Multi-Criteria Impact Assessment of MVML in performance of Interactive Systems for People with Disabilities

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Abstract**:** The impact assessment of MVML with different criteria is a primary step in the optimisation of Interactive Systems for People with Disabilities (DPISs). This study aims to assess the impact of MVML in comparison with other active learning methods based on multiple criteria. We apply a model of mathematical fuzzy Multi Criteria Decision Making (MCDM) for evaluation of active learning methods. We determine the critical factors that are effective in the performance of interactive systems for people with disabilities. An expert's judgment is used to compare the methods with each other for all criteria. The fuzzy set theory is applied to fuzzify the human judgments. The impact assessment of active learning methods is conducted by calculating the eigenvector from pairwise comparison matrixes. We found "Usefulness", "Feedback Adequacy", "Error Handling Adequacy", "Modality Appropriateness" and "System Response" are critical factors. The results show that MVML has the highest impact in usefulness and feedback adequacy. The overall impact of active learning methods illustrates the high impact of SVML in comparison with other methods for applications in DPISs.

Keywords**:** Interactive Systems, people with disabilities, Active Learning, MVML, Fuzzy MCDM, Assessment.

1. Introduction

People with disabilities are those with a physical or mental impairment who are significantly restricted in their ability to perform daily living activities. People who suffer from disabilities usually have problems using computer-based systems. They are a special group of computer-based systems users whose needs cannot be met by general services available to all normal users. They are handicapped one way or another and are unable to use keyboards, touchscreen or mouse such that using computers may become a very difficult task. It is even more challenging for people with speech disabilities because the processing of impaired utterances is highly complex. Therefore, most state-of-the-art commercial interactive systems are designed for people with normal speech, (i.e. non-speech disordered) and unsuitable for those with speech disabilities (Young and Mihailidis, 2010). These systems provide lower performance for people with speech disorders than people without speech disabilities; this is because impaired speech and normal speech are significantly different (Hux, et al. 2000). As an illustration, according to Rudzicz (Rudzicz, 2012), accuracy of normal speech recognition systems used for the speech-disabled were 26.2% to 81.8% lower than those of people with normal speech. Interactive Systems for People with Disabilities (DPISs) are the interactive systems which take into consideration the people with disabilities. Researchers apply different methodologies in DPISs to address various types of disabilities (Braithwaite, Waldron, & Finn, 1999; Brown et al., 2011; Chang, Chen, & Huang, 2011; Dewsbury, Taylor, & Edge, 2001; Sears & Young, 2002; Stephanidis et al., 1998). The use of methodologies in DPISs should be different from those in normal interactive systems. Speakers with dysarthria, a neurological disability that damages the control of motor speech articulators (Zhang & Sun 2010) are a type of disabled people. They are often physically incapacitated. Automatic speech recognition is the most helpful DPIS for people with this type of disability. Active learning algorithms are frequently applied in these systems for recognition of speech of disabled people who suffered from dysarthria (S. R. Shahamiri & S. S. Binti Salim, 2014a, 2014b). The multiple criteria impact assessment of MVML in comparison with other active learning methods for DPISs can be used in selecting the proper techniques to maximise the accuracy of DPISs. The objective of this study is to evaluate and rank the active learning methods toward assessment of MVML impact in comparison with other active learning methods in DPISs.

Due to the improvements of active learning methods and their applications in DPISs in the last few decades, the demand for assessment and evaluation of such technologies increase significantly. The evaluation of active Learning methods can be formulated as Multiple Criteria Decision Making (MCDM) since multiple critical factors are considered (Zeleny & Cochrane, 1982). We determine the important criteria of evaluation based on literature of interactive systems evaluation and experts' opinion. Five qualitative criteria are determined: "usefulness", "modality appropriateness", "feedback adequacy", "system response" and "error handling adequacy".

The expert's judgment is used for comparison of active learning methods. An expert expresses her/his opinion by linguistic variables. The classic MCDM methods do not address the uncertainty of qualitative factors. Therefore, we apply fuzzy set theory (Zadeh, 1965) in MCDM method to measure qualitative factors accurately. The Fuzzy pairwise comparison, which is inspired by AHP method (Saaty, 1980) has been employed for evaluation of active learning methods.

The remainder of this paper is organised as follows. Section 2 provides the background of research. The methodology of active learning methods evaluation using fuzzy MCDM method is explained in Section 3. Section 4 provides the results of weighting determined criteria and ranking of active learning methods. Section 5 concludes the paper.

2. Background

Active learning is an interactive approach applied to reduce the burden of labelling abundant examples; it works by discovering and asking the users to label only the most informative ones (Sun, 2013). Active Learning methods are employed from two approaches: multiple views or single view, multiple learners or single learner. Hence, four combinatorial methods are derived from them: SVSL, MVSL, SVML and MVML (Wang and Zhou, 2008).

The most basic method of active learning algorithms is SVSL; it assumes there is one single learner of a single view. Based on this scenario, if several multiple views are available and all of them are suitable to infer the prediction relationship, we can merge all the available views into one. As SVSL active learning is not adequate for solving multiple view problems, MVSL active learning, by exploiting multiple views is considered to solve the problem. The prediction relationship of a problem from multiple views differentiates between MVSL and SVSL active learning (Sun, 2013).

There is no doubt that if we use all the views appropriately for inferring the relationship, a better learner can be reached. The multiple views are not combined into one view when MVSL active learning is used; instead, each view is applied to infer the relationship. In other words, MVSL active learning uses only one learner in each view and the applied learner will label data for the other, and they will collaborate to boost the process (Sun, 2013; Muslea, Minton, & Knoblock, 2000).

Ensemble learning has proved that a certain kind of ensembles can boost almost every kind of classification (Sun, Zhang, & Zhang, 2007). The ensemble technique is applied in SVML to integrate multiple learners into one-view problems. SVML active learning runs different learners on the same feature set while MVSL active learning trains a single learner on different feature sets of the labelled data. SVML active learning mainly leverages on the fact that different learners have different biases (Sun, 2013).

Multi Views Multi Learners (MVML) (Zhang & Sun 2010; Sun & Zhang, 2011) theory is a solution proposed to solve the problem of approximating highly complex functions. The general principle of MVML is that when the function under simulation is complex due to the presence of multiple views, using multiple-learners increases the classification performance compared with using a Multi-Views Single-Learner (MVSL) method. This is because a single learner may not be able to approximate the function under simulation accurately. The researchers have proposed different MVML methods such as multi-net artificial neural network to increase the performance of MVML technique (S. R. Shahamiri & S. Binti Salim, 2014).

Gosselin (Gosselin & Cord, 2008) employed the active learning method for content-based image retrieval in interactive systems and emphasised that Active learning methods were frequently applied in interactive systems for multimedia applications. The use of active learning methods in automatic speech recognition can boost the process of interaction between users and systems especially for users who suffer from dysarthria, a neurological disability that damages the control of motor speech articulators (Zhang & Sun 2010).

3. Methodology

The impact assessment of MVML is conducted through the comparison and evaluation of four active learning methods (SVSL, SVML, MVSL, MVML). The proposed methodology for multiple criteria evaluation of active learning methods is shown in Fig.1.

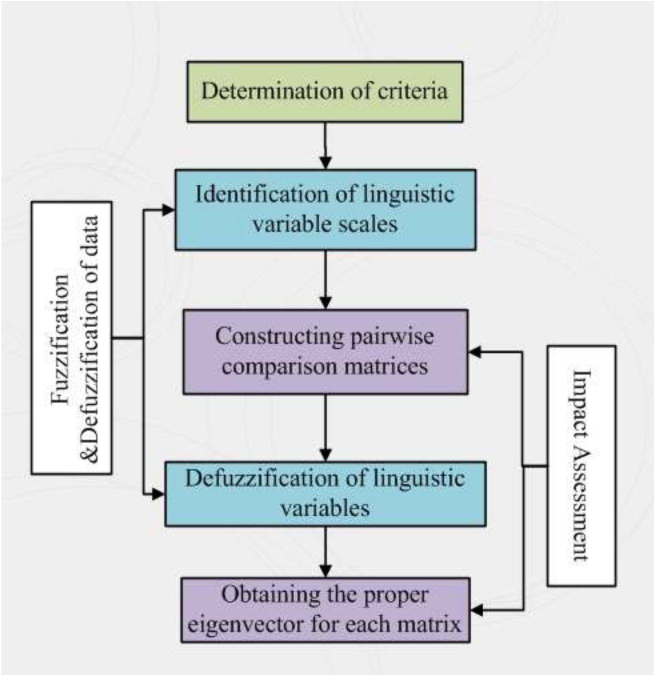

Figure 1. Proposed methodology

It involves three main operations: i) determination of criteria, ii) fuzzification and defuzzification of data, iii) impact assessment of active learning methods. The second and third operations are not separated; however they have sub operations that are integrated to increase the accuracy of assessment. After the determination of criteria, we ask an expert to compare the methods for each of the criteria; the expert uses linguistic terms such “very strong” to do this comparison. We apply fuzzy set theory to calculate the related crisp value for these terms. We define the scales of linguistic variables based on identification and classification of linguistic terms expressed by the expert. This operation is the first step (sub-operation) for fuzzification of linguistic terms. A triangular fuzzy number is considered for each linguistic scale. Next, we construct the pairwise comparison matrices that are a part of AHP method (Saaty, 1980) with triangular fuzzy numbers instead of linguistic variables. For each criterion, there is one pairwise comparison matrix of methods. Defuzzification of fuzzy numbers is conducted by defuzzification method of Shyi-Ming Chen (S.-M. Chen, 1996). Through defuzzification of fuzzy numbers, the matrices change to matrices with crisp values. We obtain the eigenvector related to each matrix by the sum of each column, normalising the matrix and averaging across the words. As discussed, each matrix is related to one criterion. The obtained eigenvector for each matrix involves the impact of methods in considered criterion. The final impacts of methods are obtained by the sum of their impacts in all criteria.

3.1 Determination of Criteria

There are various parameters and factors for evaluation of interactive systems (Preece et al., 1994). Comparative evaluation of results is often carried out at the system response level, i.e. the database response, the translated utterance or, more generally, on the appropriate action the system is supposed to take. An end-to-end interactive system for people with disabilities which includes pattern recognition, semantic analysis, multimedia management, and system response generation, is a black-box configuration which can be evaluated as a whole (Minker, 1998). Therefore, evaluation of active learning methods for DPISs is more specific than evaluation of interactive systems. We prepare a list of criteria with more than 23 criteria from literature of interactive systems evaluation. However, the evaluation of active learning methods in DPISs is more specific through measuring the ability of methods to deal with people with disabilities. Therefore, we ask the experts to choose the suitable criteria for evaluation of active learning methods in DPIS (Fig 2). Based on the expert's opinion, the following criteria are selected as the most proper criteria for the considered evaluation.

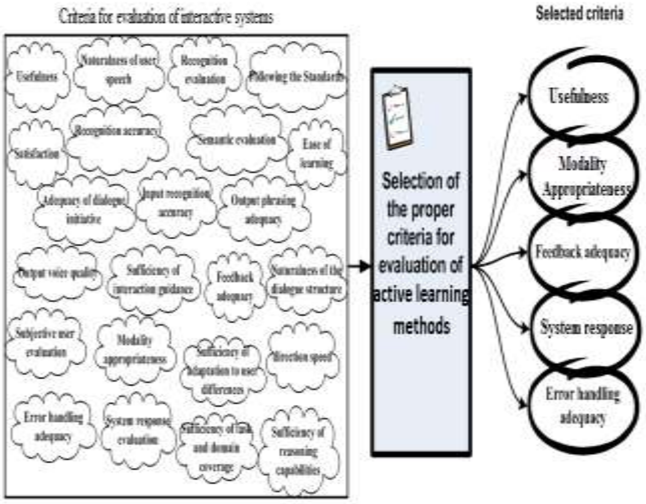

Figure 2. Determination of criteria

- **Usefulness:** The usefulness of a system indicates clearly that it is easy for users to use the system. It means the system is user friendly with fewest steps possible to accomplish a task in the course of interacting with the system (Sturm et al., 1999).
- **Feedback adequacy:** The feedback adequacy comes from the idea that the system must understand and provide confidence to users that input information is as intended by the users. In addition, users must be aware of the actions the system has taken and what the system is currently working on (Sturm et al., 1999).
- **Error handling adequacy:** The error handling happens when both the system and users initiate error handling meta-communication. This means that one component fails to hear or understand the other. Error Handling Adequacy must resolve three issues: firstly, failure to hear or understand; secondly, falsehoods produced in hearing or understanding; and thirdly, clarifications required to hear or understand. These problems must be solved for both users and the system (Spiliotopoulos et al., 2009).
- **Modality appropriateness:** The modality appropriateness pertains to the inputs and outputs or their combinations with other input/ output modality as an appropriate modality choice for a planned application (van Erp et al., 2006).
- **System response:** System response level evaluation is an appropriate method used for comparative evaluation of results. System response can be evaluated in various ways. We can employ experts' opinion to evaluate an interactive system including speech recognition, semantic analysis, dialog management, and system response generation. (Minker, 1998).

3.2 Fuzzification and defuzzification of data:

In this study, the evaluation of active learning methods is based on experts' opinion. The experts compare the methods with each other using linguistic variables. For example, he/she says "the MVML is very strong in comparison with MVSL in terms of system response". The phrase "very strong" is a linguistic variable or a fuzzy variable. Linguistic variables are variables with linguistic term values. The concept of linguistic variable is very useful in dealing with situations which are too complex or too ill-defined to be reasonably described in conventional quantitative expressions (C. T. Chen, 2000; Zadeh, 1965). The linguistic variables cannot be used for calculation of eigenvector. However, the linguistic value can be used for approximate reasoning within the framework of fuzzy set theory to handle effectively the ambiguity involved in the data evaluation and the vague property of linguistic expression. Normal trapezoid or triangular fuzzy numbers are used to characterise the fuzzy values of quantitative data and linguistic terms used in approximate reasoning. There are two steps to convert a linguistic variable to a crisp number:

Fuzzification of linguistic variables for converting the linguistic variables to a fuzzy numbers;

Defuzzification of fuzzy numbers for converting the fuzzy numbers to a crisp numbers.

Fuzzification of linguistic variables is the process of converting linguistic variables to fuzzy numbers. There are two types of fuzzy numbers: Triangular Fuzzy Number (TFN) and Trapezoidal Fuzzy Number (TPFN). TFN uses three numbers and TPFN uses four numbers to fuzzify linguistic variables. Applying TFN is easy and it is the most popular method for fuzzification of linguistic variables.

A TFN $\tilde{t}$ is defined through a trio (a, b, c); then the membership function $\mu_{\tilde{t}}(x)$ is defined as below (van Laarhoven & Pedrycz, 1983):

$$\mu_{\tilde{t}}(x) = \begin{cases} \frac{x-a}{b-a} & a \leq x \leq b \\ \frac{c-x}{c-b} & b \leq x \leq c \\ 0, & x < a \\ 0, & x > c \end{cases} \quad (1)$$

In this study the linguistic terms expressed by experts are identified and classified into seven scales. We determine their related Triangular Fuzzy Numbers (TFN) and replace them with linguistic variables (Table 1).

Table 1. The experts' linguistic variable scales and their related fuzzy numbers

Linguistic variables	Related TFN
Very Strong (VS)	(7, 9, 10)
Fairly Strong (FS)	(5, 7, 9)
Strong (S)	(1, 3, 5)
Equal (E)	(1, 1, 1)
Weak (W)	(1, 1/3, 1/5)
Fairly Weak (FW)	(1/5, 1/7, 1/9)
Very Weak (VW)	(1/7, 1/9, 1/10)

Defuzzification is the process of converting fuzzy numbers to crisp values. We use the defuzzification method of Shyi-Ming Chen (Chen, 1996) for converting the TFN $\tilde{t}$ to a crisp value by the following equation:

$$t = (a + b + b + c) / 4 \quad (2)$$

When the variable "t" consists of the crisp value of $\tilde{t}$.

3.3 Impact assessment of active learning methods

Impact assessment of active learning algorism including MVML is based on multi criteria evaluation of active learning methods. In active learning methods evaluation, we construct pairwise comparison matrixes to compare the active learning methods for each criterion. In this comparison, the active learning methods are compared in DPISs. The comparison here is not based on a human idea; however, it is premised on the technical ability of active learning methods. The technical abilities of Active learning methods are compared by an expert. The obtained data is input into the pairwise comparison matrices. We apply squaring, summarisation and normalisation operations on pairwise comparison matrixes to obtain the eigenvector. The proper eigenvector is the priority vector that shows the impact of active learning methods. Each pairwise comparison matrix is related to one criterion, so the obtained eigenvector for each matrix involves the impact of methods in a considered criterion. The assessment of final impacts of methods is conducted by the sum of their impacts in all criteria.

4. Results and discussion

The proposed methodology determines the criteria and produces the impact of active learning methods in each criterion as well as the final impact of methods including MVML. Through a questionnaire, we ask the expert to compare the active learning methods with each other in determined criteria and using defined linguistic variable scales (Table 2).

Table 2. Feedback of the expert for comparison of methods

METHOD	Criteria	Comments
MVML vs MVSL	Usefulness	**MVML** is **FS** in comparison with **MVSL**
	Feedback Adequacy	**MVML** is **FW** in comparison with **MVSL**
	Error Handling Adequacy	**MVML** is **FW** in comparison with **MVSL**
	Modality Appropriateness	**MVML** is **FW** in comparison with **MVSL**
	System Response	**MVML** is **FW** in comparison with **MVSL**
MVML vs SVML	Usefulness	**MVML** is **FS** in comparison with **SVML**
	Feedback Adequacy	**MVML** is **FS** in comparison with **SVML**
	Error Handling Adequacy	**MVML** is **FW** in comparison with **SVML**
	Modality Appropriateness	**MVML** is **FW** in comparison with **SVML**
	System Response	**MVML** is **FW** in comparison with **SVML**
MVML vs SVSL	Usefulness	**MVML** is **VS** in comparison with **SVSL**
	Feedback Adequacy	**MVML** is **VS** in comparison with **SVSL**
	Error Handling Adequacy	**MVML** is **FW** in comparison with **SVSL**
	Modality Appropriateness	**MVML** is **FW** in comparison with **SVSL**
	System Response	**MVML** is **FW** in comparison with **SVSL**
MVSL vs SVML	Usefulness	**MVSL** is **FS** in comparison with **SVML**
	Feedback Adequacy	**MVSL** is **FW** in comparison with **SVML**
	Error Handling Adequacy	**MVSL** is **FW** in comparison with **SVML**
	Modality Appropriateness	**MVSL** is **FW** in comparison with **SVML**
	System Response	**MVSL** is **FS** in comparison with **SVML**
MVSL vs SVSL	Usefulness	**MVSL** is **E** in comparison with **SVSL**
	Feedback Adequacy	**MVSL** is **E** in comparison with **SVSL**
	Error Handling Adequacy	**MVSL** is **E** in comparison with **SVSL**
	Modality Appropriateness	**MVSL** is **FW** in comparison with **SVSL**
	System Response	**MVSL** is **W** in comparison with **SVSL**
SVML vs SVSL	Usefulness	**SVML** is **FS** in comparison with **SVSL**
	Feedback Adequacy	**SVML** is **S** in comparison with **SVSL**
	Error Handling Adequacy	**SVML** is **S** in comparison with **SVSL**
	Modality Appropriateness	**SVML** is **FS** in comparison with **SVSL**
	System Response	**SVML** is **FS** in comparison with **SVSL**

We construct the pairwise comparison matrix for each criterion. Table 3 shows the comparison matrix related to criterion "usefulness".

Table 3. Pairwise comparison matrix related to usefulness through linguistic variables

	MVML	MVSL	SVML	SVSL
MVM	E	FS	FS	VS
MVSL	-	E	FS	E
SVML	-	-	E	FS
SVSL	-	-	-	E

We replace the linguistic variables with their corresponding fuzzy numbers determined in Table 1. Table 4 shows the fuzzified comparison matrix of usefulness.

Table 4. Fuzzy pairwise comparison matrix related to usefulness

	MVM	**MVSL**	**SVML**	**SVSL**
MVM	(1,1,1)	(5,7,9)	(5,7,9)	(7,9,10)
MVSL	-	(1,1,1)	(5,7,9)	(1,1,1)
SVML	-	-	(1,1,1)	(5,7,9)
SVSL	-	-	-	(1,1,1)

Equation 2 is applied for defuzzification of comparison matrix of usefulness (Table 5).

Table 5. Defuzzified pairwise comparison matrix related to usefulness

	MVML	**MVSL**	**SVML**	**SVSL**
MVML	1	7	7	35/4
MVSL	1/7	1	7	1
SVML	1/7	1/7	1	7
SVSL	4/35	1	1/7	1

We obtain the eigenvector of defuzzified pairwise comparison matrix related to usefulness. It is considered as the impact vector of methods in usefulness criterion (Table 6).

Table 6. Impact of active learning methods in usefulness

Method	**Impact**
MVML	0.609701
MVSL	0.209054
SVML	0.11857
SVSL	0.0626755

We use the same procedure for obtaining the impact of methods in other criteria (Table 7).

Table 7. Impact of methods in all criteria

	Usefulness	**Feedback Adequacy**	**Error handling Adequacy**	**Modality Appropriateness**	**System Response**
MVML	0.60970	0.34056	0.04279	0.036215	0.02648
MVSL	0.20905	0.30748	0.16921	0.093077	0.44744
SVML	0.11857	0.29441	0.59382	0.632602	0.31333
SVSL	0.06267	0.05753	0.19417	0.238106	0.21273

Figure 3 shows that the MVML has the highest impact in usefulness and feedback adequacy. However, it has the lowest impact for error handling adequacy, modality appropriateness and system response.

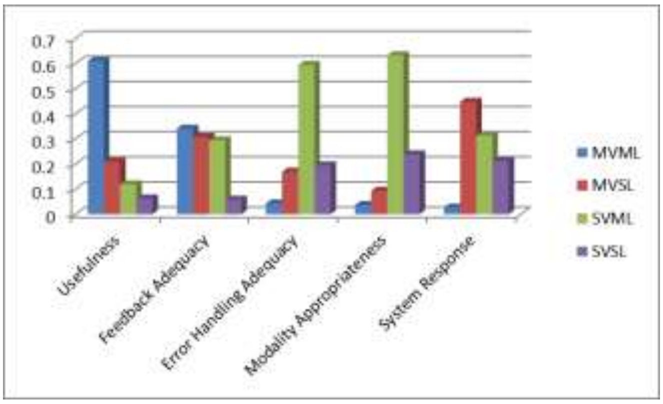

Figure 3. Impacts of active learning methods in determined criteria

SVML has the maximum impact in error handling adequacy and modality appropriateness. On the other hand, MVSL has the maximum impact in system response.
The overall impact of active learning methods shows that SVML has the maximum overall impact and MVML has the third priority to be employed in interactive systems for people with disabilities (Table 8).

Table 8. Overall Impacts of methods

Method	**Impact**
SVML	1.952746

MVSL	1.226272
MVML	1.055758
SVSL	0.765226

5. Conclusion

In this study a set of criteria are determined for evaluation of active learning methods in DPISs. A fuzzy multi criteria decision making method is applied for evaluation of active learning methods. This method can deal with multiple weighted criteria for evaluation of active learning methods. To the best of our knowledge, it is the new application of MCDM methods. The fuzzification scale of linguistic variables is designed based on the identification and classification of the linguistic variables expressed by experts. The applied fuzzy MCDM method assesses the impact of four active learning methods in optimising the performance of DPISs.

From the results, we conclude that MVML has the highest impact in usefulness and feedback adequacy. However, it has the lowest impact for error handling adequacy, modality appropriateness and system response. SVML has the maximum impact in error handling adequacy and modality appropriateness. On the other hand, MVSL has the maximum impact in system response. SVML obtains the highest score in final calculations. Therefore it is concluded that, SVML is the most suitable active learning method for application in DPISs.

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