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THE BASEBALL CARD AS A REPURPOSED DATA-RICH SOURCE FOR TABLETOP GAME SIMULATION

Los cromos de béisbol como fuente reutilizada de datos para la simulación de juegos de mesa

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ABSTRACT: The current project looks at the nature of baseball cards, commonly denoted as historical artifacts, and the means by which each baseball card is in essence a unique 'player historical database'; a snapshot in time whose data and mathematical potential can be exploited within the realm of game-simulation. The primary aim is to rejuvenate and repurpose the traditional perspective of the baseball card, and via statistical resampling analyses, validate its worth as a data-rich game piece that can be utilized to generate accurate tabletop baseball simulation results. A manual dice-roll game using 8 unique dice, specific dice-roll strategies, and innovative game design, was applied to a 16-team, 256-game season (16 games per team). All gameplay results were recorded in proprietary scoring software so as to generate data for mathematical comparison. Statistical resampling results indicate no difference in team Earned Run Average (ERA) and team Batting Average (BA) for all 16 teams, when simulation data were statistically compared to actual historical data.

KEYWORDS: baseball, simulation, design, statistical, historical

RESUMEN: *El presente proyecto analiza la naturaleza de los cromos de béisbol, comúnmente denominadas piezas históricas, y los medios por los que cada uno de los cromos de béisbol es en esencia una "base de datos histórica de jugadores" única; una instantánea en el tiempo cuyos datos y potencial matemático pueden ser explotados en el ámbito de la simulación de juegos. El objetivo principal es rejuvenecer y reutilizar la perspectiva tradicional del cromo de béisbol y, mediante análisis estadísticos de remuestreo, validar su valor como pieza de juego rica en datos que puede utilizarse para generar resultados precisos de simulación de béisbol de mesa. Se aplicó un juego de tirada de dados manual con 8 dados únicos, estrategias específicas de tirada de dados y un diseño de juego innovador, a una temporada de 16 equipos y 256 partidos (16 partidos por equipo). Todos los resultados del juego se registraron en un software de puntuación propio para generar datos para la comparación matemática. Los resultados del remuestreo estadístico indican que no hay diferencias en el promedio de carreras ganadas (ERA) y el promedio de bateo (BA) de los 16 equipos, cuando los datos de la simulación se comparan estadísticamente con los datos históricos reales.*

PALABRAS CLAVE: Béisbol, simulación, diseño, estadístico, histórico

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1. Introduction

The baseball card may be as unique as the pastime of baseball itself. Each card holds a longitudinal statistical story of a player, reflecting everything from a rookie year, to an entire career—all on a single piece of cardboard. Most cards end up in storage; few end up on display; all end up having little if any 'utility' beyond that which is printed on them. However, if one looks more in-depth, one can see that baseball cards, and the data they contain, readily lend themselves as 'statistical resources.' When it comes to baseball cards, it is by far the 'look' of card that gives it its value—visual aesthetics are known to be critical in the context of interactive environments and products (Soranzo, Petrelli, Ciolfi, & Reidy, 2018; Tractinsky, 2013), and albeit the baseball card exudes such aesthetics as its predominant purpose, it is not what one would deem a 'highly interactive product'. However, when used innovatively, the baseball card can yield an entertainment value far beyond that of simple visual aesthetics.

The current paper puts forth the idea that baseball cards can extend beyond their visual-aesthetic bounds and the scientifically validated concept of tactile elements as contributors to positive interaction experience, to become data-rich game piece's such that a stack of cards for any two teams, easily becomes a statistical simulation game waiting to be played. It was hypothesized that the use of baseball card statistical data, via innovative game design and the completion of a 'simulated competition' consisting of a series of games, could yield statistically accurate simulation results mathematically consistent with actual historical data.

2. Game Structure, Sequence, and Rules: A Roll of the Dice

The game as designed is known as 'Bubble Gum Baseball' (BGB), and the gaming sequence begins with the roll of all 8 dice, and an interpretation of the roll results (Appendices A & B) contain decision-making 'flow-charts that provide full details on dice, die values, and decision-flow based on die values). A Pink 6-side die was first utilized to determine if the batter-card (values 1 - 4), or pitcher-card (values 5, 6) would be consulted when determining outcome/results. At this point, it is of paramount importance to clarify the obvious 'imbalance' in pink die roll values for determining consultation of the batter card (1, 2, 3, 4), as opposed to the pitcher card (5, 6)—an imbalance that was intentionally 'engineered' using historical data.

2.1. Balancing event occurrences

Without applying an imbalanced system, the default for the pink 6-side die roll is .50/.50 with 1, 2, 3 referencing the batter-card and 4, 5, 6, values referencing the pitcher-card. However, being that batter-card batting average (BA) and pitcher-card Earned Run Average (ERA) would be compared to Red-White-Blue dice roll values to determine if a hit-event had occurred, the assessment of historical data from 1982 to 2011 (Smith, D., Retrosheet.org) was consulted to compare overall BA to overall ERA for this 30-year period, to assess their 'equality'. The question was if raw non-decimal values for BA and ERA were somewhat equivalent across a large sample of Major League Baseball (MLB) data—they were not. Batting average for this period was .258, and ERA was 4.20. Using non-decimal values, one comes up with 258 and 420 respectively as the earlier mentioned 'raw non-decimal values'—and it becomes apparent that the Red-White-Blue dice roll total values used to compare against BA and ERA values would fall below 420 (pitcher-card result) more readily than it would fall below 258 (batter-card result). Such occurrence would be undesirable in that it would result in a greater number of hit-events occurring against pitcher-cards, as opposed to batter-cards.

The solution to this disparity was to look at the *difference* between BA and ERA for this historical period—which amounts to 420 – 258 = 162—which interestingly, is 162 / 1000 or .162, which is nearly the exact probability value of a single digit of a 6-sided die (1 / 6 = .166). Thus, the design strategy was to weight the batter-card pink die-roll by an extra die roll digit of value .166—which made the pink batter-card die roll values 1, 2, 3, 4 = .666, and the pink pitcher-card die roll values 5, 6, = .333. Therefore, a 'counterbalance effect' was achieved for the 6-side pink die roll: batter-cards would be consulted more frequently due to pink die rolls, but in the long-run, it should be more difficult to achieve a hit-event against batter-cards—conversely, pitcher-cards would be consulted less frequently, but in the long-run it should be easier to achieve hit-events against pitcher-cards.

This issue of a hit-event occurring due to the batter, as opposed to the pitcher, and vice versa, is rather unique when trying to capture realistic baseball simulation results using a complex set of dice roll values. The pitcher/batter outcome is a known factor of difficulty that has to be modeled accurately in order to exact realistic simulation results (Hastings, 1999). This is due to the fact that within a real baseball game, there is no way to truly determine if a hit-event actually occurred due to something the pitcher did, or due to something the batter did—the hit event as an outcome is always 'subjective'; batters will nearly always insist it was the result of 'good hitting', and pitchers will nearly always insist it was the result of 'poor pitch selection or location', or perhaps even luck on the part of the batter. In essence, it is important to keep in mind that every hit in a baseball game occurs 'off of' the pitcher, but not every hit in a baseball game occurs 'due to' the pitcher. Events of unpredictability, such as whether batter skill or pitcher skill-failure was the cause of a hit-event, are known as 'random-effects factors'—a variable whose occurrence is unsystematically or randomly selected from a larger pool of its own possible values (Keppel, 1991). For example, the number of men who might be on base when any one batter comes up to bat, is a random-effects factor, as there is no way to know ahead of time exactly how many men will be on base when that batter steps into the batter's box on his next at-bat—save for a leadoff hitter. However, it is known that a man who will bat second at the start of an inning could have no more than one man on base; a man who will bat fourth could have no more than 3 men on base, and any/all at-bats could have 'zero' men on base when they begin (e.g. previous batter hits a home run) and so on. Thus, each men-on-base situation is indeed representative of its own pool of possible values—but it is an outcome pool that escapes pre-definition, and thus can be said to be randomly attributed.

Conversely, batting average is not a random factor as it is clearly known what the probability of a hit will be for any batter stepping into the box for his next at-bat; BA is not randomly selected from a pool of its own possible values prior to an at-bat—as a variable, BA is fixed due the fact that data representing BA have been gathered for all levels of BA that are of interest (Brauer & Curtin, 2017) (e.g., all at-bats in all situations). As a non-random event, BA—also called a 'fixed-effects factor'—is selected systematically (e.g., 'batting order') and meets the assumption that it is representative of the entire population of its own possible values (Keppel, 1991).

In addition to random factors, when it comes to modeling player performance over time, the concept of 'situational effects' must also be considered as an impactful influence on statistics such as batting average Albert & Bennet (2007). Albeit there is no way to know how many men would be on base the next time any one player stepped into the batter's box (a random factor) likewise, there are many instances where one does not know how a specific situation might influence a batter. These situational effects that on might see influencing long-term simulation performance can range from that of *no effect*—where is there is no true situational effect, and differences observed over a season simulation are merely via chance variation; *bias*, whereby a true situational effect indeed has influence—but influence that is equivalent among all players; or *ability effects*, which indicates players have different true situational effects (Albert & Bennett, 2007). In creating a simulation game, this concept of ability is difficult to ascertain when it comes to how ability itself is influenced; the main idea is to understand how much of the variation in baseball data (and other ancillary data) can be explained by chance, and how much is due to some "real" causation, like player skill level (Albert, 2003). Ultimately, one has to arrive at acceptance that certain situational effects, are 'built in' to the historical data for all players—they are reflected in player data, many with an unknown magnitude of influence upon that data (e.g. game temperature; light rain/no rain; number of fans in attendance; indoor/outdoor stadium), and others with clearly known influence—such as Runner-In-Scoring-Position batting average, one of the most critical situational effect performance parameters connected to winning (Rees, Rakes, & Deane, 2015).

2.2. The Batter Card

For the card of the player up at-bat, the data on the back of the card was referenced as-is by referring to the final line of data at the bottom of the card referencing career totals. Such reference was done by merely comparing the three Red-White-Blue dice roll values to the batting average as reported on the card (ignoring the decimal point) when the dice roll specified the batter card was to be referenced.

A hit occurs when the ordered Red-White-Blue dice roll values attain a combined value that is equal to or less than the referenced batting average for the player as listed on the back of the card. For example, a dice-roll of 314 is less than 345—Willie Mays' 1954 batting average (Note: The Yellow die is ignored for a batter-card result; it is used for pitcher-card results only). Once a hit/non-out event is determined to have occurred, the 12-sided speckled die is consulted to determine the type of hit: 1 – 7 = single; 8 – 9 = walk; 10 = double; 11 = triple; 12 = home run. A black pyramid 4-sided die was used to determine the 'type' of hit for both infield and outfield hit events (e.g., groundball, line drive, or flyball). Table 1 provides detail on all eight dice configurations and their function toward determining outcomes.

Table 1. Dice configurations and functions

Die description	**Function**
PINK 6. Side 1-6	Determines if batter card (dice values 1, 2, 3, 4) or pitcher card (dice values 5, 6) will be referenced
RED 10. Side 0-9	The first digit of the 4-digit HIT/NON-HIT value
WHITE 10. Side 0-9	The second digit of the 4-digit HIT/NON-HIT value
BLUE 10. Side 0-9	The third digit of the 4-digit HIT/NON-HIT value
YELLOW 10. Side 0-9	The fourth digit of the 4-digit HIT/NON-HIT value
GREEN 20. Side 1-20	Determines location of a batted ball OUT; e.g. 7=LF; 4=2nd base; 2=catcher, 5=3rd base; 1=pitcher; 18=CF; 15=3B; 16=SS or whether a K/BB pitcher result occurred [10, 11] or foul-out occurred [12, 20]
BLACK Pyramid 4. Side 1-4	Determines type of OUT for infield: 1=lineout; 2-3=groundball; 4=pop out b. determines type of OUT for outfield: 1=lineout; 2-4=flyout
BLUE-GRAY 12. Side 1-12	Determines type of HIT that can occur 1-7=SINGLE; 8-9=WALK; 10=DOUBLE; 11=TRIPLE; 12=HOME RUN

Green 20-side die values 1-9 and 13-19 were used to indicate the location of non-hit out or walk events, such as 1=pitcher; 5=3B; 8=CF)—for values of 13-19 only the second digit is used (e.g., 16=SS; 18=CF). Green die values of 10 and 11 were either K or BB pitcher events, and values 12, and 20 were consulted as foul-out events.

2.3. The Pitcher Card

Similar to the batter card, consultation of the pitcher card was determined by the pink 6-side die roll (values 5, 6). However, pitcher event results were supplemented by the calculation of 4-digit 4 decimal-place values representing the probability of a Double, Triple, Home Run, or Strikeout/Walk (called SOBB)—each of which, along with their respective calculation formula, can be seen in Table 2 below. The purpose of calculating these 4-digit values was due to the fact that pitcher baseball cards do not list data that align with the cumulative occurrence of these hit events, and thus the simple reference of the first three of these events can't be done by simply glancing at the back of the card (however, strikeouts and walks are indeed available within pitcher card-back statistics).

Table 2. Pitcher-card formulas for double, triple, HR, & SOBB value

Item	**Formula**
Double value	Earned Runs ÷ Innings Pitched
Triple value	Losses ÷ Innings Pitched
Home Run value	Walks ÷ Innings Pitched
SOBB value	Strikeouts ÷ Strikeouts + Walks

These 4-digit values could be compared against the dice-roll results of the four Red-White-Blue-Yellow dice. Figure 1 shows the different values that were derived and then written to labels affixed to the back of the card-protector plastic sleeve for each pitcher card.

2B	3B	HR	SOBB	ERA
4735	0389	2062	7546	3.36

Figure 1. Calculated pitcher-card values using Brett Saberhagen's 1987 statistics (1988 Topps).

Albeit the Table 2 formulas appear to be somewhat arbitrarily defined, these values actually reflect the necessity of creating reasonable representative probabilities that would reflect the historical frequency of these respective events, on a consistent basis within the data. For example, the triple is the rarest occurring hit event. Thus, it was necessary to calculate a value that would have a ratio representing such rarity—such as the 10 losses, divided by 257 innings pitched as per Brett Saberhagen's 1987 statistics from his 1988 Topps card (Figure 1). The resulting value here for a triple is 0389 as seen in Figure 1 (dropping the decimal). For a double using this same card data, one uses 96 earned runs, divided by 257 innings pitched, which is 3735. Therefore, given that a 4-digit die roll would need to be equal or less than 389 for a triple, but only equal or less than 3735 for a double, both hit events should occur with a frequency that reasonably represents historical accuracy. Figure 2 provides a sample of die-roll results and their potential interpretation, as they might be compared against pitcher/batter card probability calculations.

Event	Die-Roll results							
Single	3	2	4	6	5	4	8	4
Pink=3 (consult batter card); Red-White-Blue=246 is less than batter AVG of .268 so HIT occurs; Yellow die=ignore; Blue-Gray die=4 so SINGLE; Green die =ignore; Black=4 indicates popup (bloop) style of hit since it was a single								
Groundout to 1B	1	3	8	9	2	8	13	1
Pink=1 (consult batter card); Red-White-Blue=389 is > than batter AVG of .302 so Non-Hit Event; Yellow die=ignore; Blue-Gray die=ignore; Green die = 13 so OUT occurs, location is 1B; Black die=1 so it was a groundball								
Walk	6	6	3	5	3	5	10	3
Pink=6 (consult pitcher card); Red-White-Blue value=635 is > pitcher ERA of 3.67, so Non-Hit Event; Green die=10 so Strikeout or BB; Roll Red-White-Blue-Yellow dice again, if 4-digit value > pitcher SOBB Value, result=BB; if value < pitcher SOBB Value, result=K; Black die=ignore								
Homerun	4	1	2	1	5	7	6	2
Pink=4 (consult batter card); Red-White-Blue value=121 is less than batter AVG of .263, so HIT occurs; Yellow die=ignore; Blue-Gray die=12 so HOMERUN; Green die=ignore; Black die=1 so line-drive type hit								
Flyout RF	1	2	2	4	6	5	17	1
Pink=1 (consult pitcher card); Red-White-Blue=224 is > than pitcher ERA of 2.13 so Non-Hit Event; Yellow die=ignore; Blue-Gray die=ignore; Green die = 17 so flyball OUT to LF; Black die=1 so line-drive type flyball								
Double LF	5	2	1	3	8	10	14	4
Pink=5 (consult pitcher card); Red-White-Blue=213 is less than pitcher ERA of 3.19 so HIT occurs; Yellow die=ignore; Blue-Gray die=10 so DOUBLE; Green die =ignore; Black die=4 so flyball type is high-flyball								

Figure 2. Sample die-roll results and possible interpretations

With respect to Figure 2 information and die-roll outcomes, it must be clarified that ‘hit events’ which occur do not have a location associated with them however, non-hit events do have locations associated with them so as to provide information for potential fielding error occurrence. Thus, the ability to track the popular ‘spray-chart’ type of event data would be possible, but only for non-hit events.

It should also be mentioned that the calculation of pitcher-card values (Figure 1) could be done using the career statistics data of the player, or one could select a specific row of data representing a specific year’s statistics for that player, and thus calculate the pitcher-card values based only on data for that year. Therefore, it is possible to have 5, 6, even 7 or more sets of these Figure 1 pitcher-card values affixed to the back of the card sleeve at a single time—with each set of values representing a specific year. This means one would only need to have Don Drysdale's baseball card from the last year of his career in order to calculate the pitcher-card values for every year of Drysdale's career, rather than actually possessing a Don Drysdale card for each year of his career. Similarly, when it comes to position players, one would only need the baseball card from Willie Mays' last year in baseball to be able to use Mays as a player within any simulation game reflecting any year that he played.

3. Method

3.1. Game Pieces

The game in its most basic form consists of two teams (minimum) of Topps (Topps Trading Card Co.) brand baseball cards, and 8 gaming dice of differing configurations and functions (as detailed in Table 1). In addition, a laptop computer with the free baseball scoring/statistics programs BallScore and BallStat (Habel, J., 2013), was also utilized to score the game and compile all statistics. Baserunner information at any point in time is reflected by the BallScore program; this information was also tracked during the simulation using a cardboard ball-diamond placard on which player cards were placed.

3.2. Experimental Season Setup

Sixteen baseball card team sets of various eras were used to generate the data via a 16-team 'season' that consisted of 128 manual dice-roll games. This resulted in the generation of 256 individual team game data sets whereby each team played its 16 games in randomly assigned configurations of 1, 2, 3, 4, or 5 games series, against randomly chosen opponents. First, a random team was selected, then a random number from 1 to 5 was generated to determine the number of games in the series. A number from 1 to 16 was then generated to determine the opponent for that series. This process was carried out until the schedule for each of the 16 teams had a total of 16 games across 'X' number of series.

3.3. Gameplay, Scoring and Data Aggregation

Each game consisted of two team sets of baseball cards whereby using the BallScore program, team lineups were created and saved via a database that is stored within the BallScore program. Data aggregation was done using the free BallScore companion program named 'BallStat'. The BallStat program is designed to allow the export of the BallScore game data into a custom user-defined database within the BallStat program. BallStat is a highly versatile program for generating customized reports of all types, including the export of comma-delimited, text-file, and even proprietary data formats such as Microsoft Excel.

4. Results

Upon completion of the 128-game season, all data were exported from the BallStat database into a master file that could be analyzed in Microsoft Excel. Table 3 presents the team results from the 128-game simulation, including win/loss records and winning percentages.

Table 3. Results from the 128-game simulation.

Team	**W**	**L**	**WP%**	**BA**	**ERA**
SLN1985	13	3	.813	.325	3.76
OAK1990	10	6	.625	.238	3.11
NY11953	10	6	.625	.280	2.18
CIN1990	9	7	.563	.256	3.70
BRO1953	9	7	.563	.219	3.11
BAL1988	9	7	.563	.278	4.59
KC11963	9	7	.563	.273	4.39
KCA1985	9	7	.563	.232	2.44
PIT1963	8	8	.500	.267	3.57
KCA1971	7	9	.438	.263	4.14
DET1954	7	9	.438	.268	4.02
HOU1963	6	10	.375	.248	4.12
NYA1954	6	10	.375	.250	3.82
SLN1954	6	10	.375	.275	4.64
SFN1963	5	11	.313	.214	4.00
PIT1954	5	11	.313	.260	5.78
Totals	**128**	**128**		**.260**	**3.82**

Data analysis consisted of a resampling (bootstrapping) procedure—a computer-based methodology used in statistical inference problems that circumvents stringent data-structure assumptions for the random process that generates the data (Lahiri, 2013). The bootstrapping was conducted using a Microsoft Excel add-in from Real-Statistics.com (Zaiontz, C., 2020), that compared differences between simulation team batting averages (BA) and team earned run averages (ERA), with the actual historical year data-counterpart values for all team card set years that were used (Table 4). For example, Table 4 shows a real team batting average for the 1985 St. Louis Cardinal's was .264, and real ERA was 3.10. Difference score values were created (Diff.) that represented the difference between the actual historical values, and these same values as represented in the simulation data.

Table 4. Simulation vs Real: Team BA and Team ERA

	Team BA			**Team ERA**		
Team	**Sim**	**Real**	**Diff.**	**Sim**	**Real**	**Diff.**
SLN1985	.325	.264	.061	3.76	3.10	.660
OAK1990	.238	.254	-.016	3.11	3.18	-.070
NY11953	.280	.271	.009	2.18	4.25	-2.070
CIN1990	.256	.265	-.009	3.70	3.39	.310
BRO1953	.219	.285	-.066	3.11	4.10	-.990
BAL1988	.278	.238	.040	4.59	4.54	.050
KC11963	.273	.247	.026	4.39	3.92	.470
KCA1985	.232	.252	-.020	2.44	3.49	-1.050
PIT1963	.267	.250	.017	3.57	3.10	.470
KCA1971	.263	.250	.013	4.14	3.25	.890
DET1954	.268	.258	.010	4.02	3.81	.210
HOU1963	.248	.220	.028	4.12	3.44	.680
NYA1954	.250	.268	-.018	3.82	3.26	.560
SLN1954	.275	.281	-.006	4.64	4.50	.140
SFN1963	.214	.258	-.044	4.00	3.35	.650
PIT1954	.260	.248	.012	5.78	4.92	.860

The resampling procedure consisted of 10,000 samples drawn via sampling-with-replacement, using a test value of '0' to compare Table 4 team batting averages and ERA difference score column (Diff.) data against the test value. The results of the resampling analysis were not significant. For the batting average resampling analysis p = .754, and for the ERA resampling analysis p= .580, with both analyses performed at the alpha = .05 level. Thus, there was no significant difference between historical and simulation data, with respect to these difference scores. Table 5 presents the confidence interval of the difference results indicating both upper and lower confidence interval values for team batting average and team ERA each contain a value of zero, thus indicating that 'zero difference' is indeed a member of these confidence intervals.

Table 5. Confidence intervals for historical vs simulation team BA and team ERA data

Team BA		**Team ERA**	
95% Confidence Interval		**95% Confidence Interval**	
Lower	**Upper**	**Lower**	**Upper**
-.0125	.0168	-.3093	.4587

5. Discussion

The results do indicate support for the hypothesis that player data on the back of baseball cards, when coupled with specifically designed dice-roll strategies, can yield an outcome that is consistent with historical data. However, it is important to point out that the full-scope of baseball strategies were not covered by this simulation experiment. First, there was no base-stealing or extra-base-advancement system in place so as to allow runners to advance independent of specific hit types (e.g., when a double occurred, runners could only advance 2 bases). Such runner advancement opportunities are mathematically known to influence 'expected runs scored' and pitcher replacement strategies (Hirotsu & Wright, 2013), and therefore can indeed factor in and influence statistics such as ERA, thus such omission highlights the 'simplicity' of the current simulation as opposed higher levels of complexity that could be tested. And even though a strategy such as base-stealing itself can lead to nearly 4 added wins per season for every one-standard deviation increase (Demmink, 2010), the omission of such a system from the simulation should not diminish the fact that its absence was an experimental constant across all teams.

Similarly, there was no pitcher-fatigue system implemented during the simulation. Although pitchers were removed and replaced at times during the game, this was done by sheer recognition of a sequence of hitting or pitching events that would warrant such replacement—but those recognized event sequences were not more likely to occur as the game moved along due to some type of fatigue factor that was in place. As a footnote, and for the sake of potential future replication of gameplay by others, there was a theorized pitcher-fatigue system that was not applied during the experiment. This pitcher-fatigue system consisted of merely reversing the pink die roll results after a certain number of elapsed innings—such as the start of inning 6—whereby values 1, 2, and 3 would then lead to consultation of the pitcher card. This would basically consist of abandoning the strategy as highlighted earlier in the 'balancing event occurrences' section. Subsequently, one could even add an additional fatigue factor at some point after inning 6 by weighting dice-roll outcomes further toward pitcher-card event outcome probability at the start of inning 8 for example, by making pink die rolls 1, 2, 3, and 4 be determined by the pitcher-card results—which then makes the system the exact opposite of the way dice-roll outcome 'event occurrence balancing' was done for the first 5 innings of the game. Such disparity would clearly weight the system more toward hit event occurrence, which is the desired result if one wants to demonstrate presence of pitcher-fatigue.

Another weakness of the game is the fact that errors lacked representation within the simulation data—an oversight due to the absence of fielding percentage data on baseball cards. Although intentional, this was not an oversight that would inordinately affect ERA or BA given that error-events leading to runs do not count against ERA, nor would errors be a beneficial event positively influencing BA—albeit in all fairness, other baseball modeling endeavors have made claim that errors could be substantial in their influence on simulation results given their role as an unexpected (e.g., random) result relative to fielding (Jensen, Shirley, & Wyner, 2009). For those who may want to replicate the game with greater accuracy, a theoretical design was indeed in-place that could have been applied, albeit it would not reflect 'individual' fielding probabilities, but rather would merely interject the possibility of errors into the game at a reasonable rate. This design merely consisted of recognizing the following sequence in any initial die roll: green die value = 20, and blue-gray die = 1, then an error has occurred. Any pink die value of 1, 2, or 3 showing would indicate a 1-base error, and 4, 5, or 6 a 2-base error—the green 20-side die would be rolled again to determine location (e.g. 5 or 15 = third base; 3 or 13 = first base; 8 or 18 = CF etc.).

In addition, given that these were historical matchups, the data derived by players were specific to that era in which they played. For Example, Sal Maglie of the 1951 New York Giants pitched in an era where starting pitchers quite often threw complete games, as opposed to the modern day 'platooning' of pitchers who specialize in long-relief, short-relief, or as a 'closer'. Albeit this could be an influence, it should not be considered a negative influence—in fact, it is highly consistent with other types of statistical baseball games that allow cross-era historical/fantasy matchups to be played out using card data generated specifically via each player's unique era (see Strat-O-Matic Game Company).

The use of career batting average and ERA totals as the reference data for dice-roll outcomes, instead of data from a specific year, also presents a compromise when it comes to accuracy in game design. This referencing of career total data was necessitated to provide a consistent data reference across all data and cards—but the limitation that it creates is a limitation in the game's ability to use 'true' team card sets that reflect the actual data from a specific year. The lone consistent line of data on the back of any card for an entire Topp's baseball card team for any year, is the last (most recent) season's data—and that data does not represent the year of the card that it is printed on, it represents the previous year's data. Thus, if one wishes to "purely" simulate the 1954 New York Giants vs the 1985 Kansas City Royals, one would need to 'assemble' these team sets from the full 1955 and 1986 baseball card sets respectively—the reason being that due to trades, free agency, or retirement etc., not all players will still be on their previous years' teams.

6. Conclusion

Albeit the game-design does a have range of limitations, the outcome of the analysis does demonstrate that ordinary baseball cards can be used in a boardgame-type simulation to arrive at realistic outcomes. In addition, simply being able to handle one's own baseball cards, and utilize them in some sort of way that generates a realistic baseball outcome gives them added value—which was one of the most satisfying experiences derived from the experiment. When it comes to making this type of simulation game appealing, the aesthetics of handling of actual cards provides a strong emotive type of dynamic re-experiencing. There exists good evidence supporting that judgements of aesthetics do not solely rely upon perceptual input of the here-and-now, but that such a dynamic result can occur via combining experiencing of the object, with higher order factors of cognition (e.g., specific memories) to help catalyze and influence one's preferences (Gallace & Spence, 2014; McCabe, Rolls, Bilderbeck, & McGlone, 2008).

And although some of the missing strategies such as base stealing, application of a pitcher-fatigue system, hit-and-run, etc. would indeed interject more reality into such a simulation game, these elements were not necessary to arrive at basic data that could empirically deem the core design of the game valid—which was the primary objective of the project.

Ultimately, and perhaps the main sticking-point if one were to refine and include any of the omitted advanced strategies so as to round-out a completed consumer-type of game, is the question: How receptive would collectors or fans actually be toward the physical handling and use of their highly valued cards, under such boardgame conditions?

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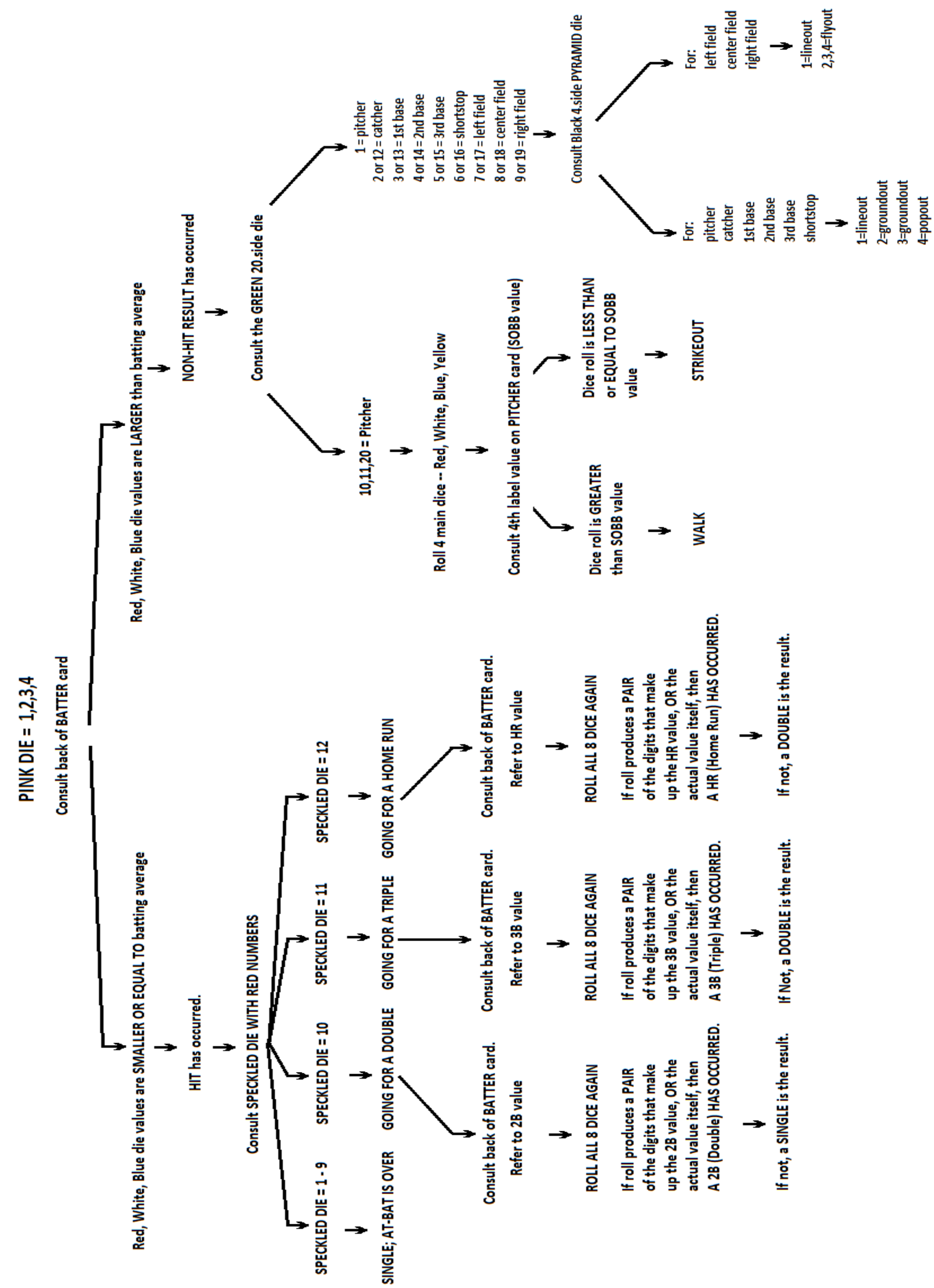
Strat-O-Matic Game Company. Glen Head, NY. http://www.strat-o-matic.com

Topps Trading Card Company. http://www.topps.com

Appendix A. Flow Chart for batter card result



Appendix B. Flow Chart for pitcher card result