search test are lr with a value of 0.001, l2 with a value of 0.00001, and hidden_size with a value of 100. After determining the best parameters for the baseline, an evaluation matrix will be calculated to see which model is superior.

TABLE III
RESULTS OF HR AND MRR FOR MODEL COMPARISON WITH BASELINE

Next-One Recommendation				
Model	**HR@10**	**HR@20**	**MRR@10**	**MRR@20**
Baseline (SRGNN)	43.53	48.39	29.75	30.10
Our Model	44.25	49.16	30.36	30.71
Improvement (%)	1.65	1.61	2.05	2.04
Next-New Recommendation				
Model	**HR@10**	**HR@20**	**MRR@10**	**MRR@20**
Baseline (SRGNN)	32.34	36.60	22.91	23.20
Our Model	32.69	37.06	23.34	23.64
Improvement (%)	1.10	1.27	1.89	1.89

The results of the comparison with the baseline are presented in Table III. Our model outperforms the baseline model for all evaluation metrics with an improvement in the range of 1% to 2% for next-one music recommendation and an improvement in the range of 1% for next-new music recommendation.

Table III shows that the performance of the base model that only captures part of the item history is not much better than our model that captures the entire item history. In addition, the model formed from a graph with entity relationships between users, music, albums, and artists performs much better than the graph with no entity relationships between users, music, albums, and artists.

V. CONCLUSION

In this paper, we implement a combination of graph neural networks with attention mechanisms for sequential music recommendations adapted from the GASM model. Graph neural networks capture the relationships between users and items, while attention mechanisms capture changes in preferences during a session. Experiments with Music4All data demonstrate that our model can effectively recommend music despite facing a wide distribution of users. Optimal performance is achieved through appropriate parameters for learning rate, small regularization, and large embedding size. Additionally, the short-term attention mechanism proved to be highly influential, as losing information about changes in user preferences led to a drastic decline in all evaluation metrics. Other preferences, such as long-term and dynamic, also complement each other in creating good recommendations. This was demonstrated when losing one of these preferences caused the model to fail to achieve its best evaluation. In addition, the combination of heterogeneous graphs with user preference and item information enables the model to absorb complex information for accurate recommendations. In the future, research can be conducted by testing the scalability of the model on larger and more diverse music datasets, exploring more varied parameter settings to maximize model evaluation results, and evaluating the model's generalization ability to other recommendation domains such as movies or books to demonstrate the model's capabilities in the SRS approach.

REFERENCES

[1] I. A. P. Santana and M. A. Domingues, "Context-aware music recommendation with metadata awareness and recurrent neural networks," *Computing and Informatics*, vol. 41, no. 3, pp. 834–860, 2022.

[2] Y. Deldjoo, M. Schedl, and P. Knees, "Content-driven music recommendation: Evolution, state of the art, and challenges," *Computer Science Review*, vol. 51, p. 100618, 2024.

[3] S. Ahmad, I. Ullah, F. Mehmood, M. Fayaz, and D. Kim, "A stochastic approach towards travel route optimization and recommendation based on users constraints using Markov chain," *IEEE Access*, vol. 7, pp. 90 760–90 776, 2019.

[4] T. F. Boka, Z. Niu, and R. B. Neupane, "A survey of sequential recommendation systems: Techniques, evaluation, and future directions," *Information Systems*, p. 102427, 2024.

[5] L. Pan, W. Pan, M. Wei, H. Yin, and Z. Ming, "A survey on sequential recommendation," *arXiv preprint arXiv:2412.12770*, 2024.

[6] J. Chang, C. Gao, Y. Zheng, Y. Hui, Y. Niu, Y. Song, D. Jin, and Y. Li, "Sequential recommendation with graph neural networks," in *Proceedings of the 44th international ACM SIGIR conference on research and development in information retrieval*, 2021, pp. 378–387.

[7] H. Weng, J. Chen, D. Wang, X. Zhang, and D. Yu, "Graph-based attentive sequential model with metadata for music recommendation," *IEEE Access*, vol. 10, pp. 108 226–108 240, 2022.

[8] C. Gao, Y. Zheng, N. Li, Y. Li, Y. Qin, J. Piao, Y. Quan, J. Chang, D. Jin, X. He *et al.*, "A survey of graph neural networks for recommender systems: Challenges, methods, and directions," *ACM Transactions on Recommender Systems*, vol. 1, no. 1, pp. 1–51, 2023.

[9] S. Wang, L. Hu, Y. Wang, L. Cao, Q. Z. Sheng, and M. Orgun, "Sequential recommender systems: challenges, progress and prospects," *arXiv preprint arXiv:2001.04830*, 2019.

[10] Z. Fan, Z. Liu, Y. Wang, A. Wang, Z. Nazari, L. Zheng, H. Peng, and P. S. Yu, "Sequential recommendation via stochastic self-attention," in *Proceedings of the ACM web conference 2022*, 2022, pp. 2036–2047.

[11] M. Zhang, S. Wu, X. Yu, Q. Liu, and L. Wang, "Dynamic graph neural networks for sequential recommendation," *IEEE Transactions on Knowledge and Data Engineering*, vol. 35, no. 5, pp. 4741–4753, 2022.

[12] B. Khemani, S. Patil, K. Kotecha, and S. Tanwar, "A review of graph neural networks: concepts, architectures, techniques, challenges, datasets, applications, and future directions," *Journal of Big Data*, vol. 11, no. 1, p. 18, 2024.

[13] M.-H. Guo, T.-X. Xu, J.-J. Liu, Z.-N. Liu, P.-T. Jiang, T.-J. Mu, S.-H. Zhang, R. R. Martin, M.-M. Cheng, and S.-M. Hu, "Attention mechanisms in computer vision: A survey," *Computational visual media*, vol. 8, no. 3, pp. 331–368, 2022.

[14] Z. Niu, G. Zhong, and H. Yu, "A review on the attention mechanism of deep learning," *Neurocomputing*, vol. 452, pp. 48–62, 2021.

[15] W.-C. Kang and J. McAuley, "Self-attentive sequential recommendation," in *2018 IEEE international conference on data mining (ICDM)*. IEEE, 2018, pp. 197–206.

[16] M. Domingues, I. Pegoraro Santana, F. Pinhelli, J. Donini, L. Catharin, R. Mangolin, Y. Costa, and V. D. Feltrim, "Music4all: a new music database and its applications," in *27th International Conference on Systems, Signals and Image Processing, IWSSIP*, 2020.

[17] C. Xu, P. Zhao, Y. Liu, V. S. Sheng, J. Xu, F. Zhuang, J. Fang, and X. Zhou, "Graph contextualized self-attention network for session-based recommendation." in *IJCAI*, vol. 19, no. 2019, 2019, pp. 3940–3946.

[18] Z. Pan, F. Cai, W. Chen, H. Chen, and M. De Rijke, "Star graph neural networks for session-based recommendation," in *Proceedings of the 29th ACM international conference on information & knowledge management*, 2020, pp. 1195–1204.

[19] K. Zhang, A. Yousefpour, D. Pan, J. Li, and G. Hu, "Ai-empowered consumer behavior modeling framework for music recommendation over heterogeneous electronics products," *IEEE Transactions on Consumer Electronics*, 2024.

[20] S. Wu, Y. Tang, Y. Zhu, L. Wang, X. Xie, and T. Tan, "Session-based recommendation with graph neural networks," in *Proceedings of the AAAI conference on artificial intelligence*, vol. 33, no. 01, 2019, pp. 346–353.