CSV: Visual Support for Understanding Card Synergy in Digital Collectible Card Games

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Abstract: Digital Collectible Card Games (DCCGs) are a popular genre of video games that typically feature a continuously expanding pool of cards, requiring players to construct their own decks in order to play. However, the complexity of the game rules and the large number of cards cause information overload, resulting in various issues. In this research, we propose a framework to help users overcome information overload by providing a clear visualization of card synergies using 3D graphs. We employ text analysis and the co-occurrence network to calculate synergy scores between cards, and then represent the cards as nodes and their synergies as edges in our integrative 3D graph. In our experiment, we collected the decks of elite players as our dataset and visualized the synergies among approximately 1,000 cards in "Yu-Gi-Oh! Master Duel". To evaluate our framework, we conducted a questionnaire survey and a usability test with people experienced in playing DCCGs. The results indicate that our framework effectively assists users in deck construction and understanding of the game, and also provide valuable insights for the further development into a full-scale supporting tool.

1 INTRODUCTION

Digital collectible card games (DCCGs) are a popular genre of video games that typically emulate collectible card games (CCGs, sometimes also known as trading card games) on digital platforms. Because of the advantages of being digital, the game mechanics of DCCGs are usually more creative and flexible. Although traditional CCGs remain very popular, the popularity of DCCGs has increased significantly over the past few years, reaching millions of players around the world. "Hearthstone" and "Magic: The Gathering" are two famous DCCGs that have been all the rage in recent years (Turkay and Adinolf, 2018).

DCCGs inherit the characteristics of traditional CCGs, which require players to build a personalized deck to engage in turn-based one-versus-one matches. In the same way as CCGs, *deck building* and *match gameplay* are two key components that constitute the core experience of DCCGs (e Silva Vieira et al., 2024). However, DCCGs also inherit some of the issues of CCGs, such as *information overload* (decision making challenges due to too much information) and *power creep* (updates causing older cards to become underpowered) (Zuin et al., 2022).

Since the playability of CCGs largely depends on the variety of cards, both DCCGs and CCGs typically have a large pool of cards that are frequently updated. The extensive libraries of available cards, often numbering in the thousands, can be overwhelming and confusing for beginners who are not yet familiar with the games. A case in point is the well-known title "Yu-Gi-Oh! Master Duel", which boasts a card pool that exceeds 10,000 unique cards (Konami Digital Entertainment, 2021). Although many card databases offer powerful search functions, inexperienced players may still struggle to identify potential card *combos* due to the overwhelming volume of information, where a combo refers to a sequence of actions that provides significant benefit. From the perspective of game designers, the issue of imbalanced card designs often arises due to power creep, leading to a continuous cycle of needing stronger cards to remain competitive (Zuin et al., 2022). Even though game designers utilize mathematical models to maintain the balance of card values, the additional effects resulting from interactions between cards are sometimes overlooked, which can lead to certain cards becoming overpowered. To address this issue, designers often implement a ban list or make direct modifications to card effects. However, there is still room for improvement in the evaluation process during the de-

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sign phase (Zuin et al., 2022; Vieira et al., 2020).

The main approach to addressing these issues typically involves the use of artificial intelligence (AI) based on simulated combat data. However, these AI models are usually black boxes, which means that users do not significantly deepen their understanding of the cards or the game. Moreover, due to the complexity of DCCGs, the performance of these AIs still has considerable room for improvement (Zuin et al., 2022; Vieira et al., 2020). Since information visualization presents complex data in an intuitive format, which could reduce information overload and enable quicker understanding and decision-making, our goal is to provide visual support based on transparent analytical methods to enhance users' comprehension of the game (Strother et al., 2012).

In this research, we introduce a novel framework designed to visually support users in understanding *card synergies* within DCCGs. A card synergy refers to the strategic interactions between cards that produce a combined effect greater than their individual abilities, a core element of gameplay and deck building (Dockhorn and Mostaghim, 2019). For our research methods, we use the deck data of elite players as the dataset to calculate synergy scores between cards based on card effect analysis and the co-occurrence network technique. We then conceptualize cards as nodes and their quantified synergies as edges to construct an interactive 3D graph visualization. In the end, our results of subjective evaluations indicate that our visualizations effectively help users understand the synergy between cards, which demonstrates the feasibility of this research.

2 RELATED WORK

2.1 Research on CCGs and DCCGs

There is limited research on card synergies and relationships in CCGs and DCCGs. Most studies addressing challenges in CCGs and DCCGs focus on training powerful AI. For example, a framework uses deep learning to recommend resource scaling for better game balance (Zuin et al., 2022). It combines neural networks with gradient-boosted decision trees to predict card values and employs explanation tools to help developers understand the factors influencing these predictions. In the context of AI agents for CCGs, deep reinforcement learning has been applied to optimize the drafting process, while neural networks are used to develop draft agents capable of building competitive decks (Vieira et al., 2020). Additionally, “Q-DeckRec” is a fast deck recommendation system for CCGs that applies Q-learning to suggest optimal decks based on player preferences and game state, which significantly enhances the deck-building experience with quick and personalized recommendations (Chen et al., 2018). These studies are part of mainstream research in CCGs, focusing on AI applications to assist users, with promising results. However, they provide limited support for our visualization research because of differing perspectives on problem solving.

2.2 Co-Occurrence Network

Since words in context and cards in DCCGs share similar properties, we can conceptualize cards and decks in DCCGs as analogous to words and sentences in linguistic structures. To analyze the relationships among these entities, natural language processing techniques may offer valuable insights for our research. The co-occurrence network is a technique for text analysis that calculates the co-occurrence of entities and often utilizes graphic visualization to uncover potential relationships among entities within written content. In terms of applications, co-occurrence networks have been used to analyze Twitter data from a sample of 3,000 tweets (Puerta et al., 2020). The analysis indicates that co-occurrence networks, especially those from pre-processed text, reveal structural relevance among terms, offering valuable insights for broader text analysis. Another study examined political tweets related to Hillary Clinton's 2016 presidential campaign using co-occurrence networks to explore the sentiment and structural properties of word relationships (Fudolig et al., 2022). By constructing networks with nodes as words and edges as co-occurrences, the study illuminates connections between words and sentiments, and reveals complex patterns and clusters within the data, which demonstrates the utility of co-occurrence networks in identifying hidden word relationships. Given its effectiveness in revealing relationships between entities, we incorporate co-occurrence network analysis as part of our methodology to construct a relationship map for cards in DCCGs.

2.3 3D Force-Directed Graph

Since DCCGs have numerous cards and complex relationships, we seek a visualization method that can handle large amounts of information. 3D graphs, with their strong interactivity and intuitive presentation, offer an ideal solution. Among the various types of 3D graphs, 3D force-directed graphs stand out for their excellent performance in visualization research. An example of 3D visualization in action is a web-based tool designed to explore scientific literature in 3D space (Swacha, 2021). It represents papers as nodes and citations or co-occurrences as edges, enabling researchers to analyze complex networks. This approach enhances the ability to detect relationships and trends in large datasets, uncovering hidden connections often missed in 2D visualizations. Furthermore, some studies have adopted 3D force-directed graphs, which not only produce clear visuals but also allow for interactivity. For instance, a study has shown that integrating geographic constraints with 3D force-directed layouts significantly enhances the visualization of relationships among entities (Wang et al., 2023). This method enables interactive exploration, helping users intuitively understand complex patterns within large datasets. The results of these studies indicate the practicality of using 3D force-directed graphs for our research. Therefore, we adopt this approach to visualize the synergies between cards.

3 METHOD

In this study, we employ both text analysis and the concept of co-occurrence rates as metrics to evaluate the synergy between cards.

3.1 Synergy Score

First, we provide a brief overview of card characteristics in DCCGs. Generally, most DCCGs classify cards into two main types: minion cards and spell cards. For example, Figure 1 shows a minion card from the game Hearthstone. A minion card has the following elements: card name, mana cost, effect, type, attack points, health points, and rarity. Minion cards can engage in battles on the game field until they are defeated, and their effects can sometimes persist beyond a single turn. A spell card, in contrast, does not have health or attack points. They are typically single-use cards with immediate effects (Figure 1).

A card's defining feature is clearly its effect, which shapes interactions and synergies with other cards. Therefore, the most effective way to evaluate card synergy is by analyzing the text of these effects, as synergy largely depends on them. Therefore, we would like to calculate a synergy score based on the effects between two cards.

However, in practice, many card effects in DCCGs lack strong connections to other cards. The "Faerie Dragon" mentioned above is a prime example (Figure 1). For cards with isolated effects, analyzing synergy through text alone is challenging. In such cases,

Figure 1: A minion card and a spell card from "Hearthstone".

we can utilize co-occurrence networks to incorporate player choices as a supplementary analytical method. Co-occurrence networks could reveal clusters of cards that frequently appear together, which suggest that these cards may have strong synergy with each other. We use the co-occurrence rate between two cards, calculated based on co-occurrence networks, to assist in calculating the synergy score.

Overall, the synergy score between two cards c_s and c_t is calculated based on the following formula:

$$\text{synergy}(c_s, c_t) = \text{base}(c_s, c_t) \cdot \text{cor}(c_s, c_t)$$

where $\text{base}(c_s, c_t)$ represents the *basic synergy score*, derived from analyzing the effects and parameters of the two cards, and $\text{cor}(c_s, c_t)$ represents the *co-occurrence rate*, calculated based on the co-occurrence rate between the two cards. The product of these two values yields our final synergy score. In the following sections, we explain how to calculate these elements.

3.2 Text Analysis

In DCCGs, most cards typically have various parameters and effects recorded in their text. We analyze these texts to detect the synergy between cards. For example, in "Yu-Gi-Oh!", "Reinforcement of the Army" (lower in Figure 2) has the effect of adding a Level 4 or lower Warrior-type monster to the hand, and "Sky Striker Ace - Raye" (upper in Figure 2) meets this condition, making it a valid target for the effect of "Reinforcement of the Army". Two cards that can trigger effect interactions will be considered to have synergy. Moreover, there are various types of interactions, and the synergy scores we derive will vary depending on the nature of these interactions.

The synergy score obtained in this way is referred to as the basic synergy score. The specific calculation formula is as follows:

$$\text{base}(c_s, c_t) = \max\left(\boldsymbol{w} \cdot \boldsymbol{\sigma}(c_s, c_t), \text{base}_{\min}\right)$$

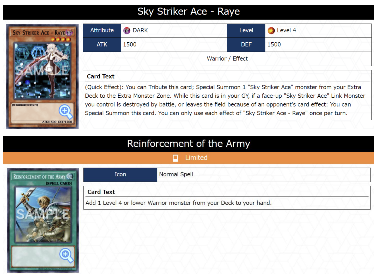

Figure 2: A monster card and a spell card from "Yu-Gi-Oh!".

where

$$\begin{aligned} \boldsymbol{w} &= \left[w_{\text{effect}}, w_{\text{archetype}}, w_{\text{material}}\right] \\ \boldsymbol{\sigma}(c_s, c_t) &= \left[\sigma_{\text{effect}}(c_s, c_t), \sigma_{\text{archetype}}(c_s, c_t),\right. \\ &\qquad \left.\sigma_{\text{material}}(c_s, c_t)\right] \end{aligned}$$

Vector-valued function $\boldsymbol{\sigma}(c_s, c_t)$ represents the scores for each evaluation criterion, while vector $\boldsymbol{w}$ represents the weights of criteria. Additionally, we designed base_{min} (= 1 by default), which serves as a safeguard to prevent the basic synergy score between cards from falling to zero, particularly ensuring that the synergy between cards frequently used together is properly evaluated.

Regarding the evaluation criteria, they are categorized into the following types:

- **Effect Score** $\sigma_{\text{effect}}(c_s, c_t)$: This is an indicator function that shows the degree of relevance between the effects in the text of the two cards. It determines a value based on whether the any card elements (e.g., card name, archetype, attack points, etc.) is mentioned in the effect text. If the full card name is mentioned, the value is 2. If the archetype is mentioned, the value is 1. If other elements are mentioned, the value is 0.5. Otherwise, it is 0.
- **Archetype Score** $\sigma_{\text{archetype}}(c_s, c_t)$: A card may belong to an *archetype* (also called a series) that means a group of cards supported each other. In "Yu-Gi-Oh!", cards belonging to an archetype may contain a common string (e.g., "Blue-Eyes White Dragon" and "Blue-Eyes Abyss Dragon") (Yu-Gi-Oh! Wiki, 2024). In Hearthstone, the archetype is represented by the card type. These cards usually support each other by their card effects. If cards c_s and c_t belong to the same archetype, the value is 1. Otherwise, it is 0.
- **Material Dependency Score** $\sigma_{\text{material}}(c_s, c_t)$: Sometimes, playing a card requires prerequisites. If card c_t is specified as a *required material* for card c_s, where a required material refers to any resource or condition needed to play or activate a card, the value is 1. If c_t meets the conditions to be used as a material but is not strictly required, the value is 0.5. Otherwise, it is 0.

Additionally, the calculations for σ_{effect} and σ_{material} would be performed twice. The first calculation is based on the text of the first card, and the second is based on the text of the second card. Finally, the two calculated values of such scores would be summed as the final score.

Next, the following explain the weights of evaluation criteria:

- **Effect Weight** w_{effect} (= 3 by default): This represents the importance when a card is explicitly referenced in the effect text. Since this element indicates a direct interaction between cards, it carries the highest weight.
- **Archetype Weight** $w_{\text{archetype}}$ (= 2 by default): This indicates whether the cards belong to the same archetype. Since the consistency of the archetype is important in deck construction, a relatively high weight is assigned to this element.
- **Material Dependency Weight** w_{material} (= 1 by default): This indicates whether the cards could serve as required materials to play another card (such as summoning a minion or casting a spell). Although some cards rely heavily on specific materials, this is typically mentioned in the effect text, or the cards may directly belong to the same archetype. In most cases, the majority of cards do not require prerequisites to be played. Therefore, this weight is assigned a relatively low weight.

3.3 Co-Occurrence Rate

The co-occurrence rate between two cards represents the frequency at which they appear together in a given dataset. A high co-occurrence rate may indicate that players frequently use the two cards together, which suggests they have complementary effects, form part of a popular deck archetype, or provide a strong tactical advantage when combined. Analyzing these rates could help in understanding card synergies.

In general, we will collect a large dataset of decks from elite players to analyze the co-occurrence rate between pairs of cards. We define "co-occurrence" as the concurrent presence of two cards within the same deck. The formal definition of the co-occurrence rate is as follows:

Given cards $c_1, c_2, \ldots, c_n$ and decks $D_1, D_2, \ldots, D_m$, where each deck is a multiset $D_j = \left\{c_{i_{j,1}}, c_{i_{j,2}}, \ldots, c_{i_{j,k_j}}\right\}$ of k_j cards, the co-occurrence rate $\text{cor}(c_s, c_t)$ of two cards c_s and c_t is defined as the ratio of the number of decks, where the two cards co-occur to the number of decks that have at least one of the cards.

$$\mathrm{cor}(c_s, c_t) = 1 + k \cdot \frac{\left|\{D_j \mid c_s \in D_j \wedge c_t \in D_j\}\right|}{\left|\{D_j \mid c_s \in D_j \vee c_t \in D_j\}\right|}$$

In this formula, the adjustment coefficient k ($= 1$ by default) is used to control the extent to which it influences the synergy score. Moreover, in order to visualize newly designed cards by designers (as unimplemented cards cannot have co-occurrence rates calculated), the co-occurrence rate has the minimum value of 1.

3.4 Visualization

A 3D force-directed graph is ideal for visualizing synergies between cards in DCCG, as it can effectively represent complex networks with a large number of nodes and edges. The layout algorithm uses attractive and repulsive forces to naturally cluster related cards and separate unrelated ones, which could provide a clear view of card relationships. As a result, we represent cards as nodes and synergy scores as edge lengths to construct a 3D force-directed graph for visualizing card synergies.

To simplify the graph, we define a threshold denoted as α with $0 \leq \alpha \leq 1$ to filter out unnecessary information. If the synergy score is higher than this threshold, it is inferred that a meaningful relationship exists between the two cards, allowing them to be incorporated into our visualization.

In addition, we use the synergy score as a pivotal factor in determining the length of an edge connecting the cards c_s and c_t, which is calculated by $\delta/\mathrm{synergy}(c_s, c_t)$, where $\delta \geq 0$ is a coefficient for the adjustment of visualization. The shorter the length, the higher synergy between two cards.

For implementation, we built upon the Force Directed Diagram plugin (Forgin Bits, 2024) in Unity, modifying it for our purposes. In addition to the default rotation and zoom features, we have added filtering functionality (which reduces the opacity of non-adjacent nodes when a node is selected) and a search feature (allowing users to jump to the corresponding node by searching for keywords) to enhance the overall user experience.

4 CASE STUDY

To validate our approach, we selected "Yu-Gi-Oh! Master Duel" (YGOMD) as the primary subject of our case study. YGOMD is a digital version of "Yu-Gi-Oh!" (YGO) with the same game rules and card

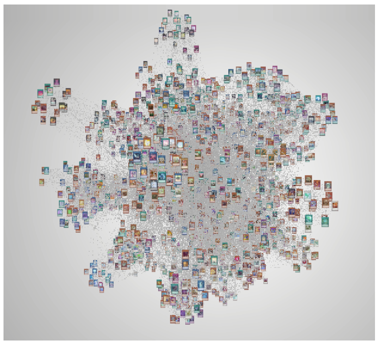

Figure 3: Overall view of the 3D force-directed graph with 1,700 cards.

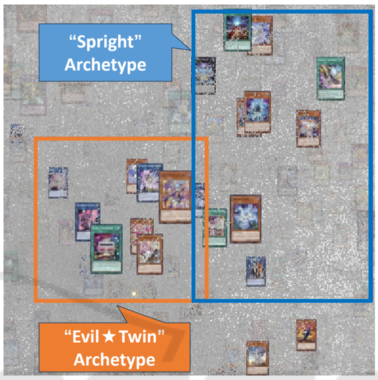

Figure 4: Partial view of a 3D force-directed graph related to "Spright" and "Evil Twins" cards.

pool. We chose YGOMD because it lacks the resource constraints that other DCCGs such as "Hearthstone" and "Shadowverse" impose with mana costs, which typically force players into multiple rounds of battles. In YGO, a player's deck is nearly the entire resource. The strength of a deck highly depends on the interactions among the cards, and it is common for players to end a match in one or two turns by using multiple card combinations, which makes visualizing card synergy highly valuable.

To prepare a necessary dataset for our analysis, we have collected approximately 1,000 decks belonging to elite players from the "Master Duel Meta" website (Duel Links Meta LLC, 2024) by using a Python-based web scraper. After calculating the synergy scores through programs, we build a 3D force-directed graph to visualize the card network by Unity. The results are shown in Figures 3 and 4.

Recall that the length of an edge in our visualization represents the synergy between two cards. Although we did not employ a specific clustering method (through the application of physical simulation principles only), we observed that cards belonging to the same archetype naturally formed small clusters. From Figure 4, we could see that "Spright" cards and "Evil Twins" cards formed clusters respectively. In fact, these two archetypes are often combined in a single deck. Through our visualization, users can better understand the synergy between different archetypes, as those that work well together are positioned close to each other within our network. The filtering feature we implemented also makes the synergy between cards simple and easy to understand.

5 EVALUATION

Given the absence of previous studies with which we could compare our research, we assessed our study by conducting a questionnaire survey and a usability test among DCCG players.

5.1 Questionnaire

5.1.1 Survey Design

We created an online questionnaire with 13 questions using Google Forms and asked participants to try our tool. It gathered basic user information, assessed their understanding of DCCGs as part of the pre-study, and collected their feedback on our visualization in the post-study section. The answer scale is primarily based on a 5-point ordinal scale.

Here are the questions included in the questionnaire, except for the first 3 questions that ask for personal information (name, age, and gender). The following are all required multiple-choice questions:

- **Pre-study Part**

  Q1: *How familiar are you with DCCGs?*

  Q2: *Do you think that learning to play a DCCG requires a lot of time and effort?*

  Q3: *If you have ever played DCCGs, did you find it challenging to build your own deck when you were a beginner?*

  Q4: *How familiar are you with Yu-Gi-Oh?*

- **Post-study Part**

  Q5: *What kind of information did you get from our 3D graph?*

  Q6: *How clearly does the visualization show the synergies between cards?*

  Q7: *How easy was it to interact with the 3D force-directed graph?*

  Q8: *Do you think this visualization would help you in building or optimizing a deck for a DCCG?*

  Q9: *How accurate do you find the results of the visualization?*

  Q10: *How appealing do you find the overall design of the visualization?*

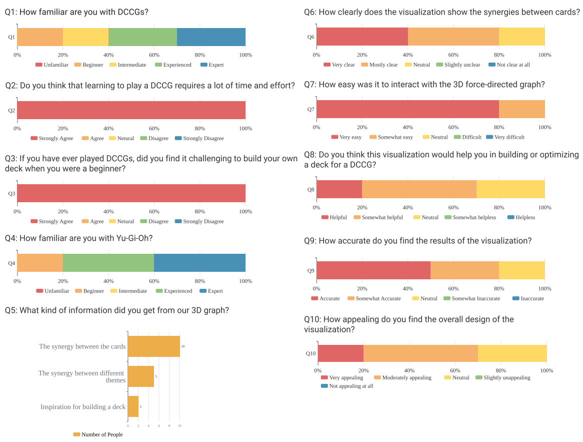

Figure 5: The results of questions Q1 to Q10.

5.1.2 Results

Since our visualization does not provide any information on game rules, we require users to have a basic understanding of DCCGs. Therefore, we surveyed 10 individuals with varying levels of experience in YGO. Based on the feedback, all participants are males aged 20 to 29. Regarding familiarity with DCCG (not limited to YGO), the participants included 2 beginners, 2 intermediate players, 3 experienced players, and 3 expert players (Q1 in Figure 5). All had played YGO, with 2 being beginners, 4 being experienced players, and 4 being expert players (Q4).

To confirm the presence of information overload, which leads to high learning costs, we asked participants if learning to play a DCCG requires significant time and effort. According to the results (Q2), all participants answered “Yes”. We also asked whether they struggled to build their own decks as beginners, and all participants again responded “Yes” (Q3).

To evaluate our research, participants explored the interactive 3D graph and identified the types of information obtained during the process, with multiple answers allowed. The results showed that 100% of participants gained insights into card synergies, the primary goal of the visualization. Additionally, 50% learned about archetype synergies, and 20% found inspiration for deck building (Q5).

We further assessed the visualization using multiple-choice questions focused on usability, aesthetics, accuracy, practicality, and clarity. For “How clearly does the visualization show the synergies between cards?” 40% rated it “very clear”, 20% “mostly clear”, and 20% “neutral” (Q6). Regarding “How easy was it to interact with the 3D force-directed graph?” 80% found it “very easy”, while 20% rated it “somewhat easy” (Q7). When asked “Does this visualization help in building or optimizing a DCCG deck?" 20% said "helpful", 30% "somewhat helpful", and 20% were "neutral" (Q8). In terms of accuracy, for "How accurate do you find the visualization results?" 50% rated it "accurate", 30% "somewhat accurate", and 20% "neutral" (Q9). On design appeal, "How appealing is the overall visualization design?" received 20% "very appealing", 50% "moderately appealing", and 30% "neutral" (Q10).

5.2 Usability Test

To assess the usability of our research, we conducted a usability test involving two groups of players: 2 beginners and 2 experienced players. This test consists of 3 sections: Pre-study Questionnaire, Task Performance Assessment, and Post-study Questionnaire. Since our previous questionnaire was designed to fulfill both Pre-study and Post-study functions, participants have already completed it as outlined in the previous section, and these responses have been included in our prior statistical analysis.

5.2.1 Design of Task Performance Assessment

The task performance assessment involves guiding players through a series of tasks that we have designed, with difficulty increasing incrementally. For each task, we record the completion time, and observe participants' approaches to understand their behaviors. The assessment includes the following 3 primary tasks:

T1: *Identify the three cards that have good synergy with "Dark Magician".*

T2: *Identify two archetypes that has good synergy with "Blue-Eyes" Deck.*

T3: *Use this tool as a reference to create a competitive "Hero" deck in YGOMD.*

5.2.2 Results

Table 1 shows the task completion times for each participant. For T1, all players used the search bar immediately, completing it in about 10 seconds. Experienced players completed the task flawlessly, while beginners often included *staple* cards (commonly used powerful cards) among the top synergy cards instead of focusing solely on those truly with good synergy (Yu-Gi-Oh! Wiki, 2024). In T2, beginners took 50 seconds and 1 minute 2 seconds, respectively, while experienced players finished in 23 and 26 seconds. Beginner actions revealed that the visualization does not clearly convey archetype synergy, which leads to confusion, despite cards within the same archetype

Table 1: Task completion times for each participant.

Participant	T1	T2	T3
Expert 1	12s	23s	5m2s
Expert 2	9s	26s	4m37s
Beginner 1	13s	50s	6m19s
Beginner 2	10s	1m2s	7m44s

forming distinct clusters. For T3, experienced players took 5 minutes 2 seconds and 4 minutes 37 seconds, while beginners needed 6 minutes 19 seconds and 7 minutes 44 seconds. Experienced players created decks of higher quality, comparable to those in actual gameplay. In contrast, beginners' decks were less organized, often including all related cards without strategic considerations.

The Task Performance Assessment shows experienced players completed tasks faster and with higher quality due to prior knowledge. Beginners, though slower and less accurate, still performed reasonably well with the tool's assistance.

6 DISCUSSION

6.1 User Feedback Analysis

Based on user feedback, we can conclude that our visualization effectively helped players understand the synergies among cards. The survey confirmed that DCCGs often have a high entry barrier due to information overload. For all questions evaluating different aspects of the visualization, participants provided either neutral or positive responses.

Nevertheless, the results also indicate that while the visualization is relatively clear, simply understanding the strength of card synergies provides limited assistance in deck building and overall game comprehension. Additionally, the tool's effectiveness seems to be influenced by the player's experience level in DCCGs. For example, in task T1, beginner players who were less familiar with the concept of staple cards demonstrated relatively lower accuracy in their responses. Offering clearer delineation of cluster boundaries could help address this issue.

6.2 Application on Other DCCGs

Our goal is to propose a method for visualizing card synergies across a wide range of DCCGs. In this research, the visualization experiment was conducted exclusively with YGOMD. While this demonstrates that our approach could be effective for games where cards have strong interactions, additional visualization experiments on a variety of DCCGs are planned to further validate the feasibility of our method.

In addition, in games like the "Pokémon Trading Card Game", card texts often lack explicit interactions, which necessitates relying primarily on co-occurrence rates for synergy score calculations. To address this limitation, we plan to simulate and collect gameplay data to evaluate how cards interact in practice, aiming to explore hidden synergies that are not explicitly described in their texts.

6.3 Reflection on the Evaluation Method

The lack of similar studies on DCCGs presents a significant challenge to conducting objective, cross-comparative evaluations of this tool. This has resulted in current evaluations relying heavily on subjective responses, which are less convincing.

Furthermore, the small and homogeneous sample size used in the evaluation limits the generalizability of the findings. Since our study does not include features to introduce the game, participants were required to have a basic understanding of DCCGs. Relying solely on experienced DCCG players may introduce bias by excluding the perspectives of beginners. Expanding the participant pool to include a more diverse audience and integrating qualitative data is one of our future plans to strengthen the robustness of the evaluation.

7 CONCLUSIONS AND FUTURE WORK

In this paper, we introduced a novel approach to visualizing card synergies to overcome information overload in DCCGs through a graph-based visualization framework. To test it, we visualized card synergies for YGOMD and conducted a questionnaire survey with a usability test involving recruited volunteers. Although there are areas that require improvement, participant feedback confirmed the effectiveness of our visualization approach.

Our ultimate goal is to evolve this framework into a comprehensive support tool, enabling our synergy analysis method to be applied across most DCCGs. Based on the results of this study, we will continue refining the framework to benefit both players and game designers, helping users gain deeper insights into card synergies and the game itself.

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REFERENCES

Chen, Z., Amato, C., Nguyen, T.-H. D., Cooper, S., Sun, Y., and El-Nasr, M. S. (2018). Q-DeckRec: A fast deck recommendation system for collectible card games. In *Proc. IEEE CIG*, pages 1–8.

Dockhorn, A. and Mostaghim, S. (2019). Introducing the Hearthstone-AI competition. *arXiv*, 1906.04238.

Duel Links Meta LLC (2024). Top decks. https://www.masterduelmeta.com/top-decks.

e Silva Vieira, R., Tavares, A. R., and Chaimowicz, L. (2024). A taxonomy of collectible card games from a game-playing AI perspective. *arXiv*, 2410.06299.

Forgin Bits (2024). Force directed diagram. https://www.youtube.com/watch?v=hWt5WPO8c6A.

Fudolig, M., Alshaabi, T., Arnold, M., Danforth, C., and Dodds, P. (2022). Sentiment and structure in word co-occurrence networks on Twitter. *Appl. Netw. Sci.*, 7:9.

Konami Digital Entertainment (2021). Yu-Gi-Oh! Master Duel has over 10,000 cards to unlock. https://www.konami.com/games/us/en/topics/1752/.

Puerta, P., Laguna, L., Vidal, L., Ares, G., Fiszman, S., and Tárrega, A. (2020). Co-occurrence networks of Twitter content after manual or automatic processing. a case-study on "gluten-free". *Food Qual. Prefer.*, 86:103993.

Strother, J. B., Ulijn, J. M., and Fazal, Z. (2012). Visualizing instead of overloading: Exploring the promise and problems of visual communication to reduce information overload. In *Information Overload: An International Challenge for Professional Engineers and Technical Communicators*, pages 203–229. Wiley-IEEE Press.

Swacha, J. (2021). Three dimensions of science: A web tool for 3d visualization of scientific literature. In *Proc. ACM/IEEE JCDL*, pages 274–277.

Turkay, S. and Adinolf, S. (2018). Understanding online collectible card game players' motivations: a survey study with two games. In *Proc. OzCHI*, page 501–505. ACM Press.

Vieira, R., Tavares, A. R., and Chaimowicz, L. (2020). Drafting in collectible card games via reinforcement learning. In *Proc. SBGames*, pages 54–61. IEEE CPS.

Wang, S., Li, W., and Gu, Z. (2023). GeoGraphViz: Geographically constrained 3D force-directed graph for knowledge graph visualization. *Trans. GIS*, 27(4):931–948.

Yu-Gi-Oh! Wiki (2024). Gaming terms. https://yugioh.\linebreak[0]fandom.com/wiki/Category:Gaming_Terms.

Zuin, G., Chaimowicz, L., and Veloso, A. (2022). Deep learning techniques for explainable resource scales in collectible card games. *IEEE Trans. Games*, 14(1):46–55.