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Prediction of Students' Self-confidence Using Multimodal Features in an Experiential Nurse Training Environment

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Abstract. Simulation-based experiential learning environments used in nurse training programs offer numerous advantages, including the opportunity for students to increase their self-confidence through deliberate repeated practice in a safe and controlled environment. However, measuring and monitoring students' self-confidence is challenging due to its subjective nature. In this work, we show that students' self-confidence can be predicted using multimodal data collected from the training environment. By extracting features from student eye gaze and speech patterns and combining them as inputs into a single regression model, we show that students' self-rated confidence can be predicted with high accuracy. Such predictive models may be utilized as part of a larger assessment framework designed to give instructors additional tools to support and improve student learning and patient outcomes.

Keywords: Experiential Learning · Simulation-based Training · Multimodal Learning Analytics (MMLA) · Self Confidence · Machine Learning

1 Introduction

In recent years, experiential learning has gained popularity as an effective approach to training for specialized skills, especially in nursing and healthcare. Experiential learning emphasizes hands-on experiences and reflection [3]. In nursing education, experiential learning has seen application through simulation-based training programs. These nursing simulations use high-fidelity manikins to expose students to realistic patient scenarios in a safe and repeatable environment.

Simulation-based experiential learning environments have many advantages. For example, they provide students opportunities to increase their confidence

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through deliberate repeated practice in a safe environment [4], which is a critical component of an effective nursing curriculum. It influences students' engagement, motivation, and overall performance, directly impacting patient outcomes [5]. However, measuring and monitoring self-confidence is challenging because it has multiple interpretations; it can be measured as a *personality trait* or as a *metacognitive process* [1].

In this paper, we propose a novel approach to predicting students' metacognitive self-confidence in an experiential nurse training environment by combining information from student eye gaze and speech patterns. We develop predictive models of students' self-rated confidence in their simulations, which can contribute to the development of new methods for assessing and enhancing metacognitive self-confidence. This has implications for developing data-driven performance monitoring systems that could be used by students and instructors to improve learning outcomes and better characterize student readiness.

2 Background

Previous work has shown that careful consideration must be made when measuring students' self-confidence to ensure that the correct construct is being measured. Burns et al. [1] showed that self-confidence can be broken down into a spectrum between an online metacognitive judgement and a personality trait based on how it is measured. The metacognitive self-confidence is linked to cognitive and metacognitive processes and is typically measured online as a post-task question; i.e. "How confident are you that your answers/actions are correct?" or "How confident are you that you were successful in completing your assigned task?" Personality trait self-confidence, on the other hand, is linked to personal experience and emotional tendencies and tends to be less related to specific task performance [1]. In our study, we measure the metacognitive aspects of self-confidence by having students rate their confidence as part of an individual performance rating after they review and reflect on a video of their training exercise (see Sect. 3.2). Because of the task-specific nature of this question, the measurement can be interpreted as students' metacognitive self-confidence. Therefore, when building our predictive models, we used students' self-reported confidence as the ground truth for their metacognitive self-confidence (see Sects. 3.3 and 4).

3 Methods

3.1 Experiential Nursing Simulation

Student nurses trained in a simulated hospital room containing standard medical equipment and a manikin patient simulator. Students entered the room and performed routine evaluations of the manikin patient, and then performed relevant prescribed treatments based on their evaluation. For more details on the simulation environment, see [7]. All students provided their informed consent to collect video and audio data as they performed their training activities, and some students volunteered to wear Tobii 3 eye-tracking glasses. In this paper, we analyze the data from 14 students who used eye-tracking glasses.

3.2 Individual Guided Reflection Debriefing

After participating in their instructional simulations, students were given the opportunity to engage in guided reflection designed to promote metacognitive reflection on their performance. Initially, we showed the students their own egocentric eye-tracking footage from the simulation in which they participated. After this, the students re-watched this footage while identifying meaningful event units by pressing a key when they detected a transition from one event to another [10]. Students then reviewed the marked events repeatedly and answered six reflection questions based on that event. One of these questions evaluated teamwork, asking students to rate "To what degree were you working individually versus as a team during this event segment?" on a Likert scale from 1 to 5, and this rating is used later in this paper for feature selection. After answering the questions for each event segment, to conclude the reflection, the students were asked to reflect on the entire simulation experience. They were given a 10-point scale asked, "Please rate YOURSELF on the following measures:" engagement, confidence, patient safety, positive patient outcomes, and scenario objective completion. This paper's main focus is predicting the "Confidence" item in this overall assessment.

3.3 Machine Learning Modeling

We analyzed students' captured eye gaze and speech behavior as an indicator of their overall confidence in the simulation. Using the multimodal eye gaze and speech data collected from the students as features and students' responses to the guided self-reflection as a ground truth for their confidence, we trained a regression model to predict students' self-rated confidence.

We initially developed 27 features derived from the eye gaze and speech data. For each of the students' event segments, we computed these 27 features from the observed data. These initial features were selected in a somewhat post-hoc fashion, partially based on previous work with similar nursing student data [7], and partially based on the features which were easily available from the sensor systems. Because of this post-hoc strategy, not all of these features may be relevant to the prediction of students' self-confidence, so further refinement of the feature set through feature selection processes was necessary.

We performed feature selection by building a mixed effects linear model to measure the fixed effects of the features on self-confidence when controlling for participants. However, in the guided reflection, students only rated their metagcognitive confidence for the overall simulation, not for each event segment. So, we utilized a proxy target variable instead. Utilizing the relationship between teamwork and self-confidence [7], we built the mixed-effects model with students' self-rated teamwork in each segment as the target variable and measured the fixed effects between each of the features and students' self-rated teamwork.

Twelve features shown in Table 1 showed statistically significant effects on teamwork in our feature selection model ($p \leq 0.05$). Seven features were produced automatically by the Tobii glasses 3. One additional eye gaze feature, *PersonGaze*, was computed by the researchers by measuring the overlap between

Table 1. The 12 sequence features extracted from eye gaze and speech data used in the final regression model

Feature	Description
PersonGaze	Percentage of time spent looking at another person
AvgSacHz	Average number of saccades per second
MinSacAmp	Minimum amplitude over all saccades
AvgSacAmp	Average amplitude over all saccades
AvgSacPeakVel	Average peak velocity of over all saccades
StdSacPeakVel	Standard deviation of peak velocity over all saccades
AvgFixHz	Average number of fixations per second
AvgFixPupilDiameter	Average pupil diameter during fixations
MinValence	Minimum emotional speech valence
MaxArousal	Maximum emotional speech arousal
AvgArousal	Average emotional speech arousal
MaxDominance	Maximum emotional speech dominance

the Tobii gaze coordinates and any person-class bounding box produced by the YoloV5L object detection model. The other four features, computed using a trained deep-learning model on sections of the students' speech audio, measured emotional valence, arousal, and dominance of student speech [7,8].

Having selected these 12 features, we then return to the task of predicting metacognitive self-confidence. However, these 12 features are computed for each event, and different students segmented events in different ways. Since our goal was to predict self-confidence over the entire simulation, we formulated the regression as a sequence-to-one regression problem. While several techniques can be used to perform sequence-to-one regression, due to the small sample size of this study we chose to extract basic statistics of the feature sequences to use as the final input features of the regression. For each student's sequence of the 12 features previously identified, we extracted the minimum, maximum, mean, and standard deviation as features to describe the sequence. These four statistical features were calculated for each of the 12 sequence features, leading to an overall 48-dimensional input feature vector for the final regression.

4 Results

For the regression of students' self-confidence scores, because of the small sample size and class imbalance, we used Gradient Boosted Regression Trees with leave-one-out cross-validation. For evaluation, we examined the average root mean squared error (RMSE) and R^2 correlation coefficient compared to the students' self-reflections. The model achieved 0.53 ± 0.17 RMSE and $R^2 = 0.81$. Considering the range of prediction and other limitations, this performance represents a fairly high level of accuracy, which could be informativein a variety of ways.

To explore the model further, we performed a local explainable AI feature contribution analysis using the *Decision Contribution* method [2]. We found 5 unique feature ranking patterns that covered all 14 students. It is most notable that all 5 rankings had the same top-ranked feature: Minimum of AvgSacAmp. which accounted for significantly more of the decision than any of the other features, scoring an absolute sum of decision contributions of 11.99. This was much greater than even the second highest ranked feature, which scored 0.65. However, re-running the regression with only the Minimum of AvgSacAmp feature yielded 1.07 ± 0.16 RMSE and $R^2 = 0.58$, suggesting that while they contributed less, other features still contributed significantly to the overall model performance.

5 Discussion

The analysis presented here was fairly exploratory in nature, given the small sample size and initial post-hoc feature selection methodology. However, the preliminary results suggest several important implications and should be used to drive future research on multimodal prediction of metacognitive self-confidence.

5.1 Saccade Behavior

Saccade behavior seems to be very important in the predictive model's ability to determine students' self-confidence, suggesting that saccade behavior, and its associated cognitive processes, are related to metacognitive self-confidence in some way. 4 out of the 5 top-ranked features were derived from saccade behavior. Extending this, we find a moderate positive Spearman rank correlation between minimum average saccade amplitude and self-confidence ($0.40 \leq \rho \leq 0.92, n = 14$ with Fisher z-score transformation). In other words, larger average saccade amplitudes are linked to higher self-confidence. Prior work has shown relationships between higher-amplitude saccades and goal-directed ideation behavior [9]. Since these simulations tasked students with identifying an unknown problem and coming up with a solution, it is very likely that more confident students spent more time in goal-directed ideation to come up with problem solutions as compared to their peers. However, further work should focus on identifying this relationship more concretely.

5.2 Implications for Instructors

The model presented here also represents a data-driven objective method for instructors to examine and evaluate students' metacognitive self-confidence. With further development, this kind of evaluation could allow instructors to provide more in-depth debriefing and targeted interventions to improve self-confidence, especially for students who have low confidence. Extending this idea, the work is a small step toward a more holistic objective assessment of performance. By aiding instructors' evaluations using data-driven assessments, bias and errors in subjective judgment can be reduced, and the burden of assessment on instructors can be lessened. While self-confidence is only one measure that such data-driven assessments would generate, this work helps to illustrate the longer-term goal and demonstrate that such assessments can be made with multimodal data.

6 Conclusions

In this paper, we showed how multimodal data can be leveraged to model students' self-rated metacognitive confidence scores that are connected to their ability to make metacognitive judgments of their performance. Some limitations of the current study include the small sample size for training the model, as well as the lack of demographic data. In order to show the generality of the methods, future work should repeat this modeling with more students, including students from different populations. Since this model combines self-report with objective measurement, such larger populations would present an excellent opportunity to study diversity and inclusion issues in nursing education. Additionally, future work should apply predictive modeling to other performance concepts, which would allow for a more holistic automated assessment of nurse performance.

References

1. Burns, K.M., Burns, N.R., Ward, L.: Confidence-more a personality or ability trait? it depends on how it is measured: A comparison of young and older adults. Front. Psychol. **7**, 518 (2016)
2. Delgado-Panadero, A., Hernández-Lorca, B., García-Ordás, M.T., Benítez-Andrades, J.A.: "Implementing local-explainability in gradient boosting trees: Feature contribution. Inform. Sci. **589**, 199–212 (2022)
3. Durlach, P.J., Lesgold, A.M.: Adaptive technologies for training and education. Cambridge University Press (2012)
4. Labrague, L.J., McEnroe-Petitte, D.M., Bowling, A.M., Nwafor, C.E., Tsaras, K.: High-fidelity simulation and nursing students' anxiety and self-confidence: A systematic review. In: Nursing Forum, vol. 54, pp. 358–368. Wiley (2019)
5. Lundberg, K.M.: Promoting self-confidence in clinical nursing students. Nurse Educ. **33**(2), 86–89 (2008)
6. Vatral, C., Biswas, G., Cohn, C., Davalos, E., Mohammed, N.: Using the dicot framework for integrated multimodal analysis in mixed-reality training environments. Front. Artifi. Intell. **5**, 941825 (2022)
7. Vatral, C., et al.: A tale of two nurses: Studying groupwork in nurse training by analyzing taskwork roles, social interactions, and self-efficacy. In: 2023 International Conference on Computer Supported Collaborative Learning (2023), (In Press)
8. Wagner, J., et al.: Dawn of the transformer era in speech emotion recognition: closing the valence gap (2022). https://doi.org/10.48550/ARXIV.2203.07378
9. Walcher, S., Körner, C., Benedek, M.: Looking for ideas: Eye behavior during goal-directed internally focused cognition. Conscious. Cogn. **53**, 165–175 (2017)
10. Zacks, J.M., Swallow, K.M.: Event segmentation. Curr. Dir. Psychol. Sci. **16**(2), 80–84 (2007)