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Call for Articles

The IEEE Technical Committee on Learning Technology (TCLT) has been founded on the premise that emerging technology has the potential to dramatically improve learning. The purpose of this technical committee is to contribute to the field of Learning Technology and to serve the needs of professionals working in this field.

The Bulletin of the Technical Committee on Learning Technology aims to report (1) the up-to-date outcome of the emerging learning technologies, (2) the review of learning technology related books, instruments or reports, (3) the collaboration opportunities of work-in-progress research ideas and projects, (4) the current development status of learning technology in the developing countries, and (5) the announcements of the upcoming activities that the learning technology community may interest. It would also serve as a channel to keep everyone aware of Technical Committee’s activities.

The bulletin is calling for articles in the following sections:

- **Emerging Learning Technologies**: an article with up to 8 pages the research outcome of learning technologies, including systems, tools, apps, etc., no theoretical or concept only research would be accepted.
- **Equity, Diversity & Inclusion (EDI)**: an article with up to 4 pages to discuss the issues for minorities in STEM education and how the community deal with the matter.
- **Book & Report Reviews**: an article with up to 4 pages.
- **Collaboration Opportunities**: an article with up to 4 pages to talk about the research progress and stage outcome as well as the aspects and needs of looking for collaborations.
- **Report from Developing Countries**: an article with up to 6 pages to describe the current research progress/difficulties/needs/limitations of the learning technology in the developing countries.
- **Event Info & Call for Event Host**: 1 page.

The bulletin articles have to give readers clear idea and vision of the advanced learning technologies with rich and proper figures, screenshots, and diagrams.

For preparing your manuscript, please follow the IEEE guidelines and use the template at [https://ieeewhat.wpengine.com/wp-content/uploads/Transactions-brief-short-or-communications-article-template.doc](https://ieeewhat.wpengine.com/wp-content/uploads/Transactions-brief-short-or-communications-article-template.doc). Please submit your manuscript to tclt-bulletin@ieee.org in Word format with the subject title “Bulletin Submission for [section]” (section indicates which section you would like to submit). All figures should be in high resolution and embedded in the main text.

The bulletin is included in Emerging Sources Citation Index (ESCI). The first decision for the submission is in 24 days.
Editorial

Maiga Chang, Rita Kuo, Ahmed Tlili, Jerry Chih-Yuan Sun, Jun Chen Hsieh

The International Conference on Advanced Learning Technologies (ICALT) is an annual international conference organized by IEEE Computer Society and IEEE Technical Committee on Learning Technology (TCLT). After its kick-off as IWALT (International Workshop on Advanced Learning Technology) in New Zealand, 2000, ICALT has been held in many different countries to bring together people who are working on the next generation of e-learning systems and technology.

ICALT 2021 was held on July 12 to 15 as an online conference and first organized by the TCLT solely without local organizer. After rigorous review process with 19.3% full paper acceptance rate, there were 134 papers accepted. 403 Track Program Committee members from 44 different countries helped the review process. Besides 135 registered authors, there were 59 additional attendees joined the conference. The TCLT executive committee thanks all the participants for the success of ICALT 2021.

Although there was no nomination of Early Career Researcher in Learning Technologies for Winter 2021 selection this year earlier, the bulletin invited the 2019 award winner – Dr. Ig Ibert Bittencourt – to write a letter to the TCLT community. Dr. Bittencourt discussed his research field and how he got involved in it at an early age. Finally, he concluded by sharing his personal advice with those young researchers about the research journey. The nomination of the Early Career Researcher Award Winter and Fall selection are in March/April and November/December every year. We strongly encourage community members to nominate successful early career researchers for the award.

Besides the Early Career Research Award, the Women in Engineering (WiE) Panel was also another important event in ICALT since 2017. The Women in Engineering Panel in ICALT usually invites female scholars, students, or researchers in STEM areas as panelists discussing the issues regarding the challenges they have encountered in their career path. The Report from Women in Engineering Panel at IEEE ICALT 2021 written by the panel chair and panelists – Rita Kuo, Michelle Banawan, Jaelyn Domingo, Elvira Popescu, and Ramyaa Ramyaa – is published in this issue. The report summarized the issues brought out from the panelists, such as the impact of COVID-19 on careers of women in academia and the discrimination of females in STEM fields. The report also describes the solutions of solving issues from the panelists, such as the involving activities student clubs for community support and applying the strategies learnt from the success female scholars. We hope this report can help the TCLT community understand the issues and concerns of women in the STEM area and deal with the crisis of low employment in female engineers together.

Besides the letter from the award winner and the report from the WiE panel, there are one article in Emerging Learning Technologies, one article in Collaboration Opportunities, and one article in Event Info & Call for Event Host published in this issue. The article entitled “Student engagement recognition from videos: A comparison between deep learning neural network architectures” in the Emerging Learning Technologies section is written by Werlang and Jaques. The article presents three deep learning models (i.e., the transfer learning model, the three-dimensional convolutional model, and the engineered features model) for recognizing the learners’ emotion of engagement in learning status. The authors analyze the accuracy of the models to find the most accurate approach. Based on the emotion of learners, intelligent learning environments can provide feedback to change learners’ learning motivation and behaviors and help them achieve learning goals. The three models are trained with the DAISEE dataset that includes 9068 videos. The results indicated that the three-dimensional convolutional model is the most accurate.

In the Collaboration Opportunities section, the article “What can we take from the pandemic to the future of Education?” written by Affouneh and Salha discusses how COVID-19 pandemic affected the educational systems worldwide. The research team has already investigated teachers’ perspective, challenges, and best practices toward online learning during the pandemic in Palestine. The research team is looking for collaboration in comparative analysis between different countries in order to find the common and different factors related to culture and society. Activities and projects could be one future collaboration feature that focusing on the instructional design under emergency cases and presenting the outcomes in the conferences or workshops.

Last but not the least, Mitrovic and Rodrigo promote the 29th International Conference on Computers in Education (ICCE 2021) in the Event Info & Call for Event Host section. ICCE is an annual conference organized by the Asia-Pacific Society for Computers in Education (APSCE, https://www.apisce.net/) and provides researchers as well as educational practitioners interested in the design, development, use and evaluation of technologies as an academic channel for in-depth discussion on e-learning in diverse disciplines. Being held online (22-26 November, 2021), ICCE 2021 includes keynote speeches, theme-based invited speeches, expert panels, workshops, Work-in-Progress Posters (WIPP), Extended Summary (ES) papers, Doctoral Student Consortia (DSC), and Early Career Workshop (ECW) in which research related to all aspects of use of computers in education is promoted.

The current submission statistics in the Bulletin of TCLT show that authors receive the first decision notification in average 23.74 days, and for the accepted articles the authors get the acceptance notification in average 44.40 days. The accepted articles are published online in average 91.43 days after they were submitted. The editorial board also decided to add a new section – Equity, Diversity & Inclusion (EDI) – which responds crisis of minorities in STEM area that addressed in the WiE panel in ICALT 2021. The section is looking for articles that discussing the issues for minorities in STEM education and how the community deal with the matter. We encourage the researchers in the engineering departments submit the current work of outreach activities in public schools – especially in the rural area – for engaging STEM education, program that ensure providing equal opportunity in employment and promotion for all person regardless the gender, race, etc., and plans for supporting a diverse engineering workspace.

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Letter from the 2019 IEEE TCLT Early Career Award Winner

Ig Ibert Bittencourt, Member, IEEE

In 2019, I was the first Latin-American researcher to be honored with the important award from IEEE “Early Career Researcher Award in Learning Technologies”. Such award is presented annually to a leading early career researcher as an acknowledgement of the impact and significance of their research work in the area of Learning Technologies. Currently, I am an Associate Professor at Federal University of Alagoas (Brazil) and Co-Director of the Center of Excellence for Social Technologies and my career paths can be organized in three categories: i) scientific research on Artificial Intelligence in Education; ii) Public Policy in Basic Education; iii) Social Entrepreneurship in Education.

My interest on Education started when I was in high school and taught math and physics to some friends. Then, when I was in Higher School, I decided to create a startup with two other friends focused on simulating a jury trial and law students could act with the role of a lawyer, prosecutor or judge. Since my friends and I were not able to develop such solution, I decided to do a master and PhD in Artificial Intelligence in Education. Thus, my research career has been dedicated to Artificial Intelligence in Education (AIED), working on the design, development and experimentation of educational technologies. In particularly, I am investigating Gamified Intelligent Tutoring Systems by observing the construction (with ontologies and co-designing with teachers), use (in Basic Education) and its impact (on flow, engagement, and learning). I am doing interdisciplinary research by using computational solutions and psychological theories to know how to provide a better learning experience, on which I have as a grand research challenge How the design and use of Intelligent Educational Systems can promote an Optimal Learning Experience? The problem of optimal learning experience is its foundations on Flow Theory which has been researched in the field of Positive Psychology. I am tackling such problem in two different ways: i) investigating learning scenarios on which students can achieve the optimal learning experience: some of the results we achieved in our research was regarding supporting teachers to design and maintain gamified learning tasks. We proposed an authoring tool (called T-Partner) to support instructors making informed pedagogical decisions to manage their online course. T-Partner promotes the cooperation between artificial and human intelligences, and we designed two versions (lightweight and heavy-weight) of the T-Partner. We evaluated both versions and they equally benefit teachers to make to pedagogical decision-making. Two other studies were about competitive scenarios, in the first one we proposed a peer assessment model where gamification elements are used to engage students. We verified that the average grade given by students to an assignment was 3.0 and we are able to reproduce the aforementioned study by observing aggressivity and flow. The results indicated that male-stereotyped environment increase the level of aggressivity and no significant effect about flow on women in stereotyped.

Beyond my career as a researcher, I have had interesting results to bridge the gap between science and innovation. I co-founded four startups and cooperated with other to transfer technologies. Some of the companies are: i) MeuTutor (currently eyeduc) which was the first gamified educational platform launched in Brazil and more than 300 thousand students used our solutions. In 2015, MeuTutor was considered the most innovative educational company of Brazil (Rio-Info); ii) eNeuron Cognitive Computing was founded in 2018 and it develops Machine Learning solutions to education. The main solution is called Plataforma Analise (launched in 2019) that automatically correct essays. Until the moment, the platform analyzed around 250 thousand essays and it is expected to analyze around 1 million until 2022. In the past 8 years of social entrepreneurship, it was generated around 50 direct and 200 indirect employments. In addition, such companies invested on research and innovation around US $1 million.

Over the past 6 years, I am involved with public policies in education. My first experience was in 2015 and I was a member of a commission to map creative and innovative schools in Brazil. In 2017, I was the PI of a policy from Ministry of Education to redesign the evaluation and acquisition of educational technologies in Brazil. We designed an evidence-based policy and a distributed and decentralized process to evaluate technologies in three dimensions: technological, pedagogical and accessibility. Based on our involvement, in 2019 we supported Lemman Foundation and CIEB to design the evaluation process of the BNDES Connected Education Program. Currently, my team and I are supporting the State of São Paulo (SEDUC) to design a process to evaluate and acquire educational technologies. Another public policy we are supporting the Ministry of Education and National Fund for Educational Development (FNDE) since 2018 is the National Program of Textbook (PLND). In PLND policy, we developed the technology responsible for the selection of the books (2018 – 2023) and we are designing the policy for the acquisition of digital textbooks and Digital Educational Resources.

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Finally, I believe we need a paradigm shift in a way we can build a bridge between social relevant practices with scientific approaches to better understand how to improve and positively transform the world. I am strongly committed to collaboratively involve, engage, and work with different stakeholders of the ecosystem of Education to shape the 21st Century and I believe this award is showing that my team and I are on the right direction.

For those young researchers interested on dedicating their lives to science, I have three tips for you: First, do what you love and what you believe, otherwise the challenges on the road and demotivate you. Secondly, focus on giving your best on the journey because this is all you can somehow control. Thirdly, have fun.

**Ig Ibert Bittencourt** is an Associate Professor at Federal University of Alagoas (Brazil) and Co-Director of the Center of Excellence for Social Technologies. He received his Ph.D. in Computer Science in 2009 from Federal University of Campina Grande (Brazil) and his Post-Doctoral degree in Computer Science in 2013 from University of Campinas (UNICAMP, Brazil).
Report from Women in Engineering Panel at IEEE ICALT 2021

Rita Kuo, Member, IEEE, Michelle Banawan, Jaelyn Domingo, Elvira Popescu, Senior Member, IEEE, and Ramyaa Ramyaa

I. INTRODUCTION

Females are minorities in STEM fields [1][2]. According to the data of the Bureau of Labor Statistics in the United States in 2020, 46.8% of employees are females. However, in the computer and mathematical occupations, only 25.2% of the employees are females [4]. To help the IEEE Technical Committee on Learning Technology (TCLT) community understand the crisis of low employment in female engineers, the Women in Engineering Panel is hosted annually at the International Conference of Advanced Learning Technologies (ICALT) starting from 2017.

The Women in Engineering Panel in ICALT usually invites at least two women scholars, at least one student, and one professor/engineer/researcher working in STEM areas at her early career stage. The panelists discuss various issues such as:

- Which challenges have you encountered (if any) for women in engineering at any level?
- What are potential solutions – perhaps from your experience, or at a systemic level – to address these challenges and encourage more women in engineering?
- What should the women in leadership positions project?

At the end of the panel, the TCLT chair responds on how the technical committee could address some of the issues, concerns, comments, and recommendations for promoting Women in Engineering raised by the panelists and ICALT participants.

II. WOMEN IN ENGINEERING PANEL AT ICALT 2021

IEEE ICALT was held online in 2021 from July 12 to July 15. The Women in Engineering Panel was presented on July 13 at 4pm (GMT). The panelists include:

- Dr. Michelle Banawan from Arizona State University, USA. She is a postdoctoral researcher in the Science of Learning and Educational Technology (SoLET) laboratory of Dr. Danielle McNamara. She was formerly an assistant professor in the Computer Science Department in Ateneo de Davao University in the Philippines.
- R. Kuo is with New Mexico Institute of Mining and Technology, Socorro, MN 87801 USA (e-mail: rita.mcsl@gmail.com).
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- E. Popescu is with University of Craiova, Craiova, Romania (email: elvira.popescu@edu.ucv.ro).
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- Jaelyn Domingo, an undergraduate student in the Department of Computer Science & Software Engineering at California Polytechnic State University. She was also the outreach director in the Women Involved in Software and Hardware (WISH) club in 2020-2021 term.
- Dr. Elvira Popescu from University of Craiova, Romania. She is also the Vice Chair of IEEE Women in Engineering Romania Section Affinity Group.
- Dr. Ramyaa from New Mexico Institute of Mining and Technology in the USA. She is also a member of the Women in Computer Science (WiCS) program in the Department of Computer Science & Engineering.

Dr. Popescu first introduced the mission of IEEE Women in Engineering, which includes aiding with the formation of new IEEE WIE Affinity Groups and supporting ongoing activities, organizing workshops at major technical conferences to enhance networking and to promote membership in IEEE WIE, facilitating the development of programs and activities that promote the entry into, and retention of, women in engineering programs [5]. The Romania Section Affinity Group has conducted multiple activities, such as student meetings, technical presentations, and round tables in-person in the past few years and has moved the activities online in the last year due to the pandemic.

Her presentation also addressed the impact of COVID-19 on the careers of women in academia. Because of the pandemic, almost all educational institutions worldwide imposed some restrictions on face-to-face activities, including teaching and research. This translated into higher work demands for shifting to online instruction and substituting laboratory-based research. This was coupled with an increase in the caregiving and domestic tasks (and especially childcare due to school closures), whose burden was predominantly carried by women. According to the report in [3], the most commonly mentioned effects of the pandemic on the professional work of women faculty included: increased workload due to more meetings, longer hours, more emails; decreased productivity and efficiency, with difficulties in finding focus and being always behind schedule; challenges in interacting with peers and students and in adapting to remote teaching, as well as overall negative effects on research. Furthermore, among women faculty with children, over 71% reported increased childcare demands, also more behavioral and academic needs due to homeschooling, coupled with a lack of childcare accessibility and affordability [3]. Some coping strategies and boundary management tactics were also discussed.

Dr. Popescu ended her presentation with a few open questions that the participants can discuss with their colleagues regarding how to help females in academia to face the crisis during the pandemic. The questions include what changes implemented at institutional level can support participation and advancement of women in STEM and how does the switch to online events impact collaboration and mentoring relationships.

Dr. Ramyaa has a different experience with regards to gender discrimination. She faced no discrimination when she was in the...
single-Gender school in her early ages and the sex-segregated undergraduate school in India. However, when she went to the United States for graduate programs, she was usually the only girl in the department or in the class. Most people believe science and math are the areas for men, not women. Because of the discrimination, she only asked questions in the class only after establishing her credentials as a strong student; she was afraid that a naive or basic question will make others believe that she is stupid. She felt that she was the only person representing the minority group among the majority group, so any contribution she made – positive or negative – reflected on the entirety of the community.

When she became a teacher, females were also minorities in her class. Female students – especially international female students – prefer to team with other female students and this makes their team to be the only minority group. If she put the female students in the same team, does it mean that she prefers the minorities should be in the same team? If she rejects students’ requests, does it mean that she does not allow students to stay with the people in their comfort level? A similar dilemma happened when hiring research assistants from the current students. If she hired minorities, will the majors believe she picked them up because they are minorities? She left this question to the community.

Jaelyn Domingo introduced the missions of the WISH club in California Polytechnic State University, which includes providing a community of support for womxn in computing majors and minors and rectifying the gender gap in the computing field. The club hosts Industry Talk to give opportunities to women for internships/jobs and manages the mentorship program that pairs upperclassmen to undergrads so participants have someone to talk to if they meet problems in their class.

Jaelyn’s major responsibility in WISH is to outreach to people in the central California community that was mostly underserved schools. They expose women in those younger ages, like kindergarten through high school, to computing and most of the students have not really had technology. Most of the participants in WISH are women, but some male allies joined the club recently. It shows more people are concerned to support the community.

Dr. Banawan proposed several strategies she learnt from some successful female scholars – women champions – in engineering and computational fields. First, the women champions usually find exemplars who pave the way for them as they subsequently evolve to become exemplars themselves. She has mentioned some women exemplars who have made significant contributions in the fields of artificial intelligence in education, affective computing, computational linguistics, and cognitive learning sciences. She has been fortunate to have worked with them or under their mentorship. These academic exemplars include Dr. Didith Rodrigo of the Ateneo de Manila University in the Philippines, Dr. Jaylyn Occumpaugh of the University of Pennsylvania, Dr. Laura Allen of the University of New Hampshire, and Dr. Danielle McNamara, SoLET lab Director, Arizona State University. These women exemplars have established themselves in their respective academic communities and beyond. For young and aspiring women in academia, finding exemplars will not only give inspiration for success but a roadmap of how to navigate inequities and challenges.

The second strategy is to find value in establishing networks and connections, regardless of gender. Opportunities for collaboration are endless. From her experience, seasoned academic scholars were always eager to collaborate and mentor. Also, female scholars should be bold to take on leadership positions within and outside their circles. Taking on leadership roles will foster growth and help establish your own research identities. This leads to the third strategy, i.e. mentoring young women. She quotes Benjamin Disraeli: “The greatest good you can do for another is not just to share your riches but to reveal to him his own”. Mentoring benefits both the mentor and mentee. Even as junior researchers, helping mentees will scale the knowledge transfer and bring about a cycle that will benefit entire communities and societies. She has observed that the women exemplars she has worked have many things in common, and one of these is that they were passionate mentors who paved the way for inexperienced researchers to feel more confident about themselves and what they could eventually bring to the table.

III. FEEDBACK FROM TCLT

At the end of the panel, Prof. Maiga Chang – the Chair of TCLT – gave responses to the panelists. Starting from the ideas and challenges outlined in the panel, the TCLT will implement several actions, such as:

- setting up the award of the outstanding women in learning technology field
- supporting women who help TCLT as volunteers in various positions to apply for senior membership of IEEE
- increasing the opportunities of female scholars to join TCLT or ICALT organization
- encouraging participants to join the ICALT Future Collaboration Panel to enhance collaboration opportunities for female academics
- supporting mentoring programs to provide mentorship for students
- proposing the collaboration with student clubs for minorities, such as WISH
- encouraging male participants in TCLT to join the WiE Panel
- holding webinars for mentoring young women.

The TCLT is currently working with the Equality, Diversity and Inclusion team in the Department of Computer Science at the University of Sheffield. We are looking for mentors for the dissertation project for senior undergraduate students and speakers for the Spotlight Talks for high-school outreach activities. The TCLT will organize community volunteers to help build the inclusive environment for STEM areas. We encourage student clubs who are focusing on equality, diversity, and inclusion in the STEM education to contact the TCLT and we will support the clubs in different ways.

REFERENCES


Rita Kuo is a visiting assistant professor in the Department of Computer Science and Engineering, New Mexico Institute of Mining and Technology (New Mexico Tech). Her research interests include e-learning, computerized adaptive testing, computerized item generation, cognitive theory, intelligent agent, mobile learning, and game-based learning. She currently is the Vice Chair in EDI (Equity, Diversity & Inclusion) & Event in IEEE Technical Committee on Learning Technology (TCLT), the Editorial Board in Educational Technology & Society (ET&S), and the Chair of Education Gamification and Game-based Learning special interest group in Asia-Pacific Society for Computers in Education (APSCE). She is also a member of the Women in Computer Science (WiCS) program in the Department of Computer Science & Engineering in New Mexico Tech.

Michelle Banawan is a postdoctoral researcher in the Science of Learning and Educational Technology (SoLET) lab of the Department of Psychology in Arizona State University. She is working with Professor Danielle McNamara. Her research interests include: Artificial Intelligence in Education, Intelligent Tutoring Systems, Natural Language Processing and Machine Learning. She currently serves as chair of the AIED/ITS Special Interest Group of the Asia Pacific Society for Computers in Education.

Jaelyn Domingo was an undergraduate student in the Department of Computer Science & Software Engineering at California Polytechnic State University with Computing for Interactive Arts minor. She was the member of Society of Women Engineers and Hui-O-Hawaii student clubs. She was also the outreach director in the Women Involved in Software and Hardware (WISH) clubs in 2020-2021 term. She currently is a software engineer in Intuit in California, United States.

Elvira Popescu is a full professor at the Computers and Information Technology Department, University of Craiova, Romania. Her research interests include: technology enhanced learning, adaptation and personalization in Web-based systems, learner modeling, computer-supported collaborative learning, learning analytics, intelligent and distributed computing. She currently serves as the Vice Chair for the IEEE Women in Engineering Romania Section Affinity Group, Associate Editor for IEEE Transactions on Learning Technologies & Smart Learning Environments journal, Executive Board member for the International Association of Smart Learning Environments (IASLE) and member of the Women in Engineering Committee for IEEE TCLT.

Ramyaa Ramyaa is an assistant professor of Computer Science at New Mexico Tech. She did her PhD at Indiana University, USA. Post doctoral research at Ludwig Maximilian University, Munich and has masters degrees from Carnegie Mellon University, USA and University of Georgia, USA. She was a fellow at Simons institute of Theory, UC Berkeley, USA.

Her primary fields of research are Theory of Computation (and complexity) and Logic, focusing on implicit complexity (relating logical complexity of concepts to computational, resource-based complexity). Her secondary research area is Artificial Intelligence, focusing on machine learning.
Student Engagement Recognition from Videos: A Comparison Between Deep Learning Neural Network Architectures

Pablo S. Werlang and Patrícia A. Jaques

Abstract— Emotions play an essential role in learning. Thus, it is necessary to detect students’ emotions in learning environments. Neural network models, especially deep learning models, have shown excellent performance in recognizing basic emotions (happiness, sadness, fear, disgust, anger) from faces in videos. However, basic emotion occurrence is low in learning environments. Cognitive emotions, such as engagement, confusion, frustration, and boredom, happen five times more frequently than basic ones. However, while basic emotions are relatively easy to distinguish from one another, cognitive emotions are much subtler, thus requiring more complex models for their recognition. This paper presents a comparative study between different deep neural network architectures focusing on student engagement recognition in videos. Using the DAiSEE dataset, we have trained and evaluated fine-tuning models, Conv3D models, and engineered feature models with multiple hyperparameter settings. Our results show that fully trained Conv3D models performed better than fine-tuned VGG16 and ResNet50 models, or even the LSTM model trained with popular engineered features.

Index Terms—Engagement recognition, Emotions in learning, Deep Learning

I. INTRODUCTION

Online learning has existed for some time, but recently it has received more attention from people in every field of knowledge [1]. Such increasing demand has also increased the importance of online learning environments. However, this kind of learning traditionally has lacked a way to account for human psychology. Emotions are an affective state that significantly influence the learning process. While reduced in the past to the counterpoint of human cognition, emotions are nowadays known to be part of the cognitive process [2]. The affective computing field emerges from this need to improve the human-computer interaction by recognizing, simulating, and understanding human emotions [3].

Even though natural for human beings, recognizing emotions is much harder for machines because humans use vision for detecting danger and recognizing other humans’ hidden intentions and emotions [4]. Thus, using visual input is a suitable medium when trying to imbue machines with that capacity. Through facial recognition techniques advancements, it is now possible to use video cameras to recognize emotions [5]. Using hardware present in standard computers instead of expensive and intrusive devices is also a bonus because it makes the technology more likely to be used in everyday lives.

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Most research concerning automatic emotion recognition concerns the six basic emotions: happiness, sadness, fear, anger, surprise, disgust [6]. The presence and manifestation of these emotions are seen in every geographic and cultural setting, making them very important to affective computing works or any studies regarding human emotions. The great majority of attempts of automatic emotion recognition through face videos, such as [7, 8], work with these emotions.

Research on emotion recognition in learning environments is a novel trend, and successful endeavors in that field will significantly impact how people learn with the help of computer-based systems [9]. In such learning situations, basic emotions are not as frequent. According to [10], the emotions engagement, confusion, frustration, and boredom (Fig. 1) are shown five more times than basic emotions in learning environments, and [11] shows that there is a correlation between the learning process and those emotions. From that group, engagement is the most expected and desired from a student. For that reason, there are many works in the machine learning field related to recognizing the occurrence of that emotion from various ways, such as video, text, voice, physiological signals, and the like.

Given the increasing amount of data available from different fields of knowledge, the advent of Big Data, recent discoveries on neural networks, and Deep Learning models, several works on emotion recognition through video using deep neural networks have emerged. Many models achieved outstanding performance in basic emotion recognition, such as [7] and engagement recognition [12].

While most works focus on overall performance, measuring higher accuracy for classifiers or lower mean square error for regressors, none found compared specific deep learning model architectures for the engagement recognition task on videos. Such comparative studies are important as they provide helpful guidance for future researchers struggling to decide which models for implementing their solutions. This kind of work with models trained on public datasets also encourages future works on the same samples, improving the overall comparability of those models' performance.

In this work, three popular deep learning models are implemented and trained to recognize the engagement emotion from students in videos: A fine-tuned convolutional VGG network architecture [13] wrapped in a recurrent network, a convolutional three-dimensional (C3D) [14], and a recurrent network fed with engineered (not discovered) features from the videos. The goal of these models is to help students in their learning process by providing means of intelligent learning environments to acknowledge its user's emotions and allowing these systems to take actions based on them to improve
students' motivation and behavior towards learning success. We discuss a comparison between the models' performances and propose a fusion model.

II. RELATED WORK

Models for recognizing engagement in learning situations can be built to work from various kinds of modalities, such as user input [15], self-reports as questionnaires [16], or face images/videos [12, 17, 18, 19]. Those using visual input can do it through image samples [17] or from image sequences (videos) [18].

Being a modern approach, engagement recognition from videos recently had many works published. The availability of free public datasets about student engagement, such as DAiSEE [20] and EmotiW [21], has greatly helped the community to develop models for that task.

In [22, 20], the authors present the DAiSEE dataset as well as build several deep learning models to serve as a baseline for other works, including a C3D [14], CNN+LSTM model, as well as fine-tune an Inception [23] network.

Besides different network topologies covered in section III, works in engagement recognition usually create models for binary classification (engaged vs. not engaged) [19], multi-level classification [18] (like four different levels of engagement), or intensity regression models [12]. While the first two map the input to specific labels for output, the regression models predict the engagement intensity from a given input in continuous values.

Using the second approach, EmotiW [21] presents a baseline model for engagement intensity prediction and provides the EmotiW dataset, which is used in the competition of the same name.

Works like [12] use more than one model to achieve their goals, employing model fusion techniques. Fusing models with non-redundant features can increase the overall model performance, as seen in the winner models [21, 24].

Despite the kind of model those works employ, specifically of deep learning, some trending architectures and feature extraction techniques are extensively used for the engagement recognition task. The present work intends to explore them individually, test three different models, compare their performances, and propose a deep learning model fusion approach. By reporting specific models' topology, hyperparameters and showing each architecture's performance results, such endeavor will surely clear doubts and encourage future researchers to recognize engagement, especially those training on the same dataset.

III. PROPOSED APPROACH

This section describes the designed approach to recognize engagement from video input, such as details about facial feature extraction and the chosen architectures for the models and their characteristics. Table I shows a comparison between the three model architectures implemented, highlighting their main differences.

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>MAIN CHARACTERISTICS OF THE THREE MODEL ARCHITECTURES IMPLEMENTED</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>Transfer Learning</td>
</tr>
<tr>
<td>---------</td>
<td>-------------------</td>
</tr>
<tr>
<td>Spatial Features</td>
<td>X</td>
</tr>
<tr>
<td>Depend on Pre-Trained Weights</td>
<td>X</td>
</tr>
<tr>
<td>Full Training</td>
<td>-</td>
</tr>
<tr>
<td>Native Temporal Feature</td>
<td>-</td>
</tr>
<tr>
<td>Less Resource-Intensive</td>
<td>-</td>
</tr>
</tbody>
</table>

A. Transfer Learning Model

Transfer learning is a technique that uses the knowledge learned from a machine learning model to help in the training process of a second model [25]. In short, to employ such a technique, one must acquire a model trained in a domain similar to the desired model's domain. Then remove the top layers of that model and replace them with new untrained layers. Finally, the model must be trained with...
those starting layers frozen, ensuring that the new training weights
will not overwrite the previously learned weights. This process is
called fine-tuning, and it works because the initial layers have learned
more generic and abstract features about the domain, something that
the old samples and new ones have in common. When the training
adjusts the weights of the final layers, it learns to map the initial
features into more specific ones from the new samples. The fine-
tuning process helps training complex models without consuming a
high amount of time or machine resources.

In this work, we used the pre-trained VGG-Face model [26] for the
transfer learning task: an implementation of the VGG16 architecture
[13] using the Labeled Faces in the Wild dataset [27] as the base
model. Then we froze all the layers, removed the top three fully
connected, and used the model as input to a recurrent GRU network.
Since the original model was trained to recognize static images, and
our goal is to make engagement recognition in videos, a time
component was inserted through the temporal layers, as shown in Fig.
2.

The GRU network [28], as a recurrent network, can learn features
using memory information from the past steps. While the traditional
RNN network suffers from the vanishing gradient problem [29], the
GRU (and the LSTM) overcome that problem by adding a forget
gate, allowing the network to discard less useful or old information
during the training process. These kinds of networks quickly became
the go-to networks to use when modeling time-dependent problems.

B. Three-Dimensional Convolutional Model

For the second model, we created a fully trained convolutional
model. Even though not benefiting from transfer learning knowledge,
this approach should yield good results because it can discover
features during training that is truer to the specific task, besides
tailoring the model architecture as needed.

In this case, the model chosen to capture spatial-temporal aspects
from the videos is a three-dimensional convolutional network, or
C3D [14]. Three-dimensional convolutional networks work similarly

to the regular two-dimensional counterpart, but instead, they execute
the convolution process in a three-dimensional space. In the case of
videos, the third dimension used is time. The main difference
between C3D and a regular convolutional network wrapped in
recurrent layers is that the former model learns the temporal features
in the same step as the spatial features. Fig. 3 shows our
implementation of the C3D network.

C. Engineered Features Model

While convolutional networks perform exceptionally in emotion
task, not all models are based on automatic feature
discovery. Some engineered features carry valuable information for
recognizing engagement, such as eye gaze, head pose, and Action
Units.

Eye gaze represents the direction each subject's eye is looking
relative to the camera. The head pose indicates the position in space
and the three-axis rotation of the subject's head relative to the camera.
The Action Units (AUs) are part of the Facial Action Coding System
(FACS) [30]. This system maps different parts of the face and labels
its muscles contraction or relaxation as numbers, called Action Units,
as shown in Fig. 4. The combination of different AUs can represent
every kind of human facial expression. The FACS system uses facial
expressions to represent emotions [6], and they are an important
feature to be considered when building emotion recognition models.

This work creates the third model using three features: eye gaze,
head pose, and action units. It receives these features as input and
builds a classifier from a temporal model. It implements the model
using a recurrent LSTM network [31], which like the GRU, can
overcome the vanishing gradient problem from traditional RNN
networks. Fig. 5 shows the third model, which receives the stream of
engineered features through the time and outputs if the video shows
an engaged or not engaged person.

D. Feature Extraction

Each model receives facial features as input and performs the
classification task. The transfer learning model and the three-
dimensional convolutional model discover the features directly from
images, while the engineered features model gets them from third-
party software.

OpenFace is a tool specific for the affective computing community
and for developing applications based on facial behavior analysis. As
shown in Fig. 6, it implements facial detection, landmarks detection,
eye movement, head positioning, and features extraction such as
Action Units recognition. In addition, OpenFace achieved excellent
performance in all of these tasks, managing its processing in real-
time and obtaining performance compatible with the best results
observed in other implementations [32].
In this work, we use OpenFace to break every video into frames and extract the aligned face from each frame. It extracts the aligned faces detecting landmarks from specific points in the subject's face, then removing the background and centering the face in a new normalized size image, like in Fig. 7. Those aligned faces are used as input to the transfer learning model and the three-dimensional convolutional model. The training process of the model discovers all features. The engineered features used as input on the third model uses the eye gaze, head pose, and action units extracted from OpenFace.

![Aligned face from a video.](image)

**Fig. 7.** Aligned face from a video.

### IV. EXPERIMENTS

This section presents the details about the dataset, the approach to address dataset imbalance, implementation details and hyperparameters, and experimental results.

#### A. Dataset

We trained all models using the DAISEE dataset [22, 20], which provides 9068 videos with approximately 10 seconds. The videos take place in different locations and luminosity settings (referred to as in the wild setting) and showcase 112 students from age 18-30, 32 female and 80 male, all Asian. They obtained annotations from a collaborative commercial platform, and annotation redundancy and outlier exclusion are used as methods to ensure annotation reliability. They record the subjects' reactions from watching educational and recreational videos. Each of the following emotions: engagement, confusion, frustration, and boredom gives a score ranging from one to four by the annotators, where one represents no presence. Four represents a high-level presence of the given emotion.

#### B. Data Imbalance

The dataset samples are split into training, validation, and test sets, each containing 5482, 1720, and 1866 respectively. Each set is subject-independent, meaning that no video from the same subject is present in more than a single split. However, engaged videos (engagement videos labeled with intensity three and four) represent 94.15% of the total samples, leading to inadequate training because the classification algorithm ignores the less represented class, as the penalty for that is too forgiving. Three techniques were employed to counter that problem.

Undersampling was used to randomly discard samples from the engaged class in the training set until we obtained a 20-80% ratio. After that, the SMOTE technique [33] was employed to generate synthetic samples from the not engaged class until we obtained a 40-60% ratio. From that point, the classification was conducted using weights of 0.6 and 0.4 (to not engaged and engaged classes, respectively) to reflect the slight imbalance still present in the training set.

#### C. Implementation Details

We implemented three kinds of deep learning models. All of them had the purpose of recognizing engagement from face videos. All models used categorical cross-entropy as loss function, softmax as activation function in the last layer, and Adam optimizer [34] with learning rate $1e^{-4}$ and accuracy as metric.

As the goal of the work is to classify engaged from not engaged videos, the labels 0 and 1 from the dataset were relabeled as not engaged (value 0), and labels 2 and 3 were relabeled as engaged (value 1).

The training and validation sets' inputs were composed of the preprocessed samples described in section IV.BIV.-B, and test set samples are kept unchanged for the sake of comparison between other works. We describe the topology of each model in section III.

The first two models (from sections III.A and III.B) used images as input. Those images are frames from videos extracted using OpenFace aligned faces module from the dataset. The aligned face images are grayscale and 224x224 pixels in size. The videos' framerate was reduced from 30 to 15 fps for memory reasons, and we used 30 frames for each time window, which means that videos had 2 seconds each. Each video was used with a 50% overlap, meaning that a new video starts on the last half of the previous video.

The third model (from section III.C) used OpenFace software to extract the features from the same videos the two other models used. The features extracted are left and right eye position, gaze position and angle, head position and rotation on three axes, and action units intensity and occurrence. We used the same time window and video overlap configuration as in the first two models.

#### D. Result and Analysis

For all the models, training was halted when validation loss stopped decreasing for ten epochs. The learning rate was also decreased every three epochs of not improving validation loss.

For the Convolutional 3D model, the variant implementations involved:

- Changes in the size of the convolutional blocks (from one to two).
- The number of blocks (from one to three).
- The width of each block.
- The number of layers and width in the fully connected (FC) layers (from one to three and four to 256).

The results from those competing models are shown in Table III.
The transfer learning model uses the fine-tuning technique, using a pre-trained network, in this case, VGG16 and ResNet50. These networks were trained on the VGG-Face dataset [26] for identifying subjects’ names. Since we trained the models to recognize faces, the models’ bottom layers should contain generic facial features. Thus, after removing the fully connected layers from the top of those models (one implemented using VGG16 architecture and the other ResNet50), some GRU/LSTM layers were added to make the network receive image temporal data (videos). Each model fine-tuned was tested for different widths and depths of recurrent layers, and Table III shows the best performance from each kind.

<table>
<thead>
<tr>
<th>TABLE II</th>
<th>COMPARISON BETWEEN THE BEST THREE-DIMENSIONAL CONVOLUTION MODELS TOPOLOGIES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conv block</td>
<td>Fully Connected</td>
</tr>
<tr>
<td>(4-8)</td>
<td>16-8</td>
</tr>
<tr>
<td>(4-8) (8)</td>
<td>32-16</td>
</tr>
<tr>
<td>(4-8-16)</td>
<td>32-16</td>
</tr>
<tr>
<td>(4-8) (16-32)</td>
<td>32-16</td>
</tr>
</tbody>
</table>

We trained the engineered features model using 329 feature values from 12821 videos segments using a recurrent LSTM network. We used several topologies, ranging from adjusting the number of LSTM layers (from one to six), the width of each layer (between three to 256 in various combinations), Dropout values (from 0.1 to 0.8), number and width of fully connected layers (from one to three layers and from 5 to 1024 neurons). We even tried a recurrent version of a topology inspired by ResNets. As shown in Table IV, the best result achieved by this model was 61.54% using the model from Fig. 5, which led us to believe that for engagement recognition, we need more data to train this model with only these features and without training directly on the images. Nevertheless, the engineered features model can be a powerful tool as a complementary model when fused with a convolutional model [35].

<table>
<thead>
<tr>
<th>TABLE III</th>
<th>COMPARISON BETWEEN THE BEST PERFORMING MODELS OF THE TRANSFER LEARNING</th>
</tr>
</thead>
<tbody>
<tr>
<td>Architecture</td>
<td>RNN</td>
</tr>
<tr>
<td>VGG16</td>
<td>GRU(5) &gt; Fully Connected(10)</td>
</tr>
<tr>
<td>ResNet50</td>
<td>GRU(5-5) &gt; Fully Connected(10)</td>
</tr>
</tbody>
</table>

From Table IV, we can see that C3D models tend to perform better than the Conv+LSTM models for the engagement recognition task. One explanation for this is that 3D convolution networks learn appearance and motion features simultaneously [14], connecting the feature discovery process for temporal and spatial information.

We should note that the models’ performance is tied to its implementation, and different topology and hyperparameters decisions lead to different model results. This work not exhaustive for every model implementation using the chosen architectures but rather a guide for those aiming to know the main differences and expected results for these networks.

<table>
<thead>
<tr>
<th>TABLE IV</th>
<th>COMPARISON BETWEEN THE BEST PERFORMING MODELS FROM EACH CATEGORY</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>Accuracy</td>
</tr>
<tr>
<td>Transfer learning model</td>
<td>71.64%</td>
</tr>
<tr>
<td>Three-dimensional convolutional network model</td>
<td><strong>82.05%</strong></td>
</tr>
<tr>
<td>Engineered features model</td>
<td>61.54%</td>
</tr>
</tbody>
</table>

V. Conclusion and future works

Engagement recognition is not easy because it is a much subtler emotion than the six basic ones. In learning situations, though, it is the most important because it indicates that the student keeps up with the tutor’s tasks.

The present work showed a comparison of some popular network models for engagement recognition in videos. The three-dimensional convolutional networks showed better performance from the three model architectures, followed by the transfer learning models and, lastly, by the engineered features. Though the last kind could not perform well, consistent with most related works, it is best used as a supporting model for the main model, which discovers features directly from videos.

It is also worth noting that few datasets are available featuring videos of people watching videos with labels describing the engagement emotion. The dataset used, DAiSEE, shows extreme data imbalance. This required measures for rebalancing the dataset, as well as harmed the generalization capacity of the model. As the study used only the data available in that dataset, our models were not tested in other scenarios, so we cannot attest to its performance in real-life conditions.

It was also challenging to find model hyperparameters that avoid overfitting with the available data. Thus, a model fusion implementation would help as more features would be fed to the training, improving its performance. Consider that the cognitive emotion manifestation usually follows a specific two-directional flow, meaning that to a student experiencing engagement to become bored, he will first become confused, then frustrated, and then bored (the other way around is also accurate). A sample model fusion network for future works could use as input the outputs of each model and predict a more precise emotion through the training process of a regular LSTM network considering the emotion prediction history of the input models.

References


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What can we take from the pandemic to the future of Education?

Saida Affouneh, and Soheil Salha

Abstract— Covid-19 pandemic has affected the educational systems worldwide, causing the closure of higher education institutions and schools in many countries in the world. It was a sudden transformation to distance learning. Educational institutions, teachers, students, and families were not ready to confront the challenges of this emergency case. This paper presents ongoing project research, which aims at investigating and documenting the knowledge and skills that were gained through the pandemic by students and teachers and can reshape the future of their education. It aims to measure the teachers and the students interaction and engagement during online learning. Qualitative and quantitative methods will be used to collect needed data and provide policy makers with indicators in order to be able to develop the educational policies. Several tools will be designed to collect data. Collaboration is needed in this project in order to be able to conduct, and compare different perspectives and contexts from several backgrounds and countries. Moreover, collaboration includes joint projects, conferences, and workshops.

Index Terms— Skills, Future of education, Pandemic

I. INTRODUCTION

The pandemic has affected all education systems around the world in different ways. Many countries have switched to technology and online teaching in response to crises and shutdown of schools and universities [1].

The impact of the COVID-19 pandemic on research in response to the pandemic highlighted the importance of research, challenges of research during disasters, and opportunities and resources for making research more efficient and cost-effective [2]. Researchers around the world tried to investigate the effects of COVID-19 like the scientific globalism, research collaboration, and open access publications on COVID-19 [3] and it was found that scientific globalism occurs differently when comparing COVID-19 publications with non-COVID-19 publications during and before the pandemic. [4] aimed to find out the global status and trends of coronavirus research, and the results were categorized into four main themes. The four themes were pathological research, epidemiology research, clinical research, and mechanism research.

In Palestine education has also been disturbed. Schools and universities have been closed and forced to move to distance learning. Many studies have documented the impact of the pandemic on ensure the right to education in Palestine and have found that many children have been deprived of their right to good education. Many others were unable to access online education due to lack of computers or smart devices, while others have suffered from the low speed of the internet or the continuous shortage of electricity, especially in specific marginalized areas [5]. A recent study investigated the challenges associated with emergency remote teaching in Palestine, and it found that digital inequity and digital privacy were key challenges in online teaching [6].

Palestinians have been under crisis for the last 70 years and their education have been interrupted several times for long periods and tried to find different solution to continue their education [7]. Palestinians have valued their education and considered it as an important tool for better life. So, the Palestinian case is very rich for further investigation in the research of education under crisis situations, especially on the topic of how they transform previous knowledge and experience into a new one in the pandemic and learned from the past.

For young students age between 6-12, students’ motivations for learning and teaching have been decreased since they lost the ability to see their friends, interact, and play with them, which usually consider as the most important factor that children value at going to school. Other children find it entraining to go online through their parents’ smart devices and interact with their teachers and colleagues in the beginning, and then they start getting bored of it.

Schools' and universities' teachers could be divided into three main categories regarding their skills and attitudes toward technology, the first are the young generations who have easily transferred online, the second are the motivated generation but lack digital competencies and needs to be trained, while the third are people who rejected the transformation and lack digital skills. Each category has been trained and starts working in different levels of quality, and this indirectly affects the learning outcome. So, each category has its own experience and own way to respond to the crisis, which needs to be analyze and documented.

II. PREVIOUS RESEARCH

At An Najah National University, we have started investigating the impact of the pandemic on students' learning at schools and universities, and found many common factors that affect the results such as gender, geographical area, type of school, availability of infrastructure, parents background, students' wellbeing and motivation for schools, teachers' skills and capabilities, etc. Many of these variables could be similar to other countries around the world, but of course there was particular and special interpretations for it from the Palestinians' perspectives due to their previous understanding of crisis and closure. More understanding of their perspectives and the impact of political, social and economic issues could be discussed.

The researchers have also investigated teachers' perspectives, challenges, and best practices in the beginning and after one year of the shift towards online learning in order to share their experiences globally for empowering the knowledge communities. The researchers used a mixed approach through qualitative and quantitative methods to measure the size of the problem and at the same time to learn deeply and analyze participants’ understandings, attitudes, engagement, and behaviors. Survey, interviews, and focused groups have been used according to the research goals and objectives.
III. Future Research Collaboration

Future directions focus on studying the knowledge and skills gained by teachers and students from the last period during the pandemic since they were forced to work online or in the distance from their homes, and they have been able to produce different types of learning material to deliver it to their students, also they were able to find different ways and tools to communicate with their learners. Self-learning skills were developed and also appreciated.

It is expected that the results of this study will inform policy makers in Palestine and around the world with qualitative and quantitative indicators of how to reshape the future of education after the end of Covid-19 crisis, building on their previous experiences and lessons learned. It is also expected to have a comparative analysis between different countries in order to find common features and factors and different ones related to culture and society. We need to document how did teachers survive their teaching and how did students continue their learning despite of all the challenges, and what are the main skills that they would like to emphasize for tomorrow generations in order to reshape future education. Moreover, future collaboration could be presented by shared activities, projects, programs for instructional design under emergency case. The outcomes of future collaboration may be addressed in conferences and workshops.

REFERENCES


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29th International Conference on Computers in Education
(22-26 November 2021)

Antonija Mitrovic, Maria Mercedes T. Rodrigo

I. INTRODUCTION

The 29th International Conference on Computers in Education (ICCE 2021, https://icce2021.apsce.net/), organized by the Asia-Pacific Society for Computers in Education (APSCE, https://www.apsce.net/), will be held 22-26 November 2021 in cyberspace. The society was established in 2004, and its objective is to promote research related to all aspects of use of computers in education. Although the primary focus of APSCE is on Asia-Pacific, every year the participants of ICCE conference come not only from that region, but also from various European countries, and North/South America.

ICCE 2021, as was the case with the previous conferences, includes seven theme-based subconferences. The C1 subconference on Artificial Intelligence in Education/Intelligent Tutoring Systems (AIED/ITS) and Adaptive Learning focuses on interactive and adaptive learning environments for all levels of education. C2 subconference on Computer-supported Collaborative Learning (CSCL) and Learning Sciences emphasizes the design of technology-based formal/informal learning settings and learning analysis in collaborative environments. C3 subconference on Advanced Learning Technologies (ALT), Learning Analytics and Digital Infrastructure focuses on standards development. C4 subconference on Classroom, Ubiquitous, and Mobile Technologies Enhanced Learning (CUMTEL) covers approaches for facilitating pedagogical practices in mobile, contextualized, and ubiquitous learning settings. C5 subconference on Educational Gamification and Game-based Learning (EGG) focuses on game-based learning theories, technologies, humanistic design, and practices for all aspects of learning. C6 subconference on Technology Enhanced Language Learning (TELL) examines theories and systems for enhancing language teaching and learning. Finally, C7 subconference on Practice-driven Research, Teacher Professional Development and Policy of ICT in Education (PTP) includes research, dissemination, and pedagogical implementation of ICT in education.

All submissions to the main conference are subject to single-blind review by at least three reviewers and one meta-reviewer. The acceptance rate for this year’s conference was 26%.

In addition to the subconferences, ICCE 2021 will include keynote speeches, theme-based invited speeches, expert panels, workshops, Work-in-Progress Posters (WIPP), Extended Summary (ES) papers, Doctoral Student Consortia (DSC), and Early Career Workshop (ECW) where international research communities could interact and share ideas for research in the field of computers in education.

Accepted papers in the main conference, Workshops, WIPP, DSC, ECW, and ES will be published in proceedings indexed in Scopus. Proceedings of the main conference will also be submitted to Clarivate for inclusion in the Conference Proceedings Citation Index. Authors of accepted distinguished full papers are invited to submit extended versions of the papers for consideration of publication in Research and Practice in Technology Enhanced Learning (RPTEL), the official academic journal of APSCE.

II. KEYNOTE AND THEME-BASED SPEECHES

Every year, ICCE conference include four keynote speakers, and three theme-based speeches.

In the order of subconferences, the keynote speaker for C1 will be Tiffany Barnes, from the North Carolina State University (USA), who will talk about engaging human and AI for better learning experiences.

Pierre Dillenbourg from the Swiss Federal Institute of Technology (Switzerland) will give a keynote speech for C2 entitled The classroom as a digital system.

The theme-invited speaker for C3 is Jon Mason from the Charles Darwin University (Australia), who will give a talk entitled Questioning and the digital environment.

The keynote speaker for C4 is Gwo-Jen Hwang, from the National Taiwan University of Science and Technology, whose speech is entitled Applications and research issues of artificial intelligence in education in the mobile era.

Baltasar Fernández-Manjón from the Complutense University of Madrid (Spain) will give a theme-based invited speech for C5 entitled Systematizing game learning analytics for improving serious games lifecycle.

The theme-based invited speaker for C6 is Ana Gimeno from the Universitat Politècnica de Valencia, (Spain), who will give a talk entitled Do massive open online language courses (LMOOCs) satisfy learner needs.

Kuthilda Tuamsuk from the Khon Kaen University (Thailand) will be the theme-based invited speaker for C7, and will give a talk entitled Digital Learning Ecosystem for transforming classroom into learning community: Experiences from the Khon Kaen University Smart Learning Academy.

The conference programme will available soon.

III. MATH

With ICCE 2021 turning virtual, the registration fee has been greatly reduced (https://icce2021.apsce.net/registration/).

- October 8, 2021: Early bird registration
- October 29, 2021: Regular registration