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A Data Driven Review of Board Game Design and Interactions of Their Mechanics

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ABSTRACT Board games have often been recognised as a tool to model complex concepts in abstract environments for entertainment, education, and research in fields such as military and artificial intelligence. With more board games being designed and published, it is timely to draw attention towards board game design strategies and mechanics which capture the attributes that drive game play. The game design and the mechanics used define the structure, functionality, and play experience of these games. Towards this end, this paper presents a data driven review of board game mechanics and play-related attributes, their interactions and relationships. The analysis expects to draw insights into how board games can be utilised across diverse domains as a tool to understand and explore complex concepts through abstract models. The investigations focus on identifying the trends and patterns of board games being published and their individual mechanics over time. Moreover, the correlation between mechanics and play-related attributes such as game complexity, rating, and duration are explored. The interactions and similarities between individual mechanics based on co-occurrence, mutual information, and clustering based approaches are also illustrated. The results show that the level of complexity and engagement of a game is not a simple function of the set of mechanics used, but rather the interactions that exist between mechanics, and the nature of their specific implementation are the critical factors in determining play experience of a board game.

INDEX TERMS Board games, board game mechanics, data analytics.

I. INTRODUCTION

Board games have a history dating back to approximately 7000 BC [1]. The earliest board games designs were primarily influenced by the social and cultural environments that prevailed at the time. Abstract and strategy games such as 'Go ', 'Chess', 'Checkers', and 'Mancala' are games that were designed as a means of modeling battle strategies and training exercises on a board, and these games are still enjoyed by board gamers to the present day.

Recent studies show that board games are seeing a renaissance in game design and play in the 21st century [2]. More board games are being designed in the present than the previous history of more than thousands of years, covering more domains than ever. War themed games such as 'Twilight Imperium', 'Star Wars: Rebellion', and 'Twilight Struggle'; adventure games involving characters following a quest such as 'Gloomhaven' and 'Nemesis'; card games such as '7 Wonders Duel and 'Wingspan'; party games including 'Codenames' and 'Secret Hitler'; and science fiction related games such as 'Terraforming Mars' and 'Scythe' are popular examples of only a few of the categories of modern board games. With the enhanced design choices that improve immersion, diversity, and complexity of themes, there is an increase in engagement in board games as a hobby or a passion [3].

Certain fields are embracing board games as a potential tool to teach, understand, and explore complex concepts in an abstracted environment. Education researchers are using custom-designed board games to promote engagement and enhance the learning experiences of academic subjects such as language, mathematics, and history [4], [5], and even of complex scientific concepts such as quantum mechanics, nano-bio technologies, and medicine [6], [7] by designing

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the game rules and mechanics around these principles. Board games are also studied in the scientific field of psychology as a means to explore intelligence and skill levels of human cognition [8], [9]. Military research fields have been using board games for tactic analysis, training, and mission preparations for centuries [10], [11]. Board games are also used as platforms to design new challenges for artificial intelligence (AI)-based tools. Go [12], Chess [13], and Blood Bowl [14] are examples which were used as challenges for AI to develop new techniques for heuristic design and search algorithms.

The presented study is motivated by these emerging interests around board games as a tool for entertainment, education, and research. Closer exploration of board games reveal features (referred to as *mechanics* herein) that capture different structural and functional aspects that drive the game play in different directions. Modern board games employ a vast array of mechanics, through which synergies lead to a variety of game domains and diverse levels of complexity and player experiences. A deeper investigation into design strategies and mechanics that define the nature, functionality, and complexity of games can provide insights towards utilising board games as a platform to model and study complex real-world challenges in multiple domains. Despite these benefits, research and study of board games has been sparse and sporadic [15]. This paper aims to address this gap by exploring the importance of understanding the relationship between mechanics and other attributes related to game play, and the impact of interactions within mechanics in capturing the essence of specific challenges, themes, and settings of games.

The most widely accepted taxonomy of board game mechanics is available in BoardGameGeek (BGG) [16] which, at the time of writing, is the largest online collection of board game data. The analysis presented here employs a board game data set of the top 10,000 ranked games from more than 100,000 games in the database. This data set is used to investigate board game mechanics with a view to offering insights for future modeling. The contributions of this paper can be listed as follows:

- An empirical analysis of board games over the period of 1980-2020 is presented to investigate the trends in selected board game attributes.
- A correlation analysis exploring the relationship between attributes such as complexity, rating, rank in BGG database, and number of mechanics is conducted to understand the impact of attributes on each other.
- The interactions among individual board game mechanics are explored to derive insights on their co-occurrence and mutual dependence based on common characteristics.
- Similarity of mechanics is explored based on board game domains that employ them to identify mechanic clusters with similar features.

The paper is organised as follows. Section II summarises other studies that have explored board games, their design strategies, and mechanics. The methodology adopted in analysing the data is presented in Section III and the respective data set used for the investigations is presented in Section IV. Section V presents the statistical results and discussions on their implications in three main focus areas: Section V-A presents trends observed of board game attributes over time; Section V-B discusses the level of correlation of these attributes; Section V-C outlines a deeper analysis of individual board game mechanics and their interactions based on co-occurrence and mutual information analyses and their similarities based on board game domains. Finally, Section VI concludes the paper with a discussion of the analysis and directions for future research.

II. RELATED WORK

Compared to the relatively abundant studies related to the evolution of board games and their genres [17]–[19], there is a scarcity in studies investigating board game design and their mechanics. The recently published 'Building Blocks of Tabletop Game Design - An Encyclopedia of Mechanisms' [20] is the only widely accessible taxonomy of board game mechanics, apart from the BGG collection that catalogues many aspects of modern board gaming design. An ontology of board game mechanics is presented by Kritz *et al.* [21] based on the BGG database where the mechanics are hierarchically organised by grouping them based on their dynamics and aesthetics. Adams and Dormans [22] and Salen and Zimmerman [23] have investigated game mechanics in general, although they have not specifically focused on board game mechanics. As these studies are focussed on building a classification or a taxonomy of board game mechanics, they lack an in-depth analysis of the use of individual mechanics and their implications towards board game design.

In terms of analysing the design strategies and the use of mechanics in board games, Chircop [24] presents a comparative tool to differentiate traits of board games based on characteristics that impact the player experience such as rules, randomness, interaction, and theme. Board game styles, their design processes, and culture are discussed in the perspective of people of diverse backgrounds in [25], which sheds light on various approaches to game design and relative flaws and benefits of design strategies. Several studies have also opted to analyse specific sub-domains of board games. For example, Knizia [26] analyses dice games and their variations including the mechanics and rules adopted in these games; and Cooper and Klein [27] analyse aspects of war themed board games identifying characteristics of decision making and control. Other researches have also explored dynamics and mechanics of cooperative board games [28], narrative-centric board games [29], and card games [30]. The BGG database has been the foundation of several studies into board games, such as [31] and [32] although they have not specifically focused on individual mechanics and their interactions. The existing literature lacks an exploration of the interactions between individual mechanics, and relationships

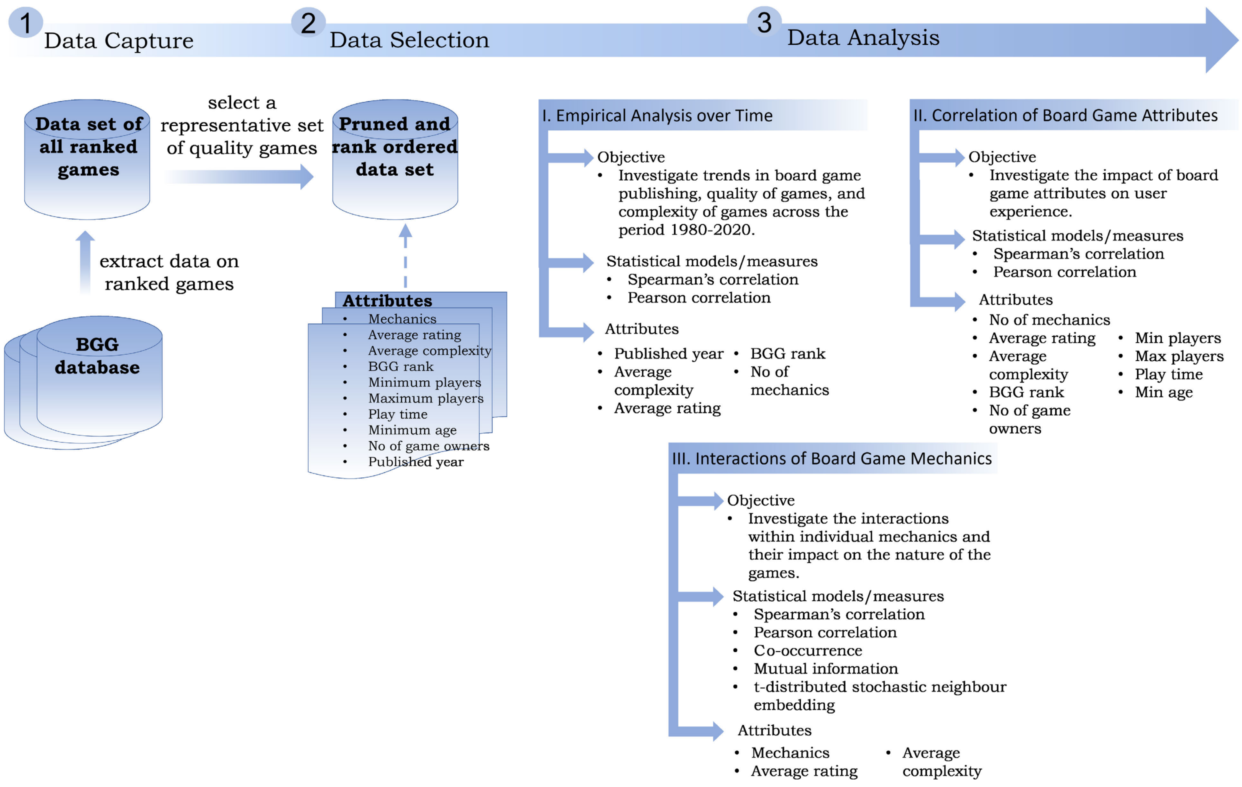


FIGURE 1. Proposed methodology for data driven review of board game design. As the first step, data is captured from the BGG database which is then pruned in the next step to select a sufficient and representative set of quality board games available in the database. Finally, data analysis is performed in three main areas of focus to investigate the design aspects of board games.

between mechanics and gaming experience related attributes such as complexity. The analysis presented in this paper is inspired by these studies and aims to fill the research gap by investigating mechanic interactions and their implications on modeling future board games.

III. METHODOLOGY FOR DATA DRIVEN ANALYSIS

Figure 1 illustrates the adopted methodology in analysing the board game design attributes. The analysis is based on a data set collected from the BGG website [16]. With an online community of more than two million registered users and gaming information on a collection of more than 100,000 games, BGG is the largest source for board game content [16]. The voluntary online community contributes to the site with reviews, ratings, images, videos, session reports, and live discussion forums on the expanding database of board games. As the first step, data on all ranked games is extracted from the BGG database. Unranked games are ignored as they have not been rated by enough BGG users (a game should receive at least 30 votes to be eligible for ranking [16]) which render the quality of games unsatisfactory to be considered for the analysis. As the next step, the data set is further pruned using statistical measures (as discussed in Section IV) to determine an appropriate set of quality games out of the entire collection. The necessary attributes for the analysis are also determined and extracted at this stage. As the final step, detailed investigations are then designed to focus on three primary areas.

The analysis starts with an investigation of the trends in board game publications and design attributes across a period of 40 years. The number of board games published, and the changes in complexity, number of mechanics used, and the ratings received by the games over the years are analysed to determine where the board game designs are headed.

The next section of analysis is focused on evaluating the impact of board game design attributes on the user experience and their correlations. The BGG rank, the average rating and complexity a board game has received from the community define the user experience aspect of the game. This analysis investigates if attributes such as number of mechanics present, the recommended play time, minimum age of players, and number of players show a direct correlation with how players perceive a game. Pearson correlation coefficient is used as a quantitative statistical measure of the strength of relationships between the considered continuous attributes. Spearman's correlation is used with ranked attributes to evaluate the monotonic relationships.

Once a general understanding of the board game attributes and their correlations is established, the analysis then delves deeper into individual board game mechanics, their interactions, and the impact of mechanics on board game design. As a first step, the relationships between individual mechanics and other game attributes is analysed to understand if particular mechanics can generate more complex or highly rated games. Next, the trends of individual mechanics being adopted over time is discussed to determine the significant changes that board game designs have faced in terms of the types of mechanics used. The analysis then focuses on discussing the interactions among mechanics using a co-occurrence analysis and a mutual information analysis to investigate the general trends of mechanics being used together and characteristics they share. Finally, a similarity clustering technique is used to identify similar mechanics in terms of their appearance in different board game domains.

The details of the data set and the pruning process are discussed in Section IV and the evaluations and results are presented in Section V discussing their implications towards board game designs.

IV. DATA SET

Several data sets on board games collected from BGG are available online such as [33] collected in May 2014 and [34] collected in January 2020. However, these snapshots represent older data and are not suitable to discuss the most recent trends in the field. Therefore, a new data set was collected in February 2021 using the BGG1tool [35] which is a Windows freeware application for downloading game information from the BGG website. The downloaded data set consists of data with respect to all ranked games (there were 20,343 ranked games out of more than 100,000 total games) in the BGG database at the time of data collection.

As the investigations presented in this paper are directed towards the aspects that influence modelling of board games, the following game attributes in the BGG database were used in the investigations:

- Mechanic(s) adopted by the games: the functional aspects of games (182 mechanics).
- Domain(s) that each board game belongs to (8 domains).
- Average rating of games: the average of all the ratings of a particular game given by registered BGG users (range: 1-10).
- Average complexity (weight) rating of games: the average of all complexity ratings for how difficult a game is to understand (based on aspects such as complexity of the rule-book, playtime, technical skills required and proportion of time required to be spent planning in comparison to acting; range: 1-5).
- BGG rank of the games: A ranking derived based on the average rating but with several alterations. 'Dummy' votes (votes that are added purposefully to manipulate results) are added to the ratings to avoid games with relatively few votes being misinterpreted, before calculating the BGG rank (range: 1-10,000).
- Minimum number of players that can play the game (recommended by publishers)
- Maximum number of players that can play the game (recommended by publishers)

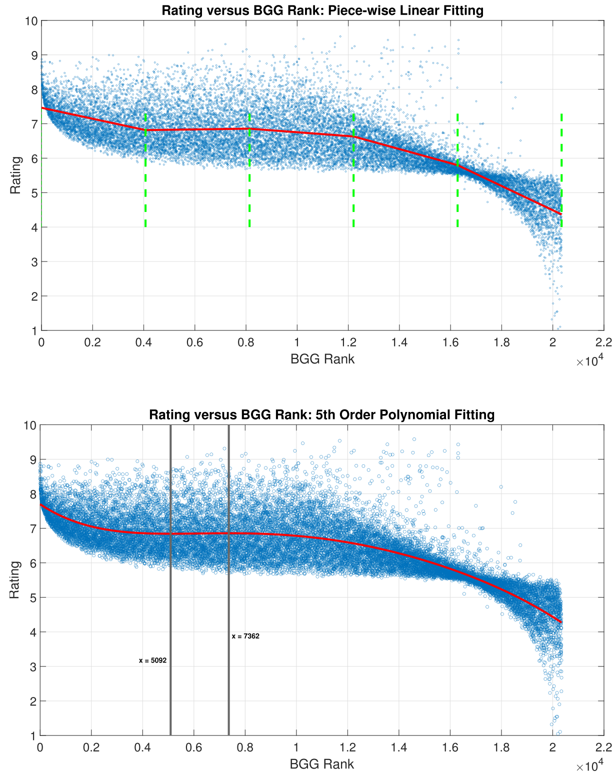


FIGURE 2. Distribution of rating compared to BGG rank for all ranked games (20,343) in the BGG database. Top: Piece-wise linear fitting. Bottom: Fifth order polynomial fitting. The vertical lines identify the concavity changes in curves.

- Play time of the game (recorded in minutes)
- Minimum age of game players (recommended by publishers)
- Number of game owners as recorded on BGG
- Published year of games

As the BGG site contains information on a variety of board games, it was essential to decide an appropriate subset of high-quality games for the analysis to ensure a constructive evaluation. Therefore, the BGG rank was used as a quantifier to determine the suitable data set to conduct the rest of the analysis. The exact function for calculating the BGG rank is intentionally undocumented in BGG to avoid tampering attempts. However, the rank is decided based on a *geek rating* which is a Bayesian average of the ratings designed to push the board games with a very low number of votes towards the average of the entire set. Only the games with at least 30 ratings are ranked, and bogus 'shill' or 'hate' ratings are also filtered out. This mechanic helps prevent the games with only a few high rating scores dominating the rank list [36].

Figure 2 illustrates the distribution of the average rating and BGG rank of the original data set of 20,343 games.

We performed a fifth order polynomial curve fitting and a piece-wise linear fitting to identify appropriate mathematical models that express the relationship between the two variables. The fifth order polynomial was chosen after adjusting the order to fit the data as closely as possible. Based on

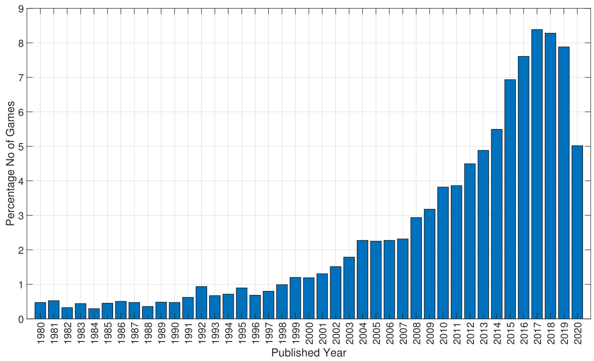


FIGURE 3. Distribution of number of games published across the period of years 1980-2020 as a percentage of the total number of games (9,504 games) in the top 10,000 ranked games published over this period.

the polynomial fit, the critical points of the curve where the concavity changes can be identified as the points where rank is equal to 5,092 and 7,362 (rounded to the nearest value). The average ratings of games up to the rank ∼5,092 demonstrate a steady decrease after which they show a slight upward trend. The ratings gradually start declining again after the rank ∼7,362 with a steeper drop after the rank ∼12,000 according to the piece-wise linear curve. Therefore, based on the nature of the distribution of ranks and ratings, the set of games up to rank 10,000, of which the rating values remain sufficiently higher, was selected as a suitable set to conduct the rest of the analysis.

V. DATA ANALYSIS

This section presents the results of the data analysis conducted with the BGG data set of top 10,000 games. The analysis is divided into three focus areas: (1) to investigate the trends of board game attributes over time; (2) to investigate the correlations among board game attributes; and (3) to understand the interactions among board game mechanics and their impact on game design. The following sub sections present the details of the evaluations and discuss the results.

A. EMPIRICAL ANALYSIS OF BOARD GAME ATTRIBUTES OVER TIME

This section presents an analysis of board game trends across the period of 1980-2020 in terms of the number of board games released, the ratings, complexity, and mechanics of the board games published in each year.

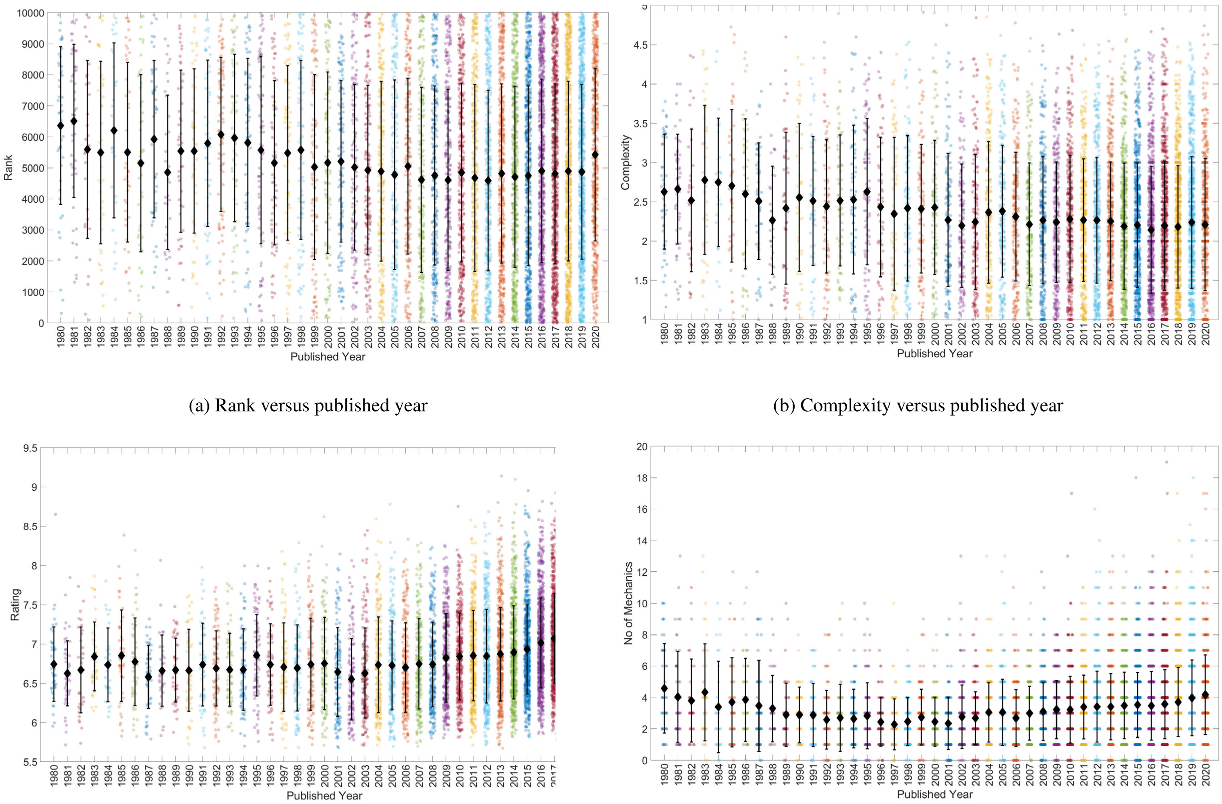
Figure 3 illustrates the number of games released in each year from 1980-2020 as a percentage of the total number of games in the top 10,000 ranks in the current data set.

According to the analysis, 9,504 games out of the 10,000 were published within this period and the results show that there exists a significant growth in the number of board games released over the years (Spearman's $\rho = 0.97$). This observation supports the recent claims on the increasing popularity of board games, despite their limitations in comparison to video games, in the digital age [2]. An exponential increase is observed from the start of the year 2000 and a majority of the games in the top 10,000 ranked games were published since 2015. Board games published in the year 2020 show a significant drop in comparison to the previous year. There could be several reasons for this observation. Firstly, due to the novelty of the games and the relatively smaller number ratings they have received as they are yet to reach a larger community of users, some games may not have reached the top 10,000 list. A future analysis in a year's time could provide evidence towards this aspect. Further, this observation could be specific to the year 2020 given the impact of COVID-19 pandemic [37] which caused turbulence in releasing new games despite the sudden surge in buying patterns of board games due to lock downs [38].

The variation of the rank, complexity, rating, and number of mechanics in games across the period of 1980-2020 is illustrated in Figure 4. The figure shows the scattered individual ranks, complexities, ratings, and number of mechanics of each game grouped based on the published year. Further, the average value of each year can be identified with the bold black points along with the error bars depicting the standard deviation. It depicts the trends of correlations that exist between the published year and each of the three attributes over the period of 1980-2020.

According to the analysis, there exists a strong correlation between rank and the published year as the more recent games are ranked higher (corresponding to a lower rank number) in the spectrum (Spearman's $\rho = -0.76$). The correlation analysis takes into account the variation in the number of games published in each year and their relative positioning of ranks. Therefore, the number of games published shows an increase in numbers as well as rank over the years. Similarly the more recent games are also rated highly (Spearman's $\rho = 0.62$) in comparison to old games. It is observed that the average complexity of the board games show a steady decrease (Spearman's $\rho = -0.88$) although the change is occurring in small amounts. Further, a significant trend in the average number of mechanics used in the games cannot be observed over the years (Spearman's $\rho = 0.04$). The general trend shows a decrease in the average number of mechanics from 1980 to 2000s and then it starts gradually increasing. A few recent games tend to use a large number of mechanics as high as 19 which indicate the potential for future games with more mechanics and higher complexity. To further investigate such trends, analysis results on the correlation of board game attributes such as mechanics and complexity are presented in Section V-B.

In conclusion, the results suggest that there is an exponential increase in the number of games published in the 21st century in comparison to those of the late 20th century and the board game community is more attracted to those games published in the recent years. There was also a slight downward trend observed with the number of mechanics used in the games until the year 2000, however, it is currently moving in the opposite direction with the more recent games using more mechanics.



(a) Rank versus published year

(b) Complexity versus published year

(c) Rating versus published year

(d) Number of mechanics versus published year

FIGURE 4. Distribution of the (a) ranks, (b) complexity, (c) rating and (d) number of mechanics of board games in the top 10,000 ranks published across the period of years 1980-2020. Each scattered individual point corresponds to the respective value of a single game. The points in black depict the average value of all games in a particular year and the error bars depicting the standard deviations are shown in black.

B. CORRELATION AMONG BOARD GAME ATTRIBUTES

This section investigates the relationships between user experience and other attributes of the board games in general. The user experience is captured with the board game rank, rating, and complexity scores which are compared against attributes such as play time, number of mechanics, number of game owners (recorded on BGG), age of players recommended by publishers, and minimum and maximum players allowed as recommended by publishers. Pearson's correlation coefficient was used with pairs including continuous attributes and Spearman's correlation coefficient was used with pairs that include BGG rank which is an ordinal attribute to determine the correlation.

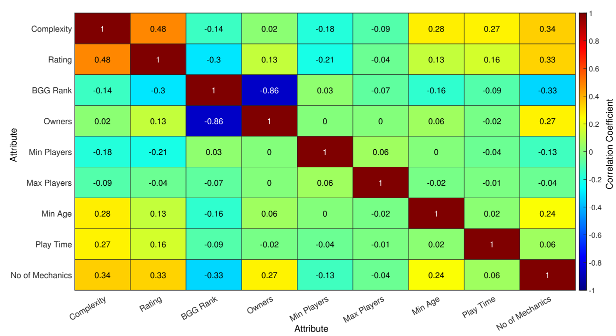
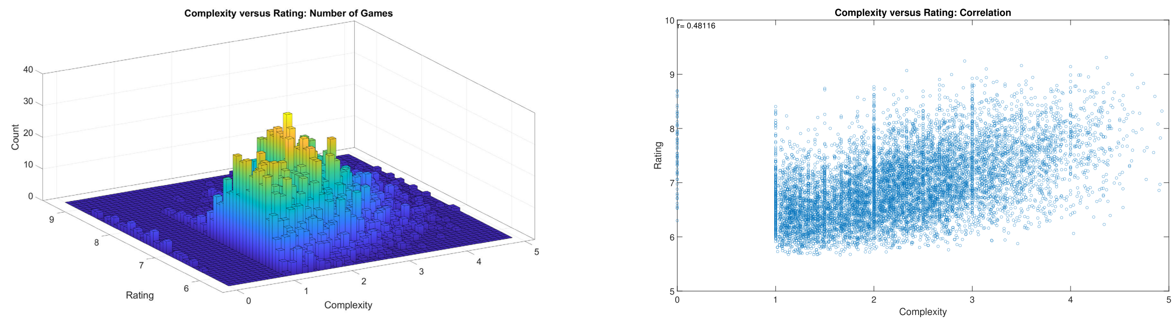


FIGURE 5. Correlation matrix for board game attributes. Pearson's correlation coefficient was used with continuous attributes and spearman's correlation coefficient was used with pairs including ordinal attributes (BGG rank).

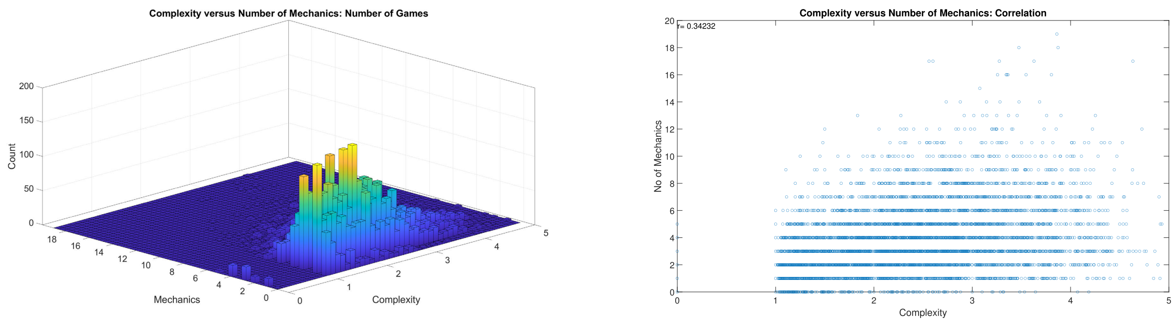
1) CORRELATION ANALYSIS

Figure 5 illustrates the correlation coefficient matrix for all relevant pairs. The strongest correlation is observed between BGG rank and the number of users who own a particular game (Spearman's $\rho = -0.86$) which indicates that games with a higher rank (hence lower rank number) tend to be owned by a majority of the population. However, only weak, and moderate correlations are observable within pairs that include the attributes such as complexity, rating, and the number of mechanics. The correlations between these three attributes are further explored in Figure 6. The sub figures on the right column depict the variation of number of games along the axes of each attribute pair. It provides an overview of the most common attribute-pair values that are present in the top 10,000 games. The sub figures on the left column illustrate the correlation trends between each attribute pair.

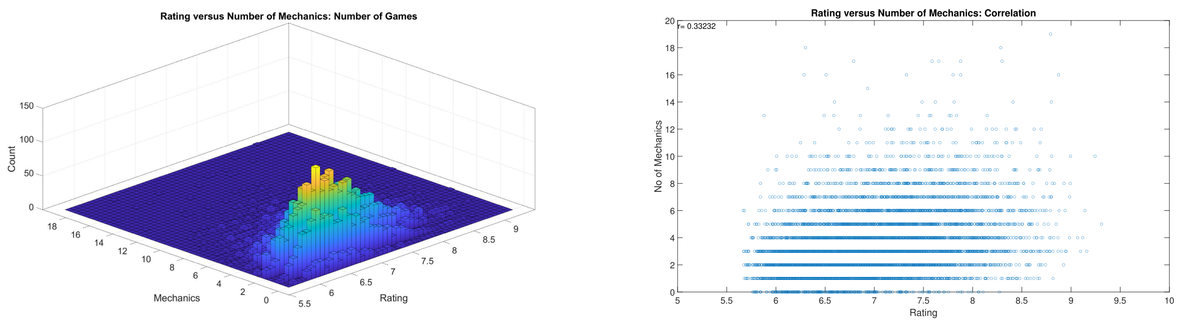
There exists a positive correlation between the complexity and rating of games (Pearson's r = 0.48). This indicates that more complex games are likely to be more appealing to avid users thus receiving higher ratings. As BGG captures



(a) Complexity versus Rating



(b) Complexity versus Number of Mechanics



(c) Rating versus Number of Mechanics

FIGURE 6. Correlation between complexity, rating, and number of mechanics of the board games. The figures on the right depict the variation of number of games along the axes of each two-attribute combination. The figures on the left depict the correlation between the two attributes considered.

only a subset of players more devoted to board games than casual players that are not inclined to contribute in the BGG community, the results cannot be generalised across all board game players. Figure 6a illustrates the distribution of the two attributes. Many of the games are distributed in the complexity range 1-3 and rating range 6-8. Comparatively, only a small number of games are highly complex with a value greater than 4 and they tend to be highly rated as well.

The complexity of games is also moderately correlated (Pearson's r = 0.34) with the number of mechanics. Most games have 0-6 mechanics, but some of the highly complex games have many mechanics as large as 19 according to Figure 6b. It should also be noted that the data set consists of 324 games (out of 10,000) with 0 mechanics. It is likely that the BGG users have not attributes mechanics for games that have not been popular among the BGG community. Given that it is only 3.24% of the total data set, the rest of the games provide a sufficient pool to analyse the correlation with a satisfactory level of accuracy.

Similarly, the rating of games is also moderately correlated (Pearson's r = 0.33) with the number of mechanics as shown in Figure 6c. Most games lie within the range of 0-6 mechanics and a rating between 6-8. 324 of top 10,000 games record 0 mechanics on BGG which could be due to game players not having submitted any mechanics related to these games due to their low popularity, rather than the games not having used any mechanics from the BGG categorisation. However, some highly rated games such as 'Gloomhaven' (rating: 8.79; no. of mechanics: 19), 'Maracaibo' (rating: 8.28; no. of mechanics: 18), and 'On Mars' (rating:8.3; no. of mechanics:17) tend to also have a higher number of mechanics which results in the moderate correlation.

In addition, the number of mechanics is also correlated with the BGG rank (Spearman's $\rho = -0.33$) and the number of game owners on BGG (Pearson's r = 0.27). This can be explained based on the previous observations. The ratings and complexity of a game increase as the number of mechanics, which in turn improves the rank. Further, as previously discussed, players are inclined to own a game with a higher rank in the database. Therefore, it influences a correlation between number of mechanics and the rank. A moderate negative correlation is also observed between the BGG rank and rating (Spearman's $\rho = -0.30$) in comparison to relatively stronger correlation between BGG rank and number of game owners in BGG (Spearman's $\rho = -0.86$). The correlation between BGG rank and rating is not as strong potentially due to the alterations done to avoid highly rated games with a few numbers of votes dominating the ranked game list as described in Section IV. Minimum recommended player age has a slight correlation with complexity (Pearson's r = 0.28) and the number of mechanics (Pearson's r = 0.24) which illustrates that the games designed for adult players tend to have more mechanics and be more complex.

2) DISCUSSION

The analysis shows that although relationships among attributes are visible, most correlations are at most moderate. There could be several reasons for the lack of strong correlations. With regard to mechanics, they do not have a base degree of complexity and the number of mechanics does not cater for the emerging complexity derived by specific combinations such as card/power combinations. The board game 'Chess has only four mechanics related to its grid and movement of pieces within the grid (*grid movement*, *pattern movement*, *square grid*, and *static capture*; and 'Go has only two mechanics (*square grid* and *enclosure*). Despite the small number of mechanics involved, these games can create a highly complex decision space unveiling an exponential number of winning strategies with each turn of game play. As a result, these games can also cater to a wider array of players. While kids as young as 6-8 years can enjoy the game by learning the simple rules of movement, the games also facilitate the formulation of complex strategies and techniques that drives interest of more advanced adult players.

Similarly, the interactions among board game mechanics can change the complexity and the overall feel of a game in a significant manner. Consider the example mechanics combination: *hand management* (a mechanic that refers to the use of cards in the game and rewards the players for playing them in certain sequences according to game rules) and *card play conflict resolution* (where the players play one or more card simultaneously or sequentially modifying the outcome of a conflict and applying special abilities). They can create a more complex game than the combination which includes *acting* (where players communicate through acting or mimicry) and *card drafting* (where players have a choice in drawing a card from a pile to meet some objective or gain an advantage), although both involve cards and have two mechanics.

Further, the nature of implementing a particular mechanic also impacts the overall complexity of the game in different ways. For example, the mechanic *worker placement* (which requires the players to select individual actions from a pool of available actions often by placing game pieces or tokens, that represent workers, on the selected actions) can be implemented to support both complex and simple game strategies. The game 'Agricola' uses a simple strategy of *worker placement* for resource management. The family members should be placed in a farm to perform actions such as plowing, sowing collecting items and expanding the farm. Each action space can be occupied by only one family member in a single round which simplifies the use of *worker placement*. A classic example of *worker placement* is 'Stone Age' which uses game strategies that are relatively more complex to allocate workers to different regions of the board such as the hunting ground, farm, quarry or the tool shed to maintain a tribe in the early days of human history. Different action spaces require different number of workers and a dice is used to determine benefits of actions which introduces complexity to the game. On a more sophisticated level, 'Paladins of the West Kingdom' uses workers of different types such as labourers, fighters, scouts, and merchants in different numbers for different tasks. The interactions among workers, actions, and associated costs are more intricate, placing it above both 'Agricola' and 'Stone Age' in terms of the complexity.

There are many factors that can impact the rating of a game than complexity. For example, family games such as 'Crokinole (rating: 7.9, complexity: 1.25), 'Azul (rating: 7.83, complexity: 1.77) and party games such as 'Monikers (rating: 7.78, complexity: 1.06) are highly rated even though they are far less complex than other highly rated games. This shows that even though these games are easy to understand and master, they are still capable of maintaining interest and engagement of players. While the enjoyment derived from a board game is analogous to the rating it receives, it is often very subjective and influenced by many factors.

Finally, it can be deduced that there are more interactions within game mechanics, and other external factors that are not captured within this analysis, that impact the complexity and rating of a board game. Mechanics are investigated in detail in the next section to gain insight into some of these interesting interactions and combinations.

C. INTERACTIONS OF BOARD GAME MECHANICS

The analysis presented in this section delves deeper into the specifics of board game mechanics and insights that can be derived from their interactions with each other. The analysis identified 182 unique mechanics associated with the top

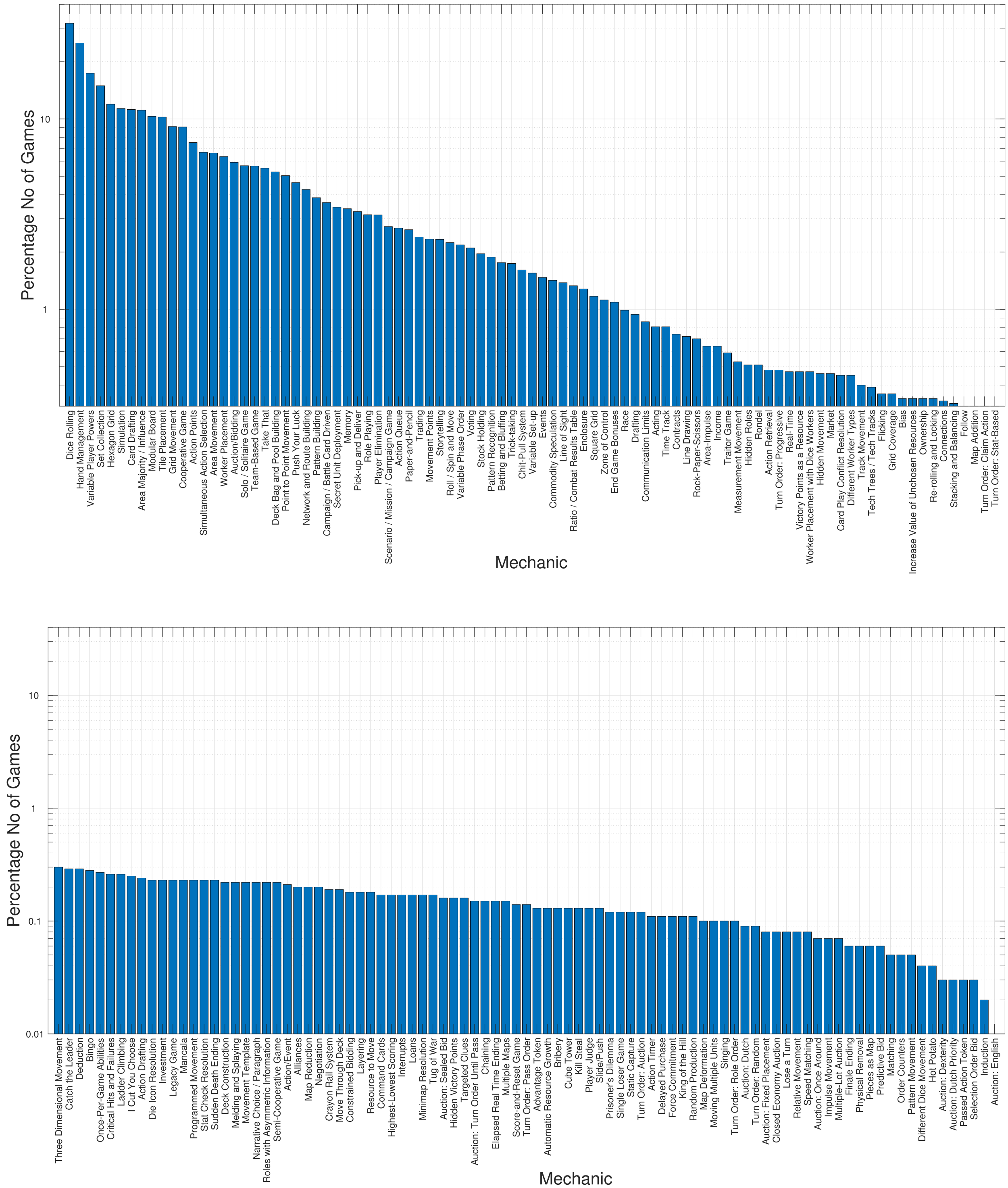


FIGURE 7. Percentage number of games out of the 10,000 games selected, that use each board game mechanic (the figure on the bottom is a continuation of the illustration of the top figure).

10,000 board games of the BGG database. Each mechanic describes a feature or a component associated with the board game in relation to various aspects, such as the structure and configuration of the game, resource and capability distribution, victory triggers, sequencing and temporal properties, actions and action resolution methods.

1) RELATIONSHIP BETWEEN INDIVIDUAL MECHANICS AND OTHER GAME ATTRIBUTES

Figure 7 illustrates the percentage number of games, out of 10,000, associated with each mechanic. There are 54 mechanics which are used in more than 100 games (1% of total games) of which only 10 are used in more

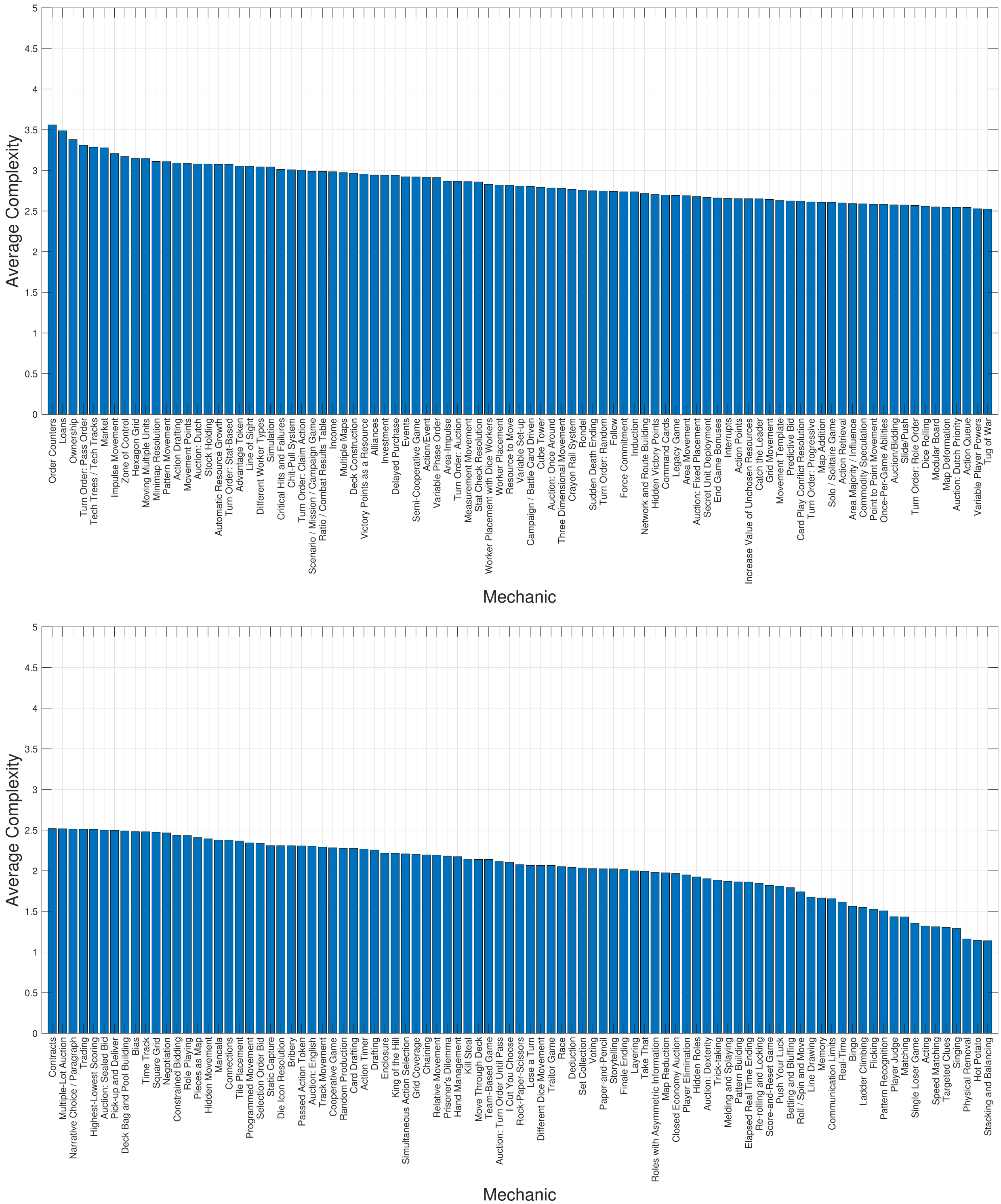


FIGURE 8. **Average complexity of all games that use each board game mechanic (the figure on the bottom is a continuation of the illustration of the top figure).**

than 1000 games (10% of total games). A majority of the mechanics (102 out of 182) are used in 10-100 games. The most frequently used mechanics are *dice rolling* (where a die is used to introduce randomness into the game) and *hand management*, each being used in more than 2000 games (20% of all games). The most frequently occurring mechanics such as *hand management*, *variable player powers*, *set collection*, *hexagon grid*, *simulation*, *modular board*, and *tile placement* can be identified as mechanics that are concerned with the structure, configuration, and resource

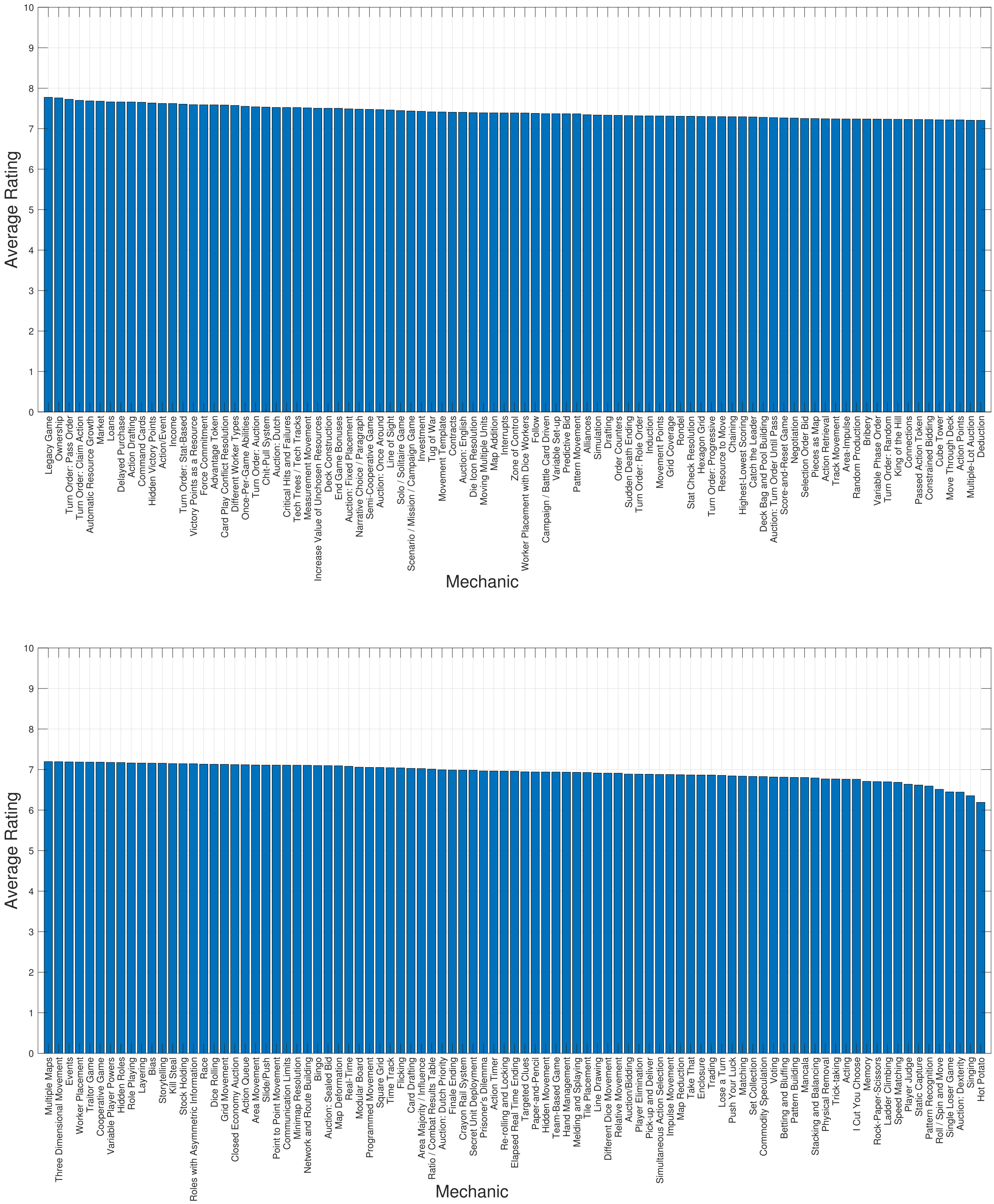


FIGURE 9. Average rating of all games that use each board game mechanic (the figure on the bottom is a continuation of the illustration of the top figure).

and capability distribution of the game. *Dice rolling* and *card drafting* are exceptions to those as these mechanics primarily define the actions the players can take and how they are resolved within the game play. The least frequently used mechanics such as *auction* (placing a bid on game items in an auction to enhance one's position in the game) and *turn order* (players take turns in playing based on a specific order) are used by only a handful of games and can also be described by their composition and how they are resolved.

Figure 8 illustrates the average complexity of games, using each mechanic based on the top 10,000 games. According to the results, there are 25 mechanics with an average complexity above 3 (out of 5). The mechanics: *order counters* (where players can place order tokens in regions of the board to indicate their actions in that particular region), *loans* (where the players have the option to take a loan from a bank to get more money) and *ownership* (where players own entities or resources and collect merits based on actions performed on these entities), have the highest average complexities respectively.

However, according to Figure 9, there is not an observable difference between the average rating of games using particular mechanics. This implies that the types of mechanics present do not impact how games are rated.

2) TRENDS IN ADOPTING INDIVIDUAL MECHANICS OVER TIME

Section V-A presented the general trends of board game attributes across a period of 40 years which showed that the number of mechanics that prevail in individual board games has not changed significantly over that period of time. Additionally, there are no identifiable trends in individual mechanics that may show an increase or decrease in popularity over time. Therefore, to further explore the trends in individual mechanics, Figure 10 illustrates the adoption of mechanics through the period of 1980-2020. The figure shows changes in the use of each mechanic in five year intervals based on the percentage number of games that use the mechanic out of all board games that are published until that time starting from the year 1980. Only the mechanics that demonstrated a change of more than 1% within at least one interval are shown to easily recognise the significant trends.

Several mechanics gaining popularity among board game designers can be identified from the analysis. *Hand management* shows the most significant positive shift in interest from only 4.4% games using it in 1980 to 25.7% of games utilising the mechanic by the year 2020. Further, *variable player powers*, *card drafting*, *area majority/influence*, *action points*, *worker placement*, and *deck bag and pool building* are steadily gaining popularity with 17.72%, 11.54%, 11.4%, 7.71%, 6.5%, and 5.47% of games respectively using them by the year 2020. Conversely, there are several mechanics that are losing popularity with board game designers, with a decline in their adoption with the recent games being published. A noteworthy observation is that, although *dice rolling* is still used in more than 30% of the games and is the most frequently used mechanic in the top 10,000 list of board games in BGG, the use of this mechanic is in steady decline. More than 55% of the board games published in 1980 used *dice rolling* whereas this percentage has decreased across the total number of games published since then.

Similarly, other mechanics such as *hexagon grid*, *simulation*, and *grid movement* are also being used far less in the recent games in comparison to 40 years ago. Mechanics such as *set collection*, *cooperative game*, *modular board*, and *pattern building* have lost popularity after their initial boom; however, they are recently gaining some attention among newly released games. 'Gloomhaven' which was published in 2017 and currently ranked as the no. 1 game on BGG adopts both *modular board* and *cooperative game* mechanics. *Set collection* is used in 'Terraforming Mars', published in 2016, which is very popular among the board game community, ranking fourth in the list. 'Azul' is another popular game recently published (in 2017) which incorporates the *pattern building* and *set collection* mechanics. It should also be mentioned that although a majority of the significant shifts (which includes only 52 out of 182 mechanics) are seen to be in the declining end of the spectrum, the overall trend of mechanics when the entire set is taken into consideration shows an increase although in small percentages.

3) CO-OCCURRENCE ANALYSIS OF MECHANICS

In order to derive further insights into the nature of games and the impact of mechanics on their design, the mechanics that co-occur frequently were investigated. Figure 11 illustrates the co-occurrence matrix for the mechanic pairs that co-occur in more than 1% of the top 10,000 games.

Three significant mechanic pairs can be identified which show a co-occurrence in more than 8% of games, each while the other co-occurrences appear in less than 6.2% of games. *Dice rolling* appears in the top three most frequent co-occurring pairs. The most frequently co-occurring pair is *dice rolling* (where a die introduces randomness into the game) and *simulation* (games that attempt to model real situations and/or events) which appear together in 8.58% of all games. These games include high ranking board games such as 'Twilight Struggle', 'War of the Ring', and 'Star Wars: X-Wing Miniatures Game'. 8.2% of games such as 'Twilight Imperium and 'Star Wars: Rebellion' adopt both *variable player powers* (which refers to a mechanic where each player has a special action that only they can perform or can modify a standard action) and *dice rolling* mechanics together in game design. *Dice rolling* mechanic is also frequently seen with *hexagon grids* (in 8.06% of games) in games such as 'The Castles of Burgundy' and 'Mage Knight Board Game'.

According to Figure 11b, *dice rolling* (in 33 of 130 pairs), *hand management* (in 23 of 130 pairs), and *variable player powers* (in 21 of 130 pairs) are the mechanics that most frequently appear with other mechanics in pairs while the others occur in less than 15 pairs. However, it can be observed that the three most common paired mechanics are also the most frequently occurring mechanics in general, as depicted in Figure 7. Therefore, the co-occurrence results are biased towards the popularity of the mechanics. A mutual information analysis is more suited to eliminate this bias.

4) MUTUAL INFORMATION ANALYSIS OF MECHANICS

Based on the observations of the previous section and the derived conclusions, a mutual information (MI) analysis is conducted in this section to identify the mechanic pairs that occur together independent of their popularity in general.

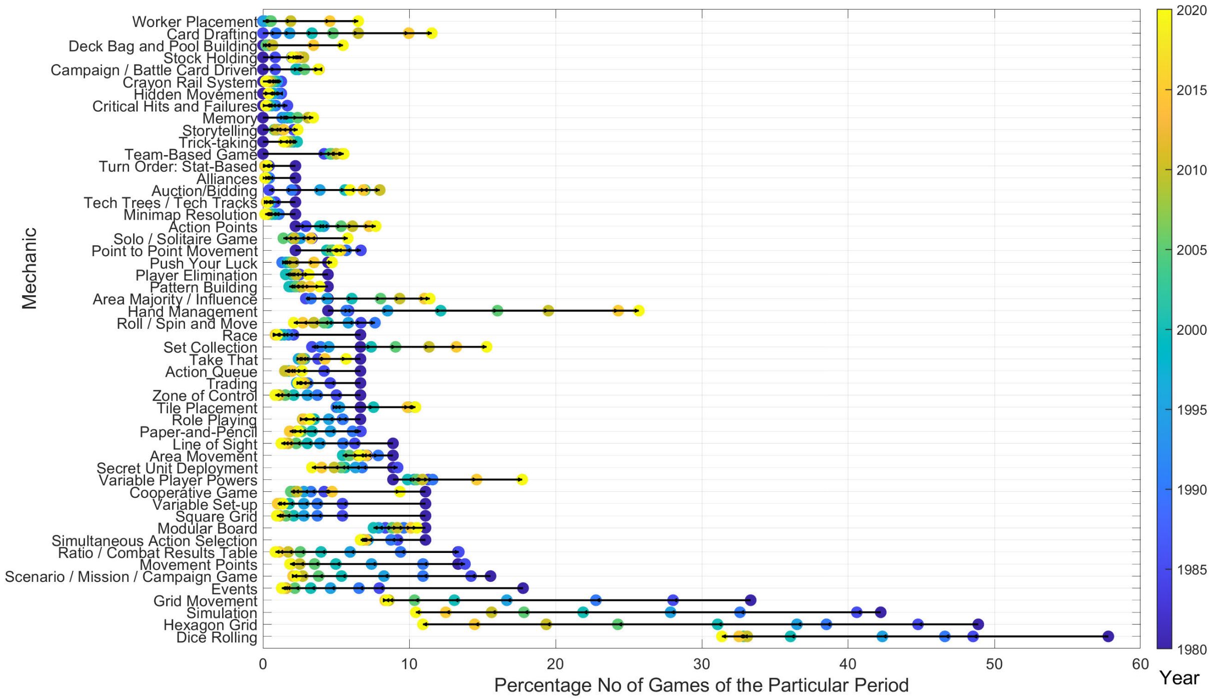


FIGURE 10. Trends in adopting mechanics over time for mechanics that appear in more than 1% of games in comparison to its prevalence five year earlier in the period of 1980-2020. The percentage values are calculated from the total number of board games in the top 10,000 list published from the year 1980 up to the particular year in consideration.

MI determines the mutual dependence between two random variables. It gives a quantitative measure of the amount of information that can be learned about one variable by observing the other. Therefore, the presented MI analysis investigates the mechanics that occur together due to common attributes shared by both mechanics. MI between mechanic pairs was calculated using the normalised pointwise mutual information (NPMI) measure given in the Equation 2 which normalises the MI value that can be calculated with the Equation 1 within the range [−1 1].

For mechanics A and B:

$$PMI(A;B) = log_2 \frac{P(B|A)}{P(B)} = log_2 \frac{P(A \cap B)}{P(A)P(B)} \quad (1)$$

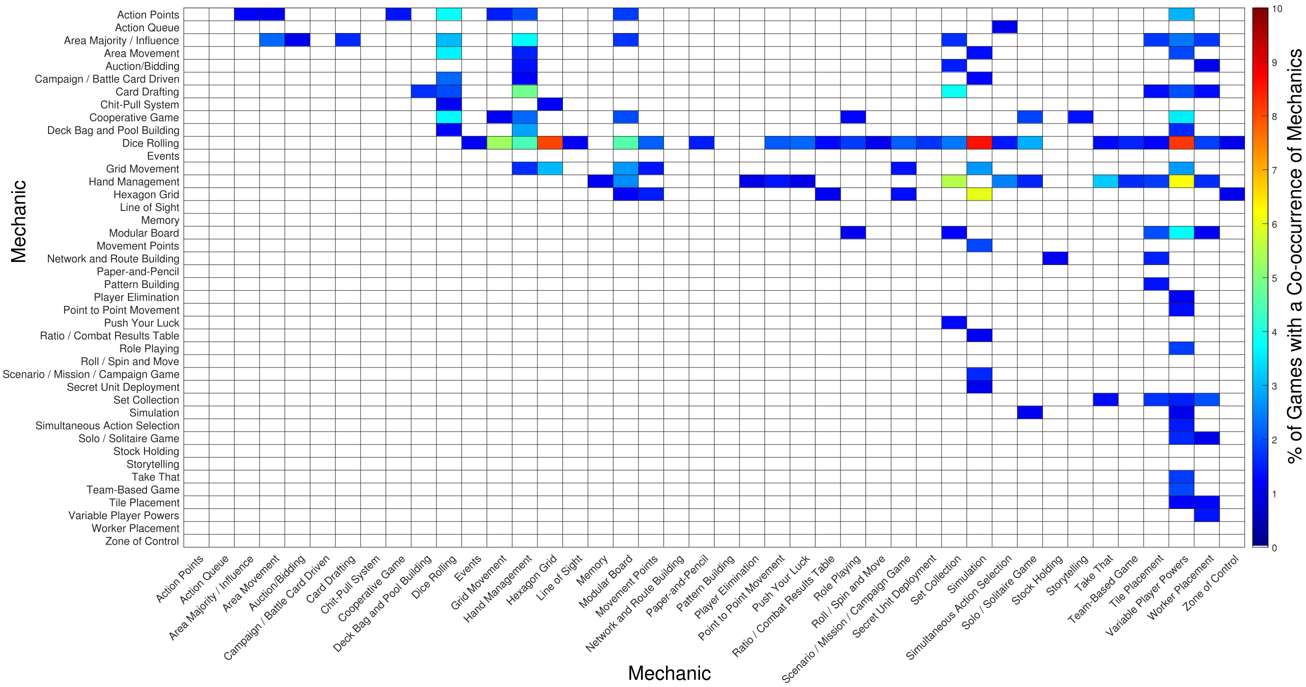
$$NPMI(A;B) = \frac{log_2 P(A)P(B)}{log_2 P(A \cap B)} - 1 \quad (2)$$

Figure 12 depicts the matrix of mechanic pairs with a MI greater than 0.65 which are more likely to appear together unbiased from the frequency of mechanic usage in the games. There are 66 pairs with a MI greater than 0.65 of which 6 have a MI greater than 0.9.

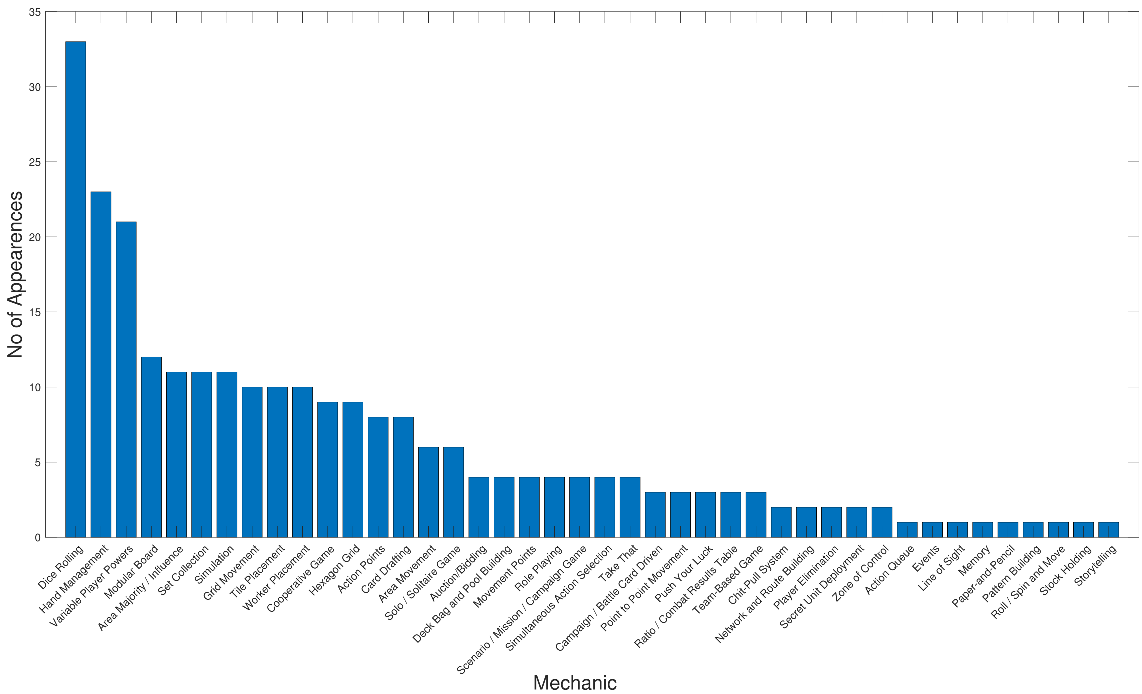
According to Figure 12b, *worker placement* is the most common mechanic that appears with other mechanics (in 48 pairs out of 66). It often shares common information with *auction* and *turn order*-based mechanics which implies that, most games that require players to select individual actions from a set tend to use auctions to bid on items, or resources that are useful in enhancing the player's position in the game. Further, mechanics related to configuration and structure of games such as *pattern movement*, *pieces as map*, and *physical removal* are also found to be closely associated with *worker placement* demonstrating high MI values.

Auction and *turn order*-based mechanics also often seem to depend on each other. For example, *auction: English* (where the auctioneer asks for bids of a certain amount and the players can show their willingness to bid at that amount) and *auction: once around* (where each player get the opportunity to bid once) has a high MI (0.79). The order of the bids is usually determined by turn order structures, which is the reason for higher MI in mechanic pairs such as *auction: English* and *auction: Turn order until pass* (MI = 0.71). Games such as 'Five Tribes', 'Keyflower', and 'Railways of the World' are examples of high-ranking games that use these mechanics.

Other pairs that do not involve the above mechanics, but have characteristics that are closely associated, can be discussed as follows. *Action/event* and *tug of war* (MI = 0.65) is a pair commonly seen in games such as 'Twilight Struggle' and 'Watergate' where the players play a card showing action points and an event and choose to perform either one of those (*action/event*) and a sliding marker is used to determine victory (*tug of war*). *Pattern movement* and *static capture* has a MI of 0.77. Games that adopt *pattern movement* use pieces that can move in a specific pattern on the board and the games that use the *static capture* mechanic are those which have pieces that can be captured with another piece by passing over or occupying their space. Therefore, for the *static capture*



(a) Co-occurrence matrix for mechanic pairs appearing together in more than 1% of top 10,000 games.

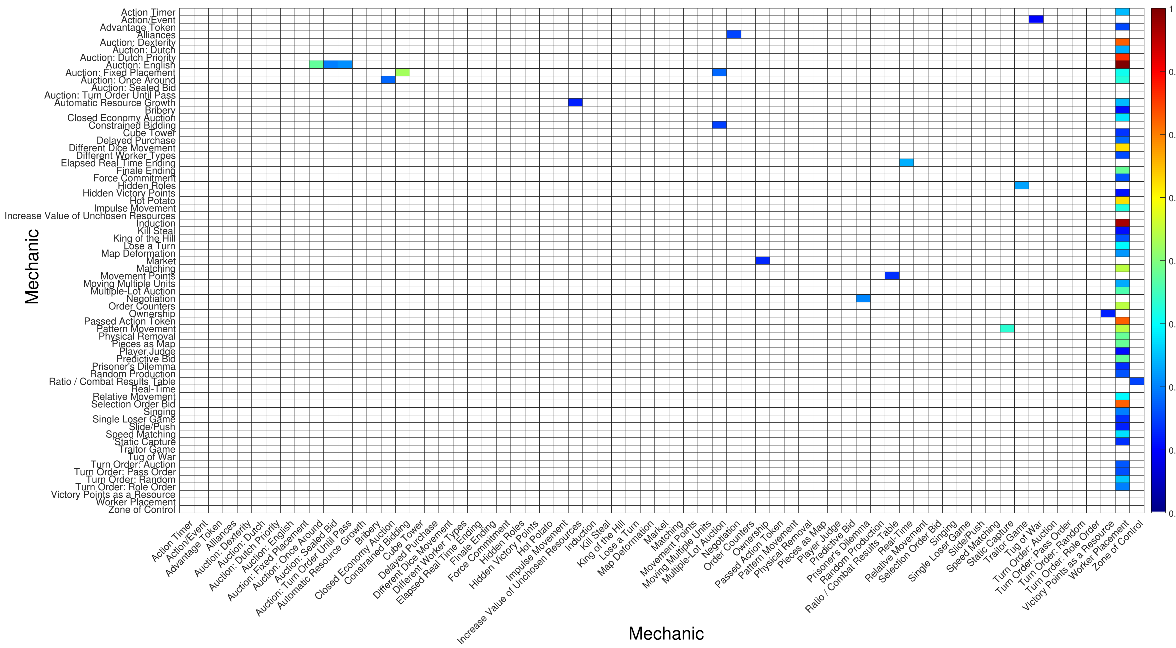


(b) Order of mechanics based on the number of appearances in a high value pair with a co-occurrence in more than 1% of top 10,000 games.

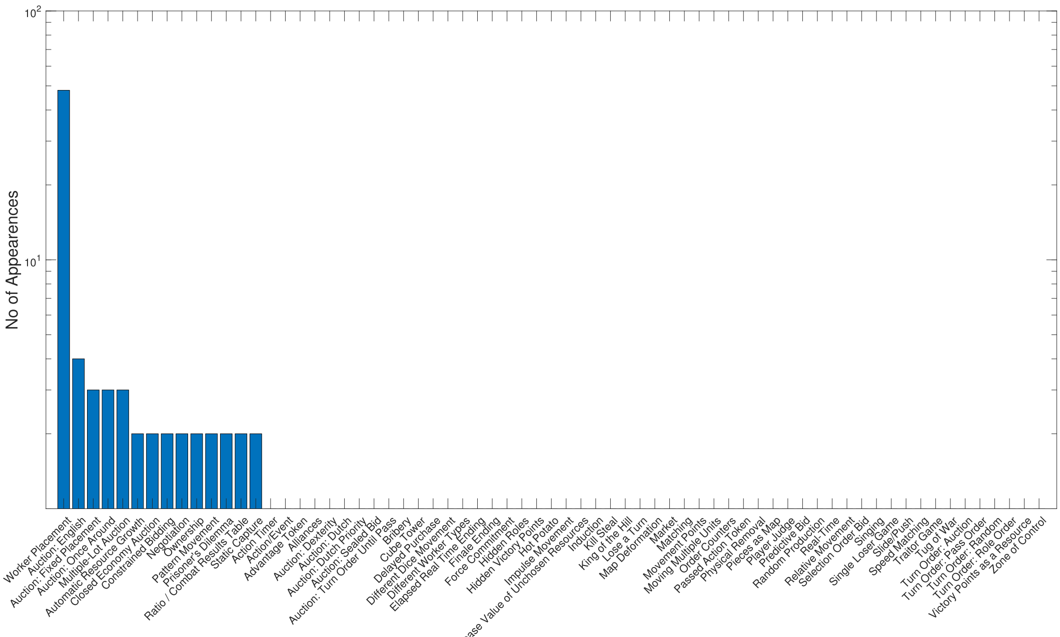
FIGURE 11. Co-occurrence analysis of board game mechanics.

mechanic to be used, they should have the *pattern movement* capacity. Games such as 'Chess' and 'Onitama' are examples for this combination. The mechanic pair: *alliances* (where the players maintain formal relationships) and *negotiation* (where the players agree between options on the courses of actions to be taken) also has a MI of 0.68 appearing together in games such as 'Rising Sun' and 'Cosmic Encounter'.

It is observed that majority of the mechanic pairs that have a MI greater than 0.65 are those that are associated with actions the players can perform and how they are resolved within the course of the game, rather than the structure or configuration related mechanics. Figure 12b shows that *worker placement* is the most common mechanic followed by *auction*-based mechanics.



(a) Mutual information matrix for mechanic pairs with a mutual information greater than 0.65.



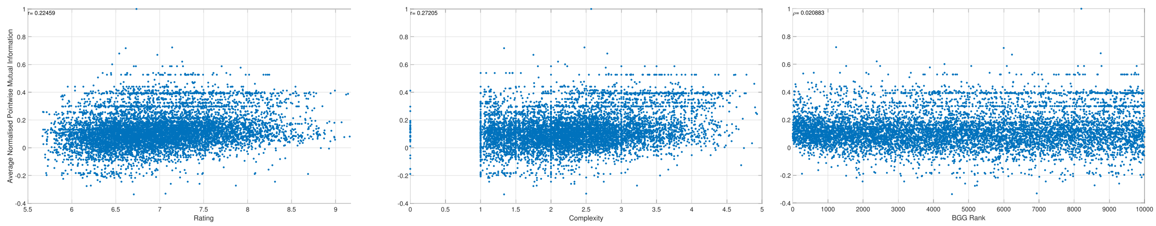
(b) Order of mechanics based on the number of appearances in a high value pair with a mutual information greater than 0.65.

FIGURE 12. Mutual information analysis of board game mechanics.

The average MI of all the mechanic pairs in each game was also analysed in comparison to their rating, complexity, and BGG rank as given in Figure 13 for all games. According to the figure, there is not enough evidence to suggest a strong correlation between the average MI and rating (Pearson's r = 0.25), complexity (Pearson's r = 0.27) or BGG rank (Spearman's $\rho = 0.02$). Therefore, a relationship cannot be identified between using mechanics with a mutual dependency in game design and the overall appeal towards a game.

5) SIMILARITY OF MECHANICS BASED ON BOARD GAME DOMAINS

This section extends the analysis on mechanics towards their similarities based on the board game domains that frequently use them. Figure 14 illustrates the similarity of mechanics based on t-distributed stochastic neighbour embedding (t-SNE) technique. BGG database identifies eight primary domains of board games, namely: abstract games, children's games, customisable games, family games, party games, strategy games, thematic games, and war games. The domains



(a) Average mutual information versus rating. (b) Average mutual information versus complexity. (c) Average mutual information versus BGG rank.

FIGURE 13. The variation of average mutual information of all mechanic pairs in the top 10,000 games in comparison to rating, complexity, and BGG rank respectively.

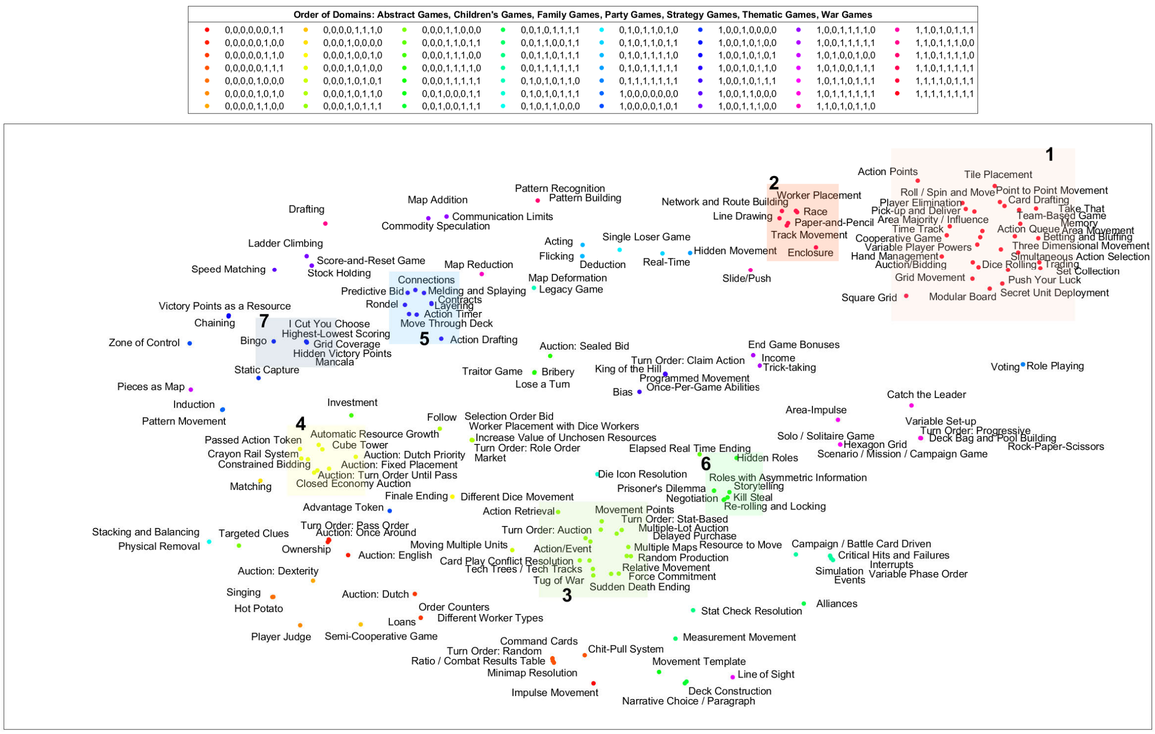


FIGURE 14. Visualisation of similarity in mechanics based on board game domains that utilise them.

applicable to each mechanic were identified by matching the domain of each board game in the top 10,000 set and their respective mechanics. t-SNE was used to find the pairwise similarity between the mechanics in the eight dimensional space, mapping it to a two dimensional representation to generate a visualisation.

According to the similarity values, several clusters can be identified in the space and a few significant clusters are numbered in the figure. Cluster 1 represents the set of mechanics that are used in all board game domains. The most frequent mechanics which were identified in Section V-C1 such as *dice rolling*, *hand management*, and *variable player powers* appear in this cluster which justifies their appearance in a majority of the games.

The mechanics that appear in cluster 2 are adopted in all domains except abstract games, such as ‘Chess’ and ‘Go’ which tend not to use hidden information, a particular theme, or randomisers such as dice. Mechanics such as *worker placement*, *network and route building*, and *track movement* fall under this category of mechanics.

Cluster 3 represents the mechanics that appear only in the four domains: family games, strategy games, thematic games and war games. Mechanics such as *movement points*, *multiple maps*, *force commitment*, and *relative movement* are used in generally advanced games that often simulate historical events or some narrative, requires the skills of strategic decision-making, and associated with conflicts or military operations of some kind. The relatively simpler kids or party games do not utilise such mechanics in their design.

Several *auction*-based mechanics, *constraint bidding*, and *passed action tokens* mechanics appear in cluster 4, which are common to family and strategy games. These mechanics are used in games where players take turns to bid on items which is used to enhance one’s position during the game play.

Cluster 5 groups the mechanics that are common to the domains: abstract games, family games, strategy games, and thematic games. It is noteworthy that war games and abstract games use distinct mechanics in their designs although they share characteristics of strategy games, thematic games, and family games. Using an *action timer* to decide the action spaces or location of action pieces, *moving through a deck* of cards, *layering* game components above other components (which inactivates certain icons/areas) are several mechanics that are not visible in war games. However, they are prevalent in abstract games which have no hidden information or non-deterministic elements.

Mechanics such as *storytelling*, *negotiation*, and *hidden roles* appear in cluster 6. These are visible in the set of: family games, party games, strategy games, thematic games, and war games. Both simple party games and relatively complex war games use these mechanics to convey and implement the narrative and strategy of the game.

The mechanics that are common to only strategy, family, and abstract games are presented in cluster 7. In comparison to cluster 5, mechanics such as *bingo*, *hidden victory points*, and *highest-lowest scoring* are not used in thematic games but tend to be used with abstract games that do not rely on a theme and generally played with a game-board, cards or tiles.

Further, there are several mechanics that are present only in a single domain of board games such as *singing* and *hot potato* (where players try to avoid a single bad item) which are used in designing party games, *pattern movement* which is only used in abstract games, and *ownership* used only in strategy games. Accordingly, these similarity clusters based on domains provide insights on characteristics common to board game mechanics and help understand their synergistic effects.

6) DISCUSSION

Based on the analysis of board game mechanics, out of the 182 mechanics associated with the top 10,000 games that were studied, the mechanics *dice rolling*, *hand management*, and *variable player powers* stand out as the most frequently used mechanics and those that co-occur mostly with other mechanics in board game designs. This can be explained based on the functionality of these mechanics.

Dice rolling is a mechanic that can be used in multiple settings, for example as a counter, as a mechanic to narrow down or limit the search space, or as a means to derive an outcome which enclose a wider pool of game strategies; thus appealing to a wider range of board games. Similarly, *hand management* can also be used in designing diverse game strategies for card-based games by customising the management based on number of cards, the sequence they are played, and outcomes/uses to generate unique ways to resolve actions. *Variable player powers*, as the name suggests, facilitates the design of special actions for each player or powers that can modify their standard actions. This allows for the expansion of a game strategy towards unique and interesting designs. Further, these mechanics can be incorporated equally into both simple as well as complex game designs and are generally easy to understand in a game setting.

However, the analysis of mechanic use by designers over time suggests that although mechanics such as *dice rolling*, *hexagon grid*, and *simulation* are used in a majority of the current top 10,000 games, the tendency to use them in new board games is gradually decreasing (at least in well rated games). In contrast, mechanics such as *hand management*, *variable player powers*, and *worker placement* are gaining more attention of the board game designers in the recent years.

The co-occurrence and MI analysis show that the *worker placement* mechanic tends to have a mutual dependency with several mechanics, showing high MI values in a significant number of pairs. This mechanic is about having a set of tokens (workers), and players taking turns to assign them into different actions. This suggests that it relies on several other factors and has the scope to interact and share information with multiple other mechanics. The order of taking turns, the components and structure of the action space, and the outcomes should all be decided based on associated mechanics such as *turn order*, *auction*, *pattern movement*, *pieces as map*, and *physical removal*, leading to its significant dependence on other mechanics.

Further, while these mechanics are distinctive among others, due to their prominence in being used in board games, there are also interesting relationships between certain mechanic pairs that arise from common characteristics they share (as discussed above). The similarity comparison based on board game domains reveal several interesting clusters of mechanics. The abstract game domain appear to influence most of the cluster formations generating several combinations. For example, there are several mechanics such as *worker placement* and *network and route building* that are used in all domains except abstract games; mechanics such as *action timer*, *move through deck*, and *layering* which are used with abstract games but not war games; and mechanics such as *hidden victory points* and *highest-lowest score* that are used in thematic games but not with abstract games.

VI. CONCLUSION

The 21st century is a period which is observing a massive increase in the popularity of board games and a boom in game designs and publishing. The emerging interest in board games as a popular medium for entertainment and education emphasises the importance of closely studying game design strategies and their mechanics to understand their impact on game play. The analysis presented in this paper was focused on addressing the research gap in this area by investigating the interactions between board game mechanics, their relative frequencies, inherent qualities, and their relationships with other game-related attributes to draw out design lessons.

The analysis was conducted based on BGG, which is the largest available online repository of board game data, and the top 10,000 most regarded games chosen for the analysis.

It should also be noted that the nature of the BGG database restricts the data to the views of avid board game players, who are actively engaged in and contributing to the online board games community. Therefore, the data may not accurately reflect the casual board game players' views, who do not generally contribute to such platforms.

Among the more important findings of the analysis, the many claims [2], [20], [39] on the recent boom in board game productions have been supported. The evaluations over a period of 40 years shows that there is an exponential growth in board games published after the year 2000 and the more recently published games tend to be ranked highly in the BGG database. The analysis on trends in individual mechanics over time also showed some insights into the types of mechanics that are flourishing as well as those that are stagnating.

The correlation analysis and the results of the analysis between individual mechanics and complexity and rating variations show that there is no simple answer to the question of how to design an appropriately complex and interesting game that will dominate the BGG ranked list. In fact, the correlations between complexity, rating, and the number of mechanics are, at most, moderate which suggests that the complexity, or the number of mechanics has little contribution towards making a game more appealing. This can be attributed to several factors: the interactions between mechanics can drastically change the overall experience of a game; and that a particular mechanic label is a coarse categorisation that encompasses quite a range of settings that can vary greatly across implementations.

The analysis on co-occurrences, MI, and similarity clustering demonstrate that mechanics share common characteristics and thus have a tendency to be used together depending on the domain of implementation. Certain mechanics such as *worker placement* are often used in multiple combinations and support the function of other mechanics. In contrast, mechanics such as *acting* or *singing* often appear independently or in limited combinations. Most frequently used mechanics such as *dice rolling* and *hand management* are often adoptable across all kinds of board game domains, whereas certain domains, such as abstract games, restrict the use of some mechanics due to their inherent characteristics that conflict with the properties associated with such mechanics.

Based on the analysis results we suggest a deeper exploration of the relationships between mechanics for future work to understand the distinctions in the impact of mechanics on play experience, the quality, and complexity of a game. The current analysis employed the top 10,000 ranked games with the objective of investigating board game design strategies and mechanic combinations that drive game play. A future comparative analysis on the strategies and mechanics that are used in highly ranked versus poorly ranked games may give further insights to facilitate the choice of mechanics and their combinations in designing a successful game. Further, a more nuance categorisation of mechanics that can capture the independent attributes, and their characteristics in different settings, would enhance the grasp of their role in board game design.

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