A Hybrid Framework Integrating GNN-LSTM-CNN to Map the Impact of MSME User Behavior on Digital Transformation

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***Abstract*—MSMEs need a recommendation system that simultaneously captures the evolution of user intent over time and the relationship structure between entities (users, products, sessions, categories, and security events). The problem with this research is that LSTM excels in sequence, but its performance drops on a rare timeline, a general situation in MSME logs. GNN is strong for cross-entity relationships, but it does not explicitly model temporal dynamics. The gap arises because many pipelines still separate design signals, temporal behavior, and session security, reducing explainability and long-term reliability. Our contribution proposes a calibrated and security-aware hybrid that integrates CNN, heterogeneous GNN with reverse edges, and LSTM for behavioral sequences. Multitask-trained models (BCE for purchase links and λ· BCE for session risk) with L2 regularization and post-practice calibration, chronological data sharing prevents leakage. The goal is to design and evaluate CNN-plus CNN-enhanced GNN-LSTM hybrids to improve the accuracy of recommendations and reduce risk. The results on partner MSME data: ROC-AUC 0.965 (val)/0.946 (test), PR-AP 0.943/0.910; risk ROC-AUC 0.984, PR-AP 0.982, surpassing a CNN-BiLSTM baseline (0.93/0.91). Brier scores 0.161 (links) and 0.176 (risk) enable safer personalization. Going forward, we are focusing on per-segment calibration with ECE/MCE reporting, compute efficiency, multimodal expansion, ablation, and explainability (GNNExplainer, CNN saliency), as well as online retraining and drift monitoring to maintain production performance**.

Keywords*—*CNN; e-commerce; hybrid model; LSTM; MSME; user behavior prediction

I. INTRODUCTION

The competitiveness of MSMEs is increasingly supported by digital transformation, which is understood not only as technology absorption, but as a twin engine of technology assimilation and business model innovation that updates strategy and performance [1]. Digital transformation requires a proactive attitude to build capabilities in data processing, skills, processes, and governance so that digital tools translate into durable value [2],[3],[4],[5]. Digital tools in the form of e-commerce certainly require consequences, especially with risk and resilience: AI can reduce SME business risks and strengthen the resilience of service supply under disruption [6],[7], even as companies have to keep pace with shifting customer expectations and align digital marketing practices accordingly [8],[9].

On the demand side, user experience is crucial. E-commerce displays in the form of visual presentations include aesthetics, accessibility, readability, and interactive features or AR, clearly shape engagement and purchase intent [10],[11],[12]. With an increasingly multimodal data e-commerce view, feature matching captures cross-modal relevance under production constraints, complemented by a lightweight and interpretable relevance architecture and scalable NLP flows for opinion mining [13],[14],[15],[16]. The use of chatbots influences trust through interactivity and perceived humanity, conditioning adoption and further outcomes in digital commerce [17],[18].

User security and privacy are inseparable in e-commerce. The lack of security in e-commerce causes MSMEs to routinely face phishing, bots, card testing, account abuse, and the threat of multimodal fake reviews that erode trust and directly shape user behavior [19],[20],[21],[22]. At the same time, the well-documented privacy-personalization paradox underscores the need for recommenders who pair accuracy with responsible data practices and transparent decision-making [23],[24],[25]. However, despite the rapid advances in AI for e-commerce and the increasing adoption of social and omnichannel tools by SMEs, most production pipelines still optimize conversions while degrading security to a separate layer that ignores how design cues and session-level risk together affect behavior over time [26],[27],[28].

In this study, conducted in [26] [6], the LSTM model is effective at capturing sequential user dynamics central to the recommendation system, enabling MSMEs to infer needs and predict purchase intent for a more personalized experience and higher conversions. However, LSTMs require heavy training and computing costs, large parameter footprints, and prolonged optimization cycle constraints, which clash with the limits of MSME resources [29],[30],[6],[31]. They also inherit the opacity of deep learning, complicating diagnosis and refinement of strategies [15],[29]. The large amount of model data in the training data has an impact on performance; data inadequacy can worsen when MSME logs are sparse, noisy, or incomplete, especially for sequence-dependent architectures such as LSTM [31].

The contribution of this research is to improve the accuracy of modeling the impact of MSME user behavior on the digital transformation agenda. To close the gaps, we designed a unified

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architecture that integrates three key sources of information: design and user experience signals extracted from product imagery with CNN, user–product–session relational contexts along with security incidents modeled through GNN-based heterogeneous graphs, as well as long-term behavioral dynamics represented by LSTM. This integration allows the system to increase the relevance of recommendations and maintain security resiliency, so that user trust is maintained.

II. Previous Research Study

Digital transformation in MSMEs is not only about technology absorption but also about how to build business model innovations that reshape performance and strategy [1]. Transformation requires a proactive attitude that demands capabilities, data, skills, processes, and adaptive governance to maintain the conditions of value creation that are often highlighted in Indonesian MSMEs and under the pressure of Industry 4.0 [2],[13],[32]. Meeting these demands requires models that connect design, behavior, and networks. Visual design display, accessibility, and readability are the drivers of purchase intent; CNN can be used to extract these signals from product imagery [11]. Long-term shifts in intent and engagement require LSTMs to robustly model daily or weekly sequences under shocks and seasonality [6]. Meanwhile, purchasing journeys, sessions, categories, and even security events form a relational substrate that GNN can capture, in line with the reality of platformization in the MSME ecosystem [28],[27],[33],[37]. CNN, LSTM, and GNN answered marketing calls to track evolving expectations with measurement-driven, disciplined practices [9]. Multimodal fusion research shows clear advantages of combining images, text, and behavioral signals [13],[14] and emphasizes the need for a lightweight, interpretable relevance model at production scale [15], while review-centric NLP still struggles with domain shifts and multimodal grounding [16].

Security in transactions, privacy, and trust are the basis when MSMEs carry out digital transformation through e-commerce. E-commerce is constantly exposed to phishing, bots, card testing, and account abuse that erodes trust and conversions [21], with multimodal fake reviews further contaminating reputation signals [22]. Paradoxically, personalization requires transparency, user control, and calibrated decisions [23], echoing the approach of preserving trust in adjacent domains [24]. Predictive analytics in MSMEs has progressed from data-mining studies of purchasing patterns to LSTM models (strengthened by exploratory analysis) that improve online sales forecasting [34]. In parallel, GNNs bring structure-aware learning for interaction, supply, and cyberattack networks, supporting anomaly and threat detection to reduce operational risk, though scalability can be challenging for resource-constrained MSMEs [35],[6],[36].

The research gap is that most MSME-oriented recommenders still handle design cues, temporal behavior, and security risk in isolation, which limits explainability and undermines long-horizon reliability. This research contribution is a hybrid CNN-LSTM-GNN architecture that encodes product-design quality from images, models users' temporal dynamics, and propagates information across a heterogeneous graph of users, products, sessions, and categories, including security events. The approach is expressly designed to map and make explainable how user behavior both drives and reflects digital transformation in MSME e-commerce, closing the integration and interpretability gap while remaining suitable for production deployment. while reporting rigorous ranking and reliability metrics ROC-AUC, PR-AP, and probability calibration (Brier/ECE) to enable trustworthy and cost-conscious deployment.

III. Proposed Research Methodology

The methodology for this study is illustrated in Fig. 1.

A. LSTM

LSTM dynamics (single layer), the equation used is shown in Eq. (1):

$$h_t = LSTM(x_t, h_{t-1}),\ \hat{y} = \sigma(Wh_T + b) \quad (1)$$

LSTM in Eq. (1) variable summary (concise): At time t, $\boldsymbol{x_t}$ is the feature vector (e.g., daily user aggregates such as event count, dwell time, discounts), typically $x_t \in \mathbb{R}^F$ (or $\mathbb{R}^{TxF}$ for full sequences). The previous hidden state $\boldsymbol{h_{t-1}} \boldsymbol{\epsilon}\ \mathbb{R}^{\boldsymbol{H}}$ carries memory. After ingesting x_t, the LSTM outputs $h_t \in \mathbb{R}^H$ (with an internal cell state ct, omitted here). Over a sequence of length $\boldsymbol{T}$, $\boldsymbol{h_T}$ summarizes the entire history. The final prediction is computed by a linear map and activation: $\hat{y} = \sigma(Wh_T + b)$, with $W \in \mathbb{R}^{1xH}, b \in \mathbb{R}$ for binary (sigmoid), or $W \in \mathbb{R}^{KxH}, b \in \mathbb{R}^K$, for multi-class (softmax). In short, x_t provides the current signal, h_{t-1} the memory, h_T the sequence summary, and (W, b, σ) convert it to calibrated probabilities.

B. GDBT

The GBDT additive learner (m trees) equation is shown in Eq. (2):

$$F_m(x) = F_{m-1}(x) + vh_m(x),\ \ m = 1, \ldots, M \quad (2)$$

GBDT in Eq. (2) is explained as follows: In this boosting formulation, x denotes the feature vector for a single sample. The algorithm proceeds over iterations $m = 1, \ldots, M$, where M is the total number of weak learners. At each step, the current ensemble prediction $F_{m-1}(x)$ is updated by adding a new weak learner $h_m(x)$, for example, a small regression tree trained on the residuals/gradients at step m. The update is scaled by the learning rate $v(0 < v \leq 1)$; smaller v makes changes more conservative and typically requires more iterations. The result is the new ensemble prediction $F_m(x)$ after incorporating h_m at iteration m.

C. CNN

CNN encoder (feature map pooled to embedding) is shown in Eq. (3):

$$z^{img} = Pool(\phi_{CNN}(I)) \quad (3)$$

CNN in Eq. (3) is explained as follows: I is the input product image (RGB tensor $HxWx3$). $\phi_{CNN}(.)$ is a convolutional backbone that converts I into a feature map $F \epsilon \mathbb{R}^{H'xW'xC}$ capturing color, texture, layout, and readability. $Pool(.)$ (global average/max/adaptive) compresses F into a fixed-length vector. $z^{img} \epsilon \mathbb{R}^{d_{img}}$ is the resulting image embedding a compact design/UX representation fed to downstream models.

Fusion (weighted blending of branch scores) is shown in Eq. (4):

$$\hat{p} = w_{CNN}\hat{p}_{CNN} + w_{LSTM}\hat{p}_{LSTM} + w_{gdbt}\hat{p}_{gdbt},\ w_k \geq 0, \sum_k w_k = 1 \quad (4)$$

Eq. (4) is explained as follows: here, $\hat{p}$ denotes the final ensemble prediction (e.g., purchase probability or session-risk score), obtained by blending three branch outputs: $\hat{p}_{CNN}$ from the image/design stream, $\hat{p}_{LSTM}$ from the temporal-behavior stream, and $\hat{p}_{GDBT}$ from the tabular/exogenous Gradient Boosting stream. The blend uses non-negative weights $w_{CNN}, w_{LSTM}, w_{GDBT}$ that sum to one, ensuring a convex combination and thus a valid probability. The optional multi-task objective (purchase & risk) is shown in Eq. (5):

$$\mathcal{L} = BCE(\hat{p}_{link}, y_{link}) + \lambda BCE(\hat{p}_{risk}, y_{risk}) + \beta||\theta||_2^2 \quad (5)$$

Eq. (5) is explained as follows: here, $\mathcal{L}$ denotes the total training loss the model minimizes. It has three parts: 1) a binary cross-entropy term for purchase link prediction, $BCE(\hat{p}_{link}, y_{link})$, which measures how well the predicted purchase probability $\hat{p}_{link}$ matches the ground-truth label $y_{link} \epsilon \{0,1\}$; 2) a session-risk binary cross-entropy term, $\lambda BCE(\hat{p}_{risk}, y_{risk})$, scaled by $\lambda \geq 0$ to control its influence, by comparing the predicted risk $\hat{p}_{risk}$ to $y_{risk} \epsilon \{0,1\}$; and 3) an L_2 regularization penalty, $\beta||\theta||_2^2$, where θ are all trainable weights (e.g., from the CNN/LSTM/GNN). The coefficient β controls weight decay to curb overfitting by discouraging excessively large parameters.

D. Evaluation

To evaluate, ROC-AUC is shown in Eq. (6), PR-AP in Eq. (7), Brier score in Eq. (8), and ECE in Eq. (9):

$$\text{Po}\chi\text{–AYX: area under } TPR(t) vs FPR(t) \quad (6)$$

$$\Pi\text{P–A}\Pi\text{:}\ AP = \int_0^1 P(R)dR \quad (7)$$

Precision@K/Recall@K: on top-K ranked pairs

$$\text{Brier score: } \frac{1}{N}\sum_{i=1}^{N}(\hat{p}_i - y_i)^2 \quad (8)$$

$$\text{EXE (calibration): } \sum_b \frac{n_b}{N}|acc(b) - conf(b)| \quad (9)$$

Decision policy (thresholding) is shown in Eq. (10):

$$\hat{y} = 1\{\hat{p} \geq r\},$$
$$r = argmax\ \mathbb{E}[gain - cost_{FP} - friction_{risk}] \quad (10)$$

TPR(t), in Eq. (6), is explained as follows: true-positive rate at threshold t. FPR(t): false-positive rate at threshold t. Eq. (7) is explained as follows: here, P(R): precision as a function of recall R. Brier in Eq. (8) is explained as follows: score N: number of evaluated examples. $\hat{p}_i$: predicted probability, for example i. $y_i \epsilon \{0,1\}$: ground-truth label, for example i. ECE (Expected Calibration Error) in Eq. (9) is explained as follows b: probability bin (e.g., 0.0–0.1, …, 0.9–1.0). $\boldsymbol{n_b}$: number of examples in bin b. acc(b): empirical accuracy in bin b. conf(b): average predicted probability (confidence) in bin b. Decision policy (thresholding) in Eq. (10) is explained as follows: y ̂=1{p ̂≥r}: predicted class is 1 if probability p ̂ exceeds threshold r. $r = \arg\max \mathbb{E}[gain - cost_{FP} - friction_{risk}]$: choose the threshold r that maximizes expected net utility, balancing conversion gain, false-positive cost $cost_{FP}$, and user-experience friction from risk controls.

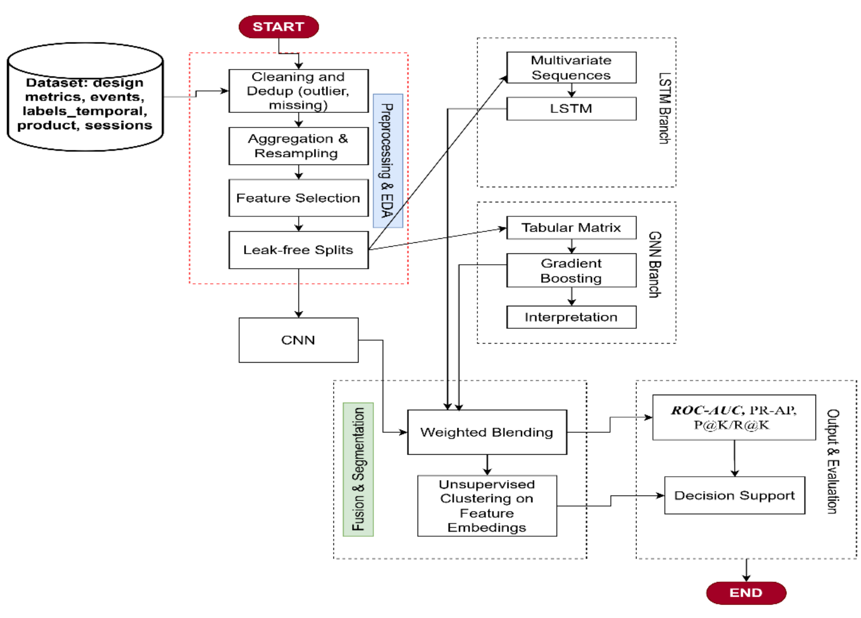

Fig. 1. Proposed research methodology.

IV. Experimental Results and Analysis

The data that has been obtained is stored in the datasets. All data is processed by preprocessing. The next process is carried out by reverse edge, which is meant by reverse edge as follows: Original edge: ('user', 'purchase', 'product') means that the user buys the product. Reverse edge: (product, purchase_rev, user) means product purchased by the user (inverse direction of information).

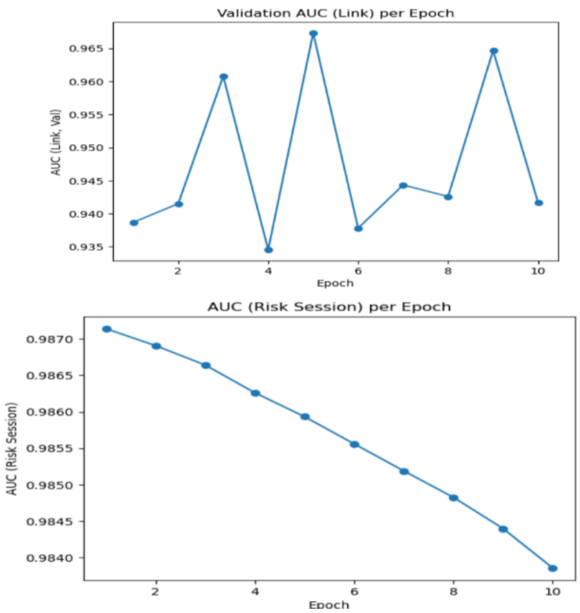

Fig. 2. Tracking and plotting results.

In Fig. 2, Link AUC remains consistently high (~0.94–0.97) with minor saw-tooth fluctuations typical of epoch-wise negative resampling or small validation sets, yielding a stable ≈0.95+ ranking quality for user–product pairs. The security head also stays very strong (risk AUC ~0.984–0.987) with a slight dip; together with a lower BCE, this points to improved calibration. Any small ranking drift is likely negligible and attributable to class imbalance, mild label noise, or train–evaluation distribution differences.

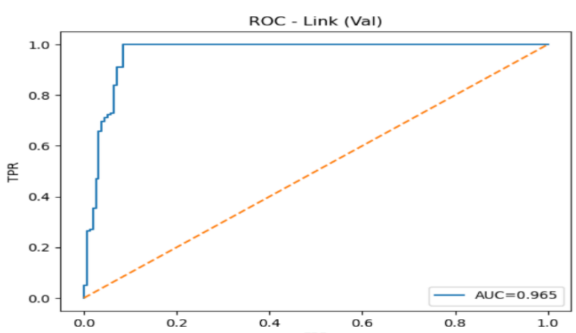

Fig. 3. ROC results - link (Val).

In the ROC–link (Val) curve in Fig. 3, AUC = 0.965 indicates excellent ranking. The curve hugs the top-left, achieving high TPR at low FPR. True buyer pairs are pushed to the top with a few false ranks. Probabilistically, AUC 0.965 ≈ 96.5% chance of a positive score above a negative, leaving ample flexibility to set thresholds for either high-recall or high-precision operation. In Fig. 4, the ROC curve climbs sharply at low FPR and hugs the top-left, indicating strong separation. AUC = 0.946 means the true pair scores higher in ~94.6% of positive–negative pairs. The small drop from validation (AUC ≈ 0.965) signals good generalization without overfitting. Practically, this affords flexible thresholding—low false positives with high TPR—and, alongside PR-AUC/Precision@K, confirms the model reliably prioritizes high-propensity user–product pairs.

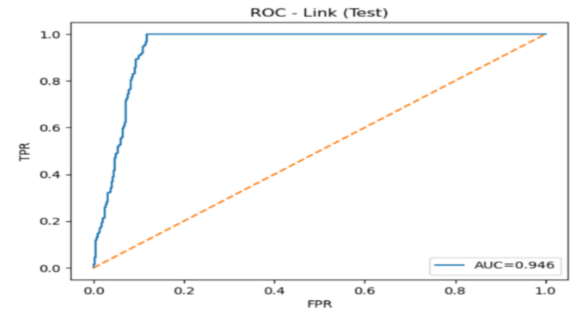

Fig. 4. Hasil ROC - link (Test).

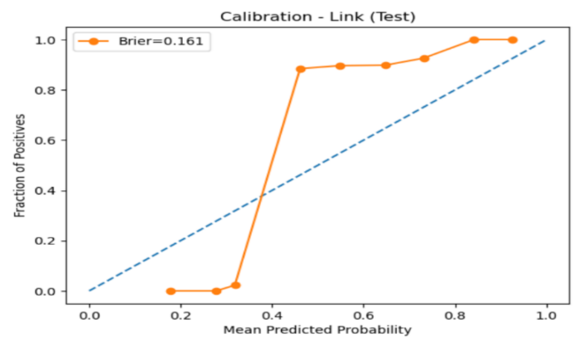

Fig. 5. Calibration - link (Test).

In Fig. 5, the curve shows mild over-confidence at low scores (~0.15–0.30), clear under-confidence in the mid range (~0.35–0.45), and persistent under-confidence at high scores (>0.5–~0.95); predictions near ~0.95–1.0 are very reliable. Brier = 0.161 indicates reasonably good calibration on imbalanced data, with most room for improvement in the middle band. Given the strong ROC/PR, ranking is already solid; light per-segment recalibration (Platt, isotonic, or beta) will make probabilities more proportional and safer for MSME personalization.

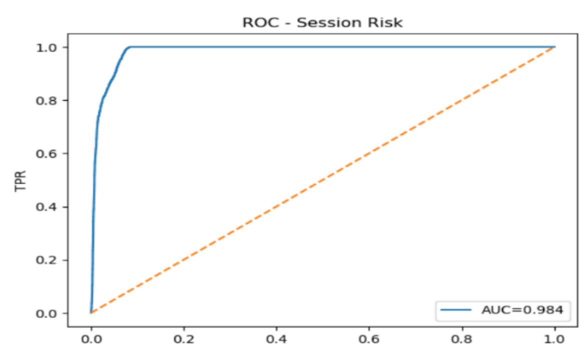

Fig. 6. ROC - session risk.

In Fig. 6, the ROC curve rises steeply at low FPR and hugs the top-left (AUC = 0.984, ≈98.4% pairwise separability). This reflects the security-aware heterogeneous graph, where severity, threat type, and outcomes propagate over session→user→sec_event (with reverse edges). Operationally, sustaining TPR ≥ 0.90 at FPR ≤ 0.05 supports risk-adaptive friction: higher thresholds to block, lower selective thresholds for CAPTCHA/2FA on borderline cases yielding accurate early warnings at low error cost and stronger security without harming legitimate UX.

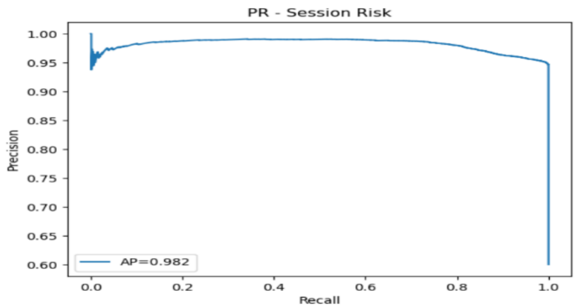

Fig. 7. PR - session risk.

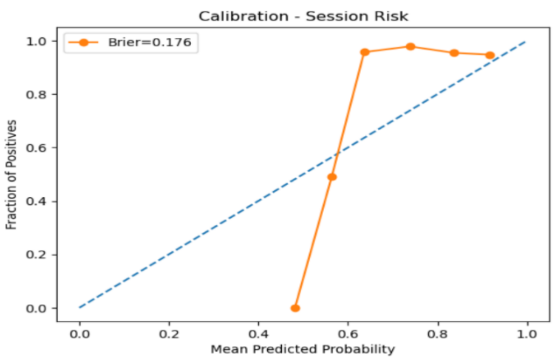

Fig. 8. Calibration - session risk.

In Fig. 7, precision stays ~0.95–1.0 across a wide recall range (AP = 0.982), indicating few false positives and near-perfect ranking. The curve is flat >0.95 through mid–high recall, dropping only near recall ≈1.0 as borderline cases enter. Operate at recall 0.7–0.9 (precision ≥0.95) to enable risk-adaptive friction (selective 2FA/CAPTCHA) with minimal user burden. Results are consistent with the security-aware heterogeneous graph, where severity/type/outcome signals propagate via session–user–sec_event relations (with reverse edges) to deliver accurate early warnings at low cost. The reliability curve in Fig. 8 shows: 1) local over-confidence at ~0.50–0.58 (below the y=x line), 2) real under-confidence at ~0.60–0.70 (curve beyond y=x), and 3) systematic under-confidence in the high range of ~0.70–0.95, while at ~0.95–1.0 the prediction is highly trusted. A Brier score of 0.176 indicates a fairly good calibration in the imbalanced scenario, but needs improvement in the medium probability (~0.55–0.65). Overall, the model excels in the rankings (high PR/ROC), but tends to underestimate the risk at medium–high scores.

In Table I, the hybrid model (CNN + LSTM + heterogeneous GNN with reverse edges) clearly outperforms the CNN–BiLSTM baseline: purchase ROC-AUC rises from 0.93/0.91 (val/test) to 0.965/0.946 with PR-AP 0.943/0.910; the security head reaches ROC-AUC 0.984 and PR-AP 0.982. Calibration is tighter (Brier 0.161 link; 0.176 risk), enabling easier thresholding (e.g., P@K, risk gating) with lower error costs. Gains stem from richer relational context, bidirectional message passing, and multi-task training. Remaining limits: mild mid-range under-confidence and sensitivity to graph/label quality.

TABLE I. COMPARISON OF CNN–BILSTM BASELINE VS. HYBRID CNN+LSTM+GNN ON PARTNER MSME DATA

Aspect	CNN–BiLSTM (Baseline)	Hybrid CNN+LSTM+GNN (Proposed)
ROC-AUC (Purchase)	0.93 (val) / 0.91 (test)	0.965 (val) / 0.946 (test)
PR-AP (Purchase)	—	0.943 (val) / 0.910 (test)
ROC-AUC (Session Risk)	—	0.984
PR-AP (Session Risk)	—	0.982
Calibration (Brier)	— (often less stable for sequence-only models)	0.161 (link) / 0.176 (risk)
Relational context modeling	Limited to temporal user sequences	Yes (user–product–session–category–sec_event) via GNN
Bidirectional message passing	—	Yes (reverse edges; stabilizes embeddings, helps cold/near-cold)
Safe personalization (risk gating)	Limited	Enabled: calibrated thresholding & policy control
Multi-task objective (link + risk)	No	Yes (regularizes representations, reduces conflict)
Key limitations	Sensitive to sparse/noisy sequences; limited explainability	Mild mid-probability under-confidence; performance bounded by graph quality

V. CONCLUSION

This research shows that the hybrid architecture of CNN+LSTM+GNN can provide safe personalization for MSMEs. For the purchase stage, the proposed model achieves a ROC-AUC of 0.965 (val) / 0.946 (test) and a PR-AP of 0.943 / 0.910, exceeding the CNN-BiLSTM baseline (0.93 / 0.91). For session risk detection, performance was close to perfect (ROC-AUC 0.984, PR-AP 0.982). The predicted probability is adequately calibrated (Brier 0.161 for links; 0.176 for risk), making it suitable for operational thresholds. These gains are driven by multi-tasking learning and two-way messaging that exploits relational contexts across users, products, sessions, categories, and security events that generate more accurate recommendations without sacrificing user security or trust. It can be concluded that the CNN+LSTM+GNN hybrid model can be used as an accurate, safe, and measurable recommendation in MSME e-commerce.

Looking ahead, we will pursue multimodal expansion integrating text (titles/reviews), payment/logistics signals, and campaign indicators to enrich decision context, alongside per-segment calibration and cost–benefit evaluation to ensure reliable and cost-effective deployment.

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