AN APPLICATION OF REGRESSION:
# Market Mix Modelling (MMM)

Market Mix Modelling (MMM) is a technique that helps quantify the impact of several marketing inputs on sales or Market Share. The purpose of using MMM is to understand how much each marketing input contributes to sales, and how much to spend on each marketing input.

Marketing Mix stands for all different marketing channels that a company uses such as advertising, social media promotions, etc.

Modelling- Statistical models, usually regression analysis used to measure the influence of each marketing channel on sales.

Market Mix Modelling uses the principle of Multi-Linear Regression. The dependent variable could be Sales or Market Share. The independent variables usually used are Distribution, price, TV spending, outdoor campaign spending, newspaper and magazine spending, below-the-line promotional spending, Consumer promotions information, etc. Nowadays, Digital media is highly used by some marketers to increase brand awareness. So, inputs like Digital spending, website visitors, etc., can also be used as inputs for MMM.

An equation is formed between the dependent variables and predictors. This equation could be linear or non-linear depending on the relationship between the dependent variable and various marketing inputs.
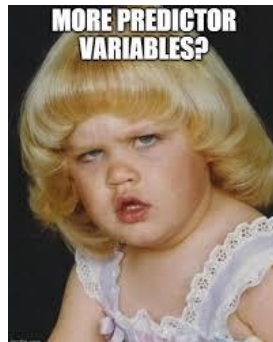
The betas generated from Regression analysis help in quantifying the impact of each of the inputs. The beta depicts that one unit increase in the input value would increase the sales/profit by Beta units, keeping the other marketing inputs constant.

Let us understand this concept via an example,
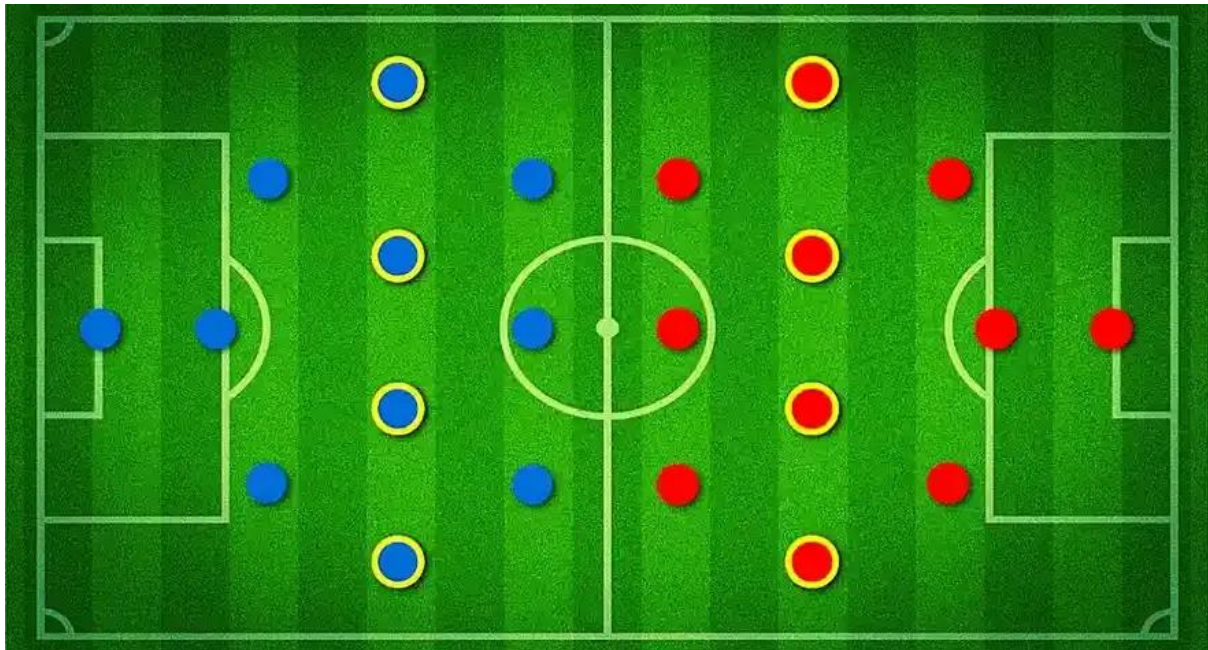
There are 11 players in each team, but no one person can lead the team to victory. Let's jump back into the shoes of our soccer coach who (hypothetically) identifies a set of core KPIs that will be tracked for each player. This includes the number of passes, goals, and assists. This allows us to employ an MMM-style approach.

Applying a marketing mix modelling approach to one single game might not give you that much valuable data. After all, it's a small sample size. In a marketing context, that would be like trying to define performance attribution based on a single day's worth of data.

However, if we view these KPIs across an entire season (or several months to a year in the case of a campaign), we can start to see valuable attribution insights rising to the surface. Those insights can help to shape the strategies for the next season or campaign.

A similar analogy holds for marketing and promotional activities. While performing efforts across digital channels may be easier to link to a goal, print plays a role as well.

Where is MMM used?

1. ROI- MMM helps in ascertaining the effectiveness of each marketing input in terms of Return on Investment. In other words, a marketing input with a higher return on Investment (ROI) is more effective as a medium than a marketing input with a lower ROI.

2. Forecasting- Understanding what future expenditures in marketing might look like and optimizing resources accordingly.

3. Pricing- If you drop the price of your product or service, will more customers flock to it? Will you steal market share from a competitor? Or, does a price decrease lower the perceived

value of said product or service? These are all incredibly difficult and complex questions to ask, requiring equally complex analysis to arrive at a reliable conclusion.

DISADVANTAGES

One of the drawbacks of market mix modelling is that it requires a lot of high-quality data. That might be a problem if you are working with a small marketing budget or if your organisation has only just begun media buying at scale. (Most marketing mix models require at least two years of historical data to forecast.)

EXAMPLE DATASET

Date	Website Sessions	Online Service Enquiries	Unit Sales	Own price (average unit price)	Own distribution	Door to Door Advertising (total £)	Own promotions (£)	Competitor promotions (index)	Competitor advertising (total) (index)	Social Media followers (Facebook)	New Social Media followers (Facebook)	Number of positive mentions (Twitter)	School Holidays
31/12/18	87804	71472	175607	4	87	3000	0	1	0	5271	203	203	1
07/01/19	90171	72678	180342	4	87	3000	0	1	0	5451	180	264	0
14/01/19	98198	79147	196396	4	89	3000	0	1	0	5648	196	14	0
21/01/19	103582	73544	207165	4	84	3000	0	0	1	5855	207	153	0
28/01/19	113942	80443	227884	4	88	27926	0	1	0	6083	228	171	0
04/02/19	111094	79766	222188	4	88	27172	0	0	1	6305	222	57	0
11/02/19	139586	90173	279172	3	88	24066	0	1	0	6584	279	130	1
18/02/19	78362	66608	156724	4	87	5000	0	1	0	6741	157	131	1
25/02/19	83737	70674	167473	4	87	5000	0	1	1	6908	167	88	0
04/03/19	83794	72734	167589	4	86	5000	0	1	1	7076	168	181	0
11/03/19	61098	53522	122197	4	87	5000	0	1	0	7198	122	253	0
18/03/19	67323	58706	134647	4	88	5000	0	1	1	7333	135	89	0
25/03/19	157655	101530	315310	3	88	23698	0	0	0	7648	315	181	0
01/04/19	135503	90516	271006	3	88	32388	0	1	1	7919	271	240	1
08/04/19	279347	129058	558694	2	97	32677	10575	0	0	8478	559	214	1
15/04/19	253768	139573	507537	3	94	3000	10299	0	0	8985	508	105	0
22/04/19	217320	118222	434640	3	93	3000	10189	0	0	9420	435	382	0
29/04/19	209209	118831	418417	3	94	3000	10190	0	0	9838	418	248	0
06/05/19	178315	138373	356631	4	85	3000	0	1	1	10195	357	208	0
13/05/19	174254	134524	348500	4	85	3000	0	1	0	10544	349	213	0
20/05/19	163990	124304	327979	4	85	3000	0	0	0	10871	328	69	0
27/05/19	191974	170857	383948	4	85	46468	10000	0	0	11255	384	210	1
03/06/19	199112	178006	398224	4	86	46257	10027	1	1	11654	398	172	1
10/06/19	182693	163693	365385	4	86	46349	10000	0	0	12019	365	372	1

Z5 = 0

	School Holidays	Average number of hours watching TV per household	Seasonality	Weather (daylight/ Sunshine)	Seasonal Index	Price Index	Material Prices	Total GDP per capita	Const	Promotion A	Promotion B	Promotion C	Promotion A Spend	Promotion B Spend	Promotion C Spend
	1	19	7	4	87	116	34	6656	1	0	0	0	0	0	0
	0	23	7	3	87	115	34	6656	1	0	0	0	0	0	0
	0	23	4	1	87	115	34	6656	1	0	0	0	0	0	0
	0	23	5	2	87	101	34	6656	1	0	0	0	0	0	0
	0	26	7	3	63	101	34	6661	1	0	0	0	0	0	0
	0	26	6	3	63	103	34	6661	1	0	0	0	0	0	0
	1	24	8	3	63	92	34	6661	1	0	0	0	0	0	0
	1	22	2	3	63	121	34	6661	1	0	0	0	0	0	0
	0	20	4	2	63	121	34	6661	1	0	0	0	0	0	0
	0	23	6	2	55	124	34	6680	1	0	0	0	0	0	0
	0	23	4	3	55	125	34	6680	1	0	0	0	0	0	0
	0	18	3	1	55	125	34	6680	1	0	0	0	0	0	0
	0	27	13	3	55	92	34	6680	1	0	0	0	0	0	0
	1	23	12	6	125	95	33	6663	1	0	0	0	0	0	0
	1	31	10	8	125	66	33	6663	1	1	0	0	10575	0	0
	0	26	13	4	125	79	33	6663	1	1	0	0	10299	0	0
	0	32	11	4	125	78	33	6663	1	1	0	0	10189	0	0
	0	27	13	5	118	81	32	6729	1	1	0	0	10190	0	0
	0	29	15	9	118	111	32	6729	1	0	0	0	0	0	0
	0	29	16	7	118	110	32	6729	1	0	0	0	0	0	0
	0	25	14	3	118	108	32	6729	1	0	0	0	0	0	0
	1	29	17	6	118	127	32	6729	1	0	1	0	0	10000	0
	1	30	18	8	127	128	32	6702	1	0	1	0	0	10027	0
	1	26	16	7	127	128	32	6702	1	0	1	0	0	10000	0

Promotion A Clicks	Promotion B Clicks	Promotion C Clicks	NEW MEMBER SIGNUPS	NEW FREE TRIAL SUBSCRIPTIONS	Upweight F	Downweigl	Door to Door Promotion Leaflets edit
0	0	0	15	41	0	0	0
0	0	0	7	29	0	0	0
0	0	0	7	29	0	0	0
0	0	0	6	25	0	0	0
0	0	0	9	38	0	0	0
0	0	0	4	45	0	0	0
0	0	0	16	67	0	0	0
0	0	0	4	55	0	0	0
0	0	0	3	10	0	0	0
0	0	0	5	8	0	0	0
0	0	0	1	4	0	0	610.9828
0	0	0	4	9	0	0	2019.703
0	0	0	12	30	0	0	1576.55
0	0	0	19	31	0	0	1355.032
4578	0	0	71	88	0	0	2793.471
4133	0	0	55	43	0	0	7613.05
3993	0	0	57	33	0	0	6519.604
3822	0	0	59	45	0	0	4184.173
2855	0	0	45	40	1	0	3566.308
1932	0	0	30	55	1	0	5227.628
0	0	0	33	57	0	0	1639.895
0	5889	0	44	63	0	0	3839.476
0	5799	0	78	124	0	0	5973.354
0	5567	0	90	160	0	0	1826.926
0	4732	0	80	107	0	0	2269.82

MODELLING FOOTBALL CROWD ATTENDANCE THROUGH MARKET MIX MODELLING- a case study

What are the key drivers of crowd attendance and to what extent are marketing and social media efforts driving increment in attendance?

Focus: Non-rival matches played at home grounds.

Dataset:
1. Media campaign spending across various social media platforms,
2. Ticket Sales from various platforms
3. Past attendance records
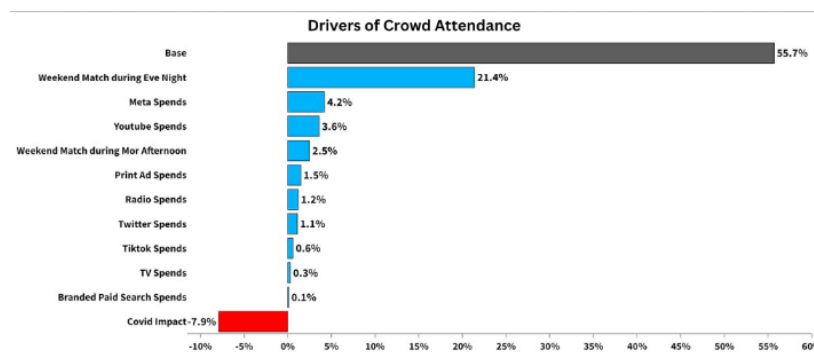4. Team performance and match outcomes
5. Weather conditions

Initial EDA

1. Media spending for both digital and offline channels was thoroughly examined. They Analyzed and studied the media spending on various platforms.
2. Streak Analysis was conducted to better understand the patterns of win/loss streaks.
3. Attendance and match results were analyzed for games between local rivals and other opponents for comparison.
4. Tickets sold through different mediums were compared.
5. Tickets sold for weekday matches were compared with weekend matches held at different times of the day.
6. New features were considered to better capture the relationship with crowd attendance such as weather conditions (rainfall), impact during Covid etc.

Modelling

After identifying the right features, they built their model using the Novel Trifecta Approach. And then calibrated using R Square, Adj R Square, MAPE, Divergence, Chebyshev's inequality, etc.

Key Insights

Drivers of Crowd Attendance

| Driver	Value
Base	55.7%
Weekend Match during Eve Night	21.4%
Meta Spends	4.2%
Youtube Spends	3.6%
Weekend Match during Mor Afternoon	2.5%
Print Ad Spends	1.5%
Radio Spends	1.2%
Twitter Spends	1.1%
Tiktok Spends	0.6%
TV Spends	0.3%
Branded Paid Search Spends	0.1%
Covid Impact	-7.9%

1. Weekend matches during the evening/night were the highest contributor to attendance. People prefer to watch games in the evening/nighttime on a weekend.

2. Among media variables, Meta and YouTube were found to be the most effective platforms in bringing incremental crowds.
3. TV spends and Branded Paid Search Spends have minimal impact and are less effective compared to other digital channels.
4. Covid during 2022, shows a huge negative impact on crowd attendance by almost 8%.

Results
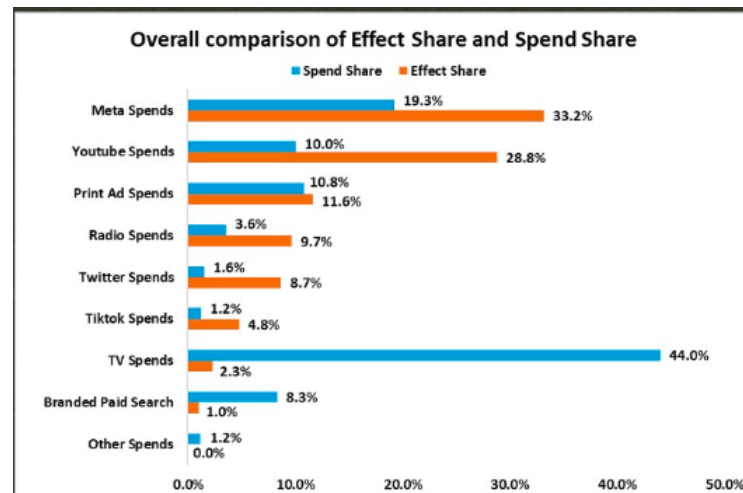
1. Media spending on various platforms (digital and non-digital) was analyzed. They computed the spend share and effect of each marketing channel.
2. Meta and YouTube Spends are the top variables showing significantly high effect shares.
3. TV Spends despite having the highest spending every year, showcases lower effectiveness.
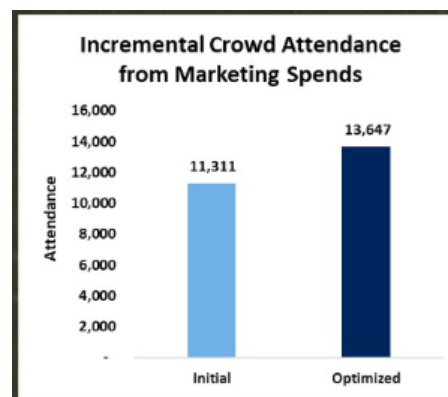
Also, they saw that with an increase of 15% in the marketing budget next season, an additional 2000 people are likely to attend the matches.
Analysing the Cost Per Acquisition (CPA) of each attendee, they saw:

Initial vs Optimized CPA: 15% Increase in Budget
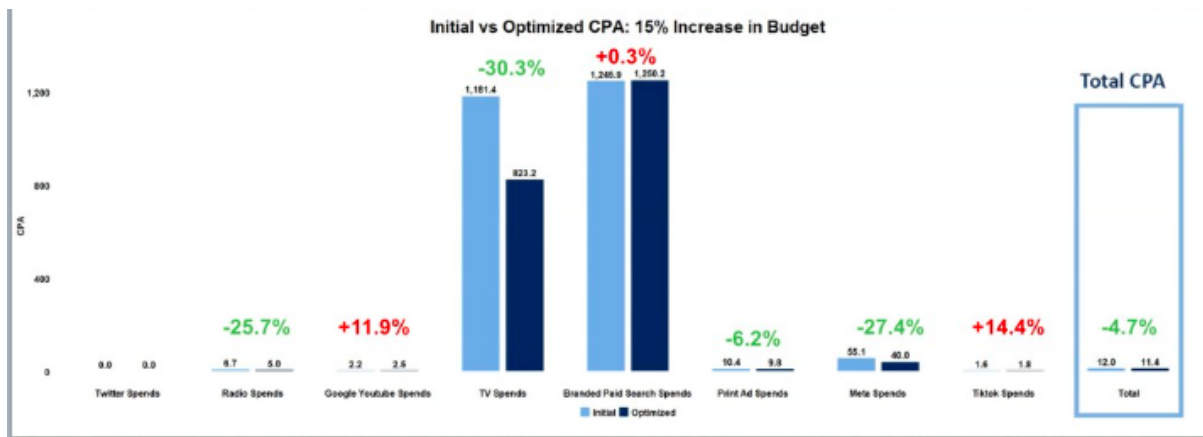
TV Spends and Meta Spends showed the most significant CPA reductions, indicating that they were the most effectively optimized channels.
Google, YouTube and TikTok spend experienced in CPA, suggesting that the additional budget did not translate to improved efficiency.

Thus, the club got to know which media channels were driving the most crowd attendance.