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I^3-MRec: Invariant Learning with Information Bottleneck for Incomplete Modality Recommendation

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Abstract

Multimodal recommender systems (MRS) improve recommendation performance by integrating complementary semantic information from multiple modalities. However, the assumption of complete multimodality rarely holds in practice due to missing images and incomplete descriptions, hindering model robustness and generalization. To address these challenges, we introduce a novel method called **I^3-MRec**, which uses **I**nvairant learning with **I**nformation bottleneck principle for **I**ncomplete **M**odality **Rec**ommendation. To achieve robust performance in missing modality scenarios, I^3-MRec enforces two pivotal properties: (i) cross-modal preference invariance, ensuring consistent user preference modeling across varying modality environments, and (ii) compact yet effective multimodal representation, as modality information becomes unreliable in such scenarios, reducing the dependence on modality-specific information is particularly important. By treating each modality as a distinct semantic environment, I^3-MRec employs invariant risk minimization (IRM) to learn preference-oriented representations. In parallel, a missing-aware fusion module is developed to explicitly simulate modality-missing scenarios. Built upon the Information Bottleneck (IB) principle, the module aims to preserve essential user preference signals across these scenarios while effectively compressing modality-specific information. Extensive experiments conducted on three real-world datasets demonstrate that I^3-MRec consistently outperforms existing state-of-the-art MRS methods across various modality-missing scenarios, highlighting its effectiveness and robustness in practical applications.

CCS Concepts

• **Information systems → Personalization**; **Recommender systems**; **Collaborative filtering**.

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Multimodal Recommendation, Invariant Learning, Information Bottleneck, Collaborative Filtering

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1 Introduction

Multimodal data has experienced explosive growth across various online platforms, including Amazon [1], YouTube[2], and TikTok[3]. To mitigate information overload and help users discover relevant items, Multimodal Recommender Systems (MRS) [24–26, 30, 54, 59, 65, 69, 76] leverage rich information from various modalities (e.g., item images, review texts) to model user preferences and generate more accurate recommendations. However, most existing MRS methods assume the availability of complete modality information to effectively extract recommendation-relevant signals [3, 35]. This assumption often fails in real-world settings, where incomplete modality data is often encountered in real-world applications, such as information retrieval [36, 49, 63], computer vision [50], and video-sharing platforms [23]. As illustrated in Fig. 1, many existing multimodal recommendation models suffer from performance degradation or even fail when confronted with missing modalities[4]. This frequent occurrence poses a substantial challenge to the robustness and practical applicability of MRS in real-world deployments.

To address the challenge of missing modalities, several efforts have been proposed [3, 14, 23, 27, 39, 49, 53, 63]. Early approaches often resorted to discarding items with incomplete modality information [39, 53], but this strategy worsens data sparsity and leads to substantial performance degradation. More recent efforts have attempted to recover missing modality data through various content generation techniques [3, 14, 23, 27, 49, 63]. For instance,

[1]https://www.amazon.com
[2]https://www.youtube.com
[3]https://www.tiktok.com
[4]For fair comparison, results are reproduced using the official code of the referenced method on the same dataset.

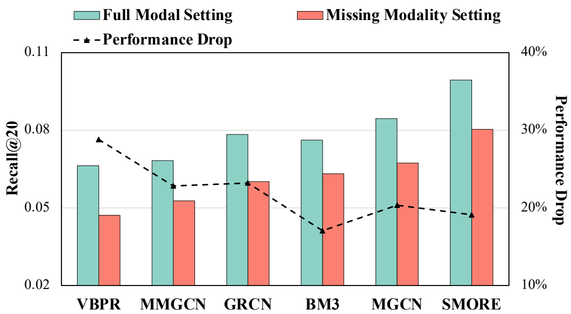


Figure 1: Performance of MRS methods on the Baby dataset under two settings. "Full Modality" indicates no missing modality during training and testing. "Missing Modality" follows the MTMT setup (Section 4.3), with random modality missingness in both phases.

CI^{2}MG [27] employs hypergraph convolution and cross-modal transport to generate missing modality features. In addition, representation learning approaches, such as feature propagation [36] and invariant learning [3], have been proposed to learn robust preference representations that remain effective under missing modality scenarios.

Although these methods have demonstrated promising effectiveness, the core challenges associated with missing modalities remain inadequately addressed: *How should an optimal recommender system perform when confronted with modality missingness?* On the one hand, generative methods [23, 27] often require extensive and time-consuming pre-training for each modality. This requirement contradicts the missing modality assumption, as it presumes the availability of large-scale, fully annotated multimodal data. On the other hand, existing representation-based approaches overlook the distinct characteristics of each modality. For example, MILK [3] adopts a modality-wise mixup strategy to simulate modality-missing environments. However, such operations can disrupt modality-specific semantic structures, ultimately making the model more vulnerable to performance degradation under real-world missing modality conditions.

We argue that a robust recommendation model should satisfy two key properties:

- **Cross-modal Preference Invariance:** User preferences are inherently stable across different modality sources [12]. A robust model should therefore learn preference-oriented user/item representations that remain invariant across modalities. This ensures that each individual modality representation can sufficiently support accurate preference prediction, thereby mitigating the negative impact of missing modalities.
- **Compact yet Effective Multimodal Representation:** The learned multimodal representations should maximally preserve user preference information pertinent to recommendation tasks while minimizing dependence on the raw modality information. As modality information becomes unreliable in such scenarios, especially when missing modalities randomly occur during training, reducing the dependence on modality-specific information is particularly important [34, 42, 62].

These two principles together promote recommendation robustness by ensuring robust representations and reducing the model's dependency on potentially unavailable modality data. To address this critical challenge, we propose **I^3-MRec** (Invariant learning with Information Bottleneck for Incomplete-Modality Recommendation), a unified framework specifically designed for robust recommendation under modality-missing scenarios. To achieve the goal, I^3-MRec adopts an invariant learning framework that explicitly treats each modality as a distinct semantic environment. It leverages a GCN-based architecture combined with Invariant Risk Minimization (IRM) to learn robust user and item representations (*thereby satisfying the first property*). Furthermore, we introduce a missing-aware fusion module guided by the Information Bottleneck (IB) principle [20, 46, 47] to explicitly simulate diverse modality-missing scenarios during training, maximizing mutual information between multimodal representations across these scenarios while minimizing the mutual information between the multimodal representation and each raw-modality feature. (*in alignment with the second property*). We have released the code and relevant parameter settings to facilitate repeatability as well as further research[5].

In summary, the main contributions of this work are as follows:

- We propose I^3-MRec, a novel framework that addresses the limitations of existing multimodal recommender systems in modality-missing scenarios. By integrating invariant learning with the information bottleneck principle, our method enhances model robustness and generalization.
- We introduce a principled invariant learning approach that models each modality as a distinct semantic environment. This enables learning of preference-oriented user/item representations, improving resilience to missing modality inputs.
- We design a missing-aware fusion module guided by the Information Bottleneck principle, which selectively retains preference-relevant information while compressing modality-specific information, resulting in compact yet effective multimodal representations.
- We have conducted extensive experiments on three real-world datasets, demonstrating the superiority of our method over state-of-the-art baselines.

2 Related Work

2.1 Multimodal Recommendation and Modality Missingness

Multimodal Recommender Systems leverage various multimedia content to enhance user-item interactions, offering significant advantages in applications such as online shopping [21, 29], video sharing platforms [5, 61], and social networks [75]. Early approaches [7, 17, 21] incorporated multimodal data as auxiliary features to enhance item representations. For instance, VBPR [17] integrates visual embeddings with item ID embeddings to better model user preferences. With the development of Graph Neural Networks (GNNs)[19, 31, 32, 55], subsequent work extended these models to incorporate multimodal signals into graph-based learning[6, 33, 60, 61], improving the quality of user and item node representations. Some methods, such as LATTICE [72], capture item-item semantic

[5] https://github.com/HuilinChenJN/I3-MRec.

affinities via modality-aware graphs. while DualGNN [52] models user-user relations to reveal latent preference patterns. In addition, recent advances have incorporated attention mechanisms [29], self-supervised learning [45, 76], and contrastive learning [27, 58] to better align and integrate cross-modality information.

Despite their effectiveness, these methods typically assume the availability of complete modality information. In practice, missing modalities can lead to significant performance degradation [3, 35]. To address this challenge, existing solutions fall into two broad categories: Generation-based approaches aim to reconstruct missing modality features through modality generation techniques [3, 14, 23, 27, 49, 63]. While effective in controlled settings, these methods typically incur high computational costs and lack flexibility when handling random or modality-specific missing patterns. e.g., MoDiCF [23] requires an auxiliary diffusion model to reconstruct missing modalities. Representation Learning-based methods focus on directly learning robust representations that remain effective even when specific modalities are missing [3, 36]. For instance, MILK [3] introduces a modality-invariant learning strategy; however, it assumes complete modality availability during training, which limits its applicability in real-world scenarios. By formulating the task within an invariant learning framework and incorporating an IB-guided fusion strategy, I^3-MRec generalizes effectively across various modality-missing scenarios.

2.2 Invariant Learning in Recommendation

Invariant learning (IL) [1, 2, 9, 22, 41] is emerging as a pivotal technique to enhance model generalization. This approach often posits that certain stable features exist within the data that causally determine the target labels. Moreover, the relationship between these stable features and labels remains invariant in different environments [68]. Recently, efforts have been made to incorporate invariant learning principles into recommendation systems [3, 12, 56, 70, 73]. For example, InvPref [56] estimates heterogeneous environments corresponding to different types of latent bias, while InvRL [12] exploits spurious correlations in user-item interactions caused by modality noise to differentiate environment sets. Departing from MILK [3], which ensures that modality-specific preferences remain stable in cyclic mixup-based heterogeneous modality environments, we treat modality-missing patterns as heterogeneous environments to learn stable, preference-oriented modality representations.

2.3 Information Bottleneck

The Information Bottleneck (IB) principle, based on information theory, is widely applied in machine learning tasks such as model robustness [11, 64, 71], fairness [15], explainability [13, 51], and recommendation systems [57, 66, 67, 74]. For input data X, hidden representation Z, and prediction label Y, IB principle suggests that an effective representation retains minimal sufficient information for the prediction task [20, 46, 47]: $Max : I(Y;Z) - \beta I(X;Z)$. where $I(Y;Z)$ and $I(X;Z)$ are the mutual information between variables, with β balancing the two terms. Calculating mutual information for continuous variables is difficult, especially in deep learning. Approximations using neural networks, such as MINE [4], InfoNCE [38], and variational methods [47], are commonly used. Recently, CLUB [8] has emerged to estimate the upper bound of mutual information using a log-ratio contrastive loss, which is more general for high-dimensional tasks without prior assumptions.

This work applies IB learning to multimodal recommender systems, making them robust to modality missingness. Given the difficulty of estimating the upper bound of mutual information, we use InfoNCE and CLUB to approximate and optimize the mutual information between modality features.

3 Preliminaries

3.1 Multimodal Recommendation Task

Let $\mathcal{U}$ and $\mathcal{I}$ denote the sets of users and items, with $|\mathcal{U}| = N_u$ and $|\mathcal{I}| = N_i$ representing the number of users and items. Items associated with multimodal features $X \in \mathbb{R}^{N \times D_k}$, where N is the number of modalities, and $k \in \{v, t, a\}$ indexes modality types (visual, textual, and acoustic); D_k is the dimension of k-th raw modality feature. The historical user-item interaction is denoted by the interaction matrix $\mathcal{R} \in \mathbb{R}^{|U| \times |I|}$, where $r_{u,i} = 1$ indicates an observed interaction between user u and item i; otherwise, $r_{u,i} = 0$. Thus, the multimodal recommendation task can be formally defined as predicting the probability $\bar{r}_{u,i}$ of user u and item i:

$$\bar{r}_{u,i} = \Gamma(u, i, \boldsymbol{X}_i | \Theta). \tag{1}$$

Here, $\Gamma(\cdot)$ is any recommender learning function parameterized by Θ to predict preference probability. $\boldsymbol{X}_i$ represents the multimodal feature set of item i.

3.2 Modality Missingness Problem

MRS typically models user preferences by first extracting modality features and then fusing them into a unified item representation. Formally, this process can be described as:

$$\boldsymbol{E}^k = g_{\theta_1}(\boldsymbol{X}^k), \qquad \boldsymbol{Z} = h_{\theta_2}(\boldsymbol{E}^a, \boldsymbol{E}^t, \boldsymbol{E}^v), \tag{2}$$

where $g_{\theta_1}(\cdot)$ learns task-relevant semantic representations $\boldsymbol{E}^k$ from each modality input $\boldsymbol{X}^k$, and $h_{\theta_2}(\cdot)$ integrates them into a unified item representation $\boldsymbol{Z}$ for user preference prediction. The overall objective is defined as:

$$\mathcal{L}_0 = \mathcal{L}(p(\boldsymbol{E}_u, \boldsymbol{Z}), R), \tag{3}$$

where $\boldsymbol{E}_u$ denotes user embeddings derived from user IDs[6], and R is the ground-truth interaction label.

However, this modeling paradigm heavily depends on the availability of complete multimodal inputs. When certain modalities are missing, both the feature extraction and fusion stages become unreliable, resulting in degraded preference modeling. To mitigate this, we propose a robust framework that integrates invariant learning and the information bottleneck principle.

4 Methodology

In this section, we present I^3-MRec (Invariant learning with Information Bottleneck for Incomplete-Modality Recommendation), as illustrated in Fig. 2, which consists of **Preference-oriented Multimodal Representation Learning** and **Missing-aware Feature**

[6]We adopt ID embeddings as user representations, assuming that user preferences are consistent across modalities.

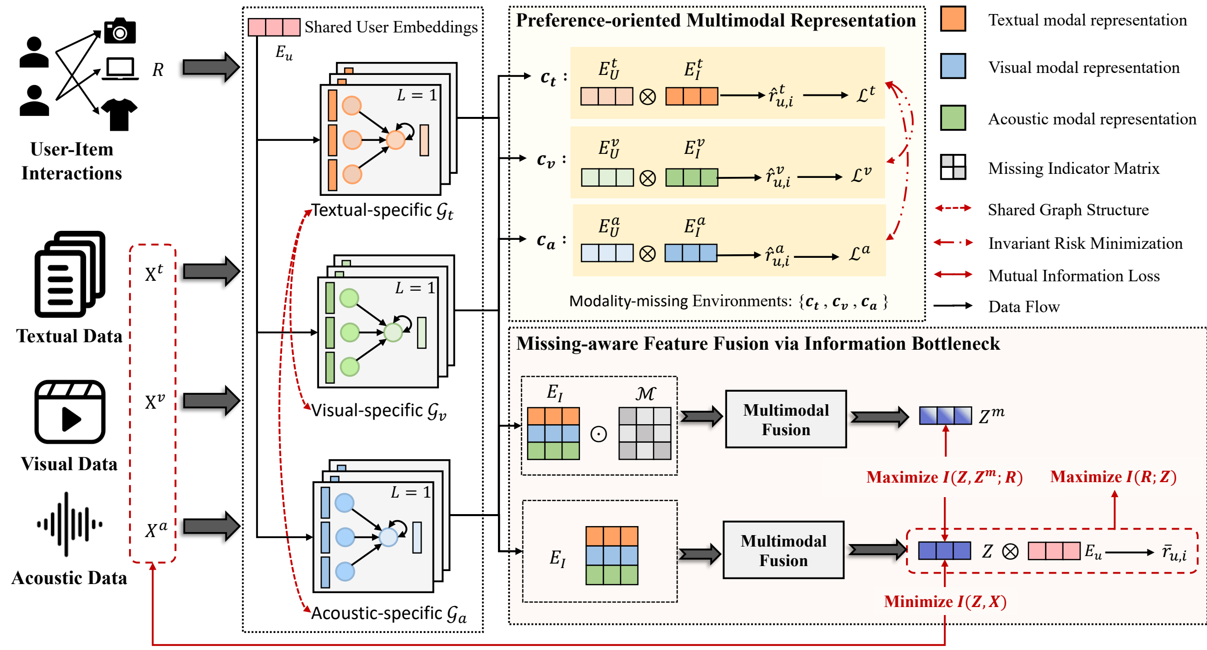


Figure 2: Overview of the proposed I^3-MRec framework. The model first learns preference-oriented user/item representations using a graph-based approach, guided by IRM to ensure invariance across modalities. Then, an IB-based fusion module generates compact yet effective representations by maximizing preference-relevant information while compressing modality-specific information.

Fusion via Information Bottleneck . Next, we provide a detailed description of the overall optimization procedure.

4.1 Preference-oriented Multimodal Representation Learning

Existing invariant learning methods [1, 3, 12] commonly construct environments via synthetic distribution shifts, such as spurious correlations or artificial noise. In contrast, modalities in multimodal recommendation (e.g., text, image) naturally encode diverse yet complementary semantics. Given the consistency of user preferences across modalities [12], we treat each modality as a distinct environment to exploit this semantic invariance.

4.1.1 Collaborative Modality Graph Learning. Formally, given K modalities, we define the environment set $C = \{c_k : 1 \leq k \leq K\}$, where c_k represents the scenario where only the k-th modality is available. Then, we adopt modality-specific graphs to perform the representation learning of users and items. From the interaction matrix $\mathcal{R}$, we construct user-item interaction graph $\mathcal{G} = \{\mathcal{G}_a, \mathcal{G}_t, \mathcal{G}_v\}$. Each graph $\mathcal{G}_k$ maintains the same graph structure and only retains the item features associated with each modality. Note that all modality-specific graphs share the same user embeddings for each user ID [61].

Given the raw modality features, we first employ a non-linear transformation to project each raw modality feature into a low-dimensional vector space:

$$F^k = \sigma(W_k X^k + b_k), \tag{4}$$

where $W_k \in \mathbb{R}^{D_k \times d_k}$ and $b_k \in \mathbb{R}^{d_k}$ denote the weight matrices and bias vectors for the $k-$th modality, respectively. $\sigma(\cdot)$ is the activation function. To capture high-order collaborative signals, we employ the same message-passing strategy as LightGCN [19] to propagate and refine user and item representations across the user-item interaction graph. The l-th layer propagation is defined as:

$$E^{(k,l)} = (D^{-1/2} A D^{-1/2}) E^{(k,l-1)}, \tag{5}$$

where A is the adjacency matrix built from user-item interactions $\mathcal{R}$ and its transpose $\mathcal{R}^T$, and D is the corresponding diagonal degree matrix. By aggregating node features across L propagation layers, the final preference-oriented embeddings can be obtained:

$$E^k = \frac{1}{L+1} \sum_{l=0}^{L} E^{(k,l)}. \tag{6}$$

Here, $E^k = \{E_U^k, E_I^k\}$ represents preference-oriented representations of users and items. Based on the learned representations, we can estimate the preference score of the user u for item i in the k-th modality environment:

$$\hat{r}_{u,i}^k = \mathcal{F}(e_u^k, e_i^k), \tag{7}$$

where $\mathcal{F}(\cdot)$ denotes the prediction function, implemented as the inner product between user and item embeddings.

4.1.2 Invariant Learning Optimization. After obtaining predictions across K modality environments, we explicitly encourage the consistency and stability of the learned representations across modalities. Specifically, we employ Invariant Risk Minimization [1, 2, 12] to guide the learning of preference-oriented representations that remain invariant across environments. The corresponding optimization objective is formulated as follows:

$$\mathcal{L}_{IRM} = \mathbb{E}_{k\in\{a,t,v\}}\mathcal{L}^k + \delta\|Var_{k\in\{a,t,v\}}(\nabla_{\theta_1}\mathcal{L}^k)\|^2. \quad (8)$$

The first term, $\mathcal{L}^k$, represents the modality-specific loss for each environment. The second term penalizes the variance of the gradients (with respect to the shared parameters θ_1) between different modalities. Minimizing this gradient variance encourages the model to capture invariant preference features that are stable across modality environments, thereby reducing its sensitivity to missing modalities.

To ensure effective learning of user preferences, we adopt the Bayesian Personalized Ranking (BPR) loss as the modality-specific objective:

$$\mathcal{L}^k = \sum_{(u,i^+,i^-)\in O} -ln\sigma(\hat{r}^k_{u,i^+} - \hat{r}^k_{u,i^-}), \quad (9)$$

where $O = (u, i^+, i^-)|(u, i^+) \in \mathcal{R}^+, (u, i^-) \in \mathcal{R}^-$ is the training triplet set, (u, i^+) represents observed (positive) interactions, and (u, i^-) denotes randomly sampled negative interactions. $\sigma(\cdot)$ is the sigmoid activation function. Through this design, our method ensures stable and accurate user preference prediction even in modality-missing scenarios.

4.2 Missing-aware Feature Fusion

To ensure robust performance under modality-missing scenarios, we design a missing-aware feature fusion module grounded in the Information Bottleneck (IB) principle, as illustrated in the lower part of Figure 3. As discussed above, modality-specific information can become unreliable in such scenarios, which may hinder accurate user preference prediction. To address this, the module is guided to preserve preference-relevant information while compressing modality-specific information, thereby generating compact yet effective multimodal representations.

4.2.1 ***Modality-Missing Scenarios Simulation***. Instead of directly integrating all modality features, we introduce a binary mask to simulate modality-missing scenarios, which is dynamically sampled during training. Specifically, the mask vector $\mathcal{M} \in \{0,1\}^K$ is applied to replace the features of missing modalities with zero vectors, where $m_k = 0$ indicates that the k-th modality is absent. The resulting masked representation is then fed into a single-layer MLP-based fusion function to generate the final item embedding:

$$z_{i,m} = h_{\theta_2}(\{e^a_i, e^t_i, e^v_i\}_m), \quad m \in \mathcal{M}. \quad (10)$$

This strategy exposes the proposed model to various modality-missing scenarios during training, thus encouraging the fusion module to generate robust multimodal representations that ensure stable and consistent recommendation performance across different modality-missing conditions.

4.2.2 ***Information Bottleneck-guided Feature Fusion***. Given generated representations, we employ the Information Bottleneck principle [20, 46, 47] to guide the optimization of the feature fusion module. It explicitly balances mutual information maximization and minimization, encouraging the model to retain task-relevant signals while compressing modality-specific information. Inspired by previous works [28, 57, 67], the Information Bottleneck optimization objective in recommender systems can be formulated as:

Table 1: Basic statistics of the experimental datasets.

Dataset	#User	#Item	#interactions	#Modalities	Sparsity
Baby	19,445	7,050	160.792	V,T	99.88%
Clothing	39,387	23,033	278,677	V,T	99.97%
Tiktok	9,319	6,710	68,722	V,A,T	99.89%

$$IB = I(Z;R) + I(Z, Z^m;R) - \beta I(X;Z), \quad (11)$$

here, $I(Z;R)$ encourages the model to preserve information relevant to the recommendation task; $I(Z, Z^m;R)$ promotes consistency across representations generated under different modality-missing conditions; and $I(X;Z)$ penalizes excessive dependence on raw modality content, controlled by a trade-off parameter β.

Term1: Maximizing Mutual Information with Recommendation Signals. This term aims to maximize the mutual information between generated representations and the recommendation target. Given the user embedding e_u and the generated representation z_i, the predicted preference score is computed as $\bar{r}^k_{u,i} = e^T_u, z_i$. We select popular BPR ranking loss [40] to optimize this term:

$$\mathcal{L}_{rec} = \sum_{(u,i^+,i^-)\in O} -ln\sigma(\bar{r}_{u,i^+} - \bar{r}_{u,i^-}), \quad (12)$$

Term2: Promoting Robust Item Representation Consistency. In general, enforcing consistency across different views has been shown to improve performance in downstream tasks [48]. Motivated by this, we encourage semantic alignment between item representations generated under different masking conditions. Following standard contrastive learning setups [38, 44], we employ the InfoNCE loss [16] to estimate the mutual information $I(Z, Z^m;R)$:

$$\mathcal{L}_{pcon} = \sum_{\substack{m,m'\in\mathcal{M},\\ m\neq m'}} \sum_{i\in\mathcal{I}} -\log\frac{exp(\int(z_{i,m}\cdot z_{i,m'})/\tau)}{\sum_{j\in\mathcal{B}} exp(\int(z_{i,m}\cdot z_{j,m})/\tau)}, \quad (13)$$

where $\int(\cdot)$ measures the similarity between two representations, we employ the widely used cosine similarity function in our work; $\tau \in \mathbb{R}^+$ indicates the temperature parameter. Note that negative examples of each item are updated at each epoch due to item j being sampled from the current batch training data.

Term3: Minimizing Mutual Information for Redundancy Reduction. This term aims to compress the negative impact of modality-specific information by minimizing the mutual information between the generated representation and the raw modality input. In other words, it reduces the model's reliance on potentially unreliable modality information. However, directly computing mutual information between two high-dimensional variables is intractable. To address this, we adopt the Contrastive Log-ratio Upper Bound (CLUB) [8] in our work, which uses a variational distribution $q^k_\phi(\cdot|\cdot)$ for each modality to approximate the mutual information:

$$\mathcal{L}_{comp} = \frac{1}{|K|}\sum_{k\in\{a,t,v\}}\sum_{i\in\mathcal{I}}\left[\log q^k_{\phi^k}(z_i|e^k_i) - \log q_{\phi^k}(z_i|x^k_i)\right] \quad (14)$$

here, $q_{\phi}^{k}(\cdot|\cdot)$ is implemented as a two-layer MLP with modality-specific parameter ϕ^k, optimized in a sample-based manner. Minimizing $\mathcal{L}^{comp}$ effectively reduces the task-irrelevant and modality information, yielding a more compact and effective representation.

Model Training The overall training objective optimization of our framework is defined as:

$$\mathcal{L} = \mathcal{L}_{rec} + \mathcal{L}_{IRM} + (\alpha\mathcal{L}_{pcon} + \beta\mathcal{L}_{comp}). \tag{15}$$

This unified loss function integrates four components: the recommendation loss ($\mathcal{L}_{rec}$), the invariant representation learning loss ($\mathcal{L}_{IRM}$), the preference consistency loss ($\mathcal{L}_{pcon}$), and the information compression loss ($\mathcal{L}_{comp}$). The hyperparameters α and β control the relative importance of the mutual information regularization terms. By jointly optimizing these objectives, the model learns compact and effective preference representations that generalize well to modality-missing scenarios.

5 Experiments

5.1 Experimental Setup

5.1.1 ***Datasets.*** We evaluate our method on three widely used real-world datasets: Amazon Baby, Amazon Clothing, and TikTok, following the 5-core setting adopted in prior works [37, 60, 76]. The Amazon datasets[7] consist of user-item interactions derived from product ratings. For each item, we extract 4096-dimensional visual features using VGG16 [43] (from the second fully connected layer), and 1024-dimensional textual features using BERT [10], based on the concatenation of brand, title, description, and category, following [30]. The TikTok dataset [3] contains user viewing histories on short videos, with pre-extracted visual, acoustic, and textual features. We directly use the released modality features and data splits to ensure consistency and fair comparison. Following [30], we adopt the same training, validation, and test partition strategy. Dataset statistics are summarized in Table 1.

5.1.2 ***Missing Modality Setting.*** Similar to previous works [3, 23, 27], we evaluate the effectiveness of our method under missing modality scenarios using the following experimental settings.

- **Full Training Missing Test (FTMT)**: In this setting, all training data are assumed to have complete modality information. During testing, we simulate missing modalities by randomly selecting 50% of the test items and replacing their modality features with zero vectors. For datasets with two modalities, each selected item may randomly lose one or both modalities. For datasets with three modalities, each item is randomly assigned one or two missing modalities to simulate diverse missing scenarios.
- **Missing Training Missing Test (MTMT)**: This setting simulates a more realistic scenario in which missing modalities also occur during training. Specifically, 30% of the training items are randomly assigned missing modalities, using the same missing strategy as in the test phase. The test phase follows the same setup as FTMT.

5.1.3 ***Baselines.*** To verify the efficacy of our proposed method, we conduct comprehensive benchmarking against a diverse set of state-of-the-art (SOTA) recommender models, which can be broadly categorized into three main groups: **Unimodal Recommendation Methods**: MF-BPR [40], InvPref [56], and LightGCN [19]. These methods rely solely on user-item interaction data to infer user preferences, without incorporating auxiliary content features. **Multimodal Recommendation Methods**: feature-based models (VBPR [17], BM3 [76], InRL [12]), graph-based models (GRCN [60], MMGCN [61], LATTICE [72], DualGNN [52]), and hybrid models (MGCN [69], SMORE [37]). **Incomplete Modality Recommendation Methods:** These models are specifically designed to alleviate modality-missing problems, which include representative approaches (MILK [3], SIBRAR [14]), and Generative models(MoDiCF [23]).

5.1.4 ***Evaluation Metrics.*** Two widely-used evaluation metrics are adopted for top-n recommendation: *Recall* and *Normalized Discounted Cumulative Gain* (NDCG) [18]. Recommendation accuracy is calculated for each metric based on the top 20 results. Note that the reported results are the average values across all testing users.

5.1.5 ***Parameter Settings.*** The PyTorch framework [8] is adopted to implement the proposed model. In our experiments, all hyperparameters are carefully tuned. For all datasets, the embedding size of the users and items is set to 64. The mini-batch size is fixed to 1024. The learning rate for the optimizer is searched from $\{10^{-5}, 10^{-4}, \cdots, 10^{+1}\}$, and the model weight decay is searched in the range $\{10^{-5}, 10^{-4}, \cdots, 10^{-1}\}$. In the mutual information $I(Z, Z^m; R)$, the temperature τ is tuned from$\{1e-2, 1e-1, 1, 1e+1\}$. We carefully searched the best parameters of α, β, and δ, and found that I^3-MRec achieves the best performance when $\{1e-3, 1e-5, 300\}$ on Baby, $\{1e-2, 1e-3, 1\}$ on Clothing, and $\{1e-3, 1e-6, 1000\}$ on TikTok dataset. Besides, the early stopping strategy is adopted. Specifically, the training process will stop if recall@20 does not increase for 20 successive epochs.

5.2 Overall Comparisons

Table 2 presents the performance comparison between I^3-MRec and several SOTA baselines across three datasets. To better simulate real-world scenarios where modality information may be randomly missing during both training and inference, we conduct evaluations under two experimental settings: Full Training Missing Test (FTMT) and Missing Training Missing Test (MTMT). The key observations are summarized as follows:

The first block reports the performance of unimodal recommender methods, including MFBPR, InvPref, and LightGCN, which are unaffected by modality missingness. InvPref achieves noticeable improvements over MFBPR, demonstrating the effectiveness of invariant learning in enhancing robustness and generalization. LightGCN further outperforms both MFBPR and InvPref by leveraging high-order neighborhood information to enrich user and item representations, underscoring the strengths of graph-based methods in mitigating data sparsity and improving representation quality. Building upon a similar GNN-based architecture, the proposed I^3-MRec additionally integrates invariant learning to learn robust multimodal representations.

The second block presents the performance of multimodal recommender methods. As shown, most MRS methods outperform

[7] http://jmcauley.ucsd.edu/data/amazon.

[8] https://pytorch.org.

Table 2: Performance of our method and the competitors over three datasets.

Settings	Full Training Missing Test (FTMT)						Missing Training Missing Test (MTMT)					
Datasets	Baby		Clothing		Tiktok		Baby		Clothing		Tiktok	
Metric	Recall@20	NDCG@20	Recall@20	NDCG@20	Recall@20	NDCG@20	Recall@20	NDCG@20	Recall@20	NDCG@20	Recall@20	NDCG@20
MFBPR	0.0554	0.0237	0.0346	0.1256	0.0558	0.0220	0.0554	0.0237	0.0346	0.1256	0.0558	0.0220
InvPref	0.0562	0.0241	0.0356	0.0147	0.0572	0.0272	0.0562	0.0241	0.0356	0.0147	0.0572	0.0272
LightGCN	0.0687	0.0320	0.0436	0.0145	0.0736	0.0382	0.0687	0.0320	0.0436	0.0149	0.0736	0.0382
VBPR	0.0472	0.0205	0.0462	0.0207	0.0406	0.0170	0.0433	0.0162	0.0413	0.0184	0.0359	0.0150
MMGCN	0.0527	0.0218	0.0289	0.012	0.0874	0.0368	0.0402	0.0165	0.0258	0.0107	0.0753	0.0306
GRCN	0.0602	0.0255	0.0381	0.0161	0.0709	0.0280	0.0572	0.0242	0.0340	0.0144	0.0602	0.0236
DualGNN	0.0622	0.0275	0.0432	0.0193	0.0716	0.0340	0.0538	0.0247	0.0386	0.0172	0.0603	0.0297
LATTICE	0.0632	0.0278	0.0511	0.0215	0.0743	0.0324	0.0542	0.0241	0.0437	0.0187	0.0627	0.0284
InRL	0.0663	0.0284	0.0568	0.0237	0.0752	0.0321	0.0551	0.0237	0.0421	0.0178	0.0618	0.0276
BM3	0.0683	0.0296	0.0572	0.0252	0.0760	0.0319	0.0611	0.0257	0.0510	0.0225	0.0670	0.0287
MGCN	0.0788	0.0322	0.0591	0.0268	0.0861	0.0352	0.0697	0.0272	0.0527	0.0239	0.0745	0.0310
SMORE	0.0792	0.0332	0.0610	0.0278	0.0903	0.0372	0.0712	0.0308	0.0540	0.0247	0.0756	0.0316
MILK	0.0415	0.0184	0.0226	0.009	0.0399	0.0182	0.0375	0.0168	0.0202	0.0084	0.0352	0.0157
SIBRAR	0.0472	0.0217	0.0264	0.011	0.0542	0.0218	0.0429	0.0198	0.0236	0.0098	0.0468	0.0190
MoDiCF	0.0798	0.0348	0.0602	0.0273	0.0902	0.0385	0.0724	0.0318	0.0537	0.0244	0.0775	0.0329
Ours	**0.0815***	**0.0361***	**0.0635***	**0.0285***	**0.0929***	**0.0398***	**0.0744***	**0.0325***	**0.0551***	**0.0254***	**0.0804***	**0.0343***
Improv.	2.10%	3.62%	3.94%	2.49%	2.76%	3.65%	2.70%	2.17%	2.14%	3.54%	3.63%	4.22%

The symbol * denotes that the improvement is significant with $p - value < 0.05$ based on a two-tailed paired t-test.

unimodal baselines by leveraging richer semantic inputs. However, since they are not specifically designed for modality-missing scenarios, their performance remains sensitive to modality missingness. For instance, MMGCN relies on complete modality for node initialization and message passing. When modalities are missing during testing (FTMT), their performance drops below that of unimodal models. Introducing missing modalities during training (MTMT) results in a substantial performance drop of up to 23%, indicating the model's vulnerability to modality-missing problems across the learning process. In contrast, I^3-MRec explicitly accounts for modality missingness during training, yielding consistently strong performance across various modality-missing scenarios. InRL also adopts the invariant learning paradigm to learn preference-invariant representations. However, it relies on raw multimedia content to infer interaction environments, which becomes unreliable under missing modalities, causing performance degradation of up to 25%. These findings highlight the importance of explicitly alleviating modality-missing problems in multimodal recommendations.

In the third block, we analyze the performance of missing modality-aware recommender methods. Both SiBraR and MILK are primarily designed for cold-start scenarios, and thus do not fully exploit collaborative filtering signals [14]. This partly explains their lower performance compared to unimodal baselines. Nevertheless, these models show strong robustness to missing modalities. For example, on the Baby dataset (top-20), SiBraR's performance only drops from 0.0472 (FTMT) to 0.0429 (MTMT), a decrease of just 9.1%, indicating better stability than other multimodal baselines in modality-missing scenarios. Second, MoDiCF performs well on the Baby dataset due to its effective generation and debiasing design, but its performance drops notably on TikTok and Clothing. This is because TikTok's uneven three-modality structure and weak cross-modal correlation hinder reliable imputation, while Clothing depends heavily on visual features, making image absence particularly damaging. In contrast, I^3-MRec avoids reconstruction and achieves consistently strong results across all datasets and settings (FTMT and MTMT).

These observations highlight the inherent limitations of existing multimodal methods in realistic modality-missing scenarios. In

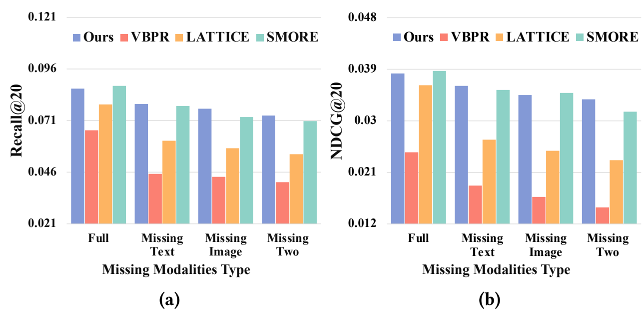


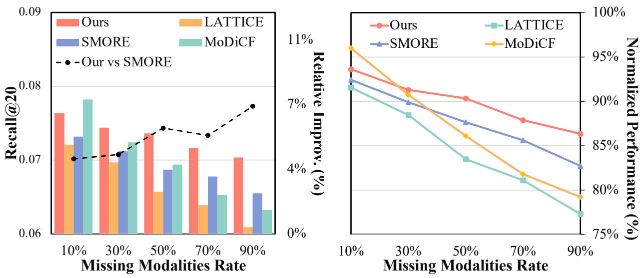
Figure 3: Performance on different types of missing modality on the Amazon Baby dataset. The "Full" setting indicates that the baseline models were trained with complete modality scenarios.

contrast, our proposed method consistently delivers stable and superior performance across all datasets and settings, demonstrating its effectiveness and robustness.

5.3 Improvements on Modality Missingness

5.3.1 Performance at Different Missing Modality Types. In Figure 3, we evaluate the performance of the proposed model and MRS (e.g., VBPR, LATTICE, SMORE) across different types of missing modalities. To simulate the real-world scenario, we select the MTMT strategy as the experimental setting[9]. From the observation of the figure, we can find that 1) I^3-MRec consistently outperformed all baselines across all modality-missing scenarios. This demonstrates the effectiveness of our framework in learning robust representations even in the absence of two modalities. 2) Benefiting from the introduction of invariant learning and information bottleneck, I^3-MRec can yield compact yet effective representation, which maximally preserves user preference information while minimizing dependence on the

[9]The MTMT setting simulates realistic and diverse missing cases, including mismatches between training and test missing modalities (e.g., training with missing image, testing with missing text or both



(a) (b)

Figure 4: (a) Recall@20 under varying missing modality rates on the Amazon Baby dataset. (b) Normalized performance with respect to the full-modality setting.

raw modality content. As shown in the figure, our model maintains stable performance regardless of which modality is missing. while traditional MRS models are especially sensitive to the absence of visual features, leading to a sharp performance drop. 3) Beyond robustness under modality-missing conditions, I^3-MRec also performs competitively in full-modality settings, achieving results on par with the recent work SMORE. Interestingly, the motivation of SMORE is to capture both uni-modal and fusion preferences while simultaneously suppressing modality noise. This suggests that reducing modality dependence through the Information Bottleneck principle benefits generalization in modality-missing scenarios.

5.3.2 Performance under Varying Missing Ratios. To evaluate the robustness of I^3-MRec under varying degrees of modality missingness, we conduct experiments with missing ratios of {10%, 30%, 50%, 70%, 90%} in the MTMT setting. For each item, both the items with missing modalities and the types of missing modalities are randomly selected and fixed across all settings. For example, if an item's textual modality is missing at a 10% ratio, the same modality for that item remains missing at higher ratios.

Figure 4(a) reports the Recall@20 results of I^3-MRec compared with LATTICE, SMORE, and MoDiCF on the Amazon Baby dataset. I^3-MRec consistently outperforms all baselines across all missing ratios. While existing methods suffer substantial performance degradation as the missing rate increases, I^3-MRec remains notably stable. The relative improvement over the strongest baseline, SMORE, increases steadily with the missing ratio and reaches over 7% at 90%, highlighting the effectiveness of our method under both moderate and extreme modality-missing conditions. Figure 4(b) further presents the normalized performance with respect to the full-modality setting. I^3-MRec demonstrates the smallest performance drop, with only a 12% degradation at a 90% missing rate, clearly indicating superior robustness compared to all other methods.

Interestingly, MoDiCF performs well under low missing ratios, retaining 98% of full-modality performance at 10%. However, as missingness increases (50%-90%), its effectiveness declines sharply, with recall dropping by nearly 20%, revealing the limitations of generation-based strategies in modality-missing scenarios. In contrast, I^3-MRec learns compact and effective representations, maintaining stable performance even when most modalities are unavailable, demonstrating the model's robustness and generalization.

5.4 Ablation Study

Table 3 presents the ablation results of I^3-MRec under the FTMT and MTMT settings. We first analyze the individual contributions of the IRM and IB modules to user preference modeling in the presence of missing modalities. The variant **I^3-MRec$_{\mathbf{IRM}}$**, which applies only invariant learning across modality-specific environments, outperforms the IB-only variant **I^3-MRec$_{\mathbf{IB}}$**, demonstrating that environment-based invariant learning effectively enhances robustness under modality-missing conditions. IRM encourages consistency in user preference modeling across different modalities, leading to better generalization.

While **I^3-MRec$_{\mathbf{IB}}$** is less effective on its own, it still improves upon a naive baseline, confirming that the IB module contributes to robustness by guiding the model to learn compact yet effective representations focused on preference-relevant semantics, thereby reducing the impact of modality missingness.

To further examine the role of the IB module, we introduce **I^3-MRec***, a variant that incorporates both IRM and IB but omits the information compression (minimization) term. Its performance lags behind the full model, particularly under the MTMT setting, indicating that without information compression, the model becomes more susceptible to missing modality inputs during training.

Table 3: Ablation studies on the components of our proposed method.

Settings	FTMT		MTMT	
Variants	Recall@20	NDCG@20	Recall@20	NDCG@20
I^3-MRec$_{IB}$	0.0763	0.0338	0.0596	0.0254
I^3-MRec$_{IRM}$	0.0799	0.0348	0.0638	0.0279
I^3-MRec*	0.0809	0.0351	0.0727	0.0307
I^3-MRec	0.0817	0.0361	0.0744	0.0325

6 Conclusion

In this work, we make a principled contribution to robust multimodal recommendation by explicitly identifying two fundamental properties essential for effective recommendation under missing modality conditions: (i) cross-modal preferences invariance and (ii) compact, preference-oriented representation. Grounded in these properties, we propose I^3-MRec, a novel and generalizable framework that integrates Invariant Risk Minimization (IRM) and the Information Bottleneck (IB) principle. Specifically, IRM enables the model to learn stable, reference-oriented representations across modality-specific environments, while IB encourages the model to preserve preference-relevant information and reduce reliance on modality-specific information. This design allows I^3-MRec to achieve robust and accurate recommendations in realistic modality-missing scenarios. Extensive experiments on three real-world datasets demonstrate that I^3-MRec consistently outperforms unimodal, multimodal, and modality-missing aware baselines across a range of missing ratios and evaluation settings (FTMT and MTMT). These results validate the robustness and generalization capabilities of our framework.

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