LIVESTREAM SHOPPING: ANALYTICAL DASHBOARD DEVELOPMENT

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1. INTRODUCTION

Livestream shopping (retailing or eCommerce) is an emerging and swiftly growing sector of eCommerce. Unlike traditional television home shopping, livestream shopping integrates live customer interaction and leverages the trust associated with streaming personalities to enhance product sales, elevate customer engagement, and reduce purchase consideration times. While this sector has matured in East Asian markets, notably China, it is now gaining momentum globally. There are many competing livestream shopping platforms ('merchants') in the global market[5] and country-specific domestic markets. Typically, each platform hosts its own analytics dashboard where stakeholders are required to log in to gather relevant data, detailed metrics and insights[9].**[Q2]** Therefore, we propose to develop a 'one-stop' livestream shopping analytics dashboard tool that covers multiple streaming platforms to provide stakeholders (merchants, customers, streamers & platform managers)**[Q4]** with convenient access to detailed metrics, descriptive analytics and data insights to facilitate their decision-making.**[Q1,Q3]**

2. PROBLEM DEFINITION

The problem at hand is the lack of a unified analytics solution for livestream shopping stakeholders. Stakeholders in this field, including merchants, customers, streamers, and platform managers, are currently burdened by the **need to access multiple platform-specific analytics dashboards**, hindering their ability to efficiently gather data, compare metrics, and make informed decisions. Our solution is to develop a centralized livestream shopping analytics dashboard tool that aggregates data from multiple platforms, provides insights and can predict promotional campaign performance (i.e. expected revenue), all to streamline stakeholder decision-making process.

3. BACKGROUND & LITERATURE REVIEW

This literature review was undertaken following the Nine Heilmeier Questions process[8] to both justify future research and help formulate the project scope. In the age of big data, businesses must acknowledge technological evolution and adapt proactively to maintain competitiveness, especially in e-Commerce, including Livestream, where data streams are fully digital[2]. Moreover, the global Livestream market has grown at a blistering 21% compounded annually from $988m in 2021[18] to $1.24b in 2022 and $1.49b in 2023[17], and is predicted to grow at this rate until 2023[18]. Livestream introduces a new online shopping experience, enabling a novel communication channel between sellers and consumers[19]. This new type of commerce introduces platforms and streamers into the business, broadening the seller base. In this new marketplace, platforms provide robust infrastructure; streamers build their credibility on interacting with consumers; sellers evaluate operation metrics and decide budgets on various platforms, streamers and other influencers. All these users need insightful analytical tools for monitoring their operations.**[Q4]** Furthermore, research of 1,500 online retailers, showed adopting descriptive analytics can lead to a revenue increase of 4%-10% within six months[3].**[Q6]** In addition, brands frequently collaborate with influencers on platforms like Instagram Live and TikTok for live commerce. However, these platforms often withhold customer data, creating a dependent relationship[9]. Recognizing these challenges, many brands are integrating live streaming features into their own online stores, though they may overlook crucial aspects like data analysis and retargeting.**[Q2,Q6]** Noting the significant rise and impact of the Livestream market and also acknowledging these challenges and shortcomings of the current state of the market offerings, our objective is to facilitate business goals and user convenience by developing a comprehensive monitoring and analytics dashboard for merchant clients (and other stakeholders) engaged in live streaming shopping across multiple platforms.**[Q1,Q3]** In terms of research specific to descriptive and predictive analytics, current research on live stream shopping sales is typically platform-specific per study and primarily examine descriptive characteristics and behaviors of streamers and products. Such metrics and characteristics include streamer popularity, viewer count, gender[(22)], broadcast time, social engagement[(11,15)], audience age[(13)], product type, product assortment within categories[(13)], product price, and brand prestige[(16)], often using final sales or clicks (or similarly equivalent metrics) as response variables. Further research utilizes these descriptive characteristics and employs deep learning architectures to build predictive models [(12)]. Conversely, other studies emphasize predictive models based solely on long-term temporal sales volume using traditional statistical learning and time series methods[(21)]. Effective customer engagement during live streams boosts purchase intent[(24)], informs product development and marketing, and improves streamer content. Acknowledging this, we will endeavor to contribute to this academic discourse and user ease-of-use by providing metrics and insights in our dashboard that are consistent with the most notable descriptive characteristics of streams and products. Further, if possible, we will attempt to provide predictive and prescriptive analytics in our dashboard tool in the form of estimations and suggestions, respectively, by leveraging an assortment of algorithm architectures, as different inputs fit different model assumptions and architectures in the literature.[Q1,Q3]

4. OUR METHOD

We proposed an analytics dashboard that offers critical metrics such as view counts, view duration, shopping cart clicks and revenue to enable clients to evaluate streaming shopping event effectiveness, aligning with the Strategize, Plan, Monitor/Analyze, and Act/Adjust business management framework[(10)]. The analytics dashboard reflects identified room-for-improvement and aims to boost streaming efficiency, consumer engagement and sales performance. [Q5]

Acquiring a comprehensive dataset for live streaming commerce proves to be a formidable and costly task due to the decentralized distribution of information across platforms and the confidentiality surrounding sales orders, often leading to redirections to external websites. Despite these inherent challenges, coupled with the difficulty in distinguishing user sources, our research and the proposed analytics tool focusing on live shopping platform behaviors retain significant value [(14,23)]. This endeavor provides merchants with valuable sales insights, contributing to enhanced performance, while platforms stand to gain improved traffic and load management capabilities [(6)]. The innovations are:

1) Centralized livestream shopping analytics dashboard tool that **aggregates data from several largest livestream platforms** in the South Korean market. Platforms include Naver, 11st Street, Kakao Shopping, CJ Onstyle, H Mall. Currently, there are no centralized platforms that aggregate data across livestream shopping platforms and users must log in to each individual platform to gain data insights.

2) **Predicting marketing campaign revenues** using several machine learning algorithms. Through the literature review, previous studies [(11,12,21)] are focused on predictive models developed only for a specific streaming platform. At the time of writing, there are also no prediction or forecasting tools and features built into existing platform analytics dashboards.

3) **Interface design** of both tools will leverage design heuristics and will be intuitive, easy-to-use, and require no prior usage of documentation. Further the dashboard tool will offer a broad selection of analyses, with shallow options for novices and deeper insights for domain experts.

4.1 Overall System Architecture

Figure 1 Project System Design

The project's scope and methodologies encompass several stages. Given the streamer provider's existing system for capturing shopper activity in the cloud, the project commences with Data Extraction. This data is subsequently stored in a raw database table, which is regularly updated with daily inputs. A Python program is then employed to read these tables, conducting data processing activities like cleaning, aggregation, and predictive calculations. The results are stored back in the database. Finally, an analytical dashboard, developed in Tableau, serves as the front-end layer of the system, facilitating the delivery of insights to the merchant. This project system design and flow is depicted in **Figure 1**.

4.2 Data Extraction, Data Processing & Data Storing

The data for this project is sourced from diverse channels, encompassing third-party data agencies like live.ecomm-data.com, as well as prominent e-commerce platforms in the South Korean market, such as Naver, 11st Street, Kakao Shopping, CJ Onstyle, and H Mall. There are 4 primary tables extracted from the streaming system:

1. **Viewer Activities** (22,181,076,853 rows, 32 columns)**:** Captures extensive interactions, e.g., viewing time, likes, chat participation categorized by merchant, campaign, and user.
2. **Clicks** (101,374,173 rows, 27 columns)**:** Logs campaign aggregate click interactions, includes product and banner activities.
3. **Product Information** (140,404 rows, 31 columns)**:** Contains product details which relate to campaign revenue estimates
4. **Campaign Information** (126,551 rows, 19 columns)**:** Provides campaign details.

4.3 Analytical Dashboard

Through a combination of survey data and insights gathered from previous iterations (see **Figure 2**), we identified a set of metrics crucial for merchants, classifying them under correlation, trend, and product categories (see **Figure 3**). We prepared four analysis pages shown below.

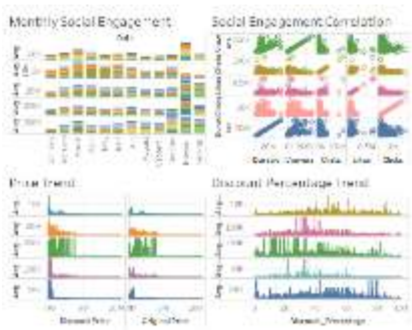


Figure 3 Previous Dashboard Iterations

Figure 2 New Dashboard

1. **Executive summary page.** This page is for e-commerce corporation executives who care about not only corporation level and campaign level revenue, but also viewers' behaviors such as clicks, chats, likes, pageviews of different platforms and campaigns. The dashboard offers a date range filter and a platform filter to help executives explore the data.

2. **Correlation Analysis page.** For campaign managers who keep close watch on viewers behaviors of a running livestreaming, it is helpful to look at correlations between revenue and users' interaction. This page gives a view on how revenue changes when number of users' clicks, chats, likes change.

3. **Trend Analysis page.** This page is for merchant managers who allocate marketing budgets on various livestreaming platforms. The dashboard positions a platform by its MOU (minutes of use by a viewer) as x-axis and ARPC (average revenue per click) as y-axis, and scales a platform by its total revenue as circle size. Running data of views interaction shows below platforms evaluation.

4. **Product Analysis page.** Product managers could be merchants themselves or suppliers of merchants. Or platform managers may wonder what kind of products match their user base well. This dashboard ranks products by revenue generating capability, and clusters products by popularity (measured by clicks received), and profitability (measured by discount offered).

4.4 Product Clustering Tool – Machine Learning Algorithms

One of the solutions offered in this project is the product clustering tool, which automatically clusters different products marketed in the campaign by their attributes. This will help merchants to optimize their sales selling several products together in a single campaign. Based on the dataset that we obtained, each product has 3 important dimensions: discount rate, original price and clicks generated. A K-means clustering is then run against a scaled version of the attributes for 3 cluster centers. Based on **Figure 4**, we can see that the products are clustered nicely to explain different categories of products, namely attractive products (those that generate clicks but small revenue i.e. loss leaders) via red labels, and products with high revenue but are not attractive (low volume) via green labels. Therefore, this tool will allow merchants to mix both products together in a single campaign to optimize their sales.

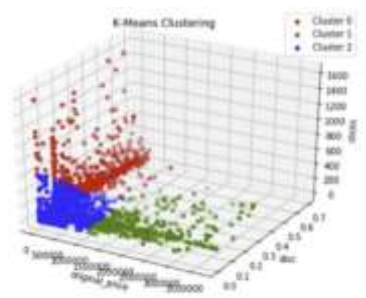


Figure 4 Product Clustering

4.5 Campaign Performance Prediction Tool – Machine Learning Algorithms

In addition to the analytic dashboard which offers descriptive analytical insights, a web application (app) that can predict campaign revenue performance will be developed to provide predictive analytical insights to users. The web app will be developed in the *Flask* framework, Python, HTML and CSS. The web app will utilize the most robust and high-performing machine learning models from the Python *scikit-learn* package after training and testing cycles. Marketing campaign revenue in $USD (i.e. the response variable) will be predicted using viewer count, pageviews, average view time (seconds), chats, likes and shopping cart clicks (i.e. the predictor variables). For data preparation, outliers (such as $0 revenue campaigns) and redundant predictor variables for the predictive models (row identifiers and dates) are removed, and then predictor data is standardized to a 0-1 scale. Data is then split into 70/30 Training and Testing sets. After 5-Fold CV Grid Search training and testing cycles are undertaken on a range of hyperparameters for seven different supervised regression model architectures, model performance will be evaluated. The regression model architectures and their hyperparameters are: 1. ElasticNet Linear Regression, *l-1* ratio (*l-1*: LASSO, *l-2*: Ridge); 2. K-Nearest Neighbors (*KNN*), *k* number of neighbors; 3. Support Vector Machine Regression (*SVR*), *C* regularization parameter, *ε* margin of tolerance; 4. Random Forest Regressor, number of trees and minimum samples per leaf (i.e. model complexity); 5. AdaBoost Regressor, number of estimators and learning rate; 6. Gradient Boosting Regressor, number of estimators and learning rate; and 7. Neural Network, *α* penalty term and hidden layer architectures (single layer or dense multi-layer). Robust and high performing models will be imported to a basic *Flask* web app. Users will manually input values for predictors into a HTML form and Python *Flask* will perform predictions using the exported *sci-kit-learn* model, outputting the predicted revenue to the web app user interface.

5. EXPERIMENT/TESTING, EVALUATION & RESULTS

We are using an Agile development process for this project, iterating through development, deployment, feedback, evaluation cycles. Due to project time constraints, there will only be one feedback and evaluation cycle. Key performance and user feedback metrics and methods are outlined below for testing and evaluation.

5.1 Dashboard - User Testing & Evaluation Plan & Results

- **Is this dashboard helpful to evaluate a campaign or a platform?**

To evaluate the usability of the tool, we have designed a user survey for the streaming platform i.e. the streamer, merchant or platform. The survey asks participants to evaluate the dashboard tool's

usability with respect to good structure, proper display style, insightful metrics and cascaded information, discoverability, simplicity, ease-of-use, robustness across IT systems. Further, the survey asks participants to evaluate if the novelties we claimed are realized and useful. Survey questions are either dashboard-specific categorical questions or 5-point Likert Scale questions relating to user satisfaction and tool perceived performance i.e. usability. The survey can be found in **Appendix A.1**.
Survey Results: Total 10 respondents: user types of 3 streaming platforms, 2 streamers, 2 merchants, and 3 merchants/streamers. Streamers focused on user viewership and click-through rate, while merchants emphasized chat ratio and PV/UV. Respondents agreed with the dashboard layout and key metrics but stressed the importance of smooth operation across different systems. Positive feedback was received for analytic tools like performance insights, campaign evolution indicators, and user-product category clustering. The overall score from the respondents were "**agreed**" with the dashboard but suggested it would be more satisfactory with customization options for different user types. The entire survey result can be found in **Appendix A.2**.

<u>5.2 Prediction Tool – User Testing & Predictive Performance - Evaluation Plan & Results</u>

- **Can a user make a revenue prediction based on campaign characteristics?**
- **Is the revenue prediction model accurate and robust?**

The dataset was processed for machine learning applications as outlined in **Section 4** and then data was split into one main dataset (covering all streaming platforms, dataset size: 1598) and four subsets for each of the four largest streaming platforms by marketing campaign volume – platform/customer_ids: id_3: 267 datapoints, id_51: 91 datapoints, id_141: 116 datapoints and id_171: 873 datapoints. Seven machine learning model architectures were trained, tested and evaluated as per the steps in **Sections 4**. To find the most robust and high-performing models for each architecture, high r^2, the coefficient of determination i.e. explained linear variance, and low mean squared error, *MSE* i.e. squared average magnitude of errors were used to evaluate model performance. The full results of this process can be found in **Appendix B.1**.

The machine learning models were found to achieve at most r^2=0.19 which means that models can only at most explain 19% of the linear variation of marketing campaign revenue using the provided predictor variables. Given the breadth of the model architectures trained and tested, this implies that the provided input data either: lacks sufficient predictor variables to describe the variation in revenue, or the dataset is not large enough to describe the variation in revenue. Additional predictor variables such as product types, streamer trustworthiness, and audience demographic information may help to explain the variation in revenue among campaigns considered 'similar' by the existing models. In addition, a larger dataset may assist the algorithms in finding any patterns they are not able to currently identify. Furthermore, it was found that Random Forest, KNN, ElasticNet and SVM generally perform best across all five datasets.

Figure 5 Prediction Tool User Interface

After assessing the performance metrics of machine learning models across datasets by balancing higher r^2 scores against lower *MSE* scores, it was determined that the best way forward would be to develop the prediction tool using the 'best' model only from the models trained on the full dataset containing all streaming platforms combined. The 'best' and most robust model is the Random Forest Regressor with hyperparameters: max features randomly selected for node split (*max_features*)

= ‘sqrt’; minimum leaf size (*min_samples_leaf*) = 1; and number of trees (*n_estimators*) = 50, which achieved a *MSE* of 2.836×10^{11} and a r^2 of 0.19 (the *MSE* is the best, relative to the magnitude of revenue and other model architectures).
This Random Forest model was then exported to a *Flask* web application, developed into rudimentary prototype and distributed to the project team for feedback. This prototype can be viewed in **Appendix B.2**. Common pain points were that the user interface was too homogeneous and the instructions were unclear. Following feedback, the user interface of the prediction tool was improved to leverage structure, color, text style and section alignment to guide users. The design was also made in a similar stylization to the dashboard tool to enhance user familiarity. The addition of color also introduced the necessity to test for color blindness. Eight color blindness tests can be viewed in **Appendix B.3** and are shown to be satisfactory, except for monochromacy. The final user interface for the prediction tool can be seen in **Figure 5**.

6. CONCLUSION

The Livestream Shopping Analytical Dashboard project represents a significant improvement toward addressing the challenges faced by stakeholders in the livestream shopping ecosystem. This rapidly growing sector faced a unified analytical solution which burdened merchants, customers, streamers and platform managers with the inefficiency of accessing relevant data to optimize their business.

The proposed solution not only bridges this gap but also introduces innovative features. The tool aggregates data from major South Korean livestream shopping platforms and offer descriptive data insights to assist decision-making including product selection, campaign monitoring, and social engagement impact. The development of machine-learning for insights related to product clustering also shown to be helpful for merchants to strategize their campaigns. This, coupled with prediction tool would be a powerful tool for the stakeholders to anticipate revenues and profits.

The methods starts from data extraction, processing and storing that ensure a comprehensive and clean dataset for analysis. The analytical dashboard, developed using Tableau, provides a user-friendly interface and offer various insights to the stakeholders. The campaign performance prediction tool, once achieved better performances through more data collection and features engineering, coupled with product clustering adds a predictive dimension to aid strategic decision making.

All team members have contributed a similar amount of effort.

7. FUTURE WORKS & DISCUSSION

For the future iterative development cycles, we can consider scaling up to cover **longer dataset time** periods; to cover additional **market regions** or be a **global platform with selectable regions**; to feature increased functionality and diversity in available data insights; and to **serve a growing number of peak users** as it gains popularity. In addition, we can also consider two areas for improving performance: **1) Resource Utilization**: Review CPU Utilization, Memory Usage and Network Utilization of AWS EC2 instances of Tableau Server. Storage Utilization of AWS S3 Buckets. Assess predicted service costs; and **2) Response Time, Throughput and Latency:** Using AWS CloudWatch and Elastic Load Testing to monitor S3 Buckets and EC2 Servers, assess how quickly the dashboard application processes. Determine an estimate of the response time vs cost tradeoff of deploying the dashboard. Lastly, the clustering tool could be further developed to allow users to select different amounts of clusters via a web app powered by clustering algorithms in *Flask*.

8. REFERENCES

1. Arora, A., Glaser, D., Kim, A., Kluge, P., Kohli, S. & Sak, N. (2021). *It’s showtime! How live*

commerce is transforming the shopping experience. McKinsey (& Company) Digital. Retrieved from https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/its-showtime-how-live-commerce-is-transforming-the-shopping-experience.
2. Baden-Fuller, C., & Haefliger, S. (2013). *Business Models and Technological Innovation*. Long Range Planning, 419-426.
3. Berman, R., & Israeli, A. (2021). *The Value of Descriptive Analytics: Evidence from Online Retailers*. Harvard Business School.
4. Benjiang Lu, Zhenjiao Chen (2021). *Live streaming commerce and consumers' purchase intention: An uncertainty reduction perspective*. Information & Management Volume 58, Issue 7, November 2021, 103509 https://doi.org/10.1016/j.im.2021.103509
5. Bharadwaj, N., Ballings, M., Naik, P. A., Moore, M., & Arat, M. M. (2022). A New Livestream Retail Analytics Framework to Assess the Sales Impact of Emotional Displays. Journal of Marketing, 86(1), 27-47. https://doi.org/10.1177/00222429211013042
6. Chaithanya, H.V., Prerana, M.S., & Mohan, P. (2023). *Towards Detection of Network Attacks by Snort Analysis Using Machine Learning Techniques*. IEEE https://ieeexplore.ieee.org/abstract/document/10235153
7. Chau, D. H. (2023). CSE 6242 Data and Visual Analytics OAN Fall 2023 - Course Schedule. Retrieved from https://poloclub.github.io/cse6242-2023fall-online/
8. DARPA. (1975). *The Heilmeier Catechism*. Retrieved from https://www.darpa.mil/work-with-us/heilmeier-catechism
9. Deng, J., Binti, R., Tajuddin, M., Ren, B., & Chen, Z. (2023). *From Social Presence to Virtual Presence: Insights into E-Commerce Consumer Behavior*. Modern Management Based on Big Data IV. DOI:10.3233/FAIA230169. https://ebooks.iospress.nl/doi/10.3233/FAIA230169
10. Eckerson, W. (2010). Performance Dashboards. John Wiley & Sons.
11. Guo, Y., Zhang, K., & Wang, C. (2022). *Way to success: understanding top streamer's popularity and influence from the perspective of source characteristics*. J. Retailing Consum. Serv. 64, 102786 https://doi.org/10.1016/j.jretconser.2021.102786.
12. Lin, Q., Jia, N., Chen, L., Zhong, S., Yang, & Gao, T. (2023). *A two-stage prediction model based on behavior mining in livestream e-commerce*. Decision Support Systems, Volume 174, 2023, 114013, ISSN 0167-9236. https://doi.org/10.1016/j.dss.2023.114013.
13. Lu, B., Li, G. & Ge, J. (2023). *Effects of streamer effort and popularity on livestream retailing performance: a mixed-method study*. Electron Commer Res. https://doi.org/10.1007/s10660-023-09757-7
14. Luis V. Casaló a, Carlos Flavián b, Sergio Ibáñez-Sánchez (2020). *Be creative, my friend! Engaging users on Instagram by promoting positive emotions*. Journal of Business Research https://www.sciencedirect.com/science/article/pii/S0148296320301089
15. Meng, L. (Monroe), Duan, S., Zhao, Y., Lü, K., & Chen, S. (2021). *The impact of online celebrity in livestreaming e-commerce on purchase intention from the perspective of emotional contagion*. J. Retailing Consum. Serv. 63, 102733. https://doi.org/10.1016/j.jretconser.2021.102733.
16. Song, D., Chen X., Guo, Z., & Gao, X. (2021). W*hat drives sales of e-commerce live streaming? Evidence from Taobao*. Proceedings of the 14th China Summer Workshop on Information Management. 225-231. https://ink.library.smu.edu.sg/sis_research/6755.
17. The Business Research Company. (2023). *Live Streaming Global Market Report 2023. Research and Markets Global Report*, March 2023, ID 5766965, Retrieved https://www.researchandmarkets.com/r/8qf3mb.
18. Vantage Market Research. (2022). *Live Streaming Market Global Industry Assessment & Forecast, Technical Repor*t, VMR-1412, Vantage Market Research, Washington, DC, United

States.
19. Wang, Y., Lu, Z., Cao, P., Chu, J., Wang, H., & Wattenhofer, R. (2022). *How Live Streaming Changes Shopping Decisions in E-commerce: A Study of Live Streaming Commerce Computer Supported Cooperative Work*. (CSCW) (2022) 31:701–729. https://doi.org/10.1007/s10606-022-09439-2
20. Wongkitrungrueng, A., Dehouche, N., & Assarut N., (2020) *Live streaming commerce from the sellers' perspective: implications for online relationship marketing.* Journal of Marketing Management, 36:5-6, 488-518, DOI:10.1080/0267257X.2020.1748895 https://doi.org/10.1080/0267257X.2020.1748895
21. Wu, Z., Chen, X., & Gao, Z. (2023). *Bayesian non-parametric method for decision support: Forecasting online product sales*. Decision Support Systems, Volume 174, 2023, 114019, ISSN 0167-9236. https://doi.org/10.1016/j.dss.2023.114019.
22. Yang, X., Liu, Y., Dong, J., & Li, S. (2023). *Impact of streamers' characteristics on sales performance of search and experience products: Evidence from Douyin*. Journal of Retailing and Consumer Services, Volume 70, 2023, 103155, ISSN 0969-6989. https://doi.org/10.1016/j.jretconser.2022.103155.
23. Yogesh, K., Dwivedi A., Ismagilova, E.B., Laurie, D., & Hughes, C., and others. (2021). *Setting the future of digital and social media marketing research: Perspectives and research propositions*. International Journal of Information Management. https://www.sciencedirect.com/science/article/pii/S0268401220308082
24. Zheng, R., Li, Z., & Na, S. (2022). *How customer engagement in the live-streaming affects purchase intention and customer acquisition, E-tailer's perspective.* Journal of Retailing and Consumer Services, Volume 68, 2022, 103015 https://www.sciencedirect.com/science/article/pii/S0969698922001084

APPENDIX A.1: Survey

1. Who are you (or chose to be on behalf of) in Live Streaming Commerce business?	
	a) streaming platform
	b) streamer
	c) merchant
2. Which metric(s) is/are most important for you? (choose all that applied)	
	a) Minutes Of User Viewership
	b) Click Through Rate

	c) Chat Ratio
	d) Like Ratio
	e) PV, UV, and PV/UV
	f) Others (please specify)
3. To what extent do you agree with the statement: The layout of dashboard is properly arranged, and information properly organized.	
	a) Totally agree
	b) Agree
	c) Neutral
	d) Disagree
	e) Totally disagree
4. To what extent do you agree with the statement: Key metrics are displayed with right chart style and distinguishable color scheme, so that users can easily comprehend the information and pick out anomaly.	
	a) Totally agree
	b) Agree
	c) Neutral
	d) Disagree
	e) Totally disagree
5. To what extent do you agree with the statement: The hierarchy of the dashboard is well	

designed, so that users could easily dive into lower-level details of a particular metric to find out why, when, or how the key metric changed.	
	a) Totally agree
	b) Agree
	c) Neutral
	d) Disagree
	e) Totally disagree
6. To what extent you agree with the statement: The dashboard runs smoothly whichever Operation System or Brower I choose.	
	a) Totally agree
	b) Agree
	c) Neutral
	d) Disagree
	e) Totally disagree
7. To what extent do you agree with the statement: The dashboard responses instantly whatever data range I query	
	a) Totally agree
	b) Agree
	c) Neutral
	d) Disagree

	e) Totally disagree
8.Which of the analytic tools the dashboard rendered is/are totally new and very useful to you? (optional/choose all applied)	
	a) Performance of campaign, like how many minutes of viewing transferred to a click, and how many clicks transferred to an order.
	b) Key performance indicator of a campaign evolving over time so that you can dynamically adjust the budget.
	c) User - product category clustering for a more consumer targeted campaign strategy.

APPENDIX A.2: Survey Results

Total 10 respondents: 3 streaming platforms, 2 streamers, 2 merchants, and 3 merchants/streamers. Streamers showed interest in metrics like user viewership and click-through rate, while merchants emphasized metrics like chat ratio and PV/UV. Overall, respondents generally agreed with the dashboard layout and display of key metrics, expressing a need for smooth operation across different systems. The analytic tools receiving positive feedback included performance insights, campaign evolution indicators, and user-product category clustering for targeted strategies. Overall results were "**Agree**".

1. Who are you (or chose to be on behalf of) in Live Streaming Commerce business: **Varied Responses**

2. Which metric(s) is/are most important for you: **Varied Responses**

3. To what extent do you agree with the statement: The layout of dashboard is properly arranged, and information properly organized. **Average Results: Neutral**

4. To what extent do you agree with the statement: Key metrics are displayed with right chart style and distinguishable color scheme, so that users can easily comprehend the information and pick out anomaly. **Average Results: Neutral**

5. To what extent do you agree with the statement: The hierarchy of the dashboard is well designed, so that users could easily dive into lower-level details of a particular metric to find out why, when, or how the key metric changed. **Average Results: Somewhat Agree**

6. To what extent you agree with the statement: The dashboard runs smoothly whichever Operation System or Brower I choose. **Average Results: Strongly Agree**

7. To what extent do you agree with the statement: The dashboard responses instantly whatever data range I query. **Average Results: Totally Agree**

APPENDIX B.1:

Dataset sizes breakdown by platform/customer_id

Total size: 1,598 data points

	customer_id	COUNT(*)
2	3	267
3	10	29
4	17	52
5	20	19
6	29	27
7	51	91
8	82	52
9	141	116
10	164	72
11	171	873

Machine Learning Training and Testing Performance Results – 7 Architectures

Dataset: All platforms (all customer ids)

	Reg Model Type	MSE best params	MSE	r2 best params	r2
0	ElasticNet	{'l1_ratio': 1}	3.016355e+11	{'l1_ratio': 1}	0.085476
1	KNN	{'n_neighbors': 5}	3.338435e+11	{'n_neighbors': 11}	0.162526
2	SVM	{'C': 10, 'epsilon': 1}	3.494897e+11	{'C': 10, 'epsilon': 1}	-0.059612
3	RandomForest	{'max_features': 'sqrt', 'min_samples_leaf': 1...	2.835939e+11	{'max_features': 'sqrt', 'min_samples_leaf': 1...	0.191106
4	AdaBoost	{'learning_rate': 0.1, 'n_estimators': 50}	3.911161e+11	{'learning_rate': 0.1, 'n_estimators': 50}	-0.205641
5	GradientBoost	{'learning_rate': 0.1, 'n_estimators': 100}	4.205180e+11	{'learning_rate': 0.1, 'n_estimators': 100}	-0.355871
6	NeuralNet	{'alpha': 1e-05, 'hidden_layer_sizes': (400,)}	3.493079e+11	{'alpha': 1e-05, 'hidden_layer_sizes': (400,)}	-0.059057

Dataset: Customer_id == 3

	Reg Model Type	MSE best params	MSE	r2 best params	r2
0	ElasticNet	{'l1_ratio': 0}	1.617187e+12	{'l1_ratio': 0}	-0.001936
1	KNN	{'n_neighbors': 11}	1.749806e+12	{'n_neighbors': 11}	-0.084101
2	SVM	{'C': 0.5, 'epsilon': 0.1}	1.745225e+12	{'C': 0.5, 'epsilon': 0.1}	-0.081263
3	RandomForest	{'max_features': 'sqrt', 'min_samples_leaf': 5...	1.583432e+12	{'max_features': 'sqrt', 'min_samples_leaf': 5...	0.016503
4	AdaBoost	{'learning_rate': 0.1, 'n_estimators': 50}	1.593663e+12	{'learning_rate': 0.1, 'n_estimators': 50}	-0.004168
5	GradientBoost	{'learning_rate': 0.5, 'n_estimators': 200}	1.991053e+12	{'learning_rate': 0.1, 'n_estimators': 100}	-0.027768
6	NeuralNet	{'alpha': 0.001, 'hidden_layer_sizes': (400,)}	2.155791e+12	{'alpha': 0.2, 'hidden_layer_sizes': (400,)}	-0.335634

Dataset: Customer_id == 51

*very low revenue range $0-$9.8, so very low MSE

	Reg Model Type	MSE best params	MSE	r2 best params	r2
0	ElasticNet	{'l1_ratio': 0}	0.018624	{'l1_ratio': 0}	0.006790
1	KNN	{'n_neighbors': 9}	0.015206	{'n_neighbors': 9}	0.189070
2	SVM	{'C': 0.5, 'epsilon': 0.1}	0.015680	{'C': 0.5, 'epsilon': 0.1}	0.163797
3	RandomForest	{'max_features': 'sqrt', 'min_samples_leaf': 5...	0.018177	{'max_features': 'sqrt', 'min_samples_leaf': 1...	0.038671
4	AdaBoost	{'learning_rate': 0.25, 'n_estimators': 50}	0.017584	{'learning_rate': 0.1, 'n_estimators': 50}	-0.151846
5	GradientBoost	{'learning_rate': 0.5, 'n_estimators': 400}	0.045641	{'learning_rate': 0.5, 'n_estimators': 400}	-1.153406
6	NeuralNet	{'alpha': 0.001, 'hidden_layer_sizes': (50,)}	0.022052	{'alpha': 0.1, 'hidden_layer_sizes': (6, 3, 2)}	-0.433046

Dataset: Customer_id == 141

*very low revenue range $0-$8.5, so very low MSE

	Reg Model Type	MSE best params	MSE	r2 best params	r2
0	ElasticNet	{'l1_ratio': 0}	0.372490	{'l1_ratio': 0}	-0.753459
1	KNN	{'n_neighbors': 11}	0.456776	{'n_neighbors': 5}	-2.189654
2	SVM	{'C': 0.5, 'epsilon': 0.5}	0.268057	{'C': 0.5, 'epsilon': 0.35}	0.012489
3	RandomForest	{'max_features': 'sqrt', 'min_samples_leaf': 2...	0.332859	{'max_features': 'sqrt', 'min_samples_leaf': 2...	-0.673124
4	AdaBoost	{'learning_rate': 0.1, 'n_estimators': 50}	0.613972	{'learning_rate': 0.1, 'n_estimators': 50}	-2.092115
5	GradientBoost	{'learning_rate': 0.5, 'n_estimators': 200}	2.576012	{'learning_rate': 0.1, 'n_estimators': 100}	-8.452208
6	NeuralNet	{'alpha': 0.5, 'hidden_layer_sizes': (10,)}	0.390251	{'alpha': 0.5, 'hidden_layer_sizes': (5, 5)}	-0.602220

Dataset: Customer_id == 171

	Reg Model Type	MSE best params	MSE	r2 best params	r2
0	ElasticNet	{'l1_ratio': 0}	1.649347e+06	{'l1_ratio': 0}	-1.310043e+06
1	KNN	{'n_neighbors': 13}	6.210522e+07	{'n_neighbors': 13}	-4.932897e+07
2	SVM	{'C': 10, 'epsilon': 1}	1.304396e+00	{'C': 0.5, 'epsilon': 0.5}	-5.823265e-02
3	RandomForest	{'max_features': 'sqrt', 'min_samples_leaf': 5...	7.508317e+06	{'max_features': 'sqrt', 'min_samples_leaf': 5...	-4.632423e+06
4	AdaBoost	{'learning_rate': 0.25, 'n_estimators': 200}	6.573138e+06	{'learning_rate': 0.1, 'n_estimators': 50}	-5.220915e+06
5	GradientBoost	{'learning_rate': 0.25, 'n_estimators': 100}	6.570939e+06	{'learning_rate': 0.25, 'n_estimators': 200}	-5.219217e+06
6	NeuralNet	{'alpha': 0.8, 'hidden_layer_sizes': (400,)}	1.208574e+03	{'alpha': 0.5, 'hidden_layer_sizes': (6, 3, 2)}	-1.083009e-01

APPENDIX B.2 - Prototype of Prediction Tool Web Application

Marketing Campaign Performance Prediction Tool - All Platforms

This model covers ALL streaming platforms. Random Forest, r^2 = 0.191106

Enter the values for the features and estimate marketing campaign revenuse $USD

viewers:

*typical range of viewers is 520 to 266270. Units = count

pageviews:

*typical range of pageviews is 613 to 293050. Units = count

viewtime:

*typical range of viewtime is 24.35238 to 960.02037. Units = seconds

chats:

*typical range of chats is 0 to 105875. Units = count

likes:

*typical range of likes is 0 to 225468. Units = count

clicks:

*typical range of clicks is 17 to 150736. Units = count

Estimate Revenue

The estimated revenue of the marketing campaign is $624.16

APPENDIX B.3 - Prediction Tool Web Application – Color Blindness Test

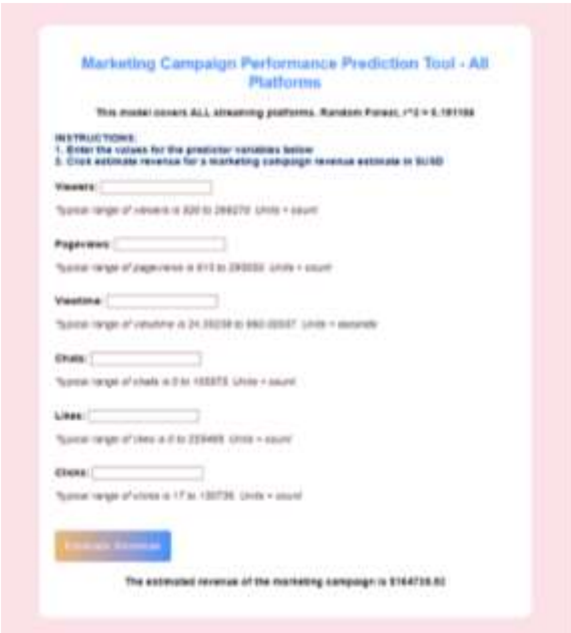
Test at: https://www.color-blindness.com/coblis-color-blindness-simulator/

Red-Weak/Protanomaly **Green-Weak/Deuteranomaly**

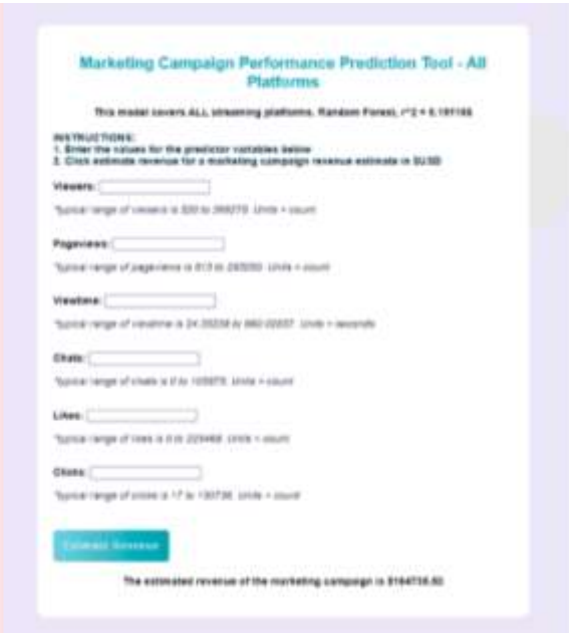
Blue-Weak/Tritanomaly

Red-Blind/Protanopia

Green-Blind/Deuteranopia



Blue-Blind/Tritanopia



Monochromacy/Achromatopsia **Blue Cone Monochromacy**