How the Business Model of Customizable Card Games Influences Player Engagement

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***Abstract*—In this paper, we analyze the gameplay data of three popular customizable card games where players build decks prior to gameplay. We analyze the data from a player engagement perspective, how the business model affects players, how players influence the business model and provide strategic insights for players themselves. Sifa *et al.* found a lack of cross-game analytics, whereas Marchand and Hennig-Thurau identified a lack of understanding of how a game's business model and strategies affect players. We address both issues. The three games have similar business models but differ in one aspect: the distribution model for the cards used in the game. Our longitudinal analysis highlights this variation's impact. A uniform distribution creates a spread of decks with slowly emerging trends while a random distribution creates stripes of deck building activity that switch suddenly each update. Our method is simple, easily understandable, independent of the specific game's structure, and able to compare multiple games. It is applicable to games that release updates and enables comparison across games. Optimizing a game's updates strategy is the key, as it affects player engagement and retention, which directly influence businesses' revenues and profitability in the $95 billion global games market.**

***Index Terms*—Business intelligence, clustering algorithms, data analysis, game analytics, machine learning.**

I. Introduction

GAME data analytics transforms the complex data from games into understandable information. It can: inform game design (for a game and its future releases); inform gameplay; and improve player engagement, which in turn increases the game's revenue as players play more often and for longer. The field of game analytics has been growing rapidly, as demonstrated by coverage in *Science* [1] and the publication of the first textbook specifically on this topic [2]. However, Sifa *et al.* [3] found that game analytics has generally been restricted to individual games. Studies [4] and [5] have analyzed players' motivations for playing individual games, players' progress, players' playtime/disengagement [6], [7] or players' play styles. There are very few comparative analyses and techniques. Hence, the cross-game applicability of analytics and the knowledge generated from such analyses remains largely unknown. There is a clear need for game data analysis techniques that are efficient, effective, easy to use and, most importantly, generic for multiple games [3], [4]. Furthermore, Marchand and Hennig-Thurau [8] state that more knowledge integration is required to generate a complete understanding of participation in games and how the business model [9] and strategies affect players.

The contribution of this paper is to address the twin issues of cross-game data analytics and how business models affect players and their strategies identified above. We analyze how two very similar business models but with different distribution strategies entail very different player engagement and motivations and develop an analytics method that can be generalized to longitudinal data for similar games even allowing multigame comparisons. We produce generic heatmaps to provide a clear and easily understandable tool for company strategists and players to analyze past, present, and future game update strategies. We compare and contrast the player motivations and player engagement of three popular card games for which suitable data are available, *Android: Netrunner (A:NR)*, *Hearthstone: Heroes of Warcraft (H:HOW)*, and *Magic: The Gathering (M:TG)* and link our findings to the games' respective business models.

Our findings are relevant to similar games that release updates. Downloadable content (DLC) and expansion packs have become a vital constituent of business's overall revenue and profitability in the $101 billion global games market[1] [10]. Electronic Arts sold $1.2 billion in DLC in 2016.[2] Hence, "Keeping the players' quality of experience is of critical relevance for ... games, and the reason is simple: they can choose not to play" [11]. If players decide to leave a game in large numbers, then

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Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

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[1]UKIE Games Industry, 2017. Available at: https://ukie.org.uk/research

[2]Forbes, 2017. Available at: https://www.forbes.com/sites/mattperez/2017/05/09/electronic-arts-sold-1-2-billion-in-dlc-last-year/#70b0cdc7c26c

TABLE I
TABLE COMPARING THE DISTRIBUTION STRATEGY AND SPECIFIC ASPECTS OF THE BUSINESS MODELS OF THE THREE GAMES

Game	Game Type	Card Distribution	Card Trading?	Card Retirement?	Card Crafting?
A:NR	Living	Fixed-content packs	No	No	No
M:TG	Collectible	Random packs	Yes	Yes	No
H:HOW	Collectible	Random packs	No	No	Yes

"the whole business model collapses since the act of playing is directly related to the act of paying" [11]. In particular, the mobile video games market is dominated by free-to-play games with optional in-game purchases. Hence, maintaining player engagement and how players engage is key to profitability. We show that the format of game updates influences how players engage with the game, once the update is released and identify the gameplay strategies that players then adopt.

The paper provides an overview of customizable card games in Section II, Section III analyzes the literature of customizable card games, Section IV evaluates how the business model of a game affects the players by analyzing player data from three customizable card games over time, the results of these analyses are summarized and assessed as a whole and then generalized to the broader games industry in Section V, and finally the paper provides a conclusion and assessment of further work in Sections VI and VII, respectively.

II. CUSTOMIZABLE CARD GAMES

Customizable card games are mass-produced games where players design decks of cards by selecting a required number of cards from a large pool of cards and by following the game's rules of deck building. Players can build a range of decks but use only one deck to play against an opponent's deck during gameplay. The manufacturers release new cards about once a month, keeping the games in a constant state of flux. The appeal of card games is found in their variety. *A:NR* and *M:TG* were two of the earliest games originally devised by Garfield in 1996 and 1993, respectively. *H:HOW* is a recent challenger developed and published by Blizzard Entertainment in 2014 using a similar game model. These three games have data available for a range of skill levels and provide an ideal comparison due to their similar foundations. Other card games include *Pokémon* published by Nintendo and *Yu-Gi-Oh!* by Konami.

Both *A:NR* and *M:TG* are available as traditional table-top games. *M:TG* is also available as a digital card game (Magic Online). *A:NR* is available as a free online playable version. In contrast, *H:HOW* is a digital-only game. *A:NR* is produced by Fantasy Flight Publishing, Inc. and sold via their website, third-party websites, such as Amazon Market Place and high street retailers. No current revenue figure is available for *A:NR* but it sold ∼500,000 units in 2014[3] and interest on discussion groups remains high and comparable with other games. *M:TG* is produced by Wizards of the Coast LLC, a subsidiary of Hasbro, Inc. and sold via third-party websites and high street retailers. The online version *Magic Online* generated $21 million in revenue in 2016[4] by combining microtransaction payments with tactical, competitive gameplay. *H:HOW* is published by Blizzard Entertainment Inc. The advantage of an online only game is that it is cheap to publish so *H:HOW* players can play for free with optional purchasable expansion packs. In 2016, it generated >$25 million every month with 20 million players.[5] The total estimated revenue for digital TCGs in 2016 was $1.4 billion and $4.3 billion for physical games.[6] Hence, the value creation, capture, and delivery aspects of these games' business models is vital to the business and needs to be fine-tuned and optimized.

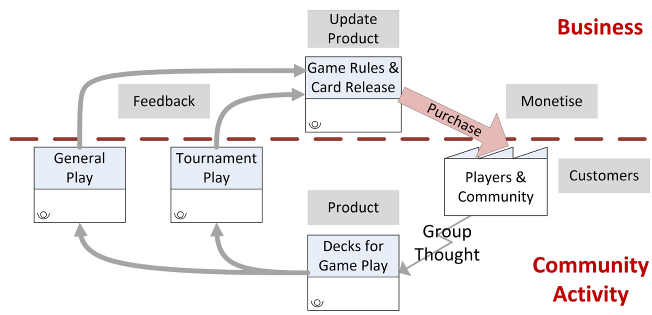

Fig. 1. Figurative representation of the game development, customer engagement, and revenue stream aspects of the business model for the three customizable card games. The top half represents the businesses' game development, monetization, and user feedback. The bottom half represents community activity.

Fig. 1 provides a figurative overview of the customer engagement and revenue stream constituents of the business cycle for the three games illustrating how the businesses generate revenue, engage a community, and incorporate that community's feedback. The community represents the bottom half of the figure and community members purchase game products (including expansion packs), formulate collective strategies, and provide important feedback to game designers. Many players rely on this collective thinking to develop their own game strategy. Much of the community's activity is online providing access to deck building strategy and community sentiment. Table I provides an overview of the business models and card distribution strategies of the three games.

A. Android: Netrunner

A:NR is a living card game (LCG). In LCGs, players customize a deck of cards ready for play. New cards are released

[3]Eurazeo, Investor Day, 2014. Available at: https://www.eurazeo.com/wp-content/uploads/2014/11/Investor-Day_-Global_FINAL_DIFFlight21.pdf

[4]SuperData, Digital Collectible Card Games Market, 2016. Available at: https://www.superdataresearch.com/market-data/digital-card-games/7

[5]SuperData, Digital Collectible Card Games Market, 2016. Available at: https://www.superdataresearch.com/market-data/digital-card-games/

[6]SuperData, Digital Collectible Card Games Market, 2016. Available at: https://www.superdataresearch.com/market-data/digital-card-games/

in fixed card distributions (i.e., packs with fixed contents). Nonrandomized expansion packs are released monthly containing specific cards to supplement the existing pool along with deluxe expansion packs released periodically that contain powerful new cards. Players can either use their own knowledge of the game to build their deck or download ready-made deck-lists from the Internet from community websites. In *M:TG* and *H:HOW*, players focus on building a single deck. In contrast, *A:NR* is an asymmetric information game [12], where players construct two decks. One deck represents a sinister cyberpunk corporation, the "Corp," whereas the other "Runner" deck aims to destroy the Corp deck during the gameplay. During a game of *A:NR*, one player's Runner deck is pitted against the other player's Corp. The Runner needs to steal the "Agenda" cards from the Corp deck, which represent the corporation's plans, while the corporation has to slowly advance these plans to completion. In *A:NR*, decks are subdivided into factions, which are subthemes of the meta-game, and dictate the play style for that faction. The deluxe expansion packs target two specific factions with their new cards, one Corp faction and one Runner faction. It is the effect of these powerful expansion packs that we analyze in this paper.

B. Magic: The Gathering

M:TG is the oldest and one of the most popular trading card games (TCGs) (often called collectible card games) with 20 million players worldwide generating $300 million in revenue annually, a thriving tournament scene and professional leagues.[7] The revenue generated from expansion pack purchases is a vital part of the company's profitability. Before gameplay commences, each player constructs a "main" deck (referred to as simply "deck" hereafter), which consists of 60+ cards drawn from the pool of all cards, allowing players to pursue an enormous number of strategies and card combinations. The only limitations are the rules and regulations of the game [13], [14]. Players can either use their own knowledge of the game to build their deck or download ready-made deck-lists from the Internet, which exist as crowdsourced, community efforts. TCGs are characterized by players purchasing booster packs of cards containing a random set of cards and then trading or purchasing cards to build their desired decks. Wizards of the Coast periodically release expansion packs containing new card sets with more than 80 sets of cards released over the past 22 years. At the same time, they incrementally retire older cards and increase the capabilities of newer cards. The expansion packs contain three sets of cards: one large set of more than 300 cards designed on a number of gameplay themes, followed by two smaller sets of fewer than 200 cards each. The smaller sets continue the themes introduced in the large set. More recently, the larger sets have reduced in size to about 250 cards. The popularity of TCGs derives from the complex interplay of thousands of cards. Each game represents a battle between wizards known as "planeswalkers," who employ spells, artefacts, and creatures depicted on individual *M:TG* cards to defeat their opponents.

[7] *The Guardian*, 2015. Available at https://www.theguardian.com/technology/2015/jul/10/magic-the-gathering-pop-culture-hit-where-next

C. Hearthstone: Heroes of Warcraft

Blizzard Entertainment's *H:HOW* is a free-to-play, online (digital) TCG with cash-prize tournaments hosted by Blizzard and other organizers. Again, in *H:HOW*, players customize a deck of cards ready for play using either their own knowledge of the game to build their deck or by downloading ready-made deck-lists from community websites on the Internet. Players focus on building a single deck. Players begin the game with a large collection of basic cards. They are able to acquire rarer and more powerful cards by purchasing extra booster packs of cards or as rewards from specific game modes. Blizzard release annual expansion packs and adventure packs electronically. Expansions contain more cards than adventures, with the former containing around 145 cards whereas the latter only contains around 30 cards. The contents of each pack are random as with *M:TG* but each pack is guaranteed to contain at least one rare card. *H:HOW* is a turn-based card game between two opponents. The players take turns to summon minions to attack their opponent or to cast spells. The ultimate goal is to reduce the opponent's health to zero.

III. Literature

Data analysis of customizable card games has mainly focused on analyzing players during gameplay [15] and not the wider impacts. Hau *et al.* [16] aimed to predict tournament performance of *M:TG* decks and also grouped decks into clusters using *k*-means clustering. However, they found that identical decks can have vastly different tournament performance based on player skill and luck. We only consider deck usage activity and not deck performance. Sanchez *et al.* [17] explored the task of automated deck building for *H:HOW* using a genetic algorithm to synthesize decks. Authors have also investigated opponent's deck content prediction from a small number of visible cards in *H:HOW* [18] and *A:NR* [19], using Shannon's information theory [20] techniques, such as n-gram frequency and the Apriori algorithm [21].

There has been limited work on analyzing the effect of business models on players. The most similar work is Oh and Ryu [22], who analyzed the game design issues when online games include an item-selling payment model. The authors stated that these games need to incorporate in-game communities into the process. Our analyses are based on online communities. Charles *et al.* [23] investigated adaptive games where the game is specifically designed to be responsive to a wide range of players. This implicitly includes the business model into the analysis and adaptation cycle. We investigate broader impacts across many players and illustrate those impacts. Alves and Roque [11] studied business models to investigate the four main actors: the game, its producer, its players, and its business model. This helps understand the alignment with respect to the business model.

Our review reinforces the current gap in the literature with respect to understanding players' participation in games and how the business model and strategies affect players as observed by Marchand and Hennig-Thurau [8].

IV. Evaluation of How the Business Model Affects Players

We empirically examine how the business model affects the players by analyzing how the focus of deck building changes with time as the game evolves and new cards are released. All three card games have deck categories; we could simply use these categories to cluster the decks for our analyses. However, these deck categories are often broad and diverse, and the decks within a category have high variance with respect to the cards in the decks. We need cohesive clusters for analysis. Additionally, the complex card interactions, the dependencies and evolving strategies during and between these games, and the lack of comprehensive historical data prevent us from producing accurate statistical prediction models for predicting the future effects of individual new cards. Therefore, we use statistical analyses to cluster historical decks, track deck popularity over time, correlate previous card releases with decks/clusters, and examine the effects of card releases on players. Our motivation is to produce a simple and generic method to highlight the effects of new releases in games coupled with visualizations that are accessible to all.

A:NR, *H:HOW*, and *M:TG* have very similar business models but differ in their card release strategy. The release dates and contents of expansion packs are available in detail on the game manufacturers' websites. The high similarity between these three games allows us to focus on how much a variation in one aspect of the business model—distribution—affects how players play the game. As discussed previously, these games have large, active player communities that focus primarily on deck analysis and collaboration. This collaboration is largely the result of players building decks at home and then uploading them on to community websites for further discussion and analysis by other players. These three games include imperfect information games where the player only sees a small subset of the opponent's cards and the information space fluctuates throughout gameplay [12]. Hence, deck building in these games is an optimization problem.

For this evaluation, we obtained *A:NR* deck data from the popular *A:NR* community website (www.netrunnerdb.com) giving 23 952 decks in total constructed from 639 different cards (which may be repeated up to three times per deck) and tagged with the month of construction (between October 2013 and March 2016 inclusive). The *A:NR* decks have between 15 and 53 different (unique) cards in a deck. Decks range in all sizes but the median size is 49 cards. The *M:TG* dataset comprises 33 043 decks from the popular community website (www.mtgdecks.net) constructed from 13 651 potential cards (as of April 11, 2016). Each deck is tagged with the month of construction (between October 2012 and July 2015 inclusive). Deck sizes are a minimum of 60 cards and are from the "Standard" deck format. Finally, we downloaded 27 949 *H:HOW* decks from (www.hearthpwn.com). The decks generally contain 30 cards for standard gameplay but can range up to 60 cards for special games. Cards are selected from 922 potential cards. Again, each deck is tagged with the month of construction (between June 2013 and August 2016 inclusive). We note that none of the three websites provide deck usage (popularity) information for gameplay and only some websites provide online statistics (such as views and downloads) for the decks. The websites are essentially discussion forums where people upload their decks for discussion and comment. Additionally, all games in *A:NR* and many *M:TG* games are played offline. Hence, to ensure genericness, we use the deck building activity in the cluster as a proxy for popularity, as a good deck with high popularity will likely spawn imitations manifesting as high activity in that cluster.

Expert game players[8] analyzed randomly selected decks from each of the three datasets and confirmed that each dataset covers a broad range of decks, a broad range of players, and a wide range of player expertise from novice to top level. Only tournament level players are unlikely to contribute to these community websites as they seek to conceal their tactics and strategies for tournament play. The experts also analyzed the results, helped compare the heatmaps to the release dates and contents of expansion packs to ensure they correlate and, thus, ensured that our findings are valid.

This analysis requires a partitional clustering method [24] to partition the data for analysis. Hence, we use the popular k-means clustering algorithm variant k-medoids (or partitioning around medoids [25]) coupled with edit distance (ED) to cluster *A:NR*, *H:HOW*, and *M:TG* decks. k-medoids performs k-means clustering for symbolic data. k-medoids characterizes the clusters by means of typical objects (medoids), which represent the "typical" features of objects under investigation. The advantage of k-medoids over k-means is that the cluster prototype is an actual data point in k-medoids, whereas k-means uses an average point as the cluster center so k-medoids allows us to examine actual decks as the cluster prototypes. We will use these prototypes (medoids) in our analyses in Section V to analyze the deck building foci over time.

We evaluated varying the number of clusters k between 20 and 2000 for *A:NR*, *H:HOW*, and *M:TG* and found that there was no elbow in the intracluster distances, so no ideal number of clusters. The intracluster distances decrease slowly as the number of clusters increases. We include the chart for *M:TG* as Fig. 2 to illustrate this.

For this analysis, our clustering does not have to be as accurate as it would for a classification or regression task. It needs to partition the data at sufficient accuracy to group similar decks to allow the user to be able to analyze regions of activity. It also needs to allow a true comparison both within a game and across games. Hence, we chose to use $k = 50$ as it allows the user to see the activity changes in different partitions while maintaining sufficient decks in each cluster to prevent sparsity (as too few decks in clusters lacks generality). We are able to see the effects of expansion packs on clusters, as confirmed by the experts, so we feel $k = 50$ is ideal and generic.

Initially, we generate 50 clusters from the *A:NR* data, 50 clusters from the *H:HOW* decks, and 50 clusters from *M:TG* data.

[8]Three experts (one author and two from the research group: including an international tournament referee) that have played one or more games extensively.

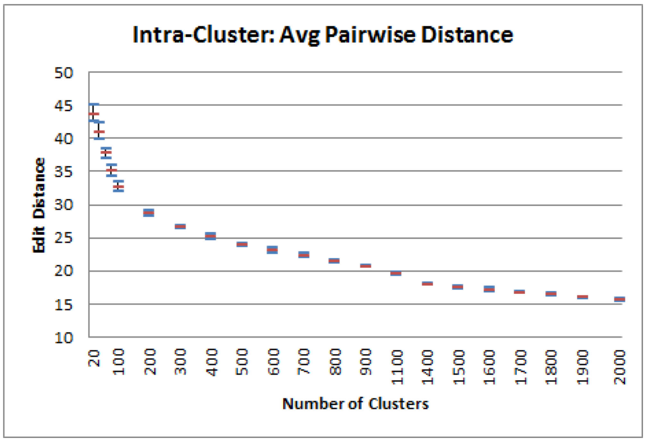

Fig. 2. Chart showing the average ED versus number of clusters for *M:TG* deck data. For each cluster, we calculate all pairwise EDs within that cluster and then average all distances. This is repeated for each cluster. There are five runs for each k-value with the spread of results shown in the chart.

For each game, we then count how many decks map to each cluster for each month and transform these to "the percentage of all decks built that month that fall in that cluster." This produces a heatmap with columns representing clusters and rows representing months and generates a longitudinal analysis of deck building and player engagement. Using month-wise percentages smooths the monthly variations in the total number of decks uploaded per month. The absolute value heatmap without month-wise smoothing is generally similar but provides more of an overall view rather than a monthly breakdown view. The absolute values are also susceptible to website outages. In months with reduced overall activity, the absolute values can be cool across all clusters even though some clusters are active in comparison to the other clusters. The month-wise smoothing reveals more detailed information. Accordingly, we focus on monthly percentages and do not include the absolute value heatmaps due to page limitations.

A. k-Medoids Clustering

ED [26] is used to calculate the dissimilarity between sequences of symbols, such as letters in words for spell checking [27]. The higher the distance, the more dissimilar the two objects are. The minimum ED between two sequences is the minimum number of editing operations: "insertion," "deletion," or "substitution" required to transform one sequence into the other sequence. The cards in the decks are numbered and can be repeated in decks. However, the numbers do not represent card similarity; they are symbols that identify the card. Thus, the decks are ordered, variable-length multisets with repetitions making ED ideal, as it is designed for spell checking that compares words as ordered, variable-length multisets of letters with repetitions. ED takes into account both the order of the symbols and the morphology of the sequence. Hence, we sorted the cards in each deck into numerical order and then compared the decks as sorted sequences to calculate the ED between deck pairs. A *medoid* is defined as the cluster object, whose average dissimilarity (ED) to all the objects in the cluster is minimal. The algorithm proceeds in the following two steps.

1) *BUILD:* This step sequentially selects k decks to be used as initial medoids.
2) *SWAP:* This step iterates through the set of decks. For each deck d in the set of all decks D, assign it to the cluster v_d with the closest medoid mv_d using the ED function $\mathrm{ED}(\mathrm{deck}, \mathrm{medoid})$. When all decks have been assigned then, for each cluster, replace the existing medoid with the medoid of the decks in the cluster. The k "typical" decks should minimize the objective function given in (1), which is the sum of the dissimilarities of all n decks to their nearest medoid

$$\text{Objective function } = \sum_{d \in D} (\mathrm{ED}(d, mv_d)). \tag{1}$$

If the objective function can be reduced by interchanging (swapping) a selected (medoid) deck with an unselected deck, then the swap is performed. The SWAP step repeats until the objective function can no longer be decreased or the algorithm has performed a maximum number of iterations through the dataset. We set the maximum number of iterations to 20 to ensure that the algorithm does not terminate early but, at the same time, does not run longer than necessary. This termination condition was never reached in our evaluations.

In the BUILD step, the algorithm selects k medoids. Standard k-medoids has strong dependence on the initial (random) choice of cluster medoids. We use the enhanced variant k-medoids++, which uses a more careful cluster initializing schema [28]. It improves the dependence on the initial choice of cluster center mv_1 by using probabilistic selection of initial medoids to minimize the following:

$$\frac{(\mathrm{ED}(d, mv_1))}{(\sum_{d \in D} (\mathrm{ED}(d, mv_1)))}. \tag{2}$$

k-medoids++ replaces a random number generator to select clusters by selecting the first medoid randomly from the set of all decks, but then selecting the remaining $k-1$ medoids to cover the data space using the xth squared distance to the nearest cluster center we have already chosen. We sum all squared distances to give $s = \sum_{d \in D} \mathrm{ED}(d, mv_d)^2$, multiply a randomly generated double between 0 and 1 by the sum to give r, $r = s*$ *randomDouble* and then sum the squared distances again and stop at the first deck d where $\sum_{d \in D} \mathrm{ED}(d, mv_d)^2 > r$. Deck d is the new medoid.

Following the BUILD and SWAP steps, the algorithm has partitioned the dataset into k clusters ($k = 50$ for our evaluation). Each deck from the dataset is then assigned to the nearest medoid (least dissimilar according to ED). Thus, deck d is put into cluster v_d, when medoid mv_d is nearer than any other medoid mw, i.e., select the cluster where $\mathrm{ED}(d, mv_d) < \mathrm{ED}(d, mw)$ for all $w = 1, \ldots, k$

B. A:NR

Fig. 3 shows the heatmap of clusters for the *A:NR* data between October 2013 and March 2016. The clusters are in no

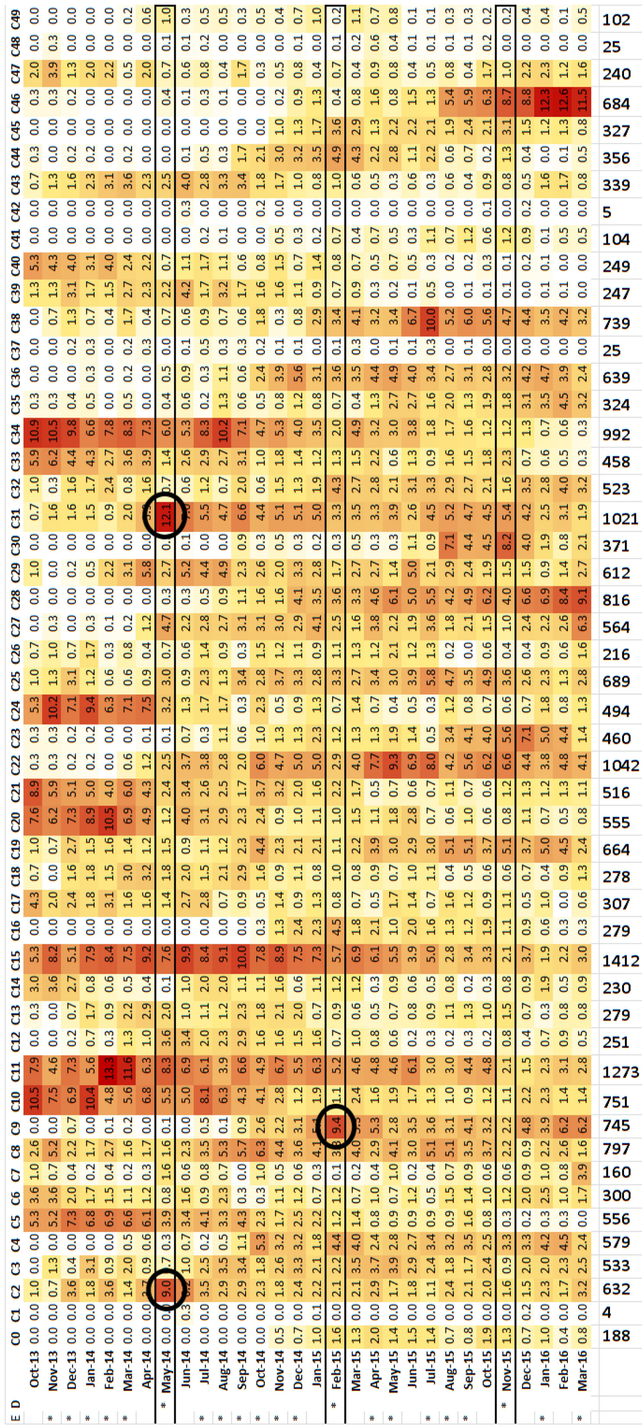

Fig. 3. Heatmap of the *A:NR* data where white is cool (no activity) and red is hot (high activity). For each month (October-2013–March-2016 inclusive), the heatmap lists the percentage of all decks built that month that fall in each cluster [of 50 clusters (C0 to C49)]. The release of deluxe expansion packs (powerful releases) is denoted by "*" in the first column and the right column lists the number of decks in each cluster.

particular order; just the order that they were created. We label expansion packs releases and, more importantly, when the more significant deluxe expansion packs were released. The deluxe expansion pack months have a bold border.

In Fig. 3, deck building activity continues within clusters throughout the months shown, ignoring four outlier clusters ($C1$, $C37$, $C42$, and $C48$) that contain 4, 25, 5, and 25 decks, respectively, and represent very limited deck building activity. There is variation where clusters become more and less popular over time but there is a consistent underpinning of deck building for each cluster. The level of deck building activity generally increases with time across all three games. In *A:NR*, the first month (October-13) only had 304 decks uploaded, later months have >1000 decks uploaded. Thus, a small change in the number of decks uploaded during the early months can cause a bigger change in the percentage. This may account for the variations in February-14 for C11 and March-14 for C20.

We have used experts to cross-reference the expansion pack contents against cluster medoids to validate the correlation between new cards and deck building foci. Inevitably, when deluxe expansion packs are released there is a focus switch to clusters that correlate to the cards in that deluxe expansion pack. Expansion packs generally have much less effect than deluxe expansions. However, the August-15 expansion included a particularly popular card used in 45% of possible decks. This increased the activity particularly in clusters C19, C30, and C46 for August-15, as seen in Fig. 3.

While expansions switch the focus of deck building activity to certain clusters, there is still considerable deck building activity in the other clusters. The game is maintaining a balanced engagement strategy. In particular, we highlight two instances from the deluxe expansion pack of May 2014 and one from the expansion pack of February 2015.

In *A:NR*, decks can be either "Corp" or "Runner," as stated in Section I. These decks are subdivided into factions that are subthemes of the meta-game and dictate the play style for that faction. In May 2014, new cards were released for the *Jinteki* (a faction from the "Corp" side) and *Criminal* (a faction from the "Runner" side) in the deluxe expansion "Honor and Profit." We have circled the two clusters in Fig. 3, where deck building focused in May-14. In $C2$, the activity increased from 26 decks in April-14, to 93 decks in May-14, and fell to 43 decks in June-14. Likewise in $C31$, the activity increased from 27 to 125 and then fell to 49 decks in the three months April-14, May-14, and June-14, respectively. Out of all decks in May-14, 9% were in cluster $C2$. If we analyze the other monthly percentages in $C2$, then May-14 has a likelihood of belonging to $C2$ of $p = 0.000002$ using *t*-test *p* values. Out of all decks in May-14, 12% were in cluster $C31$, which has a likelihood of belonging of $p = 0.00004$ compared to the other monthly percentages for $C31$. The two prototypical (medoid) decks for these clusters are: (*4956:Fast Jinteki Shi Kyu*) for cluster $C2$ and (*4954:Silgrift*) for cluster $C31$, which represent "Jinteki—Honor and Profit" and "Criminal—Honor and Profit" factions, respectively, correlated with expansion packs.

In February-15, deck uploading focused on cluster $C9$ (circled in Fig. 3) with activity increasing from 57 decks to 129 decks between January-15 and February-15 and then falling to 60 decks in March. Out of all decks in February-15, 9.4% were in cluster $C9$, which has a likelihood of belonging of $p = 0.0035$ with respect to the other monthly percentages for $C9$. $C9$ represents a “Weyland Consortium—Order and Chaos” deck named (12297:Titan—Fast Investment (AtlasTrain)—Version 2). The expansion pack for February 2015 was called “Order and Chaos” and focused on “Weyland Consortium” faction “Corp” decks and “Anarch” faction “runner” decks.

Thus, we can see our cluster medoids align exactly with the expansion pack contents. Hence, releasing new cards inevitably switches focus to deck building with those cards but other deck building activity continues and activity falls back in the month after expansion release. The monthly percentages for $C2$ and $C31$ in May-14 and $C9$ in February-15 have p values <0.05 with respect to the likelihood of belonging when compared to ALL monthly percentages across ALL clusters showing that the deck activity is statistically significant at expansion pack releases. This supports the statistical significance shown above when comparing activity at expansion release with other activity levels in the cluster.

C. *M:TG*

Fig. 4 shows the *M:TG* cluster heatmap for each month, October-12–July-15. Again, the clusters are in no particular order but just the order that they were created. We labeled when new packs were released. The new pack months have a bold border.

Activity is not continuous within clusters, it is discrete in approximately 12 month cycles. This is consistent with the release model of cards in yearly cycles with new cards created, the power of existing cards changed and cards retired. The players are following the game’s developments closely. *M:TG* also releases smaller booster packs that generally have little effect on deck building. Two exceptions are May-13, which increased the activity in C45 and decreased the activity in C32, and March-15, which increased the activity in C33 and C27 a month later. The medoids for C45, C27, and C33 all contain cards from the corresponding booster releases. There are two clusters where the activity does continue throughout, $C2$ and $C48$. In $C2$, there is clear 12 month cycles of activity. $C48$ is the exception where there is a background of deck building throughout.

We have circled three 12-month cycles in Fig. 4. In $C2$, the percentage activity increased from 7.1% to 15.4% between August-14 and September-14. The number of new decks in C2 fell from 49 in August-14 to 44 in September-14 but the overall new decks also fell from 689 to 286. Out of all decks in September-14, 15.4% were in cluster $C2$, which has a likelihood of belonging of $p = 0.0004$ with respect to the other monthly percentages for $C2$, excluding the percentages in the high activity stripe. The medoid deck for the 12-month cycle, September-14 onwards, in $C2$ is (230800:Abzan Aggro). This deck was created in April-15, so is a typical representative of this 12-month deck building cycle.

In $C18$ there was high activity at the beginning of our timeline for 12 months. Activity then fell from 304 decks in August-13, to 72 in September-13, to 1 deck in October-13. 44.1% of all decks in August-13 were in cluster $C18$, which has a likelihood of belonging of $p = 0.0013$ with respect to the other monthly percentages for $C18$ excluding the percentages in the high activity stripe. The medoid deck for $C18$ is (51851:Jund), which was created in May-13 so again is typical of the cycle.

Finally, the third cluster with high activity is $C29$, where the activity increases from 0 to 19 to 91 decks between August-13 and October-13, and then falls from 177 to 53 to 0 decks from August-14 to October-14. 6.6% of all decks in Septenber-13 were in this cluster, which has a likelihood of $p = 0.0019$ with respect to the other monthly percentages for $C29$ (excluding the percentages in the high activity stripe). The medoid deck for $C29$ during peak activity between September-13 and August-14 is (74637:Jund Monsters), which was created in May-14 so is representative of the cycle.

In *M:TG*, the deck building activity forms discrete blocks in contrast to the continuous deck building activity of *A:NR*. Players are engaging maximally with new releases while dropping decks from previously high activity regions. The monthly percentages for $C2$ in September-14 and $C18$ in August-13 have p values <0.05 with respect to likelihood of belonging when compared to ALL monthly percentages across ALL clusters. This supports our findings mentioned above when comparing the activity at expansion pack release to other values in the cluster. The percentage for $C29$ in September-13 has $p = 0.11$ likelihood of belonging when compared to all monthly percentages across all clusters, but the likelihood is a statically significant $p = 0.03$ in October-13. The rise in the deck activity is statistically significant at expansion pack releases for *M:TG*. At the end of the 12 month cycle, the activity falls to statistically insignificant levels ($p > 0.05$) within 1–2 months.

D. *H:HOW*

Fig. 5 shows the heatmap of clusters for the *H:HOW* data, for each month, June-13 to August-16. The clusters are simply in the order that they were created. Again, we labeled when new packs were released. The new pack months have a bold border.

At a glance, the heatmap appears most similar to the *A:NR* heatmap. Activity continues within clusters throughout the months shown, ignoring a number of outlier clusters that contain 40 or fewer decks and represent very limited deck building activity. There is variation where clusters become more and less popular over time but there is a consistent underpinning of deck building for each cluster.

However, a closer inspection reveals some activity more analogous to *M:TG*. There are stripes of activity between expansion packs but they are less well defined compared to *M:TG*. Additionally, the stripes are not bounded by consecutive expansion packs but span multiple expansion releases. Some exemplar stripes are circled in black.

Cluster $C27$ shows elevated activity although the increase in activity is gradual and not statistically significant when compared to other months. Comparing the percentage share for July-14 after the expansion pack release gives a likelihood of belonging $p = 0.39$ but May-15, in the middle of the stripe, gives $p \approx 0$ with respect to the other monthly percentages for $C27$, excluding the percentages in the high activity stripe.

Cluster $C37$ became popular at expansion pack “Goblins versus Gnomes” released December-14. The number of uploaded

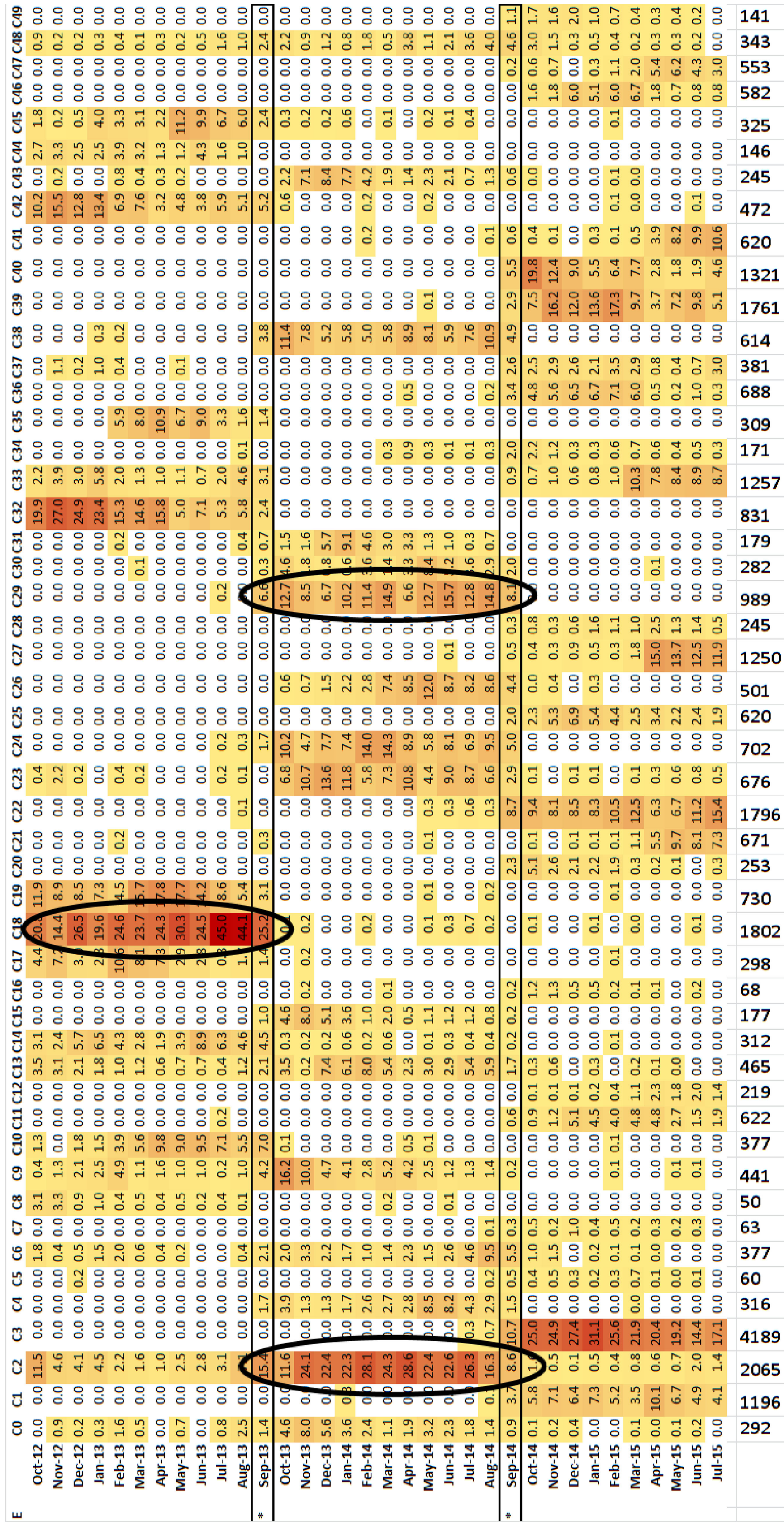

Fig. 4. Heatmap of the *M:TG* data where white is cool (no activity) and red is hot (high activity). For each month (October-2013–March-2016 inclusive), the heatmap lists the percentage of all decks built that month that fall in each cluster [of 50 clusters (C0 to C49)]. The release of expansion packs is denoted by "*" in the first column, and the right column lists the number of decks in each cluster.

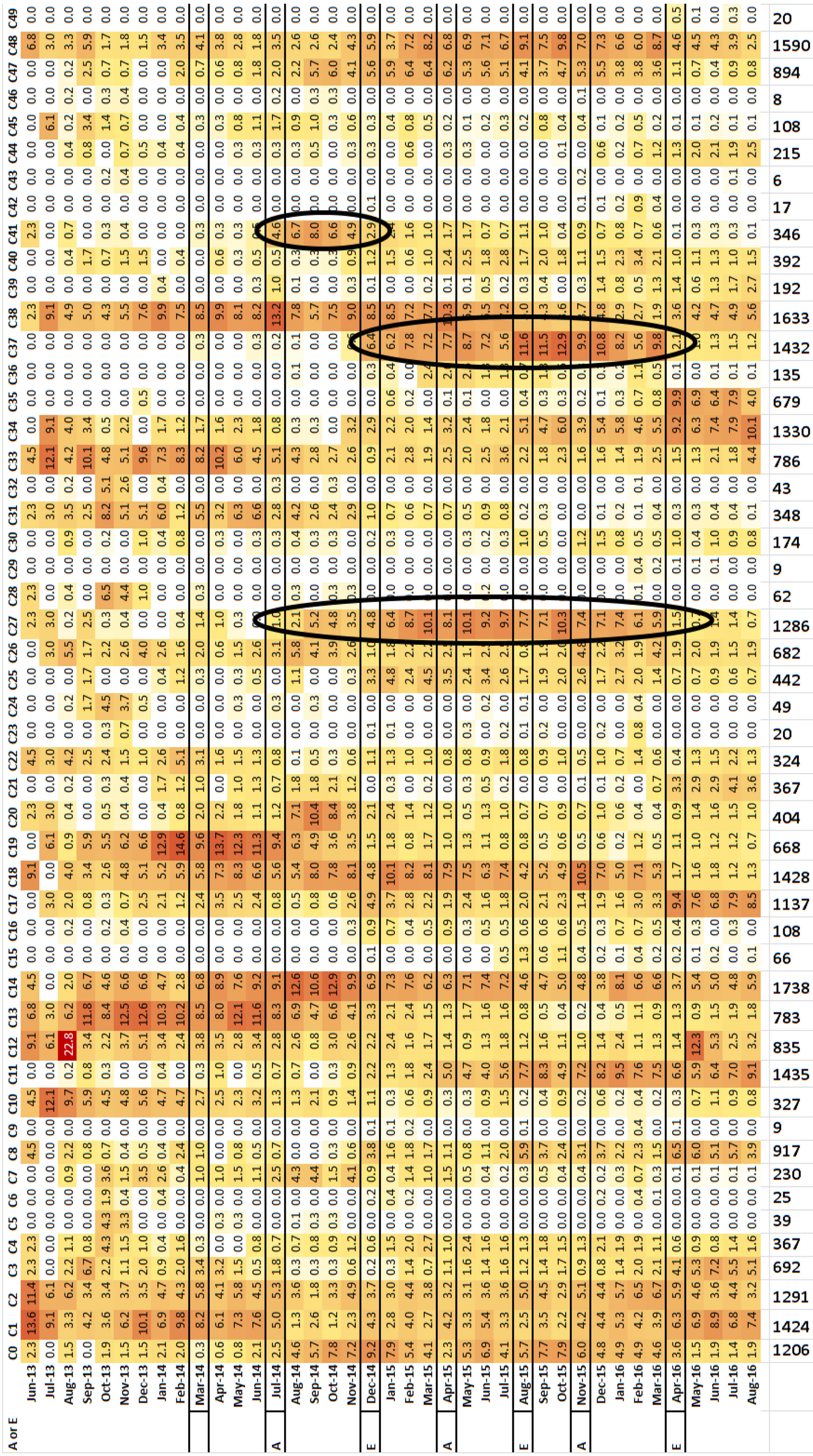

Fig. 5. Heatmap of the *H:HOW* data where white is cool (no activity) and red is hot (high activity). For each month (June-2013–August-2016 inclusive), the heatmap lists the percentage of all decks built that month that fall in each cluster [of 50 clusters (C0 to C49)]. The release of adventure packs and expansion packs is denoted by "A" and "E," respectively, in the first column, and the right column lists the number of decks in each cluster.

decks increased from 2 in November-14 to 73 in December-14 while 6.4% of monthly uploads were in $C37$ in December-14, which gives a likelihood of belonging $p \approx 0$ with respect to the other monthly percentages for $C37$, excluding the percentages in the high activity stripe. Cross-referencing the contents of the deck medoid for cluster $C37$ (359389:Mid–pally) with the cards released in "Goblins versus Gnomes," the deck medoid contains cards introduced in this expansion pack including (12182:Dr Boom) and two copies of (12257:Shielded Minibot). This cluster became even more popular during "The Grand Tournament" expansion in August-15. Again, the typical (medoid) deck contains cards from this expansion including (22362:Murloc Knight).

Cluster $C41$ became more popular corresponding with the adventure pack release July-14. This adventure pack allowed players to win cards. The number of uploaded decks increased from 2 in June-14 to 28 in July-14. In July-14, 4.6% of monthly uploads were in $C41$, which gives a $p \approx 0$ with respect to the other monthly percentages for $C41$, excluding the percentages in the high activity stripe. The medoid deck (94933:treant druid) for $C41$ contains cards that were available to win including two of (7756:Haunted Creeper) and two of (7738:Nerubian Egg).

Thus, the players are engaging with the expansion packs more than *A:NR* producing the stripes of activity bounded by card releases but the striping is much less marked than for *M:TG*. Activity continues across a range of clusters and activity can build slowly, so month comparisons do not always show a statistically significance. None of the three monthly percentages for $C18$, $C27$, and $C37$ have p values <0.05 with respect to the likelihood of belonging when compared to ALL monthly percentages across ALL clusters. Change is gradual and not statistically significant per month. The activity is only statistically significant in clusters at expansion pack release when compared to other values in that cluster and then in only two of the three examples discussed above. Card releases are encouraging players to use the new cards but not compelling them, as activity continues across the range of decks unlike *M:TG*. At the end of the cycle, activity falls to statistically insignificant levels ($p > 0.05$) but takes longer than *M:TG*. For example, cluster $C41$ falls gradually over ten months.

V. Analysis

The two card distribution strategies of the business models evaluated here (LCG versus TCG summarized in Table I) generate different player engagement profiles. Not retiring cards maintain the spread of decks across the data space, as illustrated by the heatmaps for both *A:NR* and *H:HOW*. In *A:NR*, some columns (clusters) move from red to white and others vice versa, and the level of activity is statistically significant around expansion packs. This implies that in *A:NR*, deck building has trends as decks in a particular part of the data space move in and out of fashion. This artefact is not visible in *H:HOW*. *H:HOW* is maintaining interest across the data space throughout time and keeping a spread of decks. *H:HOW* changes the power of cards on each expansion pack, which may manifest as spreading the decks by increasing the strength of weaker cards and preventing them going out of fashion. In contrast, *M:TG* shows a very different profile compared to the other two games with stripes of deck building activity in the sections of the data space between expansion packs (12 month cycles). We hypothesize that this is an artefact of the distribution policy. *M:TG* releases rare cards, changes the strength of cards on each expansion cycle, and also retires cards to keep the game fresh. In particular, retiring cards are likely to cause the cessation of the deck-building activity at the end of the stripes.

Business innovation in many games is led by players (customers) much more than in other business domains, as exemplified by these games. The three customizable card games are user led with huge communities that have evolved in online forums such as Reddit (www.reddit.com) and discussion boards. They entail mass customization and user-led innovation similar to the Wikipedia model. They foster community involvement and encourage crowdsourcing of strategies, theorycraft [29], to generate the meta-game. The game producers can tap into the collective thoughts to provide input to future game developments. These communities and tournament players highlight overly powerful cards and card combinations, which the manufacturers can then correct or release a new card to neutralize the power. Hence, engaging players and communities is vital for the success of many games including customizable card games. Mathews and Wearn [30] state that word-of-mouth and user reviews are key to marketing games.

A:NR employs a cyclic release schedule of "datapacks," which contain the same cards for each purchase. Thus, *A:NR* focuses on creative gameplay with periodic expansion packs to freshen the game and introduce new directions for the meta-game while maintaining interest across the data space, as shown in Fig. 3. What *A:NR* loses by abandoning the hidden and more random factors of *M:TG*, it gains by increasing the players' focus on optimizing decks and keeping up with the current "meta" or "theorycrafting" [29]. This meta represents the collective thoughts of the players in which certain cards and stratagems fall in and out of favor as more cards are published.

M:TG and *H:HOW* also use a cyclic release schedule but, in contrast, release randomized booster packs. *M:TG* embraces ordinality, through set creation and collection, as a correlative meta-game. Fig. 4 shows how strategy is constantly in flux. Players construct their decks from a common card pool. Wizards of the Coast govern this card pool via both official regulations and sanctions where cards are frequently retired from official play to harmonize the introduction of new cards, to keep the card pool tractable and to freshen the game, and, a purposefully constrained supply chain. By design, *M:TG* borrows the collectible model of trading cards from sports and pop culture, such as the famous Panini football stickers [31]. This model uses scarcity and concealment (through the randomized expansion packs of unknown card content) to make collection a game within a game. The randomized release strategy of *M:TG* makes deck building more competitive as players can only access a subset of cards.

H:HOW adopts a hybrid approach with some randomness but still focuses on strategy and collective thinking, see Fig. 5. Cards are not retired but cards can gain new features. Also, it is purposefully designed to exclude card trading unlike *M:TG*.

Players can sacrifice unwanted cards for credit, which can then be used to create new cards of the player's choice. This sacrifice for credit model prevents the requirement for trading of cards between players and, thus, prevents rare cards becoming expensive. It removes the perception of "pay-to-win" where players can effectively buy success by purchasing the rare and powerful cards. The feeling of pay-to-win can be a problem with *M:TG*.

Lessons can be learned by the video-games industry from this evaluation regarding the update strategy and its effect on players and their engagement in games. Ensuring that updates improve gameplay, maintain player engagement and enjoyment and thus ensure ongoing revenue is vital. The method we have proposed can be applied to games where longitudinal data are available on player actions and strategies. The data can be clustered using a suitable partitioning strategy, such as clustering game characters, and the distance metric can be easily changed to suit the data and partitioning strategy. Individual and groups of games can then be analyzed and compared. We discuss this further in Section VII.

VI. Conclusion

Marchand and Hennig-Thurau [8] observed a current lack of understanding of consumers' participation in games and how the business model and strategies affect players. Sifa *et al.* [3] observed that current game data analytics focus on individual games. In this paper, we have presented a multigame method to cross-reference game updates with player activity that will assist businesses to predict how players and the community will strategize their game and thus how their revenues will be affected. Our heatmaps in Figs. 3–5 are simple to generate and easy to understand; they even allow multiple games to be directly compared. They will be valuable to businesses and the community to allow developers and players to analyze deck-building evolution to discover trends; allowing developers to optimize the game and future releases and for players to optimize their deck building strategy. The heatmaps also provide an indication of likely decks that players' opponents will play. These analyses can be generalized to the game industry more widely as updates and in-game purchases are essential sources of revenue to most games companies and, ensuring that updates are optimized and balanced and being able to predict the likely effects of updates will help ensure ongoing revenues and profitability. Our method is independent of a game's structure and just requires an appropriate partitioning strategy (i.e., deciding what and how to cluster) and a suitable distance metric for the game data.

We analyzed three popular customizable card *A:NR*, *H:HOW*, and *M:TG*. *H:HOW* is available as a digital card game (online) only, *M:TG* is also available online but *M:TG* and *A:NR* are both available as table top (physical) card games. The total estimated revenue for digital TCGs in 2016 was $1.4 billion and $4.3 billion for physical games. Hence, game developers need to ensure that players and the gaming community are engaging with their games and engaging with game updates to ensure continued revenue generation from these games. These communities are an important resource for many games in general and the ongoing engagement and positive sentiment of a community is vital to continued monetization. *M:TG* and *H:HOW* both have 20 million players so analyzing the collective strategies is a key component of gameplay for players and a vital monitoring tool for businesses.

We performed a longitudinal quantitative and qualitative analysis of deck building on the three games over time to investigate how the release of cards affects players. Through cluster analysis over time, we were able to find that in *A:NR*, which is less probabilistic, deck building continues across all clusters although activity does focus on clusters related to new card releases. Conversely, in *M:TG* deck activity is discrete and focuses on specific clusters for 12 month periods dictated by card releases, card strength changes and card retirements. *H:HOW* is a hybrid of these. Deck building is spread but there is evidence of striping, indicating that expansion packs are controlling play to some extent. This tallies with *H:HOW's* business model, which is a hybrid of *A:NR* and *M:TG*. Cards are not retired, which is analogous to *A:NR*. However, new features are introduced to cards in expansion packs analogous to *M:TG*. Players cannot trade cards unlike *M:TG* but can sacrifice cards to achieve credit that can be used to create the cards of their choice.

This data analysis has demonstrated that releasing random packs of cards to update a game and releasing rare cards generates a different model of player engagement and strategy compared to releasing uniform updates. This has relevance to all games with updates in the $101 billion global games market where on-going charges and microtransactions are key to businesses' profitability. Uniform updates such as *A:NR* will create a greater spread of player engagement and player strategies compared to random updates and strict changes to or retirement of features, which focus player engagement. This model does not force players to purchase expansion packs so, in online discussions such as Reddit, this model is received best among players. The *M:TG* model in Fig. 4 clearly shows a high level of player engagement with each expansion pack release and *M:TG* generated $21 million in revenue in 2016.[9] Although the random release model of *M:TG* is undoubtedly more lucrative, it can generate negative sentiment among the players and community as it forces purchases of new cards when old cards are retired or changed and players report a feeling of "pay-to-win." *H:HOW* generates the highest revenue of the three games, >$25 million every month with 20 million players[10] in 2016. It adopts a hybrid model of random release packs with no card retirement, which appears to improve monetization over *A:NR* while avoiding the "pay-to-win" negativity of *M:TG*. Fig. 5 shows a good spread of *H:HOW* deck building activity across clusters and across months. There is a fine balance between community sentiment and successful monetization.

VII. Future Work

In future work, we aim to include other game case studies into our analyses, focusing on games with large online communities that provide rich data for analyzing player engagement and player sentiment. For example, our method would be applicable

[9]SuperData, Digital Collectible Card Games Market, 2016. Available at: https://www.superdataresearch.com/market-data/digital-card-games/

[10]SuperData, Digital Collectible Card Games Market, 2016. Available at: https://www.superdataresearch.com/market-data/digital-card-games/

to multiplayer character-based games played by millions online including multiplayer battle arena games, such as Valve's *Dota 2* and Riot Games's *League of Legends*, or multiplayer first-person shooters, such as Blizzard's *Overwatch*, which periodically release new characters or character updates. In these team-based games, each player in a team selects a game character (hero) to play. Our technique could analyze the individual popularity of heroes, the combinations of characters in teams as they change over time and even compare across games. Longitudinal analysis could determine how updates influence the popularity of characters, the sets of characters in teams, and also how teams change with respect to the changing strengths and characteristics of each character in the team.

This will also allow us to investigate different similarity metrics within the k-medoids clustering that account for correlations and groups when comparing multisets and sequences, such as Bhattacharyya coefficient, TFIDF comparisons or pairwise similarity lookup tables, such as those used in Symbolic Aggregate approXimation (SAX) [32]. These games release game updates cyclically as per the customizable card games. The heatmaps will allow us to pinpoint the effect of game updates on character popularity, success rates, and character correlations, which can fed back to the game developers. We will also look to broaden the analysis to other facets of the business model aside from the revenue streams, such as customer segments, customer relations, and cost structures.

Blizzard introduced rotation into *H:HOW's* distribution model in the April 2016 expansion release, where the cards are retired in two year cycles. Similarly, Fantasy Flight changed *A:NR's* business model with respect to the release strategy for expansion packs in Spring 2017 to incorporate rotation similar to the *M:TG* and new *H:HOW* models. Hence, we propose analyzing the new data once sufficient of them are available to allow us to analyze the new release model compared to the old model. This analysis will illustrate whether changing the release model has changed the player behavior with respect to the deck building strategy and engagement with expansion packs and will allow further insights and comparison between *A:NR*, *M:TG*, and *H:HOW*.

REFERENCES

[1] J. Bohannon, "Game-miners grapple with massive data," *Science*, vol. 330, no. 6000, pp. 30–31, 2010.

[2] M. S. El-Nasr, A. Drachen, and A. Canossa, *Game Analytics: Maximizing the Value of Player Data*. Berlin, Germany: Springer-Verlag, 2013.

[3] R. Sifa, A. Drachen, and C. Bauckhage, "Large-scale cross-game player behavior analysis on steam," in *Proc. 11th AAAI Conf. Artif. Intell. Interactive Digit. Entertain.*, 2015, pp. 198–204.

[4] E. Andersen, Y.-E. Liu, E. Apter, F. Boucher-Genesse, and Z. Popović, "Gameplay analysis through state projection," in *Proc. ACM 5th Int. Conf. Found. Digit. Games*, 2010, pp. 1–8.

[5] K. Hullett, N. Nagappan, E. Schuh, and J. Hopson, "Empirical analysis of user data in game software development," in *Proc. ACM-IEEE Int. Symp. Empirical Softw. Eng. Meas.*, 2012, pp. 89–98.

[6] M. Viljanen, A. Airola, J. Heikkonen, and T. Pahikkala, "Playtime measurement with survival analysis," *IEEE Trans. Games*, 2017, doi: 10.1109/TCIAIG.2017.2727642.

[7] H. Xie, S. Devlin, D. Kudenko, and P. Cowling, "Predicting player disengagement and first purchase with event-frequency based data representation," in *Proc. IEEE Conf. Comput. Intell. Games*, 2015, pp. 230–237.

[8] A. Marchand and T. Hennig-Thurau, "Value creation in the video game industry: Industry economics, consumer benefits, and research opportunities," *J. Interactive Marketing*, vol. 27, no. 3, pp. 141–157, 2013.

[9] N. Goumagias *et al.*, "A strategic roadmap for BM change for the video-games industry," in *Proc. R&D Manage. Conf.*, Cambridge, U.K., 2016.

[10] J. Cook, "From expansion packs to DLC: The evolution of additional video game content," *The Artifice*, Oct. 2016. [Online]. Available: http://the-artifice.com/expansion-packs-dlc-evolution-additional-video-game-content/

[11] R. T. Alves and L. Roque, "Because players pay: The business model influence on MMOG design," in *Proc. Situated Play Digit. Games Res. Assoc. Conf.*, 2007, pp. 658–663.

[12] C. Macklin and J. Sharp, *Games, Design and Play: A Detailed Approach to Iterative Game Design*. Reading, MA, USA: Addison-Wesley, 2016.

[13] P. Barclay, M. Gottlieb, B. Moursund, B. Rose, and M. Tabak, "Magic: The Gathering Comprehensive Rules, Wizards of the Coast LLC," 2016. [Online]. Available: http://magic.wizards.com/en/gameinfo/gameplay/formats/comprehensiverules, Accessed on: 22 Jul., 2016.

[14] M. Tabak, "Magic: The Gathering, Basic Rule Book," 2016. [Online]. Available: http://media.wizards.com/images/magic/resources/rules/EN_MTGM14_PrintedRulebook_LR.pdf, Accessed on: 22 Jul., 2016.

[15] S. Adinolf and S. Turkay, "Collection, creation and community: A discussion on collectible card games," in *Proc. 7th Int. Conf. Games+ Learn.+ Soc.*, 2011, pp. 3–11.

[16] R. Hau, E. Plotkin, and H. Tran, "Magic: The gathering deck performance prediction," Stanford Univ., Stanford, CA, USA, Tech. Rep. CS229, Dec. 2012.

[17] P. G. Sanchez, A. Tonda, G. Squillero, A. Mora, and J. Merelo, "Evolutionary deckbuilding in the collectible card game hearthstone," in *Proc. IEEE Conf. Comput. Intell. Games*, Santorini, Greece, Sep. 20–23, 2016, pp. 102–109.

[18] E. Bursztein, "I am a legend: Hacking Hearthstone using statistical learning method," in *Proc. IEEE Conf. Comput. Intell. Games*, Santorini, Greece, Sep. 20–23, 2016, pp. 102–109.

[19] N. Sephton, P. I. Cowling, S. Devlin, V. Hodge, and N. H. Slaven, "Using association rule mining to predict opponent deck content in Android: Netrunner," in *Proc. IEEE Conf. Comput. Intell. Games*, Santorini, Greece, Sep. 20–23, 2016, pp. 102–109.

[20] C. E. Shannon, "A mathematical theory of communication," *ACM SIGMOBILE Mobile Comput. Commun. Rev.*, vol. 5, no. 1, pp. 3–55, 2001.

[21] R. Agrawal and R. Srikant, "Fast algorithms for mining association rules," in *Proc. 20th Int. Conf. Very Large Databases*, 1994, vol. 1215, pp. 487–499.

[22] G. Oh and T. Ryu, "Game design on item-selling based payment model in Korean online games," in *Proc. Situated Play Int. Conf. Digit. Games Res. Assoc.*, 2007, pp. 650–657.

[23] D. Charles *et al.*, "Player-centred game design: Player modelling and adaptive digital games," in *Proc. Digit. Games Res. Conf.*, Jun. 16–20, 2005, vol. 285, pp. 285–298.

[24] A. K. Jain and R. C. Dubes, *Algorithms for Clustering Data*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1988.

[25] M. Van der Laan, K. Pollard, and J. Bryan, "A new partitioning around medoids algorithm," *J. Stat. Comput. Simul.*, vol. 73, no. 8, pp. 575–584, 2003.

[26] V. Levenshtein, "Binary codes capable of correcting deletions, insertions, and reversals," *Soviet Phys. Doklady*, vol. 10, pp. 707–710, 1966.

[27] V. J. Hodge and J. Austin, "A comparison of standard spell checking algorithms and a novel binary neural approach," *IEEE Trans. Knowl. Data Eng.*, vol. 15, no. 5, pp. 1073–1081, Sep./Oct. 2003.

[28] D. Arthur and S. Vassilvitskii, "k-means++: The advantages of careful seeding," in *Proc. 18th Annu. ACM-SIAM Symp. Discrete Algorithms*, 2007, pp. 1027–1035.

[29] C. A. Paul, "Optimizing play: How theorycraft changes gameplay and design," *Game Stud.*, vol. 11, no. 2, 2011.

[30] C. C. Mathews and N. Wearn, "How are modern video games marketed?" *Comput. Games J.*, vol. 5, no. 1, pp. 23–37, 2016.

[31] K. Hayes and A. Hannigan, "Trading coupons: Completing the world cup football sticker album," *Significance*, vol. 3, no. 3, pp. 142–144, 2006.

[32] J. Lin, E. Keogh, W. Li, and S. Lonardi, "Experiencing sax: A novel symbolic representation of time series," *Data Mining Knowl. Discovery*, vol. 15, no. 2, pp. 107–144, 2007.