Communication is recognised as a core skill for doctors and is key to transforming clinical knowledge into practice, as such it is an essential component of clinical competence.1,2 Yet, despite the knowledge that doctor-patient communication is pivotal in determining positive outcomes from consultations, the commonest mistakes reported to the Irish Medical Council [Irish Medical Council Conference, 2012] and the American Medical Association are still ones of communication (rather than failures of knowledge).

Consultation training serves to model the important paradigm shifts that need to be enacted by doctors, as they develop approaches to patient centred consultation.1 Intensive experience is generally assumed to produce more favourable learning outcomes, but recent research suggests that assessment can be a more powerful driver of student learning depending on instructional format.3-5 Knowledge-based instruction alone may not be sufficient for imparting communication skills in medical education, but aligned with pedagogically sound teaching delivery, practice with stimulated patients and contextualised assessment may have a higher impact on student performance.6

Adaptive simulations and personalised learning are becoming an innovative feature of international medical schools for teaching and assessment.7,8 In an adaptive simulation, the simulation environment is not fixed but rather can be modified (or adapted) by the lecturer for optimal pedagogical effect.9 Simulations can also adapt to the student as they engage in real time with the tasks and scenario presented to them.

The adaptive simulation platform (called SkillSims)10 allowed the student to self-assess, practice and master their skills through immersive video based simulations. The scenarios used were psychiatric consultations with two patients respectively portraying mania and depression. The student assumed the role of the doctor, and was required to develop approaches to patient centred consultation.11 The scenarios used were psychiatric consultations with two patients respectively portraying mania and depression. The student assumed the role of the doctor, where they could choose (decision points) what the doctor should say and how they should say it, and exhibited various communication skills (optimal and not), accumulating scores as they progressed.

The expert rater of the psychiatry simulations used a scoring system which encompassed knowledge of the consultation process and communication skills for student performance, as it pertains to Calgary Cambridge model of the consultation interview.12 Students are presented with a dialogue options, pre-scripted by the expert-rater using an authoring tool within SkillSims13 to form multiple branching dialogue trees (figure 1). Each branch consists of a decision point and a pathway. Both were assigned a score, based on how well that branch demonstrated the communication skills competencies required (within the Calgary Cambridge Model), when compared to the other branching pathway options available.11,13,15

This score for decision points and communication skills were examined as part of this Generalizability study. Typically a low score was produced if a student prematurely proceeded from one section to another, or skipped a section entirely (according to expert judgement). The decision making scores are cumulative with the final score being presented to the student once they had

---

### RESULTS

The results produced by the G study on the decision points variable, indicating clinical decision making and confirming user knowledge of the process of the Calgary Cambridge guide to consultation were positive, with the significance level attained being similar to those obtained with expert raters. The G coefficient for two cases was 0.23, which is consistent with other performance assessment results. In summary, the automated scores using the decision points variable are similar to those obtained with rater-based scores. The results produced by the G study on the decision points variable, demonstrated that it could be used as an indicator of knowledge of the process of Calgary Cambridge consultation skills.

---

### ACKNOWLEDGEMENTS

Dr. Fionn Kelly, Sen. Reg., (Expert rater), Prof. Ronan Conroy, DSc, Dr. Conor Gaffney, PhD, Dr. Declan Dagger, and Gordon Power, MSc for their constructive comments on this manuscript.

---

We would like to thank EmpowerTheUser (ETU Ltd.) for allowing us access to this data.

---

### REFERENCES


2. A Generalizability analysis was conducted on the IT data analytics collected from the first use of the adaptive simulation, obtained when undergraduate medical students (psychiatry module) at Trinity College Dublin, interacted with two adaptive simulations (as a mandatory part of communication skills training (using the Calgary Cambridge model).13

3. For the purposes of this study, we looked at the scoring mechanisms of these two adaptive simulations to investigate validity and reliability of scoring. The data analytics were provided by the research team who conducted an initial study in 2012 as part of a EU unREAL project to carry out research and development in the field of experiential virtual training.11,15,16

4. A simple person-by-case (P x C) Generalizability study using existing data of these two cases was used to examine variance components. The variance component estimates from the generalizability study are displayed in Table 1. The generalizability study was conducted on a dataset (n=129) for the variable for a score (y-axis on figure 2) indicating knowledge of process and skills.

5. Table 1: Generalizability (G) study on ‘Score’ using a person-crossed-with-cases randomised model

<table>
<thead>
<tr>
<th>Effect</th>
<th>Degrees of freedom</th>
<th>Variance Comp.</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>129</td>
<td>0.0024270</td>
</tr>
<tr>
<td>C</td>
<td>1</td>
<td>0.105367</td>
</tr>
<tr>
<td>PC</td>
<td>129</td>
<td>0.0138640</td>
</tr>
</tbody>
</table>

6. For the purposes of this study, we looked at the scoring mechanisms of these two adaptive simulations to investigate validity and reliability of scoring. The data analytics were provided by the research team who conducted an initial study in 2012 as part of a EU unREAL project to carry out research and development in the field of experiential virtual training.11,15,16

7. One simple person-by-case (P x C) Generalizability study using existing data of these two cases was used to examine variance components. The variance component estimates from the generalizability study are displayed in Table 1. The generalizability study was conducted on a dataset (n=129) for the variable for a score (y-axis on figure 2) indicating knowledge of process and skills.

8. A simple person-by-case (P x C) Generalizability study using existing data of these two cases was used to examine variance components. The variance component estimates from the generalizability study are displayed in Table 1. The generalizability study was conducted on a dataset (n=129) for the variable for a score (y-axis on figure 2) indicating knowledge of process and skills.

9. For the purposes of this study, we looked at the scoring mechanisms of these two adaptive simulations to investigate validity and reliability of scoring. The data analytics were provided by the research team who conducted an initial study in 2012 as part of a EU unREAL project to carry out research and development in the field of experiential virtual training.11,15,16

10. A simple person-by-case (P x C) Generalizability study using existing data of these two cases was used to examine variance components. The variance component estimates from the generalizability study are displayed in Table 1. The generalizability study was conducted on a dataset (n=129) for the variable for a score (y-axis on figure 2) indicating knowledge of process and skills.

11. A simple person-by-case (P x C) Generalizability study using existing data of these two cases was used to examine variance components. The variance component estimates from the generalizability study are displayed in Table 1. The generalizability study was conducted on a dataset (n=129) for the variable for a score (y-axis on figure 2) indicating knowledge of process and skills.

12. A simple person-by-case (P x C) Generalizability study using existing data of these two cases was used to examine variance components. The variance component estimates from the generalizability study are displayed in Table 1. The generalizability study was conducted on a dataset (n=129) for the variable for a score (y-axis on figure 2) indicating knowledge of process and skills.

13. A simple person-by-case (P x C) Generalizability study using existing data of these two cases was used to examine variance components. The variance component estimates from the generalizability study are displayed in Table 1. The generalizability study was conducted on a dataset (n=129) for the variable for a score (y-axis on figure 2) indicating knowledge of process and skills.

14. A simple person-by-case (P x C) Generalizability study using existing data of these two cases was used to examine variance components. The variance component estimates from the generalizability study are displayed in Table 1. The generalizability study was conducted on a dataset (n=129) for the variable for a score (y-axis on figure 2) indicating knowledge of process and skills.

15. A simple person-by-case (P x C) Generalizability study using existing data of these two cases was used to examine variance components. The variance component estimates from the generalizability study are displayed in Table 1. The generalizability study was conducted on a dataset (n=129) for the variable for a score (y-axis on figure 2) indicating knowledge of process and skills.

16. A simple person-by-case (P x C) Generalizability study using existing data of these two cases was used to examine variance components. The variance component estimates from the generalizability study are displayed in Table 1. The generalizability study was conducted on a dataset (n=129) for the variable for a score (y-axis on figure 2) indicating knowledge of process and skills.

---

### DISCUSSION

The automated assessment of decision points in the simulation are of similar robustness to those obtained with expert raters and so this approach and scoring has potential for wider use in automated assessment of medical students.

The findings indicate that this approach to adaptive simulations has potential as a teaching and assessment tool for undergraduate medical consultation skills.

The use of simulation and technology for learning, teaching and assessment has increased and virtual patient simulations are becoming an innovative feature of technology enhanced learning (TEL) to support learning and assessment. This study explores whether this approach is a feasible and robust technology solution for supporting automated learning and assessment.

---

### CONCLUSION

In this adaptive simulation of the medical consultation to assess student performance the automated scoring of decision points in the adaptive simulation produced results similar in robustness to those obtained with expert raters. This approach and scoring have potential for wider use in automated assessment of medical students.

The findings indicate that this approach to adaptive simulations has potential as a teaching and assessment tool for the medical consultation, which requires further development and research.

---

**INFORMATIONAL VALIDITY OF VIRTUAL PATIENT SIMULATIONS FOR SELF-DIRECTED LEARNING AND ASSESSMENT IN THE MEDICAL CONSULTATION**

**Catherine Bruen**, **Clarence Kreiter**, **Vincent Wade** & **Teresa Pawlikowska**.