Physiological Electrosignal Asynchronous Acquisition Technology: Insight and Perspectives

WITH great pride and enthusiasm, we present the inaugural edition of IEEE TRANSACTIONS ON COMPUTATIONAL SOCIAL SYSTEMS (TCSS) for 2024. Reflecting on the year gone by, 2023 stands as a hallmark of academic excellence and prolific output, wherein our journal has successfully disseminated a substantial volume of scholarly work—301 articles encompassing approximately 3600 pages, distributed across six distinct issues.

We are thrilled to share some remarkable milestones and achievements IEEE TCSS has realized over the past year. A noteworthy highlight is the remarkable ascent of our CiteScore, which has reached an unprecedented peak of 10.0. This is a significant leap from the previous scores of 9.3 in 2022, 7.9 in 2021, and 6.1 in 2020. Such a trajectory not only exemplifies our journal's growing influence but also cements our standing in the academic landscape. Specifically, IEEE TCSS now proudly ranks within the top 2% of journals in the "Social Sciences" category, standing at the 10th position among 502 journals. In the realms of "Modeling and Simulation" and "Human–Computer Interaction," we are ranked 12th and 19th among 316 and 135 academic journals, respectively, placing us comfortably within the top echelons of these categories according to CiteScore rankings. This represents a substantial improvement and a testament to our journal's escalating prominence.

Furthermore, as per the latest metrics from the Clarivate Journal Citation Reports, the Journal Impact Factor for IEEE TCSS has been determined to be 5. This impressive figure situates IEEE TCSS as the 6th among 24 journals in the "Computer Science, Cybernetics" category, elevating us to the prestigious Q1 JCR Quartile based on the Journal Citation Indicator (JCI).

As we move forward, our unwavering commitment remains to foster and advance the field of computational social systems. Our goal is to continually enhance the impact factor, ranking, and overall influence of IEEE TCSS within our scholarly community. In this pursuit, the invaluable contributions of our editorial team, reviewers, authors, and readers cannot be overstated. Your dedication and support are the cornerstone of our journal's success. We extend my heartfelt gratitude to each one of you for your relentless commitment and support toward IEEE TCSS.

We wish you all a Happy New Year and look forward to a year filled with groundbreaking research and academic pursuits!

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In this issue, along with the customary introduction to our 122 regular articles, we delve into an intriguing and forward-looking discourse on "Physiological Electrosignal Asynchronous Acquisition Technology: Insight and Perspectives," which promises to offer profound insights and stimulate intellectual curiosity.

I. Scanning the Issue

In [A1], the authors aim to address the role-correlation-based adaptive group role assignment with a training plan (RCA-GRATP) in this article. This article contributes two aspects to the literature on adaptive collaboration. 1) The RCA-GRATP problem is abstracted based on adaptive collaboration and group role assignment. 2) A comprehensive formalization of RCA-GRATP and two solving algorithms for diverse situations are proposed to solve the formalized problems. Experiments are carried out to verify the effectiveness of the proposed algorithms in diverse scenarios.

In [A2], to fully understand the impact of interventions responding to COVID-19 on urban mobility, the authors construct urban mobility networks among points of interest, using large-scale anonymous mobility data from de-identified mobile phone users. They investigate the changes in urban mobility networks during two waves of the COVID-19 pandemic in Beijing from both graph and subgraph perspectives. Beyond an overall mobility reduction in Beijing, they find that the mobility change is spatially and temporally heterogeneous among different urban regions.

In [A3], the authors first explore the evolution process of knowledge dissemination in blended learning networks and the blended learning interaction process of learners. Second, two kinds of effective regulation strategies are proposed. They establish an optimal regulation system intending to maximize the dissemination of knowledge. Then, they propose a knowledge dissemination regulation task allocation method based on the collaborative participation of users, and the reverse auction theory is used to quickly solve the task allocation scheme while ensuring performance.

In [A4], the authors begin the analysis by showing the hardness of co-activity maximization (CoAM) under two diffusion models that are generalized from wildly used diffusion models. They design a submodular function that acts as a lower bound to the objective, by exploiting which they can devise a greedy algorithm with a provable approximation guarantee. To overcome the P-hardness of diffusion calculation, they further extend the notion of random reverse-reachable (RR) set to devise a scalable instantiation of their approximation algorithm.

In [A5], Zhu et al. investigates three well-known adversarial attack methods which aim at some machine learning algorithms. It is found that different attack methods have their specific attack preferences for changing the target network structures. Such attack patterns are further verified by experimental results on some real-world networks, revealing that, generally, the top-4 most important network attributes in detecting adversarial samples suffice to explain the preference of an attack method. Based on these findings, the network attributes are utilized to design machine learning models for adversarial sample detection and attack method recognition with outstanding performance.

In [A6], social networks and their trust-based applications in a distributed environment have seen increasing attention in the research community. In this regard, the authors present a social community cloud implementation model, where friendly relationships determine resource provisioning. The issues of fairness and allocation of time are of great importance and they are thoroughly investigated. They use extensive simulations to illustrate that the communities can be employed to construct cloud infrastructures, such that the shared resources can be utilized fairly and efficiently.

In [A7], the authors conduct a review 20 of recent advances in social computing with fuzzy technologies in cyber-9 physical-social systems (CPSSs). First, they analyze the characteristics and advantages of social computing through fuzzy methods. Second, they also elaborate on existing fuzzy-technology-empowered social computing methodologies. As in a range of social spaces, they review and analyze related advances in human-in-the-loop systems. They also reveal the trend of decentralized, autonomous, and organized computing in cyber–physical–social space with fuzzy-based methods and propose a framework to categorize related studies in CPSS. Finally, they conclude the research trends and hotspots based on current studies.

In [A8], the authors proposed a third-party advanced metering infrastructure service model based on differentially private federated learning. Instead of sending the private energy data to the cloud server, the proposed service model trains the neural network models locally, and only model parameters are shared with the central server. Moreover, the identity of individuals is eliminated by adding random Gaussian noise during the secure aggregation. Furthermore, an attention-based bidirectional long short-term memory neural network model is adopted to solve the long-range dependency problem of conventional neural networks.

In [A9], a mathematical model based on evolutionary game theory is established to analyze the interaction between parameter servers and participants, considering that the participants are not completely rational in the long-term dynamic decision-making process. The evolutionarily stable status of the federated learning (FL) system and the strategies of the parameter servers and participants were analyzed under eight different scenarios. Based on the model analysis and results of the numerical experiments, managerial insights for maintaining a sustainable FL system are summarized.

In [A10], the authors propose a new model for influence maximization in this article called MapReduce-based dynamic selection of influential nodes (MR-DSINs) that has the ability to cope with the huge size of real social networks. In fact, their approach is based on a graph sampling step in order to reduce the network's size. Given that reduced version, MR-DSIN can select dynamically influential nodes. They proposal has the advantage of considering the dynamics of information that can be modeled by users social actions (e.g., "share," "comment," and "retweet"). Experimental results on real-world social networks and computer-generated artificial graphs demonstrate that MR-DSIN is efficient for identifying influential nodes, compared with three known proposals.

In [A11], the authors proposed a novel biclustering-based subevent detection method from the Twitter dataset for retrospective analysis of disaster events. First, they clustered the data matrix using spectral co-clustering. Then, they identified subevents (words) and formulated a ranking framework to find the top-ranked subevents within the clusters. Finally, through statistical analysis, they have shown that the proposed framework works better than other existing subevent detection methods. This method works because it first creates proper tweet-word clusters, and then takes into consideration the parts of speech, named entities with their frequency, and finally informative phrases based on numerical information.

In [A12], a feature extraction network based on a convolutional neural network (CNN) is designed to extract the deep features of the three models. The extracted deep features are inputted into the emotion classification CNN to classify the emotions, including interest, happiness, confusion, and boredom. In this method, two novel features are proposed: the feature of coordinate difference of eyemovement (FCDE) and pixel change rate sequence (PCRS). FCDE is extracted by combining eye movement coordinate trajectory and video optical flow trajectory, which can represent the learner's attention degree. PCRS is extracted from the video image, which can represent the speed of image switching.

In [A13], a novel collaborative optimization approach to learning team formation is proposed based on a refined learner model and the environments-classes, agents, roles, groups, and objects model. With the proposed approach, a learner is modeled by combining 5-D characteristics (i.e., cognitive ability, leadership, sociability, learning style, and personality) and three types of constraints (e.g., conflicts, genders, and the number of members), and an assessment mechanism is designed to measure the comprehensive abilities of learners for identifying an ideal team leader and selecting the team members for a team.

In [A14], the authors proposed an agent-based model to explore the properties of the market. The study shows that crowding types of tourists in destinations together with a very simple revenue management heuristic can produce counter-intuitive results affecting the distribution of surplus in the markets. When all the managers in a market overreact by raising prices as a consequence of a high occupancy rate, they appropriate a larger portion of the surplus of the market. When managers are risk-averse and rapidly reduce prices when occupancy is low, they deliver more welfare to tourists.

In [A15], the authors provide a tool aiming to automate the process of anomaly detection and reporting. They combine anomaly detection and video captioning models to create a pipeline for anomaly reporting in descriptive form. A new set of labels by creating descriptive captions for the videos collected from the UCF-Crime dataset has been formulated. The anomaly detection model is trained on the UCF-Crime, and the captioning model is trained with the newly created labeled set UCF-Crime video description. The tool will be used for performing the combined task of anomaly detection and captioning.

In [A16], current solutions for multimedia-based recommendation (MMRec) are limited by multimodal noise contamination. To address this problem, this article proposes a hierarchical framework to separately learn collaborative signals and multimodal preference cues, thus preventing multimodal noise from flowing into collaborative signals. Then, this article proposes to extract semantic entities from multimodal content that are more relevant to user interests. Furthermore, the full multimodal features are used to model content-level multimodal preferences like the existing MMRec solutions, which ensure the sufficient utilization of multimodal information.

In [A17], Fionda and Pirrò face three novel challenges when designing deception techniques for networks with attributes: 1) how to model and encode attributes most flexibly; 2) framing attribute-aware community deception as an optimization problem; and 3) solving the optimization problem by leveraging network topology and attributes also arises. This article leverages a simple way to model network attributes as edge weights to solve the above challenges.

In [A18], to investigate the effectiveness of large-scale targeted network interventions in real-world settings, this article builds a stochastic agent-based network model informed by the comprehensive online social networking and dating behavior data and epidemiological data among men who have sex with men (MSM) in Zhuhai, China. A new method is proposed, namely, RiskRank, to prioritize nodes for targeted interventions by incorporating: 1) their topological features on the online social network; 2) the underlying epidemic dynamics; and 3) the position of identified HIV-infected individuals on the sexual network.

In [A19], an adaptive interpretable ensemble model based on a 3-D convolutional neural network (3DCNN) and genetic algorithm (GA), i.e., 3DCNN+EL+GA, was proposed to differentiate the subjects with Alzheimer's disease (AD) or mild cognitive impairment (MCI) and also identify the discriminative brain regions significantly contributing to the classifications in a data-driven way. More importantly, in these identified brain regions, the discriminative brain subregions at a voxel level were further located with a gradient-based attribution method designed for convolutional neural networks (CNNs) and illustrated intuitively. Besides these, the behavioral domains corresponding to every identified discriminative brain region (e.g., the rostral hippocampus) were analyzed.

In [A20], Qi et al. propose a new approach that combines image processing and machine learning to capture the relationships between sentiment-related features and asset movement. The proposed research is based on the tick-level SPY options transactions, and the dataset contains around 1.5 million trading records. In particular, this research obtained the gap between the call surface and the put surface as the second-level implied volatility surface (IVS). Besides, this project creatively proposes the interframe difference approach to the optimized convolutional neural network (CNN) and a recurrent CNN (RCNN) to fully utilize spatial and temporal features of the IVS data.

In [A21], Qin et al. first considers the employment issues of different types of workers with government benefits (WGBs) and establishes a new parallel disassembly balancing model that considers WGB. In order to quickly find the optimal solution of the model, a new salp swarm algorithm (SSA) for the encoding and decoding process is proposed. In addition, the article designs appropriate heuristic strategies, encoding methods, and decoding methods. The correctness of the model and the effectiveness and efficiency of the SSA algorithm are verified through experiments. The results indicate the superiority of SSA.

In [A22], Yang et al. first proposes a search scheme based on node classification, which searches for different types of nodes in different ways. Divide nodes in the network into two categories: candidate central (CC) nodes and noncentral (NC) nodes. On this basis, a multiobjective evolutionary algorithm (MOEA) based on node classification is proposed, named NCMOEA. In addition, the algorithm also proposes hybrid representations, genetic operators, and initialization strategies to better search for two types of nodes in different ways. The experimental results show that the proposed NCMOEA outperforms nine representative community detection algorithms.

In [A23], Angelopoulou et al. propose a framework that applies natural language processing (NLP) techniques, such as sentiment and bigram analyses. By collecting tweets and using a preprocessing framework to categorize them into compliance (positive) or resistance (negative), targeting three themes: wearing masks, maintaining social distance, and isolation. Emotional analysis and binary schema analysis identified the most commonly discussed topics for expressing positive and negative emotions in different age and gender groups. The methods and results proposed in the article provide a novel and potentially valuable contribution to public policymakers.

In [A24], Chen et al. propose a viewpoint topic evolution analysis method. This method first models the topics in the document based on a pretrained language model and then performs clustering analysis to determine the topics and keywords. An abbreviated large-graph clustering (ALGC) algorithm is designed to obtain the representation of documents and topics, reducing the dimensionality of the attention matrix and adjacency matrix to reduce the overhead caused by the high computational complexity of large images. The experiment shows that the method performs well and maintains high clustering accuracy.

In [A25], He et al. explore the social impact of signature networks. On the basis of discussing the role of homogeneity and xenophobia in the dynamics of neighbor behavior in signature networks, the authors propose a generalized Pólya urn model that considers the impact of negative relationships and can understand the specific mechanisms of homogeneity and xenophobia in dynamics. Through mathematical deduction, authors found that the trend of social influence guided by signature networks tends toward equality. Simulations indicate that higher effects or a larger proportion of negative relationships may disrupt self-reinforcement and make the market more equal.

In [A26], most network-based epidemic models do not synthetically consider the temporal and spatial features of human structured contact behaviors. They combined a social network with a bipartite network to build a multilayer agent network to model heterogeneous individuals' temporal and spatial structured contacts. They used the largest collective outbreak of H1N1 influenza at a Chinese university in 2009 as a case study. Experimental results indicate that the models can reproduce individuals' daily travel and social contact patterns, as well as the H1N1 influenza outbreak.

In [A27], Sharma et al. collect a moderate-sized representative corpus of tweets (over 200 000) pertaining to COVID-19 vaccination spanning for a period of seven months (September 2020–March 2021). Following a transfer learning approach, the authors utilize a pretrained transformer-based XLNet model to classify tweets as misleading or nonmisleading and manually validate the results with random subsets of samples. They leverage this to study and contrast the characteristics of tweets in the corpus that are misleading in nature against nonmisleading ones and outline how these insights provide the foundations for a more actionable approach to mitigate misinformation.

In [A28], Xu et al. review current research on gait-based emotion detection, particularly on how gait parameters can be affected by different emotion states and how the emotion states can be recognized through distinct gait patterns. The authors focus on the detailed methods and techniques applied in the whole process of emotion recognition: data collection, preprocessing, and classification. Finally, they discuss possible future developments of efficient and effective gait-based emotion recognition using state-of-the-art techniques in intelligent computation and big data.

In [A29], Qi et al. replace the Merkel-tree-based transaction structure within the block by directed acyclic graph (DAG) and proposes a novel design of open blocks to enable user nodes to participate in verifying the transactions in blockchain systems. They designed a new segmented market structure, in which each miner serves only a group of users instead of all users, so as to reduce miners' workload and thus scale transaction processing capabilities. Their work can help improve the scalability of cryptocurrencies by evolving the underlying blockchain systems to graph-based distributed ledgers and is expected to shed new light on designing blockchain-based decentralized markets.

In [A30], the authors propose new multimodality multiview graph representations and knowledge embedding (MMGK) framework to diagnose mild cognitive impairment (MCI). First, they extract multiview feature representations from magnetic resonance imaging (MRI) and genetic data. Then, all subjects are constructed into a graph based on the different single-view feature representations, respectively. Furthermore, demographic data are utilized through knowledge embedding. Finally, to perform MCI diagnosis on multiview graphs, graph convolutional networks (GCNs) are utilized, and a two-step ensemble learning method is proposed. Experimental results show that the proposed framework achieves good performance with accuracy reaching 0.888, and outperforms some state-of-the-art methods.

In [A31], the authors expand the state-of-the-art by exploring the impact of social contagion on social alignment, i.e., whether the decision to socially align oneself with the general opinion of the users on the social network is contagious to one's connections on the network or not. Finally, they find that a user's decision to socially align or distance from social topics and sentiments influences the social alignment decisions of their connections on the social network.

In [A32], Mao et al. investigate the cost function learning in social information networks, wherein human memory and cognitive bias are explicitly taken into account. The authors first propose a model for social information-diffusion dynamics, and then propose a memorized model and maximum-entropy-based inverse reinforcement learning building on the dynamics model. Finally, the effectiveness of the proposed social information-diffusion model and the algorithm is validated by the online social media data.

In [A33], Kaur et al. proposed a blockchain-based donation mechanism for convenience during disasters, pandemics, and other emergencies. All transactions can be traced in blockchain, giving donors visibility into where and how their funds are utilized. Ethereum blockchain is used to implement the proposed framework and provides a convenient donation platform. Smart contracts are used to make donations, which build trust between contributors, beneficiaries, and charity organizations. The blockchain-based donation method saves time, lowers donation costs, and eliminates the chances of dubious campaign funds.

In [A34], the authors propose a novel urban overtourism detection (UOD) framework based on graph temporal convolutional networks (TCNs). More specifically, they propose the grid overtourism mode (GOM) to detect urban overtourism on a grid level and propose the overtourism detection mechanism. Then, they construct the GOM graphs of the candidate regions. Next, they employ the graph TCNs to model the complex spatiotemporal relations of urban overtourism and predict the future GOM graph at the next time interval. Finally, they calculate the urban overtourism scores based on the prediction results.

In [A35], the authors first assume that every community contains a centroid node and search the centroid node of each potential community. Thereafter, they propose a new algorithm to uncover multiple communities related to the query node. First, the algorithm explores the paths from the query node to find the centroid nodes using a localized metric. Then, for each centroid node, the algorithm combines the nodes along the paths as a set of initial seeds and applies a personalized PageRank or heat kernel to generate each community.

In the context of COVID-19, [A36] presents an assessment-to-control decision-making support scheme to tackle propagation effect uncertainties of supply chains considering product changes. The bullwhip effect (BE) with operational and behavioral causes is quantified as cascading amplified inventory fluctuations. The ripple effect (RE) from large-scale supplier disruptions driven by COVID-19 is quantified as increased entropy rates. Then, the system studied is integrated as a closed-loop control system under provided change control. Moreover, some criteria are derived for the existence of controller gains/decision coefficients to stabilize the closed-loop system with the BE mitigation under the RE.

In [A37], Khurana et al. present RobinNet: a RoBERTa- and inception-ResNet-V2-based novel multimodal network for speech emotion recognition. The model employs transfer learning to build two unimodal systems for text and audio features and then incorporates them into a single classifier through intermediate fusion. This work has been created after carefully analyzing the performance of various top-performing unimodal systems and then utilizing a fine-tuned RoBERTa-based model to represent the textual features. Furthermore, they utilize an inception-ResNetV2 pretrained network for speaker identification and employ transfer learning to train it for the task of emotion recognition through speech using spectrogram augmentation.

In [A38], Teng et al. propose a novel method, named kernel-based sparse representation learning with global and local low-rank label constraint, which strengthens the semantic information and ensures the semantic features invariant during learning. First, they map the data into a high-dimensional feature space to learn the linear representation of samples. Second, global and local low-rank label (GL3) constraint is used to ensure the semantic invariance, low-rankness, and discrimination of features during learning. Third, a 2,1 is imposed to explore the sparseness of the subspace. Mathematical analyses show that GL3 can retain the intrinsic properties of data during learning.

In [A39], Lan et al. propose a mechanism to solve the above issue using the distributed differential privacy framework. The proposed mechanism collects locally differential private rankings from individuals, and then randomly permutes pairwise rankings using a shuffle model to further amplify privacy protection. The final representative is produced by hierarchical rank aggregation. The mechanism was theoretically analyzed and experimentally compared against the existing methods and demonstrated competitive results in both output accuracy and privacy protection.

In [A40], the authors developed an anti-drug chatbot for young people on a popular online social platform. They can detect potential risks, obtain warnings from the user-entered query, and provide these to professional consultants for help. In this article, they present a hierarchical system with bidirectional encoder representation from transformers (BERTs) to efficiently recognize and classify a user's intent. They use the Chinese BERT-based model to utilize contextual information to perform classification and recognition. They evaluate their proposed system on their conversational dataset.

In [A41], real data for Steemit are used as a case study herein to examine the collusion of users in blockchain online social media. Two user collusion behaviors (group voting and vote-buying) are defined and measured. On this basis, an identification and evolutionary survival analysis of the two collusion behaviors are conducted for colluding users and colluding groups, and the behavior patterns of user collusion under the token system are deconstructed. The results of this study improve stakeholders' understanding of user participation behavior in new online communities and serve as a reference for decision-making in community governance and token design.

In [A42], Rajesh and Aljabhan use a sustainability framework for social sustainability to identify the social sustainability factors for supplier selection. Based on this and the related literature, this article identifies and classifies the factors into six categories. Furthermore, this article proposes a two-layered gray stratified decision-making (GSDM) model for identifying the best suppliers, by considering the attributes of social sustainability, along with the primary performance attributes of supplier selection, subject to a set of diverse objectives.

In [A43], Alam address the limitations of understanding the capability of the publicly available pretrained models for crisis tasks by investigating ten different network architectures for four different tasks using the largest publicly available datasets for these tasks. This article also explores various data augmentation strategies, semisupervised techniques, and a multitask learning setup. The investigation on semisupervised and multitask learning suggests new research directions for the community. This article also provides some insights into activation maps to demonstrate what class-specific information is learned by the network.

In [A44], the threshold elliptic curve digital signature algorithm (ECDSA) is difficult to adapt to real crypto-asset applications, and can hardly support large-scale processing operations in real life. This article proposes an innovative computation method called asynchronous threshold ECDSA with batch processing, based on the interactive threshold signature protocols. The method provides a reliable solution for critical operational scenarios, such as threshold signing and distributed key generation (DKG) in crypto-asset custody, and can be a future reference in secure data distribution mechanisms.

In [A45], Lu et al. introduce a painting captioning dataset (named the ArtCap dataset), which contains 3606 paintings and five descriptions for each painting. For the annotation quality, this article compares the global characteristics, annotation content, and annotation consistency of the dataset with other painting descriptions datasets. For application effectiveness, this article employs the dataset and other painting descriptions datasets to train image captioning models and analyze the captioning performances.

In [A46], Choudhry et al. annotate four fake news detection and rumor detection datasets with their emotion class labels using transfer learning. The correlation between the legitimacy of a text with its intrinsic emotion for fake news and rumor detection is shown, which can be used for improved feature extraction. Based on this, this article proposes a multitasking framework for fake news and rumor detection, predicting both the emotion and legitimacy of the text. A variety of deep learning models in singletask and multitask settings for a more comprehensive comparison is trained.

In [A47], existing studies based on sparse trajectory data are not sufficient to infer an individual's missing mobility in his/her historical trajectory. To address this concern, this article proposes a temporal context-aware framework that incorporates multiple factors to model the time-sensitive individual-location interactions in a bottom-up way. Based on the idea of feature fusion, the driving effect of heterogeneous information on individual mobility is gradually strengthened. This article leverages Bayesian personalized ranking to optimize the model, where a novel negative sampling method is employed to alleviate data sparseness.

In [A48], existing context-aware recommendation systems (CARSs) fall short in: 1) handling the high sparsity of data; 2) designing scalable solutions in real-time; and 3) providing more personalized solutions with the current limited static contexts. This article proposes a multi-CARS based on consensus clustering (MCARS-CC) to solve these challenges. The item-based contextual information is acquired using explicit static and inferred contexts by applying sentiment analysis to the users' reviews.

In [A49], Kansal and Pandey propose a time-varying epidemiological model with two classes of compartments, reported and unreported, and considers influential latent factors, for example, undetectable infections, the false-negative rate of testing, testing hesitancy, vaccination efficacy, dual contact dynamics, and the possibility of reinfection in recovered as well as vaccinated individuals. Furthermore, this article provides a sensitivity analysis of various latent factors and predictions for the third wave in India. Moreover, for unseen or coming variants of the virus for which vaccine efficacy is low, the available vaccine requires a high vaccination rate to control future waves.

In [A50], Mao et al. study social system inference from a single noisy trajectory of public evolving opinions, wherein observation noise leads to the statistical dependence of samples on time and coordinates. This article first proposes a cyber–social system that comprises individuals in a social network and a set of information sources in a cyber-layer. Based on the proposed cyber-social model, this article studies the sample complexity of least-square auto-regressive model estimation. Building on the identified social model, this article investigates social inference.

In [A51], Fazli and Amanihamedani aim to investigate how a central authority (e.g., a government) can increase social welfare (SW) in a network of markets and firms. This article assumes that the government has a budget by which it can supply some goods and inject them into various markets. How the central authority can best allocate its budget for the distribution of goods to maximize SW is discussed. This article shows that the solution is highly dependent on the structure of the network. Then, using the network's structural features, a heuristic algorithm for the target problem is presented.

In [A52], Singh et al. introduce a financial complaints (FINCORP) resource, a collection of annotated complaints arising between financial institutions and consumers expressed in English on Twitter. The dataset has been enriched with the associated emotion, sentiment, and complaint severity classes. The dataset comprises 3149 complaint and 3133 noncomplaint instances spanning over ten domains (e.g., credit cards and mortgages). For a comprehensive evaluation of the dataset, this article develops a multitasking framework for complaint detection and severity classification with emotion recognition and sentiment classification as the additional tasks and compares it with several existing baselines.

In [A53], the scenario of blockchain online social media (BOSM), where users can acquire cryptocurrency through their social actions, the phenomenon of "the rich-get-richer" has not yet been studied. This article proposes a methodological framework composed of three hypotheses that can help study the rich-get-richer phenomenon through a set of measures and indices. In addition, the proposed framework to the Steem case study is applied, showing how unevenly wealth is distributed on its blockchain and comparing these results to other scenarios.

In [A54], it is still an open question of how to utilize customers' social networks to design profitable and feasible referral incentive strategies. To this end, this work establishes a game model by introducing the referral incentive strategies of different forms based on the analysis of the marketing process. This work finds it is an NP-hard problem of solving the model and further proposes an approximate algorithm. In order to cope with large-scale datasets. Then, theoretical analysis, numerical experiments, and real applications are conducted to validate the performance of the model.

In [A55], vision transformer (ViT)-based methods have been used in unsupervised domain adaptation (UDA), but ViT lacks strength in extracting local feature details. To handle this, the purpose of this article is to demonstrate how to take advantage of both convolutional operations and transformer mechanisms for adversarial UDA by using a hybrid network structure called transformer fused convolution (TFC). TFC integrates local features with global features to boost the representation capacity for UDA which can enhance the discrimination between foreground and background. Moreover, to improve the robustness of the TFC, this article leverages an uncertainty penalty loss to make incorrect classes have consistently lower scores.

In [A56], Khan et al. design a capsule-long short-term memory (LSTM) model, abbreviated as CapsLSTM, capable of classifying human activities with scarce labeled activity data. The proposed CapsLSTM model is used to recognize multiple human activities sensed by the accelerometer and the gyroscope sensors embedded in smartphones leveraging the spatio-temporal information. The proposed framework based on two human activity recognition (HAR) databases is validated, namely, UCI-HAR and MotionSense. The CapsLSTM model yields close test accuracies for different fractions of the training data, unlike the other models such as LSTM, 1-D convolutional neural network (1D-CNN), convolutional LSTM (ConvLSTM), and CNN-LSTM.

In [A57], Yu et al. propose a deep graph learning model called PANDORA, which predicts the risk of coronavirus disease 2019 (COVID-19) infection by considering comprehensive factors. By constructing a geographic network based on geographic location and flight information, these factors are expressed in terms of node attributes and structural features. Four important node attributes were also considered, including climate, medical conditions, economy, and personnel mobility.

The authors also proposed three different aggregators. The experimental results show that regardless of which aggregator is chosen, PANDORA outperforms the benchmark method in terms of accuracy and convergence speed.

In [A58], Zhou et al. investigate a new solution for anti-money laundering in cryptocurrency exchanges and proposes a new algorithm for detecting suspicious money laundering accounts. A user interface consisting of four coordinated visualization components and a set of interactions was designed to visualize algorithm results and related transaction data to support the daily work of cryptocurrency exchange trading supervisors. Finally, the effectiveness of this method was verified through algorithm performance experiments, case studies, and on-site research.

In [A59], Zhu et al. propose a bidirectional weighted similarity measurement method for normal cloud models based on the quantity distribution and membership of cloud droplets. First, the analysis of cloud droplets was conducted to obtain their quantity distribution and membership characteristics under different cloud modes. Second, a bidirectional and weighted similarity measurement method was proposed and compared with two commonly used similarity measurement methods for normal cloud models. The results indicate that this method has high rationality, effectiveness, and applicability in perceiving and calculating the operational status of urban rail transit.

In [A60], Hsu et al. propose and study a new research problem that considers the diversity of group member attributes and social compactness, namely, socially aware diversity-optimized group extraction (SDGE). In addition, this article proposes an effective algorithm, which is the group shrinking for diversity maximization (GSDM) algorithm with a performance guarantee. GSDM is the three approximation algorithm for the SDGE problem studied in this article. The authors further improve the efficiency of GSDM through three pruning strategies. The experimental results show that the GSDM proposed in this article is significantly superior to other baselines.

In [A61], Zhang et al. propose a solution to the task offloading problem for mobile users based on the combination of mobile edge computing small cellular network and prospect theory framework and models the actual selection of users. For the task offloading problem in small cellular network scenarios, the artificial fish swarm algorithm is used to optimize the system with limited delay energy. The experimental results demonstrate the effectiveness of the proposed scheme and the impact of user behavior on system energy optimization.

In [A62], Chen et al. investigate community privacy protection for community edge target individuals targeting multiple adversarial community detection attacks. The authors propose a target individual hiding method based on edge node pairs of deep graph learning and select these node pairs as the intersection of various community detection methods. Finally, various community detection attacks were conducted on many real social graphs, and experimental results showed that the method can more effectively hide edge-sensitive user pairs than the baseline.

In [A63], Ma et al. propose a new method for modeling radar cognitive countermeasures under incomplete information, which first sorts out radar anti-interference measures based on domain knowledge and public information, and then proposes empirical formulas for corresponding anti-interference improvement factors. The proposed radar anti-interference improvement factor and interference benefit calculation method can meet the practical needs of engineering and have strong universality, providing a new way to solve the problem of cognitive adversarial effectiveness evaluation using game theory. Finally, the effectiveness of the game was tested in a specific adversarial environment.

In [A64], Sun et al. achieve a balance between the total numbers of nodes in different partitions through SG k-way partitioning of multiplayer repeated games. In this game model, k target partitions are used as game participants, and all possible actions of the participants selecting new nodes are used as the policy set. Some effective constraint rules are given to minimize the policy space. On this basis, the utility function of game players was defined. A large number of experiments have shown that the algorithm proposed in this article has a better performance.

In [A65], Min et al. propose a multiagent system (MAS) based on agent-based modeling (ABM) to analyze fine-grained opinion dynamics (FODs). The authors propose two mechanisms, namely, agent-based opinion formation (AOF) and agent-based opinion propagation (AOP), to enable agents to independently form and disseminate opinions. Deeply analyzed the multidimensional impact characteristics of agent self, neighbors, and theme communities, and applied them to AOF and AOP. The test results indicate the rationality and effectiveness of the MAS-FOD system.

In [A66], Fan et al. propose a new heterogeneous graph neural network with attribute enhancement and structure-aware attention (HGNN-AESA) to fully utilize the sparse node attributes in a heterogeneous information network with missing attributes. First, an attribute enhancement module is designed to connect more useful attribute nodes to the target node. Second, heterogeneous structure-aware attention layers (HSALs) are proposed to learn node representations. Finally, the experimental results of node classification tasks on three real datasets show that the model proposed in this article outperforms the most advanced methods currently available.

In [A67], Wang et al. propose a parallel enterprise management model based on decentralized autonomous organization (DAO) of enterprises, achieving distributed management of enterprises. Constructed artificial enterprise DAO corresponding to actual enterprises, which form a parallel system through virtual real interaction and parallel execution. Through the DAO-based decision-making mode under the parallel management framework, descriptive, predictive, and prescriptive intelligence in enterprise management can be achieved. The experimental results confirm the superiority of the DAO-based enterprise parallel management model proposed in this article.

In [A68], Maity et al. propose a multitask (MT) framework called MTBullyGNN based on graph neural network (GNN) for sentiment-aware MT network bullying detection in a mixed code paradigm. The core idea is to use sentence similarity to create a graph structure, where nodes are sentences. To connect nodes, cosine similarity is applied between sentences, and a single text graph is created for the BullySend network bullying corpus, which mixes benchmark code. The experimental results indicate that MTBullyGNN is superior to state-of-the-art methods.

In [A69], Guan et al. propose an enhanced grammar and semantic graph convolutional network based on contrastive learning. To address the challenges of introducing noise and distinguishing weights between semantics and syntax in syntax parsers. Supervised contrastive learning based on emotional polarity and unsupervised contrastive learning based on syntactic reliability further enhances semantic and syntactic representation. In addition, the authors also learned label embedding for syntactic reliability to determine the weights of syntactic and semantic information. A large number of experimental results indicate that the model proposed in this article is superior to the current level of technology.

In [A70], Chen et al. propose a depth graph neural network framework with a sine function, which has global information on the network. Specifically, a layered pooling mechanism has been developed to encode advanced features of the network. In addition, graph convolutional layers are introduced to aggregate the positive and negative information of adjacent nodes. By extracting global information from the network, the representation learning ability of the signature network can be enhanced, and a large number of experiments have proven the effectiveness and superiority of this method.

In [A71], Kumar and Singh propose a deep neural network-based model for extracting location references from bilingual (English–Hindi) disaster-related tweets. The suggested method has also been evaluated using English or Hindi tweets in monolingual contexts. This system can accurately locate locations of different granularities such as streets, buildings, towns, and villages with high precision. The model proposed in this article incorporates conditional random fields in the final layer, which performs better than other models.

In [A72], Zhang et al. construct a new sparse graph transformer with contrastive learning for graph representation learning, called SGTC. This model proposes a graph pruning scheme that removes redundant topological information from the input graph based on the influence of nodes and edges. By perturbing the trimmed graph, two different enhanced views are obtained, and node representations are learned through comparison. In addition, a new sparse attention mechanism was proposed to capture the structural features of the graph, effectively saving memory and training time. The experimental results confirm its superior performance on the most advanced baseline.

In [A73], Zhong et al. propose an evolutionary framework for automatic crowd navigation path planning in public scenes. The proposed framework contains a new fitness evaluation mechanism that can quantitatively evaluate the quality of a path planning strategy by considering both crowd safety and flow speed. Based on the fitness evaluation mechanism, a framework based on multiobjective differential evolution is developed to efficiently evolve path planning strategies. Simulation results on two synthetic scenes and a real-world metro station scene show that the proposed framework can provide good path-planning strategies.

In [A74], Meng et al. focus on the consensus-reaching process (CRP) for group decision-making with self-confidence (SC) and considers personalized individual semantics (PIS). This article first uses PIS to transform linguistic variables into numerical variables, by which initial SC-based adjustment intervals are derived. Furthermore, maximum and minimum programming models at three layers are conducted to derive adjustment intervals. Moreover, the rationality of SC-based revision adjustment intervals is judged by consensus models. Finally, the proposed method is applied to select ideal medical care and nursing institutions, and sensitivity and comparative analyses are performed.

In [A75], the authors used image processing, text recognition tools, and social network analysis to explore their curated dataset of over 15 700 collage images, and over 142 000 face images of meeting participants. They demonstrate that video conference users are facing prevalent security and privacy threats. The results indicate that it is relatively easy to collect thousands of publicly available images of video conference meetings and extract personal information about the participants, including face images, age, gender, usernames, and even full names.

In [A76], a prediction model has been proposed for spatial–temporal attention heterogeneous graph convolutional networks (STAHGCNs). First, the authors propose a user representation fusion mechanism to learn the user characteristics. Second, a temporal attention mechanism strategy is used to encode time into the heterogeneous graph to obtain a more expressive user representation. Finally, the obtained user representation is input into the multihead attention mechanism for information propagation prediction. Experimental results performed on the Twitter, Douban, Digg, and Memetracker datasets have shown that the proposed STAHGCN model increased by 8.80% and 6.74% at hits@N and map@N.

In [A77], Zhang et al. proposed and evaluated four image–text similarities, namely, textual similarity, semantic similarity, contextual similarity, and post-training similarity. The textual and semantic similarities indicate the original image–text similarities in terms of the text information and image caption information. The contextual similarity reflects the image–text similarity in the format of meaningful named entities. By evaluating the proposed similarity measurements on three real-world datasets, they find that fake news image–text similarity is higher than real news image–text similarity in most of the cases.

In [A78], Ahmad and Wu introduce a light-weighted spatial-deep features integration using multilayer GRU (SDIGRU). First, they extract spatial and deep features from frames sequence of realistic human activity videos via utilizing a lightweight MobileNetV2 model and then integrate those spatial-deep features. Then, they select rich informative features from spatial-deep appearances. Furthermore, they train multilayer gated recurrent unit (GRU) and feed informative features to learn the temporal dynamics of human activity frames sequence at each time step of GRU. The results on benchmark YouTube11, HMDB51, and UCF101 datasets of human activity recognition show that the method achieved significant recognition performance with low computational complexity and quick response.

In [A79], Zhang et al. propose a supplementary independent cascade and discuss the supplementary influence maximization problem. The problem is NP-hard, and the computation of the objective function is P-hard. The efficient reverse influence sampling techniques cannot be applied to the problem directly even though the objective function is submodular. They utilize the sandwich approximation strategy to obtain a data-dependent approximate solution. Furthermore, they define the supplementary-based reverse reachable sets and then propose a heuristic algorithm. Finally, the experimental results on three real datasets support the efficiency and superiority of the methods.

In [A80], the consensus-reaching process (CRP) is an effective tool for reducing differences of opinion. They hold that the decision-maker with high compatibility but low consensus can reduce the adjustment amount by actively losing some compatibility. In this study, a multistage multicost consensus model is developed, and the impact of different types of consensus costs on CRP. Finally, the feasibility and characteristics of the proposal are revealed through a case study and comparative analysis of the supply chain financing model selection.

In [A81], Paul et al. develop a deep-learning-based streaming data clustering approach for scientific articles, GAN-RS. The developed method finds the topics that are currently in trend and is also used to find the scope of a topic. ArXiv, which is the modified version of the multilabel scientific article data ArXiv, is used and tested to evaluate the proposed topic recommendation system. The comparison between the baselines and the existing methods illustrates the superiority of the proposed method. The representation of scientific article data in multilabel scenarios and utilizing the model in a multilabel framework helps to generate good quality clusters as well as in predicting trending topics.

In [A82], Kumar et al. propose a gated recursive and sequential deep hierarchical encoding (GraSHE) method for detecting in-congruent news articles by extending the hierarchical structure of the news body from the body to the word level and incorporating incongruity weight. From various experimental setups over three publicly available benchmark datasets, the experimental results indicate that the proposed model outperforms baseline models with bag-of-word-based features and sequential, hierarchical, and headline-guided attention-based encoding methods.

In [A83], Xu et al. design an end-to-end multitask semantic parsing model [MSP-bidirectional and auto-regressive transformers (BART)] that identifies question categories while converting questions. Meanwhile, a reinforcement learning-based model fusion strategy is proposed which enables multi-institution joint modeling and data privacy protection using cross-domain knowledge and reduces the negative impact of low-quality clients on the global model. Furthermore, a prompt learning-based entity disambiguation method is proposed to address the semantic ambiguity problem because of joint modeling. The experiments show that the question-and-answer results of the proposed approach outperform the approach of using only a single institution.

In [A84], the authors prepared a Twitter dataset of five popular online learning platforms: Coursera, Udemy, Udacity, Khanacademy, and edX, and analyzed their proposed metrics on them. Prediction of USS into loyal and not loyal customers is carried out using Twitter data and dense neural networks (DNNs). The performance of DNN is compared with random forest classifier (RFC), eXtreme gradient boosting (XGB), and support vector classifier (SVC). DNN gave the highest classification of 98.62% on tenfold cross-validation.

In [A85], the authors conduct a comprehensive analysis of fundraising and donation behaviors based on one of the most popular medical crowdfunding platforms called easy fundraising in China from 2016 to 2020. Four indicators, namely, diversity, uncertainty, concentration, and consistency are proposed to characterize the preferences of individual donors in choosing the donation amounts. They investigate the fundraising temporal dynamics and collective donation characteristics. Results show that the first three days after the creation of a crowdfunding campaign is the most efficient fundraising period that largely determines the completion of the campaign. Donors who donate early are more generous than those who donate later.

In [A86], the authors propose a novel approach called LUSTC for predicting links and unlinks with structural information, temporal information, and node content information on dynamic attributed networks. LUSTC first collects higher-order structural information using a random walk method based on the active nodes. Then, LUSTC generates two global matrices as well as a sequence of auxiliary matrices. After optimizing the matrices, LUSTC estimates the similarity matrix for future snapshots to predict the links that are more likely to be formed or broken. The experimental results on various dynamic attributed networks demonstrate the effectiveness of LUSTC on the link prediction and unlink prediction tasks.

In [A87], the authors propose HateMAML, a model-agnostic meta-learning (MAML)-based framework that effectively performs hate speech detection in low-resource languages. HateMAML utilizes a self-supervision strategy to overcome the limitation of data scarcity and produces better language model initialization for fast adaptation to an unseen target language or other hate speech datasets. Extensive experiments are conducted on five datasets across eight different low-resource languages. The results show that HateMAML outperforms the state-of-the-art baselines by more than 3% in the cross-domain multilingual transfer setting. They also conduct ablation studies to analyze the characteristics of HateMAML.

In [A88], Wang et al. propose a novel personality recognition method using fuzzy logic. Different from previous classifications, their new method categorizes the individual in a continuous space and represents one's personality on a more fine-grained level. They have designed comparative psychological tests for 77 people. The validation experiments on such tests indicate that the fuzzy-logic-based method is not only consistent with the classic Myers-Briggs type indicator (MBTI) tests (in the sense of defuzzification) but also provides uncertainty for each personality type.

Online remote tests from engineering courses at Técnico Lisbon are used as a case study in [A89]. The authors show that the cumulative contribution of concordant responses between students, when recurrent, offers a way of signaling fraud behavior. Separating content production from consumption reveals the underlying student role played in potential fraud acts. Collusion behavior is assessed against null models of fraud and conformity, therefore being statistically framed and offering a solid criterion to guide tutors in ascertaining fraud and discouraging communication.

In [A90], Li et al. introduce a novel group-gravitational field (GGF) model to investigate the opinion evolution based on group behavior by the following aspects: 1) the GGF model reduces a cluster in the social network into a charge and the whole network into a gravitational field; 2) the GGF model calculates the initial influence of a cluster according to the topology information and further constructs a gravity matrix of the network based on the Coulomb law; and 3) opinion-leader clusters exert the internal field force on common opinion clusters inside the gravitational field.

In [A91], Jeong identifies "always-the-same-rating" reviewers (ASRs), that is, reviewers who give the same star rating for all reviewed products and who write many reviews on Amazon. This study identifies ASRs in 29 product categories by analyzing 230 million individual reviews on Amazon. This study empirically demonstrates that star rating, the helpfulness of reviews, the length of headline and review, prior reviews, and holidays are potential indicators of reviews written by ASRs. This article may help in the segmentation of online consumers and a better understanding of online consumer review behaviors.

In [A92], the authors examine the effects of the illumination, pose, perspective, and occlusion components on person reidentification accuracy. They also analyze in detail how to extract attention information containing contextual information and discriminative pedestrian features in open scenes. Therefore, they construct an attention-pooling mechanism that can extract information. It can learn attention maps by automatically focusing on the visually salient regions of pedestrians. It effectively avoids the influence of factors on the accuracy of pedestrian reidentification.

In [A93], the authors proposed the reinforcement learning model integrating the cognition and affection (RLCA) model. In RLCA, the cognitive response generator can conduct commonsense reasoning based on the speaker's utterances. The obtained commonsense reasoning information was used to improve the perceptual ability of the cognition aspects of the model. The emotional regulator evaluates the output of the cognitive response generator at the sentence level to provide a model with a higher level of emotional expression. Finally, further interaction between the cognitive response generator and emotion regulator is performed to help the model learn to express patterns of empathy in human conversations.

In [A94], the authors introduced an approach to classifying the learning modalities (LMs) of the learner using machine learning (ML) techniques. They compared the effectiveness of five ML classifiers, namely, the random forest, multilayer perceptron neural network, K-nearest neighbor), support vector machine, and Naïve Bayes. They also compared three existing feature selection algorithms (recursive feature elimination, Boruta algorithm, and ReliefF)-integrated into the five ML classifiers as data feature reduction techniques.

In [A95], a passive radio frequency identification (RFID)-based classroom action recognition system LD-recognition is proposed. The system pastes the label on the right side of the desk, and the learning state of the students was judged by recognizing the four movements of raising the left hand, raising the right hand, nodding off, and holding the book. The system uses a multichannel attentional graph convolutional neural network to deeply learn the phase and signal strength of actions and conduct action recognition. LD recognition verifies the accuracy of actions from different distances, different experimenters, and different network models.

In [A96], Sun et al. propose three strategies to obtain the optimal policy: 1) given the current emotional transition matrix, use the emotional Markov decision process (E-MDP) algorithm to calculate the optimal stimulus policy for each target emotion; 2) given the emotional transition sequences, use the emotional Monte Carlo algorithm to calculate the optimal stimulus policy; and 3) given the emotional transition sequences, use the Q-learning algorithm to calculate the optimal stimulus policy. Besides, the authors improve the Markov chain Monte Carlo algorithm to sample emotional transition sequences and design a metric to evaluate the effectiveness of policies.

In [A97], the authors study career mobility from a market-driven perspective based on large-scale online professional networks. Specifically, they propose an uncertainty-aware graph autoencoder framework, which can simultaneously discover potential job title transition patterns and predict job durations. Furthermore, they design two task-specific decoders that can preserve the asymmetric relationships between job titles, namely, the gravity-inspired decoder and the energy-inspired decoder, for predicting potential transition patterns and corresponding duration, respectively.

In [A98], a novel practical and flexible regularization method is presented to obtain higher generalization and interpretability. Specifically, the feature maps are decoupled by global suppression and partial suppression from various scales and locate the salient feature with strong low-resolution semantic information. Moreover, the guided discarding specification for feature decoupling by measuring the feature contributions to network decisions leads to the logic with better interpretability. Subsequently, the max values of the feature map are suppressed by discarding the corresponding salient features.

In [A99], the authors first define the consensus measure to calculate the agreement degree among decision-makers by considering the ordinal information and cardinal information at the same time. On this basis, they construct a minimum adjustment optimization model in terms of the threshold-based value-driven sorting method. Following this, an optimization model that aims to minimize the distance between all decision makers and the group with respect to alternatives' comprehensive values and sorting results is developed to determine the group sorting result for alternatives.

In [A100], the authors propose a novel vehicle speed and image fusion for the driving behavior classification network (SIFDriveNet), which classifies driver behaviors into normal driving, aggressive driving, and drowsy driving. In addition, they evaluated their model on the public UAH-DriveSet and compared it with the most advanced model. Experimental results show that the model has a better performance, and the $F1$-score is 97.9% on all roads. In addition, the inference speed reaches 411 frames/s, enabling real-time needs.

In [A101], Ma et al. propose an analytical framework, adopting sequential and periodic pattern mining techniques, to effectively discover residents' routine behavior patterns. The effectiveness of the proposed framework is demonstrated in a case study of American public behavior based on a large-scale venue check-in dataset. The findings uncovered interesting behavioral patterns and venue visit information of residents in the United States during the pandemic, which could help the public and crisis management in cities.

In [A102], Nian et al. investigate the information spread process in modern online social networks and the influence of online social behavior on the spread process. According to the information posting rules of modern online social, two types of information retweeting methods, topic retweeting and relationship retweeting, are distinguished. The constructed information retweeting methods and the influence of social behavior are also considered together, and the trend of online information spread is analyzed.

In [A103], an individual evolutionary game model guided by global evolutionary optimization is proposed to solve the vehicle energy station distribution problem (VESDP). This model describes the VES market from individual and global perspectives and designs a policy formulation method for the government to heal the divergence between these two perspectives. Experiments are performed on both square grids and real-world networks. Experimental results demonstrate the effectiveness of the proposed model.

In [A104], the authors review some representatives of the latest graph node clustering methods, which are classified into three categories depending on their principles. Extensive experiments are conducted on real-world graph datasets to evaluate the performance of these methods. Four mainstream evaluation performance metrics are used. Based on the experimental results, several potential research challenges and directions in the field of deep graph node clustering are pointed out.

In [A105], Li et al. propose a new perspective on detecting depression in clinical interviews as a dialogue information extraction task. The authors encode the local and dialogue-level context with the input sequence using a bidirectional long short-term memory network. Then, they build a heterogeneous graph to model the participant's depression state and use the graph attention network to aggregate depressive clues from the entire clinical interview. Finally, they read word nodes and state nodes to identify the depressed individual from the clinical interview. Meanwhile, they use the focal loss as an optimization objective to address data-imbalanced depression detection.

In [A106], the authors collected 70 000 geotagged vaccine-related tweets in nine African countries, from December 2020 to February 2022. The tweets were classified into three sentiments classes-positive, negative, and neutral. The quality of the classification outputs was achieved using Naíve Bayes, logistic regression, support vector machines, decision tree, and K-nearest neighbor machine learning classifiers. The outcome of this research shows that discussions on social media can be analyzed to identify hotspots during a disease outbreak, which could inform health policy in planning and management of vaccine hesitancy in Africa.

In [A107], Tang and Liao introduce a graph model for conflict resolution (GMCR) model to address construction conflicts among different social entities. To process uncertain and vague information in preferences, this study allows decision-makers to use intuitionistic fuzzy information to express their preference information. To analyze the influence of attitudes, they originally introduced the concept of soft consensus in GMCR. Then, three kinds of attitudes, i.e., positive attitude, neutral attitude, and negative attitude, are identified.

In [A108], the Wiener model was introduced to analyze and predict the complex dynamics of COVID-19 incidence in Washington with the use of climate variables including temperature and humidity, along with a set of epidemic-related search queries from Google Trends. Their results validated the feasibility of using Google Trends data to identify the chaotic process of COVID-19. Moreover, the performances of models with various subsets of features were investigated and compared. Motivated by these performances, a highest weight feature-selecting strategy was proposed to further optimize the model, which proved to outperform other models.

In [A109], the methodology of this study focused on the development of a single deep learning algorithm, which is robust and reliable to estimate the active cases of COVID-19 in different provinces of India. The concept of transfer and federated learning is involved to enhance the estimation of active cases of COVID-19 by the federated-convolutional neural network-gated recurrent unit model. The study considered the active cases per day dataset for 36 provinces in India from 12 March, 2020 to 17 January, 2022.

In [A110], Liu et al. propose a new feature-aware disentangled graph neural network (FDGNN) for the recommendation. By learning the relationship between user behavior and important features of items, the model aims to achieve better recommendation performance and model interpretability. In the end, they first realize the feature partition based on mutual information and then design an attention-based graph disentangling model to realize the fine-grained disentangling of user intents. In addition, to further ensure the independence of the disentangled intents, they augment the model with disagreement regularization. Through multilayer embedding propagation, FDGNN can display a capture collaborative filtering effect in feature semantics.

In [A111], first the authors design an interpretable heterogeneous graph neural network, which can adaptively determine the optimal depth to obtain more accurate node embedding. Second, they use the attention coefficient to measure the importance of different semantics and use the residual blocks to control the information transmission between layers, thus addressing the shortcomings of existing methods that require predefined meta-path length. Third, they propose the selected DropLink to selectively remove the links with negative information interactions, which further compensates for the defects due to the over-smoothing and aggregates more distal features.

In [A112], Li et al. propose a novel solution based on the deep neural network and the Shapley value to compute the factor-factor interactions in different coalitions based on coalitional game theory. Analyzed by different factor categories, the new finding is that some factors, e.g., body mass index and social media, play a crucial role in happiness prediction but are rarely considered in social science studies. Specifically, there are some heavy interactions across multicategories, such as personal information (health and age) with economics (insurance and income). Therefore, this solution can theoretically support the implications of social decision-making.

In [A113], the authors introduce a meta-heuristic approach named service placement problem differential evolution algorithm (SPP-DEA) to handle service placement problem (SPP), which originates from the DEA with a shared parallel architecture. The proposed method takes advantage of the scalable and deployable nature of microservices to minimize resource utilization and delay as much as possible. SPP-DEA is developed based on monitoring, analysis, decision-making, and execution with a knowledge-based (MADE-k) autonomous planning model with the aim of compromising between service cost, response time, resource utilization, and throughput.

In [A114], the authors propose a prompt-based topic-modeling method for depression detection (PTDD) on low-resource data, aiming to establish an effective way of depression detection under the above challenging situation. Specifically, based on the question-and-answer routine during the interview, they first reorganize the text data according to the predefined topics for each interviewee. Via the prompt-based framework, they then predict whether the next-sentence prompt is emotionally positive or not. Finally, the depression detection task can be achieved based on the obtained topicwise predictions through a simple voting process.

In [A115], first based on public facial expression databases [JAFFE, Oulu CASIA, RaFD, and Cohn-Kanade (CK)], by studying the feature deviations between different expressions of the same person, an expression deformation constraint criterion (EDCC) that is conducive to maintaining recognizable features is proposed. Then, by comparing features between the source line portrait and reference expression portrait, the expression features are calculated. Finally, under the EDCC, based on expression features, a recognizable expression line portrait is generated through image topological deformation based on a triangle coordinate system. In addition, they can synthesize different degrees of expression line portraits.

In [A116], the authors propose a new Siamese network-based object tracking framework that eliminates this inconsistency by unifying classification and additional branch tasks to achieve learning location quality estimation. Furthermore, regression tasks for bounding boxes are widely formulated based on Dirac δ distribution. Though this assumption works well for many scenarios, it restricts the prediction of regression branches. To overcome this restriction, they propose discretizing the continuous offset of the regression branch into multiple offset predictions, which enables the network to learn more flexible distributions automatically.

In [A117], the authors propose an incentive mechanism for the sponsored content provider (CP) market in which the communication of users can be represented by a graph, and the private information of the users is assumed to have a continuous distribution function. The CP stipulates incentive rewards to encourage users to reveal their private information truthfully and increase their content demand, which leads to an increase in advertising revenue. They prove that all users gain a nonnegative utility and disclose their private information truthfully. Moreover, they study the effectiveness and scalability of the proposed mechanism in a case study with different network structures.

In [A118], first the authors proposed a quantitative method to measure knowledge adoption behavior on a collective level based on the knowledge network. Then, they discussed knowledge concept adoption and knowledge relationship adoption. To build knowledge networks and analyze their structural features, this work collected 74 761 knowledge concepts from the Zhihu platform and 62 368 knowledge concepts from the stack overflow platform. The regression analysis results showed that the structural characteristics of knowledge concepts and knowledge relationships substantially affect their adoption.

In [A119], the authors propose a two-stage general framework for multidocument AspSumm. The model first discovers the latent relationship among aspects and then uses relevant sentences selected by aspect discovery to generate abstractive summaries. They exploit latent dependencies among aspects using a tag mask training (TMT) strategy, which increases the interpretability of the model. In addition to improvements in summarization over aspect-based strong baselines, experimental results show that the proposed model can accurately discover multidomain aspects on the WikiAsp dataset.

In [A120], the authors release a new dataset with users and social relationships. To encode community information, they construct social graphs based on the user's historical behavior information and social relationships. Moreover, they propose a model based on graph attention networks (GATs) and fusion features for offensive language detection (GF-OLD). Specifically, the community information is directly captured by the GAT module, and the text embeddings are taken from the last hidden layer of bidirectional encoder representation from the transformer. Attention mechanisms and position encoding are used to fuse these features.

In [A121], the authors then measure variation in these degrees over time to identify relevant spatiotemporal civil war aspects. The network model is constructed using 0.5° grid locations as nodes, counting nearby and over time connections. They then extract the temporal community structure behind the data. Their findings indicate that the relationship between state capacity and climate stress shows opposite correlations with civil war as those identified by studies that use count-based indicators. Counterintuitively, their results show that conflict intensifies and spreads in locations where the state is stronger and where climate conditions are improved.

In [A122], the authors propose a temporal recommendation system using the Gaussian distribution and attention mechanism, which considers the sequentiality and interaction among items. They first deploy the word vector space along the time dimension as sequence features. Then, they use the Gaussian process to effectively represent the duration influence of items and the context interaction between items as high-level features. Finally, an innovative attention mechanism is used to capture the hidden correlation relationships between representation subspaces of different levels of features.

II. Physiological Electrosignal Asynchronous Acquisition Technology: Insight and Perspectives

The neural physiological activity of the brain possesses inherent asynchronous properties [1], [2], [3]. Electroencephalogram (EEG) acquisition technologies based on synchronous circuits are used to capture the electrophysiological activities of different brain regions. However, this synchronous recording way fails to provide precise characterization and interpretation of the brain's asynchronous activities, significantly limiting the further analysis of brain functional mechanisms and the pathophysiology of brain functional disorders.

A. Why Could Physiological Electrosignal Asynchronous Acquisition Technology Help?

Since the year 2000, significant advancements have been made in neuromorphic chip technology. The United States first introduced asynchronous architecture in this field, followed by China incorporating neuromorphic computing in its 13th Five-Year Plan in 2015. Key developments include IBM's TrueNorth chip in 2014 [4], featuring one million neurons and 256 million synapses, and Tsinghua University's Tianjic chip in 2019, offering a hybrid platform with multicore architecture and reconfigurable components [5]. In 2020, Intel's Loihi chip achieved online learning for artificial olfaction [6], and Zhejiang University introduced the Darwin 2nd generation neuromorphic chip supporting spiking neural networks (SNNs) [7], [8], [9]. The following year, the Swiss Federal Institute of Technology unveiled the DYNAP-SE2 chip for real-time EEG signal processing [10]. Most recently, in 2023, Tsinghua University developed ANP-I, China's first ON-chip learning-capable asynchronous neuromorphic chip, capable of tasks like gesture recognition and image classification [11]. These advancements in artificial intelligence (AI) hardware draw inspiration from the brain's structure and functionality [12], paving the way for further innovation in asynchronous physiological signal acquisition technology.

Studies show that when the brain receives external information (e.g., auditory or visual stimuli), it autonomously triggers perceptual neurons to generate pulse signals. These pulse signals are transmitted through synapses to surrounding feedback neurons, thereby completing the processing and handling of information. These processes do not comply with a predetermined order, as shown in Fig. 1, hence exhibiting asynchronous properties [1], [2], [3], [13]. Available EEG acquisition techniques based on synchronous clock circuits require synchronous drive electrodes over different brain regions to record EEG signals [14], [15]. Subsequently, the signal's temporal characteristics are analyzed offline to interpret the timing of excitation and conduction of EEG signals in different brain regions. However, this approach struggles to authentically and

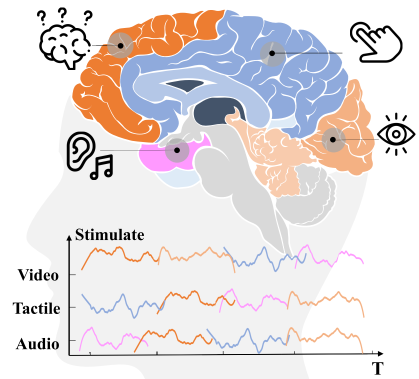

Fig. 1. Schematic of asynchronous EEG sequences generated in different brain regions under various stimuli, with colors indicating distinct brain areas.

accurately reflect the stimulation and conduction timing of EEG signals in different brain regions. It fails to provide a precise characterization and explanation of asynchronous activities in different brain areas, significantly limiting the in-depth analysis of the working mechanisms of the brain and the underlying pathophysiology of functional brain disorders.

Asynchronous circuit advantages inherent low power consumption, robust anti-interference capabilities, and exceptional temporal accuracy. Asynchronous EEG acquisition technology, substituting traditional synchronous clock mechanisms with event-triggered mechanisms (initiated by specific auditory or visual stimuli), aligns seamlessly with the asynchronous nature of brain neurophysiological activities. In this setup, EEG signal variations from different brain regions, prompted by continuous audiovisual stimuli, create an event stream. This stream triggers specific tasks and prompts corresponding circuit modules to perform these tasks, thus establishing an event-driven asynchronous EEG acquisition framework [16]. Contrasted with conventional synchronous EEG systems, this asynchronous approach exhibits heightened sensitivity to the timing of excitation and conduction of EEG signals across various brain regions. It enables real-time analysis of the sequence and evolution patterns of EEG signals in disparate brain areas [17].

B. What Can Asynchronous Physiological Electrosignal Achieve? Using the EEG Signals as an Example

1) Revealing the Temporal Interactions of EEG Signals in Different Brain Regions: Investigating EEG signal patterns in different brain regions is essential for understanding the brain's asynchronous mechanisms and functional disorders. Establishing temporal correlations between brain areas in response to asynchronous circuit events, particularly those triggered by audiovisual stimuli, is fundamental. This understanding facilitates the inference of representational association mechanisms and is pivotal in analyzing the brain's asynchronous processes and the implications for functional brain disorders.

Advancements in high-temporal-precision asynchronous EEG technology, triggered by auditory and visual stimuli, align with the brain's asynchronous neural activity. Hardware innovations, incorporating event feature enhancement and matching units, enable precise temporal mapping of EEG signals, enhancing insights into the brain's complex functions. Innovations in hardware utilize event feature enhancement and matching units to promptly identify and react to specific triggering events, ensuring high-precision temporal annotation of EEG signals from diverse brain regions.

2) Analyzing the Correlation Mechanisms of EEG Signals in Different Brain Regions: Utilizing event-triggering mechanisms to interpret EEG signal conduction across brain regions and to identify representational associations through the high temporal precision of asynchronous EEG signals represents a substantial scientific endeavor. This research is vital for an in-depth analysis of the brain's asynchronous functions and dysfunctions. It hinges on accurately interpreting how asynchronous EEG signals, prompted by specific audiovisual stimuli, represent complex interregional brain communication and processing. Recording the sequence and patterns of EEG signals from various brain areas, this technology holds promise for advanced exploration of the brain's asynchronous mechanisms and the pathophysiology of functional brain disorders. It has the potential to become a pioneering method for the early detection of EEG markers indicative of brain disorders like depression and autism, offering high sensitivity and specificity.

3) Detecting Affective Disorders: Despite advancements in the development of wearable EEG sensors for detecting affective disorders such as depression, as evidenced in several studies [15], [18], [19], [20], [21], [22], these devices encounter challenges like limited power endurance and the necessity for EEG markers of high sensitivity and specificity. The anticipated ultralow power consumption feature of asynchronous chips is expected to offer advanced technical solutions to enhance power durability in wearable technology. Furthermore, the exceptional temporal precision inherent in this technology is poised to pioneer an innovative method for the early detection of EEG markers linked to brain disorders, including depression, thereby potentially elevating the levels of sensitivity and specificity in such diagnoses.

C. Opportunities and Challenges

Previous research in the computational psychophysiology (CPP) framework has led to significant advancements across sensor materials [23], electrodes, chip technology, wearable devices, experimental methods, and AI algorithms. Building on these achievements, we expect the development of physiological electrical signal acquisition technology using asynchronous circuits to further advance and play a crucial role in artificial intelligence. This article aims to concisely outline the challenges and opportunities in this emerging field.

1) Experimental Paradigm: The brain possesses the property of an asynchronous activity mechanism [24]. However, current methods difficult to perceive temporal information about neuronal activity in different brain regions, except for magnetic resonance imaging (MRI). One of the important points is that the available experimental paradigm makes it difficult to induce more significant temporal information about brain activities. Therefore, the experimental paradigm is a crucial factor in determining the success of the whole study, and designing a more efficient experimental paradigm remains a significant challenge.

2) Signal Hardware Encoding: Previous studies using asynchronous circuit techniques have mainly focused on event cameras and brain-like chips [13], [25]. Despite the encouraging results of [10], which achieved the coding of abnormal EEG signals in epilepsy, the coding approach remains relatively simple. For affective computing, particularly in researching disorders like depression, anxiety, and bipolar disorder, it is critical to achieve accurate encoding of complex electrophysiological information flow. This includes hardware encoding of EEG signals in multiple channels across different frequency bands, to precisely perceive the causal interactions of neural activities in various brain regions, which is key to deciphering the pathogenesis of affective disorders.

3) Synchronous SNN Chip: Real-time asynchronous-pulse neuromimetic chips and brain-like chips based on asynchronous pulsed circuits have undergone rapid development over the years. Notably, the SYNAP-SE2 [26] facilitates the analysis and monitoring of EEG features. This highlights asynchronous circuit technology as a significant milestone in the field of neurophysiological electrical signal analysis. However, most brain-like chips, like Darwin and SYNAP-SE2, are primarily to enhance computational power and implement AI algorithms, with limited application in physiological electrical signal analysis. Currently, there is a lack of brain-like chips adequately suited for the acquisition and analysis of physiological electrical signals.

4) Mechanistic Insights Into Depressive Disorders: Presently, depression is identifiable through EEG modalities [15], [27], [28]; however, the biological markers associated with this condition demonstrate variability. Inconsistencies in the EEG characteristics of depressive disorders across diverse datasets impede precise mechanistic analysis. The advent of asynchronous EEG acquisition technologies is poised to unveil temporally informed novel features. Such advancements are anticipated to facilitate a more accurate delineation of the functional dynamics within various cerebral regions. This, in turn, could significantly enhance the understanding of the underlying pathophysiological mechanisms of depressive disorders.

5) Developing Interpretable Models for Depression Identification: Over the past few decades, there has been substantial progress in the development of depression identification models utilizing machine learning and deep learning techniques, with the latter demonstrating particularly encouraging results [29], [30], [31]. Despite these advancements, their clinical implementation faces significant challenges, primarily due to the models' limited interpretability. The employment of asynchronously collected EEG signals for constructing brain-like computational models presents a viable solution. This approach is anticipated to significantly enhance the integration of digital diagnostic and therapeutic strategies for depressive disorders in clinical settings.

6) Mutually Reinforcing: The development of asynchronous circuits is closely linked with neuroscience, and neuroscience can further promote the advancement of these circuits, making them smarter and enhancing the efficiency of artificial intelligence algorithms. In addition, the technology for acquiring physiological electrical signals based on asynchronous circuits offers novel tools and methods for decoding brain functional mechanisms.

D. Conclusion

Physiological electrical signal acquisition has traditionally relied on synchronous techniques, significantly advancing neuroscience research over the past decades. However, recent developments in integrated circuit technology have brought asynchronous circuit technology to the forefront in this field. This more efficient, intelligent, and precise technology in asynchronous physiological signal acquisition is poised to address challenges in synergistic perception, collaboration, and the integration of brain and artificial intelligence.

Current research in asynchronous circuit technology, particularly in affective computing, is limited, highlighting the need for greater involvement from research institutes and scientists. Despite existing challenges, the potential and innovation inherent in this area should not be underestimated. Advancements across experimentation, new materials, integrated circuits, and software environments require extensive research to explore new avenues and invigorate this emerging field. Asynchronous techniques for physiological signal acquisition and analysis are expected to open novel pathways in affective computing, provided they adhere to principles of reasonableness, legality, and compliance.

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APPENDIX: RELATED ARTICLES

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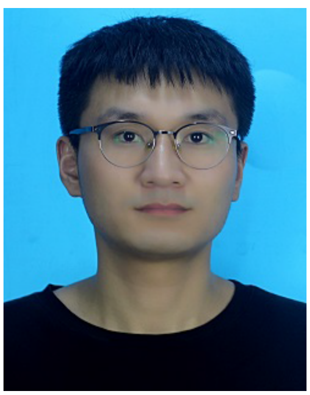

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