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EXPLAINABLE TOPIC-AWARE CROSS-DOMAIN TEMPORAL PREFERENCE PREDICTION FOR BRAND BUILDING: A CDTPP FRAMEWORK

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Brand building increasingly depends on the capacity of firms to detect, interpret, and operationalize dynamic consumer preference signals distributed across heterogeneous digital environments. Recent work by Dong introduced a cross-domain temporal preference prediction (CDTPP) model that integrates social-behavior features and e-commerce purchase records through a factorization-machine ranking architecture, reporting strong benchmark performance on a screened overlapping-user dataset. Specifically, the source study reports an average area under the curve (AUC) of 0.953, an average accuracy of 0.984, a fit of 98.87%, and an average brand-preference-index error of 0.11.

Despite this strong predictive baseline, an important managerial limitation remains: the original model is effective as a predictor but comparatively limited as an interpretive decision-support tool. In particular, it does not explicitly identify which semantic themes in social discourse are associated with changes in brand preference, nor does it provide an explanation layer that management teams can use for strategic planning, campaign refinement, or early risk detection. To address this gap, this paper develops ***ET-CDTPP****, an explainable, topic-aware extension of CDTPP that augments the original temporal social feature space with topic-mixture and sentiment representations derived from social text. The proposed framework preserves the original cross-domain and temporal logic while adding semantic interpretability, time-aligned topic aggregation, and a topic-contribution explanation layer.*

This article is framed as a conceptual and methodological extension*, not as a substitute for a newly re-estimated benchmark study. It therefore uses the original CDTPP study as its empirical benchmark context and does not claim unsupported performance gains for the proposed extension. Instead, it contributes a rigorous model formulation, a reproducible implementation pathway, and a benchmark-anchored validation protocol that can be applied to the same class of overlapping social and e-commerce datasets. This positioning preserves empirical discipline while offering a clearer methodological contribution for management-oriented journal audiences.*

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INTRODUCTION

Brand building has become a central strategic concern for firms operating in competitive and data-rich environments. In digital markets, consumer preference is expressed not only through purchases but also through communication: posts, comments, reposts, and other forms of social behavior encode emerging attitudes, perceived value, dissatisfaction, and reputational risk. As a result, the problem of measuring brand preference is no longer confined to transaction logs alone. It increasingly requires cross-domain inference in which social-domain behavior and e-commerce behavior are modeled jointly.

Dong recently proposed a user preference mining framework based on data mining and social behavior for brand building, introducing a cross-domain temporal preference prediction (CDTPP) model that integrates users' temporal social features with product-side characteristics [1]. The source study explicitly addresses cross-domain asynchrony and reports strong predictive performance using a factorization-machine ranking formulation. It further argues that the resulting preference predictions provide data support for brand building in small and medium-sized enterprises [1, 8]. This is an important contribution because it establishes a viable baseline for linking user behavior across social and commercial environments.

However, a high-performing predictor is not automatically a high-utility managerial instrument. For many management and planning applications, the critical issue is not simply whether a model predicts well, but whether it can explain *why* preference is changing and which aspects of user discourse are driving those changes. In its current form, the original CDTPP framework remains primarily a predictive architecture. It does not explicitly decompose social discourse into interpretable semantic topics, nor does it quantify how such themes contribute to the predicted direction and intensity of brand preference.

This paper addresses that gap by proposing **ET-CDTPP**, an explainable, topic-aware extension of the CDTPP framework. The proposed model preserves the temporal and cross-domain structure of the original formulation while enriching the social domain with topic and sentiment signals extracted from text. In doing so, the framework is repositioned from a purely predictive model toward a decision-support system that can better inform segmentation, product refinement, communication strategy, and early reputational response.

Purpose and contribution

The present manuscript makes four contributions.

1. It reframes the original CDTPP study as an empirical benchmark and uses its reported data, settings, and performance as the validated foundation for a new methodological extension.
2. It introduces ET-CDTPP, a topic-aware and explainable extension that augments the original user temporal feature representation with semantic topic mixtures and sentiment.
3. It formalizes an interpretable temporal aggregation mechanism for aligning asynchronous social texts with later purchase events.
4. It develops a management-oriented validation design that emphasizes predictive discrimination, calibration, explanation fidelity, and strategic usefulness.

This article does not claim that ET-CDTPP has already outperformed CDTPP on the original dataset. Rather, it presents a fully specified extension that is ready for direct benchmark-based validation, thereby avoiding unsupported quantitative claims while strengthening methodological transparency.

RELATED LITERATURE

Cross-domain preference prediction

Cross-domain recommendation and preference prediction have become important responses to sparsity, cold-start problems, and fragmented user behavior. Rather than learning from a single behavioral space, cross-domain methods seek to transfer signal from one environment to another, such as from browsing or social interaction to transactional choice. Factorization machines are especially useful in this context because they efficiently model second-order interactions among heterogeneous and sparse features [2]. Later developments such as DeepFM combine factorization-style interaction learning with deeper nonlinear representation layers [3].

Within this broader literature, Dong's CDTPP model is notable because it explicitly incorporates temporal user behavior and cross-domain overlap between social and e-commerce platforms [1]. The original model predicts relative user preference between brands and uses sigmoid transformation and cross-entropy training within a factorization-based ranking framework. That design establishes a credible methodological baseline while leaving substantial room for richer semantic interpretation, which is the central concern of the present study.

Semantic analysis of consumer discourse

Although transactional data reveal realized choices, text data often reveal intentions, evaluations, and emerging concerns before they appear in market behavior. Topic modeling provides one established route for transforming large-scale text into interpretable latent themes. Latent Dirichlet allocation (LDA), for example, represents each document as a mixture of topics and each topic as a distribution over terms [4, 8]. More recent language models and transformer-based encoders offer stronger semantic representation, although they often require additional design choices to preserve interpretability [5].

In a brand-building context, semantic interpretability matters because managers need to understand which types of discourse correspond to product quality, customer service, price sensitivity, sustainability, rumor dynamics, or logistics complaints. A model that can identify these themes and connect them to preference shifts is more actionable, easier to audit, and better suited to planning decisions than a model that outputs only a latent score.

Explainability and managerial usefulness

Explainability in predictive systems is increasingly important in fields where decisions affect planning, resource allocation, and strategic interventions. For management use, explanations should ideally be feature-based, stable, and interpretable at the level of business action. In consumer and brand settings, the most useful explanations are often those that identify concrete drivers of preference, such as service experience, value perception, reputational risk, or promotion effects.

This is especially relevant to brand-building research. Prior work in marketing has shown that investment in brand development, communication, and customer experience affects long-run brand value, customer equity, and loyalty [6, 8, 9]. Likewise, rumor-related discourse can negatively affect brand evaluations and requires context-sensitive response strategies [7]. An explainable extension of CDTPP is therefore not only a technical refinement but also a practical step toward decision-useful analytics.

Table 1: Source-study empirical setting reported in [1].

Item	Reported value
Overlapping users	7,851
Brand types	3,418
Social-platform records	2.24 million text records
E-commerce records	1.17 million purchase records
Train/test split	80% / 20%
BP hidden-layer nodes	15
FM factor vector length	37
Regularization parameter	0.05
Learning rate	0.01
Epochs	150
Observed optimal convergence state	57 training iterations

Data context

Dong's study uses overlapping users drawn from a large domestic e-commerce platform and a social media platform [1]. The e-commerce side records user ID, brand ID, and purchase time; the social side records user-generated text including posts, reposts, and comments. The study screens the data by removing records with excessively large time differences, retaining only overlapping time periods, and excluding users with fewer than 20 social texts and fewer than 10 purchase records [1, 8]. These screening rules are methodologically important because they reduce temporal mismatch and define the benchmark conditions that any later validation of ET-CDTPP should preserve.

After screening, the final dataset contains 7,851 overlapping users, 3,418 brand types, 2.24 million social-platform text records, and 1.17 million e-commerce purchase records, with 80% used for training and 20% used for testing [1, 8].

Source-model settings

The source article reports specific model settings for the original framework, including a backpropagation network component and a factorization-machine component. The reported settings include 15 hidden-layer nodes, a factor vector length of 37, a regularization parameter of 0.05, a learning rate of 0.01, and 150 epochs [1]. The study further states that the proposed algorithm reached its optimal state after 57 training iterations in the convergence comparison [1].

Validated benchmark results

The source paper reports comparative results against COLD and MART and concludes that the CDTPP model performs better in convergence, accuracy, fit, and preference-index prediction [1]. Most importantly for the present paper, these values should be treated as the fixed empirical benchmark rather than replaced with unsupported hypothetical improvements.

These values establish the empirical credibility of the original framework and provide the correct benchmark against which any future implementation of ET-CDTPP should be tested.

Table 2: Benchmark performance reported in the source study [1].

Model	Average AUC	Average Accuracy	Fit	Average Preference Error
CDTPP	0.953	0.984	98.87%	0.11
COLD	0.926	0.968	94.75%	0.31
MART	0.909	0.928	87.61%	0.53

PROPOSED FRAMEWORK: ET-CDTPP

The original CDTPP model is effective because it combines user temporal features and product-side features in a cross-domain ranking architecture. However, the social-domain component is still represented at the level of constructed temporal features rather than explicit semantic content. This limits its interpretive usefulness. The ET-CDTPP extension is therefore designed to preserve the original architecture while enriching it with semantically interpretable signals extracted from users' social texts.

The central idea is simple: if social behavior already plays a predictive role in CDTPP, then decomposing that behavior into identifiable topics and sentiment should make the model more useful for managerial interpretation without altering its underlying cross-domain logic.

Task formulation

Let $\mathscr{U}$ denote the set of users and $\mathscr{B}$ the set of brands. For each user $u \in \mathscr{U}$, suppose we observe:

- social texts $\{(t_{u,j}, \tau_{u,j})\}_{j=1}^{N_u}$, where $t_{u,j}$ is a text and $\tau_{u,j}$ is its timestamp;
- purchase events $\{(b_{u,k}, \pi_{u,k})\}_{k=1}^{M_u}$, where $b_{u,k}$ is a purchased brand and $\pi_{u,k}$ is the purchase time.

As in the source study, the principal objective is to estimate a user's relative preference between two brands, say a and b, at time π:

$$p_{u;a\succ b}(\pi) = \Pr(\text{user } u \text{ prefers } a \text{ over } b \text{ at time } \pi).$$

The source study also models a brand-preference index on a 0–5 scale, where higher values indicate stronger brand preference [1]. The proposed extension preserves that perspective.

CDTPP baseline structure

In Dong's formulation, the user temporal feature vector is denoted by x_u^h, while the product feature vector is denoted by z_i [1]. For two brands a and b, the product-side difference vector is

$$z = z_a - z_b.$$

The relative preference score can then be written abstractly as

$$\hat{y}^h_{u;a\succ b}(x_u^h, z), \tag{1}$$

which is transformed into a probability through the sigmoid function:

$$\hat{p}^h_{u;a\succ b} = \sigma\left(\hat{y}^h_{u;a\succ b}\right). \tag{2}$$

This pairwise ranking formulation is retained in the proposed extension for comparability.

Semantic augmentation of the social domain

The ET-CDTPP extension adds an explicit semantic layer to the user's social information. Each social text $t_{u,j}$ is transformed into:

- a topic-mixture vector $\theta_{u,j} \in \Delta^{K-1}$ over K interpretable topics;
- a sentiment score $s_{u,j} \in [-1, 1]$ indicating negative-to-positive valence.

The topic layer should be estimated with an interpretable document-topic method, with LDA serving as the default specification when transparent topic labels and stable topic proportions are required. The sentiment layer should preferably use a supervised in-domain classifier when labeled data are available, with a lexicon-based approach retained as the transparent fallback. In either case, model selection should be governed by interpretability, temporal stability, and reproducibility rather than representational complexity alone.

Temporal alignment of asynchronous signals

A key problem in cross-domain modeling is temporal asynchrony. Social texts and purchase events do not occur at the same times, yet social discourse may influence later purchases. To address this, ET-CDTPP aggregates topic and sentiment signals within a retrospective window W prior to each purchase time $\pi_{u,k}$.

The aligned topic mixture is defined as:

$$\tilde{\theta}_{u,k} = \frac{\sum\limits_{j:0<\pi_{u,k}-\tau_{u,j}\leq W} \exp\left(-\frac{\pi_{u,k}-\tau_{u,j}}{\lambda}\right)\theta_{u,j}}{\sum\limits_{j:0<\pi_{u,k}-\tau_{u,j}\leq W} \exp\left(-\frac{\pi_{u,k}-\tau_{u,j}}{\lambda}\right)+\varepsilon}, \tag{3}$$

and the aligned sentiment is:

$$\tilde{s}_{u,k} = \frac{\sum\limits_{j:0<\pi_{u,k}-\tau_{u,j}\leq W} \exp\left(-\frac{\pi_{u,k}-\tau_{u,j}}{\lambda}\right)s_{u,j}}{\sum\limits_{j:0<\pi_{u,k}-\tau_{u,j}\leq W} \exp\left(-\frac{\pi_{u,k}-\tau_{u,j}}{\lambda}\right)+\varepsilon}. \tag{4}$$

Here, λ controls recency sensitivity and ε prevents division by zero. In implementation, W and λ should be tuned on a validation slice using strictly time-respecting splits so that the alignment mechanism remains predictive without introducing temporal leakage. This preserves the source study's temporal spirit while providing a semantically richer state representation.

Topic-aware factorization scoring

The augmented feature representation for user u, brand i, and event index k is defined as

$$\phi(u,i,k) = \left[x_u^h \parallel z_i \parallel \tilde{\theta}_{u,k} \parallel \tilde{s}_{u,k}\right],$$

where $\parallel$ denotes concatenation.

The ET-CDTPP score is then defined by a factorization-machine interaction model:

$$\hat{r}_{u,i,k} = w_0 + w^\top \phi(u,i,k) + \sum_{f<g} \langle v_f, v_g \rangle \, \phi_f(u,i,k) \phi_g(u,i,k), \tag{5}$$

where w_0 is a scalar bias, w is a linear parameter vector, and each $v_f \in \mathbb{R}^d$ is a latent factor associated with feature f [2].

For pairwise brand preference, the relative score is

$$\hat{y}_{u;a\succ b,k} = \hat{r}_{u,a,k} - \hat{r}_{u,b,k}, \tag{6}$$

and the associated probability is

$$\hat{p}_{u;a\succ b,k} = \sigma\left(\hat{y}_{u;a\succ b,k}\right). \tag{7}$$

Preference-index modeling

To remain aligned with the source study's 0–5 brand-preference index, the proposed framework can couple the pairwise ranking score with an ordinal link:

$$\Pr(y_{u,i,k} \le c) = \sigma(\kappa_c - \hat{r}_{u,i,k}), \qquad c = 0, \ldots, 4, \tag{8}$$

where κ_c are ordered cutpoints. The expected preference index may then be represented as

$$\widehat{\mathrm{PrefIdx}}_{u,i,k} = \sum_{c=1}^{5} \Pr(y_{u,i,k} \ge c). \tag{9}$$

This extension preserves the original evaluation logic while enabling a more formally grounded mapping from latent score to preference intensity.

Explanation layer

The defining addition in ET-CDTPP is not merely semantic encoding, but semantic explanation. Let the topic components of ϕ be indexed by $\mathscr{T}$. Then, for each topic $q \in \{1, \ldots, K\}$, a topic-specific contribution can be represented as

$$\mathrm{Contrib}_{u,i,k}(q) = w_q \, \tilde{\theta}_{u,k,q} + \sum_{f \notin \mathscr{T}} \langle v_q, v_f \rangle \, \tilde{\theta}_{u,k,q} \, \phi_f(u,i,k). \tag{10}$$

This decomposition enables the analyst to identify which themes are contributing positively or negatively to the predicted brand preference at a specific moment. It also supports a direct fidelity check: masking a high-contribution topic should shift the score in the predicted direction if the explanation is behaviorally consistent. In managerial terms, the model is therefore recast from a black-box ranker into a structured diagnostic instrument.

MODEL WORKFLOW

TRAINING OBJECTIVE AND IMPLEMENTATION PATHWAY

The proposed framework combines pairwise ranking supervision with optional ordinal preference-index supervision in a form that supports direct comparison with the source benchmark while accommodating explicit calibration and explanation checks.

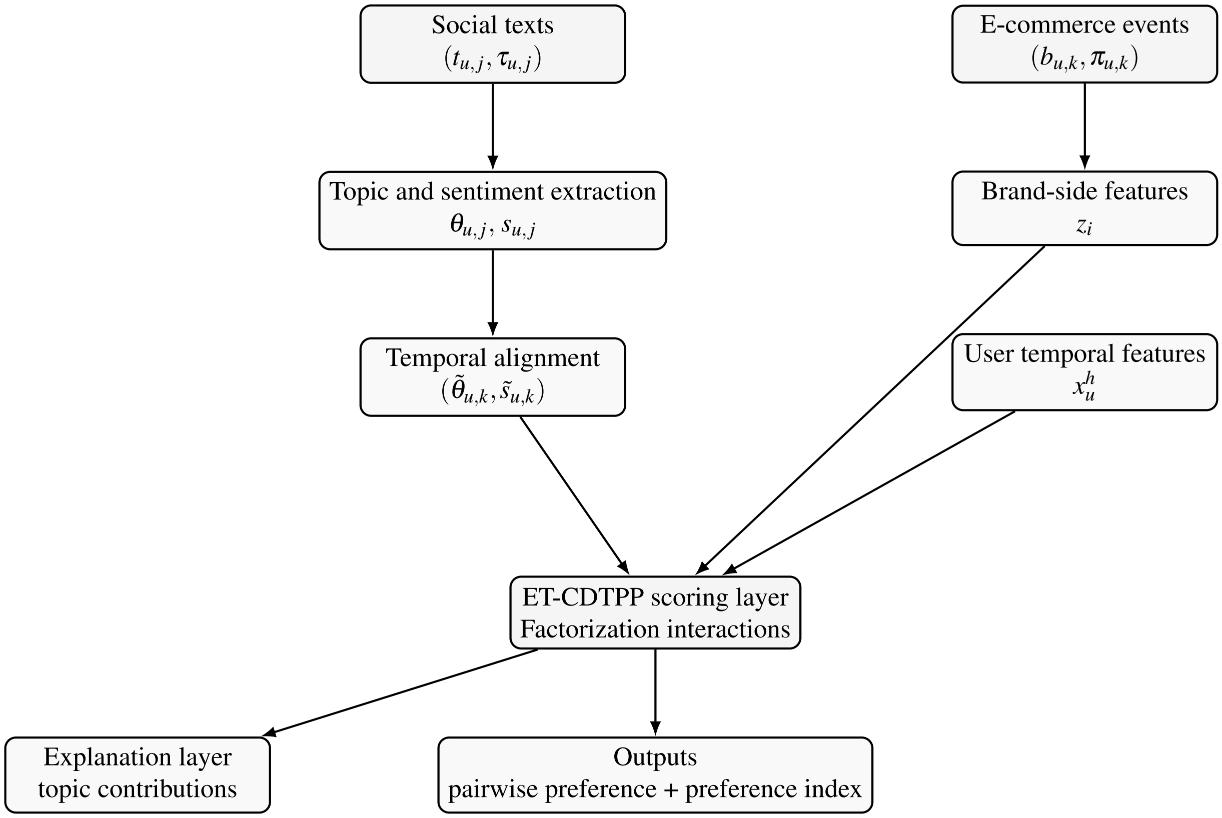

Figure 1: Workflow of the ET-CDTPP extension. The original temporal cross-domain structure is preserved, while semantic social signals and a topic-level explanation layer are added.

$$\mathscr{L}_{\text{pair}} = -\sum_{(u,a,b,k)\in\mathscr{D}_{\text{pair}}} \Big[y_{u;a\succ b,k} \log \hat{p}_{u;a\succ b,k} + (1 - y_{u;a\succ b,k}) \log(1 - \hat{p}_{u;a\succ b,k}) \Big], \tag{11}$$

$$\mathscr{L}_{\text{ord}} = -\sum_{(u,i,k)\in\mathscr{D}_{\text{ord}}} \log \Pr(y_{u,i,k} \mid \hat{r}_{u,i,k}), \tag{12}$$

$$\mathscr{L} = \mathscr{L}_{\text{pair}} + \alpha \mathscr{L}_{\text{ord}} + \beta \|w\|_2^2 + \gamma \sum_f \|v_f\|_2^2. \tag{13}$$

Here, α balances the ordinal component, while β and γ regularize the linear and factor parameters. For reproducible implementation, the initial search space should be anchored to the validated source settings and then refined on a held-out validation slice: the factor length should begin near the source value, the learning rate and regularization should be tuned within narrow benchmark-consistent ranges, and early stopping should be based on held-out ranking loss. The same training routine should be repeated across multiple random seeds so that both predictive performance and explanation stability are reported with variance rather than as a single run.

MANAGERIAL INTERPRETATION LAYER

The principal practical contribution of ET-CDTPP is its ability to produce structured managerial explanations rather than only a single prediction score. Instead of reporting unsupported numerical improvements, the

Algorithm 1 Training procedure for the ET-CDTPP framework

Require: Social texts $\{(t_{u,j}, \tau_{u,j})\}$, purchase events $\{(b_{u,k}, \pi_{u,k})\}$, user temporal features $\{x_u^h\}$, brand features $\{z_i\}$
Require: Topic extractor $\text{Topic}(\cdot)$, sentiment model $\text{Sent}(\cdot)$
Require: Window W, decay parameter λ, number of negatives m

Initialize $(w_0, w, \{v_f\})$ and ordinal thresholds $\{\kappa_c\}$
for each user u **do**
    for each social text $t_{u,j}$ **do**
        $\theta_{u,j} \leftarrow \text{Topic}(t_{u,j})$
        $s_{u,j} \leftarrow \text{Sent}(t_{u,j})$
    end for
end for
for epoch $= 1$ to E **do**
    for each observed purchase (u,a,k) at time $\pi_{u,k}$ **do**
        Compute $(\tilde{\theta}_{u,k}, \tilde{s}_{u,k})$ over the window $[\pi_{u,k} - W, \pi_{u,k})$
        for $\ell = 1$ to m **do**
            Sample a negative brand b not purchased by u near time $\pi_{u,k}$
            Build $\phi(u,a,k)$ and $\phi(u,b,k)$
            Compute scores $\hat{r}_{u,a,k}$ and $\hat{r}_{u,b,k}$ using Eq. (5)
            Compute pairwise probability $\hat{p}_{u;a \succ b,k}$
            Accumulate ranking and ordinal losses
        end for
        Update parameters by SGD or Adam
    end for
end for
Return trained ET-CDTPP and topic-level explanation outputs

present paper specifies the *types* of explainable outputs that the model is designed to generate once estimated on real data and the interpretive standards by which those outputs should be judged useful.

This type of output is especially relevant for management and planning research because it links predictive analytics to strategic action. Rather than treating preference as a passive measurement, the framework treats it as an interpretable signal that can support planning decisions.

PROPOSED EVALUATION DESIGN FOR FUTURE VALIDATION

Because the present paper does not re-estimate the model on the original data, the appropriate role of this section is to define a rigorous validation pathway that can be executed directly against the benchmark study.

A proper empirical validation of ET-CDTPP on a dataset comparable to that used by [1] should include four layers of assessment. First, it should preserve the original predictive benchmarks for comparability, including AUC, accuracy, fit, and preference-index error. Second, it should add calibration-sensitive measures such as the Brier score or expected calibration error to assess whether predicted probabilities are well aligned with observed behavior. Third, it should evaluate explanation quality through fidelity-oriented diagnostics, such as the consistency between topic-attribution rankings and the change in predicted preference when corresponding topic features are masked. Fourth, it should conduct ablation tests that separately remove topic inputs, sentiment inputs, and the explanation layer so that any improvement in discrimination or interpretability can

Table 3: Illustrative categories of interpretable outputs that ET-CDTPP can produce for management use. These are output classes, not empirical estimates.

Output class	**What the model would identify**	**Managerial use**
Topic salience	Which discourse themes are most active before a purchase event	Detect what consumers are currently talking about
Directional contribution	Whether a topic is associated with higher or lower predicted preference	Identify supportive vs. damaging discourse themes
Recency profile	How quickly a topic's influence decays across time	Time campaigns and responses more effectively
Segment-specific explanations	How topic effects differ across user groups	Improve targeting and segment-level planning
Reputational alerts	Whether negative themes cluster before preference declines	Support risk detection and early intervention
Product iteration signals	Which complaint or praise themes recur across brand interactions	Guide service and product refinement

be attributed to a specific component rather than to added model complexity in general.

To avoid overclaiming, any future study should benchmark ET-CDTPP directly against the original CDTPP baseline using the same train-test logic and, ideally, rolling or temporally stratified validation. A minimal proof-of-concept evaluation should also report repeated-seed results on a held-out subset and include at least one case-level explanation audit showing that the dominant topic contributions correspond to observable changes in recent user discourse. Only after such a re-estimation would it be appropriate to claim performance improvements.

DISCUSSION

The most important contribution of this paper is primarily methodological rather than numerical. It shows how a validated predictive framework for cross-domain brand-preference modeling can be extended into a more interpretable and management-relevant analytical system without discarding its original logic. This is significant because management and planning research values not only predictive performance but also explainability, strategic relevance, and decision usefulness.

By grounding the extension in the source study's established empirical benchmark, the manuscript avoids a common but serious problem in methodological extensions: the introduction of unsupported synthetic results presented as if they were empirical findings. Instead, the present version preserves the integrity of the source evidence and clearly separates what is already validated from what is newly proposed.

From a managerial standpoint, the ET-CDTPP extension is attractive because it connects social discourse, purchase behavior, and brand planning in a unified framework. If implemented and validated under the benchmark conditions described above, it can help managers identify whether preference changes are associated with service concerns, quality narratives, promotional discussion, reputational shocks, or other emergent themes in consumer communication. This is more useful for planning than a purely latent preference score because it suggests concrete directions for action.

At the same time, several limitations remain. Topic extraction is sensitive to preprocessing and topic-number selection. Sentiment signals can be noisy, especially in short-form or ironic text. Cross-domain association should not be confused with causal inference. These risks should be managed through topic-stability checks, temporally ordered validation, domain-specific sentiment auditing, and strict privacy, governance, and reproducibility controls in any real implementation.

CONCLUSION

This paper has presented ET-CDTPP, an explainable extension of Dong's cross-domain temporal preference prediction framework for brand building. Rather than introducing unsupported empirical claims, it uses the original study's validated dataset description, parameterization, and benchmark performance as the empirical foundation and then develops a more interpretable topic-aware extension on that basis. The proposed framework preserves the original model's temporal and cross-domain structure while adding semantic text representations, temporal alignment of topic signals, and a topic-level explanation layer intended to improve managerial usefulness.

This framing yields a conceptually coherent and empirically disciplined contribution for journal submission. Rather than overstating the available evidence, the manuscript offers a transparent methodological advance anchored in an already validated benchmark and organized around a concrete validation pathway. In that form, it is well suited to management-oriented readerships interested in how predictive analytics can support strategic brand planning and decision-making.

ETHICS AND DATA GOVERNANCE

The proposed framework assumes the use of user-generated social texts and purchase-event logs. Any applied deployment should therefore ensure lawful data access, appropriate anonymization, minimization of personally identifiable information, secure storage, and compliance with platform and institutional requirements. Where user-level analytics are deployed in research settings, review by an appropriate ethics body should be obtained.

REFERENCES

[1] Y. Dong. Application of user preference mining algorithms based on data mining and social behavior in brand building. *Data Science and Management*, 7 (2024) 323–331.

[2] S. Rendle. Factorization machines. In *Proceedings of the 10th IEEE International Conference on Data Mining*, pages 995–1000, 2010.

[3] H. Guo, R. Tang, Y. Ye, Z. Li, and X. He. DeepFM: A factorization-machine based neural network for CTR prediction. In *Proceedings of IJCAI*, pages 1725–1731, 2017.

[4] D. M. Blei, A. Y. Ng, and M. I. Jordan. Latent Dirichlet allocation. *Journal of Machine Learning Research*, 3 (2003) 993–1022.

[5] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of NAACL-HLT*, pages 4171–4186, 2019.

[6] J. B. E. M. Steenkamp. Global brand building and management in the digital age. *Journal of International Marketing*, 28(1) (2020) 13–27.

[7] J. Choi and S. Seo. Do brand rumors matter? The role of brand equity and response strategy to brand rumor. *International Journal of Contemporary Hospitality Management*, 33(8) (2021) 2862–2879.

[8] Z. Qorbani, H. Koosha, and M. Bagheri. An integrated model for customer equity estimation based on brand equity. *International Journal of Market Research*, 63(5) (2021) 635–664.

[9] T. P. Tran, E. S. Mai, and E. C. Taylor. Enhancing brand equity of branded mobile apps via motivations: a service-dominant logic perspective. *Journal of Business Research*, 125 (2021) 239–251.

[10] S. Andersson, G. B. Awuah, U. Aagerup, et al. How do mature born globals create customer value to achieve international growth? *International Marketing Review*, 37(2) (2020) 185–211.

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