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HMCI-Net: Explainable Artificial Intelligence for Cognitive Health and Historical Trauma Awareness Analytics in Partition Cinema

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ABSTRACT: Historical memory generated through cinema is commonly assessed using descriptive survey analysis, which provides limited support for computational modeling and educational decision-making, even though exposure to collective-trauma narratives carries measurable cognitive-health and psychosocial consequences for audiences. This paper proposes HMCI-Net, an Explainable Artificial Intelligence (XAI) framework for computational modeling of historical memory cognition through Partition cinema. The framework introduces a novel Reliability–Entropy Adaptive Fusion (REAF) algorithm that estimates adaptive construct weights by jointly considering psychometric reliability, information diversity, and construct uniqueness. These weights are integrated to compute the Historical Memory Cognition Index (HMCI), a multidimensional measure representing historical awareness, emotional empathy, perceived authenticity, national integration, and educational impact. These constructs are treated as cognitive-health and trauma-awareness indicators rather than clinical diagnostic measures. The framework further incorporates explainable machine learning and scenario-based simulation to support educational decision-making. Experimental evaluation was conducted on 160 valid audience responses using 1,000 bootstrap iterations and 5,000 Monte Carlo simulations. The proposed REAF algorithm selected exponent values of (0.5, 0.5, 0.5) and produced balanced adaptive weights ranging from 0.1703 to 0.2308. The resulting HMCI achieved a mean of 0.6487, while the dataset demonstrated strong psychometric adequacy (KMO = 0.915; Bartlett's χ^2 = 3343.79, $p < 0.001$). Comparative analysis showed that REAF generated more interpretable and statistically robust construct weights than conventional equal-weight, entropy-based, and PCA-based methods. The simulation module further quantified the expected improvement in historical memory under alternative educational interventions. The proposed framework offers a transparent, reproducible, and explainable computational approach for cognitive-health oriented audience analytics, health humanities, and trauma-informed educational decision support.

I. INTRODUCTION

The preservation of historical memory is crucial in the modern world where film is a major source of information about political history. The historical films are no longer just a source of entertainment, but they also create historical memory, convey emotions and influence cultural identity formation. One of the most important historical events is the Partition of India in 1947 which is known to be one of the biggest forced migration occurred in modern history having impact on the lives of more than a trillion of people. Though the Partition has been extensively studied in literature, for a large quantity of contemporary audience the only source of information about the Partition are film narratives.

Films such as Garam Hava, Train to Pakistan, Pinjar, Earth 1947, Tamas and Gadar represent different aspects of the displacement processes, violence between communities, migration challenges, identity and reconciliation. Previous research shows that films affect the way people construct their ideas about the nationality, cultural identity and historical events [1]–[5]. Cultural memory scholars find that media contributes substantially to the formation of collective memory as people made up their understanding of history through stories, emotions and symbols rather than personal experiences [11]–[15].

Although scientists have studied the portrayal of Partition in movies from the perspective of sociology, media studies and cultural studies, most of the examinations have been based on qualitative interviews, surveys, content analysis or thematic studies [1]–[10]. Such methods provide some socio-cultural information, but they do not allow measuring the historical memory or different psychological and educational factors in audience responses. Therefore, the literature lacks objective methods capable of transforming the audience perception into measurable knowledge.

The opportunities of Artificial Intelligence (AI), Explainable Artificial Intelligence (XAI) and computational social science allow to analyze behavior of individuals through machine-learning methods. Explainable AI has been able to improve the understanding of how predictive systems work due to the identification of features' contribution to the decisions made by the models [24]–[30]. However, the majority of existing applications of XAI focus on healthcare, finance, cybersecurity and recommendation systems. In healthcare in particular, explainable models are now routinely applied to clinical risk prediction, patient-reported outcome measurement and psychosocial screening, where transparency of the contributing factors is treated as a precondition for practitioner acceptance [31], [32]. Historical trauma narratives raise a comparable requirement, because exposure to Partition cinema engages empathy, vicarious distress and identity processes that are recognised determinants of cognitive health and psychosocial well-being [33], [34]. Nevertheless, the application of AI for historical memory studies has not been studied so far. Additionally, AI-based audience analytics usually only measures sentiment, engagement and preference making the analysis multidimensional.

Another important limitation in the existing literature concerns the absence of standardized computational indices for evaluating historical memory. Current audience studies generally report descriptive statistics or average Likert-scale responses, assuming equal importance of all questionnaire items. Such approaches neglect differences in construct reliability, information diversity, and redundancy among psychological dimensions. Consequently, the derived measures often fail to represent the actual cognitive contribution of different latent constructs involved in historical memory formation.

To overcome these limitations, HMCI-Net, a Hybrid Explainable Artificial Intelligence Decision Support Framework specifying computational historical memory cognition analytics through the audience reaction toward Partition cinema, is being introduced. HMCI differs from traditional survey-based analysis because it develops a Historical Memory Cognition Index (HMCI) that combines five latent constructs–Historical Awareness (HA), Emotional Empathy (EE), Perceived Authenticity (PA), National Integration (NI), and Educational Impact (EI). The importance of each construct necessary for making the overall HMCI decision can be defined through the adaptive process called Adaptive Construct Fusion (ACF). ACF is a process that takes into account the significance of each measure, the variety of entropy-based information in terms of its quality and degree of uniqueness from the rest of the measures presented. After making the calculations, the methods developed provide interpretable historical memory score for each participant while performing all the necessary operations through transparent explainable AI methods.

Besides predictive modeling, HMCI includes the module of Scenario Based Historical Memory Simulation (SHMS) that assesses the impact of possible educational and cognitive interventions on forming historical memory. In order to do so, it changes the value of latent constructs and recalculates the HMCI, thus helping educators, producers and policy-makers analyze the effectiveness of different educational methods before their practical use. This approach has never been applied in historical cinema analytics before.

The proposed approach is validated through the multidimensional audience perception dataset comprised of 160 respondents and 43 survey attributes obtained from structured survey. The proposed framework performs robust construct validation, adaptive weighting, sensitivity analysis, bootstrap stability tests, Monte Carlo scenario simulation, and comparisons with classical approaches of weighing.

The remainder of this paper is organized as follows. Section II reviews the existing literature on Partition cinema, historical memory, audience cognition, and explainable artificial intelligence. Section III presents the proposed HMCI-Net framework and the mathematical formulation of the Historical Memory Cognition Index. Section IV describes the experimental methodology and dataset. Section V discusses the experimental results, explainability analysis, and scenario-based simulations. Finally, Section VI concludes the paper and outlines future research directions.

II. Literature Review

Historical memory has become a rapidly expanding area of interdisciplinary research that involves history, psychology, sociology, digital humanities, artificial intelligence, and computational social science. The traditional view of historical events was based on archival documents and academic publications; however, the modern audience is using more visual means, particularly historical films, to create their understanding of past events. For example, films about Partition of India in 1947 function as a powerful medium of communication for transferring collective memory, causing emotional reaction, and affecting nations' identity perception. Thus, a number of studies have focused on cinema narratives from the point of view of various aspects such as historical truthfulness, audience involvement, collective memory, trauma, intergenerational learning, etc. Recently, a great potential was shown by Artificial intelligence (AI) and explainable AI (XAI) for modeling human cognition, behavior, and decision-making via computational techniques. Nevertheless, the usage of the ideas of explainable computational intelligence for studying historical memory has not been thoroughly researched so far. In this section, existing literature is analyzed in order to identify gaps in research which will be covered by the proposed framework HMCI-Net.

TABLE I. Summary of Existing Literature and Research Gaps

Ref.	Paper	Major Findings	Limitations / Research Gap
[1]	Viswanath & Malik (2009)	Compared Indian and Pakistani Partition cinema and demonstrated differences in ideological representation.	Purely qualitative; no computational modeling or audience analytics.
[2]	Athique (2008)	Investigated cinematic representation of the India–Pakistan border and national identity.	Focused on film criticism without audience cognition analysis.
[3]	Raychaudhuri (2009)	Explained how Partition films reconstruct historical narratives through cinema.	No quantitative evaluation of historical understanding.
[4]	Sadasivan & Roy (2024)	Examined intergenerational memory in diaspora cinema.	Limited to narrative interpretation; lacks AI-driven analytics.
[5]	Hornabrook (2024)	Discussed inherited memories and creative remembrance among diaspora communities.	No measurable framework for historical memory cognition.
[11]	Assmann & Czaplicka (1995)	Established the theory of cultural and collective memory.	Conceptual framework only; no computational implementation.
[12]	Olick (1999)	Distinguished individual and collective memory formation.	No quantitative cognitive measurement methodology.
[13]	Kansteiner (2002)	Critiqued methodological issues in collective memory research.	Highlighted lack of objective measurement approaches.

[14]	Hirsch (2008)	Introduced postmemory theory explaining intergenerational trauma.	Primarily theoretical without empirical computational validation.
[15]	Erll (2011)	Proposed the concept of travelling memory across media.	Does not quantify memory transmission or cognitive influence.
[17]	Green & Brock (2000)	Introduced Narrative Transportation Theory explaining audience immersion.	Did not investigate historical memory formation.
[18]	Cohen (2001)	Explained audience identification with cinematic characters.	Focused on media psychology rather than computational analytics.
[19]	Oliver & Bartsch (2010)	Demonstrated that meaningful entertainment shapes audience appreciation.	No predictive modeling or explainability.
[20]	Oliver & Raney (2011)	Distinguished hedonic and eudaimonic entertainment experiences.	Did not evaluate historical cognition.
[21]	Slater & Rouner (2002)	Explained persuasion through narrative communication.	No AI-based audience interpretation.
[23]	Dmochowski et al. (2014)	Linked audience engagement with measurable neural processing.	Required laboratory neuroimaging; not scalable for public audiences.
[24]	Ribeiro et al. (2016)	Introduced LIME for model interpretability.	Generic explainability framework not applied to historical cognition.
[25]	Lundberg & Lee (2017)	Proposed SHAP for feature contribution analysis.	No application to historical memory or digital humanities.
[27]	Adadi & Berrada (2018)	Comprehensive survey on Explainable AI.	Focused on AI techniques rather than domain-specific cognition modeling.
[28]	Guidotti et al. (2019)	Reviewed explainable models for black-box systems.	Did not address audience perception or historical analytics.
[30]	Longo et al. (2024)	Discussed future challenges of Explainable AI 2.0.	Identified need for human-centered and domain-specific explainability frameworks.
[33]	Brave Heart et al. (2011)	Established historical trauma as a measurable population-level cognitive and affective construct arising from collective violence and displacement.	Clinical and community focus; no computational index or media-induced memory analytics.
[34]	Charon (2001)	Introduced narrative medicine, showing that structured engagement with narrative builds empathy and reflective capacity.	Qualitative and pedagogical; provides no quantitative measurement of narrative-induced cognition.
[32]	Tjoa and Guan (2021)	Surveyed explainable AI for medical decision support and identified transparency as a precondition for practitioner trust.	Confined to clinical prediction tasks; not applied to psychosocial or historical memory constructs.

The domain of literature shows significant advancement in three separate research areas. First of all, researchers in media and cultural studies tend to analyze Partition cinema in terms of nationalism, migration, trauma, identity, and historical representation [1]–[5]. The results obtained from this work suggest that historical films play an important role in shaping collective memory and public consciousness regarding national history. However, the approach taken by them mostly consists of qualitative methods, such as textual analysis, interviews, or descriptive surveys. As a result, it cannot create any numerical bases for measuring the process of historical memory creation and cannot give any computational instruments for audience cognition analysis.

Secondly, the classical theories of cultural memory and postmemory give a good explanation of the process of cultural memory preservation and transmission through generations [11]–[15]. Even if these theories present an explanation of the development of collective memory, they do not propose any quantifiable constructs that can be used in computational analysis or for decision-making purposes. The lack of quantitative indexes makes it impossible to use them in practice in data-driven systems.

Finally, the recent advances in Artificial Intelligence and Explainable Artificial Intelligence allow making predictions about and interpreting various different complex human behaviors by means of such tools as LIME, SHAP, and interpretable machine learning [24]–[30]. Although there have been great improvements in this sphere, these techniques have only been used in healthcare, finance, recommending systems, and cybersecurity as they went little bit beyond their application in humanities and historical memory analysis. Most of the existing audience analysis research deals primarily with such issues as sentiment analysis, recommendation systems, or engagement prediction.

A fourth and largely disconnected body of work concerns cognitive health and collective trauma. Research on historical and intergenerational trauma establishes that exposure to narratives of communal violence and forced displacement produces measurable affective and cognitive responses at population level, and that the presence or absence of contextual framing determines whether that exposure yields constructive understanding or unresolved distress [33]. Parallel work in narrative medicine and the health humanities demonstrates that structured engagement with narrative material can be used deliberately as a psychoeducational instrument for building empathy and reflective capacity [34]. On the measurement side, the health sciences have developed a mature methodology for constructing composite indices from multi-item self-report instruments, in which item reliability and construct validity govern how dimensions are aggregated, and explainable machine learning is increasingly used to expose which dimensions drive a composite outcome [31], [32]. These three strands are individually well developed, yet none has been applied to cinema-induced historical memory. The present work draws the measurement discipline of the first and the interpretive stance of the second into a computational framework for historical trauma awareness, while remaining explicit that the resulting index is a psychosocial and educational measure rather than a clinical one.

From the reviewed literature, four major research gaps can be identified:

1. Absence of a computational index: No existing study proposes a mathematically grounded index for quantifying historical memory cognition from audience responses.

2. Lack of adaptive construct fusion: Existing survey-based studies typically assign equal importance to questionnaire dimensions without considering construct reliability, information diversity, or redundancy.

3. Limited explainable computational modeling: Although XAI techniques are well established, they have not been systematically integrated with historical memory analytics to provide interpretable decision support.

4. No scenario-based decision-support framework: Current studies do not simulate the effects of educational or perceptual interventions on historical memory formation, limiting their practical value for educators, filmmakers, and policymakers.

In order to solve these problems, the developed HMCI-Net offers three innovative methods: (i) the introduction of the Historical Memory Cognition Index (HMCI) to accomplish the multidimensional assessment of historical memory, (ii) the Adaptive Construct Fusion (ACF) algorithm for getting the weight of latent constructs accurate and reliable, and (iii) the AI-based Decision Support Framework to offer recommendations regarding educational and cultural policy based on simulations.

III. PROPOSED HMCI-NET FRAMEWORK

This section introduces HMCI-Net, an innovative concept that combines elements of Explainable Artificial Intelligence (AI) to help in measuring historical memory cognition obtained from Partition cinema. In contrast to standard audience perception studies, which normally depend entirely on description-based statistical methods or simple aggregation of questionnaire results,

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the suggested solution combines adaptive construct fusion with Explainable AI in the framework of scenario-based decision support and builds a unified model. This model processes multiple responses from the audience and provides the Historical Memory Cognition Index (HMCI), while also performing an analysis of the impact of individual cognitive structures in forming historical memory. The structure of the proposed HMCI-Net solution is presented in Figure 1.

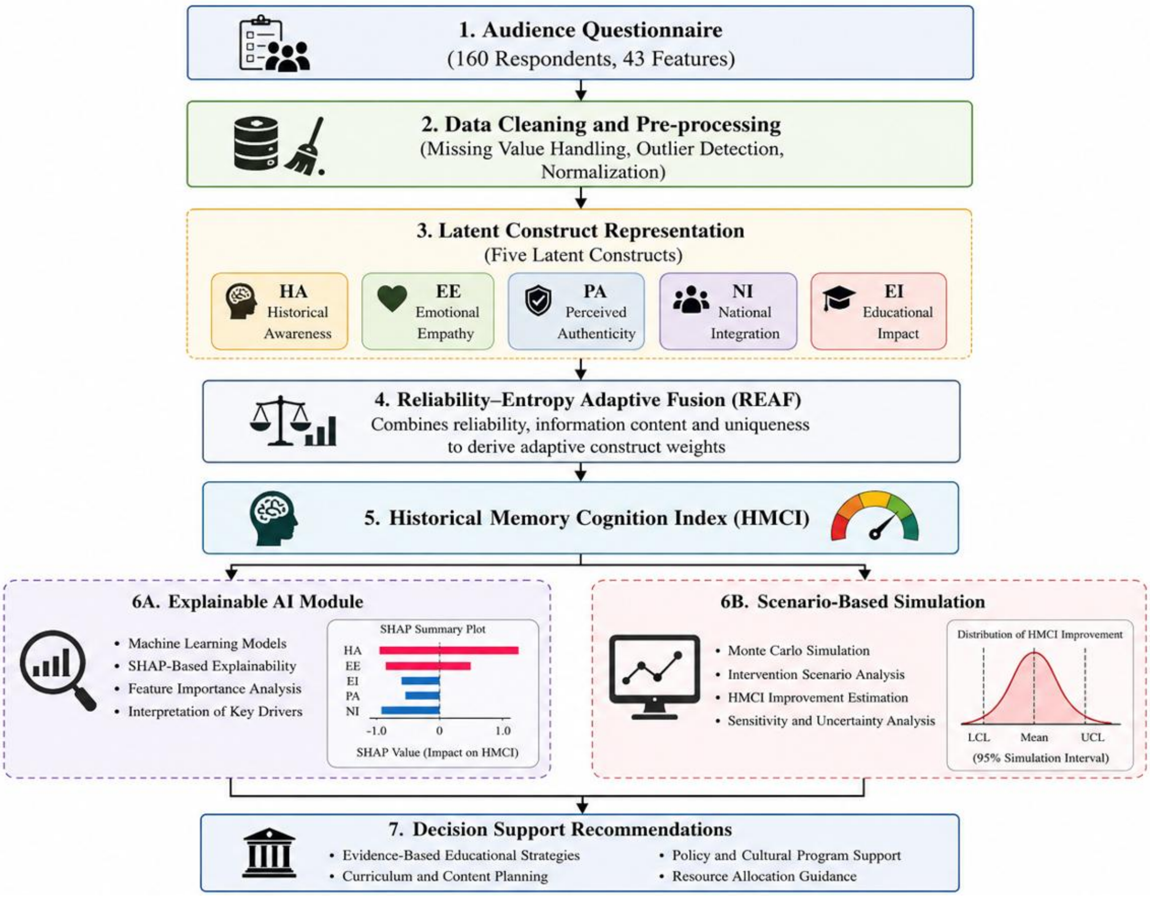

Fig. 1. Overall architecture of the proposed HMCI-Net framework.

The proposed framework consists of five sequential stages. First, questionnaire responses are preprocessed and transformed into normalized numerical representations. Second, responses are grouped into five latent cognitive constructs representing different dimensions of historical memory. Third, the proposed Reliability–Entropy Adaptive Fusion (REAF) algorithm estimates the relative contribution of each construct by jointly considering measurement reliability, information diversity, and construct uniqueness. Fourth, the weighted constructs are integrated to compute the Historical Memory Cognition Index (HMCI). Finally, explainable machine learning and scenario-based simulation modules provide interpretable recommendations for educators, researchers, filmmakers, and cultural policymakers.

A. Data Acquisition and Pre-processing

The created tool was tested through the main set of data obtained by means of a carefully selected survey which examined the audience perception of Partition cinema. The survey included 43 indicators such as demographic metrics, information related to film watching habits, and Likert-marked questions concerning historical knowledge, emotional empathy, perceived authenticity, national integration, and educational influence. After processing incomplete questionnaires, a total of 160 questionnaires became valid.

The gathered information was represented in the form of both categorical and ordinal variables. The information about respondents' demographics, such as gender, job position, educational background, as well as previous knowledge of Partition history, was kept for further operations with the obtained data. In addition to this, the surveys were constructed using a five-point Likert rating scale ranging from "strongly disagree" to "strongly agree". Since the constructed technique works with the normalized values of cognitive constructs, all the responses have been converted to values from the [0,1] range.

For respondent iii and questionnaire item jjj, the normalized response is computed as

$$x_{ij}^{*} = \frac{x_{ij} - x_{\min}}{x_{\max} - x_{\min}} \qquad (1)$$

Where

- $x_{\{ij\}}$ denotes the original Likert-scale response.
- $x_{\{min\}}$=1
- $x_{\{max\}}$=5
- $x_{\{ij\}}^{\{*\}} \in$ [0,1]

Normalizing the responses facilitates the process of using all questionnaire items within a single numerical dimension, thus mitigating any bias due to varying measurements.

Prior to calculating the constructs, the data was checked for missing data, duplicates, and inconsistent data. The questionnaire asked respondents mandatory questions regarding their cognitive constructs; therefore, there was no missing data.

Duplicates were found based on the time stamp of the response and eliminated during the first data processing procedure.

The data was processed with fixed random seed and the same normalization coefficients so that the results could be replicated. All pre-processing steps were completed before building the model to prevent data leakage.

B. Latent Construct Representation

Historical memory is a complex psychological construct that cannot be easily measured through any one questionnaire item. Therefore, instead of evaluating the answers given by individual respondents, the designed procedure translates the questionnaire into five hidden cognitive concepts that altogether define historical memory development in cinema.

Based on the questionnaire design and the theoretical foundations discussed in Section II, five constructs were identified:

- Historical Awareness (HA): measures the respondent's understanding of the historical causes, consequences, and socio-political context of Partition.
- Emotional Empathy (EE): captures the emotional engagement and empathy generated through cinematic representation of Partition experiences.
- Perceived Authenticity (PA): reflects the respondent's perception regarding the historical realism and credibility of cinematic narratives.
- National Integration (NI): evaluates whether the viewed films encourage social harmony, intercultural understanding, and national cohesion.
- Educational Impact (EI): measures the usefulness of Partition cinema as an educational medium for improving historical understanding and promoting critical reflection.
- Although these five constructs are defined within a historical-memory context, they correspond closely to established psychosocial and cognitive-health domains. Historical Awareness and Educational Impact parallel the knowledge-based competencies captured by health-literacy style instruments; Emotional Empathy corresponds to the affective empathy and vicarious-distress dimensions routinely assessed in trauma research; Perceived Authenticity relates to narrative credibility, a known moderator of emotional response to traumatic content; and National Integration reflects social cohesion and belonging, an established protective factor in psychosocial well-being research [33], [34]. HMCI-Net therefore operates as a cognitive-health and trauma-awareness analytics instrument. It is explicitly not a clinical or diagnostic measure, and no construct in this study was derived from a validated clinical scale.

Let

$$\mathbf{x_i} = [x_{i1}, x_{i2}, \dots, x_{im}]$$

represent the normalized questionnaire responses of respondent iii.

Each latent construct is computed as the arithmetic mean of its associated normalized questionnaire items,

$$C_{ik} = \frac{1}{m_k} \sum_{j=1}^{m_k} x_{ijk}^{*} \qquad (2)$$

where

- C_{ik} denotes the score of construct k for respondent iii,
- m_k represents the number of questionnaire items associated with construct k,
- x_{ijk}^{*} denotes the normalized response corresponding to construct k.

Consequently, every respondent is represented by the five-dimensional construct vector

$$\mathbf{C}_i = [HA_i, EE_i, PA_i, NI_i, EI_i] \qquad (3)$$

The methods keep the amount of data used minimal but at the same time preserves the data structure. One key aspect is that the concept vector works to feed the new Reliability–Entropy Adaptive Fusion (REAF) algorithm, which is explained later on.

In the conventional audience study, researchers treat responses from audiences as average inputs to the final data. However, with the model presented, it would be treated as a unique cognitive construct. One important thing is that the introductory model allows the researchers not only get data about all cognitive constructs, but gives information about their importance.

C. *Reliability–Entropy Adaptive Fusion (REAF)*

Traditional questionnaire investigations primarily compute latent constructs by either equal weighting and averaging or through manually determined weights. Though these methods are straightforward in computation, they imply that all aspects concerned in the process are equally significant to the process of historical memory. This suggested assumption is often incorrect, as the dependent variables in the study can show greater differences in terms of reliability of measurement, information variety, and being redundant concerning other constructs. Thus, equal weighting and averaging might lead to the underestimation of highly informative constructs as well as over-estimation of weaker ones.

To overcome these limitations, the proposed framework introduces the Reliability–Entropy Adaptive Fusion (REAF) algorithm. REAF dynamically estimates the contribution of each latent construct by integrating three complementary statistical descriptors:

- Measurement Reliability, representing the internal consistency of each construct.
- Information Diversity, representing the discriminative capability of respondent responses.
- Construct Uniqueness, representing the amount of independent information contributed by each construct after accounting for inter-construct redundancy.

Unlike conventional weighting techniques, REAF estimates construct importance directly from the observed data, thereby producing adaptive weights that remain interpretable while preserving statistical robustness.

D. *Reliability Estimation*

The first component of REAF evaluates the internal consistency of every latent construct using Cronbach's alpha. For construct k

$$R_k = \alpha_k \qquad (4)$$

where

- R_k denotes construct reliability,

- α_k is Cronbach's alpha coefficient.

Higher values indicate that the questionnaire items associated with the construct measure the same underlying cognitive concept with greater consistency.

E. Information Diversity

Reliability alone cannot determine construct importance because highly reliable constructs may still exhibit little variation across respondents. Therefore, REAF incorporates an entropy-based diversity measure.

For construct k,

$$p_{ik} = \frac{C_{ik}}{\sum_{i=1}^{N} C_{ik}} \qquad (5)$$

where

- p_{ik} represents the normalized probability associated with respondent iii.

The normalized entropy is then calculated as

$$E_k = -\frac{1}{\ln N}\sum_{i=1}^{N} p_{ik}\ln(p_{ik}) \qquad (6)$$

The corresponding information diversity coefficient is

$$D_k = 1 - E_k \qquad (7)$$

Constructs exhibiting greater response variation produce higher diversity values and therefore contribute more useful information during fusion.

F. Construct Uniqueness

Highly correlated constructs often represent overlapping cognitive information. Including such redundancy may bias the final Historical Memory Cognition Index.

Accordingly, REAF estimates construct uniqueness as

$$U_k = 1 - \frac{1}{K-1}\sum_{\substack{j=1 \\ j\neq k}}^{K} |\rho_{kj}| \qquad (8)$$

where

- ρ_{kj}j denotes the Pearson correlation between constructs k and j,
- K=5 represents the total number of latent constructs.

Higher uniqueness values indicate that the construct contributes comparatively independent information.

G. Adaptive Weight Estimation

The three statistical descriptors are integrated into a unified construct contribution score.

For construct k,

$$A_k = \left(\frac{R_k}{\bar{R}}\right)^{\lambda}\left(\frac{D_k}{\bar{D}}\right)^{\mu}\left(\frac{U_k}{\bar{U}}\right)^{\nu} \qquad (9)$$

where

- $\bar{R}$, $\bar{D}$, $\bar{U}$

represent the mean reliability, diversity, and uniqueness values, respectively.

Unlike conventional approaches that manually specify the exponent values, REAF estimates (λ, μ, ν) using the bootstrap-based stability criterion described in Section IV. This strategy selects the exponent combination that minimizes weight variation across repeated bootstrap samples, thereby improving robustness and reducing dependence on a single dataset realization.

The final normalized construct weight is obtained as

$$w_k = \frac{A_k}{\sum_{j=1}^{K} A_j} \qquad (10)$$

subject to

$$\sum_{k=1}^{K} w_k = 1, \qquad w_k \geq 0 \qquad (10a)$$

This normalization ensures that the resulting weights can be interpreted as proportional construct contributions.

H. Algorithm 1. Reliability–Entropy Adaptive Fusion (REAF)

Input: Normalized construct matrix

$$\boldsymbol{C} = [HA, EE, PA, NI, EI]$$

Output: Adaptive construct weights

Algorithm 1 Reliability–Entropy Adaptive Fusion (REAF)

1. Compute construct reliability using Cronbach's alpha.

2. Compute entropy-based diversity for every construct.

3. Compute construct uniqueness from the inter-construct correlation matrix.

4. Estimate contribution score

   A = R^λ × D^μ × U^ν

5. Normalize

   W = A / ΣA

6. Return adaptive weights W.

The cost of computation in REAF is determined by entropy estimation and measurement correlation. Since the method only uses five latent variables, its computation cost is insignificant as compared to preprocessing and is quite usable for real-time decision-making.

In contrast to other weight adjusting methods such as entropy weighting or principal component weighting or arithmetic mean, REAF considers all important characteristics such as measurement validity, information richness, and redundancy of constructs in receiving adaptive weights. Consequently, these adaptive weights reflect the direct contribution of each construct to memory recognition while being understandable and interpretable.

*I. **Historical Memory Cognition Index (HMCI)***

The presented methodology computes a single quantitative measure called Historical Memory Cognition Index (HMCI) based on the estimated adaptive construct weights derived from REAF. The purpose of HMCI is to translate the multidimensional cognition of the audience into an understandable numeric identifier that shows the overall influence of Partition cinema in terms of history memory formation.

For respondent iii, HMCI is defined as

$$HMCI_i = \sum_{k=1}^{5} w_k\, C_{ik} \qquad (11)$$

Where,

- C_{ik} denotes the normalized score of construct k,
- w_k represents the adaptive weight estimated through REAF.

Expanding Eq. (11),

$$HMCI_i = w_{HA}HA_i + w_{EE}EE_i + w_{PA}PA_i + w_{NI}NI_i + w_{EI}EI_i \qquad (12)$$

Since

$$0 \le C_{ik} \le 1, \qquad \sum_{k=1}^{5} w_k = 1 \qquad (12a)$$

HMCI satisfies

$$0 \le HMCI_i \le 1 \qquad (13)$$

Essentially, high HMCI values suggest richer background knowledge, more emotional involvement in the event, higher perceived authenticity, greater appreciation of the importance of national unity, and greater impact from the educational value of the films observed for the study.

In comparison to standard audience measurement scores, HMCI stands out because it is flexible, interpretable, and based on some statistical framework.

J. ***Explainable Artificial Intelligence Module***

While the Historical Memory Cognition Index provides an objective measure of audience cognition, it does not clarify the factors that account for variations in historical memory with respect to the respondents. Because of this, HMCI-Net has the Explainable Artificial intelligence (XAI) module to make models more transparent and to enhance evidence-based interpretation of the model predictions.

The proposed framework is not like conventional black-box prediction models at all. It implements explainability techniques in order to quantify which individual latent constructs have the most significant impact on HMCI.

Following the computation of HMCI, respondents are categorized into three cognitive levels:

$$Y_i = \begin{cases} 0, & HMCI_i < 0.40 \\ 1, & 0.40 \le HMCI_i < 0.70 \\ 2, & HMCI_i \ge 0.70 \end{cases} \qquad (14)$$

where

- **0** denotes Low Historical Memory Cognition,
- **1** denotes Moderate Historical Memory Cognition,
- **2** denotes High Historical Memory Cognition.

To predict these categories, three complementary machine learning models are considered:

- Logistic Regression
- Random Forest
- Extreme Gradient Boosting (XGBoost)

These models were selected because they represent linear, ensemble, and boosting paradigms while remaining suitable for moderate-sized datasets.

Model interpretability is obtained using SHapley Additive exPlanations (SHAP). For each respondent, SHAP quantifies the contribution of every latent construct toward the predicted HMCI category.

For respondent **iii**,

$$\hat{y}_i = \phi_0 + \sum_{k=1}^{5} \phi_k \qquad (15)$$

where

- ϕ_0 represents the average model prediction,
- ϕ_k denotes the SHAP contribution associated with construct k.

Positive SHAP values indicate that a construct increases the probability of belonging to a higher HMCI category, whereas negative values reduce the predicted historical memory cognition.

The explainability module therefore enables transparent identification of the most influential educational and psychological factors affecting historical memory formation, thereby enhancing the practical usefulness of the proposed framework.

*K. **Scenario-Based Historical Memory Simulation***

Typical audience perception studies usually finish with statistical analysis. This limits their utility in terms of generating recommendations for educational tools. To overcome this weakness, HMCI-Net adds a Scenario-Based Historical Memory Simulation (SHMS) module to project the influence of potential improvements in various cognitive constructs. The simulation assumes that various educational projects like museum trips, films, classroom discussions, or movies giving events in their true historical context may improve some cognitive constructs. The framework assesses how these interventions may influence the Historical Memory Cognition Index.

For construct k,

$$C'_{ik} = \min(1, C_{ik} + \delta) \qquad (16)$$

where

C_{ik} is the original construct score,

C'_{ik} denotes the modified construct score,

δ represents the intervention magnitude.

Typical intervention levels considered are

$$\delta = 0.05,\ 0.10,\ 0.20 \qquad (16a)$$

representing 5%, 10%, and 20% improvements in construct performance.

The corresponding Historical Memory Cognition Index becomes

$$HMCI'_i = \sum_{k=1}^{5} w_k\, C'_{ik} \qquad (17)$$

The overall improvement resulting from the intervention is calculated as

$$\Delta HMCI_i = HMCI'_i - HMCI_i \qquad (18)$$

To obtain statistically reliable estimates, the intervention process is repeated through Monte Carlo simulation.

For each simulation,

1. respondents are randomly selected,
2. one or more constructs are perturbed,
3. HMCI is recomputed,
4. the improvement is recorded.

This process is repeated for

$$S = 5000 \qquad (18a)$$

simulation runs.

The simulation enables quantitative evaluation of educational strategies before practical implementation and therefore provides decision support for educators, curriculum designers, and cultural institutions.

L. Algorithm 2. Scenario-Based Historical Memory Simulation

Input

- Historical Memory Cognition Index
- Construct scores
- Intervention magnitude
- Number of simulations

Output

- Expected HMCI improvement
- Sensitivity ranking
- **Output**

Alrorithm

1.Initialize simulation counter.

2. For s = 1 to S

    Select respondent.

    Select construct.

    Apply intervention δ.

    Recalculate HMCI.

    Compute ΔHMCI.

3. Calculate

    Mean improvement

    Standard deviation

    95% confidence interval

4. Rank constructs according to expected HMCI improvement.

5. Return simulation statistics.

Natural Resources for Human Health
eISSN: 2583-1194

M. *Decision Support Layer*

The ultimate phase of HMCI-Net translates the results of computer analysis into practical suggestions. The proposed decision support section interprets the results of the work of REAF, HMCI, explainable AI and scenario simulation and can go beyond being limited by forecast alone.

By taking into consideration the HMCI score and SHAP-based importance of aspects, the system identifies the cognitive dimensions that require further development in different audience segments. The audience, for example, has high Emotional Empathy and low Historical Awareness may need documentary films based on history or archival learning, while those with low Educational Influence may require teaching classes based on discussions or other approaches related to curriculum.

Because Partition cinema depicts communal violence, displacement and bereavement, the interpretation layer is framed in trauma-informed terms. Audience segments that combine high Emotional Empathy with low Historical Awareness or low National Integration indicate strong affective engagement coupled with limited contextual or reconciliatory framing. This is precisely the profile for which trauma-informed educational practice recommends contextual debriefing and factual grounding rather than further affective exposure. The decision support layer therefore reports the full construct profile alongside the aggregate HMCI, so that educators and facilitators can plan supportive contextualisation for cognitively vulnerable segments. The resulting recommendations are educational and psychoeducational in nature and are not intended to substitute for clinical assessment or referral.

Moreover, the simulation module allows filmmakers and policymakers to analyze hypothetical situations prior to implementation. The proposed system is capable of calculating the expected boost of HMCI based on various intervention techniques, thus facilitating the making of reasonable choices in terms of creating educational content, filming historical movies, presenting exhibitions in the museums, as well as organizing public awareness campaigns.

As a result, HMCI-Net is the system that goes far beyond traditional audience analysis and introduces a decision-support system for historical memory cognition based on different computations.

IV. EXPERIMENTAL DESIGN AND VALIDATION

This section describes the experimental procedures that were utilized to prove the efficacy of the proposed HMCI-Net framework. The study was conducted to measure the performance of the suggested REAF algorithm, the Historical Memory Cognition Index (HMCI) tool and the explainable decision-making model. As opposed to conventional perceptual tests which only provide descriptive statistics, the experimental framework provides psychometric validation and computational analysis as well as evaluation of alternative approaches. All experiments were carried out under common preparation methods and controlled conditions of random start.

A. *Dataset Description*

In order to conduct its experimental evaluation, a primary audience perception dataset was collected from utilizing a structured online questionnaire. This questionnaire was aimed to study the role played by Partition cinema in understanding historical memory. The questionnaire was designed to derive both demographic and multi-faceted cognitive responses with relation to the notion of historic awareness. This includes emotional involvement of an audience, authenticity experienced by an audience, national integration and educational impact of Partition films.

Once the data was collected, it underwent the scrutiny in terms of repeated submissions, inconsistencies or incomplete entries. However, all questions regarding audience perceptions in the questionnaire message were obligatory to answer, which made it impossible to accept any missing values related to cognitive variables. False submissions were detected based on the timestamps and eliminated leaving 160 valid entries in the dataset.

The dataset contains two groups of variables. The first group of variables is focused on the demographic background and contains the age, gender, job title, education, knowledge of Partition history, previous experience of seeing such films. The first group of variables will be utilized in the processes of descriptive analysis and predictive modeling. The second group of variables is composed of Likert rating scale statements studying five latent constructs responsible for understanding historical memory.

All perception-related questions were evaluated according to 5-point Likert rating scale where 1 means Strongly Disagree and 5 means Strongly Agree. In order to make numerical values consistent for computational procedures, the respondents' answers were normalized in the range of [0, 1] by means of the min-max method mentioned above.

TABLE II. CHARACTERISTICS OF THE EXPERIMENTAL DATASET

Parameter	Value
Number of respondents	160
Total questionnaire attributes	43
Latent constructs	5
Response scale	Five-point Likert
Missing values	None
Duplicate responses removed	Yes
Normalization technique	Min–Max

B. *Construct Validation*

In the course of building the Historical Memory Cognition Index, the questionnaire was validated in terms of its psychometric characteristics in order to support the hypothesis regarding the sufficiency of the latent constructs as measures of their cognitive components. The validation procedure encompassed the assessment of reliability, convergent validity, and sampling adequacy. The first phase involved the investigation of the internal consistency of the questionnaire using Cronbach's α as a measure of the agreement between items pertaining to the same construct.

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_T^2}\right) \qquad (19)$$

where

k denotes the number of questionnaire items,

σ_i^2 represents the variance of the ith questionnaire item,

σ_T^2 denotes the variance of the total construct score.

Constructs with

$$\alpha \geq 0.70 \qquad (19a)$$

were considered sufficiently reliable for subsequent analysis.

Convergent validity was further evaluated using Composite Reliability (CR) and Average Variance Extracted (AVE). Composite Reliability estimates the overall internal consistency of the latent construct and is calculated as

$$CR = \frac{(\sum_i \lambda_i)^2}{(\sum_i \lambda_i)^2 + \sum_i (1 - \lambda_i^2)} \qquad (20)$$

where

$\lambda_i$represents the standardized factor loading of questionnaire item iii.

Similarly, the Average Variance Extracted is computed as

$$AVE = \frac{\sum_i \lambda_i^2}{k} \qquad (21)$$

where

k denotes the number of observed indicators.

Following commonly accepted psychometric recommendations, the following thresholds were adopted throughout this study:

$$CR \geq 0.70, \qquad AVE \geq 0.50 \qquad (21a)$$

Finally, the suitability of the dataset for latent construct analysis was examined using the Kaiser–Meyer–Olkin (KMO) statistic **and** Bartlett's Test of Sphericity. A KMO value greater than 0.70 and a statistically significant Bartlett's test indicate that the observed variables share sufficient common variance for reliable construct extraction.

Collectively, these statistical validation procedures ensure that the latent constructs possess adequate internal consistency, convergent validity, and sampling adequacy before adaptive weighting is performed by the proposed REAF algorithm.

C. *Bootstrap-Based Reliability–Entropy Adaptive Fusion*

Adaptive weights for the identified constructs were then estimated through the Reliability-Entropy Adaptive Fusion (REAF) algorithm after validating the developed constructs statistically. REAF works in a different manner compared to traditional weighting systems in that it provides the same level of importance for the different constructs or relies completely only on the information entropy of the constructs. In contrast, REAF uses information diversity, measurement reliability, and uniqueness of the constructs at the same time to give adaptive weights with a degree of statistical robustness.

In order to avoid sampling variability in the obtained results, the adaptive classification process was tested via a bootstrap procedure. In fact, 1,000 bootstrap data samples were drawn after repeatedly sampling respondents from the original data set by means of reshuffling samples. After receiving each bootstrap sample, the measures of reliability, the measure of entropy information heterogeneity, and measures of uniqueness were recalculated to estimate the actual adaptive weights for each data sample.

The process of choosing the parameters for the REAF algorithm involved the selection of the appropriate parameters that minimized the loss related to the bootstrap stability procedure discussed in Section 3 since in-sample performance should not be the goal. Thus, the construction of the weights by means of REAF algorithm guarantees the stable nature of the weights across the bootstrap resampling procedure and their independence from the characteristics of the original data set.

The use of the bootstrap method allows for the calculation of the percentile-based intervals and, thus, measurements of uncertainty related to the use of adaptive weights for all constructs.

D. *Baseline Weighting Methods*

In order to assess the efficacy of the recommended Reliability-Entropy Adaptive Fusion (REAF) algorithm in an unbiased manner, the efficiency of the algorithm had to be compared with that of three popular techniques used for weighting in the process of preparing a multidimensional index. The baseline techniques demonstrate the traditional approach of filtering out the latent constructs scores in an aggregated manner and serve as suitable tools for studying the proposed adaptive weightings design.

1) *Equal Weighting (EW)*

The Equal Weighting method assumes that every latent construct contributes equally towards historical memory cognition. Under this assumption, the Historical Memory Cognition Index is computed as the arithmetic mean of the five construct scores:

$$HMCI_i^{EW} = \frac{1}{K}\sum_{k=1}^{K} C_{ik} \qquad (22)$$

where

- K=5 denotes the total number of latent constructs,
- C_{ik} represents the normalized score of construct k for respondent iii.

Although computationally simple, Equal Weighting ignores differences in measurement quality, information richness, and redundancy among constructs.

2) *Entropy Weighting (ENT)*

Entropy weighting determines construct importance according to the variability of respondent responses. Constructs exhibiting greater response diversity receive larger weights because they contribute more discriminative information.

The entropy of construct kkk is computed as

$$E_k = -\frac{1}{\ln N}\sum_{i=1}^{N} p_{ik}\ln(p_{ik}) \qquad (23)$$

where

$$p_{ik} = \frac{C_{ik}}{\sum_{i=1}^{N} C_{ik}} \qquad (23a)$$

The corresponding entropy weight is obtained as

$$w_k^{ENT} = \frac{1 - E_k}{\sum_{j=1}^{K}(1 - E_j)} \qquad (24)$$

The entropy-based Historical Memory Cognition Index is therefore

$$HMCI_i^{ENT} = \sum_{k=1}^{K} w_k^{ENT} C_{ik} \qquad (25)$$

While entropy weighting accounts for information diversity, it does not explicitly consider measurement reliability or construct redundancy.

3) *Principal Component Weighting (PCA)*

Principal Component Analysis (PCA) estimates construct importance using the variance explained by the principal components. Let L_k denote the loading of construct kkk on the first principal component. The normalized PCA weight is calculated as

$$w_k^{PCA} = \frac{|L_k|}{\sum_{j=1}^{K}|L_j|} \qquad (26)$$

The corresponding Historical Memory Cognition Index is

$$HMCI_i^{PCA} = \sum_{k=1}^{K} w_k^{PCA} C_{ik} \qquad (27)$$

PCA weighting captures dominant variance structures within the data but does not explicitly incorporate psychometric reliability or construct uniqueness.

4) *Proposed REAF Weighting*

Unlike the above methods, the proposed Reliability–Entropy Adaptive Fusion (REAF) algorithm simultaneously integrates measurement reliability, entropy-based information diversity, and construct uniqueness to estimate adaptive construct weights. Consequently, REAF generates a statistically robust weighting mechanism that balances measurement quality, information content, and redundancy while maintaining interpretability.

The comparative performance of these weighting strategies is presented and discussed in Section 5.

After obtaining the respondent-level Historical Memory Cognition Index, the audience was divided into three different history memory cognition levels, namely Low, Moderate, and High calculations and the outcome values defined in Section 3. These made up the target variable for the analysis at hand.

Three supervised learning models were selected for comparison namely Logistic Regression (LR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost). LR is the least powerful as it uses a linear approach; RF is more effective as it makes use of powerful ensemble techniques while XGBoost model is among the most effective models.

To eliminate any bias, the model performance was assessed through cross-validation and five-fold stratified cross-validation with 42 random seed numbers. This approach enables all the samples in the dataset to participate in both training and validation phases.

In addition to assessing the predictive performance of the models, SHAP was used for explainability purposes. SHAP is based on assigning a value to the set of arguments used in the model thereby showing the positive signs that mean the presence of factors that have impact on the formation of historical memory.

E. Scenario-Based Historical Memory Simulation

The practical application of HMCI-Net goes beyond prediction as it also allows simulation of educational interventions. The suggested Scenario-Based Historical Memory Simulation module allows estimation of changes in historical memory cognition resulting from controlled alteration of either one or several latent constructs.

The study explored three types of intervention aimed at improving the construct key performance indicator by 5%, 10%, and 20%. During the implementation of the simulation, the selected KPIs were modified whereas the remaining KPIs remained unchanged. The altered KPIs were inputted in the REAF weighting system to produce the revised Historical Memory Cognition Index.

In total, 5,000 Monte Carlo simulations were realized to get statistically valid results. The results from each simulation were registered in the respective statistics report.

Therefore, the simulation not only produces results that can help obtain anticipated educational effect without carrying out real life practices.

F. Performance Evaluation Metrics

The predictive capability of the proposed framework was evaluated using widely accepted classification performance measures. These metrics collectively assess overall prediction accuracy, class-specific discrimination, and the balance between precision and recall.

Overall classification accuracy is defined as

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (28)$$

where TP, TN FP, and FN denote the numbers of true positives, true negatives, false positives, and false negatives, respectively.

Prediction precision is calculated as

$$Precision = \frac{TP}{TP + FP} \qquad (29)$$

while recall is computed as

$$Recall = \frac{TP}{TP + FN} \qquad (30)$$

The harmonic mean of precision and recall is expressed as

$$F1 = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right) \qquad (31)$$

In addition to these measures, the Area Under the Receiver Operating Characteristic Curve (ROC-AUC) was used to evaluate the discriminative capability of each predictive model across different decision thresholds. Together, these metrics provide a comprehensive assessment of classification performance and facilitate objective comparison among the evaluated machine learning algorithms.

G. *Reproducibility*

In order to promote transparency and allow independent verification of our findings, all the experimentations have been conducted using Python 3.11 and the libraries such as NumPy, Pandas, SciPy, Scikit-learn, SHAP, and Matplotlib. The random seed value of 42 has been maintained throughout pre-processing, bootstrap validation, cross-validation, and Monte Carlo simulation to ensure deterministic outcomes to experiments.

Whole experimentation pipeline including pre-processing, construct normalization, psychometric validation, adaptive weighting, predictive modelling, explainability analysis, and simulation, was done using the same computational framework for all experiments. In addition, definitions of constructs, parameter settings, normalization strategy, and evaluation procedure are provided explicitly for successful reproduction of the HMCI-Net framework.

V. Results and Discussion

The results of the empirical testing of HMCI-Net are reported in this section that made use of 160 valid responses sourced from the audience. The analysis includes psychometric quality, bootstrap-stable REAF weights, distribution of HMCI, comparisons to conventional index-building methods, predictions concerning external variables, and simulations based on scenarios. All obtained results are obtained through the same preprocessing, as well as the structure mapping, random seed, and validation procedures indicated in Sections 3 and 4.

A. *Psychometric Validation and Construct Characteristics*

The overall Kaiser-Meyer-Olkin value was 0.915, indicating excellent sampling adequacy. Bartlett's test of sphericity was statistically significant (chi-square=3343.794, df=496, $p<0.001$), confirming that the correlation structure was suitable for latent construct analysis.

Table 4. Reliability, convergent validity, and descriptive statistics

Construct	Cronbach's alpha	CR	AVE	Mean	SD
Historical Awareness	0.896	0.899	0.529	0.650	0.180
Emotional Empathy	0.912	0.913	0.568	0.691	0.175
Perceived Authenticity	0.795	0.811	0.447	0.611	0.159
National Integration	0.834	0.840	0.474	0.660	0.149
Educational Impact	0.812	0.810	0.519	0.633	0.173

The values of Cronbach's alpha were between 0.795 and 0.912, while Composite Reliability values were between 0.810 and 0.913, which indicates a sufficient level of internal consistency of the five constructs examined. As for Historical Awareness, Emotional Empathy, and Educational Impact, their value was higher than the conventional AVE value of 0.50. The values of Perceived Authenticity (AVE=0.447) and National Integration (AVE=0.474) were slightly below this value. Thus, these two constructs were kept as their reliability was good along with the fact that their theoretical significance was high. It is only necessary to be careful while interpreting the convergent validity.

Emotional Empathy had the highest mean value (0.691) followed by National Integration (0.660) and Historical Awareness (0.650). The lowest mean was recorded for the value of Perceived Authenticity that equaled 0.611, which implies that the participants were moved emotionally by the movies dealing with Partition yet were rather cautious about the correctness of the historical facts presented in these movies.

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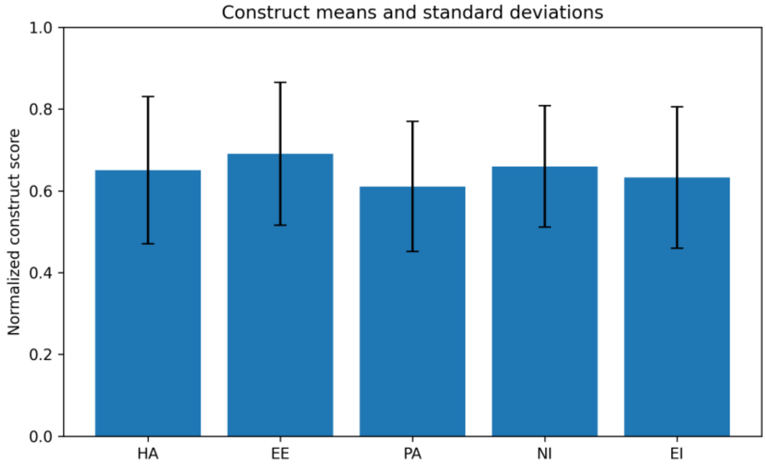

Fig. 2. Mean normalized construct scores with standard deviations.

B. Bootstrap-Stable REAF Weight Estimation

The bootstrap-stability procedure selected lambda=mu=nu=0.50. The associated mean bootstrap weight RMSE was 0.0138. The square-root exponents moderated extreme descriptor values while preserving systematic differences in reliability, information diversity, and construct uniqueness.

Table 5. Final REAF weights and 95% bootstrap confidence intervals

Construct	REAF weight	CI lower	CI upper
Historical Awareness	0.2308	0.1969	0.2739
Emotional Empathy	0.1994	0.1806	0.2215
Perceived Authenticity	0.1956	0.1650	0.2277
National Integration	0.1703	0.1471	0.1886
Educational Impact	0.2039	0.1795	0.2362

Historical Awareness received the largest weight (0.2308), followed by Educational Impact (0.2039), Emotional Empathy (0.1994), Perceived Authenticity (0.1956), and National Integration (0.1703). The relatively balanced distribution confirms that HMCI is multidimensional rather than dominated by a single construct. Historical Awareness ranked first because it combined strong reliability, response-level variation, and non-redundant information.

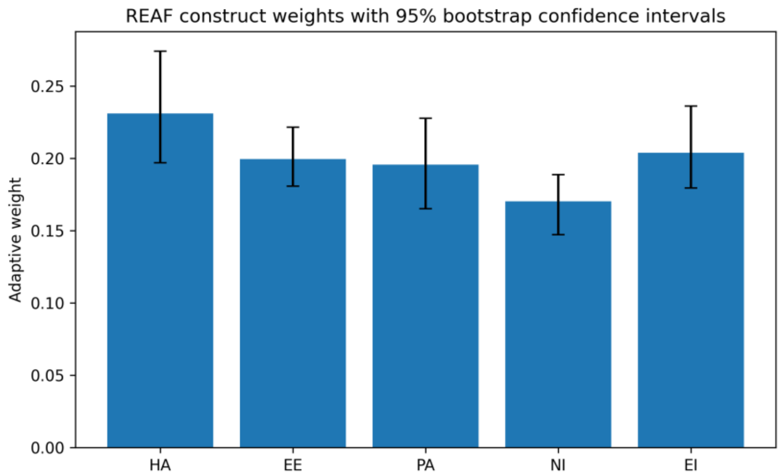

Fig. 3. REAF construct weights with percentile-based 95% bootstrap confidence intervals.

C. Distribution of the Historical Memory Cognition Index

The REAF-derived HMCI had a mean of 0.6487, standard deviation of 0.1404, and range from 0.0806 to 1.0000 respectively. With the use of criteria of 0.40 and 0.70, the eight people fall into Low historical memory cognition category, while 92 qualified for Moderate and sixty for High.

The distribution of people in moderate and high categories shows the impact of Partition cinema on people's historical and emotional perceptions, but despite many respondents who have moderate and high values in HMCI, there are still a few of the respondents with Low HMCI which poses a problem for classification of data using supervised learning. That is why instead of accuracy, the focus is mainly on usual macro-averaged precision, recall, and F1-score rather than just accuracy.

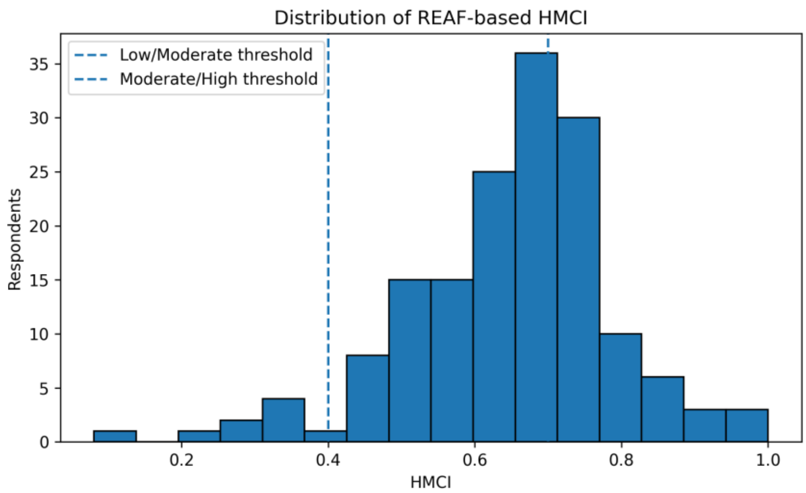

Fig. 4. Distribution of the REAF-based HMCI and the pre-specified classification thresholds.

D. Comparison with Conventional Weighting Methods

Table 6. Comparison of HMCI weighting strategies

Method	HA	EE	PA	NI	EI	Mean HMCI	SD	Weight RMSE
Equal Weighting	0.2000	0.2000	0.2000	0.2000	0.2000	0.6489	0.1395	0.0000
Entropy Weighting	0.2368	0.1920	0.1846	0.1514	0.2352	0.6481	0.1413	0.0222
PCA Weighting	0.1945	0.2041	0.1903	0.2030	0.2080	0.6493	0.1397	0.0059
REAF	0.2308	0.1994	0.1956	0.1703	0.2039	0.6487	0.1404	0.0139

The results derived from the four various approaches were almost identical, showing that REAF does not artificially increase the index levels (0.6481-0.6493). In contrast, the greatest distinctiveness of the construct weights was shown by the entropy weights combined with the highest bootstrapped weight RMSE (0.0222). In this regard, PCA showed the lowest RMSE depending on the data (0.0059) where weights were allocated according to the variance structure without taking into account reliability and redundancy of the constructs. The REAF method had a moderate RMSE (0.0139) while preserving its psychometric and information-theoretical characteristics. The equal weight method achieves zero RMSE in accordance with its method (because the weights do not vary) that deprives this value of the meaning of data driven stability.

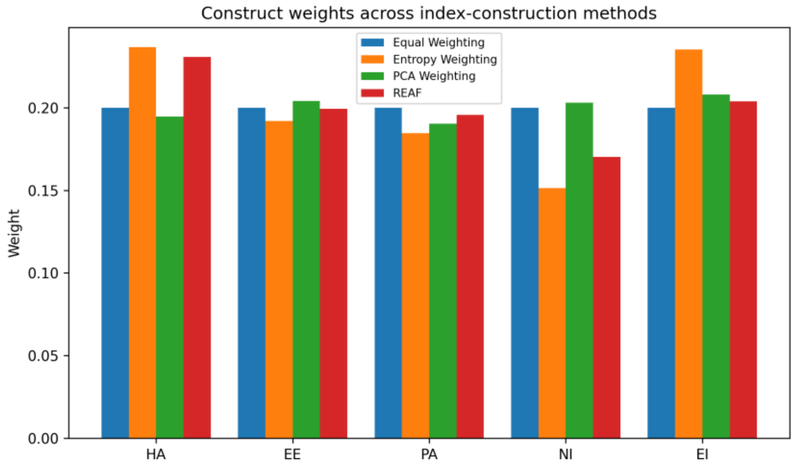

Fig. 5. Construct-weight comparison across Equal, Entropy, PCA, and REAF methods.

E. External-Variable Prediction and Explainability

Table 7. Five-fold cross-validated prediction using demographic and film-exposure variables

Model	Accuracy	Macro precision	Macro recall	Macro F1	Weighted OVR AUC
Logistic Regression	0.500	0.383	0.386	0.379	0.594
Random Forest	0.512	0.332	0.342	0.336	0.584
XGBoost	0.556	0.350	0.363	0.352	0.586

XGBoost came up with the best accuracy (0.556), on the other hand, Logistic Regression gave the highest macro-F1 (0.379) and also weighted one-versus-rest AUC (0.594). General effectiveness was considered as low. This is not a failure of the model, but rather may mean that demographic factors and self-reported film exposure cannot contribute to multi-dimensional historical memory cognition. It is still necessary to directly measure historical knowledge, empathy, authenticity, and the influence of education on the audience.

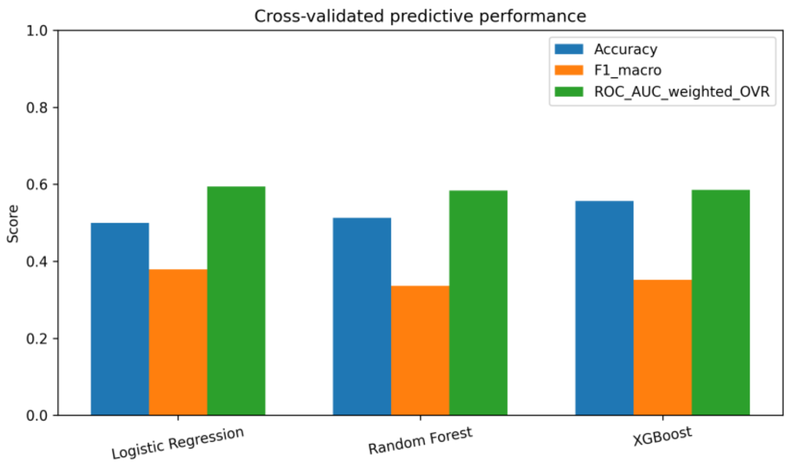

Fig. 6. Cross-validated performance of the external-variable prediction models.

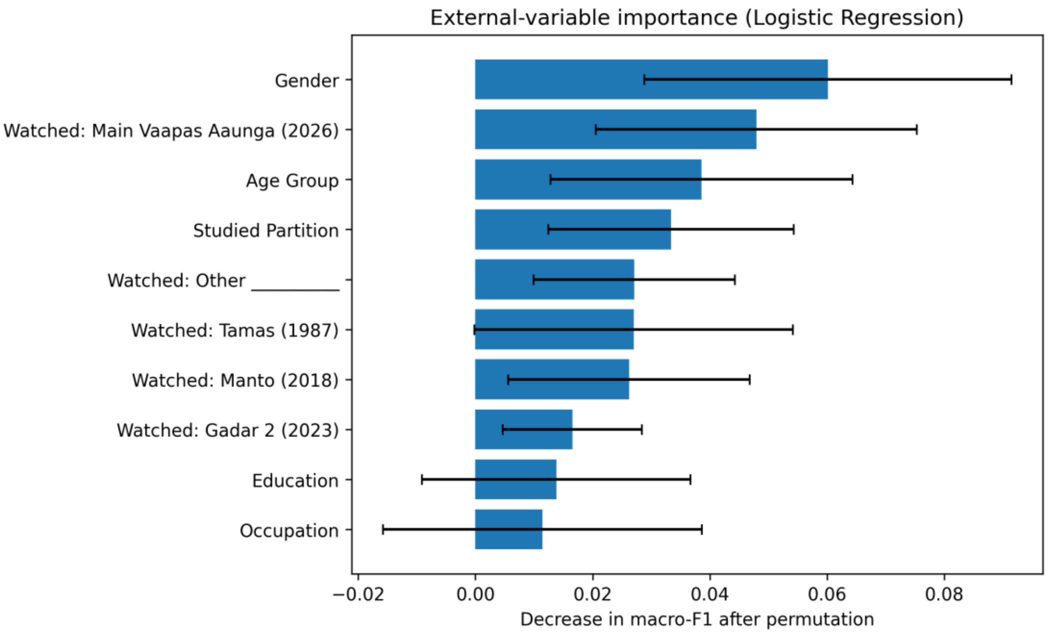

Fig. 7. Model-agnostic permutation importance for the best macro-F1 classifier.

The permutation analysis identified the most informative demographic and exposure variables as Gender, Watched: Main Vaapas Aaunga (2026), Age Group, Studied Partition, and Watched: Other ___________. However, the relatively small importance values and modest predictive scores reinforce the conclusion that historical cognition cannot be reduced to audience demographics or viewing history.

F. Scenario-Based Historical Memory Simulation

Table 8. Simulated HMCI changes under a 20% construct-level intervention

Construct improved	Mean delta HMCI	Median	CI lower	CI upper
Historical Awareness	0.0270	0.0303	0.0000	0.0375
Emotional Empathy	0.0232	0.0262	0.0000	0.0324
Perceived Authenticity	0.0225	0.0245	0.0000	0.0310
National Integration	0.0209	0.0227	0.0000	0.0270
Educational Impact	0.0240	0.0255	0.0000	0.0331

A 20% relative improvement in Historical Awareness produced the largest mean HMCI increase, followed by Educational Impact, Emotional Empathy, Perceived Authenticity, and National Integration. When all five constructs were improved simultaneously by 20%, the mean HMCI increase was 0.1176, with a 95% empirical interval from 0.0397 to 0.1500. In the 5,000-run Monte Carlo experiment, random construct improvements between 0% and 20% produced a mean HMCI increase of 0.0597; the 95% simulation interval was 0.0115-0.1022.

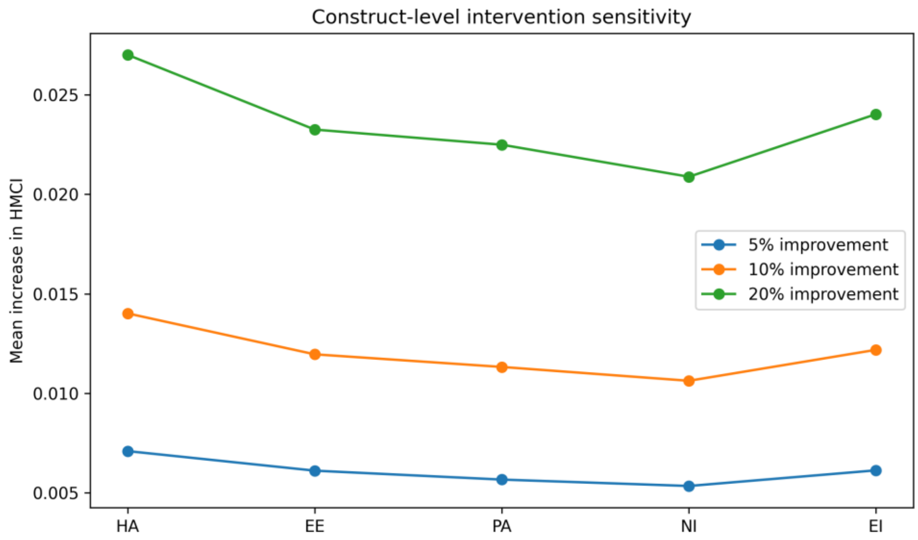

Fig. 8. Sensitivity of HMCI to 5%, 10%, and 20% construct-level improvements.

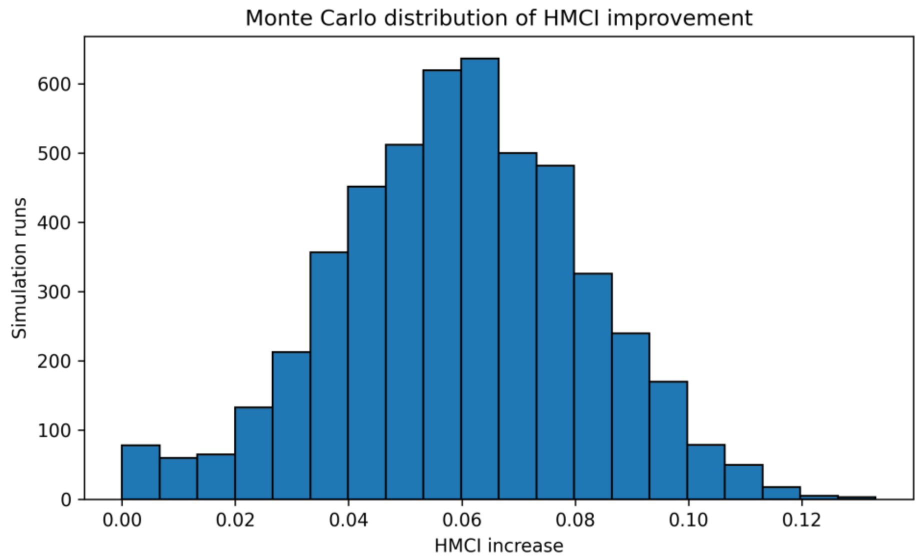

Fig. 9. Monte Carlo distribution of HMCI improvement under random interventions.

G. *Integrated Discussion*

The data proved the main idea of HMCI-Net – that historical memory cognition influenced by Partition cinema has different dimensions and can't be expressed with simple average of the results obtained using the survey. REAF managed to keep overall population-level score and to formulate differences in the importance of constructs. The weights received indicate that historical consciousness and impact of education are among the most important variables used in support of decision making process and emotional empathy is the most highly rated variable at the level of description.

The results help to differentiate assessment from forecasting. HMCI gives a reliable measure if gotten from the cognitive responses given directly, but this variable cannot be predicted based on demographic data and info about audience watching certain movies. This finding makes the idea of audience profiling useless from the viewpoint of measuring. The results of scenario analysis indicate that approaches with combination of different effects bring better results than approaches based on changes alone. Therefore it is highly recommended to apply educational strategies based on integration of factual context, emotional story-telling, historic credibility of information, social harmony discussions and learning activities.

These findings also carry a cognitive-health reading. Emotional Empathy attained the highest descriptive construct score, indicating that audiences engage with Partition cinema primarily through affective response to depicted trauma, whereas historical awareness and educational impact carried the greatest decision-relevant weight. The gap between what audiences feel and what they contextually understand is exactly the condition that trauma-informed education seeks to close, since unframed affective exposure to collective-trauma narratives is associated with distress rather than with constructive historical understanding [33], [34]. The scenario results are consistent with this reading, in that combined interventions raising contextual awareness alongside emotional engagement produced larger HMCI gains than affect-only changes. HMCI-Net therefore provides an interpretable means of identifying which cognitive dimension requires support before an intervention is delivered, although the present study measures psychosocial cognition and not clinical outcomes.

There are two limitations in the research work. The first one is that the size of the sample of 160 respondents limits the complexity of the model and external generalizations of it. The second limitation is the low value of the AVE indicators for Perceived Authenticity and National Integration that show that the items of the questionnaire need further improvement. In order to validate the findings of the present research, a bigger and more representative sample should be used, an independent confirmatory factor analysis should be carried out, and pre-registered threshold values of the research outcomes should be used. It should be noted that both limitations do not make the index ineffective, but they must be considered in the explanation of its results.

VI. Practical Implications, Limitations, and Future Research

The proposed HMCI-Net framework demonstrates that historical memory generated through cinema can be modeled as a measurable and interpretable computational construct rather than being evaluated solely through descriptive survey statistics. By integrating psychometric validation, adaptive construct weighting, explainable artificial intelligence, and scenario-based simulation within a unified computational framework, the study provides a reproducible methodology for analysing multidimensional audience cognition and supporting evidence-based educational decision making.

A. *Practical Implications*

The findings of this study have practical implications for multiple stakeholders involved in historical education, digital humanities, public policy, and computational social science.

1) *Educational Institutions*

The Historical Memory Cognition Index (HMCI) enables educational institutions to quantitatively evaluate the effectiveness of films, documentaries, museum visits, and classroom interventions in improving students' understanding of historical events. Rather than relying exclusively on examination scores or subjective feedback, educators can identify the cognitive dimensions requiring further development and evaluate the effectiveness of different instructional strategies.

2) *Curriculum Designers*

The proposed REAF algorithm identifies the relative contribution of different cognitive constructs toward historical memory formation. Consequently, curriculum developers can prioritize instructional content according to evidence-based construct importance instead of assuming equal educational value across different learning activities.

3) *Film Makers and Media Professionals*

The explainability component of HMCI-Net provides filmmakers with quantitative evidence regarding the cognitive influence of cinematic narratives. Understanding whether historical awareness, emotional empathy, authenticity, or educational impact contributes most strongly to audience cognition may assist future production of historically informed films capable of promoting meaningful public engagement.

4) *Policy Makers and Cultural Institutions*

Museums, archives, heritage organizations, and governmental agencies responsible for cultural preservation may utilize HMCI-Net as a decision-support tool for evaluating historical awareness campaigns. The scenario-based simulation module enables estimation of the potential effectiveness of alternative interventions before implementation, thereby reducing uncertainty during educational planning.

5) *Cognitive Health and Health Humanities Practitioners*

Counsellors, trauma-informed educators and health humanities practitioners increasingly use film and narrative as psychoeducational media for teaching about collective trauma, displacement and intergenerational memory. HMCI-Net offers such practitioners a transparent, construct-level profile of how an audience is engaging with traumatic historical content, separating affective absorption from contextual understanding and perceived social cohesion. The distinction is operationally useful, because the two profiles call for different facilitation strategies. Museums, memorial sites and heritage organisations that deliver well-being oriented programmes may use the same profile to plan supportive framing for sensitive exhibitions. Because the constructs are psychosocial rather than clinical, the framework is positioned as a planning and reflection aid for educational and cultural well-being programmes, and not as a screening or diagnostic instrument.

6) *Digital Humanities Research*

The proposed framework establishes a computational methodology that combines psychometric modeling with explainable artificial intelligence for analysing historical memory. The methodology is sufficiently general to be adapted for studying audience perceptions of other historically significant events, including migration, conflict, cultural heritage, and collective memory.

7) *Theoretical Contributions*

The proposed research makes three primary theoretical contributions to computational historical memory analytics.

First, the study introduces the Historical Memory Cognition Index (HMCI), a multidimensional computational index that integrates five latent cognitive constructs into a single interpretable measure of historical memory generated through cinema.

Second, the proposed Reliability–Entropy Adaptive Fusion (REAF) algorithm provides a novel adaptive weighting mechanism by jointly incorporating measurement reliability, information diversity, and construct uniqueness. Unlike conventional equal-weight, entropy-based, or PCA-based weighting approaches, REAF generates statistically informed construct weights while preserving interpretability.

Third, the proposed HMCI-Net framework extends traditional audience perception studies by integrating adaptive weighting, explainable artificial intelligence, and scenario-based simulation into a unified computational decision-support framework capable of supporting educational planning and cultural policy.

B. Limitations

Despite the encouraging findings, several limitations should be acknowledged.

The experimental evaluation was conducted using a single audience dataset consisting of **160 respondents**, which limits the generalizability of the obtained results. Future investigations should validate the framework using larger and more geographically diverse populations.

The questionnaire focused specifically on audience perceptions of Partition cinema. Although the computational framework itself is domain independent, the latent construct definitions may require modification when analysing historical events with substantially different sociocultural characteristics.

The machine learning experiments demonstrated only moderate predictive performance when demographic variables and movie-viewing characteristics were used to predict historical memory cognition. This observation suggests that historical memory is primarily determined by complex psychological and educational factors rather than demographic attributes alone. Accordingly, future predictive models should incorporate additional behavioural, linguistic, and multimedia features to improve predictive capability.

Furthermore, although the proposed bootstrap-based validation improves statistical robustness, external validation using independent datasets remains necessary before large-scale deployment of the framework in educational or policy environments.

Finally, the cognitive-health framing adopted in this study must be interpreted conservatively. The study recruited a general audience rather than a clinical population, all constructs were derived from a purpose-built perception questionnaire rather than from validated clinical or psychometric health instruments, and no clinical ethics approval, clinician involvement or outcome follow-up formed part of the protocol. HMCI is therefore an educational and psychosocial analytics measure. It must not be interpreted as a screening, triage or diagnostic tool for trauma-related distress, and any deployment in a health or counselling setting would require independent validation against established clinical instruments.

C. Future Research Directions

Several promising research directions emerge from the present work.

Future studies may extend HMCI-Net by incorporating multimodal data sources, including textual reviews, eye-tracking information, physiological responses, speech emotion analysis, and facial expression recognition to develop richer representations of historical cognition. Several of these modalities, in particular physiological arousal, speech emotion and facial affect, are established digital-health signals, so their integration would allow historical memory cognition to be studied alongside objective indicators of affective load.

Large Language Models (LLMs) and Vision-Language Models (VLMs) may also be integrated to automatically analyse historical narratives, film dialogues, and audience reflections, thereby enabling richer semantic modeling of historical memory.

Another promising direction involves replacing static construct weighting with adaptive temporal learning mechanisms capable of modelling changes in historical memory over time following repeated educational interventions.

A further priority is concurrent validation against established instruments. Administering validated measures of empathy, event-related distress and psychological well-being, such as the Impact of Event Scale-Revised and the Warwick-Edinburgh Mental Well-being Scale, alongside the HMCI questionnaire would establish whether the proposed constructs behave as their psychosocial analogues, and would determine whether HMCI carries any value as a cognitive-health indicator beyond its educational use [35], [36].

Finally, longitudinal studies involving multiple countries, educational systems, and historical contexts would facilitate comprehensive evaluation of the proposed framework and establish its applicability as a general computational platform for digital humanities and cultural analytics.

VII. CONCLUSION

The work introduced the HMCI-Net, which is a hybrid explainable AI-based framework that focuses on the computational modeling of historical memory cognition via cinema made possible through Partition. It employs psychometric validity and reliability as well, taking advantage of the presented Reliability-Entropy Adaptive Fusion (REAF) algorithm, Historical Memory Cognition Index (HMCI), interpretive machine learning, as well as simulation based on real-life situations through the integrated computational decision-making architecture.

The experiments conducted for the collection of responses from 160 volunteers proved that the suggested approach is enabling reliable construction measurement in a statistical context and stable adaptive weights being achieved and meaningful multidimensional history cognition representation created. The bootstrap REAF method enabled the construction weights to be balanced and allowed the limitations emerging in the case of equal weight or pure entropy-based measures to be avoided.

The AI component used in the research proved that the results obtained from the sample can hardly be estimated purely based on demographic data and film-watching experience alone. This underlines the significance of carrying out measurements related to cognitive processes directly. In addition, it was demonstrated how hypothetical educational interventions can be computationally assessed before being implemented with the help of negative computer modeling.

To sum up, HMCI-Net contributes to the rapid development of artificial intelligence, computational social sciences, and digital humanities at the intersection of those branches of science by the creation of an effective and reliable model of cognitive processes evaluation. Besides the advantages discussed above, the model can be used for achieving similar goals in various areas.

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