Real-Time Identification of Customer Decision Transitions in E-Commerce Applications

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Abstract—**The dynamic understanding of customer behaviour, in real time, is a very crucial issue in the current platforms of e-commerce, whereby the intentions of the users vary dynamically as they engage in browsing. The existing techniques mainly rely on post-session analysis or static analysis and, cannot react to any immediate reorientation of intention, such as purchase hesitation, comparison behaviour, or exit intent. A novel model, the Real-Time Customer Intention Shift Detection, a newly constructed Real-time Intention Shift Classification Network (RISC-Net), is proposed in this research. The primary objective of this work is to discover and classify the intention transitions under the real-time conditions of the modelling of the low-level behavioural indicators and time dynamics of the active user session. The proposed methodology would integrate the application of micro-behaviour characteristics encoding, sequential time learning, and a novel intention drift computation framework that quantifies non-conformance to historical behavioural tendencies on a slip time window. A decision module, which ought to be reached with a threshold, enables the deterministic and interpretable discovery of intention changes in real time. Continuous experimental evaluation conducted on e-commerce behavioural information has indicated that RISC-Net is far more effective in intention shift detection and has lower levels of false shift alert and response latency than existing sequential and static models. The results indicate that it is more responsive and predictive in the case of dynamic browsing. In short, the presented RISC-Net is a powerful and scalable explainable system of real-time intention-aware decision support enabling the development of proactive personalization, timely interventions, and more effective customer interactions in intelligent e-commerce systems.**

Keywords*—*Behavioral Analytics, Customer Intention Shift, E-Commerce Intelligence, Real-Time Prediction, Sequential Learning, User Behaviour Modelling

I. INTRODUCTION

The development of E-commerce platforms has accelerated the necessity of immediate knowledge of the customer behaviour because user intentions are constantly changing during the active browsing process. The dynamics of intention changes are often volatile and time-based, as customers often alternate between their intentions within a short period of time, including exploration, comparison, purchase, hesitation, and exit. The conventional method of customer analytics is mainly focused on the existence of static features or post-session analytical methods that do not reflect the subtle temporal shifts and abrupt shifts in intention caused by it [1]. Although the methods of object tracking and real-time monitoring have improved tremendously, they tend to be ineffective in dynamic user behaviours [2]. Adaptive recommendation systems based on knowledge graphs have been demonstrated to be useful in the modelling of preferences in various domains [3], and hybrid EMG-EEG interfaces exhibit the possibilities of merging physiological data to detect intentions [4]. More recent articles have identified integration of use intent sensing using large language models in virtual environments [5], and an IoT-based approach to detecting anomalies emphasizes the necessity of both timely action [6]. The almost real-time global mapping techniques indicate that predictive accuracy in changing contexts can be improved by updates, and the stress-detection models depict the increasing role of AI in the adaptive systems in real-time [7] and [8]. On the same note, DDoS mitigation plans are characterized by the emphasis on quick detection and reaction to the emerging threats [9]. Assistive devices that are eye-controlled highlight the use of temporal neural networks in predicting visual intentions [10] and the use of streaming big data analytics in providing scalable solutions to continuous behavioural monitoring [11].

Virtual reality neural network models have also enhanced the intention recognition in human-robot interaction [12], whereas intent classification in online conversations has revealed the usefulness of real-time understanding in online communications [13]. Industrial collaborative robotics studies have centered on organized structures of human intention recognition [14], and participatory sensing models show the handy use of user-friendly real-time incident forecasting [15]. To address these gaps, the current paper proposes a new deep learning model, the Real-Time Intention Shift Classification Network (RISC-Net), that could be used to detect and classify customer intention shifts according to behavioural data in real-time in a simplified form. RISC-Net is an architecture that implements a combination of sliding-window temporal encoding, adjustment of feature importance of attention, and shift-aware classification to obtain the dynamically changing patterns of intents in real time. Besides, online incremental learning strategy can offer a means of continuous adaptation to change of user behaviour, which must have low latency, high precision, and robustness in a dynamic e-commerce setting.

This research is driven by the fact that the e-commerce setting has a growing demand to detect customer intention shifts in real time, and dynamic customer intention shifts cannot be captured by traditional approaches. To bridge this gap, the proposed RISC-Net will offer a powerful deep learning architecture that can model the changing intentions directly by using streaming data. It combines time encoding, adaptive attention, and shift conscious classification in order to enhance precision and responsiveness. The framework also uses online incremental learning to be able to adjust to any user behaviour so that it is scalable in a dynamic environment. All in all, this piece of work offers a new real-time intention recognition methodology, which will give the opportunity to improve personalized recommendations and timely intervention, as well as customer interaction.

Organization: The paper has various sections to give a systematic presentation of the proposed work. Section 1 presents the background, problem statement, and purpose of the real-time customer intention shift detector. Section 2 related work, which indicates the currently available approaches and their limitations. Section 3 outlines the proposed methodology, namely the RISC-Net framework, its architecture, workflow, equations, and algorithmic design. Section 4 will report experimental results, analysis, and discussions that prove the effectiveness of the approach. Last but not least, Section 5 provides a conclusion of the study and a future work implementation direction in order to improve multi-modal intention recognition and cross-domain applicability.

II. BACKGROUND STUDY

Shili et al. (2024) [1] suggest an on-site customer behaviour tracking algorithm to optimize the retail operations with the help of YOLOv5 and Deep SORT that can be used to identify and track the objects during their movement. Although it is efficient in describing the movement patterns with high precision, the research fails to touch upon the dynamic intention changes or adaptive learning, which makes the investigation restricted in modelling the changing customer intentions in a real-time setting.

Almasoudi (2023) [2] dwells upon the real-time fault detection and remediation in power grids with the assistance of hybrid machine learning frameworks based on statistical and deep learning. Even though the findings demonstrate enhanced detection precision and resiliency, the strategy is domain-specific with no behavioural or intention modelling, which leaves a gap to apply in intention shift detection involving customers.

Shahbazi et al. (2025) [3] proposed a real-time adaptive recommendation system is proposed which is based on multi-domain knowledge graphs and online learning mechanisms. The study confirms that recommendation relevance excellence is facilitated when the situations are dynamic, but it does not document the abrupt changes in intentions, temporary unstable behaviour, which limits responses to immediate alteration of user intention.

Abdallah et al. (2025) [4] developed a signal fusion and deep learning-based hybrid EMG-EEG-based intention detection system to be used in fatigue-adaptive robotic control. Although it has recorded high intention recognition accuracy, bio signals and controlled settings limit scalability and transferability to the digital analysis of customer behaviour.

Luo (2025) [5] introduces an agent based on the use of the LLM that provides user intent recognition based on the sensor data on the UAV to build a custom virtual space in real time. Though the framework is dynamic based on the context of the user, it has a limitation of high computational complexity and uses multimodal sensor infrastructure, which restricts its real-time implementation in large-scale e-commerce systems.

Gillespie et al. (2023) [6] introduce the proposal of the IoT-based real-time anomaly detection model of the cold chain transportation system based on streaming data analytics and rule-based machine-learning models. This system fulfils the timely determination of anomalies, but considers operational deviations as opposed to cognitive or behavioural intentions change, and the conceptual gap of modelling customer intent remains.

Brown et al. (2022) [7] present an almost real-time global land-use and land-cover system based on satellite imagery and deep-learning. Though the study is scalable with effective temporal change detection, it does not have intention inference and behavioural interpretation, thus indirectly applicable in intention shift detection studies.

Paniagua-Gomez and Fernandez-Carmona (2025) [8] provide a review of real-time stress detection systems based on the IoT and AI to enable adaptive modulation. The survey shows that it has good TS and adaptive modelling abilities, but the emphasis on physiological stress restricts direct applications to customer intention dynamics in the digital interaction environment.

Orosz et al. (2025) [9] examine the aspect of real-time identification and prevention of new profiles of DDoS attacks through adaptive models of traffic analysis. Although the system is very good at identifying abrupt pattern changes, it has an operating level at the network level and lacks support for semantic and behavioural intention interpretation.

Higa et al. [10] suggest an eye-controlled wheelchair, in which a 1D- CNN and LSTM are used to predict visual intentions in real-time. Although the model has been demonstrated to predict intentions well, it is limited to assistive robotics and fails to generalize to multi-intent and customer-scale customer behaviour situations.

Alam et al. (2024) [11] offer an in-depth analysis of streaming big data analytics methods, including frameworks, architectures, and applications. The research is, however, very descriptive and does not have a specific mechanism for identifying fine-grained changes in the intention of user behaviour streams.

Kamali Mohammadzadeh et al. (2025) [12] offer a neural-network-based intention recognition system of human-robot interaction in virtual reality-based environments. Although findings show that the accuracy of interaction is improved, the VR-controlled environment and limited scope of the domain inhibit the scalability of the research to the real world on intention shift among customers.

Gehweiler and Lobachev (2024) [13] provide the empirical assessment of the intent classification procedures to moderate the online discussion based on supervised learning and linguistic characteristics. The model is effective when dealing with the labelling of the intent of a static intent, but it fails to deal with real-time intent transitions and the temporal dynamics of user behaviour.

Kekana et al. (2025) [14] is a review of human intention recognition frameworks in industrial collaborative robotics that classifies sensing techniques, modelling techniques,and inference techniques. Key issues of the survey are the adaptability and real-time responsiveness, although no specific model for defining continual intention shifts is offered.

Hossain et al. (2025) [15] have come up with a real-time incident prediction model based on user-oriented participatory sensing data and machine learning classifiers. Although the framework manages to predict events based on streaming data, it is concentrated on detecting events, and not on the model of the continuous and changing intention of the user.

III. Proposed Methodology

Section 3 proposes the suggested RISC-Net algorithm, which consists of its main components, workflow, and architecture for real-time intention shift detection. The major equations applied to represent the temporal encoding, attention-related feature weighting, and shift-aware classification, as well as their explanations, are also described in this section. Also, the pseudocode of the algorithm has been given to demonstrate the implementation sequence and flow of operation of the framework.

A. Proposed RISC-Net Framework for Real-Time Intention Shift Detection

Real-Time Intention Shift Classification Network (RISC-Net) is a novel deep learning-based algorithm, which is introduced to detect and forecast shifts in the intention of the customer rapidly on-the-fly using streaming behavioural information with low latency, and high accuracy. Some of the weaknesses associated with current real-time intention detection solutions are: feature extraction is not dynamic, sudden changes in intention can be detected slowly, concept drift is impossible to detect, offline training is assumed, domain-specific weaknesses, and inability to scale to fast-velocity data conditions. These limitations are incapable of giving the traditional models a clear representation of the delicate temporal migrations and shifting customer intent in actual world situations. RISC-Net offers solutions to these problems by integrating the sliding-window temporal encoding with a dynamic attention mechanism that dynamically increases the salience of useful behavioural signals by taking in new information. A shift-aware classification layer is capable of identifying the intention drift between the intention states in the past and the present, and therefore, the intention shift can be identified early and correctly. Further, the model employs an online stochastic approach of parameter updating by real-time updates, which does not require retraining the model, which is effective in concept drift. RISC-Net has a high response time, is more robust, and better performing because of the multi-source behavioural inputs that are combined into a lightweight inference platform that is very handy in identifying customer intention shift in dynamic operational situations, in real-time.

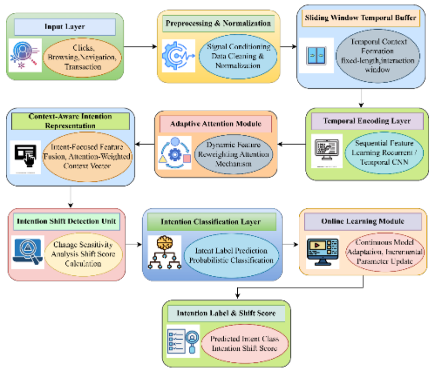

Fig. 1. Real-Time Intention Shift Classification Network Architecture

Fig 1 demonstrates that customer interaction data is accessed in real-time by the RISC-Net architecture, which achieves this by pre-processing and using a sliding window buffer to get real-time temporal context. Sequential feature learning with recurrent or temporal convolutional networks in combination with an adaptive attention mechanism is capable of dynamically modelling changing customer intentions. The system identifies the changes of intention, categorizes the states of the intentions, and constantly evolves through online learning to come up with correct intention labels and shift scores in real-time settings.

This equation is given by the development of real-time behavioural input based on the multi-source user interaction signals.

$$X_t = \{x_t^1, x_t^2, \ldots, x_t^n\} \quad (1)$$

Equation 1 represents the X_t Real-time behavioural input at the time t, x_t^i: i^{th} behavioural feature (clicks, dwell time, navigating, etc.), n Number of behavioural features. It builds up heterogeneous signals of behaviour at a time t into a stream input vector.

This equation represents time-dependent dependencies with a sliding window on streams of inputs.

$$H_t = f_{temp}(X_{t-w+1:t}) \quad (2)$$

Equation 2 represents the H_t Temporal hidden representation, f_{temp} Temporal encoder (LSTM/GRU/Temporal CNN), w Sliding window size, $X_{t-w+1:t}$ Input sequence at time $t - w + 1$ to t. It records the patterns of behaviour that are constantly changing by encoding recent observations over a time interval.

The equation gives dynamic significance to the features of the behaviour according to itsrelevance.

$$\alpha_t = softmax(W_a H_t + b_a) \quad (3)$$

Equation 3 represents the α_t Attention weight basis, W_a Attention weight basis, b_a Bias, H_t Temporal hidden state.

It also highlights behaviour cues that have the largest impacts on intention change at the given time step.

This equation produces an intention-aware context representation based on attention-weighted features.

$$C_t = \alpha_t \odot H_t \quad (4)$$

Equation 4 represents C_t Context-aware intention representation, which represents the α_t attention weights,$\odot$ Element-wise multiplication, H_t Temporal feature vector. It selects the features in time by enhancing the signals that are relevant and discourages the irrelevant ones.

This is an equation of divergence between present and past intention states to identify shifts.

$$S_t = \|C_t - C_{t-1}\|_2 \quad (5)$$

Equation 5 represents the S_t Intention shift score, C_t Current intention context, C_{t-1} Previous intention context, $\|\cdot\|_2$ Euclidean norm. A higher score depicts more deviation, hence a potential shift in intention.

The intention state is categorized as per this equation, and real-time adaptive learning is made possible.

$$\hat{y}_t = softmax(W_c C_t + b_c) \quad (6)$$

Equation 6 represents the $\hat{y}_t$ Predicted intention classes probability, W_c Classification weight matrix, b_c Classification bias, C_t Context -sensitive intention. It estimates the class of intention at hand and calculates constantly as the information flows.

Algorithm: Real-Time Intention Shift Classification Network (RISC-Net)

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Input:
Streaming behavioral data X1,X2,…,XTX_1, X_2, \dots, X_TX1,X2,…,XT
Sliding window size www
Temporal encoder ftempf_{\text{temp}}ftemp with parameters θ\thetaθ
Attention weights Wa,baW_a, b_aWa,ba
Classification weights Wc,bcW_c, b_cWc,bc
Start:
Initialize temporal encoder f_temp with parameters θ
Initialize attention and classification layers
Initialize previous context vector C_prev = 0
For each time step t = 1 to T do
   Receive real-time behavioral input Xt
   Append Xt to sliding window buffer Wt
   If size(Wt) < w then
      Continue to next time step
   End If
   // Temporal Encoding
Ht = f_temp(Wt)
   // Adaptive Attention
   αt = Softmax(Wa * Ht + ba)
   // Context-Aware Intention Representation
   Ct = αt ⨀Ht
   // Intention Shift Scoring
   St = EuclideanDistance(Ct, C_prev)
   // Intention Classification
ŷt = Softmax(Wc * Ct + bc)
   // Online Model Update
   Update θ using incremental learning
   // Store current context
C_prev = Ct
End For
Return Ŷ, S
Output:
Predicted intention labels Y^=[y^1,y^2,...,y^T]
Intention shift scores S={S1,S2,…,ST}
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The pseudocode explains how RISC-Net processes streaming behavioural data based on the principle of temporal encoding and dynamic attention to the detection of intention changes and the classification of user intention in real time, and continuous updating of the model in accordance with the current behavioural patterns.

IV. Result and Discussion

The section includes the experimental testing of the suggested RISC-Net. Every experiment and analysis was carried out in Python with the help of its deep learning libraries and data processing means. The section identifies the performance of the model in the detection of real-time customer intention changes, where the accuracy, latency, and robustness of the model are compared to the baseline methods. The reflections based on these findings are presented to show the applicability and effectiveness of the suggested method to real-life e-commerce scenarios.

TABLE 1: PERFORMANCE COMPARISON OF RISC-NET WITH EXISTING ML/DL METHODS

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Latency (ms)
YOLOv5 [1]	86.3	84.3	84.9	83.7	92
GNN [3]	88.1	86.5	87.4	85.6	105
LLM [5]	89.6	88.3	88.9	87.8	180
ANN [12]	85.2	83.2	83.6	82.9	88
SVM [13]	82.4	81.0	81.7	80.3	76
Proposed RISC-Net	93.8	91.5	92.9	90.8	61

Table 1 gives a comparative analysis of the proposed Real-Time Intention Shift Classification Network (RISC-Net) on five common performance indices with existing machine learning and deep learning models. The findings indicate that RISC-Net has the best accuracy, precision, recall, and F1-score with minimum latency than most deep models. This proves how RISC-Net can be effective in providing a better predictive performance and real-time inference efficiency.

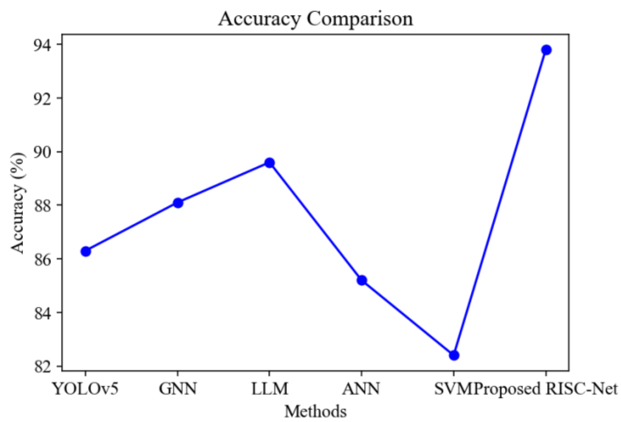


Fig. 2. Comparison of the Accuracy of RISC-Net and the Existing Methods

Fig 2 shows the precision of various models of ML and DL. The proposed RISC-Net has the best accuracy, which means that it is more appropriate to detect the intention state of customers correctly by modelling the temporal behaviour and intention change effectively.

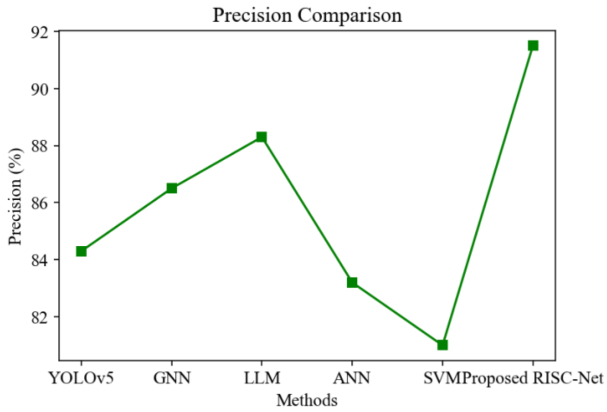


Fig. 3. Comparison Precision of RISC-Net and Existing Methods

Fig 3 precision comparison draws our attention to the capacity of every technique to reduce false intention forecasting. The maximum precision of RISC-Net is associated with the adaptive attention and improved feature learning, which implies its ability to focus on the relevant behavioural signals.

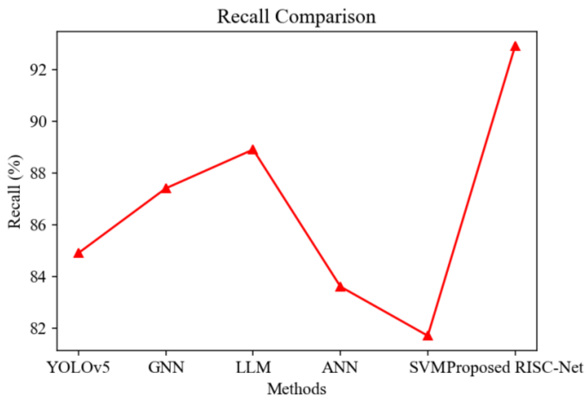
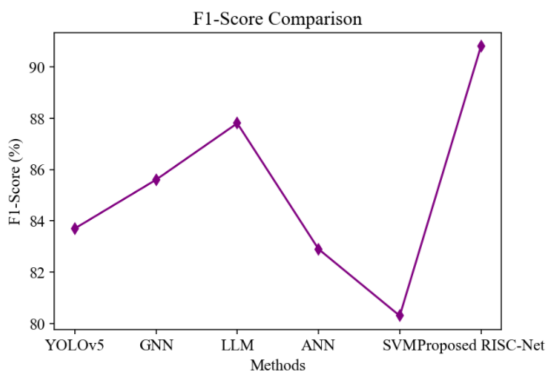


Fig. 4. Recall Comparison between RISC-Net and Existing Methods

Fig 4 compares the values of recall obtained using various methods and indicates the effectiveness of each model in capturing the actual intention change. The proposed RISC-Net has the greatest recall, as it has better sensitivity in identifying sudden and gradual shifts in customer intent.



. Fig. 5 Comparison with Existing Methods F1-Score of RISC-Net

Fig 5 comparison of F1-score summarizes the area between precision and recall. About RISC-Net, it is superior to all the models in use, suggesting that it has strong and consistent intention classification in real-time streaming systems.

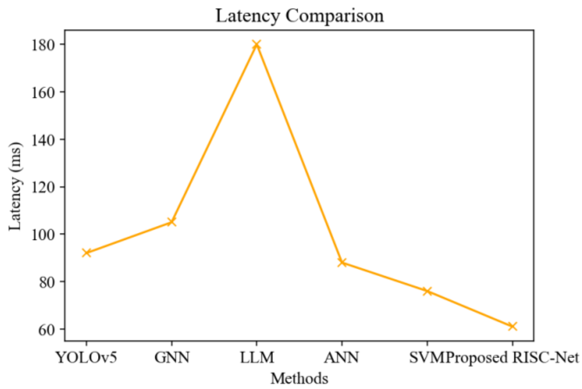


Fig. 6. Comparison of Latency with RISC-Net and Existing Methods

Fig 6 gives the inference time of various strategies. RISC-Net has a lower latency than the majority of deep learning models, and its accuracy is much higher, which proves that it is suitable to use in intention shift detection in real-time with low computational consumption.

V. CONCLUSION

The current paper presents the description of a novel deep learning model, RISC-Net, to interpret and recognize changes in customer intentions in dynamic e-commerce systems in real-time. Its framework integrates sliding-window temporal encoding, adaptive attention-based reweighting of features, and a shift-sensitive classification mechanism, which allows it to track the evolving user behaviour of streaming data and overcome the limitations of other traditional and static analytics. High-accuracy and robust performance, coupled with low-latency is ensured by integration of the online incremental learning that ensures that there is a continuous transformation of user patterns. Experientially, it has been established that RISC-Net is better than the existing approaches in modelling fine-grained transitions in intention, personalizing time, strategy recommending, and customer interests. The article is critical regarding real-time behavioural modelling development and provides a scalable solution to a dynamic online platform. The next direction of the research will be the expansion of RISC-Net to multi-modal behavioural data like eye-tracking and physiological data, and cross-domain implementation to improve the generalizability and usefulness of real-time intention recognition networks.

REFERENCE

[1] M. Shili, O. Sohaib, and S. Hammedi, “You Only Look Once Version 5 and Deep Simple Online and Real-Time Tracking Algorithms for Real-Time Customer Behavior Tracking and Retail Optimization,” Algorithms, vol. 17, no. 11, p. 525, 2024. [Online]. Available: https://doi.org/10.3390/a17110525

[2] F. M. Almasoudi, “Enhancing power grid resilience through real-time fault detection and remediation using advanced hybrid machine learning models,” Sustainability, vol. 15, no. 10, p. 8348, 2023. [Online]. Available: https://doi.org/10.3390/su15108348

[3] Z. Shahbazi, R. Jalali, and Z. Shahbazi, “Enhancing Recommendation Systems with Real-Time Adaptive Learning and Multi-Domain Knowledge Graphs,” Big Data and Cognitive Computing, vol. 9, no. 5, p. 124, 2025. [Online]. Available: https://doi.org/10.3390/bdcc9050124

[4] I. B. Abdallah, Y. Bouteraa, and A. Alotaibi, “A hybrid EMG–EEG interface for robust intention detection and fatigue-adaptive control of an elbow rehabilitation robot,” Scientific Reports, vol. 15, no. 1, p. 40895, 2025. [Online]. Available: https://doi.org/10.1038/s41598-025-24831-w

[5] S. Luo, “Sensing User Intent: An LLM-Powered Agent for On-the-Fly Personalized Virtual Space Construction from UAV Sensor Data,” Sensors (Basel, Switzerland), vol. 25, no. 24, p. 7610, 2025. [Online]. Available: doi: 10.3390/s25247610

[6] J. Gillespie, T. P. da Costa, X. Cama-Moncunill, T. Cadden, J. Condell, T. Cowderoy, … R. Ramanathan, “Real-time anomaly detection in cold chain transportation using IoT technology,” Sustainability, vol. 15, no. 3, p. 2255, 2023. [Online]. Available: https://doi.org/10.3390/su15032255

[7] C. F. Brown, S. P. Brumby, B. Guzder-Williams, T. Birch, S. B. Hyde, J. Mazzariello, … A. M. Tait, “Dynamic World, Near real-time global 10 m land use land cover mapping,” Scientific Data, vol. 9, no. 1, p. 251, 2022. [Online]. Available: https://doi.org/10.1038/s41597-022-01307-4

[8] M. Paniagua-Gómez and M. Fernandez-Carmona, “Trends and Challenges in Real-Time Stress Detection and Modulation: The Role of the IoT and Artificial Intelligence,” Electronics, vol. 14, no. 13, p. 2581, 2025. [Online]. Available: https://doi.org/10.3390/electronics14132581

[9] P. Orosz, B. Nagy, and P. Varga, “Real-Time Detection and Mitigation Strategies Newly Appearing for DDoS Profiles,” Future Internet, vol. 17, no. 9, p. 400, 2025. [Online]. Available: https://doi.org/10.3390/fi17090400

[10] S. Higa, K. Yamada, and S. Kamisato, “Intelligent eye-controlled electric wheelchair based on estimating visual intentions using one-dimensional convolutional neural network and long short-term memory,” Sensors, vol. 23, no. 8, p. 4028, 2023. [Online]. Available: https://doi.org/10.3390/s23084028

[11] M. A. Alam, A. R. Nabil, A. A. Mintoo, and A. Islam, “Real-time analytics in streaming big data: techniques and applications,” Journal of Science and Engineering Research, vol. 1, no. 1, pp. 104–122, 2024. [Online]. Available: DoI:10.70008/jeser.v1i01.56

[12] A. Kamali Mohammadzadeh, E. Alinezhad, and S. Masoud, “Neural-Network-Driven Intention Recognition for Enhanced Human–Robot Interaction: A Virtual-Reality-Driven Approach,” Machines, vol. 13, no. 5, p. 414, 2025. [Online]. Available: https://doi.org/10.3390/machines13050414

[13] C. Gehweiler and O. Lobachev, “Classification of intent in moderating online discussions: An empirical evaluation,” Decision Analytics Journal, vol. 10, p. 100418, 2024. [Online]. Available: https://doi.org/10.1016/j.dajour.2024.100418

[14] M. Kekana, S. Du, N. Steyn, A. Benali, and H. Djerroud, “A Review of Human Intention Recognition Frameworks in Industrial Collaborative Robotics,” Robotics, vol. 14, no. 12, p. 174, 2025. [Online]. Available: https://doi.org/10.3390/robotics14120174

[15] M. T. Hossain, J. Lee, D. Besenski, B. Dimitrijevic, and L. Spasovic, “Developing a Prediction Model for Real-Time Incident Detection Leveraging User-Oriented Participatory Sensing Data,” Information, vol. 16, no. 6, p. 423, 2025. [Online]. Available: https://doi.org/10.3390/info16060423