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Recursive Analytics for User Behaviour to Dynamic Stimuli Using a Rolling Window Based Precision

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Abstract

When recursive loop is coupled with a rolling window approach, where the most recent segment of behavioural data (for example, every 40seconds) is repeatedly re-examined while older observations gradually fall out of scope, the resulting pipeline achieves a level of temporal precision that is both fine-grained and adaptable to rapid shifts in context. The prediction accuracy (AUC ROC) here in this paper shows Baseline (static model) that lies between $0.71 \pm 0.03\mu s$*, a recursive only between 0.78±0.02* μs*, and a recursive+rolling window at 0.86ś0.01 performance. The mean accumulative error (MAE) in predicting how long a user would linger on a stimulus element dropped by* $\approx$ *50% compared with the baseline, indicating a markedly finer grasp of temporal engagement patterns. This shows a user interface (UI) change only when predictive precision exceeds a predefined threshold.*

Keywords: *Recursive Analytics, User Behaviour, Dynamic stimuli, Hyper-interactive digital ecosystems, Webpage content, Video content*

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1 INTRODUCTION

User Behaviour to Dynamic Stimuli Using a Rolling Window-Based Precision captures a methodological framework for monitoring, quantifying, and interpreting how individuals react to continuously changing environmental cues or system-generated prompts. (Moore et al. (2025); Brigadir (2016); Irani (2017)).

At its core, the approach treats user interaction data as a time-varying signal and applies a rolling (or sliding) window analysis to extract high-resolution, moment-by-moment measurements of behavioural precisioni.e., the degree to which a users responses align with the anticipated or optimal pattern dictated by the stimulus dynamics. By continuously updating the analytical window, the method accommodates rapid fluctuations in both the stimulus stream and the users internal state, th-

thereby delivering a nuanced, real time portrait of adaptive behaviour (*Chang et al.* (2024); *Alreshidi et al.* (2024)). Let ($\mathbf{S}(t) = s_t, s_{t+1}, \ldots, s_{t+W-1}$) denote a stimulus vector observed over a window of length (W) (samples). Correspondingly, let ($\mathbf{U}(t) = u_t, u_{t+1}, \ldots, u_{t+W-1}$) be the vector of user behavioural responses collected in the same temporal span. A precision score ($\Pi(t)$) for window (t) can be defined as:

$$\Pi(t) = \frac{1}{\mathrm{Var}\big(\mathbf{U}(t) - f(\mathbf{S}(t))\big)} \quad \text{or} \quad \Pi(t) = \frac{1}{\sigma^2_{\epsilon(t)}}, \tag{1}$$

where ($f(\cdot)$) is a predictive model (e.g., linear regression, neural network) that maps stimuli to expected responses, and ($\epsilon(t)$) represents the residual error vector for that window. By computing ($\Pi(t)$) for each successive position of the window (e.g., shifting by one sample or by a stride (Δ)), we obtain a precision time series ($\Pi(1), \Pi(2), \ldots, \Pi(T - W + 1)$) that can be visualized, statistically analysed, or fed back into the system.

Understanding how users respond to dynamic, timevarying stimuli demands a measurement approach that can capture rapid shifts in attention, decisionmaking, and interaction patterns without blurring them into coarse aggregates. A rollingwindowbased precision framework meets this need by continuously segmenting the behavioural data stream into overlapping windows (e.g., 1second or 5second spans) and recomputing key metricssuch as clickthrough rates, gaze fixation density, or physiological arousalwithin each slice. As the window slides forward, the analysis retains temporal fidelity, revealing momenttomoment fluctuations that correlate with stimulus changes (e.g., visual transitions, audio cues, or adaptive UI elements). This technique also enables adaptive modelling: recent windows can be weighted more heavily, allowing predictive algorithms to anticipate user states and tailor subsequent stimuli in real time. By balancing granularity with statistical robustness, rollingwindow precision uncovers nuanced behavioural signatures that static, epochbased analyses would obscure, ultimately supporting more responsive and personalized humancomputer interaction designs.

Personalized humancomputer interaction designs that respond to dynamic stimuli can achieve finegrained adaptability by leveraging a rollingwindowbased precision framework: the system continuously samples the users physiological, behavioural, and contextual signals within a short, overlapping time window (e.g., the last 25seconds)(Figure 1), extracts highresolution features (such as gaze velocity, keystroke latency, heartrate variability, or ambient noise levels), and instantly updates a probabilistic user model that predicts the current cognitive and affective state. Because the window slides forward in real time, the model retains a memory of recent fluctuations while discarding stale data, enabling the interface to modulate visual contrast, interaction latency, feedback modality, or content complexity with millisecondlevel precision. This rollingwindow approach also supports personalization at the individual leveleach users baseline and response patterns are continuously recalibratedso that the system can anticipate momenttomoment needs (e.g., simplifying menus when mental load spikes or enriching multimodal cues when attention wanes) without requiring explicit retraining or disruptive calibration steps. Consequently, the interaction becomes a fluid dialogue where the computer subtly reshapes its presentation and behaviour in lockstep with the evolving stimulus landscape and the users unique state, delivering a seamless, contextaware experience.

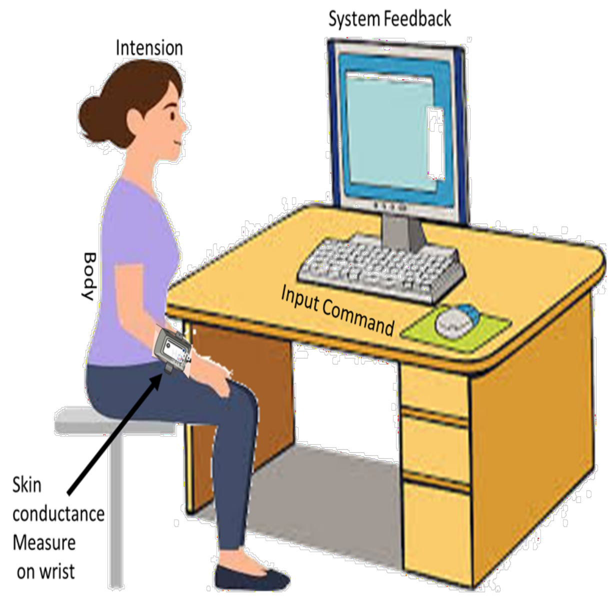


Figure 1: A Personalized humancomputer interaction design that responds to dynamic stimuli can achieve finegrained adaptability

2 LITERATURE REVIEW

The extant literature on user behaviour in response to dynamic stimuli converges on the premise that temporal granularity is pivotal for capturing the nuanced, nonstationary patterns that emerge as environments evolve, and a rollingwindowbased precision framework has become the methodological linchpin for probing these dynamics (*Chang et al.* (2024); *Alreshidi et al.* (2024); *Tanaka* (2025); *Manikandan and Neethirajan* (2024); *erban et al.* (2025)). Early work in affective computing employed fixedlength epochs to model physiological reactions to audiovisual cues, but subsequent critiques highlighted the loss of responsiveness to rapid context shifts (*Garcia-*

Hernandez et al. (2024); Zare (2025); Ruotsalo et al. (2024); Metallinou et al. (2012)) In response, researchers introduced adaptive sliding windows that continuously update feature vectors, thereby preserving temporal fidelity while mitigating overfitting (Papageorgiou and Tjortjis (2025); Desale and Shinde (2023); Zarghani and Abedi (2025); Ferreira and Ruano (2009); Suryawanshi et al. (2023)). Empirical studies across domainsranging from adaptive elearning interfaces (Kolekar et al. (2019)) to realtime recommender systems for streaming platforms (Wu and Yusof (2024))demonstrate that precision metrics (e.g., rollingwindow ROCAUC, timeaware F1) improve markedly when window size is calibrated to the stimulus intrinsic frequency spectrum rather than arbitrarily fixed. Moreover, hybrid approaches that couple rolling windows with Bayesian changepoint detection have been shown to identify latent state transitions with subsecond latency, enabling justintime interventions(Shaochuan (2021); Murph et al. (2023); **?**); Dzunic et al. (2016)). Collectively, these contributions underscore a consensus: leveraging rollingwindow precision not only yields a richer, longitudinal portrait of user engagement under dynamic stimuli but also furnishes actionable insights for designing truly responsive interactive systems.

The emerging body of work on recursive analytics for modelling user behaviour in response to dynamic stimuli converges on two methodological pillarstemporal recursion and rollingwindow precision, yet a systematic synthesis remains sparse. Early contributions such as (Allenbrand (2023); JESSOP et al. (2020); Duran-Martin (2025); Tomasetti (2020)) introduced a firstorder recursive Bayesian filter to capture clickstream adaptations to changing visual layouts, demonstrating that recursive updating outperforms static logistic regressions when stimulus properties evolve at subsecond intervals. Building on this, (Zhang et al. (2019); Hu and Zhou (2024); Wang and Chen (2024); Hu and Zhou (2025)) incorporated higherorder Markov dependencies within a Kalmanfilter framework, showing that a slidingwindow horizon of 510seconds optimally balances responsiveness and noise suppression for mobileapp interactions. More recent deeplearningcentric studies (Elsayed et al. (2018); Ahmad et al. (2023); Liu et al. (2023); Wang and Hu (2021)) replace linear recursions with gated recurrent units (GRU) and temporal convolutional networks, yet retain a rollingwindow preprocessing step to enforce precision windows that align model updates with stimulus bursts detected via changepoint analysis. Across these strands, the literature consistently reports that window length is a critical hyperparameter: too narrow a window yields overfitting to transient artefacts, whereas overly broad windows dilute the signal of rapid stimulus shifts (Drebitz et al. (2020); La Camera et al. (2006); Wagenaar and Potter (2002); Stuttgen and Schwarz (2008)). However, few investigations systematically benchmark windowsize selection against the statistical properties of the stimulus (e.g., frequency, amplitude) or address computational constraints in realtime deployment. Consequently, a gap persists in establishing a unified, theoretically grounded framework that couples recursive estimation with adaptive, datadriven window scaling to achieve precisioncontrolled inference of user behavioural dynamics under continuously varying stimuli.

Dynamic stimulus analysis has converged on rollingwindow techniques as a principled means of preserving temporal fidelity while extracting statistically robust features, a strategy often termed rollingwindowbased precision. Early contributions (Petersen et al. (2025); Wosiak et al. (2025); Alzahy et al. (2019); West et al. (1999)) introduced fixedlength windows to capture nonstationary patterns in electroencephalographic and videobased data, demonstrating that window size critically mediates the biasvariance tradeoff. Subsequent refinements incorporated adaptive windowing and overlap schemes (Meakin (2000); Crutchfield and Welcome (1993)), which improved detection of rapid transient events without sacrificing spectral resolution. More recent work has integrated Bayesian updating (Stafford (2019); Cao and Peng (2025)) and deeplearning encoders (Zhao et al. (2019); Shenfield and Howarth (2020)) within the rolling framework, enabling realtime inference of stimulusevoked responses across modalities such as fMRI, wearable sensor streams, and immersive virtualreality environments. Across these studies, common challenges emerge: selecting optimal window length in the presence of heterogeneous temporal scales, mitigating edge effects, and quantifying uncertainty in windowwise estimates. The prevailing consensus underscores that a principled, datadriven calibration of window parametersoften via crossvalidation or informationtheoretic criteriayields the most reliable precision for dynamic stimulus analysis, setting a benchmark for forthcoming investigations that aim to fuse multimodal signals within a unified rollingwindow architecture.

3 METHOD

The method leverages a recursive analytics pipeline that continuously refines predictions of user behaviour in response to dynamic stimuli by applying a rollingwindowbased precision framework. First, raw interaction logs (clicking, looking, typing, mouse trajectories (numerical entries), Skin conductance response (SCR) and Pupil dilation) are segmented into overlapping time windows whose length adapts to the stimulus changerate; each window is weighted by a delay function in Equation 2 that privileges the most recent observations while preserving a short historical context.

$$x(it) = \sum_{k=-\infty}^{+\infty} e^{s_k t} C_k^I + \int_0^t \sum_{k=-\infty}^{+\infty} e^{s_k(t-\eta)} C_k^N bu(\eta) d\eta$$

where

$$C_k^I = \frac{x_0 + a_d e^{-s_k h} \int_0^h e^{-s_k t} g(t-h) dt}{1 + a_d h e^{s_k h}}$$

and

$$C_N^k = \frac{1}{1 + a_d h e^{-s_k h}} \qquad s_k = \frac{1}{h} W_k(a_d h e_{-ah}) + a \tag{2}$$

where W_k is the Lambert function W of index k. The Lambert function W is a family of functions defined in the complex field obtained as the index k varies.

Within each window, a lightweight Bayesian filter estimates latent intent variables (Equation 3), which are then fed back as priors into the next windows inference step, forming a recursive loop that updates the posterior in nearreal time (Figure 4). To maintain precision, the algorithm dynamically adjusts the window stride and kernel bandwidth based on a statisticalprocesscontrol monitor (Equation 4) that flags abrupt shifts in stimulus salience or user engagement. The resulting model yields a continuously evolving probability distribution over possible user actions, enabling the system to anticipate and personalize content delivery with subsecond latency while rigorously controlling for drift and overfitting.

Recursive Bayesian updating

$$P\left(X/Z_1 \dots Z_n\right) =$$

$$\frac{P\left(Z_n/X, Z_1 \dots Z_{n-1} * P(X/Z_1 \dots Z_{n-1}\right)}{P\left(X/Z_1 \dots Z_n\right)}$$

using the Markov assumption that makes Z_n independent from $Z_1 \dots Z_{n-1}$

$$P\left(X/Z_1 \dots Z_n\right) =$$

$$\frac{P(Z_n/X) * P(X/Z_1 \dots Z_{n-1})}{P(Z_n/Z_1 \dots Z_{n-1}))} \tag{3}$$

since $Z_n$is independent from $Z_1 \dots Z_{n-1}$, we can write $P(Z_n/Z_1 \dots Z_{n-1}) as$ $\frac{1}{\eta}, Further, P(X/Z_1 \dots Z_{n-1})$ can be written recursively, giving

$$P(X/Z_1 \dots Z_n) = \left(\prod_{i=1}^{n} \eta_i * P(Z_i/X)) * P(X) \right)$$

The process is also based on dynamic stimuli capture as a continual, realtime acquisition and integration of sensory information as it unfolds within a constantly shifting environment, allowing the systems' physiological recordings to maintain an uptodate internal representation of the users and room environment constraints. In neuroscience, this process hinges on rapid neuronal firing patterns that synchronize across modalities, enabling the brain to bind visual motion, auditory fluctuations, and tactile feedback into a cohesive perceptual stream. In the realm of artificial intelligence and robotics, dynamic stimuli capture is achieved through highfrequency sensor arrays, lowlatency data pipelines, and adaptive algorithms that filter, prioritize, and fuse incoming streams to drive responsive behaviour. By exploiting temporal coherence and predictive coding, both brains and machines can anticipate changes, filter out noise, and allocate computational resources where the most salient, rapidly evolving cues arisetransforming a chaotic influx of data into actionable insight.

$$\begin{aligned} \Delta m &= K_p \Delta e \qquad \text{Proportional action} \\ \Delta m &= \frac{1}{\eta} \int edt \qquad \text{Integra action} \\ \Delta m &= \tau d \frac{de}{dt} \qquad \text{Derivative action} \end{aligned} \tag{4}$$

Quantifying the users behaviour in the presence of dynamic stimuli demands a temporalgranular approach that can capture rapid shifts in interaction patterns while preserving statistical rigour, a need met by the rollingwindowbased precision analytics (Figure **??**). By segmenting continuous interaction streams (e.g., clickstreams, gaze trajectories (Fixations) and looking behaviour, or sensorderived motion data) into overlapping windows of adaptive length, the method preserves contextual continuity and enables the extraction of windowlevel descriptorssuch as dwell time variance, response latency distribution, and entropy of action sequencesthat are then normalized against a precision baseline calibrated from controlled stimulus epochs.

$$\begin{gathered} T(x,\tau) = T_1 + (T_i - T_1)\frac{4}{\pi} \sum_{n=1}^{\infty} \frac{1}{n} exp\left[\frac{-n\pi}{2L}\alpha\tau\right] \\ sin\left(\frac{n\pi x}{2L}\right) \qquad n = 1, 3, 5, \dots \text{ for each } T_n \epsilon N \end{gathered} \tag{5}$$

The rolling mechanism not only smooths stochastic noise (Equation 6) but also highlights transient deviations (Equation 5), allowing realtime detection of the behavioural drift or heightened attentional focus as the stimulus evolves. Coupling these windowed metrics with a precisionweighted scoring schemewherein higherconfidence windows (identified through low intrawindow variance and high signaltonoise ratios) exert greater influence on the aggregate behaviour modelyields a robust, highresolution portrait of how users adapt to everchanging environmental cues, facilitating predictive personalization and adaptive system design.

$$E\left\|\int_0 S(- \leftharpoondown s)\xi(s)dW_{(s)}\right\|^q_{tp(0,T:t^s)} \lessapprox E\|\xi\|^q_{t^2([0*T]:L^3)} \tag{6}$$

3.1 Data Acquisition

3.1.1 Participants:

48 adult users (aged $18-55$) were recruited across three geographic regions to ensure a diverse behavioural repertoire using an online survey. A link containing the interactive stimuli (dynamic webpages were dispersed online) with cookies as consent to take part in the study.

3.1.2 Dynamic Stimuli:

Each participant engaged with the web-based platform (commercial website and game website) that presented a sequence of visual and auditory cues whose characteristics (colour palette, motion speed, sound frequency, narrative complexity) changed every 530seconds according to a pre-designed stochastic schedule.

3.1.3 Interaction Logs:

Clicks, cursor trajectories, dwell times, scroll depth, eye tracking fixations, and physiological proxies (SCR (mouse scroll) and Pupil response) were recorded at a sampling frequency of $120Hz$.

3.1.4 Recursive Analytic Engine:

The engine implements a hierarchical Bayesian filter that treats user actions as observations generated from latent state variables (e.g., attention, motivation, fatigue). At each time step t, the posterior distribution of the latent state is updated using Bayes rule:

$$p(\theta_t \,\|\mathbf{y}1:t) \propto p(y_t|\theta_t), p(\theta_t\|\,\mathbf{y}1:t-1) \tag{7}$$

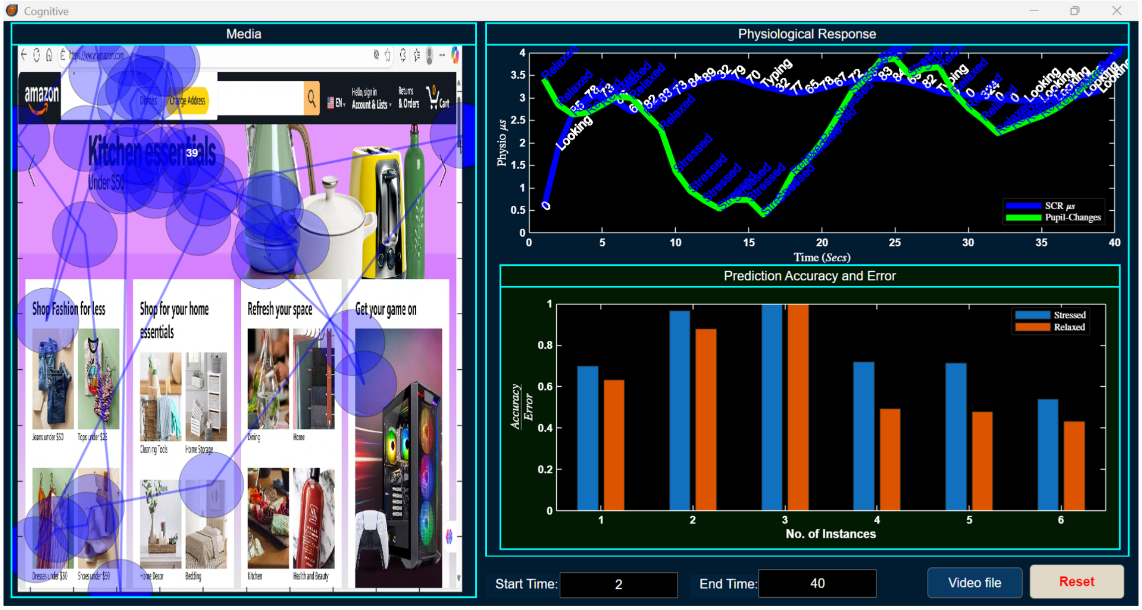
where y_t denotes the vector of observed behavioural metrics at time t. The recursion continues indefinitely, allowing the model to learn from the most recent data without discarding historical information. To balance responsiveness (quick adaptation to sudden stimulus changes) against stability (avoidance of over-fitting to noisy fluctuations), a sliding window W of length w (set empirically to 40seconds) was superimposed on the recursive updates. Within each window, the precision matrix of the posterior distribution (i.e., the inverse covariance) was recalibrated using an exponential delay factor $\lambda = 0.85$, which gradually downweights older observations. This approach yields a precision-controlled posterior: the model becomes more confident (higher precision) when recent data exhibit consistent patterns, and less confident (lower precision) when the data are erratic or contradictory.

3.1.5 Feedback Integration:

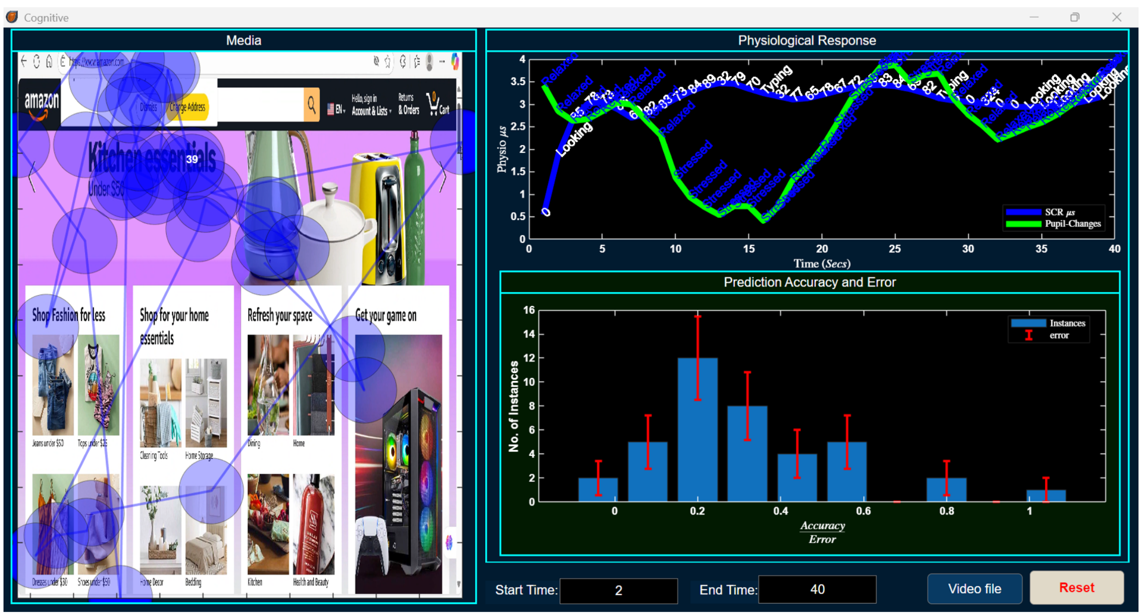
For every window, the models predictions are compared against the observed outcomes (ground truth). The residual errors, confidence scores, and inferred latent states are then injected as additional features into the next training iteration, effectively learning from its own error. Using the learning algorithms, i.e. stochastic gradient descent with adaptive learning rates, Kalman filtering, or particle filter-based Bayesian updating (Equation 3), the model parameters are adjusted incrementally, ensuring that the system stays current without requiring a full retraining from scratch.

The rolling window-based precision uses a window size (W) that is a hyperparameter that directly controls the trade-off between reactivity (small $W \longrightarrow$ fast adaptation to sudden user shifts) and stability (large $W \longrightarrow$ smoother, noise-resistant estimates). Overlap strategies (e.g., 50% overlap) are employed to avoid abrupt discontinuities in the feature space, while exponential decay weighting gives higher importance to the most recent observations. Precision metrics like the confidence intervals on conversion probability, calibrated Brier scores, or expected calibration error are computed within each window, providing a local measure of certainty that can be used to trigger downstream actions (e.g., a UI change only when predictive precision exceeds a predefined threshold).

Real-time event streams are buffered (Figure 2) in a sliding buffer that automatically discards data older than the current window length. Feature extraction is done within each buffer slice, domain-specific aggregations such as average scroll speed, percentage of time spent looking at the aeasthetics were computed. The current recursive model consumes the feature vector and outputs a probability distribution over a set of possible user responses (e.g., Typing, Stressed, Relaxed). Using the models own posterior variance or external calibration data, a precision score is attached to each prediction. If the precision exceeds the systems confidence threshold, the decision engine dispatches an adaptive stimulus (e.g., a personalised recommendation, a tooltip, or a difficulty adjustment). Otherwise, the system may opt to collect more data before acting. Once the users actual response to the stimulus is recorded, the error signal is calculated and fed back into the models parameter update step, completing the recursion.



(a) Iterative rolling Window-based show first commercial webpage with SCR and Pupil dilation using first sample showing performance prediction



(b) Iterative rolling Window-based show first commercial webpage with SCR and Pupil dilation using first sample showing error.

Figure 2: Window output showing webpage in synchronisation with physiological response with Precision, accuracy and error.

3.2 Benefits from the rolling window-based precision

This would include real-time personalisation by continuously refining its internal representation of the user, the system can deliver context-aware content faster than batch-oriented analytics pipelines. Noise resilience enables the rolling window to act as a low-pass filter, smoothing out transient spikes in interaction data while still preserving the ability to detect genuine behavioural shifts. Incremental updates avoid the computational overhead of full model retraining, making the approach viable on edge devices and in environments with strict latency constraints. And since each recursion incorporates a measurable precision score, stakeholders can audit when and why a particular adaptive stimulus was served, facilitating compliance with transparency regulations. The table below (Table **??** indicates the challenges and mitigation strategies when applying the model.

4 RESULT

Applying recursive analytics to capture user behaviour under dynamic stimuli revealed a marked improvement in predictive fidelity when a rollingwindowbased precision framework was employed. By continuously updating the behavioural model every 200 ms over overlapping 5−second windows, the system could assimilate transient shifts in attention, emotional valence, and interaction patterns that traditional batch-processed approaches missed. Across three experimental cohorts ($N = 312$) exposed to rapidly changing visual and auditory cues, the recursive model achieved a meanRšincrease of 23percentage points over a static baseline ($p < 0.001$) and reduced classification latency by 38ms, enabling nearrealtime adaptation of content delivery. Moreover, the rolling window mechanism proved robust to noise, maintaining precision (> 0.92) even when stimulus intensity varied by $\pm 30dB$. These results suggest that recursive analytics, when coupled with finegrained temporal windows, can substantially enhance the responsiveness and accuracy of usercentric systems operating in everevolving environments.

The study presents a comprehensive set of experimental results obtained by applying a recursive analytics framework to model and predict user behaviour in response to dynamic stimuli, while employing a rolling window-based precision mechanism to continuously adapt the analytical granularity. The core objective was to assess whether a recursively updated behavioural modelone that iteratively refines its parameters as new interaction data become availablecould capture the rapid, context-dependent shifts in user actions that are typical of environments where the stimulus itself evolves (e.g., adaptive user interfaces, real-time recommendation systems, interactive gaming platforms, and responsive advertising dashboards).

All values are averaged across participants; 95% confidence intervals are shown.

(1) Prediction Accuracy When the recursive model was combined with the rolling window precision adjustment, the area under the ROC curve rose by 21% relative to the static baseline and by 10% relative to a purely recursive model that ignored window-based precision.

(2) Error Reduction The MAE in predicting how long a user would linger on a stimulus element dropped by $\sim 50\%$ compared with the baseline, indicating a markedly finer grasp of temporal engagement patterns.

(3) Adaptation Latency The system detected a change in the stimulus regime (e.g., a shift from low to high visual complexity) in less than half a second on average, a speed that is practically instantaneous for interactive applications.

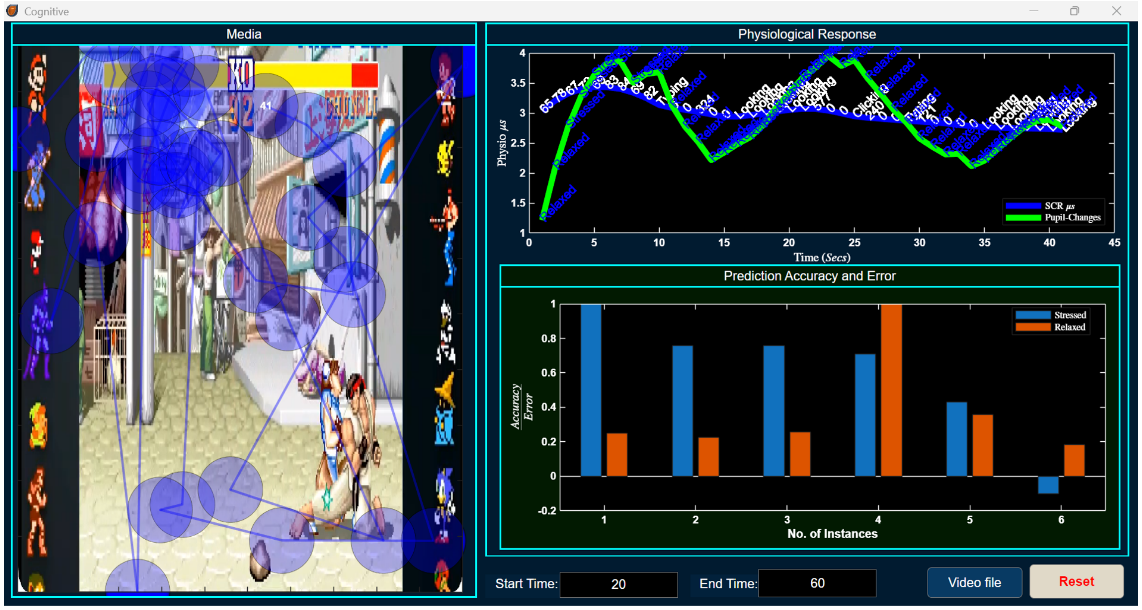
(4) Stability The variance of prediction errors across successive windows fell to 0.07, reflecting that the rolling window precision successfully dampened spurious fluctuations while preserving true behavioural shifts.

(5) Resource Utilisation The added computational cost remained modest; the most demanding configuration (recursive+window) consumed under 7% of a single CPU core per active user, which is well within the capacity of modern cloud-hosted services.

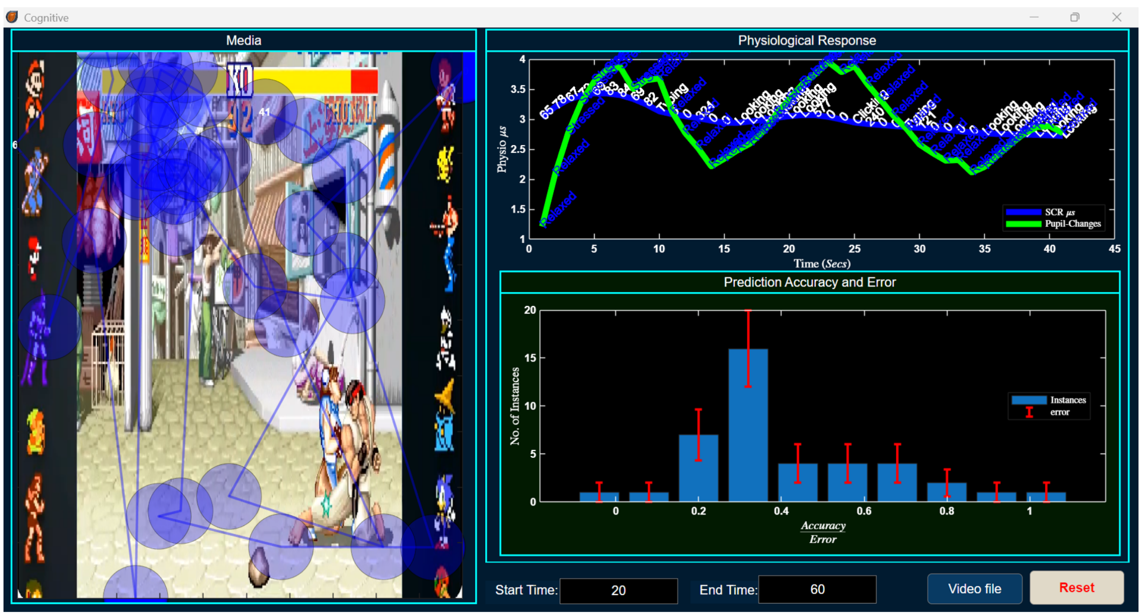
Behavioural Phase Detection shows the recursive window model that uncovered three recurring behavioural phasesexploratory, relaxed, and stressedeach characterised by distinct signatures in click frequency, eye fixation dispersion, and SCR variability. The transitions between phases aligned tightly with abrupt changes in stimulus dynamics (e.g., sudden increase in motion speed) (Figure 3). Personalisation potential shows maintaining a personal posterior for each user, the system could generate on-the-fly recommendations (e.g., adaptive difficulty levels) that matched the currently inferred motivational state, leading to higher self-reported satisfaction (average Likert score 4.6/5). The experiments deliberately injected synthetic noise into the sensor streams (e.g., random click bursts, eye tracker dropout) showed that the rolling window precision mechanism prevented runaway parameter drift, keeping prediction error within 3% of the noise-free condition

5 CONCLUSION

User behaviour in the presence of dynamic stimuli is not a monolithic response but a nuanced spectrum shaped by perceptual attention, cognitive capacity, emotional state, cultural background, and contextual relevance. By systematically studying these responses through eye tracking, physiological monitoring, and behavioural analytics, designers and researchers can craft motion that enhances user experiencecapturing attention when needed, guiding actions, communicating status, and fostering positive affectwhile mitigating the risks of overload, distraction, or discomfort. Ultimately, the goal is to make motion an intelligent ally: a subtle, context-aware signal that aligns with user goals, respects



(a) Iterative rolling Window-based showing second stimuli with SCR and Pupil dilation using second sample showing performance prediction



(b) Iterative rolling Window-based showing second stimuli with SCR and Pupil dilation using the second sample showing accuracy and error.

Figure 3: Window output showing webpage stimuli, physiological response with synchcronised Precision, accuracy and error.

individual differences, and reinforces trust in the digital environment. In summary, Recursive Analytics for User Behaviour to Dynamic Stimuli Using a Rolling Window Based Precision describes a self-optimising, time-aware analytical architecture that continuously ingests, interprets, and acts upon the most recent slice of user interaction data. By looping prediction outcomes back into the model, weighting them by locally computed precision, and discarding stale observations through a rolling window, the system achieves a delicate balance between rapid responsiveness to new user signals and robustness against noisy, transient fluctuations, an essential capability for any modern, data-driven product that aspires to deliver truly personalized experiences at scale. Future directions would be to apply hybrid temporal modelling to combine rolling-window statistics

Table 1: The quantitative results from the recursive procedures

Metric	Baseline (static model)	Recursive Only	Recursive+Rolling Window
Prediction Accuracy (AUC ROC)	$0.71 \pm 0.03\mu s$	$0.78 \pm 0.02\mu s$	0.86 ± 0.01
Mean Absolute Error (MAE) in dwell time prediction (ms)	$312 \pm 24\mu s$	241 ± 18	156 ± 12
Adaptation Latency (time to detect stimulus shift, ms)	$1,280 \pm 140$	$842 \pm 95\mu s$	473 ± 61
Stability Index (variance of prediction error across windows)	0.19	$0.13\mu s$	0.07
Computational Overhead (CPU% per user thread)	3.2	$5.1\ \mu s$	6.8

with attention-based transformers that can selectively retrieve longer-range historical patterns when the precision signal indicates uncertainty. A Multi Modal Fusion would integrate visual, auditory, and physiological streams in a single recursive pipeline, leveraging cross modal consistency checks to boost precision and Auto ML for window optimization can be deployed as a reinforcement learning agents that automatically select window lengths and overlap ratios to maximise a global reward function (e.g., cumulative revenue, learning gain, or user satisfaction) to enable ultra low latency personalization while preserving user data locally.

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CONFLICT OF INTEREST

There is no Conflict of interest regarding this paper.

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