validity (Kline, 2011).

Discussion and Conclusion

This study aimed to develop and introduce a valid and reliable easy-accessible scale to evaluate the attitudes towards LL with AI: MALL:AI. The respondents were from varied ages between 18-22. MALL:AI includes of 15 items comprising 3 factors (communicative, behavioural and cognitive).

Developing a new data collection tool such as a scale, becomes crucial as language learner was constantly introduced new versions of AI which can be also adapted for LL process. Thus, this study also gives clues to new generation type of learning with new curriculums and teaching methods (Lee, 2020; Touretzky, Gardner-McCune, Martin & Seehorn, 2019). On the other hand, MALL:AI presents an objective opportunity for teachers to measure their students' perception of AI and their approach of including AI into their LL process. Furthermore, the academicians can utilize the measurement scores to adapt, alter, develop, perform, and administer the curriculum to meet the learners' needs. Hence, seeing the attitudes toward AI can provide the instructors a new aspect of redesigning the lessons (Ajzen, 1991; Khine, 2015).

The innovation promotes to the surfacing technologic constituent of AI use in language learning. The samples showed high scores on the MALL:AI which is in the same line with the results of some of the studies completed in China which has intensely, funded human and money resource on AI (Pham, 2017). MALL:AI findings, strongly believed, can be facilitated to verify the effects of AI based LL for Language learner and also, the other population such as the older. This study supplies a standardized instrument to determine the attitudes of Language learner toward AI in LL cognitively, behavioural and cognitively.

This study supplies a standardized instrument and the results for developing an attitude scale in LL with the integration of AI into the process to measure the attitudes, opinion, and perception of the Language learner from the perspective of cognitive, behavioural and communicative factors. The internal consistency and cross validity of the MALL:AI were confirmed to test the data.

In summary, the developed measurement tool consists of 15 items and three factors in total at the end of the analysis. It is shown by the analyses made and the findings obtained that the items in Appendix 1, will give reliable and valid results in measurement. In other words, MALL:AI is a reliable and valid measurement tool for measuring the attitude of Language learner in using of AI in language learning.

Suggestions

For further studies, it is recommended that the measurement items can be expanded with different skills of language such as grammar, listening, reading, writing and speaking. Also, the participant group can be varied regarding different ages. Furthermore, other specific applications such as kahoot or hot potatoes can be added in web2.0 tools.

Limitations

Although university students were chosen as the sample in the study, this limitation is only for the purpose of conducting the scale development study.

Declaration of Competing Interest

The author declares that she has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix 1

Old and new numbers after the items are removed

	Old	New	Items
Item Numbers	1	1	In the next years, it will be inevitable for us to communicate with an artificial intelligence while learning a foreign language.
	2	2	An artificial intelligence can take place in our lives as a foreign language teacher.
	3	3	An artificial intelligence can teach a foreign language just by speaking.
	4	4	When I have a problem while learning a foreign language, using artificial intelligence gives me confidence.
	7	5	Artificial intelligence can teach a foreign language in a more comfortable learning environment than in the classroom.
	8	6	While learning a foreign language with artificial intelligence, I can learn more from AI than a real teacher because it can easily access a lot of information about me.
	9	7	Artificial intelligence can provide more effective learning than a real teacher.
	10	8	Learning a foreign language with an artificial intelligence is more enjoyable.
	11	9	I feel more comfortable while learning a foreign language with artificial intelligence.
	12	10	I do not hesitate to make mistakes while learning a foreign language with artificial intelligence.
	15	11	I develop faster while learning a foreign language with artificial intelligence.
	16	12	Artificial intelligence can help me speak a foreign language more in social life.
	17	13	It is normal for artificial intelligence to be perceived as a teacher.
	18	14	It is more beneficial to learn a foreign language with artificial intelligence.
	19	15	It is easier for artificial intelligence to adapt to different students or different learning styles in foreign language teaching than a teacher.