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A Comprehend Survey On Future Directions Of Artificial Intelligence Techniques For Social Behaviour Analytics

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Abstract

As social media platforms and digital communication channels have grown at an unprecedented pace creating vast amounts of behavioural data, Social Behaviour Analytics has become a key area of Artificial Intelligence (AI) importance. This research looks at a number of AI approaches to human behaviour analysis and prediction such as Machine Learning (ML), Deep Learning (DL), Graph Neural Networks (GNNs), Explainable AI (XAI), and Reinforcement Learning (RL). The introduction reveals how these techniques can be applied to gain insight into user interaction, sentiment and social influence in diverse domains like the business world, healthcare, and social media platforms. The survey provides a general survey of the techniques developed over the past 6 years (2020-2025), in particular highlighting the adoption of state-of-the-art deep learning and graph-based models over classical ML models. Most existing research has been done on structured data classification and prediction, and recently, models using GNNs have been developed to model relation and multimodal learning to incorporate multiple data sources. There are advantages in terms of accuracy and performance, but problems remain such as data sparseness, computational complexity, and lack of interpretability and privacy issues. The research study is a step towards state of the art and offers insights into the needs of future social behaviour analytics systems with respect to scalability, explainability and adaptability.

Keywords: Deep Learning, Explainable AI, Graph Neural Networks, Machine Learning, Multimodal Data Fusion and Reinforcement Learning.

1. Introduction

AI plays a major role in social behaviour analytics by supporting multimodal emotion recognition [1], abnormality detection [2], privacy-preserving user modeling [3], speaker identification [4], health monitoring [5], crowd behaviour analysis [6], Twitter sentiment classification [7], semantic text analysis [8], mobile app recommendation [9], cross-modal prediction [10], explainable review sentiment analysis [11], social media emotion analysis [12], multimodal sentiment analysis [13], sensor data fusion [14], and misinformation detection [15]. These studies show that AI can improve behaviour understanding, prediction, and social decision-making. Overall, recent AI models provide better accuracy, faster analysis, and deeper interpretation of human behavioural patterns. However, challenges such as privacy, data quality, model complexity, and interpretability still remain. Future research should focus on explainable, secure, scalable, and real-time AI systems. Such advancements can support trustworthy social behaviour analytics across digital platforms, healthcare, business, and public safety domains.

2. Background Study

Younis et al. (2022), [1] focused on multimodal emotion recognition using physiological, environmental, and mobile sensor data. The method used ensemble learning models such as Bagging, Boosting, and Stacking with sensor data fusion. The main limitation is real-time multimodal data collection complexity; the best result was high accuracy using Stacking.

Jadhav et al. (2024), [2] studied multimodal sensor data analysis for abnormality detection. The method used deep learning with double-stream CNN, CWT visualization, data segmentation, and preprocessing. The limitation is that accuracy depends on the number of abnormal samples; the best result was 95.10% efficiency.

Zhou et al. (2024), [3] proposed multimodal user modeling for human-centric metaverse applications. The method used personalized federated learning with model-contrastive learning. The limitation is high computational complexity; the model achieved 31.7%, 16.7%, and 21.1% F1-score gains in three cases.

Malik et al. (2026), [4] developed AI-driven speaker identification for trustworthy human-centric systems. The method used spectrogram inputs, dropout, learning-rate decay, and data augmentation. The limitation is reduced performance under noisy conditions; results were high accuracy in clean data and 90.2% accuracy at 5 dB SNR.

Alduailij (2025), [5] presented critical health monitoring using Internet of Medical Things. The method used ensemble deep representation learning with metaheuristic optimization. The limitation is healthcare-specific dependency on IoT data quality; the model achieved best accuracy.

Table 1: Recent Artificial Intelligence Techniques for Social Behaviour Analytics and Multimodal Behaviour Understanding

Author(s), Year, Ref. No.	Concept	Method Used	Limitations	Results
Alotaibi et al., (2025)[6]	Crowd density estimation in surveillance systems using explainable AI	Advanced Deep Learning Model integrated with Explainable AI (XAI)	High computational complexity and reduced performance in highly crowded scenes	Improved crowd density estimation accuracy with enhanced model interpretability
Mudarakola et al., (2025) [7]	Sentiment analysis of product reviews from Twitter data	Multi-stage sentiment analysis using optimized Machine Learning algorithms	Limited generalization across diverse social media platforms and languages	Achieved higher sentiment classification accuracy compared to conventional ML methods
Almufti, Elamine & Belguith, (2025) [8]	Semantic analysis of Iraqi dialect text	Comparative Machine Learning and Deep Learning algorithms	Dataset-specific performance and challenges in handling dialect variations	Deep learning models outperformed traditional machine learning approaches
Mirbahar, Kumar & Laghari, (2025) [9]	Mobile application recommendation using educational crowdsourced data	Machine Learning and Deep Learning-based recommendation framework	Dependence on data quality and scalability issues for large datasets	Enhanced recommendation precision and user satisfaction
Alzahrani et al.,(2025) [10]	Ransomware detection using multimodal feature fusion	RansomFormer cross-modal Transformer combining byte and API features	High training cost and resource-intensive deployment	Achieved superior ransomware detection accuracy compared to existing methods
Hashmi & Yayilgan, (2025) [11]	Sentiment analysis for Amazon product reviews	Hybrid Product Context-Aware Learning with Explainable AI	Increased model complexity and longer training time	Improved sentiment prediction accuracy and explainability
Khemani et al.,(2025) [12]	Emotion analysis in social media text	Improved Graph Convolutional Network (GCN)	Sensitive to graph structure quality and noisy social media data	Enhanced emotion recognition performance over baseline GCN models
Peng et al., (2025) [13]	Multimodal sentiment analysis using social media data	H-GNN-based Contrastive Learning with multimodal dataset	Requires large annotated datasets and significant computational resources	Achieved robust multimodal sentiment classification performance
Elhoseny et al.,(2024)[14]	Sensor data fusion for fault diagnosis and tolerance	Deep Learning-based optimized sensor fusion algorithm	Limited adaptability to highly dynamic environments	Improved fault diagnosis accuracy and system reliability
Hu et al., (2025) [15]	False information detection in social networks	Bidirectional Graph Convolutional Neural Network (Bi-GCN) integrating message content and propagation	Performance depends on availability of propagation information	Achieved higher misinformation detection accuracy than conventional GCN methods

		paths		

This table 1 summarizes recent AI-driven approaches for analysing social behaviour through sentiment analysis, emotion recognition, misinformation detection, crowd monitoring, and multimodal user modelling. It highlights the applied methods, limitations, and achieved results of machine learning, deep learning, graph-based, and transformer-based techniques, providing insights into current advancements and research challenges in intelligent social behaviour analytics.

2.1 Research Gap:
Existing AI-based social behaviour analytics approaches demonstrate high performance in sentiment analysis, emotion recognition, user modelling, and multimodal data processing; however, several challenges remain. Current methods lack unified integration of individual behavioural patterns, social relationships, and contextual information. Limitations include high computational complexity, dependency on large labelled datasets, privacy concerns, limited real-time adaptability, and reduced robustness in dynamic social environments. Therefore, a scalable, explainable, and adaptive AI framework is required for comprehensive social behaviour understanding.

3. AI techniques for multimodal behaviour analytics

Multimodal behaviour analytics utilizes Artificial Intelligence techniques to integrate and analyze diverse data sources such as sensor signals, user activities, environmental information, text, and speech data. These approaches enable accurate emotion recognition, behaviour monitoring, user modeling, and behavioural prediction by capturing complex human behavioural patterns from multiple modalities.

3.1 Multimodal AI for Behaviour Understanding

This is a focus on multi-modal data like user activity, environmental data and sensor data, which can be leveraged to observe human behavior using AI techniques. Emotions recognition, Abnormality detection and Personalised user behaviour modelling for the most part.

Younis et al. [1] proposed a method which utilizes sensor fusion techniques for performing multismodal emotion recognition using sensor data from physiological, environmental and mobile sensors. An ensemble learning method was used to classify the emotional state and demonstrated the need for integration of multimodal data for understanding behaviour.

The concept of double stream CNN is introduced and applied to propose a deep learning based multimodal abnormality detection system in the work [2] by Jadhav et al. multiple sensor inputs and data preprocessing techniques were used to investigate abnormal behavioural patterns, emphasizing the use of multimodal AI in behavioural monitoring.

Zhou et al. (2024) [3] have introduced a personalized federated learning framework with model-contrastive learning to enhance multimodal user modelling in metaverse environments centered on humans. The framework was designed to represent and predict the user behavior, in different modalities of user information in a no compromise manner of privacy of the data.

Table 2: Machine Learning-Based Techniques for Social Behaviour Analytics

Author(s), Year, Ref. No.	Concept	ML Algorithm Concepts	Results
Hashmi et al. (2025) [1]	Context-aware sentiment analysis of online product reviews.	Support Vector Machine (SVM), FastText feature extraction, Explainable ML (LIME), topic modelling.	Achieved 93–94% accuracy across product datasets; Linear SVM achieved 91% accuracy for software reviews.
Mudarakola et al. (2025) [6]	Social media sentiment classification for Twitter user opinions.	Random Forest, ensemble learning, optimized ML classification.	Random Forest achieved 88% accuracy, while hybrid ML approach achieved 95% accuracy.
Almufti et al. (2025) [7]	Semantic analysis of Iraqi dialect social feedback.	Naïve Bayes, KNN, SVM, Random Forest classification.	Naïve Bayes achieved the highest accuracy of 82.89% among ML models.
Younis et al. (2022) [12]	Multimodal emotion recognition using behavioural and sensor information.	Ensemble ML methods, KNN, Decision Tree, Random Forest, SVM, Bagging, Boosting, Stacking.	Stacking ensemble obtained the highest accuracy outperforming other ensemble models.
Mirbahar et al. (2025) [5]	Behaviour-based recommendation using crowdsourced educational data.	Collaborative Filtering, KNN-based recommendation, graph-based prediction.	KNN-based CF achieved MAE 0.548 and RMSE 0.754, showing effective recommendation accuracy.

This table 2 presents ML-based approaches applied to social behaviour analytics, including sentiment analysis, emotion recognition, recommendation systems, and behavioural classification. The reviewed studies utilize traditional algorithms such as SVM, Random Forest, Naïve Bayes, KNN, and ensemble learning methods. These techniques demonstrate effective predictive capability for structured and textual social data while supporting intelligent decision-making in behavioural analysis applications.

3.2 Human Activity and Multimodal Behaviour Recognition

Speaker identification is related to human activity and multimodal behaviour recognition because it analyzes voice-based human identity patterns. The model in [4] achieved high accuracy in clean conditions and 90.2% accuracy at 5 dB SNR.

Critical health monitoring is also related because it observes human physiological conditions using IoMT-based intelligent monitoring. The model in [5] achieved high accuracy on healthcare IoT data.

Crowd density estimation is related to human activity recognition because it monitors group-level human movement and crowd behaviour in surveillance environments. The model in [6] achieved best accuracy using an explainable deep learning framework.

3.3 Behaviour Classification and Prediction Models

Twitter sentiment classification is related to behaviour classification because it predicts user opinions and emotional responses from social media reviews. The model in [7] achieved high accuracy, 89% precision, and 89% recall.

Semantic analysis is related to behaviour prediction because it classifies text meaning and user feedback patterns from dialect-based language data. The model in [8] achieved 82.89% accuracy.

Mobile app recommendation is related to prediction models because it predicts user preferences and app usage behaviour. The model in [9] achieved MAE = 0.2246 and RMSE = 0.2516 using GRU.

Ransomware classification is only partially related because it focuses on cybersecurity prediction rather than social behaviour. The model in [10] achieves high accuracy on the static dataset and high accuracy on the combined dataset.

3.4 Deep Learning in Social Media Analysis

Hashmi & Yayilgan (2025), [11] developed a hybrid product context-aware learning and explainable AI model for Amazon user review sentiment analysis. The study used deep learning models such as LSTM, GRU, CNN, BERT, RoBERTa, and XLNet, along with LIME and LDA for interpretability. The model achieved 0.93, 0.93, and 0.94 accuracy on three product datasets, while FastText with linear SVM achieved 0.91 accuracy.

Khemani et al. (2025), [12] proposed an improved graph convolutional network for emotion analysis in social media text. The method used graph-based NLP modeling to classify emotional tones from large-scale social media content. The model achieved 78.64% and 92.38% accuracy, showing the usefulness of GCNs for social media emotion classification.

Peng et al. (2025), [13] introduced an H-GNN-based contrastive learning scheme for multimodal sentiment analysis using social media data. The method combined multimodal sentiment features and graph-based contrastive learning to improve social media behaviour understanding. The model improved accuracy by 1.7% and F1-score by 1.54% and 4.9% on MOSI and MOSEI datasets.

4. Discussion

The reviewed studies show that AI techniques improve social behaviour analytics through multimodal learning, deep learning, graph models, and explainable AI. These methods support emotion recognition, sentiment analysis, user modeling, behaviour prediction, and social monitoring. However, major challenges remain in privacy, interpretability, computational complexity, data quality, and real-time deployment. Future models should focus on trustworthy, scalable, and explainable AI systems for accurate social behaviour understanding.

5. Conclusion

This survey reviewed recent Artificial Intelligence techniques applied to social behaviour analytics, including machine learning, deep learning, graph neural networks, multimodal learning, explainable AI, and federated learning. The reviewed studies demonstrated substantial progress in behaviour recognition, sentiment analysis, recommendation systems, social monitoring, emotion detection, and user modeling. Advanced multimodal and graph-based approaches have shown superior performance in capturing complex behavioural patterns compared with traditional methods. Despite these advancements, challenges related to data privacy, interpretability, computational cost, model scalability, and real-world adaptability continue to limit practical deployment. The analysis indicates that future social behaviour analytics systems should integrate explainable, trustworthy, and privacy-aware AI mechanisms while effectively handling heterogeneous data sources. Overall, AI-driven social behaviour analytics remains a rapidly evolving research area with significant potential to support intelligent decision-making, personalized services, and human-centric digital ecosystems.

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