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Data Pipeline & Analysis

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PROJECT OVERVIEW

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PROJECT AMS

The aim of this project is to create an end-to-end ETL pipeline to extract data from a website and present the findings.

- To **scrape** tabular Dead by Daylight data from the following website: https://dennisreep.nl/dbd/
- To model the data into staging, dimension & fact tables
- To clean the data to aid in data analysis
- To feature engineer metrics to aid in data analysis
- To **analyse** the final data tables in order to understand the game, its design and its player base.

PROJECT PROCESS

In order to build our end-to-end ETL pipeline, the project will be split into 5 steps.

01.



Scrape

02



Model

)3.

Drop the 'unix' column
fact_matches.drop(columns=['unix'], inplace=True)

Clean

04.

Feature engineer

05.



Analyse

- What is the **least amount of money** you could pay to play the game with all its content?
- What unwritten player norms are there in the online player base?
- 1s the game biased towards one category of player?
- Is the game biased by design or by player skill?
- Which perks tend to be used together together and why?

PROJECT QUESTIONS

The aim of collecting the data is to provide an understanding of the game, its design and its player base.

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GAME OVERVIEW

- Dead by Daylight (DBD) is a popular online multiplayer game.
- Each game has 4 survivors & 1 killer on a randomly selected map.
- Survivors have to repair 5 generators to power an exit gate, so that they can escape.
- Killers have to stop the reparation of the generators and hook the survivors to slow their progress & prevent them from escaping.

DATA HIERARCHY

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DATA HIERARCHY

- The data tables are organised into 5 categories:
 - Character | Map | Perk | Add-on | Match
- The following table types are used:
 - Temporary Tables (temp): Used to hold data temporarily during ETL processes for intermediate processing.
 - Staging Tables (stg): Used to store raw data from source system before it is processed.
 - Dimension Tables (dim): Used to store descriptive attributes that provide context and details for data analysis.
 - Fact Tables (fact): Used to store quantitative data for analysis and reporting.

Data hierarchy: scrape

In order to acquire data to analyse, data was scraped, with permission, from the following website:

https://dennisreep.nl/dbd/

This code has two main functions: url_get_contents() and scrape_tables().

The **url_get_contents** function fetches the content of a given URL using a specific user-agent to mimic a browser.

The **scrape_tables** function extracts tables from this HTML content within a specified range (start & end date) and combines these tables into a single dataframe. Then, the dataframe is assigned to a variable name.

The following slides show the dataframes returned.

```
# Function to get the contents of the URL
def url_get_contents(url):
    req = urllib.request.Request(url=url, headers={'User-Agent': 'Mozilla/5.0 (Windows NT 10.0; Win64;
x64; rv:90.0) Gecko/20100101 Firefox/90.0'})
   f = urllib.request.urlopen(req)
   return f.read()
# Function to scrape tables and format column headers
def scrape_tables(url, start, end, dataframe_name):
   # Defining the HTML contents of the URL
   xhtml = url_get_contents(url).decode('utf-8')
   # Defining the HTMLTableParser object
   p = HTMLTableParser()
   # Feeding the HTML contents to the HTMLTableParser object
    # Initialize a list to store DataFrames
   dataframes = []
    # Loop through the specified range of tables
    for i in range(start, end + 1):
       # Create an empty list to store the split strings
        split_result = []
        # Iterate through each list in the table header (first row)
        for column in p.tables[i][0]:
            # Join all elements in the inner list into a string
            ini_string = ''.join(column)
            # Apply getVals operation to ini_string
            getVals = [val.lower() for val in ini_string if val.isalnum() or val.isspace() or val ==
1-11
            # Add underscores to separate words
           result = '_'.join(''.join(getVals).split()).replace('-', '_')
            # Append the split result to the list
            split_result.append(result)
        # Create a DataFrame for the current table
        table_df = pd.DataFrame(p.tables[i][1:], columns=split_result)
        # Append the DataFrame to the list
        dataframes.append(table_df)
    # Concatenate all DataFrames into one
    concatenated_df = pd.concat(dataframes, ignore_index=True)
    # Assign variable name
    globals()[dataframe_name] = concatenated_df
   # Return dataframe
    return concatenated df
```

DATA HIERARCHY: CHARACTERS

STG_KILLERS

name	STRING(PK)
tier	CATEGORY
rating	FLOAT
is_survivor	BOOLEAN
last_updated	DATETIME

STG_SURVIVORS

name	STRING(PK)
tier	. CATEGORY
rating	FLOAT
is_survivor	BOOLEAN
last_updated	DATETIME

DIM_CHARACTERS

name	STRING(PK)
tier	CATEGORY
rating	FLOAT
is_survivor	BOOLEAN
last_updated	DATETIME
release_date	DATETIME
is_licensed	BOOLEAN
map	STRING
dlc_title	STRING
iridescent_shard_c	ost FLOAT
auric_cell_cost	FLOAT
total_cost_euros	FLOAT

INFO

Playerable characters are split into

2 categories: survivors & killers

DATA HIERARCHY: MAPS

STG_MAPS_KILLER

map_name STRING(PK)
rating FLOAT
last_updated DATETIME
killer_name STRING

DIM_MAPS

map_name STRING(PK)
avg_score FLOAT
bias INT
last_updated DATETIME

INFO

Each game is played on one of several maps

DATA HIERARCHY: PERKS

STG_PERKS_SURVIVOR

perk_name STRING(PK)
description STRING
acquired_from STRING
tier CATEGORY
rating FLOAT
last_updated DATETIME
is_survivor BOOLEAN

STG_PERKS_KILLER

perk_name STRING(PK)
description STRING
acquired_from STRING
tier CATEGORY
rating FLOAT
last_updated DATETIME
is_survivor BOOLEAN

DIM_PERKS

perk_name STRING(PK)
description STRING
acquired_from STRING
tier CATEGORY
rating FLOAT
last_updated DATETIME
is_survivor BOOLEAN
category STRING

INFO

Perks provide characters with special powers.

DATA HIERARCHY: KILLER PERK RATINGS

STG_PERKS_KILLER_SPECIFIC

perk_name STRING(PK)

description STRING

acquired_from STRING

tier CATEGORY

rating FLOAT

last_updated DATETIME

killer_name STRING

category STRING

FACT_PERKS_KILLER_SPECIFIC

perk_name STRING(PK)
description STRING
acquired_from STRING
tier CATEGORY
rating FLOAT
last_updated DATETIME
killer_name ... STRING
category ... STRING

FACT_PERKS_KILLER_SPECIFIC_WIDE

INFO

Each character has 4 unique perks that can be taught to others

DATA HIERARCHY: PERKS

FACT_PERKS

perk_name	STRING(PK)
description	STRING
acquired_from	STRING
overall_tier	. CATEGORY
overall_rating	FLOAT
is_survivor	BOOLEAN
last_updated	DATETIME
category	STRING
tier_unknown	
tier_a	FLOAT
tier_b	FLOAT
tier_c	FLOAT
tier_d	FLOAT
tier_f	FLOAT
tier_s	FLOAT

INFO

Up to 4 perks can be used at the same time.

DATA HIERARCHY: ADDONS

STG_ADDONS_KILLER

DIM_ADDONS_KILLER

killer_addon_id STRING(PK)
name STRING
description STRING
tier ... CATEGORY
rating ... FLOAT
last_updated ... DATETIME
killer_name ... STRING

INFO

Add-ons are used to enhance characters' powers

DATA HIERARCHY: MATCHES

FACT_MATCHES

fact_match_id	. STRING(PK)
date	DATETIME
match	INTEGER
character	STRING
is_survivor	BOOLEAN
is_data_recorder	BOOLEAN
perk1	STRING
perk2	STRING
perk3	STRING
perk4	STRING
perks_equipped_count .	INTEGER
map	STRING

generators_complete	FLOAT
bloodpoints	INTEGER
notes	STRING
surv_went_to_2nd_phase	BOOLEAN
killer_alllowed_surv_escape	BOOLEAN
attempted_adept	BOOLEAN
killer_didn't_stay	BOOLEAN
surv_died_on_2nd_hook	BOOLEAN
surv_was_tunneled	BOOLEAN
player_disconnected	BOOLEAN
surv_hatch_escape	BOOLEAN
surv_moried	BOOLEAN

surv_threw_first_hook	BOOLEAN
surv_threw_second_hook	BOOLEAN
killer_friendly	BOOLEAN
match_cancelled	BOOLEAN
player_afk	BOOLEAN
killer_4k	BOOLEAN
killer_3k	BOOLEAN
killer_win	BOOLEAN
draw	BOOLEAN
survivor_won	BOOLEAN

INFO

Fact_matches consists of ~900

individual games recorded by a player

```
def format dict(d):
    return "\n".join(f"{key}: {value}" for key, value in d.items())
def dataframe_report(df):
    report = {}
    # .info() information
   buffer = io.StringIO()
   df.info(buf=buffer)
   report['info'] = buffer.getvalue()
    # Summary statistics for numerical columns rounded to 2 decimal places
    report['summary_statistics'] = df.describe().round(2).to_dict()
    # Number of duplicates in the dataframe
    num_duplicates = df.duplicated().sum()
   report['num_duplicates'] = num_duplicates
    # Duplicate rows in the dataframe
   duplicate_rows = df[df.duplicated()]
    report['duplicate_rows'] = duplicate_rows
    # Number of blanks in each column (assuming blanks are empty strings)
   blank_counts = df.apply(lambda x: (x == '').sum())
    report['num_blanks'] = blank_counts[blank_counts > 0].to_dict()
    # Number of nulls in each column
   null counts = df.isnull().sum()
    report['num_nulls'] = null_counts[null_counts > 0].to_dict()
    # Data types of each column
    report['data_types'] = df.dtypes.to_dict()
    # Number of unique values in each column
    report['num unique values'] = df.nunique().to dict()
    # Constant columns (columns with a single unique value)
    report['constant_columns'] = [col for col in df.columns if df[col].nunique() == 1]
```

Data hierarchy: clean

Now that we have data, the last step is to ensure that the dataframes are clean & fix any issues there are.

The **dataframe_report()** function generates a report containing:

- Basic dataframe information
- Summary statistics
- Number of duplicates
- Counts of blanks and nulls
- A list of affected rows for duplicates, blanks & nulls
- Number of unique values
- Constant columns

The results are stored in a dictionary called report, which is later printed (not pictured) for the user, in an easy-to-digest summary.

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Characters

Characters are categorised as 'killer' or 'survivor'. They either come with the base game (default) or can be purchased additionally (unlockable).

Total Characters

42 (54%) **36** (46%)

Survivors

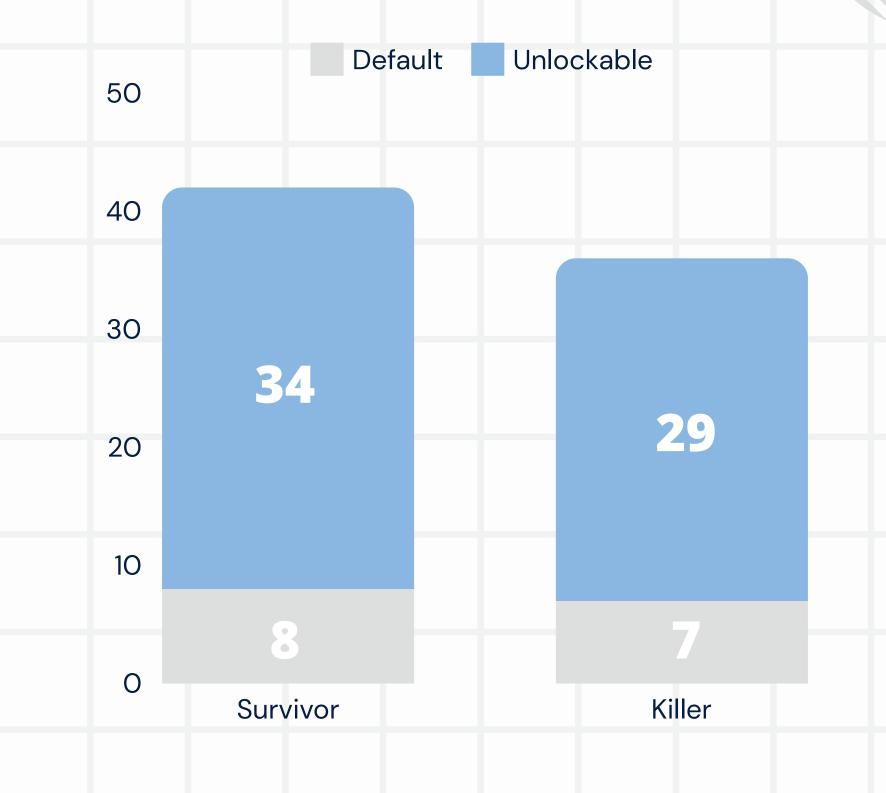
Killers

63 (81%)

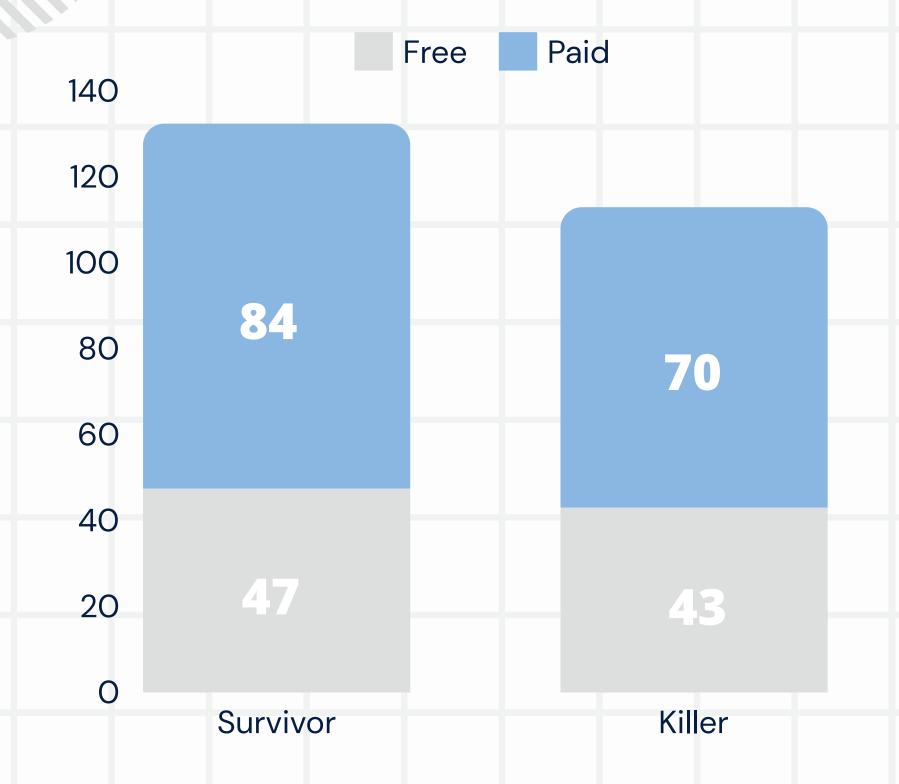
Unlockable characters

Default characters

TOTAL CHARACTERS vs CATEGORY



TOTAL COST OF CHARACTERS (€)



Character cost

Characters can either be purchased with in-game currency (iridescent shards) or with real money. Some characters can only be purchased with real money.

63

Unlockable characters

32 (51%)

31 (49%)

Free characters

Paid characters

90€

155€

Free characters

Paid characters

Game cost

[Total]

Dead by Daylight involves several costs to access its full content. How much could be spent per player, if a player bought everything?

275€

Total cost

30€

245€

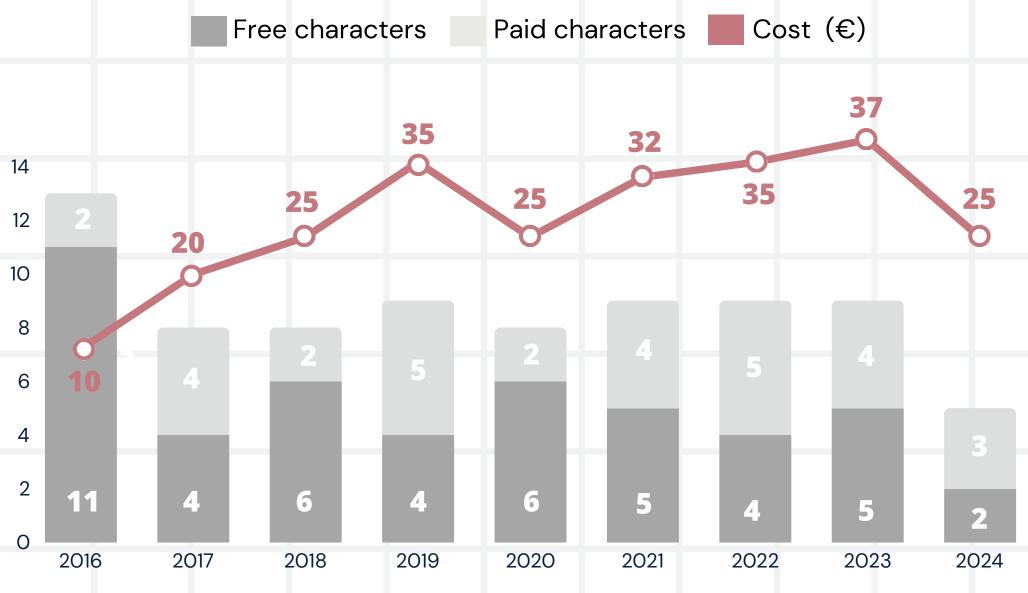
Base game cost

Total character cost

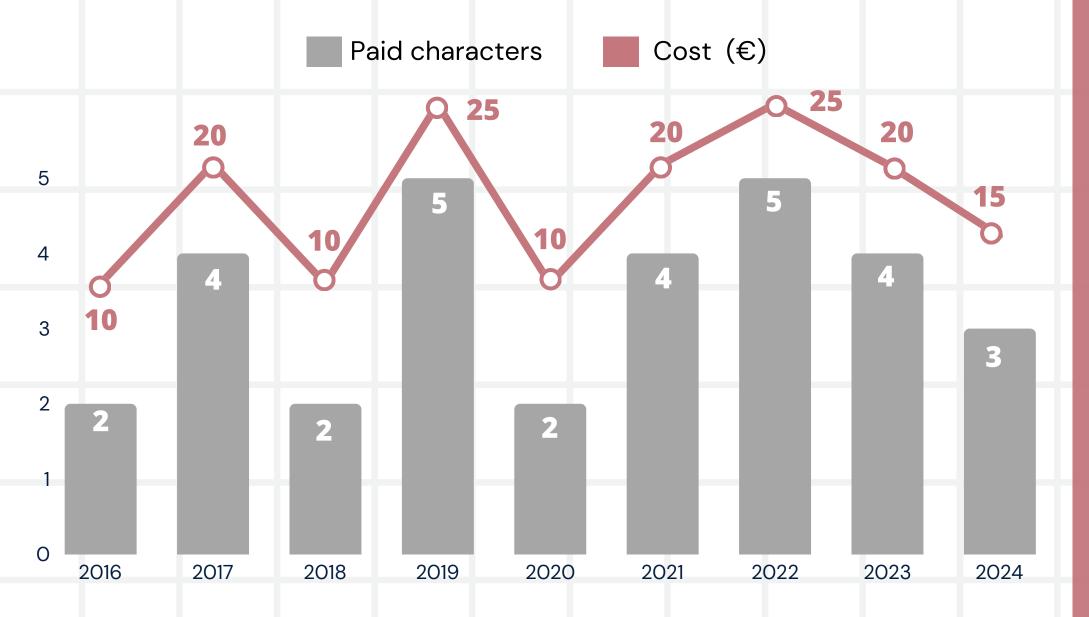
26.50€

Yearly average





PAID CHARACTER RELEASES vs PRICE



Game cost

[Not-free]

How much money do you absolutely need to spend to get all available content?

185€

Total cost

30€

155€

Base game cost

Total character cost

17.22€

Yearly average

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Player behaviour

Depending on how the game is progressing, players can choose to exploit the game in certain ways.

The term 'throwing' refers to the act of a survivor deliberately getting themselves killed, so that they can leave the game quicker.

The majority of behaviours recorded over ~900 matches were seen as negative. Only a small number of behaviours would be considered as positive.

43%

of events witnessed were negative 14%

of events witnessed were positive

PLAYER BEHAVIOUR EVENTS (%)



[CORRELATION ANALYSIS] KILLER BEHAVIOUR

# perks	0.22							
bloodpoints	0.24	0.23						
killer_allowed_ escape	-0.038	0.027	-0.0042					
adept	0.085	-0.011	0.00059	-0.0032				
killer_left	-0.24	-0.49	-0.24	-0.016	-0.022			
diconnected	-0.11	0.023	-0.11	-0.0069	-0.0097	-0.047		
killer_friendly	-0.21	0.063	-0.0091	-0.012	-0.018	-0.054	-0.038	
match_cancelled	-0.093	0.016	-0.088	-0.0056	-0.0079	-0.038	-0.017	-0.031
Ý	iller win perks equipps	ed count	oodpoints lier_allowed_survivo	or_escape player_attemn	ited_adept killer	didn't stay	sconnected killer .V	vas friendly
	, l	liy	ler an	A.				

Killer behaviour

A correlation analysis of the effect of various killer-related variables on each other.

Key findings

- Positive behaviours are punished by the game design [killer_friendly]
- Killers with fewer perks
 equipped are (i) less likely to
 stay and (ii) less likely to win,
 as a result [perks_equipped,
 killer_left]

[CORRELATION ANALYSIS] SURVIVOR BEHAVIOUR

# perks	-0.036							
bloodpoints	-0.079	0.056						
killer_allowed_ escape	-0.015	-0.00039	0.054					
died_on_2nd _hook	0.18	0.0085	-0.028	-0.027				
tunneled	0.028	-0.0011	-0.052	-0.013	-0.025			
hatch_escape	0.22	0.016	0.081	-0.022	-0.042	-0.02		
threw_1st_hook	0.11	0.016	-0.035	-0.015	-0.028	-0.013	0.067	
threw_2nd_hook	0.11	0.0036	-0.06	-0.022	-0.042	0.26	0.066	-0.022
	killer win	* Peiks	aloodpoints allows	ad escape	2nd hook	tunneled	in escape	en St. hook
			killer	91.				

Survivor behaviour

A correlation analysis of the effect of various survivor-related variables on each other.

Key findings

- Killers are more likely to be friendly if they have won the match [hatch_escape]
- Survivors are more likely end the match early if the killer pursues only them **[tunneled]**

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Game bias: design

How biased or balanced the game is towards survivors & killers is hotly discussed in the community.

The developers claim a 60% bias towards killers [source]. Does this hold true?

According to the game design itself, this holds true.

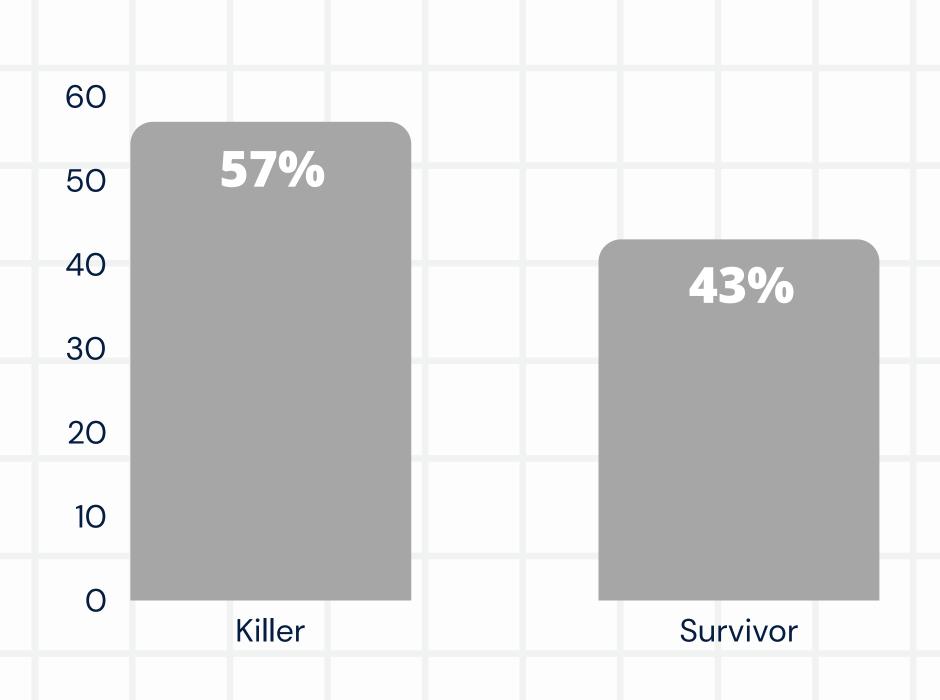
57% Killer bias: map design

25
Killer-friendly
maps

19

Survivor-friendly maps





Game bias: design

How biased or balanced the game is towards survivors & killers is hotly discussed in the community.

The developers claim a 60% bias towards killers [source]. Does this hold true?

According to the game design itself, this holds true.

57%

Killer bias: map design

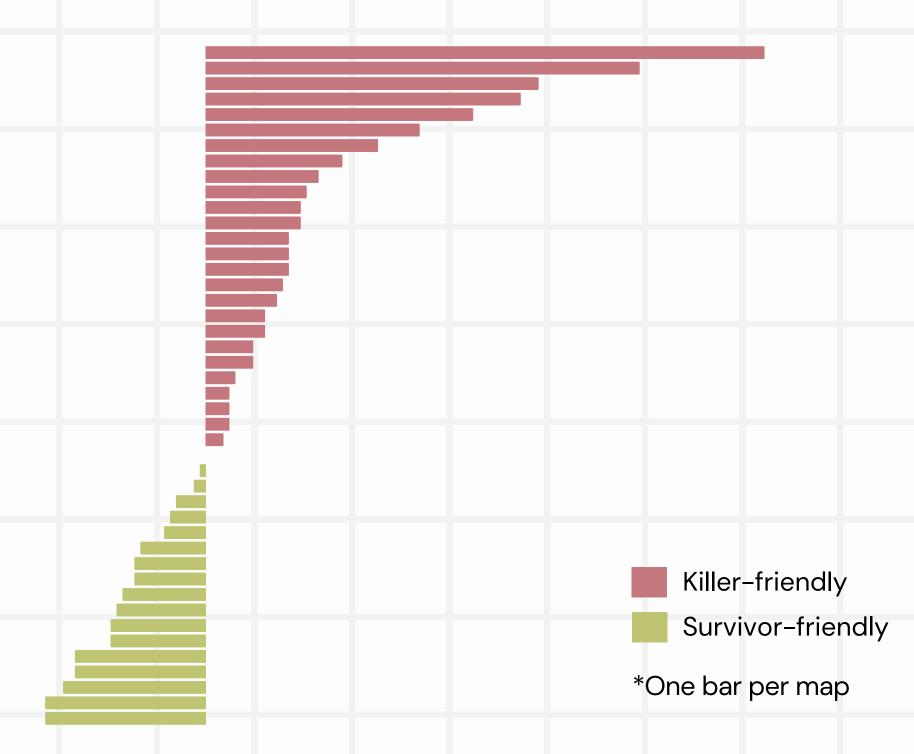
25

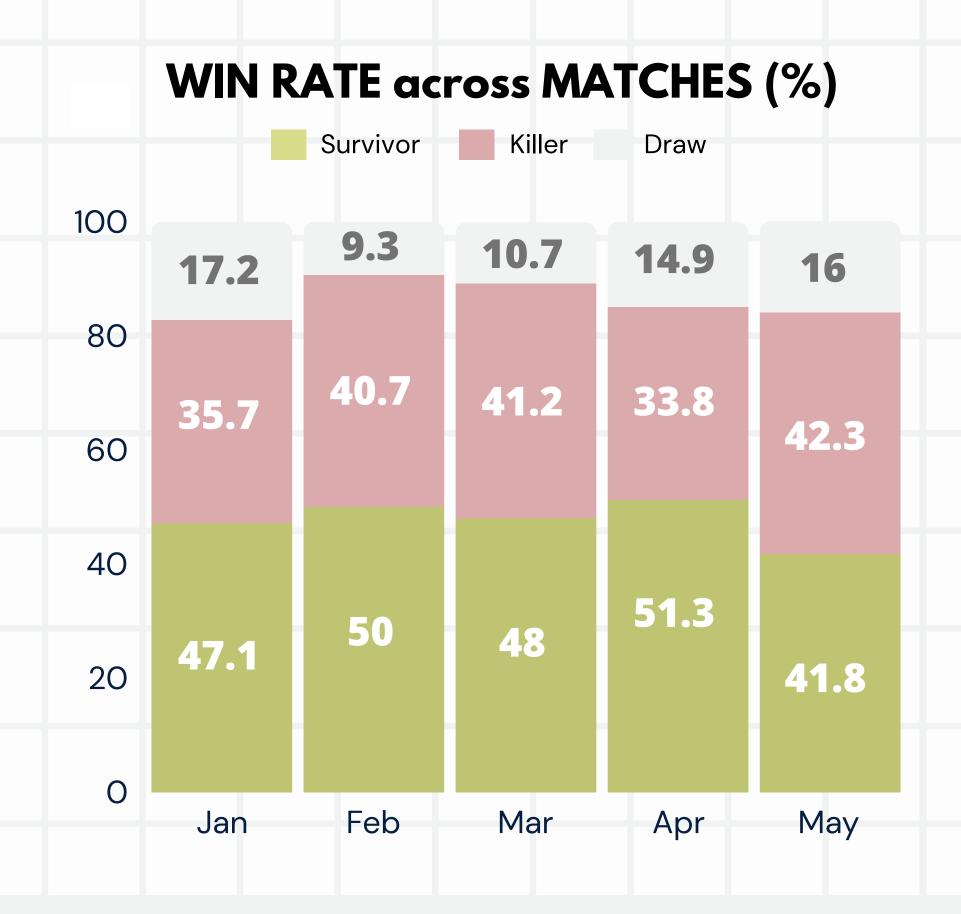
Killer-friendly maps

19

Survivor-friendly maps

MAP BIAS vs PLAYER CATEGORY





Game bias: matches

Although the game design agrees with a 60% killer bias, as the developers suggest, does this match the reality that players experience?

When we consider the match data [fact_matches], it seems not. The game appears to be in the survivors favour (47%), if we use 'win' rate as the metric for bias.

882

Matches

47.4%

38.8%

Survivor win rate

Killer win rate

13.8%

Draw rate

Killer win rate = (3 | 4) kills out of 4 **Survivor win rate** = 1 kill out of 4 **Draw** = 2 kills out of 4

Game bias: matches

The developers aim for a 60% kill rate, which they define as number of kills over a given match, with 50% being 2 kills out of 4 per match.

When calculating this metric from over ~500 games, however, the data still suggests that the game is in the survivors' favour, with an average kill rate of 46%

882

46%

Matches

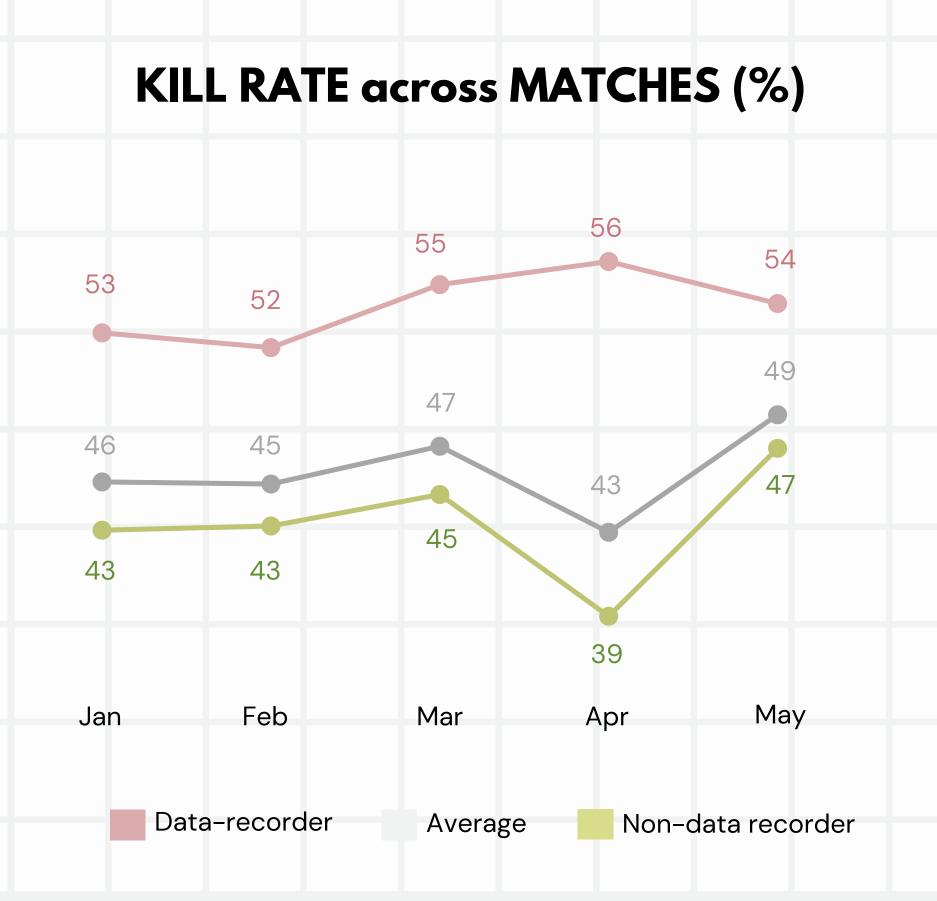
Average kill rate

44%

Average kill rate: Average hill rate: Average da

54%

Average kill rate: data recorder



Data recorder: The person who recorded the match data

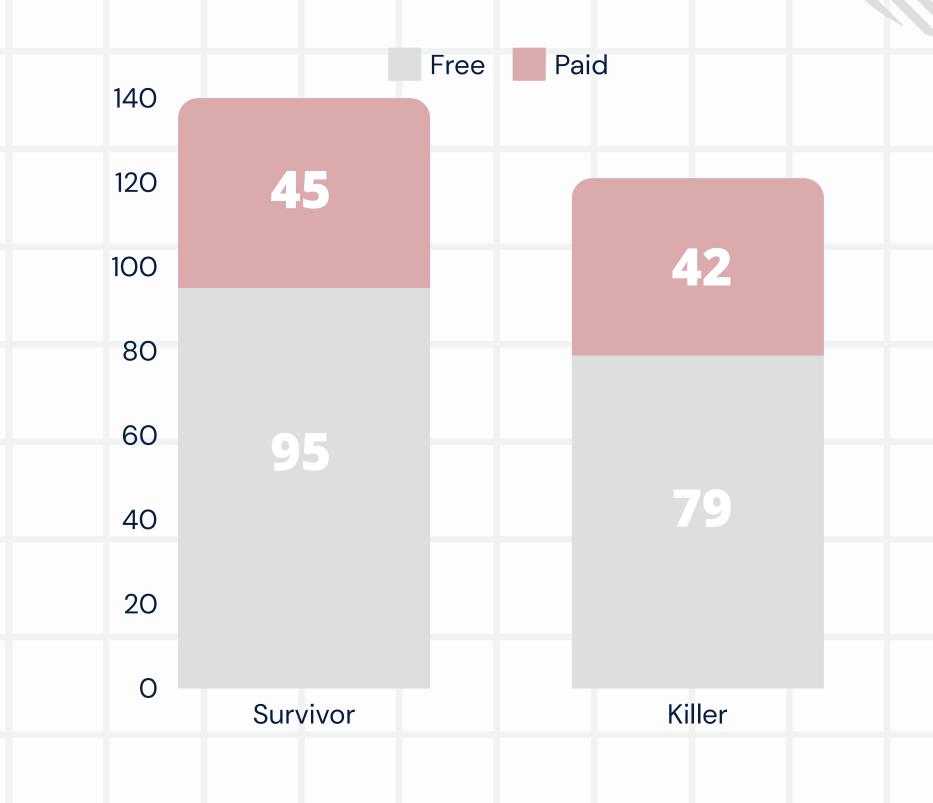
Non-data recorder: The other people who did not record the match data

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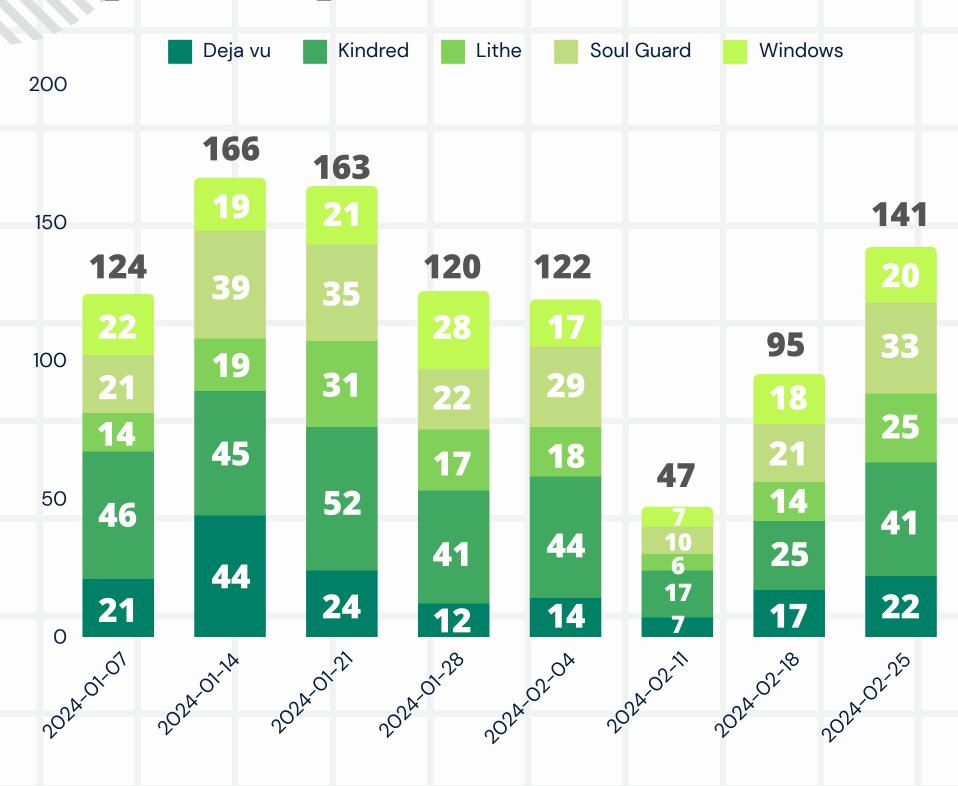
Perks Players can equip up to 4 unique perks which offer them unique bonuses during a match. Killers and survivors have their own pool of perks to choose from. **261 Total perks** 140 121 **Survivor perks** Killer perks 174 Free perks **Paid perks**

PERK COUNT vs CHARACTER TYPE & COST



Free: No real currency is needed to access **Non-free:** Real currency is needed to access

[WEEKLY] TOP 5 SURVIVOR PERKS



Perks: survivor

Most players tend to gravitate towards the perks they and the community consider the strongest ('meta perks').

For survivors, we see perks that are used for: (i) escaping killers, (ii) locating generators & (iii) finding injured survivors

> **261 Total perks**

140

Survivor perks

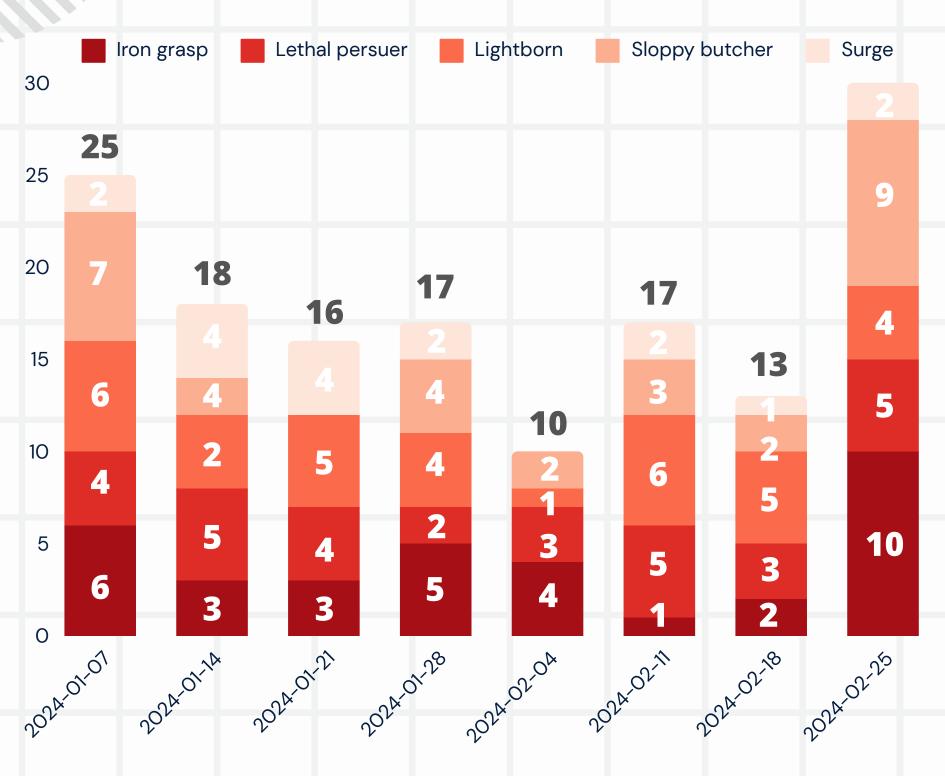
Killer perks

15,787,066 8,790,722

Possible survivor perk combinations

Possible killer perk combinations

[WEEKLY] TOP 5 KILLER PERKS



Perks: killer

Most players tend to gravitate towards the perks they and the community consider the strongest ('meta perks').

For killers, the top perks help: (i) find survivors, (ii) reduce healing effectiveness and (iii) stop generator repair progress

> **261 Total perks**

140

Survivor perks

Killer perks

15,787,066 8,790,722

Possible survivor perk combinations

Possible killer perk combinations

SURVIVOR PERKS: ASSOCIATION RULES

Antecedents	Consequents	Antecedent support	Consequent support	Confidence	Lift	Leverage
None	No perk data	0.098	0.057	0.589	10.255	0.519
No perk data	None	0.057	0.057	1	10.255	0.519
Lithe	Windows of opportunity	0.164	0.051	0.313	1.608	0.019
Windows of opportunity	Lithe	0.195	0.051	0.263	1.608	0.019

TERMINOLOGY

Support: How often both items appear together in the dataset

Lift: How much more likely two items occur together compared to if they were unrelated.

Confidence: How likely one item appears if the other item appears

Leverage: How much more frequently two items occur together than expected by chance

Perks: survivor

140

15,787,066

Survivor perks

Possible survivor perk combinations

Although there are over 15 million possible combinations of perks that survivors can choose from, there are some perks that occur statistically more often together (support >0.05).

Here we can see that two complimentary perks (i) **Lithe** and (ii) **Windows** occur frequently together.

- If **Lithe** is equipped first, there is a 31% chance that **Lithe** will follow (**confidence**).
- If **Windows** is equipped first, **Lithe** follows 26% of the time (**confidence**)

KILLER PERKS: ASSOCIATION RULES

Antecedents	Consequents	Antecedent support	Consequent support	Confidence	Lift	Leverage
None	No perk data	0.272	0.085	0.314	3.677	0.062
No perk data	None	0.085	0.272	1	3.677	0.062

TERMINOLOGY

Support: How often both items appear together in the dataset

Lift: How much more likely two items occur together compared to if they were unrelated.

Confidence: How likely one item appears if the other item appears

Leverage: How much more frequently two items occur together than expected by chance

Perks: killer

121

Killer perks

8,790,722

Possible killer perk combinations

In terms of the killer association rules, we can see that there aren't any perks that are statistically likely to occur with one another (support > 0.05).

This is likely because each killer has a different play style:

- 1 unique power per killer
- Ranged attack vs. melee attack
- Stealth focus vs. non-stealth focus

This, in turn, leads to killer perks being more differential in nature, with certain perks benefiting some killers more than others.

DATA LIMITATIONS

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01.

Data is currently scraped. Any changes to the website would make the code unusable

Solution: Use API

02.

The website data resets monthly, leading to data loss with current pipeline

Solution: Append monthly data

03

The ratings of maps & killer effectiveness are user-generated & are subject to bias and rating manipulation

Fact_matches data is manually inputted and uploaded via spreadsheet.

LIMITATIONS A STATE OF THE STA

Here are some limitations of the data collected, with potential solutions provided, where relevant.

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- Perk categories are currently manually assigned. It would be worthwhile to use machine learning to auto-generate categories from their descriptions.
- Character downloadable content data is manually inputted. It could be automated.
- Cleaning of fact_matches was done in a spreadsheet. Could automate as part of the pipeline.
- Swap over from scraped data to use the website API, for a more stable & scaleable data ingression
- Analyse the dim_addons_killer table.
 It was scraped from the website but wasn't used in the current analysis.

FURTHER IMPROVEMENT

Due to the limited scope of the current analysis, here would be some areas of improvement, that could be worked on, if more time & resources were available

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REFERENCES

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