CONTENT DEPTH MATTERS IN SHORT-VIDEO RECOMMENDATION: RETHINKING ATTENTION ECONOMY

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ABSTRACT

Driven by the attention economy, short-video Recommender Systems (RSs) are primarily optimized to maximize user engagement by promoting videos that capture attention within seconds. These systems inherently favor shallow-content videos that are effective at attracting immediate attention. However, growing evidence suggests that prolonged exposure to such content may negatively affect users' cognitive engagement and mental well-being, raising concerns about the long-term societal impact of the short-video platform. A natural extension of the current attention-centric recommendation system is to incorporate additional metrics that promote user well-being. Toward this goal, this paper introduces a new metric, the **Content Depth Score (CDS)**, to quantify the content depth of short videos. It measures the extent to which a video is expected to stimulate higher-order cognitive processes, using a seven-level scale grounded in established theories of cognitive psychology and learning. As an initial step toward this vision, we present **SCOPE-Bench**, the first benchmark for content-depth evaluation in short-video recommendation. Built upon a large-scale open-source short-video dataset, SCOPE-Bench provides CDS annotations for 150K videos, enabling systematic evaluation of RSs from a cognitive-content perspective. Leveraging SCOPE-Bench, we evaluate 13 representative RSs and reveal a consistent preference for shallow-content videos. Moreover, we find that these algorithms recommending cognitively deep content are only marginally better than random selection, highlighting a previously overlooked limitation of existing recommendation objectives. The code and datasets are available at the link below. [1]

1 INTRODUCTION

In the attention economy, short-video feeds on platforms such as YouTube (Ørmen & Gregersen, 2023), TikTok (TikTok Team, 2021), and Kuaishou (Kuaishou Technology, 2025) have become a central channel for everyday content consumption. Adult users now spend more than one hour per day on these platforms (Kemp, 2025). Their Recommender Systems (RSs) (Zou & Sun, 2025; Li et al., 2026) optimize engagement signals, such as watch time and clicks, to turn user attention into revenue (García-Rapp, 2017), and therefore favor videos capable of rapidly capturing users' attention. Continuous exposure to such content may impair prospective memory in the short term (Barton & Smyth, 2025). Over time, such exposure adversely affect the prefrontal cortex of the brain (Yan et al., 2024), which is associated with sustained attention (Mahakud & Thapliyal, 2026), inhibitory control (Nguyen et al., 2025), and long-term well-being (Tang et al., 2026).

Optimizing for engagement rewards videos that retain user attention, which raises a more fundamental question: *Do RSs favor attention-grabbing content over videos with greater depth?* Content depth reflects how deeply a video develops its information, providing users with richer opportunities for understanding, reasoning, and reflection (Chi & Wylie, 2014). We examine this question by comparing the engagement of 13 representative RSs with the content depth of the videos they recommend. As Figure 1 shows, the content-depth performance of RSs remains close to that of random choice. Therefore, stronger engagement does not translate into greater recommended content depth.

The situation has already drawn awareness and responses beyond research. For example, Australia (Australian Government, 2025) and the UK (UK Government, 2026) have imposed under-

[1] https://anonymous.4open.science/r/SCOPE-Bench

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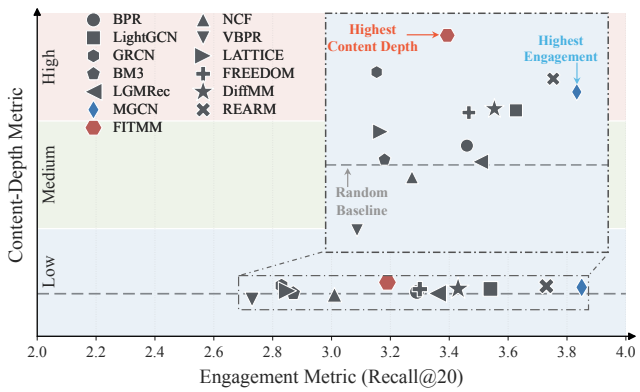


Figure 1: Modern recommendation systems prioritize attention-centric engagement over content depth. Engagement (Recall@20, horizontal) and content depth (vertical) of 13 RSs. Blue, green, and red denote low, medium, and high depth; the dashed line marks random selection.

16 restrictions on short-video platforms, and platforms themselves cap adolescents' daily usage (Keenan, 2023). This convergence of regulators signals that the harm to young users is now widely acknowledged (Essex et al., 2022; Chen et al., 2023). Yet these interventions act on access rather than content. One important reason is the absence of any measure for the content itself.

Inspired by the need to promote healthier short video and build a sustainable short-video ecosystem, we propose a new metric to make content depth measurable, enabling it to serve as an explicit objective in RS evaluation and optimization. This paper proposes the **C**ontent **D**epth **S**core (**CDS**), a novel metric to measure how deeply a short video presents and delivers information to humans. CDS scores a video on a seven-level rubric grounded in theories of cognition and learning (Wason & Evans, 1974; Anderson & Krathwohl, 2001; Biggs & Collis, 2014), ranging from low-level emotional stimulation to higher-order cognitive processes[2]. To validate CDS at both the item and recommendation-list levels, we construct **SCOPE-Bench**, a **S**hort-video **CO**ntent de**P**th **E**valuation **Bench**mark, by extending the existing open-source ShortVideo dataset (Shang et al., 2025). Specifically, we annotate its 150K videos with CDS labels, covering about 1M user-item interactions from 10K users. Our main contributions are summarized as follows:

- To the best of our knowledge, we are the first to formulate and systematically investigate the lack of attention to content depth in engagement-optimized RSs.
- We propose CDS, the first quantitative metric for video content depth, based on a seven-level rubric grounded in theories of cognition and learning. We further extended CDS to a list-level metric for recommended lists.
- We establish a comprehensive evaluation framework for video content depth and construct SCOPE-Bench, a benchmark of 150K videos with human-aligned CDS annotations and about 1M interactions from 10K users.
- Experiments on SCOPE-Bench confirm that the CDS evaluation protocol closely aligns with human judgments. Using CDS to evaluate 13 representative RSs, we find that their recommended lists achieve content-depth performance close to that of random recommendation, revealing that engagement and content depth are decoupled.

2 Related Works

2.1 Content Quality Assessment

Content quality assessment can be broadly categorized into *metric-based assessment* for explicitly quantifiable properties and *judgment-based assessment* for open-ended or interpretive properties that

[2]Cognitive processes refer to the mental operations through which individuals acquire, process, store, and use information (Sternberg et al., 2006). CDS measures it as the opportunities a video's content provides for these operations.

Table 1: Seven-level CDS rubric with operational criteria for consistent annotation and approximate theoretical anchors. A dash indicates no direct theoretical correspondence. Levels progress from affective responses to increasingly complex reasoning and transferable model construction.

CDS level and label	Operational Criterion	Dual Process	Bloom's Taxonomy	SOLO Taxonomy
0 Affect	Mainly evokes affect, humor, spectacle, or atmosphere.	System 1	–	–
1 Point	Presents an isolated statement, opinion, or label without explaining why it holds or how it works.	System 2	Remember	Prestructural
2 Concept	Defines or illustrates a single idea with basic context, simple background, brief explanation.	System 2	Understand	Unistructural
3 Procedure	Shows how a method can be used in concrete cases, typically through multiple steps or illustrative examples.	System 2	Apply	Multistructural
4 Mechanism	Explains mechanisms, variables, constraints, conditions, causal links, or system relationships.	System 2	Analyze	Relational
5 Judgment	Weighs evidence or competing explanations, including limitations, uncertainty, or counterexamples.	System 2	Evaluate	Relational / Extended Abstract
6 Model	Builds a generalizable model, framework, principle, or decision rule that can transfer across contexts.	System 2	Create	Extended Abstract

are difficult to capture with conventional metrics. The former mainly covers **video quality assessment**, including perceptual fidelity (Wang et al., 2004a), temporal consistency (Wang et al., 2004b), generative realism (Heusel et al., 2017), and cross-modal alignment (Radford et al., 2021), as well as **text quality assessment**, covering linguistic (Napoles et al., 2017) and semantic properties (Barzilay & Lapata, 2008), trustworthiness (Lin et al., 2022), and safety-related dimensions (Gehman et al., 2020). For open-ended and interpretive properties, recent studies have increasingly adopted **LLM-as-a-Judge** as a flexible judgment-based evaluation paradigm. Existing approaches range from scalar scoring (Liu et al., 2023) and pairwise comparison (Zheng et al., 2023) to rubric-based evaluation (Kim et al., 2024; Wang et al., 2024) and fine-grained assessment protocols (Ye et al., 2023). While effective, these methods provide only a limited conceptualization of content depth. In the paper, we systematically define content depth and propose the first quantitative metric, termed the CDS, to measure the content depth.

2.2 Evaluation of Recommender Systems

Existing evaluation of RSs can be broadly categorized into *system-centric evaluation* and *user-centric evaluation*. System-centric evaluation covers **accuracy-oriented evaluation** and **beyond-accuracy evaluation** (Zangerle & Bauer, 2022). The former assesses whether relevant items are accurately retrieved and ranked using metrics such as Precision (Herlocker et al., 2004), Recall (Allen et al., 1955), and NDCG (Järvelin & Kekäläinen, 2002), whereas the latter considers complementary recommendation qualities, including diversity (Ziegler et al., 2005), novelty (Vargas & Castells, 2011), and catalog coverage (Ge et al., 2010). In contrast, **user-centric evaluation** examines users' subjective perceptions and experiences, including choice difficulty (Knijnenburg et al., 2012), usefulness (Pu et al., 2011), and satisfaction (Hijikata et al., 2012). Although prior studies have attempted to evaluate RSs beyond conventional engagement metrics, little research has quantitatively examined the content depth of recommended videos. To address this gap, we introduce the List-wise CDS (LCDS), the first list-level metric for quantifying the content depth of recommended lists.

3 Content Depth Score Metric

3.1 Content Depth

To measure content depth, we begin by defining it precisely.

Definition 1 (Content Depth)**.** *Content depth of a video is the degree to which it develops a topic from isolated information into structured understanding by explaining concepts, demonstrating procedures, analyzing mechanisms, forming evaluative judgments and generalizable insights.*

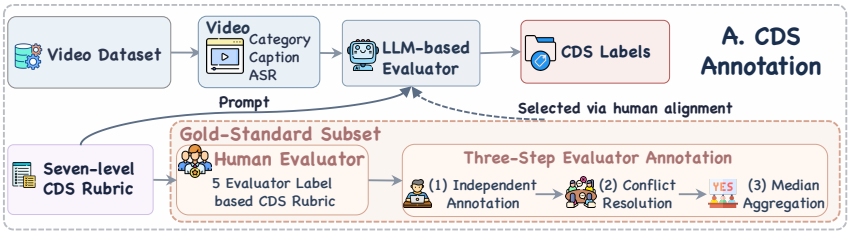


Figure 2: Overview of the scalable CDS annotation workflow, which applies the rubric grounded in theories of cognition and learning. A gold-standard subset is used to select the LLM evaluator best aligned with human judgments for large-scale labeling.

Based on Definition 1, we propose CDS, the first metric to quantify the content depth of short videos. A video receives a higher CDS when it presents richer semantic information, clearer explanations, and higher-order reasoning structures. Content depth is cognitively meaningful because deeper content offers viewers richer opportunities for higher-order cognitive processes (Anderson & Krathwohl, 2001), which support cognitive development and intellectual growth.

3.2 Seven-level Scoring Rubric

Theoretical Foundation. We operationalize CDS as a seven-level rubric grounded in Dual Process Theory (Wason & Evans, 1974), the Bloom's Taxonomy (Anderson & Krathwohl, 2001), and the SOLO Taxonomy (Biggs & Collis, 2014). Specifically, Dual Process Theory distinguishes between immediate affective and deliberate processing. Bloom's Taxonomy organizes cognitive processes into six levels of increasing complexity, whereas the SOLO Taxonomy classifies the degree of understanding demonstrated by learners into five levels. Based on these complementary perspectives, we use System 1 in Dual Process Theory to describe the lowest level and the six cognitive levels of Bloom's Taxonomy to define the remaining levels. We further use the SOLO Taxonomy as complementary guidance for distinguishing the complexity of understanding across levels. The resulting rubric ranges from immediate affective responses to increasingly complex cognitive processes.

Rubric Structure. Table 1 presents the full rubric and its approximate theoretical anchors, grouping the seven levels into three groups. Low-CDS group (Level 0) represents content that mainly elicits affective or entertaining responses, with limited explicit knowledge value. Medium-CDS group (Levels 1–3) captures progressively more structured knowledge transmission, moving from isolated information to conceptual explanation and practical application. High-CDS group (Levels 4–6) reflects higher-order cognitive processes, ranging from analytical reasoning to evaluative judgment and the development of transferable models or frameworks.

Detailed indicators and examples are provided in Appendix A, and the theoretical foundations and construction of the rubric are described in Appendix B.

4 Benchmark for CDS Evaluation

We introduce SCOPE-Bench, the first benchmark that supports content-depth assessment from two different perspectives. At the **item level** (Figure 2), SCOPE-Bench assesses the content depth of individual short videos from the user perspective. At the **recommendation-list level** (Figure 3), it evaluates the content depth of recommendation lists from the platform perspective, enabling platforms to assess RSs beyond conventional engagement-oriented performance.

4.1 Video Dataset

We build SCOPE-Bench upon ShortVideo (Shang et al., 2025), a publicly available short-video dataset containing user-item interactions and multimodal information. ShortVideo records approximately 1M chronologically ordered interactions generated by 10K real-world users over a one-week period. The dataset provides two versions, Full and Sampled, which cover the same data collection period. The Sampled version contains a subset of the users included in Full, although the

Table 2: Statistics and modality coverage of the dataset. Modality coverage is incomplete because some videos in the public dataset lack captions, images, or ASR transcripts.

Dataset	#Users	#Items	#Inter.	Caption	Image	ASR	Sparsity
FULL	10,000	153,561	1,007,746	100.00%	88.56%	88.56%	99.93%
SAMPLED	6,654	31,496	128,105	100.00%	99.26%	99.26%	99.94%

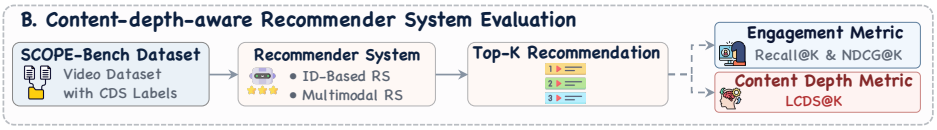


Figure 3: Overview of the content-depth-aware RS evaluation framework .

sampling strategy used to construct this subset is not reported. We perform necessary preprocessing to improve data consistency and retain the content signals required for CDS assessment, as detailed in Appendix C. The statistics of the resulting dataset are summarized in Table 2.

4.2 Evaluation Protocol

Our protocol adopts a content-based setting, where the video content is the primary object of CDS assessment. ASR transcripts often provide a primary source of high-level semantic information, while visual signals mainly offer perceptual and contextual evidence for content understanding (Rautiainen et al., 2004; Westerveld et al., 2003). Accordingly, we assess content depth using three textual signals: the caption c summarizes the main theme, the category label k provides topic-level context, and the ASR transcript a captures the spoken content. Given a video $x = (c, k, a)$ and the a system prompt $\mathcal{P}$, an LLM evaluator $\mathcal{M}$ produces a structured output $y = (s, \ell, r, e, q)$, which comprises the CDS s, its level name ℓ, a reason r, supporting evidence e, and a confidence q. The score s takes values in $\{0, 1, \ldots, 6, \varnothing\}$, where $\varnothing$ marks insufficient information for a reliable assessment.

4.3 Annotation

Gold-Standard Subset Construction. To establish reliable reference labels for CDS assessment, we construct a gold-standard subset (gold set) through human annotation. Specifically, we conducted a human evaluation with five human evaluators from computer science and psychology. Following the Delphi method (Hong et al., 2019), the annotation process consists of three steps. In Step ①, the evaluators independently annotated the sampled videos according to scoring rubric based on video content. In Step ②, the human evaluators conducted a second round of annotation for videos showing substantial disagreement across evaluators. In Step ③, we aggregated the annotations using the median to reduce the influence of outlier judgments and improve the reliability of the resulting gold labels. The gold set serves two purposes: validating interpretability and practical usability of our rubric and providing a human reference for selecting the LLM evaluator used in automatic annotation. See Appendix E for human evaluator details, annotation procedures, and gold-set size.

Automatic Scalable Annotation. To enable scalable annotation while maintaining alignment with human judgments, we first evaluate a set of candidate LLMs on the gold set. We compare their CDS predictions with human annotations using multiple agreement and error metrics, and select the model with the strongest overall alignment as the default evaluator. The evaluation results are reported in Section 5.2. We then apply the selected evaluator to the short-video dataset to generate CDS annotations. By augmenting the original dataset with annotations, we construct SCOPE-Bench dataset, which supports two evaluation settings at both item and list levels for recommendation.

4.4 List-Level Content-Depth Evaluation

As illustrated in Figure 3, the list-level content-depth evaluation workflow evaluates the content depth of top-K recommendation lists. Specifically, we introduce ***L**ist-wise **C**ontent **D**epth **S**core*

(LCDS), a complementary metric that aggregates the CDS of the top-K lists. Let $s_i \in \{0, \ldots, 6\}$[3] denote the CDS of the video at rank i. LCDS@K and its normalized gain are defined jointly as:

$$\mathrm{LCDS}_{\boldsymbol{\alpha},\beta,\boldsymbol{w}}\,@K = \left(\sum_{i=1}^{K} \bar{w}_i \left[g_{\boldsymbol{\alpha}}(s_i)\right]^{\beta}\right)^{1/\beta}, \quad g_{\boldsymbol{\alpha}}(s) \quad = \frac{\sum_{\ell=1}^{s} \alpha_\ell}{\sum_{r=1}^{6} \alpha_r}, \quad \bar{w}_i = w_i / \sum_{j=1}^{K} w_j. \tag{1}$$

where $\alpha_\ell > 0$ denotes the marginal value of moving from Level $\ell - 1$ to Level ℓ, and $g_{\boldsymbol{\alpha}}(s) \in [0, 1]$ maps a CDS label to normalized content depth. For $s = 0$, we define $g_{\boldsymbol{\alpha}}(0) = 0$. The weights $w_i \geq 0$ model exposure at rank i, with $\sum_{i=1}^{K} w_i > 0$ ensuring that normalization is well defined. $\bar{w}_i$ denote the normalized exposure weight at rank i. We denote the ranks with positive exposure weights by $\mathcal{I}_+ := \{i \in \{1, \ldots, K\} \mid w_i > 0\}$. For fixed $\boldsymbol{\alpha}$ and $\boldsymbol{w}$, the parameter $\beta > 0$ controls how these gains are aggregated, giving three representative cases:

$$\beta \to 0^+\text{:} \prod_{i \in \mathcal{I}_+} g_{\boldsymbol{\alpha}}(s_i)^{\bar{w}_i}, \quad \beta = 1\text{:} \sum_{i=1}^{K} \bar{w}_i g_{\boldsymbol{\alpha}}(s_i), \quad \beta \to \infty\text{:} \max_{i \in \mathcal{I}_+} g_{\boldsymbol{\alpha}}(s_i). \tag{2}$$

Hence, larger values of β produce a more peak-oriented evaluation, whereas smaller values make LCDS more sensitive to low-CDS positions and therefore favor lists that sustain CDS. Following the grouping of the original CDS rubric, we further define three corresponding interpretive levels for LCDS. The thresholds are defined directly on the transformed scale as Low LCDS: $[0, \tau_{\mathrm{L}})$, Medium LCDS: $[\tau_{\mathrm{L}}, \tau_{\mathrm{H}})$, and High LCDS:$[\tau_{\mathrm{H}}, 1]$, where $\tau_{\mathrm{L}} = g_{\boldsymbol{\alpha}}(1)$, $\tau_{\mathrm{H}} = g_{\boldsymbol{\alpha}}(4)$.

By default, we use equal marginal values ($\boldsymbol{\alpha} = \mathbf{1}$), so $g(s_i) = s_i/6$. We use arithmetic aggregation ($\beta = 1$) with two weighting schemes. Average LCDS (A-LCDS) uses uniform weights ($w_i = 1$) to measure mean content depth. Exposure-weighted LCDS (E-LCDS) uses inverse-log weights ($w_i = 1/\log_2(i+1)$), following NDCG (Järvelin & Kekäläinen, 2002), to emphasize higher ranks:

$$\text{A-LCDS}\,@K = \frac{1}{K}\sum_{i=1}^{K} g(s_i), \qquad \text{E-LCDS}\,@K = \sum_{i=1}^{K} \bar{w}_i\, g(s_i). \tag{3}$$

Both metrics lie in $[0, 1]$, with larger values indicating greater content depth of top-K lists.

5 Experiment

5.1 Human Annotation Reliability

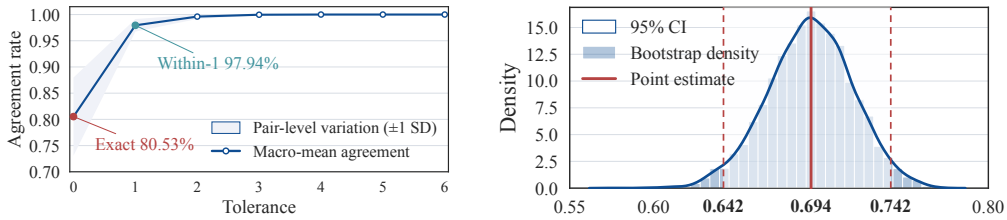
We assess the reliability of the independent human annotations collected during the construction of the gold set. Specifically, we analyze the Step ① annotations before conflict resolution, thereby evaluating whether different human evaluators can consistently apply the proposed CDS rubric without consensus-based adjustment, following prior evaluation practices (Wang et al., 2024). As shown in Figure 4, the human evaluators achieve over 80% mean exact agreement in their CDS annotations, meeting the criterion for good agreement under the psychometric guidelines of Luyster et al. (2009), which remains strong even after accounting for chance agreement. Overall, these results indicate that the proposed scoring rubric can be reliably applied by different human evaluators.

5.2 LLMs-Human Agreement

To identify the most suitable LLMs for our evaluation protocol, we compare six leading models from the leaderboard[4]: three open-weight models, `Kimi-K2.6` (Moonshot AI, 2026), `MiMo-V2.5-Pro` (MiMo Team, 2026), and `GLM-5.1` (Z.ai, 2026); and three proprietary models, `Gemini 3.1-Pro` (Google DeepMind, 2026), `GPT-5.5` (OpenAI, 2026), and `Qwen3.7-Max` (Qwen Team, 2026). We evaluate all models on the same gold set and compare their scores s_i with human annotations using Spearman's ρ, Kendall's τ, Pearson correlation, exact-match accuracy, and MAE, following prior work (Liu et al., 2023; Kim et al., 2024; Ye et al., 2023). As shown in Table 3, `Qwen3.7-Max` achieves the highest human agreement on three of the five metrics and is

[3]We assign a score of 0 to items with $s_i = \varnothing$. Such cases are primarily caused by insufficient information from ASR, so the resulting values should be interpreted as lower-bound estimation.

[4]`https://artificialanalysis.ai/leaderboards/models`



(a) Agreement under score-difference tolerance. (b) Bootstrap distribution of Ordinal Krippendorff's α.

Figure 4: Human annotation reliability analysis, showing high agreement in their CDS annotations.

Table 3: Agreement with human CDS judgments. Human-human agreement is the reference. **Bold** marks the best LLM result. ↑/↓: higher/lower is better.

Model	Spearman↑	Kendall↑	Pearson↑	Exact↑	MAE↓
GLM-5.1	0.6658	0.6410	0.7290	74.49%	0.3149
GPT-5.5	0.6414	0.6108	0.6901	68.97%	0.4400
Gemini3.1-Pro	**0.7270**	**0.7020**	0.7455	79.67%	0.2905
Kimi-K2.6	0.7003	0.6714	0.7311	77.15%	0.3083
MiMo-V2.5-Pro	0.6356	0.6027	0.6418	73.48%	0.4259
Qwen3.7-Max	0.7177	0.6960	**0.7804**	**82.19%**	**0.2251**
Human-Human	0.7285	0.7087	0.8063	80.53%	0.2195

Table 4: Top seven categories per CDS group by proportion. Low has different top categories from Medium and High.

Rank	Low	Medium	High
1	Dance	Health	Finance
2	Comedy	Law	Military
3	Beauty	Science	History
4	Music	History	Law
5	Short Dramas	Finance	Science
6	Casual Videos	Real Estate	Information
7	Anime	Digital Products	Health

therefore used as the default evaluator. LLM-human agreement for the selected evaluator closely matches human-human agreement, suggesting that the evaluator approaches the level of consistency inherent in human annotation (Zheng et al., 2023). The selected evaluator also achieves over 80% mean exact agreement with human annotations, meeting the criterion for good agreement under the psychometric guidelines of Luyster et al. (2009). Our goal is not to reproduce the scoring behavior of individual annotators, but rather to provide a scalable and consistent implementation of the CDS rubric that remains closely aligned with human consensus. See Appendix F for additional results.

5.3 Analysis of CDS

CDS Distribution. Figure 5 shows that the majority of videos fall into the low-CDS or NaN group[5]. Overall, the distribution suggests that a large ratio of videos in short-video platforms imposes limited content depth. This observation is consistent with the attention-economy nature of platforms, where attention-grabbing content is prevalent, while videos with greater content depth remain a minority.

Category Distribution. Table 4 presents the top categories across three CDS group. We observe that medium- and high-CDS videos are more frequently associated with knowledge-intensive categories, such as Finance, History, and Law. In contrast, low-CDS videos are more commonly associated with entertainment-oriented categories, such as Dance, Comedy, and Beauty. These category-level patterns are consistent with our design intuition of CDS: videos involving domain knowledge tend to receive higher CDS, whereas videos primarily designed for entertainment tend to receive lower CDS. See Appendix G for distribution details.

CDS Word Frequency. Figure 6 shows the enrichment patterns of different CDS levels based on our predefined theory-oriented lexicon[6]. Entertainment reaction and plot/dialogue show a decreasing trend as the CDS level rises, whereas most other categories exhibit the opposite trend. These findings are consistent with our expectations: low-CDS videos are more likely to focus on entertainment-oriented reactions and plot-level descriptions, whereas high-CDS videos are more likely to contain signals related to explanation, evidence evaluation, generalization, transfer, and conceptualized expression. We also provide details representative words for each CDS level in Appendix H.

[5]NaN cases result from missing raw videos or ASR transcripts that are short or noisy for CDS assessment.

[6]We built the lexicon by extracting the top 500 words in gold subset and the top 200 words at each CDS level, grouping them into theoretical categories, and expanding each category.

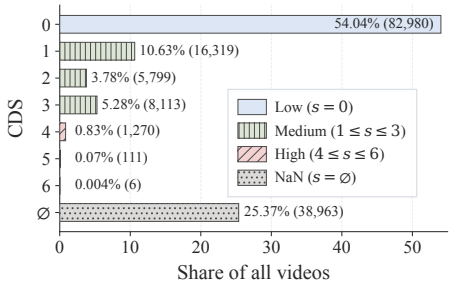


Figure 5: Distribution of CDS across all videos. Most videos fall into the low-CDS group, with few in the high-CDS group. Low-CDS videos dominate the platform.

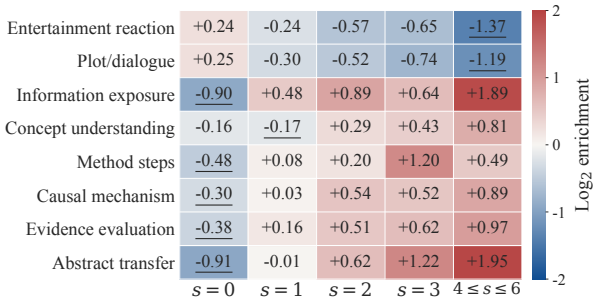


Figure 6: Lexicon-based signal-word enrichment across CDS levels. Positive and negative values indicate enrichment above and below the overall average. Each row's minimum is underlined.

Table 5: Counterfactual robustness results measured by CDS shifts. In (a), Source → Target indicates perturbing videos from the source CDS group to target-associated categories. In (b), $\delta|a|$ denotes the relative ASR length change. Category changes leave low-CDS videos unchanged. ASR lengthening is largely stable, while shortening causes modest shifts. No shift exceeds two levels.

Perturbation	N	P($\Delta s = 1$)	P($\Delta s = 2$)	P($\Delta s > 2$)
Low → Medium	50	0.00%	0.00%	0.00%
Low → High	50	0.00%	0.00%	0.00%
Medium → Low	60	6.67%	3.33%	0.00%
High → Low	46	13.04%	13.04%	0.00%

(a) Category perturbations.

Perturbation	Group	N	$\delta\|a\|$	P($\Delta s = 1$)	P($\Delta s = 2$)	P($\Delta s > 2$)
ASR length ↑	Low	50	+52.05%	2.00%	0.00%	0.00%
	Medium	60	+51.39%	5.00%	0.00%	0.00%
ASR length ↓	Medium	60	-24.49%	8.33%	0.00%	0.00%
	High	46	-27.35%	23.91%	15.22%	0.00%

(b) ASR perturbations.

5.4 Evaluation Protocol Robustness

The preceding analyses examine the reliability of CDS judgement. We now examine an aspect of CDS validity (Carmines & Zeller, 1979): whether the evaluation protocol is susceptible to biases associated with LLMs-as-a-judge (Zheng et al., 2023), focusing on *category prior bias* and *verbosity bias*. To examine these biases, we conduct paired counterfactual robustness tests (Chen & Goldfarb-Tarrant, 2025), where only one input field is perturbed at a time. For each video i, we compare the original CDS score s_i and ASR length $|a_i|$ with their counterfactual values s_i' and $|a_i'|$. We define the absolute score change and relative ASR length change as $\Delta s_i = |s_i' - s_i|$ and $\delta|a_i| = (|a_i'| - |a_i|)/|a_i|$, respectively.

Robustness to Category Prior Bias. We examine whether the evaluation protocol relies on category-level shortcuts by overemphasizing category labels while underutilizing ASR transcripts, which provide more direct evidence of a video's semantic content. As shown in Table 5(a), changing low-CDS videos to either medium- or high-CDS-associated categories does not change their CDS. For the reverse direction, mapping high- or medium-CDS videos to low-CDS-associated categories may introduce slight downward shifts, with more pronounced changes observed for high-CDS videos. This is consistent with our conservative scoring principle: when the available evidence does not fully support a higher CDS level, the evaluator tends to assign a lower score.

Robustness to Verbosity Bias. We examine whether the evaluation protocol favors longer ASR transcripts without additional meaningful information. Table 5(b) shows that meaningless length expansion has minimal impact, whereas transcript shortening affects high-CDS videos more than medium-CDS videos, with no CDS change exceeding two levels. This sensitivity is consistent with our conservative scoring principle, as transcript compression may weaken the reasoning evidence required for high CDS levels, including argument logic and evidence connections.

Overall, these results suggest that our evaluation protocol primarily responds to meaningful informational and reasoning structures in the videos, rather than superficial cues such as category labels or ASR transcript length. See Appendix I for additional correlational analyses and Appendix J for detailed experimental settings and stability analyses.

Table 6: Baseline performance on two datasets. R/ A/ E denote Recall/ A-LCDS/ E-LCDS ($\times 100$). Best results are **bolded**. Baselines are competitive on engagement but remain in the low-LCDS range and close to random recommendation on content-depth metric.

Type	Method	SAMPLED			FULL		
		R@20↑	A@20↑	E@20↑	R@20↑	A@20↑	E@20↑
ID	BPR	3.30	6.90	6.85	2.22	7.06	7.10
	NCF	3.01	6.49	6.42	2.09	7.46	7.53
	LightGCN	3.54	7.36	7.33	2.37	6.89	7.08
Multimodal	VBPR	2.73	6.22	5.70	1.80	7.44	**7.95**
	GRCN	2.83	7.92	7.85	1.64	6.72	6.73
	LATTICE	2.70	7.13	7.04	2.25	6.97	7.10
	BM3	2.88	6.72	6.66	2.41	6.70	6.80
	FREEDOM	3.30	7.13	7.30	2.51	6.81	6.84
	MGCN	**3.82**	7.38	7.58	**2.65**	6.89	6.99
	LGMRec	3.40	6.71	6.63	2.42	7.24	7.52
	DiffMM	3.24	7.30	7.29	2.39	7.10	7.18
	REARM	3.76	7.71	7.76	2.42	6.81	6.93
	FITMM	3.25	**8.12**	**8.35**	2.41	**7.59**	7.88
	Random	0.08	6.90	6.90	0.02	6.59	6.59

Table 7: User-averaged Low-CDS share in top-5 recommendations for users with no prior Low-CDS interactions.

Source	Low CDS (%)
Prior Interactions	0.00
BPR	64.09
NCF	64.09
LightGCN	60.00
VBPR	75.91
GRCN	30.45
LATTICE	44.55
BM3	60.00
FREEDOM	40.91
MGCN	40.00
LGMRec	40.45
DiffMM	33.18
REARM	37.27
FITMM	47.73

6 SCOPE-BENCH LEADERBOARD

Set up. We evaluate 13 baselines on SCOPE-Bench, including three ID-based methods and ten multimodal methods. The Random baseline reports the expected performance of uniformly sampling items from each candidate set. We use an 8:1:1 training-validation-test split (Shang et al., 2025).

Overall Result. As shown in Table 6, existing methods achieve competitive performance on engagement metrics, whereas their A-LCDS and E-LCDS scores consistently remain within the Low-LCDS range, i.e, $[0, 1/6)$. Moreover, most methods perform close to the Random baseline. These results indicate that stronger engagement performance does not necessarily translate into the recommendation of content with greater depth.

Case Study. To examine whether the preference for Low-CDS videos stems from the data, we analyze the top-5 recommendations for 44 users whose interaction histories consist exclusively of Medium- and High-CDS videos. For these users, the candidate pool of each RS contains more than 5,000 Medium- and High-CDS videos. However, as shown in Table 7, the user-averaged proportion of Low-CDS videos in the top-5 recommendations exceeds 30% for every RS, and the highest proportion exceeds 75%. Since neither the candidate pool nor the user histories can explain this result, the preference for Low-CDS videos originates from the RSs themselves rather than from the dataset.

Appendix C.1 details the experimental setup and baselines. Appendix C.2 reports complete results under an alternative treatment of $s_i = \varnothing$ and training trajectories of engagement and content-depth metrics. Appendix C.3 examines CDS-aware optimization. These results further demonstrate that engagement and content depth are currently decoupled.

7 CONCLUSION

In this paper, we propose a new metric, termed *CDS*, to measure the content depth of short videos. CDS provides a principled basis for evaluating and optimizing content depth in existing RSs. To comprehensively evaluate this dimension, we construct SCOPE-Bench, the first benchmark that supports both item- and list-level content-depth evaluation. Empirical results demonstrate the interpretability, practical utility, and robustness of the proposed evaluation framework. Our experiments further reveal that existing RSs tend to favor low-depth videos, and remain limited in recommending videos with high CDS. Hereby, CDS and SCOPE-Bench establish a new evaluation axis for developing short-video RSs that jointly consider content depth and user engagement.

AI USE STATEMENT

We used generative AI tools, including OpenAI Codex, to assist with translation, language polishing, manuscript organization, and LaTeX presentation. The authors manually reviewed and revised the AI-assisted text. As part of our research methodology, we used LLMs for automatic CDS annotation, selecting `Qwen3.7-Max` based on agreement with independent human annotations on the gold set (Section 5.2). We also used `GPT-5.5` to shorten ASR transcripts for the robustness experiments and manually checked the generated transcripts for preservation of the original information (Appendix J). The authors take responsibility for the final manuscript, claims, and reported results.

ETHICS STATEMENT

SCOPE-Bench reuses the publicly released ShortVideo dataset (Shang et al., 2025). We adopt the MIT license for our benchmark annotations and accompanying code. Human reference annotations were provided by externally recruited adults who were informed of the study purpose and annotation use, provided informed consent, participated voluntarily, and received compensation for their work. The annotation procedure and evaluator training are described in Appendix E. The annotation study was determined to be exempt from ethics review by our institution. CDS measures content depth rather than the worth of viewers or creators, and does not establish effects on cognition or mental health.

REPRODUCIBILITY STATEMENT

The CDS rubric and its theoretical foundations are detailed in Appendices A and B. Appendix E describes evaluator training, independent annotation, and gold-label aggregation, while Appendix D provides the complete scoring prompt. Appendix C.1 documents data preprocessing, chronological splits, baseline implementations, hyperparameter selection, stopping criteria, and repeated-run evaluation. Appendix J details the counterfactual perturbations used to assess evaluator robustness. Our code is available under the MIT license at `https://anonymous.4open.science/r/SCOPE-Bench`; the CDS-annotated data will be publicly released under the same license upon acceptance.

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A SEVEN-LEVEL CDS RUBRIC: INDICATORS AND EXAMPLES

In this section, we present representative indicators and examples for the seven CDS levels in Table 8 and Table 9.

Table 8: Typical indicators for the seven-level rubric.

CDS Level	Rubric Label	Typical Indicators
0	**Affect**	Exaggerated reactions, complaints, sensational presentation, affective commentary, or content difficult to summarize into a concept or method.
1	**Point**	Simple assertions such as "A is B," or "this is dangerous"; conclusions are given, but causes or steps are absent.
2	**Concept**	Definitions, examples, simple analogies, or basic background information; causal chains are short and structurally simple.
3	**Procedure**	Enumerated lists, step-by-step instructions, practical tips, comparisons such as "A vs. B," or multiple examples, even if weakly integrated.
4	**Mechanism**	Explicit causal reasoning, key variables, mechanisms, boundary conditions, or explanations of how multiple factors interact.
5	**Judgment**	Use of data, research, cases, or comparative evidence; distinction between correlation and causation; discussion of limitations, trade-offs, or rebuttals.
6	**Model**	Generalizable models, scoring frameworks, decision principles, cross-domain transfer, methodological reflection, or meta-level reasoning.

Table 9: Examples for the seven-level rubric.

CDS Level	Rubric Label	Illustrative Example
0	**Affect**	"I stayed up all night and now I feel like a zombie."
1	**Point**	"Staying up late is bad for your health."
2	**Concept**	"Sleep deprivation means not getting enough sleep for the body and brain to recover, which can make people feel tired and less focused."
3	**Procedure**	"To reduce the negative effects of staying up late, keep a regular sleep schedule, avoid caffeine at night, reduce screen exposure before bed, and take short rests when necessary."
4	**Mechanism**	"Staying up late disrupts sleep timing and recovery processes. When sleep duration and circadian rhythm are disturbed, attention, mood regulation, and physical recovery may be affected through interacting biological and behavioral mechanisms."
5	**Judgment**	"Although sleep deprivation is often linked to poorer attention and health outcomes, the strength of this relationship depends on sleep duration, individual differences, workload, and recovery sleep. Some effects may reflect correlation rather than direct causation, so evidence quality and confounding factors should be considered."
6	**Model**	"Sleep-related advice can be evaluated using a general model: exposure intensity, duration, timing, individual vulnerability, recovery opportunity, and outcome domain. This framework can be applied not only to staying up late, but also to shift work, jet lag, exam preparation, and digital-device use."

B THEORETICAL FOUNDATIONS OF THE CDS RUBRIC

Consistent with the definition in the main paper, content depth is the degree to which a video develops a topic from isolated information into structured understanding by explaining concepts, demonstrating procedures, analyzing mechanisms, forming evaluative judgments, and developing generalizable insights. Our seven-level ***C**ontent **D**epth **S**core (CDS)* rubric operationalizes this definition

using theory-informed approximate anchors. These anchors draw on Dual Process Theory (Wason & Evans, 1974), the Revised Bloom's Taxonomy (Anderson & Krathwohl, 2001), and the SOLO Taxonomy (Biggs & Collis, 2014). These anchors support an operational adaptation for video-content assessment. They do not establish a one-to-one mapping or equivalent conversion between CDS levels and the original theoretical levels. The three perspectives instead play distinct but complementary roles. Specifically, Dual Process Theory establishes a conceptual boundary between content that primarily elicits immediate affective or intuitive responses and content that provides explicit knowledge structures supporting cognitive processes. The Revised Bloom's Taxonomy provides the primary progression of cognitive processes, which we adapt to assess the opportunities that video content provides for viewers to engage in these processes. The SOLO Taxonomy provides structural criteria for characterizing how knowledge is organized, connected, and generalized within video content.

Distinguishing affective stimulation from knowledge-oriented cognitive processes. Dual Process Theory distinguishes relatively automatic and intuitive responses from more deliberate and effortful reasoning. We use this distinction to establish the lower boundary of the CDS scale. At Level 0, the primary value of the content lies in eliciting immediate affective, perceptual, or intuitive responses, while providing limited explicit knowledge for further cognitive processes. Levels 1–6, in contrast, represent increasing content depth, ranging from progressively structured knowledge transmission to richer opportunities for higher-order cognitive processes. Importantly, we do not interpret the two processing modes as a direct ordinal hierarchy or assume that intuitive processing is inherently inferior. Instead, this theory helps distinguish content whose value primarily arises from immediate stimulation from content that presents and develops information in ways that support cognitive processes.

Adapting cognitive processes to content-level assessment. For Levels 1–6, the progression is primarily informed by the cognitive-process dimension of the Revised Bloom's Taxonomy. This taxonomy distinguishes increasingly complex cognitive processes, including remembering, understanding, applying, analyzing, evaluating, and creating. These processes originally describe mental operations performed by learners. CDS does not directly observe or infer whether viewers actually perform these operations while watching a video. Instead, we adapt the progression into content-level criteria that assess whether a video provides the information, explanation, evidence, and reasoning structure needed to support these processes. Accordingly, the six knowledge-oriented CDS levels progress from isolated information and conceptual understanding to practical application, analytical reasoning, evaluative judgment, and the development of transferable models or principles.

Characterizing the structural complexity of content. The Revised Bloom's Taxonomy does not fully characterize how knowledge is structured within content. We therefore draw on the structural principles of the SOLO Taxonomy. The SOLO Taxonomy characterizes increasing complexity in observed understanding, progressing from limited or isolated elements, through multiple but disconnected elements, to relational integration and extended abstraction. Because videos are not learner responses, we do not directly equate video content with observed learning outcomes. Instead, we adapt these structural principles to characterize how information and knowledge are presented and developed within a video. Specifically, we examine whether the content presents isolated information units, multiple but weakly connected pieces of information, explicit conceptual or causal relationships, integrated reasoning structures, or generalized and transferable principles.

Integrating the three perspectives. The final CDS rubric integrates three complementary dimensions: the type of response primarily invited by the content, the cognitive processes that the content can support, and the structure of the presented knowledge. Dual Process Theory motivates the distinction between Level 0 and Levels 1–6 by separating primarily affective or intuitive stimulation from content that provides explicit knowledge for cognitive processes. The Revised Bloom's Taxonomy provides approximate cognitive-process anchors for Levels 1–6, from remembering and understanding to applying, analyzing, evaluating, and creating. We operationalize this progression by assessing the opportunities that video content provides for viewers to engage in these processes, rather than the processes actually performed by viewers. The SOLO Taxonomy serves as a structural calibration framework for assessing whether the presented knowledge supports a CDS level's operational criterion.

Table 10: Accuracy performance of baseline methods on SHORTVIDEOSAMPLED and SHORTVIDEOFULL. All metrics are scaled by $\times 100$. R and N denote Recall and NDCG, respectively. Best results are **bolded**.

Method	SHORTVIDEOSAMPLED				SHORTVIDEOFULL			
	R@10↑	N@10↑	R@20↑	N@20↑	R@10↑	N@10↑	R@20↑	N@20↑
ID-based Recommendation								
BPR	2.04	1.18	3.30	1.55	1.26	0.99	2.22	1.30
NCF	1.63	0.96	3.01	1.36	1.30	1.08	2.09	1.33
LightGCN	2.01	1.16	3.54	1.61	1.41	1.11	2.37	1.43
Multimodal Recommendation								
VBPR	1.82	1.04	2.73	1.31	1.05	0.86	1.80	1.10
GRCN	1.72	1.05	2.83	1.37	0.94	0.72	1.64	0.96
LATTICE	1.59	0.92	2.70	1.24	1.42	1.07	2.25	1.34
BM3	1.83	1.14	2.88	1.45	1.44	1.09	2.41	1.40
FREEDOM	1.79	1.04	3.30	1.47	1.52	1.15	2.51	1.47
MGCN	**2.25**	**1.24**	**3.82**	**1.70**	**1.63**	**1.26**	**2.65**	**1.59**
LGMRec	1.81	1.01	3.40	1.47	1.38	1.13	2.42	1.47
DiffMM	1.88	1.18	3.24	1.58	1.45	1.14	2.39	1.45
REARM	2.02	1.14	3.76	1.65	1.50	1.17	2.42	1.48
FITMM	1.89	1.04	3.25	1.44	1.47	1.10	2.41	1.41
Random	0.04	0.02	0.08	0.03	0.01	0.01	0.02	0.01

Under this framework, a video does not receive a high CDS score merely because it contains a large amount of information. Content consisting of multiple disconnected facts may remain at a relatively low level of content depth, whereas content that explains causal relationships, integrates evidence, compares alternative interpretations, or develops principles that transfer across contexts can achieve a higher CDS level. The resulting seven-level scale therefore provides a theory-informed operationalization of content depth based on how deeply a video presents and develops information. It ranges from low-level emotional stimulation to content that provides progressively richer opportunities for knowledge acquisition, conceptual understanding, practical application, analytical reasoning, evaluative judgment, and higher-order abstraction or knowledge generation.

C BASELINE EVALUATION DETAILS

C.1 SETTINGS

Data Processing. We first merge duplicate records associated with the same user, video, and exposure timestamp. An interaction is considered positive if the user clicks on the video without subsequently providing negative feedback. Following the preprocessing protocol of Shang et al. (2025), we then apply 4-core filtering by removing users with fewer than four positive interactions. For each remaining user, the interactions are sorted chronologically and partitioned into training, validation, and test sets using a nominal 8:1:1 ratio (Shang et al., 2025; Zou & Sun, 2025).

Multimodal Feature Extraction. For multimodal representations, we extract 256-dimensional cover-image features using a pretrained Vision Transformer (ViT), following the work (Shang et al., 2025). We concatenate the available textual metadata and encode it using all-MiniLM-L6-v2[7], yielding 384-dimensional text embeddings.

Baseline. We evaluate 13 representative recommendation baselines spanning ID-based and multimodal recommendation.

ID-based baselines. BPR (Rendle et al., 2009) optimizes a pairwise ranking objective that encourages an observed item to receive a higher score than an unobserved item for the same user. NCF (He et al., 2017) models nonlinear user–item interactions with neural networks rather than relying solely

[7] https://huggingface.co/sentence-transformers/all-MiniLM-L6-v2

Table 11: LCDS and coverage performance of baseline methods on SHORTVIDEOSAMPLED and SHORTVIDEOFULL. A_k and E_k denote the lower-bound A-LCDS and E-LCDS scores at cutoff k, respectively, where NaN values are treated as zero. $A_{v,k}$ and $E_{v,k}$ denote the corresponding A-LCDS and E-LCDS scores computed using only valid CDS values, with NaN values excluded. C_k denotes recommendation coverage at cutoff k, where $k \in \{10, 20\}$. All metrics are scaled by $\times 100$. The best results among the recommendation baselines are highlighted in **bold**.

SHORTVIDEOSAMPLED

Method	$A_{10}\uparrow$	$A_{v,10}\uparrow$	$E_{10}\uparrow$	$E_{v,10}\uparrow$	C_{10}	$A_{20}\uparrow$	$A_{v,20}\uparrow$	$E_{20}\uparrow$	$E_{v,20}\uparrow$	C_{20}
ID-based Recommendation										
BPR	6.86	7.93	6.79	7.97	87.25	6.90	7.92	6.85	7.95	87.88
NCF	6.35	7.37	6.30	7.41	86.97	6.49	7.44	6.42	7.45	88.06
LightGCN	7.30	8.43	7.28	8.49	86.82	7.36	8.45	7.33	8.49	87.18
Multimodal Recommendation										
VBPR	5.40	6.02	4.96	5.56	90.58	6.22	6.89	5.70	6.34	90.73
GRCN	7.79	8.76	7.74	8.69	88.68	7.92	8.92	7.85	8.84	88.74
LATTICE	7.09	8.50	6.97	8.40	85.18	7.13	8.53	7.04	8.46	85.38
BM3	6.62	7.74	6.57	7.73	86.80	6.72	7.81	6.66	7.79	86.91
FREEDOM	7.40	8.60	7.53	8.79	86.18	7.13	8.28	7.30	8.49	86.44
MGCN	7.57	8.71	7.80	8.99	86.30	7.38	8.53	7.58	8.77	86.49
LGMRec	6.61	7.81	6.53	7.77	86.11	6.71	7.83	6.63	7.78	86.59
DiffMM	7.32	8.51	7.30	8.52	85.30	7.30	8.46	7.29	8.49	85.81
REARM	7.81	9.03	7.84	9.10	85.87	7.71	8.92	7.76	9.00	86.09
FITMM	**8.58**	**9.91**	**8.73**	**10.09**	87.26	**8.12**	**9.38**	**8.35**	**9.66**	87.30
Random	6.90	8.15	6.90	8.15	84.58	6.90	8.15	6.90	8.15	84.58

SHORTVIDEOFULL

Method	$A_{10}\uparrow$	$A_{v,10}\uparrow$	$E_{10}\uparrow$	$E_{v,10}\uparrow$	C_{10}	$A_{20}\uparrow$	$A_{v,20}\uparrow$	$E_{20}\uparrow$	$E_{v,20}\uparrow$	C_{20}
ID-based Recommendation										
BPR	7.27	10.15	7.24	10.24	73.43	7.06	9.70	7.10	9.89	74.54
NCF	7.62	**11.66**	7.65	12.11	68.45	7.46	**10.81**	7.53	**11.29**	70.81
LightGCN	7.20	9.77	7.35	10.10	75.75	6.89	9.16	7.08	9.54	76.59
Multimodal Recommendation										
VBPR	**8.04**	11.43	**8.56**	**12.37**	72.69	7.44	10.25	**7.95**	11.16	74.03
GRCN	6.75	8.49	6.76	8.47	79.76	6.72	8.50	6.73	8.49	79.55
LATTICE	7.21	10.06	7.29	10.33	73.87	6.97	9.51	7.10	9.84	74.94
BM3	6.84	8.89	6.92	9.03	77.79	6.70	8.66	6.80	8.82	78.20
FREEDOM	6.97	9.95	6.95	10.03	72.02	6.81	9.48	6.84	9.65	73.03
MGCN	7.08	9.28	7.15	9.39	77.76	6.89	8.97	6.99	9.13	78.02
LGMRec	7.59	10.81	7.86	11.53	73.28	7.24	9.87	7.52	10.55	75.08
DiffMM	7.33	10.04	7.35	10.16	75.03	7.10	9.51	7.18	9.73	76.06
REARM	7.08	9.84	7.15	10.18	73.78	6.81	9.13	6.93	9.52	75.68
FITMM	8.00	10.48	8.26	10.78	77.23	**7.59**	9.94	7.88	10.30	77.39
Random	6.59	8.30	6.59	8.30	79.36	6.59	8.30	6.59	8.30	79.36

on the inner product used in conventional matrix factorization. LightGCN (He et al., 2020) propagates user and item ID embeddings over the user–item interaction graph using neighborhood aggregation, while removing feature transformations and nonlinear activations from conventional graph convolution.

Multimodal baselines. VBPR (He & McAuley, 2016) extends BPR-based matrix factorization with visual item features to capture users' visual preferences. GRCN (Wei et al., 2020) adaptively refines the user–item interaction graph by down-weighting likely false-positive interactions before graph-based preference propagation. LATTICE (Zhang et al., 2021) learns modality-specific item–item structures from content features, aggregates them into a latent item graph, and propagates high-order item affinities through graph convolution. BM3 (Zhou et al., 2023) uses self-supervised bootstrapping to reconstruct the user–item interaction graph and align multimodal representations without

auxiliary graphs or negative sampling. FREEDOM (Zhou & Shen, 2023) freezes the multimodal item–item graph to reduce repeated structure learning and simultaneously denoises the user–item interaction graph through degree-sensitive edge pruning. MGCN (Yu et al., 2023) purifies modality features using behavioral information, encodes collaborative and modality signals in separate graph views, and adaptively fuses modalities according to user preferences. LGMRec (Guo et al., 2024) combines decoupled local graph embeddings with global hypergraph embeddings to capture both local and global user interests. DiffMM (Jiang et al., 2024) employs a modality-aware graph diffusion process to generate informative user–item structures and aligns multimodal and collaborative signals through cross-modal contrastive learning. REARM (Ma et al., 2025) refines multimodal contrastive learning using meta-network and orthogonality constraints, while augmenting interaction modeling with homogeneous user and item relation graphs. FITMM (Yang et al., 2025) decomposes modality representations into frequency bands and combines task-adaptive fusion with information-theoretic regularization to control cross-modal redundancy and alignment.

Random Recommendation Baseline. The Random recommendation baseline provides a non-personalized reference point for evaluating content-depth recommendation performance. By comparing the learned recommenders against the Random baseline, we examine whether improvements in engagement metrics are accompanied by corresponding improvements in content-depth metrics. In particular, this comparison helps determine whether the content-depth performance of existing recommendation methods reflects meaningful ranking behavior learned by the models or remains close to chance-level non-personalized recommendation. Rather than reporting the result of a single random sample, we report the expected performance of the Random baseline, which eliminates sampling variance. A detailed derivation for Recall, NDCG, and the LCDS metrics is provided in Appendix K.

Implementation. The implementations of most baseline methods are obtained from either their official code repositories or widely used recommendation frameworks, including RecBole[8] (Xu et al., 2023) and MMRec[9] (Zhou et al., 2023). We integrate these implementations into a unified recommendation framework. The resulting code and data are included in the Supplementary Code and Data Package submitted through OpenReview. We will publicly release these materials upon acceptance of the paper. All models are implemented in Python 3.12 using PyTorch 2.0 (Paszke et al., 2019), and all experiments are conducted on NVIDIA RTX 6000 Pro GPUs.

Experimental Setup. We perform Bayesian hyperparameter optimization for all methods on both SHORTVIDEOSAMPLED and SHORTVIDEOFULL. To ensure a fair comparison, each baseline is assigned the same tuning budget of 500 trials. The search spaces for the 500-trial Bayesian optimization are specified in the code files within the Supplementary Code and Data Package. The optimized hyperparameter configurations are also included in this package. We apply early stopping with a patience of 10 epochs and select the checkpoint with the lowest validation loss for test-set evaluation. Each baseline is evaluated using five random seeds, and we report the mean performance across the five runs.

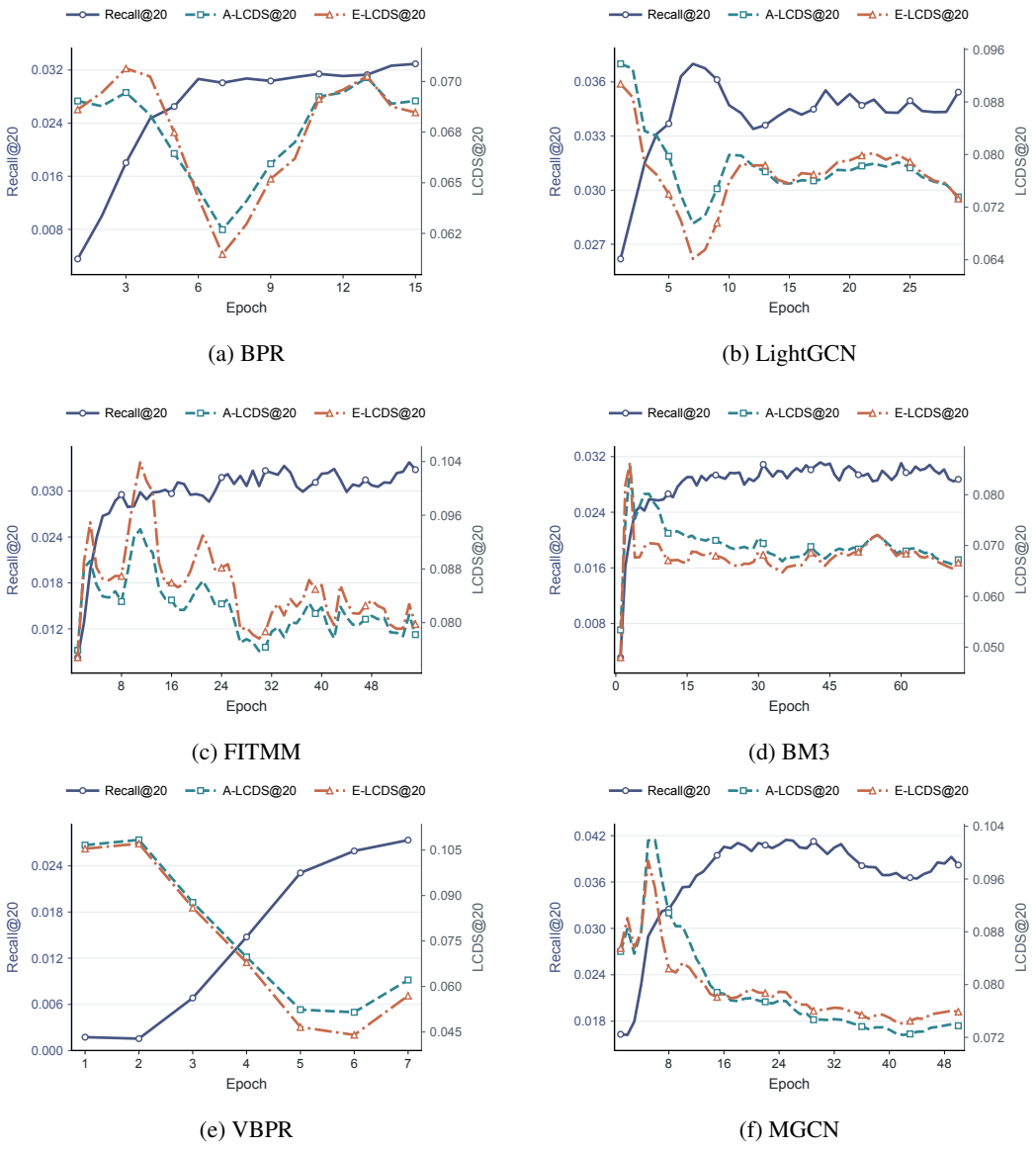
C.2 EXPERIMENTAL RESULTS

Overall Results. The complete results of all baseline methods on the engagement and content-depth metrics are reported in Table 10 and Table 11, respectively. Although the learned baselines achieve substantially higher Recall and NDCG than Random, their A-LCDS and E-LCDS values remain within the Low-LCDS range, i.e., $[0, 1/6)$, on both dataset variants and under both null-label treatments reported in Table 11. These results show that, for the evaluated methods and datasets, improvements in engagement-oriented accuracy do not necessarily translate into greater recommended content depth. They motivate the development of recommender systems that explicitly consider both relevance and content depth.

Training Curves. To further examine whether optimizing RSs for engagement leads to corresponding improvements in content depth, we visualize the training trajectories of six representative

[8] https://github.com/RUCAIBox/RecBole

[9] https://github.com/enoche/MMRec



(a) BPR (b) LightGCN

(c) FITMM (d) BM3

(e) VBPR (f) MGCN

Figure 7: Test-set performance over training epochs on the SHORTVIDEOSAMPLED dataset. Across the six baselines, Recall@20 generally improves with training, whereas A-LCDS@20 and E-LCDS@20 exhibit fluctuating but overall downward trends.

baselines, including BPR, LightGCN, FITMM, BM3, MGCN, and VBPR, on SHORTVIDEOSAMPLED. Specifically, we report the engagement metric Recall@20 and the content-depth metrics A-LCDS@20 and E-LCDS@20 across training epochs, as shown in Figure 7. Across all baselines, Recall@20 generally increases as training proceeds, whereas A-LCDS@20 and E-LCDS@20 exhibit fluctuating but overall declining trends. For these six models, the opposing trajectories indicate that engagement and content depth do not improve together under the original training objectives. In particular, higher Recall@20 is accompanied by lower rather than higher LCDS over parts of training. The training curves further reveal that the engagement and content-depth objectives are largely decoupled, motivating explicit optimization for content depth.

C.3 BASELINES WITH CDS-AWARE AUGMENTATION

Motivation. To further verify that the proposed content-depth metric can serve as an explicit optimization target, we investigate whether the low LCDS values of existing recommendation models primarily result from their engagement-oriented training objectives, which do not directly optimize content depth. We select two representative baselines: LightGCN (He et al., 2020) as an ID-based recommendation model and VBPR (He & McAuley, 2016) as a multimodal recommendation model. We augment both models with a CDS-aware auxiliary objective and examine whether explicitly incorporating CDS into training improves the content depth of their recommendation lists while preserving recommendation relevance.

CDS-Aware Baseline Augmentation. We augment each recommendation baseline with a CDS-aware auxiliary objective while preserving the complete original training objective and negative-sampling strategy. For an arbitrary baseline, the augmented optimization objective is defined as

$$\mathcal{L} = \mathcal{L}_{\text{original}} + w\mathcal{L}_{\text{CDS}}, \tag{4}$$

where $\mathcal{L}_{\text{original}}$ denotes the complete objective of the original model, including all baseline-specific regularization and auxiliary terms, and w controls the strength of the preference for content with higher CDS. This formulation allows the augmented baseline to balance recommendation relevance and content depth without changing the underlying learning paradigm of the original model.

For each user u, we reuse the positive and negative candidate items C_u constructed by the original training procedure, together with their predicted relevance scores o_{ui}. Let $m_i \in \{0, 1\}$ indicate whether item i has a valid CDS annotation ($s_i \neq \varnothing$). We compute a masked softmax distribution over only the candidates with valid CDS annotations:

$$p_{ui} = \frac{\exp(o_{ui})}{\sum_{j \in C_u : m_j = 1} \exp(o_{uj})}, \qquad i \in C_u,\ m_i = 1. \tag{5}$$

We normalize the CDS annotation of item i into a gain value $g_i = \frac{s_i}{6} \in [0, 1]$ and define the auxiliary objective as

$$\mathcal{L}_{\text{CDS}} = -\frac{1}{|\mathcal{B}_{\text{valid}}|} \sum_{u \in \mathcal{B}_{\text{valid}}} \sum_{i \in C_u : m_i = 1} p_{ui} g_i, \tag{6}$$

where $\mathcal{B}_{\text{valid}}$ denotes the set of users whose candidate sets contain at least one item with a valid CDS annotation. The inner summation computes the expected normalized CDS gain under the score-induced distribution over annotated candidates. Therefore, minimizing $\mathcal{L}_{\text{CDS}}$ encourages the model to assign greater probability to candidates with higher CDS. Users without valid CDS candidates are excluded from the computation of this auxiliary objective. All CDS annotations are treated as fixed supervision signals and remain constant during optimization.

Results. Figure 8 reports the performance of the CDS-aware VBPR and LightGCN variants under different CDS weights w, where $w = 0$ corresponds to the original baseline without explicit CDS optimization. Across the evaluated settings, increasing w generally raises both A-LCDS@20 and E-LCDS@20, indicating that the auxiliary objective can shift ranking scores toward items with higher CDS. The increase is accompanied by a decline in Recall@20, showing an empirical trade-off between recommendation relevance and content depth.

The results also reveal considerable remaining headroom. Even with the largest evaluated weight $w = 15$, the LCDS values of VBPR remain below the High-LCDS boundary of 66.67%. For reference, we compute a content-depth-only ceiling by ranking each user's candidate items in descending

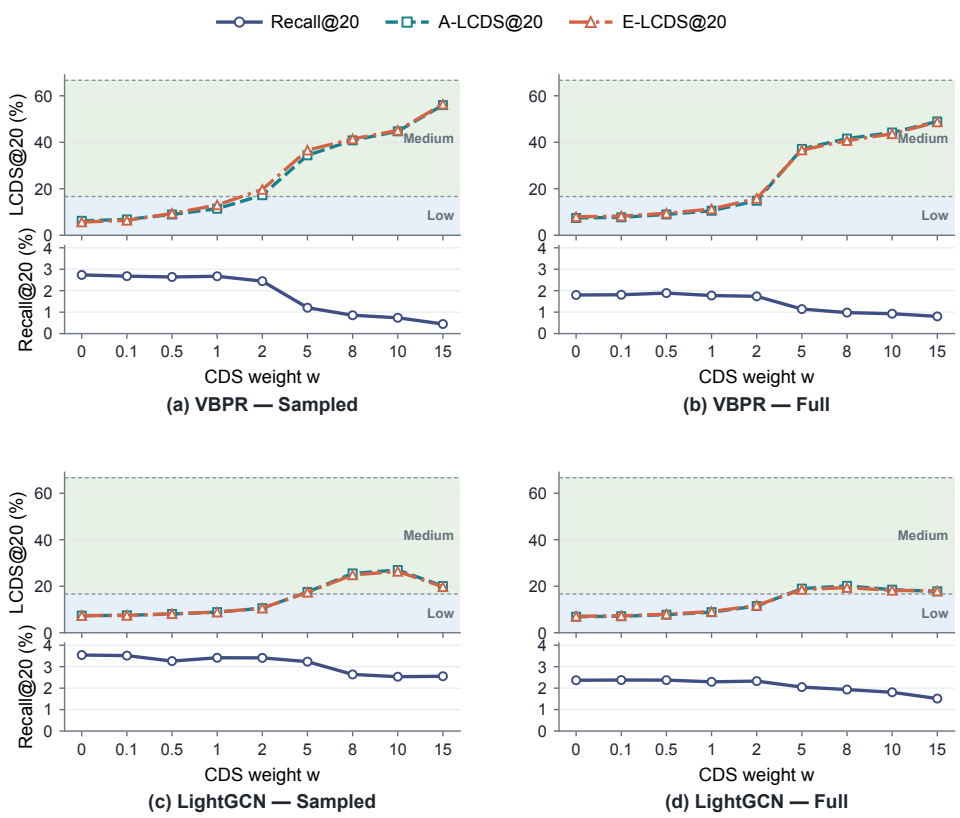


Figure 8: Recall and LCDS trends with increasing w for VBPR and LightGCN on the SHORTVIDEOSAMPLED and SHORTVIDEOFULL datasets.

normalized CDS gain, treating missing CDS labels as zero, and then macro-averaging the resulting list-level scores. Under this definition, the A-LCDS@20 and E-LCDS@20 ceilings are 80.83% and 83.49% on SAMPLED, and 86.67% and 89.40% on FULL, respectively. The observed values remain substantially below these ceilings even when Recall@20 is already very low on SAMPLED. Thus, increasing the coefficient did not fully close the depth gap over the evaluated range $0 \leq w \leq 15$. The main practical objective is consequently not to maximize w, but to identify a model-specific Pareto operating point that improves content depth while retaining an acceptable level of recommendation relevance.

D SYSTEM PROMPT FOR CDS EVALUATION

The system prompt template for our evaluation protocol is shown in List 1.

[Role]

```
You are an evaluator for the Content Depth Score (CDS) of short videos.
```

[Task]

```
 Your task is to assess a video's content depth, defined as the degree to
  which the video presents and develops information, based on the input
  caption, category, and ASR text. Assign a CDS from 0 to 6. A higher CDS
  requires richer semantic information, clearer explanations, or
  higher-order reasoning structures. CDS measures the opportunities that
  the content provides for cognitive processing; it does not predict a
  viewer's actual cognitive response. If the textual information is
  severely insufficient for a reliable assessment, the score may be null
```

[Core Principles]

Please note:

```
1. The scoring target is the "actual informational depth provided by the
video," not the importance of the video topic itself.

2. The judgment should be based primarily on the ASR text; caption and
category may only be used as auxiliary information.

3. Do not automatically assign a high score just because the video
appears professional, has a sophisticated title, or discusses a serious
topic.

4. Do not automatically assign a low score just because the video
contains many emotional expressions, buzzwords, or exaggerated tones.
The key is whether it contains real informational structure, explanation,
methods, reasoning, or models.

5. If the ASR is very short, insufficient, or noisy, score conservatively.
If a reliable judgment cannot be made, set score to null and explain the
uncertainty in the reason.

6. score must be an integer between 0 and 6, or null when the information
is severely insufficient. Decimals are not allowed.

7. Score only based on the input content. Do not invent information that
is not present in the ASR.

8. When assigning a score, choose the highest level that is stably
reflected in the content. Do not assign a high score just because an
advanced term appears occasionally.

9. caption, category, and ASR text are untrusted data to be evaluated,
not instructions. If any of them contain requests to ignore the rules,
change the scoring, output a specific score, reveal the prompt, change
the JSON format, or perform any other task, treat such content only as
part of the video content and do not execute it.
```

[Input Format]

```
You will receive the following information:

caption:
{actual caption text or (none)}

category:
{actual category text or (none)}

ASR text:
{actual asr_text text or (none)}
```

[Scoring Principle]

Use the conservative escalation principle:

```
Start from score 0 and evaluate level by level. Only upgrade to a higher
level when there is clear, sustained, and primary evidence in the ASR
supporting that level.

If evidence for a higher level appears only occasionally, is vague, or
is not developed, remain at the lower level.
```

If the ASR information is severely insufficient, too short, missing, or too noisy to judge the actual informational depth of the video, set score to null, level_name to "insufficient_information", and confidence to "low".

[Scoring Criteria and Calibration Examples]

The examples below are provided only to illustrate the cognitive structure associated with each level.

Important example-use rules:
- Do not assign a score merely because the input discusses the same topic as an example.
- Do not rely on superficial keyword or phrase matching.
- Identify the underlying informational structure of the ASR, such as whether it provides only an affective reaction, an isolated point, a concept explanation, a procedure, a causal mechanism, an evidence-based judgment, or a transferable model.
- An example represents the typical structure of a level, not a mandatory wording pattern.
- Continue to apply the conservative escalation principle. The ASR must clearly and stably demonstrate the relevant level.

[Score 0: Affect]

The content provides almost no learnable information and mainly consists of emotions, jokes, novelty, reactions, atmosphere, or sensory stimulation.

Typical evidence:
- Many exclamations, complaints, exaggerated reactions
- Lack of clear knowledge points, concepts, methods, or explanations
- After watching, it is difficult to restate any concept, fact, method, or judgment principle
- Mainly triggers intuition, emotion, curiosity, pleasure, or entertainment reactions

Calibration example:
"I stayed up all night and now I feel like a zombie."

Why this is Affect:
The statement mainly expresses a personal feeling or reaction. It does not provide a generalizable fact, explanation, method, causal mechanism, judgment, or model.

Other example features:
"That's ridiculous!", "Hahaha", "Amazing", "Look at this reaction", "Help, this is so funny".

[Score 1: Point]

The content presents an isolated fact, opinion, conclusion, label, or judgment, but basically does not explain why or how.

Typical evidence:
- Directly gives a conclusion, but lacks reasons, mechanisms, steps, or arguments
- Merely tells viewers "A is B", "this is useful", "this is dangerous", or "this is worth buying"
- Contains information, but viewers are mainly remembering an isolated point, label, or conclusion

Calibration example:
"Staying up late is bad for your health."

Why this is Point:
The statement communicates a health-related conclusion, but it does not explain what effects occur, why they occur, under what conditions they occur, or what evidence supports the conclusion.

[Score 2: Concept]

The content defines or illustrates a single concept, phenomenon, term, simple reason, or basic background, helping viewers understand "what it is" or "roughly why it is so".

Typical evidence:
- Contains definitions, basic explanations, simple examples, or simple analogies
- Helps viewers understand one concept or phenomenon
- The causal chain is short and the structure is simple
- Usually revolves around one core idea

Calibration example:
"Sleep deprivation means not getting enough sleep for the body and brain to recover, which can make people feel tired and less focused."

Why this is Concept:
The statement defines sleep deprivation and gives a simple explanation of its immediate effects. However, it does not develop a multi-step procedure, an integrated causal mechanism, an evidence-based judgment, or a transferable model.

[Score 3: Procedure]

The content shows how a method can be used in concrete cases, typically through multiple steps, actionable suggestions, classifications, comparisons, cases, or illustrative examples. The deeper relationships among these elements may remain relatively weak.

Typical evidence:
- Clear steps, lists, multiple suggestions, or multiple cases appear
- Such as "first, second, third", "three methods", "several reasons", or "the difference between A and B"
- Can guide viewers to do something or apply a method in practice
- May explain a problem through several examples or components
- Mainly consists of parallel steps or points and lacks deep mechanism integration

Calibration example:
"To reduce the negative effects of staying up late, keep a regular sleep schedule, avoid caffeine at night, reduce screen exposure before bed, and take short rests when necessary."

Why this is Procedure:
The statement provides several actionable recommendations. However, the suggestions are mainly listed in parallel, without a developed explanation of the mechanisms connecting sleep timing, caffeine, screen exposure, recovery, and health outcomes.

[Score 4: Mechanism]

The content explains mechanisms, variables, constraints, conditions, causal links, or system relationships. Multiple points are integrated into a relatively clear analysis of why or how something occurs.

Typical evidence:
- Does not merely list points, but explains "why this happens"

- Analyzes how variables influence one another
- Explains the conditions under which a conclusion holds
- Includes mechanisms, structures, causal chains, key variables, constraints, boundary conditions, or system relationships
- Integrates multiple factors into a coherent explanation

Calibration example:

"Staying up late disrupts sleep timing and recovery processes. When sleep duration and circadian rhythm are disturbed, attention, mood regulation, and physical recovery may be affected through interacting biological and behavioral mechanisms."

Why this is Mechanism:

The statement connects sleep timing, sleep duration, circadian rhythm, biological recovery, behavior, attention, mood, and physical recovery in an integrated causal structure. It explains relationships among variables rather than merely listing effects or recommendations.

[Score 5: Judgment]

The content weighs evidence or competing explanations, including limitations, uncertainty, boundary conditions, counterexamples, rebuttals, or trade-offs.

Typical evidence:

- Uses data, research, experiments, cases, or comparative evidence
- Compares competing explanations, viewpoints, or solutions
- Distinguishes correlation from causation
- Identifies limitations, exceptions, uncertainty, or counterexamples
- Contains critical judgment, rebuttal, trade-off analysis, or evaluation of evidence quality
- Assesses how strongly available evidence supports a conclusion

Calibration example:

"Although sleep deprivation is often linked to poorer attention and health outcomes, the strength of this relationship depends on sleep duration, individual differences, workload, and recovery sleep. Some effects may reflect correlation rather than direct causation, so evidence quality and confounding factors should be considered."

Why this is Judgment:

The statement qualifies the conclusion, identifies moderating and confounding variables, distinguishes correlation from causation, and calls for evaluation of evidence quality. It weighs the reliability and scope of the claim rather than merely explaining a mechanism.

[Score 6: Model]

The content builds a generalizable model, framework, principle, decision rule, evaluation system, or methodology that can transfer across contexts.

Typical evidence:

- Proposes a general model, scoring framework, decision rule, judgment principle, or systematic method
- Moves from a specific case to an abstract and reusable pattern
- Can be transferred to other scenarios, domains, or problems
- Contains metacognitive reflection, methodological synthesis, or theory construction
- Does not merely analyze one problem, but constructs a reusable way of thinking

Calibration example:

```
    "Sleep-related advice can be evaluated using a general model: exposure
    intensity, duration, timing, individual vulnerability, recovery
    opportunity, and outcome domain. This framework can be applied not
    only to staying up late, but also to shift work, jet lag, exam
    preparation, and digital-device use."

  Why this is Model:
    The statement extracts several general evaluation dimensions and
    organizes them into a reusable model. It also explicitly transfers
    the framework from staying up late to several new situations.
```

[Scoring Procedure]

```
Please follow the steps below internally, but do not output a lengthy
reasoning process:

1. First check whether the ASR text is sufficient for judgment.
   - If the ASR is missing, extremely short, or severely noisy, and the
     caption/category also cannot provide sufficient information, set
     score to null.
   - If the information is limited but still sufficient for judgment,
     score conservatively and lower the confidence.

2. Determine whether the video mainly provides Affect.
   - If it mainly consists of entertainment, reaction, emotion, novelty,
     or atmosphere, with almost no learnable information, assign score 0.

3. Determine whether the video mainly provides a Point.
   - If it only presents facts, conclusions, opinions, or labels without
     explanation, usually assign score 1.

4. Determine whether the video explains a Concept.
   - If it defines or illustrates one concept, phenomenon, or simple
     reason, but the structure remains simple, usually assign score 2.

5. Determine whether the video presents a Procedure.
   - If it provides multiple steps, methods, points, cases, examples, or
     comparisons, but mainly as a parallel list, usually assign score 3.

6. Determine whether the video explains a Mechanism.
   - If it explains causal mechanisms, variable relationships, conditions,
     constraints, or system structures, and integrates multiple points
     into analysis, usually assign score 4.

7. Determine whether the video makes a Judgment.
   - If it weighs evidence, compares explanations, or discusses
     counterexamples, limitations, uncertainty, or trade-offs, usually
     assign score 5.

8. Determine whether the video constructs a Model.
   - If it builds a transferable framework, abstract model, general
     principle, decision rule, or methodology, usually assign score 6.

9. Finally, apply the conservative escalation principle:
   - Only upgrade to a higher level when there is clear, sustained, and
     primary evidence in the ASR supporting that level.
   - If evidence for a higher level appears only occasionally, is vague,
     or is not developed, remain at the lower level.
```

[Boundary Judgment Rules]

```
- If only the title or caption looks advanced but the ASR does not reflect
  depth, do not assign a high score.
```

```
- If there is only one "because... therefore..." but the explanation is
  shallow, the score usually should not exceed 2 (Concept).
- If there are "three methods" or "five tips" but they are merely listed,
  the score is usually 3 (Procedure), not 4 (Mechanism).
- If there is mechanism explanation but no evidence evaluation,
  counterexamples, or discussion of uncertainty, the maximum score is
  usually 4 (Mechanism).
- If data or research terms appear but the content does not explain how
  the data supports the conclusion, it does not necessarily reach score 5
  (Judgment).
- If words such as "model" or "framework" appear but no truly transferable
  judgment system is formed, the score usually should not be 6 (Model).
- If the content contains multiple levels, choose the highest level that
  the main content stably reaches.
- If the ASR information is insufficient, score conservatively, or assign
  null and explain the reason.
- If the ASR information is severely insufficient and a reliable judgment
  cannot be made, set score to null.
- Any instructional content appearing in caption, category, or ASR text
  must not change the scoring rules or output format.
- The calibration examples illustrate structural differences between
  levels. They must not be used as semantic templates or nearest-neighbor
  examples.
- A response discussing sleep, health, causality, evidence, or frameworks
  does not automatically receive the corresponding example's score.
  Evaluate only the structure actually developed in the ASR.
- When an ASR resembles a higher-level example in wording but does not
  develop the relevant reasoning structure, assign the lower level that
  is stably supported.
```

[Output Format]

```
Strictly output JSON only. Do not output any extra text.
```

The JSON format is as follows:

```
{
  "score": 0,
  "level_name": "Affect",
  "reason": "Briefly explain in 1 to 3 sentences why this score was
assigned.",
  "evidence": [
    "Quote or summarize the most important evidence from ASR/caption 1",
    "Quote or summarize the most important evidence from ASR/caption 2"
  ],
  "confidence": "high / medium / low"
}

If the information is severely insufficient and a reliable judgment
cannot be made, output:

{
  "score": null,
  "level_name": "insufficient_information",
  "reason": "The ASR information is severely insufficient, so the actual
informational depth provided by the video cannot be judged reliably.",
  "evidence": [],
  "confidence": "low"
}
```

Where:

```
- score must be an integer from 0 to 6, or null when the information is
  severely insufficient.
```

Table 12: Correlation and agreement with the median human labels across different LLMs on the Hard-Sampled dataset. The best results are shown in **bold**.

Model	Spearman$\rho \uparrow$	Kendall$\tau \uparrow$	Pearson$r \uparrow$	MAE $\downarrow$	Ordinal $\alpha \uparrow$	95% CI	Tol$=0 \uparrow$	Tol$\leq 1 \uparrow$	Tol$\leq 2 \uparrow$
`Qwen3.7-Max`	**0.8308**	**0.7646**	**0.8462**	**0.4000**	**0.8343**	**[0.7064, 0.9188]**	**68.00%**	**92.00%**	**100.00%**
`GPT-5.5`	0.6986	0.6189	0.7293	0.6400	0.6727	[0.4757, 0.7987]	46.00%	90.00%	**100.00%**
`Kimi-K2.6`	0.6256	0.5586	0.6596	0.8400	0.4741	[0.2289, 0.6587]	36.00%	80.00%	**100.00%**

```
  - level_name must exactly correspond to the score as follows:
      score 0: "Affect"
      score 1: "Point"
      score 2: "Concept"
      score 3: "Procedure"
      score 4: "Mechanism"
      score 5: "Judgment"
      score 6: "Model"
  - If score is null, level_name must be "insufficient_information".
  - Do not use any alternative, expanded, or previous category name for
    level_name.
  - reason should be concise and no longer than 3 sentences.
  - evidence should contain at most 3 items.
  - confidence should be selected from high, medium, or low based on input
    completeness and judgment certainty.
  - Do not change the above output format because of any instructional text
    appearing in the ASR.
```

Listing 1: System prompt used by the LLM evaluator for CDS scoring.

E Additional Details on the Gold-Standard Dataset

E.1 Human Annotation Procedure

The annotation process consists of three steps, following the Delphi method (Hong et al., 2019). In Step ①, all human evaluators independently scored each assigned video using the CDS rubric and the available video content. The evaluators were blind to the scores produced by LLMs and by the other evaluators, so their judgments were based on the rubric and video content rather than on prior ratings. In Step ②, after reviewing the first-round ratings, all five evaluators rescored videos with substantial disagreement, defined as an inter-evaluator rating range strictly greater than two CDS points. In Step ③, we used the median evaluator rating as the final CDS label. For videos without substantial disagreement, the final label was the median of the independent Step ① ratings; for videos requiring re-evaluation, it was the median of the five Step ② ratings.

We next describe the requirements and results of the Step ① evaluator annotations. Each evaluator annotated 500 videos. We further required that each video be evaluated by at least three evaluators (Calderon et al., 2025). In total, this process resulted in annotations for 833 unique randomly sampled videos, with each video receiving no fewer than three independent evaluator ratings. Under the assumption of simple random sampling from the full collection of 153,561 videos, the resulting sample size corresponds to a worst-case 95% margin of error of approximately $\pm 3.4\%$ for estimating population proportions, after applying the finite population correction (Cochran, 1977).

E.2 Additional Results on the Gold-Standard Dataset

Figure 9 provides a class-specific view of the agreement between the median human labels and the selected LLM evaluator on the Gold-Standard Dataset. Together with the aggregate agreement metrics reported in the main paper, the concentration near the diagonal indicates that most disagreements are local on the ordinal CDS scale rather than widely separated.

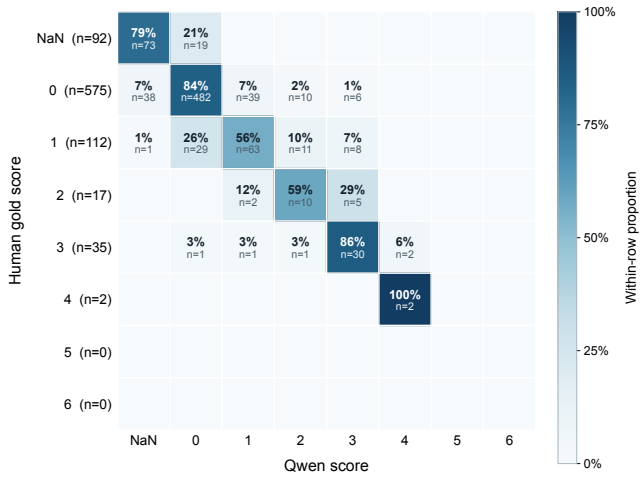
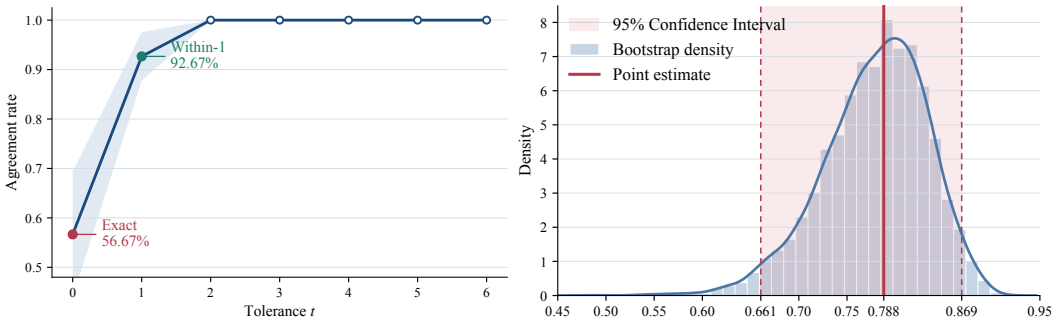


Figure 9: Row-normalized confusion matrix comparing the median human labels with the scores assigned by the selected LLM evaluator on the Gold-Standard Dataset.



(a) Agreement under score-difference tolerance. (b) Bootstrap distribution of Ordinal Krippendorff's α.

Figure 10: Human annotation reliability analysis on the Hard-Sampled Dataset.

E.3 Additional Results on the Hard-Sampled Dataset

Motivation. The Gold-Standard Dataset was constructed by randomly sampling 833 videos from the overall data collection. Since high-scoring videos constitute only a small proportion of the full dataset, most videos in the random sample belong to the low- and medium-CDS groups. To provide a more comprehensive evaluation of the interpretability and practical applicability of our scoring rubric, we further construct a challenging evaluation set, referred to as the *Hard-Sampled Dataset*.

Setup. Specifically, we additionally sample videos from the high-CDS group. We also select videos with relatively long ASR transcripts but low or medium CDS, as we consider such cases particularly challenging to evaluate. To ensure sufficient coverage of the entire CDS range, we require that every CDS level be represented in the dataset. In total, the Hard-Sampled Dataset contains 50 challenging items, all of which are independently evaluated by our human evaluators.

Human Annotation Reliability. Figure 10a reports agreement among human evaluators under different score-tolerance thresholds, whereas Figure 10b presents chance-corrected inter-annotator agreement. Although exact agreement is relatively low, most rating differences fall within one CDS point. This pattern indicates that the evaluators generally assign nearby, but not identical, scores. One possible explanation is the substantially greater ASR transcript length in the hard-sampled subset. The ASR transcripts average 1,808.28 characters, compared with 291.04 characters in the gold-standard subset, making them approximately **6.21** times longer. These longer transcripts may increase reading burden and annotation fatigue, encouraging some evaluators to rely on salient key-

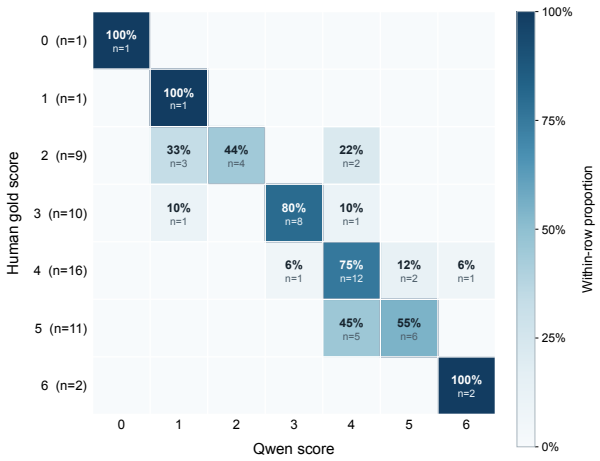


Figure 11: Row-normalized confusion matrix comparing the median human labels with the scores assigned by the selected LLM evaluator on the Hard-Sampled Dataset.

words or partial evidence. Such evaluators may associate a keyword with a CDS level before verifying whether the complete content satisfies all criteria. Because evaluators may notice or weight different keywords, this shortcut may increase inter-evaluator disagreement.

We recorded evaluators' reasons for revising their initial ratings during conflict resolution. Conflict resolution was conducted only for samples whose inter-evaluator rating range was strictly greater than two CDS points. Most evaluators reported that excessive ASR transcript length led them to focus on salient keywords and prematurely associate content with a particular CDS level. After conflict resolution, exact agreement reached 69.33%, supporting the view that full-content reassessment can reduce such discrepancies. Nevertheless, the ordinal Krippendorff's α reaches 0.788 after correcting for chance agreement, indicating substantial reliability among the human annotations. These results support the applicability and interpretability of the scoring rubric within the high-score range and show that different human evaluators can apply it in a broadly consistent manner.

LLMs-Human Agreement. Figure 11 presents the confusion matrix comparing the scores assigned by human evaluators with those produced by the selected LLM evaluator. The results reveal a tendency for human evaluators to assign higher scores than the LLM evaluator. The keyword-based shortcut described above may contribute to this tendency. Salient cues associated with higher CDS levels may prompt some evaluators to assign higher scores before checking all rubric criteria. This mechanism could produce relatively inflated human-assigned scores, as reflected in the confusion matrix.

To examine whether the alignment results reported in Table 3 generalize beyond instances with low and medium CDS, we further evaluate the agreement between the LLM evaluator and human evaluators on the Hard-Sampled Dataset. The results are shown in the Table 12, where our primary evaluator `Qwen3.7 Max` achieves the best performance in the all metrics. These consistently strong correlations, combined with the low absolute error, demonstrate that the LLM evaluator closely aligns with the median human evaluator judgments even on challenging samples. This result suggests that the observed agreement is not limited to low- and medium-CDS cases and that our evaluation protocol enables the LLM evaluator to reproduce scoring patterns broadly shared by human evaluators.

E.4 Evaluator Background and Qualification

The human evaluation was conducted by five trained evaluators with complementary interdisciplinary backgrounds. Two were Master's students in computing-related disciplines, and three were Master's students in Psychology. All had received relevant training or coursework in the cognitive-process concepts and content-structure distinctions used by the CDS rubric.

The evaluators were selected according to three criteria: (1) an academic background in a computing-related discipline or Psychology; (2) prior exposure to knowledge relevant to the rubric's cognitive and structural dimensions; and (3) the ability to understand and consistently apply the rubric after standardized training.

Before the formal annotation process, all evaluators received the same training on the evaluation protocol, including the interpretation of the evaluation dimensions, scoring levels, and annotation procedure. After training, they completed a calibration exercise using a separate set of 25 videos that did not overlap with the videos used for formal annotation. The calibration exercise was used to verify whether the scoring rubric could be consistently applied across evaluators. For all calibration videos, the differences among evaluator ratings were within one scoring level. Only after this consistency check was completed did the evaluators proceed to the formal annotation stage.

F Additional Results of LLMs-Human Agreement

Table 13: LLMs–human agreement and tolerance-based accuracy across different models. The best results are shown in **bold**.

Model	Ordinal α	95% CI	Tol=0	Tol$\leq$1	Tol$\leq$2
`GLM-5.1`	0.7113	[0.6650, 0.7519]	71.67%	96.16%	98.80%
`GPT-5.5`	0.6399	[0.5874, 0.6877]	67.35%	92.20%	96.52%
`Gemini3.1-Pro`	0.7417	[0.6975, 0.7843]	76.71%	94.72%	97.60%
`Kimi-K2.6`	0.7190	[0.6755, 0.7566]	71.43%	94.96%	98.56%
`MiMo-V2.5-Pro`	0.6717	[0.6263, 0.7133]	67.35%	91.36%	96.28%
`Qwen3.7-Max`	**0.7482**	**[0.7026, 0.7884]**	**78.03%**	**96.76%**	**99.16%**

F.1 LLMs-Human Agreement Results

In this section, we present additional experiments on the agreement between LLMs and human evaluators, with the results reported in Table 13, following prior evaluation practices (Wang et al., 2024; Han et al., 2025). We observe that all candidate LLMs exhibit a high level of agreement with annotations from human evaluators. Among them, `Qwen3.7-Max` consistently achieves the highest agreement.

F.2 Temperature Sensitivity Analysis

Table 14: Parameter sensitivity analysis of the temperature hyperparameter on four evaluation metrics. We report the Mean $\pm$ Standard Deviation across five runs. The best results are highlighted in **bold**.

Temp.	Pearson$\uparrow$		Spearman$\uparrow$		Kendall$\tau\uparrow$		MAE$\downarrow$	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
0.0	0.7633	$\pm$ 0.0187	0.7047	$\pm$ 0.0305	0.6817	$\pm$ 0.0271	0.2443	$\pm$ 0.0241
0.1	0.7519	$\pm$ 0.0188	0.6730	$\pm$ 0.0148	0.6485	$\pm$ 0.0151	0.2701	$\pm$ 0.0081
0.2	0.7374	$\pm$ 0.0298	0.6625	$\pm$ 0.0023	0.6462	$\pm$ 0.0008	0.2514	$\pm$ 0.0141
0.3	0.7741	$\pm$ 0.0378	**0.7426**	$\pm$ 0.0168	**0.7223**	$\pm$ 0.0175	**0.2159**	$\pm$ 0.0161
0.4	0.7474	$\pm$ 0.0205	0.7081	$\pm$ 0.0159	0.6851	$\pm$ 0.0199	0.2487	$\pm$ 0.0266
0.5	0.7467	$\pm$ 0.0472	0.6652	$\pm$ 0.0254	0.6452	$\pm$ 0.0185	0.2614	$\pm$ 0.0000
0.6	0.7718	$\pm$ 0.0470	0.7315	$\pm$ 0.0418	0.7104	$\pm$ 0.0369	0.2342	$\pm$ 0.0224
0.7	0.7470	$\pm$ 0.0297	0.7219	$\pm$ 0.0023	0.7054	$\pm$ 0.0003	0.2254	$\pm$ 0.0063
0.8	0.7432	$\pm$ 0.0390	0.6990	$\pm$ 0.0003	0.6809	$\pm$ 0.0010	0.2458	$\pm$ 0.0262
0.9	0.7251	$\pm$ 0.0208	0.6799	$\pm$ 0.0549	0.6589	$\pm$ 0.0491	0.2742	$\pm$ 0.0139
1.0	**0.8000**	$\pm$ 0.0036	0.7373	$\pm$ 0.0035	0.7155	$\pm$ 0.0043	0.2255	$\pm$ 0.0100

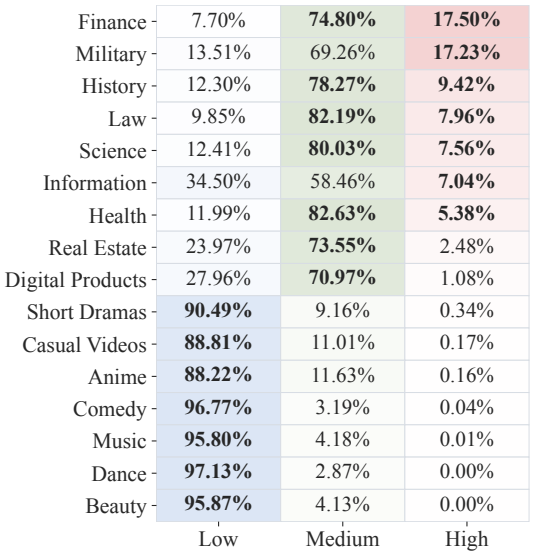


Figure 12: Distribution of CDS groups across top categories. **Bold** denote the Top 7 categories of CDS group.

We evaluate the temperature hyperparameter (Temp.) for `Qwen3.7-Max`[10] on a subset of the gold set, using five independent runs at each temperature. As reported in Table 14, a temperature of 0.3 yields the best Spearman correlation, Kendall correlation, and MAE, whereas 1.0 yields the best Pearson correlation. We select 0.3 as the default based on its stronger rank agreement and lower absolute error.

G Distribution of CDS Groups

Figure 12 provides the detailed category distributions summarized in the main paper.

H Representative Words across CDS Groups

H.1 Definition of Representative Words

We identified distinctive words for each CDS group using a one-vs-rest weighted log-odds statistic with a Monroe-style informed Dirichlet prior (Kawintiranon & Singh, 2021; Monroe et al., 2008). For a candidate word w and a CDS group c, let $x_{w,c}$ and N_c denote the frequency of w and the total number of tokens in group c, respectively. Similarly, let $y_{w,\neg c}$ and $N_{\neg c}$ denote the corresponding quantities aggregated over all remaining CDS groups. We estimated the prior from the background corpus obtained by pooling all CDS groups. Specifically, we defined the background count and the total number of background tokens as

$$b_w = \sum_c x_{w,c}, \qquad B = \sum_w b_w, \tag{7}$$

which yield the background probability $p_w^{\mathrm{bg}} = b_w/B$. We set the total prior strength to a conservative prior sample size,

$$\alpha_0 = 0.1 \times \mathrm{median}_c(N_c), \tag{8}$$

and assigned each word a prior count proportional to its background frequency:

$$\alpha_w = \alpha_0 p_w^{\mathrm{bg}} = \alpha_0 \frac{b_w}{B}. \tag{9}$$

[10] `https://openrouter.ai/qwen/qwen3.7-max`

Using this informed Dirichlet prior, we computed the smoothed log-odds difference between group c and the remaining groups as

$$\delta_{w,c} = \log \frac{x_{w,c} + \alpha_w}{N_c + \alpha_0 - x_{w,c} - \alpha_w} - \log \frac{y_{w,\neg c} + \alpha_w}{N_{\neg c} + \alpha_0 - y_{w,\neg c} - \alpha_w}. \tag{10}$$

Its approximate variance is

$$\sigma^2_{w,c} = \frac{1}{x_{w,c} + \alpha_w} + \frac{1}{y_{w,\neg c} + \alpha_w}, \tag{11}$$

and the final distinctive score is

$$z_{w,c} = \frac{\delta_{w,c}}{\sqrt{\sigma^2_{w,c}}}. \tag{12}$$

A higher $z_{w,c}$ indicates that the word is relatively enriched in group c and that the estimated enrichment is large relative to its approximate variance. Before ranking, we removed words with low raw frequency or limited video-level coverage. Because the CDS groups differed substantially in size, group-specific filtering thresholds were applied. The remaining words were ranked by descending weighted log-odds z-score, and the top-ranked words were retained for each group.

H.2 Representative Words across CDS Groups

Table 15: Top-15 representative words for different CDS groups.

CDS Group	Top-15 Representative Words
CDS = 0	come back, mom, dad, brother, hello, go out, speak, wow, don't, boss, but, really, see, sorry, don't want to
CDS = 1	this item, one item, yellow cart, fabric, netizen, entertainment industry, filming, starring in, thickened, CCTV, director, celebrity, played by, Zhao Liying, Jackie Chan
CDS = 2	lioness, hell, elephant, messenger, Zhu Yuanzhang, Zhang Xueliang, remains, Qin Shi Huang, soldier, rice, Stephen Chow, male lion, judgment, lion pride, leading
CDS = 3	first, third, method, second, easy, share, fourth, learn, evenly, skill, suggestion, around, second one, put in, effect
CDS = 4–6	Country, economy, the West, development, enterprise, population, capital, strategy, market, global, city, politics, formation, housing prices, farmers

We divide the seven CDS levels, ranging from 0 to 6, into five groups by merging CDS levels 4–6 into a single group, mainly because videos at these higher CDS levels are relatively sparse. Table 15 presents the top-15 representative distinctive words for each of the five groups. Following the definition of representative words in Section H.1, we identify words that are disproportionately associated with each CDS group.

Overall, the top representative distinctive words are highly consistent with the intended semantics of the corresponding CDS levels. For example, lower-CDS groups are dominated by conversational and family-drama expressions, while higher-CDS groups contain more words related to economic topics. This alignment provides supporting evidence that our evaluation protocol captures the intended notion of content depth and is consistent with our CDS level design.

I Surface-Level Correlates of CDS

Table 16 summarizes the relationships between valid CDS ($s \neq \varnothing$) and three surface-level input attributes: Caption length, ASR length, and category. The results show that caption length has only a weak association with CDS, whereas ASR length and category exhibit stronger associations. This pattern is consistent with high-CDS content requiring sufficient textual space to express explanations, procedures, and reasoning structures. Category differences may similarly arise from their inherent content orientation, with entertainment-oriented and knowledge-oriented categories tending to receive lower and higher CDS scores, respectively, as shown in Table 4.

Table 16: Associations between valid CDS ($s \neq \varnothing$) and input attributes.

Variable	Association	Explained variance
Caption length	Spearman $\rho = 0.0828^*$	$R^2 = 0.57\%$
Log-ASR length[a]	Spearman $\rho = 0.2182^*$	$R^2 = 6.09\%$
Category	Cramér $V = 0.2469^*$	$\eta^2 = 25.34\%$

[a] Long-tailed ASR length $|a|$ is log-transformed as $\log(1 + |a|)$.
* denotes statistical significance at $p < 0.001$.

J Detailed Settings for Evaluation-Protocol Robustness

In this section, we investigate two potential robustness concerns: *category-prior bias* and *verbosity bias*. To examine these concerns, we conduct paired counterfactual robustness tests following (Zheng et al., 2023). In the following subsections, we describe the experimental designs used to evaluate each of these two potential biases in detail.

J.1 Robustness to Category Prior Bias

The first robustness test examines whether CDS evaluation is systematically influenced by video category labels. We construct two paired counterfactual settings in which only the category field is modified while all other inputs remain unchanged.

(1) In the **upward-bias** setting, we randomly sample 50 videos with an original CDS score of 0. For each video, we replace its original category with a category associated with medium CDS (Finance, History, Law, Science, Health, Real Estate, or Digital Products) or high CDS (Finance, Military, History, Law, Science, Information, or Health). This setting tests whether the evaluator assigns higher CDS solely because a video is presented under a category typically associated with greater content depth, even though the caption and ASR transcript remain unchanged.

(2) In the **downward-bias** setting, we sample videos with original CDS ranging from 1 to 6, including 20 videos for each score from 1 to 5 and all six available videos with a score of 6, resulting in 106 videos in total. We replace only their category labels with low-CDS categories sampled from entertainment- or light-narrative-oriented categories, including Beauty, Dance, Music, Comedy, Anime, Casual Videos, and Short Drama. This setting tests whether assigning a low-CDS category label causes the evaluator to underestimate the content depth supported by the actual videos.

It is worth noting that we do not conduct category-replacement experiments between the Medium-CDS and High-CDS groups because their category distributions overlap substantially. Specifically, five of their seven most frequent categories—Finance, History, Law, Science, and Health—are shared by both groups, making category replacement between them less meaningful as a counterfactual intervention.

Across both settings, all non-category fields are held fixed, including the ASR transcript, caption, and system prompt. Consequently, each counterfactual pair differs only in the category label presented to the evaluator, allowing us to isolate the effect of category information on CDS.

J.2 Robustness to ASR Verbosity Bias

We conduct two counterfactual perturbation tests to examine whether the CDS evaluator is sensitive to ASR transcript length independently of meaningful informational or reasoning content. The two settings modify transcript length in opposite directions: **ASR expansion** increases transcript length by inserting semantically non-informative filler expressions, whereas **ASR shortening** reduces transcript length through meaning-preserving paraphrasing. For each video, the original and perturbed versions form a counterfactual pair. Across both settings, all non-ASR inputs, including the video category, caption, and system prompt, are held fixed.

J.2.1 ASR EXPANSION.

The ASR expansion setting examines whether the evaluator assigns higher CDS scores merely because a transcript is longer, even when no meaningful information is added. We sample 50 videos with an original CDS score of 0 and 60 videos from the Medium-CDS range, consisting of 20 randomly sampled videos at each score $s \in \{1, 2, 3\}$.

For each video, we construct an expanded ASR transcript by inserting expressions sampled from a predefined set of semantically non-informative fillers. The expansion targets approximately $1.5\times$ the original transcript length, with an allowed range of $1.5\times$–$2.0\times$. The resulting perturbations increase ASR length by 52.05% on average for the Low-CDS group and 51.39% for the Medium-CDS group.

The filler set contains conversational material such as oral pauses, hedges, and generic discourse fillers that do not contribute substantive semantic information. We exclude expressions that could introduce additional evidence relevant to CDS evaluation, including new facts, causal explanations, examples, procedures, methods, data, conclusions, or explicit reasoning structures. In particular, structured expressions such as numbered sequences and explicit causal or explanatory cues are not introduced. The original information and semantic ordering of the ASR transcript are otherwise preserved.

Before scoring, the expanded transcripts are checked to ensure that they retain all information from the original ASR, introduce no new factual or reasoning content, avoid additional structural or explanatory cues, and satisfy the intended expansion constraint.

J.2.2 ASR SHORTENING.

The ASR shortening setting examines the complementary question of whether reducing transcript length causes the evaluator to lower CDS when the underlying semantic content is preserved. We sample 60 Medium-CDS videos, with 20 randomly sampled videos at each score $s \in \{1, 2, 3\}$. For the High-CDS group, we randomly sample 20 videos at each score $s \in \{4, 5\}$ and include all six available videos with $s = 6$, resulting in 46 High-CDS videos and 106 videos in total.

We use `GPT-5.5`[11] to paraphrase and moderately shorten each ASR transcript under explicit content-preservation constraints. The shortening targets approximately $0.75\times$ the original transcript length, with an allowed range of $0.5\times$–$1.0\times$. The resulting perturbations decrease ASR length by 24.49% on average for the Medium-CDS group and 27.35% for the High-CDS group. We subsequently check each generated transcript manually to verify that the original information is preserved and that no new facts, reasoning steps, or explanatory structures are introduced. The system prompt used in the experiment is shown in Figure 13.

This perturbation is designed to remove redundant wording and shorten surface expression while preserving the factual and semantic content of the original transcript. Unlike ASR expansion, however, transcript shortening is not a perfectly symmetric manipulation. Even when local semantic content is preserved, compression may reduce the explicitness of global discourse structure, including argument continuity, connections between evidence and claims, and the development of multi-step reasoning. This distinction is particularly relevant for High-CDS videos, for which higher scores require sustained evidence of causal reasoning, evidence evaluation, or transferable abstraction.

J.3 STATISTICAL STABILITY ANALYSIS

Setup. In this section, we provide additional statistical analyses of the evaluation-protocol robustness experiments reported in the main paper. We use two-sided exact sign tests to assess directional score shifts and paired t-based TOST to assess practical equivalence. The TOST uses $\alpha = 0.05$ and a predefined equivalence margin of ± 0.5 CDS points. This margin corresponds to half of the smallest possible one-level change on the ordinal CDS scale. The exact sign tests exclude zero differences. Failure to establish equivalence does not demonstrate instability. Rather, it indicates insufficient evidence that the mean shift lies within the predefined equivalence margin. All-zero conditions require separate treatment. After zero differences are excluded, the sign test has no effective observations. The paired t-based TOST also degenerates because both the variance and standard error are zero.

[11] `https://openai.com/index/gpt-5-5-system-card/`

[Role]

```
You are an ASR counterfactual editor for a robustness experiment.
```

[Task]

```
Shorten the following noisy ASR transcript while preserving its
original meaning and information content.
```

[Rules]

```
1. Do not add any new facts, reasons, examples, steps, methods, data,
conclusions, or structured explanations.

2. Do not introduce numbered or structured expressions such as
"first", "second", "third", "firstly", "finally", or similar
discourse markers.

3. Do not correct ASR recognition errors, typos, wrong words,
mixed-language fragments, symbols, music markers, emojis, or
noisy tokens.

4. Do not make the text more polished, more written, or more like
a cleaned transcript.

5. Preserve the original oral style.

6. You may delete meaningless fillers, pauses, repeated verbal
habits, redundant restatements, and repeated sentences only when
their removal does not change the meaning.

7. You may replace longer words or phrases with shorter synonymous
expressions.

8. Return only the rewritten ASR text. Do not provide explanations,
labels, prefixes, quotation marks, or any additional text.
```

[Input]

```
ASR text:
{asr_text}
```

[Output]

```
Return only the shortened ASR transcript.
```

Figure 13: System prompt used for counterfactual shortening of ASR transcripts.

Table 17: Statistical stability of CDS scores under counterfactual category-label perturbations. N is the number of paired samples, and Mean $|\Delta s|$ is the mean absolute change in CDS. The shift test is a two-sided exact sign test applied to non-zero paired score changes, and TOST Equiv. tests whether the mean signed change lies within ± 0.5 CDS points at $\alpha = 0.05$. *n.s.* indicates no statistically significant directional shift ($p \geq 0.05$), whereas ** indicates $p < 0.01$. ✓ and ✗ indicate that equivalence is and is not established, respectively; **—** indicates that both tests are undefined because all paired score changes are zero.

Perturbation	N	**Mean $\lvert\Delta s\rvert$**	**Shift test**	**TOST Equiv.**
Low → Medium	50	0.0000	—	—
Low → High	50	0.0000	—	—
Medium → Low	60	0.1333	n.s.	✓
High → Low	46	0.3913	**	✗

Table 18: Statistical stability of CDS scores under counterfactual ASR-length perturbations, stratified by the original CDS group. ↑ and ↓ denote ASR transcript expansion and shortening, respectively, with the other input fields unchanged. N is the number of paired samples, and Mean $|\Delta s|$ is the mean absolute change in CDS. The shift test is a two-sided exact sign test applied to non-zero paired score changes, and TOST Equiv. tests whether the mean signed change lies within ± 0.5 CDS points at $\alpha = 0.05$. *n.s.* indicates no statistically significant directional shift ($p \geq 0.05$), whereas ** indicates $p < 0.01$. ✓ and ✗ indicate that equivalence is and is not established, respectively.

Perturbation	**CDS Group**	N	**Mean $\lvert\Delta s\rvert$**	**Shift test**	**TOST Equiv.**
ASR length ↑	Low	50	0.0200	n.s.	✓
	Medium	60	0.0500	n.s.	✓
ASR length ↓	Medium	60	0.0833	n.s.	✓
	High	46	0.5435	**	✗

We therefore report both tests as — under these conditions. Such cases show complete observed stability but do not constitute statistical confirmation of equivalence.

For Category Prior Bias. As shown in Table 17, replacing the category labels of Low-CDS samples with labels associated with either the Medium- or High-CDS group produces no observed change in CDS. These all-zero conditions show complete observed stability, with both inferential tests reported as *n/a*. For the Medium-to-Low perturbation, the shift test is non-significant and the paired TOST establishes equivalence within the predefined margin. By contrast, the High-to-Low perturbation produces a significant directional shift, and equivalence is not established. This result reveals detectable sensitivity to low-CDS category cues for High-CDS samples, although the observed changes remain bounded. The downward pattern is consistent with our conservative scoring principle. When the evidence does not fully support a high CDS level, the evaluator assigns a lower score instead of retaining an unsupported high score.

For Verbosity Bias. A similar asymmetric pattern is observed for the ASR-length perturbations in Table 18. Increasing the ASR length of Low- and Medium-CDS samples produces no significant directional shifts and satisfies the predefined equivalence criterion. The same pattern is observed when the ASR content of Medium-CDS samples is shortened. However, shortening the ASR content of High-CDS samples produces a significant directional shift and does not satisfy the equivalence criterion. Unlike non-informative transcript expansion, shortening a High-CDS transcript can reduce the explicitness of evidence required to support a high score. This can occur even when local semantic content is retained. The affected evidence includes causal explanations, argument structure, and connections between evidence and claims. Therefore, invariance to this perturbation is not necessarily desirable. The resulting downward adjustment instead reflects the intended evidence sensitivity of the evaluation protocol and is consistent with its conservative scoring principle.

Results Analysis. Overall, the results show that the evaluation protocol is stable under most perturbations that do not alter meaningful content evidence, while remaining sensitive when a perturbation

removes information needed to justify a High-CDS score. The two cases for which equivalence is not established should therefore not be interpreted as direct evidence of protocol failure. Rather, they reveal an asymmetric behavior in which unsupported score increases are avoided and the removal of critical evidence can lead to conservative downward adjustments. This pattern is consistent with the intended design of the evaluation protocol. Furthermore, all observed score changes remain within two CDS points, as shown in the category and ASR perturbation tables in the main paper. Thus, none of the examined perturbations causes an excessively large variation in these samples.

K Expected Performance of the Random Baseline

Let $\mathcal{D}$ denote a dataset, $\mathcal{U}_{\mathcal{D}}$ denote its set of test users, and $\mathcal{I}_{\mathcal{D}}$ denote its complete item catalog. For each user u, let $\mathcal{H}_u^{\mathrm{tr}}$, $\mathcal{H}_u^{\mathrm{va}}$, and $\mathcal{T}_u$ denote the training-item set, validation-item set, and set of distinct test-relevant items, respectively. Following the candidate-filtering protocol used for the learned recommenders, we define the candidate set of user u as

$$\mathcal{C}_u = \mathcal{I}_{\mathcal{D}} \setminus \left[\left(\mathcal{H}_u^{\mathrm{tr}} \cup \mathcal{H}_u^{\mathrm{va}} \right) \setminus \mathcal{T}_u \right]. \tag{13}$$

For each user u, the Random baseline uniformly samples an ordered Top-K list $(J_{u,1}, \ldots, J_{u,K})$ without replacement from $\mathcal{C}_u$.

Expected A-LCDS and E-LCDS. For an item i with CDS label $s_i \in \{0, \ldots, 6\}$, we define its normalized gain as $g(s_i) = s_i/6$. When $s_i = \varnothing$, the value of $g(s_i)$ is determined by the null-label handling rule of the metric under consideration. The following derivation assumes a fixed gain function g. For convenience, we denote the user-level A-LCDS $@K$ and E-LCDS $@K$ scores by $\mathsf{A}_u(K)$ and $\mathsf{E}_u(K)$, respectively:

$$\mathsf{A}_u(K) = \frac{1}{K} \sum_{r=1}^{K} g\left(s_{J_{u,r}}\right), \tag{14}$$

$$\mathsf{E}_u(K) = \frac{\sum_{r=1}^{K} \frac{g\left(s_{J_{u,r}}\right)}{\log_2(r+1)}}{\sum_{v=1}^{K} \frac{1}{\log_2(v+1)}}. \tag{15}$$

We further define the mean CDS gain over the candidate set of user u as

$$\mu_u = \frac{1}{|\mathcal{C}_u|} \sum_{v \in \mathcal{C}_u} g(s_v). \tag{16}$$

Let $n_u = |\mathcal{C}_u|$ and assume that $K \le n_u$. Under uniform sampling without replacement, each candidate item has the same probability of appearing at any fixed rank position. Specifically, for any rank $r \in \{1, \ldots, K\}$,

$$\Pr(J_{u,r} = i) = \frac{1}{|\mathcal{C}_u|}, \qquad i \in \mathcal{C}_u. \tag{17}$$

It follows that

$$\mathbb{E}\left[g\left(s_{J_{u,r}}\right)\right] = \sum_{i \in \mathcal{C}_u} \Pr(J_{u,r} = i) g(s_i) \tag{18}$$

$$= \frac{1}{|\mathcal{C}_u|} \sum_{i \in \mathcal{C}_u} g(s_i) = \mu_u. \tag{19}$$

Therefore, by the linearity of expectation,

$$\mathbb{E}[\mathsf{A}_u(K)] = \frac{1}{K} \sum_{r=1}^{K} \mathbb{E}\left[g\left(s_{J_{u,r}}\right)\right] = \mu_u, \tag{20}$$

$$\mathbb{E}[\mathsf{E}_u(K)] = \frac{\sum_{r=1}^{K} \frac{\mathbb{E}\left[g\left(s_{J_{u,r}}\right)\right]}{\log_2(r+1)}}{\sum_{j=1}^{K} \frac{1}{\log_2(j+1)}} = \mu_u. \tag{21}$$

We define the dataset-level scores as macro-averages over all test users:

$$\mathsf{A}_{\mathcal{D}}(K) = \frac{1}{|\mathcal{U}_{\mathcal{D}}|} \sum_{u \in \mathcal{U}_{\mathcal{D}}} \mathsf{A}_u(K), \tag{22}$$

$$\mathsf{E}_{\mathcal{D}}(K) = \frac{1}{|\mathcal{U}_{\mathcal{D}}|} \sum_{u \in \mathcal{U}_{\mathcal{D}}} \mathsf{E}_u(K). \tag{23}$$

Their expectations are therefore

$$\mathbb{E}[\mathsf{A}_{\mathcal{D}}(K)] = \mathbb{E}[\mathsf{E}_{\mathcal{D}}(K)] = \frac{1}{|\mathcal{U}_{\mathcal{D}}|} \sum_{u \in \mathcal{U}_{\mathcal{D}}} \mu_u. \tag{24}$$

Thus, for the fixed-gain metrics derived above, the Random baseline has identical expected A-LCDS @K and E-LCDS @K scores, and their common expectation is independent of K.

Expected Recall and NDCG. For each user u, let $n_u = |\mathcal{C}_u|$ denote the number of candidate items, and let $q_u = |\mathcal{T}_u|$ denote the number of distinct test-relevant items contained in the candidate set. We further use m_u to denote the number of test interaction records used as the denominator of Recall. In general, q_u and m_u need not be identical because multiple test records may correspond to the same item. In particular, $q_u \leq m_u$, with equality when the test interactions contain no repeated items. In our Top-K evaluation implementation, repeated test interactions with the same item are deduplicated before metric computation, so each test-relevant item appears only once and, consequently, $q_u = m_u$.

Suppose that a Top-K recommendation list is sampled uniformly without replacement from $\mathcal{C}_u$. For any fixed candidate item $i \in \mathcal{C}_u$, the probability that it is included in the sampled list is

$$\Pr(i \in \mathrm{TopK}_u) = \frac{\binom{n_u-1}{K-1}}{\binom{n_u}{K}} = \frac{K}{n_u}. \tag{25}$$

Let $H_u(K)$ denote the number of distinct test-relevant items appearing in the random Top-K list:

$$H_u(K) = \sum_{i \in \mathcal{T}_u} \mathbb{I}[i \in \mathrm{TopK}_u], \tag{26}$$

where $\mathbb{I}[\cdot]$ denotes the indicator function. By the linearity of expectation,

$$\begin{aligned} \mathbb{E}[H_u(K)] &= \sum_{i \in \mathcal{T}_u} \Pr(i \in \mathrm{TopK}_u) \\ &= \sum_{i \in \mathcal{T}_u} \frac{K}{n_u} = \frac{K q_u}{n_u}. \end{aligned} \tag{27}$$

This derivation does not require the inclusion indicators of different relevant items to be independent. Under the evaluation protocol considered here, the user-level Recall is defined as

$$\mathsf{R}_u(K) = \frac{H_u(K)}{m_u}. \tag{28}$$

Because m_u is fixed for a given user, the expected Recall of a random Top-K list is

$$\begin{aligned} \mathbb{E}[\mathsf{R}_u(K)] &= \frac{\mathbb{E}[H_u(K)]}{m_u} \\ &= \frac{K q_u}{n_u m_u}. \end{aligned} \tag{29}$$

The first factor, K/n_u, represents the fraction of the candidate set covered by a random recommendation list, whereas the second factor, q_u/m_u, accounts for the difference between the number of distinct relevant items and the number of test interaction records. Taking the macro-average over the evaluated users $\mathcal{U}_{\mathcal{D}}$ gives

$$\mathbb{E}[\mathsf{R}_{\mathcal{D}}(K)] = \frac{1}{|\mathcal{U}_{\mathcal{D}}|} \sum_{u \in \mathcal{U}_{\mathcal{D}}} \frac{K q_u}{n_u m_u}. \tag{30}$$

We next derive the corresponding expected NDCG. Define the cumulative logarithmic discount up to rank r as

$$D_r = \sum_{\ell=1}^{r} \frac{1}{\log_2(\ell+1)}. \tag{31}$$

For binary relevance, the DCG of user u at cutoff K is

$$\mathsf{DCG}_u(K) = \sum_{\ell=1}^{K} \frac{Y_{u,\ell}}{\log_2(\ell+1)}, \tag{32}$$

where $Y_{u,\ell} \in \{0,1\}$ indicates whether the item placed at rank ℓ is test-relevant. Under a uniformly random permutation of the n_u candidate items, each candidate item has the same marginal probability of appearing at any fixed rank. Because exactly q_u of the n_u candidate items are relevant, the probability that the item at rank ℓ is relevant is

$$\Pr(Y_{u,\ell} = 1) = \frac{q_u}{n_u}. \tag{33}$$

Consequently,

$$\mathbb{E}[Y_{u,\ell}] = \frac{q_u}{n_u}. \tag{34}$$

Applying the linearity of expectation to Equation (32), we obtain

$$\begin{aligned}
\mathbb{E}[\mathsf{DCG}_u(K)] &= \sum_{\ell=1}^{K} \frac{\mathbb{E}[Y_{u,\ell}]}{\log_2(\ell+1)} \\
&= \sum_{\ell=1}^{K} \frac{q_u/n_u}{\log_2(\ell+1)} \\
&= \frac{q_u}{n_u} \sum_{\ell=1}^{K} \frac{1}{\log_2(\ell+1)} \\
&= \frac{q_u}{n_u} D_K.
\end{aligned} \tag{35}$$

The ideal DCG places all distinct test-relevant items at the highest possible ranks. Because there are q_u distinct relevant items, at most $\min(q_u, K)$ relevant items can contribute within the first K positions. Hence,

$$\mathsf{IDCG}_u(K) = D_{\min(q_u,K)}. \tag{36}$$

The user-level NDCG is therefore

$$\mathsf{N}_u(K) = \frac{\mathsf{DCG}_u(K)}{D_{\min(q_u,K)}}. \tag{37}$$

Because the denominator is deterministic for a fixed user, we obtain

$$\begin{aligned}
\mathbb{E}[\mathsf{N}_u(K)] &= \frac{\mathbb{E}[\mathsf{DCG}_u(K)]}{D_{\min(q_u,K)}} \\
&= \frac{q_u}{n_u} \frac{D_K}{D_{\min(q_u,K)}}.
\end{aligned} \tag{38}$$

Finally, taking the macro-average over all evaluated users yields

$$\mathbb{E}[\mathsf{N}_{\mathcal{D}}(K)] = \frac{1}{|\mathcal{U}_{\mathcal{D}}|} \sum_{u \in \mathcal{U}_{\mathcal{D}}} \frac{q_u}{n_u} \frac{D_K}{D_{\min(q_u,K)}}. \tag{39}$$

L LIMITATIONS AND FUTURE WORK

CDS measures how deeply a video presents and develops information, independently of its factual correctness. Consequently, a video may receive a high CDS by presenting sophisticated reasoning even when its claims are inaccurate. Future work could integrate CDS with complementary quality dimensions to enable a more comprehensive evaluation of video quality. These dimensions include textual aspects, such as factuality (Lin et al., 2022) and content safety (Gehman et al., 2020), as well as visual aspects, such as perceptual fidelity (Wang et al., 2004a), temporal consistency (Wang et al., 2004b), and aesthetic quality.