A Systems Analysis Approach for Business Optimization: Integrating Technology Development with Data Analytics and Marketing for GolfCask

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***Abstract*— GolfCask, a newly established technology-based start-up in Charlottesville, Virginia, is dedicated to cultivating a vibrant online community centered around the shared passions of golf, travel, and whiskey. Employing a systems analysis framework, this project leverages data-driven insights to refine performance indicators and enhance system efficiency within the online community. The strategic objectives, initially structured within an objective tree, prioritize establishing a sustainable and profitable business model, fostering strong community engagement, and attracting and retaining members. A key component involves designing, validating, and deploying an innovative recommendation system to match user profiles with customized whiskey suggestions. Additional tactics in marketing and data processing are implemented and guided by data analytics and visualization tools to strengthen the technology development and enhance user engagement. Research on user acceptance testing and data integration supplies further insight into developing a user-centric design. Incorporating feedback loops and continuous data analytics refines system outputs, ensuring the recommendations and marketing strategies align with user preferences and business objectives. Integrating a comprehensive system analysis with personalized recommendations and marketing strategies, this project seeks to evaluate the effectiveness of these approaches and provide actionable recommendations for GolfCask's future technical and business developments.**

I. INTRODUCTION

GolfCask is a small business focused around building a virtual community for members who share the passions of golf and whiskey. To implement a systems analysis approach to assist GolfCask, the team identified the overarching objective of building community, along with three secondary objectives: attracting and retaining members, fostering engagement, and developing revenue streams. User engagement was chosen as the key objective branch to focus on. This paper identifies how the team achieved the decision to focus on user engagement and describes the work done to derive actionable insights and provide tangible recommendations to the client. The project encompasses work across several domains, including the development of a recommendation algorithm, the implementation of business marketing tactics, and the application of analytical methods, all aimed at enhancing user engagement to strengthen GolfCask's community.

II. PROJECT BACKGROUND

GolfCask's executive structure is mainly focused around founder Brian Bailie, who also served as the team's point of contact with the business. Brian has experience in both the golf and whiskey industries, working as a golf coach both privately and at the collegiate level as well as being a certified Bourbon Steward through Stave & Thief, a spirit tasting certification program. In collaboration with Brian, the project team generalized the project question to focus not only on developing a recommender system but also on examining the entire business model to create a more tailored experience for its clientele. This process involves understanding that the business needs extend beyond formulating strategies; it requires understanding how to integrate these strategies within the context of GolfCask's current operations to ensure they align with long-term growth objectives.

To advance this, the project team conducted exploratory and qualitative research to identify a descriptive scenario for GolfCask's current operations. Prior to the team's work, GolfCask operated mainly by gaining members within a subscription-based model, which allowed members to join email groups, gain access to exclusive content, and participate in GolfCask's organized trips and events. Technological features involved with the GolfCask infrastructure at the time included video content series about golf and whiskey, a map system to display golf courses, distilleries, and events on the website, and an email mailing list to reach out to members. The subscription-based website model and profits from organized trips acted as the central revenue stream for GolfCask. Building off this foundational understanding of GolfCask's current operations, a parallel scenario analysis of a preferred state illustrates the gaps between GolfCask's present state and its ideal community. Thus, this guides integrating multiple strategies to turn actionable goals into effective system improvement.

III. METHODS AND DESIGN PROCEDURE

A. Gap Analysis

This section conducts a gap analysis to examine the discrepancies between GolfCask's current state (descriptive scenario) and the desired future state (normative scenario) for its community. GolfCask's growth opportunities lie not only in improving its technical features but also in cultivating a more engaged and participatory community. This gap analysis highlights the above opportunity as an area for improvement and sets the stage for creating actionable goals to transition from the existing system to a more dynamic, user-engaged state.

1) *Descriptive Scenario:* The descriptive analysis of GolfCask's current state provides a clear picture of the existing system, focusing on its current operations, user engagement methods, and business processes. Currently, GolfCask relies primarily on a subscription-based model with limited technological features, such as email lists, video content, and a basic map system. The user acquisition is mainly driven by word-of-mouth, with minimal social media engagement. The system's strengths lie in its niche appeal to golf and whiskey enthusiasts, yet there are gaps in user interaction, content personalization, and scalability.

2) *Normative Scenario:* The ideal scenario for GolfCask is one where the platform evolves into a highly engaging, interactive community. Through a personalized recommendation system, the website ideally tailors content such as golf courses, whiskey tastings, and events based on individual user preferences. This system drives deeper interaction with the platform and regular, dynamic content is made available to users. Engagement-driven initiatives, like social media hashtags or achievement badges, create a vibrant online space where users interact frequently, refer others, and remain highly involved in community activities. By integrating these personalized features and optimizing for engagement, GolfCask attracts a retentive and expanding community.

B. Objective Tree

A visual format of an objective tree breaks down the overarching goals into specific, actionable components, providing a structured approach to achieving optimal system performance and operational efficiency [1]. Without defining a list of proposed solutions, this task builds on the normative state for GolfCask's community operation by translating the defined targeted state into specific goals and establishing metrics for tracking progress. These statements, guided by the descriptions of the normative state for GolfCask's preferred future community, are translated into action-oriented strategies that outline what must be achieved to realize the desired future scenario. At the top of the tree is the primary objective of building an online community centered around the passions of golf and whiskey, which serves as the foundation for all objectives below. From here, the tree branches into sub-objectives. Each sub-objective addresses critical components necessary to achieve a strong brand identity and profitable business. The three core targets identified to achieve this goal are creating monetization streams, increasing engagement, and attracting new members.

These are further divided into their respective sub-objectives. Each third-level objective details how each above action is defined within GolfCask's business structure. After establishing these sub-objectives, metrics are proposed for each branch to track effectiveness. Utilizing user trends as metrics, the most productive and viable goals are targeted and solutions are strategized, implemented, and validated against these metrics. Figure 1 outlines the complete built-out objective tree.

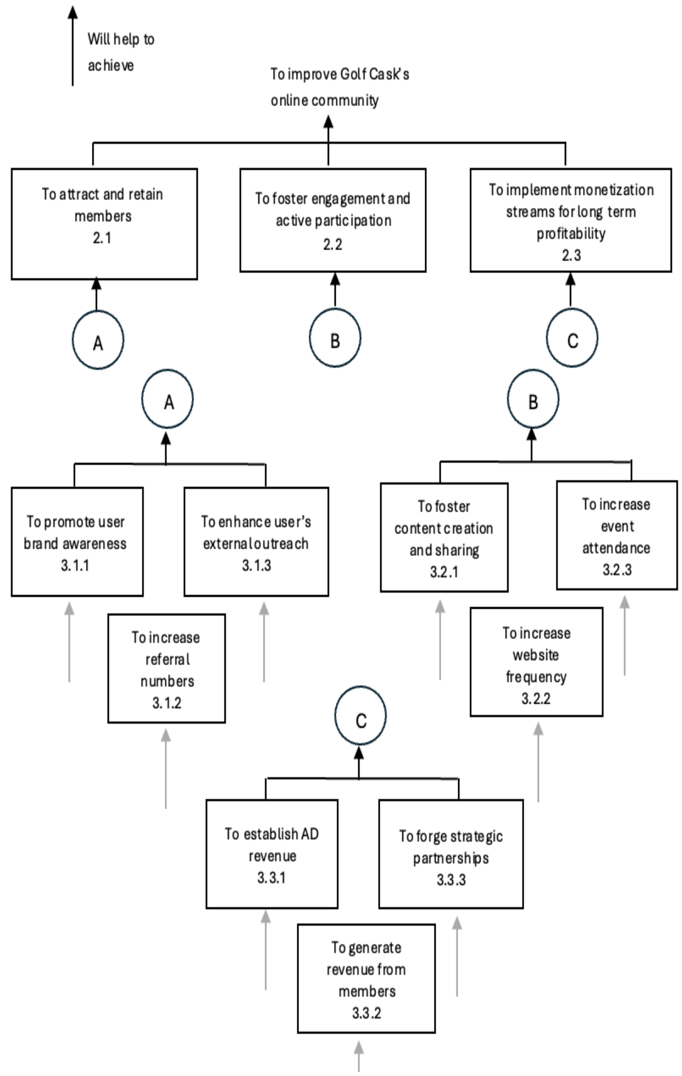

Fig. 1. Objective Tree

C. Data Analysis

This data analysis section reveals key insights that validate the intent to focus on the objective of fostering user engagement and participation. User trends from the first quarter of 2025 reveal that while signups spike intermittently, particularly around the date February 24th, engagement metrics such as the Daily Active Users to Monthly Active Users Ratio (DAU/MAU) and Daily Engaged Users show significant fluctuations. The DAU/MAU ratio peaks at 26%, indicating while there are occasional surges in traffic, sustained engagement remains low. Even more telling, the Daily Engaged Users metric only shows a sharp spike on February 24th, and afterwards, users engage minimally even with a continued surge in signups. This validates the need for promoting user engagement and participation after attracting users and getting them to click onto the website.

Moreover, the number of posts and topics follow similar trends alongside the engagement metrics. Both posts and topics spike during certain periods without reflecting a spike in daily engaged users. The new contributors metric, showing zero contributions during this timeframe, further supports the conclusion that even with successful member attraction, website traffic remains sporadic and engagement amongst new and returning members remains low.

These trends highlight the need for strategies that focus on the key objective of fostering community engagement. Thus, influencing a methodology integrating the whiskey recommender system with marketing solutions to encourage user interaction and posts, thereby contributing to improved long-term community growth.

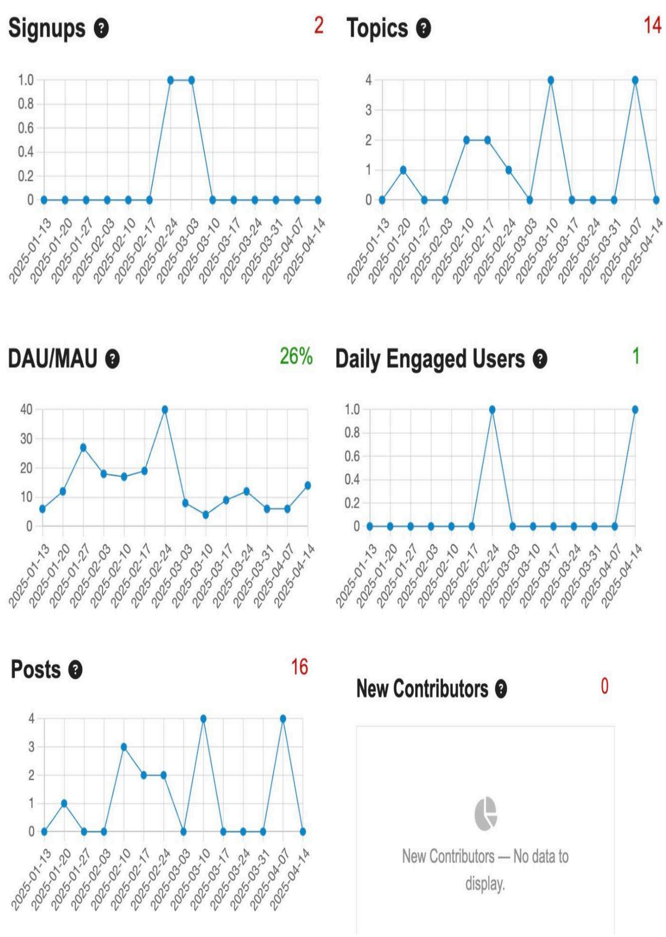

Fig. 2. GolfCask User Analytics from Discourse Dashboard between January 14 - April 14 2025

D. UTM Codes

To boost membership for GolfCask, a better understanding of how new users find the website is needed to leverage marketing strategies. Utilizing Google's UTM campaign builder, a constructed plan provides the ability to track each platform's usage along with how many members are acquired by following the traffic of various social media, websites, and emails. Each campaign or media platform is coded specifically to track metrics such as the number of sessions, page views, average time spent on each page, and conversion from clicks to members.

Since the content is generally split between golf and whiskey, it is also helpful to track what types of members are more interested in each type of media – informational posts, short videos, or blogs. UTM codes are developed for TikTok, Instagram, YouTube, Facebook, emails, and general website advertisements. These are then integrated into URL links so that they would be able to be easily tracked and further provide insight into which platforms would be most helpful to boost to increase overall membership.

IV. RESULTS

A. Whiskey Recommender System

The whiskey recommender system is designed to provide personalized recommendations by using a dataset that consists of 501 whiskeys with their 50 most similar whiskeys and corresponding scores, which are a weighted average of 65% word similarity, 20% flavor similarity, and 15% user ratings [2]. Word similarity is found using the frequency of over 300 descriptive words for each whiskey from Reddit posts describing a certain whiskey. Then, cosine similarity is used to calculate the similarity between the whiskeys by measuring the angles between the data points projected as vectors [3]. Flavor similarity is calculated by mapping these descriptive words to thirteen flavor profiles from Whiskey Classified by David Wishart [4]. Finally, user ratings from Reddit are scraped to employ item-based collaborative filtering. This recommendation style suggests "items to individual users based on a set of items that are known to be of interest to the user" [5]. For example, whiskeys A and B are similar because many of the users who enjoyed whiskey A also enjoyed whiskey B.

The recommendation process begins by collecting user ratings for whiskeys on a scale from one to five. For each whiskey, the names of similar whiskeys and their scores are extracted. The similarity score is multiplied by the user's rating, scaled between 0 and 1. If the user rates the whiskey less than 2.5, the system inverts the similarity score to prioritize whiskeys that are different from the poorly rated one. These weighted scores are compiled for all the whiskeys extracted, and it returns the top five highest-scoring whiskies which are the most relevant suggestions for the user.

When a user rates a new whiskey, the system updates recommendations by adjusting the similarity-based weightings. Highly rated whiskeys increase the rankings of similar ones while poorly rated whiskeys cause similar options to be deprioritized. As more ratings are provided, the system refines its understanding of the user's flavor preferences. The system can identify a user's flavor profile by extracting the flavor notes from the dataset based on the user's top whiskeys. This either narrows recommendations to a specific taste or broadens the options if multiple flavors are enjoyed. This adaptive process improves suggestions and increases personalization over time.

Real data from GolfCask users was used to validate the system. The data was split into 67% training and 33% testing sets. For each whiskey in the test set, the system looks up its similar whiskeys and their ratings from the training set. The predicted rating is calculated by dividing the weighted sum by the total weight. The weighted sum is found by multiplying the rating for each similar whiskey by the similarity score. The total weight is the sum of the similarity scores for all the similar whiskeys. If no similar whiskeys are found, the system defaults to the average rating from the training set. This process uses a collaborative filtering approach by using the ratings of similar whiskeys to predict the rating of a whiskey in the test set. The system's accuracy was evaluated using mean absolute error and root mean squared error. Mean absolute error (MAE) measures the average magnitude of errors in the predicted ratings, calculated by averaging the absolute differences between the predicted and actual ratings [6].

$$\frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| = MAE \, . \tag{1}$$

In this equation n is the number of observations, y_i is the actual value of the i^{th} observation, and $\hat{y}_i$ is the predicted value of the i^{th} observation. Root mean squared error (RMSE) measures the square root of the average of the squared differences between the predicted ratings and the actual ratings, putting more weight on larger errors [7].

$$\sqrt{\sum_{i=1}^{n}\frac{(y_i - \hat{y}_i)}{n}} = RMSE \, . \tag{2}$$

In this equation n is the number of observations, y_i is the actual value of the i^{th} observation, and $\hat{y}_i$ is the predicted value of the i^{th} observation. Using both helps understand how close the predictions are on average and whether the model is making any significant errors. The results from fifteen trials can be seen in Table 1.

TABLE I. AVERAGE ERROR METRICS (MAE and RMSE) ACROSS 15 TRIALS

Metric	*Average Value*	*Number of Trials*
Mean Absolute Error	0.431	15
Root Mean Squared Error	0.545	15

To demonstrate the system's ability to generate personalized whiskey recommendations, a case study is conducted using real user data. The user rates five whiskeys, three of which were highly rated (4.0–4.5), and two of which were rated poorly (2.0). The system then produces a recommendation based on these inputs. A three-dimensional scatter plot is created using Principal Component Analysis, which reduces the thirteen flavor profile dimensions into three principal components for visualization.

As seen in Figure 3, the highly rated whiskeys (orange) cluster closely together in the top left corner, reflecting a shared flavor profile. However, the two poorly rated whiskeys (also orange) appear in the bottom right corner far from this cluster. The recommended whiskey (blue) lies in between the highly rated cluster and far from the poorly rated ones. This shows that the system effectively emphasized whiskeys with flavor profiles the user enjoyed while deprioritizing those with undesirable characteristics. The spatial separation validates the recommender's ability to discern and recognize user preferences by highlighting positively rated profiles and avoiding those with low ratings.

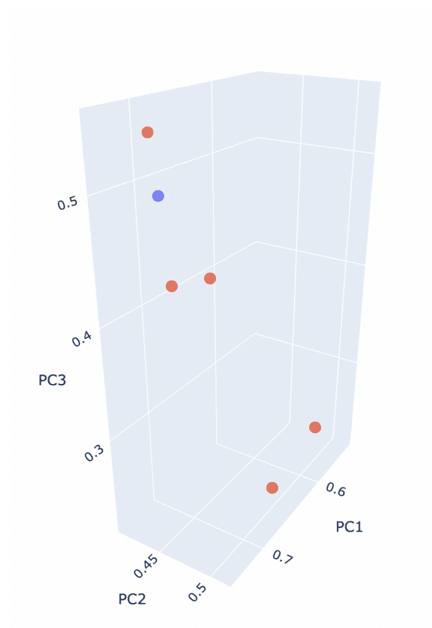

Fig. 3. Principal Component Analysis of Whiskey Flavor Profiles Highlighting User Preferences and Recommendation.

To further evaluate the system, a sixth whiskey (purple) was added to the original set of five with a user-assigned rating of 4.5. This whiskey is further to the top left of the existing cluster of positively rated whiskeys. In response to this input, the system recalculated the similarity-based weightings and produced a new recommendation (green) that shifted upward in the PCA space. As seen in Figure 4, the new recommendation moves closer to the region influenced by the newly rated whiskey.

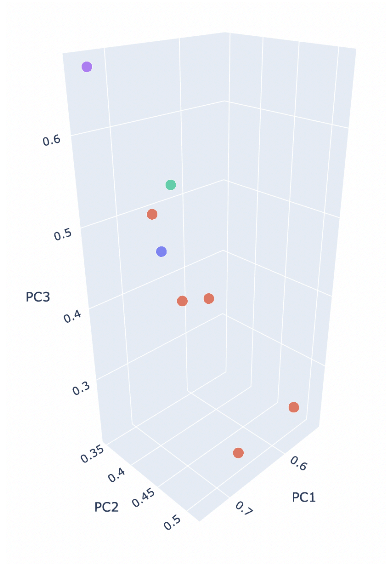

Fig. 4. Recalibration of Suggested Whiskey After Sixth User Rating.

This visual shift provides evidence that the recommender system effectively integrates new user data to refine its understanding of flavor preferences. The comparison between the original and updated plots portrays a key strength of the system. With each new user rating, the whiskey recommender further tailors its output to align with the user's evolving taste profile. This recalibration adjusts suggestions based on growing familiarity and preference patterns, demonstrating not only accuracy but also responsiveness in personalization. Over time, this behavior allows for the recommender to align more closely with a user's flavor identity even as it becomes more nuanced or shifts.

B. Marketing Analytics

To increase membership engagement on the GolfCask website and amongst other online platforms, an iterative process of implementation and outcome analysis is applied through a phased approach. The phases include focusing on specific user groups, improving the consistency of GolfCask's mission messaging, and applying UTM codes to platform links. Several social media promotion mockups, along with potential website reorganization, are provided. Each is tailored to target various groups – such as those in specific age groups, members focused more on golf rather than whiskey, and vice versa — allowing for flexibility in brand advertising in hopes of improving the conversion from interested users to enrolled members. Next, to achieve consistent messaging across all suggestions, a similar branding style and verbiage are ensured. The last step in rolling out UTM codes on specific URLs allows for the analysis of user interactions across YouTube, TikTok, Instagram, Facebook, and various emails to determine the most effective marketing strategies based on user groups. After multiple iterations, it is concluded that the use of short videos content and concise email formatting is the most successful in transforming a simple website click into a website click paired with some form of engagement on the GolfCask site.

Utilizing the insights from this approach, the GolfCask team built an engaging forum called "19th Hole" where members and interested users provide comments and discuss recently uploaded content. This platform allows members to connect more easily, offering a space for more in-depth conversation about niche topics. In addition, several volumes of a GolfCask magazine are introduced and published for members to learn about upcoming events, lessons, and general updates with the GolfCask community. Both the forum and magazine publications provide data-driven solutions that will effectively promote engagement and interaction amongst members while also driving website traffic in preparation for the future rollout of the recommender system.

V. DISCUSSION AND LIMITATIONS

Limitations of this work include the fact that the techniques and results used above are designed and implemented specifically for GolfCask. Although significant conclusions can be drawn from the implementation of systems analysis in a business situation, the exact results are unique to GolfCask and its clientele. For example, the implementation of a recommendation system is made with consideration of the overall goals of GolfCask's business and may not be applicable to other similar small businesses. Another limitation of the work described in this paper includes aspects of the work that require further development. Similar to the whiskey recommendation system, the team envisions and begins development on a recommendation system for golf courses around the country. Based on a limited dataset of 97 golf courses containing 26 feature variables, a recommendation algorithm is developed based on a euclidean distance model. The developed model as a proof-of-concept illustrates that, given a sufficient dataset of courses, a recommendation system for golf courses is both feasible and implementable. However, sufficient data regarding golf courses around the country is not able to be collected due to the lack of accessibility to necessary information. Effective data which could prove useful include yardages of individual holes, yardages of full courses, par of individual holes, par of full courses, handicaps, and more. Further research should investigate utilizing methods such as user entered data or API scraping to collect data and further develop a golf course recommendation system.

VI. CONCLUSION

Throughout this work, the project team focuses on applying a systems analysis approach to GolfCask's business model to facilitate building a community of golf and whiskey enthusiasts. First identifying overarching objectives and pairing these with key metrics of performance, the team is able to recommend several innovative solutions to the GolfCask business in support of achieving a solution to the initial problem statement at hand. The team identifies fostering community engagement as a key objective and works towards integrating a new innovative technology with other strategies to achieve GolfCask's outlined business goals. Marketing solutions backed by data analytics supports the increase in membership engagement. Thus, integrating the whiskey recommender system in GolfCask's digital infrastructure in combination with these solutions will increase user engagement and strengthen the online community. Through the implementation of a systems analysis approach from a business consulting perspective, this project successfully evaluates the effectiveness of integrating a new digital technology to an existing infrastructure in parallel with marketing and data processing strategies for online communities.

Looking ahead, GolfCask can continue to achieve operational success through building off the additional branches on the objective tree. While this project focuses mainly on member engagement, developing monetization streams presents another avenue for which GolfCask can benefit from further improvement. Additional application of a systems analysis approach would be required to develop recommendations to improve the profitability of GolfCask.

Moreover, the ongoing maintenance of the system throughout the GolfCask's lifetime will be critical in shaping future growth and success. Although the work conducted provides GolfCask with materials and strategies to sustain the normative structure recommended, further analysis will be useful for GolfCask to continue as the user base expands and new technical features are implemented. For example, while the team has provided GolfCask with multiple suggestions on UI/UX designs for social media marketing and website pages, further analysis might be conducted to address the impact of these strategies after their execution. Another avenue for further research encompasses the development of a golf course recommendation system. As outlined above, further work might investigate alternative methods of both data collection and recommendation algorithms to identify a system that optimizes the user experience when interacting with a golf course recommendation system.

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