# A Study on Detection and Reduction of Input Errors in Remote Healthcare Systems

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論文題名　：A Study on Detection and Reduction of Input Errors in Remote Healthcare　Systems
（遠隔医療システムにおけるデータ入力エラーの検知と削減に関する研究）

区　　分　：甲

# 論　文　内　容　の　要　旨

Remote healthcare data carries more errors than usual clinical data. Most of the errors occur due to the human input errors by the healthcare workers at the remote site. Data errors lead to a wrong clinical decision made by a physician. Even if an error is identified by a physician it is not cost effective to remeasure the data and fix the errors. We came up with a software solution to predict three different acceptance ranges- (a) for a particular community (b) for an age group and gender and (c) for a particular person, we call them Human Acceptance Range (HAR), Group Acceptance Range (GAR) and Personal Acceptance Range (PAR).

In order to examine our concept, we carried out statistical analysis to detect outliers. Outliers are easy to detect but not inliers. Errors exist in inliers too. We have found 18% incomplete data, where 5.86% were unusual. The challenge is to detect whether these are errors or simply unusual.

The three significant research contributions are listed below:

1. Growth pattern analysis: We analyzed 40,391 data and demonstrated the growth patterns for the anthropometric items (e.g., Height, Weight, BMI, Waist, and Hip) for both males and females. The patterns can be used to feedback the remote healthcare systems to predict and detect errors during healthcare data collection. As our aim is to identify if there is any similar groups, we analyzed anthropometric items by each age and five intervals of age groups. From the eye-ball estimation, we found three groups for each anthropometric items that can be classified with similar growth patterns. For male height, there is no sharp change until the age of 49, but after the age of 50, we observe a slight decline and a sharp decline after the age of 80. Male weight grows until the age of 49 and decline after that. Male waist and hip show similar growth characteristics with weight. For the female height there is no sharp change until the age of 44, but after 45, we can observe a slight decline. The growth pattern is quite similar to male height. Female weight grows until the age of 46 and another decremented pattern we can observe after 47. We can obtain incremental pattern up to 47 years of age in BMI and another slightly decremented pattern we observe up to 65 years of age. For waist and hip there are incremented pattern until the age 48 and mixed pattern, we observe up to 65 years of age.

2. Group Acceptance Range (GAR): Second, we proposed the Group Acceptance Range (GAR) based clinical growth patterns for both genders. In order to formulate the GAR, we identified the cut-off point based on age from the growth pattern for each anthropometric items. And from that cut-off point, we have calculated different acceptance ranges. For male height the cut-off points of are 41 years of age and 57 years of age, the cut-off points for weight is 40 years of age and 57 years of age, the cut-off points for BMI is 42 years of age and 59 years of age, the cut-off points for waist is 41 years of age and 57 years of age. The cut-off points for hip are 41 years of age and 56 years of age. In a similar process, we identified the cut-off points for female height is 40 years of age and 55 years of age. The cut-off points for weight is 41 years of age and 57 years of age, the cut-off points for BMI is 46 years of age and 68 years of age, the cut-off points for waist is 40 years of age and 56 years of age, the cut-off points for hip is 40 years of age and 56 years of age. These cut-off points help us to understand the similarity and dissimilarity among different age from 20- 100, which leads to formulating the age groups. And finally, we have identified the acceptance ranges for different groups. The GAR can be estimated by analyzing past healthcare data. This range will be applicable for the patients who come for the second time for healthcare checkup. In the existing data (N = 40, 391), we have found 18% incomplete, unusual, and uninterested data, where 5.86% are unusual. In order to evaluate the GAR, we prepared an experimental field in Bangladesh. By organizing PHC service campaign (four times) we gathered 999 healthcare data from similar patients. In the first phase, we have found 1.62% unusual and 0.00% error data. In the second phase, it reduces and we have found 1.00% unusual and 0.00% error data. In the thirds phase, the ratio was the same and, we have found 1.00% unusual and 0.00% error data. However, in the fourth phase, we have found 1.63% unusual and 0.00% error data. A major observation is the error rate was 0.00% in every cases and unusual data was reduced to 4.23%.

3. Personalized Acceptance Range (PAR): Third, we proposed the Personalized Acceptance Range (PAR) based on HAR and GAR for a particular person. PAR can be estimated from biological growth pattern of that person. The range will be applicable for a person who has enough medical records to determine a trend.

In most of the cases, medical devices/sensors, especially for non-communicable diseases, are just used to collect the healthcare data to the server end. If we can integrate the efficient algorithm and integrated the intelligence inside the devices/sensors, it would be helpful to design personalized device/sensors. However, in order to design efficiently, there are a couple of challenges. Detecting and reducing errors is one of the major arenas. The findings of this research are expected to improve the efficiency of remote healthcare systems by detecting and reducing input errors. This improved approach will help not only to increase the efficiency of remote healthcare systems but also to reduce cost and time for the services.