*International Journal of Innovation and Economic Development*
*ISSN 1849-7020 (Print)*
*ISSN 1849-7551 (Online)*

URL: https://doi.org/10.18775/ijied.1849-7551-7020.2015.86.2003
DOI: 10.18775/ijied.1849-7551-7020.2015.86.2003

*Volume 8*
*Issue 6*
*February, 2023*
*Pages 23-40*

# Marketing Education Renaissance Through Big Data Curriculum: Developing Marketing Expertise Using AI Large Language Models

Suresh Sood[1], Hugh Pattinson[2]

[1] University of Technology Sydney, Sydney Australia
[2] Western Sydney University, Sydney Australia

**Abstract:** Utilising big data sources and artificial intelligence (AI) tools with marketing activities and analysis contrast with questionnaires and small n observations, essentially creating a renaissance in marketing education. As a result, marketing education keeps pace with AI developments and ensures learners (or students) prepare for the demands of the modern marketing landscape 2025-30. The authors advocate a central focus on a big data-driven marketing curriculum for marketing education. Such a curriculum places AI and machine learning center stage to help understand, analyze and utilize large and complex marketing datasets for predictive marketing. In doing so, the potential exists for practitioners to link marketing strategy directly with marketing execution, allowing learners to use big data and AI for upstream strategy design and marketing plan development while downstream predicting the results of marketing campaigns, programs, and initiatives. But necessary changes in pedagogy are creating adaptive learning experiences breaking free from traditional assessments  In our model of learning educators enable the development of practical marketing expertise using the techniques and tools of micro-testing to nudge learners using Python data science notebooks. Overall, a renaissance in marketing education is made possible with a focus on a big data AI tools-driven curriculum. Such attention ensures learners prepare for the demands of the modern marketing landscape, moving well beyond marketing analytics using the AI technologies of Large Language Models, further expanding the use of big data Learners use role play, witnessing firsthand experiences fulfilling new hitherto emerging marketing roles  By 2025, Educators fostering a big data AI-focused marketing education curriculum ensure the next generation of AI marketers will eagerly shape the future of marketing practice and behavior with new roles combining human work with AI.

**Keywords**: Artificial Intelligence, Big Data, Large Language Models, Marketing Education, Pedagogy, Prompt Engineering

## 1. Introduction

Nowhere else is technological change so swift and beyond recognition as the discipline and practice of marketing in the workplace transform to embrace big data-driven marketing. Since the appearance of smartphones, the key driver of marketing is no longer about crafting the marketing plan driven by the human instincts of marketing managers. Instead, the management and investigation of an avalanche of customer and operational data by a cadre of marketing analysts and data scientists. The application of analytic technologies and techniques with marketing data refines and helps center the marketing activities of organizations irrespective of size, industry and online or offline presence.

By 2025, the market intelligence company IDC estimate 175 zettabytes of total data on the planet (Reinsel et al., 2018)  If available for download across an average Internet speed ( ~12

Megabits per second), “it would take you 1.8 billion years to download” (Marr, 2021)  This user-generated data comprises TikTok videos, Midjourney avatars, Reddit blog posts, Facebook clicks and likes, Instagram photos, Pinterest pins, Disqus conversations, transactions and more  Trillions of sensors are emerging (Diamandis, 2022; Bogue, 2014), complimenting the user's digital data with everyday objects communicating usage data fueling the Internet of things (Gershenfeld, Krikorian and Cohen, 2004) and further contributing to the onslaught of data engulfing the marketer  Owing to COVID, the 2025 data volume is projected to grow by over 180 zettabytes (Statista, 2022)  To give this figure some perspective, "One zettabyte is the equivalent of 36,000 years of high-definition video, which, in turn, is the equivalent of streaming Netflix's entire catalog 3,177 times” (Pappas, 2022).

What sets marketing big data apart from traditional data sources beyond the sheer volume, speed, and frequency of updates is unstructured under-utilized big data meriting new techniques for handling the data and analysis beyond traditional computing  The deluge of big unstructured data is beckoning marketers to take urgent action and embrace techniques from data science, converting the raw data to inform marketing strategy and execution  Namely, this represents "the extraction of actionable knowledge directly from data through a process of discovery, hypothesis, and analytical hypothesis analysis" (Pritzker and May, 2015) Furthermore, the data science expectation is a trending or correlation analysis over existing data using the bulk of the population (Grady, Balac and Lister, 2013)  This data science definition contrasts with Statistics representing "the deterministic causal analysis over carefully sampled data” (ibid)  Maintaining distinctions between the domains of data science, data mining, and statistics helps ensure we are emerging into a world of big data-driven marketing practice while recognizing correlation-based predictions do not necessarily mean a cause-effect relationship between variables under investigation.

The unprecedented volume and variety of data types transform marketing, products, and services. In addition, technological advances are resulting in entirely new data-driven innovations hitherto not previously witnessed. New big data sources driving innovation include telemetry data from black boxes (Sobers, 2022; Collett, 2013) for "pay as you go" car insurance  Real-time vital signals from household pets (AliveCor, 2012), Satellite imagery from a constellation of shoe-box size low earth orbiting satellites (Planet labs, 2022)  Complimenting the data innovations are the operational big data sources touching all areas of a marketing business, the big data sources are social media, email, Google searches, website data, wearables, smartphones, mobile payments, call center records from customer support and RFID tags for movement and monitoring inventory.

The previously unavailable data sources and big operational data can influence consumers' personal lives and transform industries by creating previously unforeseen opportunities. Furthermore, the advent of Large Language Models (LLMs) can potentially unleash the treasure trove of voluminous textual data in the business.

Correspondence, marketing documents and customer communications held within organizations. So, what is the nature of the marketing workflow and tasks in a big data curriculum?

# 2. Marketing Workflow, Discoveries in Data and Data Science

Immediate opportunities exist to support and encourage learners to create value from big data through a variety of marketing workflows. Enriching internal marketing data with big external data is not only limited to extracting data from popular social media networks but mining the overall WebWeb via crawling websites (Matsudaira, 2014) and considering new climate data sets and models. This includes overcoming missing or poor customer information held by marketing through external social information, e.g., university alumni databases often host poor quality information losing track of past students and benefit from sourcing professional data from LinkedIn profiles.

Investigating social media customer information extracted from existing brand or company touchpoints in terms of outlier behavior This behavior includes repeat purchasing and extreme acts of customer evangelism whereby the customer acts to support products or services as if an employee  Identifying such outliers amongst existing internal customer information helps target further supporters and influencers of the brand.

Extracting outlier customer behavior from internal marketing sources and company touchpoints, including customer service call centers and matching with similar or like-minded consumers found online in social brand pages and communities. This workflow is the reverse of commencing with social media first and enriching with customer information. Here, the process commences with internal customer information and matches customers found online on social.

Migration of the CRM to a social CRM providing support of ongoing conversations with and between consumers while handling conversational data appearing on social networks as part of the call center workflows. This information includes audio, blog posts, geolocation, likes, maps, short messages, tags, ratings, text and video. Transforming existing customer-facing processes by moving to online conversational processes using commonly found social media environments or a white label (own brand) community.

Integrating new information sources not previously available uncovering any correlations with marketing activities and subsequent outcomes. For example, the fusion of earthquake data relevant to retail shopping transactions helps present marketers with accurate predictions considering past damage to buildings and loss of life. Such a scenario forms the basis of a qualitative study exploring consumer shopping behavior in Christchurch, New Zealand, after major earthquakes in 2010 (Ballentine, Parsons and Zafar, 2014). Another unrelated but New Zealand story using interesting correlations is the ANZ research "tachometer" using heavy traffic as a predictor of the GDP directionality 6 months before the officially available data (Zollner, 2018).

**2.1 Marketing Discoveries in Data**

As big data enriches existing marketing data by detecting correlations with marketing activities, a marketing discovery process helps to extract meaningful value through exploring, analyzing, manipulating, interpreting and visualizing data. Unfortunately, such a discovery process often confuses the analytics approach with tools, including Microsoft Power BI or Salesforce.

Tableau  A 17-step discovery in big data process (table 1) is agnostic of the data type, including astrological, earthquake, traffic or social media. This approach helps marketers make discoveries from the data complimenting the hypothesis method driven by the strategic marketing questions frequently asked to help uncover the where, how and when to compete for. The "where" might look to validation of shopper types or segments in the data as comprising brand loyal, grab and go, browser or value. In the case of the discovery-driven process, the marketer as marketing investigator seeks to enrich the customer data with social media behavior data representing customer activity sequences prior to purchase events. This allows the discovery of hidden segments from the bottom up.

**Table 1**: Marketing Discoveries in Data Process (Steps 1-17)

| Step | Description |
|---|---|
| 1 | Select data sources for marketing discovery |
| 2 | Evaluate data sources, including ownership and provenance |
| 3 | Securely record any personal identifier information (PII) in the data |
| 4 | Determine the type and size of the raw data set for discovery |
| 5 | Use data in situ and online without transferring to another system |
| 6 | If the data set includes unstructured data and the intention exists to analyze the entire dataset rather than sampling, use cloud infrastructure for data acquisition and analysis |
| 7 | Select a processing framework to suit the data set |
| 8 | Prepare data (cleansing, missing data and anonymization excluding PII) |
| 9 | Marketing analyst conducts data exploration |
| 10 | Explore the entire dataset with exploratory visualization, noting any visual representations helpful in "telling the story". |
| 11 | Marketing analyst codes additional knowledge using different colors for different or similar behavioral groups of known origins |
| 12 | Exploratory visualization technique using complex systems representation, e.g., node and link with color coding of knowledge |
| 13 | Communicate knowledge gained from visualization patterns to the marketing team or use it to assist decisions about the development of a hypothesis |
| 14 | Ad hoc exploration of raw data slicing and dicing |
| 15 | Analyst commences with data science extracting value trapped in the entire big data set commencing with correlations and cycling through various algorithms based on machine learning, mathematics, and statistical techniques. |
| 16 | Communicate the story of the value extracted from the data |
| 17 | Setup relevant reporting to monitor interpretation and value delivered |

By following these steps, marketers and learners can effectively extract valuable patterns from data and communicate their findings to a marketing operations team. Some of these steps may require expertise in data science. However, using open-source Python Scikit-learn (Pedregosa et al., 2011) and Jupyter notebooks combining actual code, visualizations and narrative text providing a step-by-step explanation of the process helps alleviate the need for deep knowledge regarding the data science algorithms.

Data science contributes machine-learning techniques (table 1, step 15) to discover complex correlations and patterns scattered across many sources of disparate data representing a variety of consumer touch points online and offline. For example, interesting patterns are hidden amongst the social media-enriched data. For example, the weblog files provide the opportunity of understanding the common factors leading up to the purchase rather than after the event. However, with the new marketing workflows, the mindset of the marketer must change to a forward or predictive-looking mindset or risk being awash in a variety of big marketing data. Rather than seeking laws or generalizations in marketing activities, big data correlations help accelerate actions from the data and provide predictive power for the marketer to detect when consumers are not following typical patterns or habits. Focusing on the next best actions requires a deeper causal analysis rather than depending on correlation alone.

# 3. The Transformation of the Marketing Mindset To Predictive Marketing

The consumer's mind is frequently the focus of marketing academics and researchers, with attention given to the subconscious mind (Zaltman 2003)  However, a lack of research exists to understand the marketer's cognition  Furthermore, the problem is compounded when focusing attention on a subset of the mental processes including marketing decision making our attention is drawn to a variety of consumer decision-making processes and attempts to understand from the perspective of the inner mind of the consumer how purchase decisions are made (Fernandez 2012)  Much of the research attempts to get inside the marketer's mind and challenge the mental marketing models that emerge from the last century (Wind 2009a, 2009b, 2008, 2007, 2005, 2000, 1996, 1986,1981a, 1967)  Big data has significant implications for marketing decision-making (Lloyd 2013) but remains relatively unexplored in a systematic fashion within marketing circles yet of central interest to software vendors (SAS 2013)  One thing is certain the shift away from "gut feel marketing" of the last century is well underway (Spenner and Bird 2012; Ogden-Barnes and Lowther 2012) under the auspices of big data as a key driving force in the future of marketing (Court et al. 2013)  Machine learning algorithms trained on relevant marketing data generate models for marketing predictions.

Many studies in big data point to a scarcity of marketing data scientists (Hess, 2019; McKinsey Global Institute, 2011) required for building predictive models for marketing across various industries and roles. Despite the talent shortage, the use of recommender systems using algorithms built on crowdsourcing to recommend based on "you may also like" books, movies, music, and a plethora of other goods and services continually lies at the heart of market leaders Amazon, Netflix and Pandora  Google pioneers the correlation of search engine queries as a predictor (Mohebbi et al., 2011) marrying intentionality amongst consumers (the crowd) from search terms with real-world trends  This includes an ability to predict the onset of flu viruses, sales of cars, tourists and even major shifts in stock markets  Google is not alone in predictive power with the Twitter data more completely or

Fully formed concerning meaning than the typical search engine query. Furthermore, Twitter users are passive participants in natural settings. Twitter studies of word usage and speed of appearance of words helps stock market predictions (Grossman 2010), movie successes shortly after box office release (Asur and Huberman 2010) and crime prediction (Lever 2014)  But ignoring causality or, in effect, ignoring any theoretical underpinning or common sense to the correlation of past data with future is not without problems and detractors, as seen from "a study of Google's much-hyped flu tracker [Google Flu Trends monitors web searches associated with flu activity, e.g., cough, fever and common cold] has consistently overestimated flu cases in the US [United States] for years  It's a failure highlighting the danger of relying on big data technologies" (Hodson 2014)  However, as a signal acting as a proxy for flu and used by others as an innovative source, the Google Flu Trends method is a success in finding correlations, albeit at a point in time with "the initial Nature paper describing the experiment now has over 1,000 citations in many different fields" (Madrigal 2014)  Suppose marketers have access to sensible correlations within their sphere of interest. In that case, the dependency on gut feeling might change drastically because "marketers depend on data for just 11% of all customer-related decisions" (Spenner & Bird, 2012). The pace of software technologies making available predictive models for marketers at the push of a button is accelerating, not decreasing, with a requirement to have access to marketing analysts rather than just data scientists with great analytical skills and the ability to develop new algorithms from scratch. This trend of push-button analytics is emergent with a range of online analytics services and ongoing releases of popular Business Intelligence tools such as Microsoft's Power BI, Google Looker and Amazon QuickSight. But the judgment of the marketer in natural settings within time and informational constraints (Klein, 2008) still has a relevant role to play "…where the model fails, managerial intuition can add significant value..." (Boyde, 2013) and "the best predictions in a highly uncertain context came from mixing human and computer input…" (Seifert & Hadida, 2013) In light of this, the key opportunity lies in understanding how the marketer evolves her mindset to transform marketing to deal with a world with push-button predictive marketing available at the fingertips. Does this nudge the marketer to behave proactively, directly impacting customer outcomes? What are the new predictive marketing activities benefiting from big data correlations? What is the emerging organizational form in the future focusing on the stream of marketing data? How should the marketer conduct activities in a predictive world? What is the role of strategy in influencing marketing? Such questions help learners reflect upon the future role of marketing.

# 4. Putting Humanity Back into Marketing: Large-Scale Social Media Marketing

Statistical techniques are useful for testing the big data infrastructure and workings of predictive models. However, big data modeling and study at an entire population scale level provide a capability for understanding human behavior. Indeed, the model development is dependent on the behavior data available to individual customers. Historically, Facebook provides details of friendships and "things" liked contrasting with Twitter providing access to unconscious thinking, with LinkedIn sharing professional insights and contacts across entire industries. Never has such information been available at a population scale and even at a distance. Understanding customer behavior through an online search, social media interactions and the subsequent capture and visualization using data science techniques.

Opens the marketer to entirely new opportunities with the presence of behavioural big data Imagine the possibilities when the psychological state of a customer is understood at the time of the email, Tweet or Facebook post Knowing the customer's satisfaction with the service allows the marketer to improve customer acquisition levels or retention Similarly, a customer in distress helps to focus greater attention at the touch point and results in a satisfying interaction From a predictive viewpoint, the pre-purchase signals include intent during moments of "wow" or "aha" at a cashier checkout queue, Facebook brand pages or navigating the supermarket aisles, provides the ability to influence the purchase in leading up to and at the zero moments of truth (Lecinski 2011) These micro-moments in marketing (McLaughlin 2022) provide marketers signals to help reach out and satisfy the consumer's wants at precisely the moment of "I want" with education snippets as part of "how to videos" where to buy or ingredients.

Posts on social media help bridge the Language to the thoughts and feelings of consumers Psychological insights or patterns of thought, including happiness and deceit at the time of writing the post, are available through tracking the frequency of linguistic markers, otherwise specific category words using the popular psychology software tool linguistic inquiry and word count (LIWC; Pennebaker et al. 2007) and supporting word categories This simple word-counting software is readily applicable to big data sets The classification of Tweets by LIWC helps marketers understand the mindset of individuals at the time of messaging and apply suitable marketing interventions at a distance from the community represented by the Tweeters For example, a population exhibiting sadness might benefit from an intervention by a brand owner to provide flowers, candles, scents or a free pass to a flower show This is supported by visitors to the Auckland Flower Festival tweeting the terms "unbelievable", "OMG," or "wow," revealing the positive feelings occurring within the space of the flower show (Sood, 2011) In sharp contrast but using similar word counting techniques, the deceitful or misleading posts are recognizable from linguistic cues suggestive of fabricating and withholding information (Clikeman 2012) These techniques help pinpoint potential images on Instagram and Vine using hashtags and comments worthy of further investigation.

The use of Instagram as a source of data directly contributes to an understanding of the common trajectories consumers follow This is based on extracting the geolocation captured by the consumer's mobile phone when taking the picture and uploaded to a popular social network The popular trajectory patterns enhance the predictive capability by knowing the popular locations mobile phone users visit at some time in the future Existing research further strengthens the predictive possibilities inherent in the regularity of users with "a potential 93% average predictability in user mobility, an exceptionally high value rooted in the inherent regularity of human behaviour Yet it is not the 93% predictability that we find the most surprising Rather, it is the lack of variability in predictability across the population" (Song et al. 2010) Even more so, research shows "it is possible to predict the location of a wide variety of hundreds of subjects even years into the future and with high accuracy" (Sadilek and Krumm 2012) Such predictive capability helps make decisions around influencing consumers through advertising within the consumer location's context.

Marketing based on social media data sets is, in effect, big data marketing in people's daily lives. Hence, social media data has the potential to dramatically enrich marketing data and activities. Through Twitter and Instagram experiments, marketers are introduced to the value of mobile social media data, the data science of conducting such experiments involving the acquisition of big data, storage in non-traditional databases (NoSQL) and the use of open-source software to extract marketing knowledge from the social media conversations using machine learning techniques or humans to recognize valuable insights These experiments help formulate a data science marketing approach while harnessing the power of social media data.

Large-scale social marketing experiments for good with sharing and transparency of results represent an important tool in sharpening marketing activities in an ever-fragmenting global marketplace. Previous attempts at such experiments manipulate news feeds aiming to see impacts on emotions (Booth, 2014). Such experiments, when conducted transparently, contribute towards understanding effective marketing channels, predictive personalization of consumer brand experience and behavioral targeting. However, the major challenges for the future include the privacy of data, handling of non-English consumers and the ability of marketers to support and act on big data sets for marketing actions. These issues provide a potential agenda for future exploration and a roadmap for marketers exploring the convergence of big data and marketing to achieve marketing insights.

With big data increasingly important in marketing, organizations seek individuals with analytic skills to create value for their company and society. However, individuals must possess data literacy and knowledge of new tools and techniques before organizations can process the data and generate data-driven decision-making or evidence-based solutions. Importantly, much of the big unstructured data cannot be easily organized into tables or Excel sheets. This unstructured data includes tweets, videos, photographs, and vast troves of unexploited text that can be found within organizations and on the Internet.

# 5. Emergence of Large Language Model Artificial Intelligence

“Software is eating the world” (Andreessen 2011), but now “AI is going to eat software” (Huang 2017) is the promise being made good by Large Language Models (LLMs) Not only can LLMs understand languages, but are capable of understanding and generating software code In LLMs “Large” designates multi-billion parameter Language Models These models are probability distributions over sequences of words trained from vast amounts of multilingual text data and images The underlying statistical representation helps automatically complete a story by predicting the most likely text Considering this, the output from an LLM may appear to be an appropriate answer, plausible and verbose but not necessarily factually correct The GPT-3 LLM is pre-trained on text from the large datasets of Common Crawl representing a decade of crawling the WebWeb and billions of web pages, WebText2 captures text from Reddit links, Books1/Books2 are two internet book corpora, and Wikipedia covers all English pages An example open-source database for training LLMs is 800GB in size and is commonly called the “Pile," comprising 0.5 trillion words taken from academic, Internet, prose and dialogue (Gao, 2020) For software code generation and understanding, the “Stack’” is a 3.1 TB dataset consisting of permissively licensed source code in 30 programming languages (Kocetkov,2022).

LLMs are artificial intelligence software transforming Natural Language Processing (NLP) tasks, such as reading, summarising, translating, answering questions, generating sentences, speech recognition and translation. LLMs are generative being able to generate text based on an input prompt. Some have suggested that fluent conversational responses prove the system's being sentient (Kabir, 2022). Owing to the large amounts of data (text, speech, video or images) for pre-training LLMs demanding requirements exist for computing infrastructure, and very few organizations develop LLMs from scratch. Hence, the LLMs are primarily developed by major American and Chinese organizations, as seen from GPT-3 and WuDao 2.0. Even access to LLMs for industry and research is very limiting while major organizations, for example, Microsoft, license GPT-3.

According to Allied Market Research (AMR; 2023), the 2030 market for natural language processing is valued at $341.5 billion growing at a staggering annual growth rate of 41% from 2021 to 2030, driven predominantly by LLMs The market opportunity is driving the growth of commercial LLMs, including Open AI (GPT3), Cohere and GooseAI Open source LLMs are EleutherAI, both Meta’s NLLB (No Language Left Behind) and Blenderbot, to mention but a few Chat GPT, or Generative Pre-trained Transformer model trained on vast swathes of internet data to generate any type of text The growth of LLMs is driving an ecosystem of tools for end users and developers with playgrounds (no-code environments), prompt engineering and notebooks helping with adoption into enterprise workflows and a multitude of use cases The process of specializing or fine tuning a model is very much less intensive in data and computing Using smaller data sets labeled for specific tasks is what individual organizations can do beyond accessing a pre-trained LLM. LLMs can even be repurposed and conditioned on audio podcasts or visual input from YouTube or other sources and fine-tuned for specific tasks, such as generating video narration or podcast transcripts. In addition, various LLMs are trained to use tools such as spreadsheets or Business Intelligence while observing and interacting with a web browser. As a result, over time, marketers will no longer require understanding the intricate details of software code or the keystrokes to access tool functionality but instead, communicate and leverage the tools using the knowledge inherent within LLMs through plain English prompts or questions ChatGPT builds on the LLM developed by OpenAI, GPT-3.5 with a chatbot environment and captures the imagination of the public with YouTube videos showing how to automatically generate YouTube video scripts, software code for Excel, Power BI or Python as well as money making ideas.

### 5.1 The Importance of Prompt Engineering and Marketing

To fully leverage the power of artificial intelligence (AI) and Large language models (LLMs, e.g., ChatGPT) requires further insights into how humans use Prompt technology engineering to instruct the AI to do a task with a few sentences or lines. The prompts represent the models' inputs, and "giving better instructions gets better results" (Seth, 2022). From 2025 and beyond, the expectation is AI techniques will replace prompt engineering.

Many different LLMs exist, even from individual research laboratories such as Open AI, including software code-related models and models providing other text functions, e.g., text to video, text to music (MusicLM; Agostinelli et al., 2023) Pricing varies between models and is dependent on the number of tokens (words) consumed for input and output generated So, for basic pattern recognition tasks, we can use many open-source models on the Hugging Face Hub (https://huggingface.co/) Each model has temperature settings helping determine the randomness of the output A temperature setting of zero ensures the model output is deterministic and generates the same completion output each time rather than a random output Creative writing tasks merit a temperature setting of 0.75 to 1.0 depending upon the prompt and generate surprising results without less stringent control Other variables include the max length setting, determining the maximum size of input prompts and output length in words available Frequency and presence penalties can be useful for having the AI minimize repetition or encourage novelty by increasing frequency of new topics.

Prompts vary in complexity from a phrase to a question, even including multiple paragraphs of text. The most value created through prompting is understanding how to put together prompts to ensure quality or good output Extracting value from LLMs for professionals and learners is about writing prompts. Changing prompts even slightly can have a dramatic impact on the output. For example, how does one generate prompts for any task to yield the best results? A key method for prompts includes setting the role or personality. In this type of prompt, the AI persona is likely set as a marketer before commencing a conversation with questions. An alternative to ChatGPT, the ChatSonic AI (https://app.writesonic.com/) includes a dozen preset roles, e.g., English teacher, careers advisor, lawyer, interviewer, accountant and even a stand-up comedian and travel guide ChatGPT automatically sets itself into a personal assistant or friendly bot mode supporting general AI.

Using adjectives such as friendly, chatty, creative or even clever helps provide more context and a better understanding of the question. Left without humanistic prompts, the output typically resembles a textbook answer Another key approach to prompting is the Shot (zero, one and few) Zero-Shot uses AI for autocompletion and, after a few words, attempts to complete the input Ideal for simple prompts and queries, e.g., What is… Combining roles with one-shot prompting guides the structure, e.g., Q&A. Suggesting a role of a friendly marketer and providing a typical single Q&A, the AI uses the example to match the answer to the right tone.

Few Shot prompts expect more than a single example. This type of prompt is suitable for generating a list of ideas, e.g., different ways to generate leads. The better the few examples, the better the output. The AI looks at the role prompt provided (if any) and works through all the examples before responding. Example questions help provide the tone of voice, structure and length. Examples help guide the type of results. If expanding on the answers to the length of a paragraph, the response will likely be of a similar length. Shot models work well with LLMs as these models are pattern-generation machines (Ottley, 2023). One final method of prompting meriting discussion is the "Chain of Thought Prompting" (Huang & Chang, 2022).

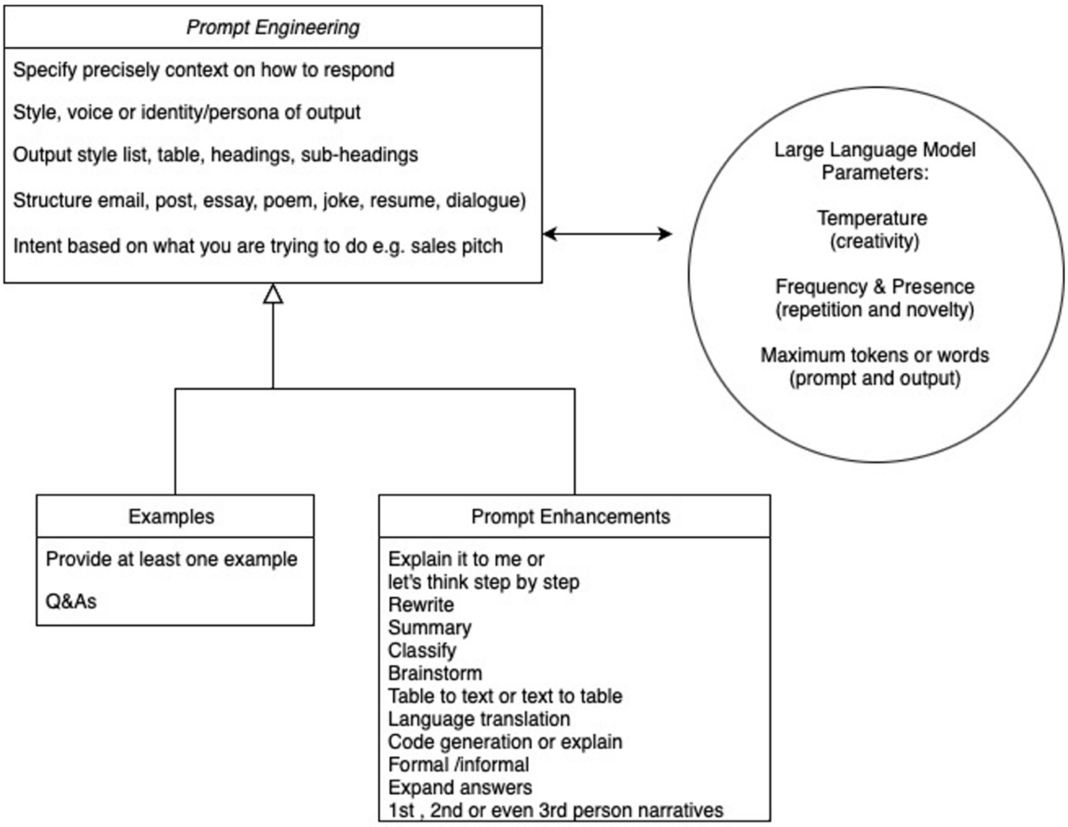


**Figure 1:** Google Colab Notebook: Combines Code, Visual Output & Text Supporting Interplay of Lecture and Tutorial

Teasing out of the model the reasons for the answers step by step helps provide transparency regarding the output by asking, “4Explain the thinking…”, “Think step by step...” Or “Explain it to me like a five-year-old child” Finally, prompt guidelines and handbooks are emerging for marketing to assist online consumers or marketing content developers for tailoring content for the business (Penn, 2023) encourages human interaction and engagement to help generate explicit reasoning rather than simply focusing on the answers.

**5.2 LLM-Driven Strategy, Marketing Planning and Execution Curriculum**

Big data readily assist marketers with Business intelligence as part of downstream marketing tasks One has only to look at the plethora of vendors, online MOOCs and university marketing analytics courses to see this focus LLMs are game-changers and provide a mechanism to inject AI into upstream marketing planning where such AI-driven capability is scarce in practice and academia The impediment to marketing planning are a key challenge The impediments commence with learners and marketers unable to fully operationalize recommendations arising from marketing analyses Workshops and classrooms are capable of delivering SWOTs, competitive positioning, and segments but often fall short on explaining or executing associating sales and tactical programs (Simkin, 2000) Intense competition, multiple channels, meager budgets and customer data privacy arise as the inhibitors Strategy development and analyses require careful consideration, scenario planning for marketing action workshops (Pattinson and Sood, 2009) and strategic recommendations for implementing tactical programs from advertising campaigns to focusing on revenue and brand development are often well thought But, a major bottleneck is beyond the analysis, strategy and program sequences to ensure plans are actioned (Cravens, Piercy and Prentice 2000).

Yet, one of the best strategic investments an organization can make is to directly impact the process around marketing planning, "The quality of managerial decision making is the single most determining factor for the success of marketing management... it is the marketing decision maker who has to evaluate the alternatives, judge the evidence and uncertainties, and decide on the marketing policy and marketing instruments" (Wierenga, 2011) Any upstream improvements are significant "raising a company's game from the bottom to the top quartile on the decision-making process improved its ROI by 6.9 percentage points" (Lovallo & Sibony, 2010).

Surprisingly, conducting marketing planning has stayed the same over a quarter of a century, "The effective allocation and coordination of marketing resources to accomplish the organisation's objectives within a specific product market As such, marketing strategy decisions involve specifying the target-market segment(s) to be pursued and the product line to be offered" (Zinkhan and Pereira, 1994) Into this landscape of strategy development, marketing planning and execution, LLMs fit like a glove Conducting analysis not only internally but on competitors and an overall market analysis requires considerable time to read plans, web pages and an evaluation Marketers employing LLMs in the planning environment and using prompt engineering can have the LLM learn from planning-related tasks and internal company textual data A user of the LLM can process and analyze company strengths (S) and weaknesses (W) while evaluating and analyzing the external opportunities (O) and threats (T) via a conversational dialogue Any user from within any company area can generate a full dialogue driven automated SWOT suitable for action The same LLM can, with relevant prompts, handle upstream planning activities such as ingesting the strategy to a fine level of textual detail while downstream generating the copy and imagery for campaigns aligning with the overall marketing and brand development strategy By allowing access to previous campaign text and performance measures, a prediction well.

In advance of running the campaign is achievable. Predicting and fine-tuning the narrative copy, including creatives and channel placements, helps optimize the marketing mix. While not a comprehensive discussion, using LLMs is a game changer for all aspects of marketing, including business intelligence dashboards to monitor the success of the automatically generating campaigns. Using a specific tool or application and having keystroke familiarity is moving to obsolescence, replaced by natural language interactions with an LLM As we near 2025, envisaging a standalone LLM operating as a universal marketing engine connecting AI-driven strategy narratives to campaign execution in real-time is a distinct reality The key is ensuring the marketing learner is aware of AI and deeply engages with LLMs, augmenting human decision-making for marketing practice.

**5.3 Changing Pedagogy - Adaptive Learning Experiences for AI Marketing**

Much debate exists regarding using LLMs in academia, focusing on ChatGPT. Some institutions such as Australia's Group of 8 are updating the academic integrity policy to consider "content generated using artificial intelligence," much like cheating websites (Panagopoulos, 2022). Yet, this seems at odds with the desire to foster innovative marketing skills for a new generation of learners using AI in the workplace. No doubt, the nature of assessments, such as essay writing or summarising academic publications, will change over time to oral presentations and reflections in the learner's own words sidestepping the use of LLMs in completing assessments.

A big data marketing course's innovation and entrepreneurship components are self-evident in a world of predictive analytics, allowing marketers to exercise a forward-looking entrepreneurial mindset when working on marketing activities. However, not as apparent but a central tenant of the proposed AI marketing course are the major risks associated with the use of LLMs Key research papers (Bender and Gebru et al., 2020; Weidinger et al., 2021) and many more point the way to the potential risks Such risks include (but not limited to) cultural risk resulting in social biases and stereotyping, toxicity meaning offensive and harmful content is generated. Misinformation providing misleading content  Significant time (30% of the course) devoted to hands-on LLMs and exercises about illuminating risks and remedies where available. Educators often exhibit caution about tools regarding pedagogy of higher importance to the actual selection of tools. A complete reversal is necessary or, at the very least, requires consideration to teach differently in AI and LLMs. For example, learners can use LLMs to generate essays, answer questions on any topic, summarise complex papers, and appear like marketing experts through role prompting (see section 4.1). In light of this, existing teaching practices and engaging with learners require significant revision or rethinking.

Tutorials provide learners with hands-on tools and are inevitably separate from a theory class, lecture or discussion  With the availability of Jupyter or Google Colab notebooks (see Figure 2) combining text, images, video and live software code within a single web page, the tutorial and lecture come together as one artefact  The multimedia artifact allows the educator to move back and forth between tutorial examples to "show and tell" the theory or concepts  This interactivity can occur online or offline and overcomes a major limitation of separately resourcing tutorials  Combining the interactive use of notebooks with flipped classroom models (Hamden et al., 2013; Lage et al., 2000) further drives the need to create adaptive learning experiences fostering the learning of major concepts and a critical perspective about the risks present in using LLMs  At the same time, while counterintuitive, encouraging learners to use LLMs and other tools in the classroom while documenting reflections of the AI "aha" moments, good and bad  Group projects using LLMs encourage collaboration between learners to provide an authentic, actionable output. The course convenor on the output from the LLM will lead to constructive criticism of the production under discussion, including any inherent biases. In addition, encouraging the learner to provide correct attribution and formal quotes of ideas from recent research papers further highlights shortcomings in the output from LLMs.

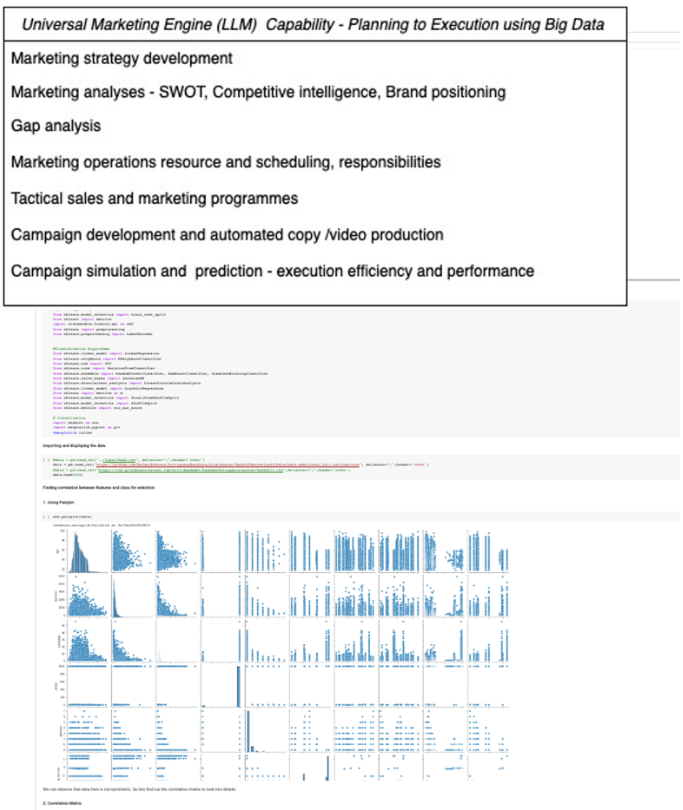


**Figure 2:** Universal Marketing Engine: Planning to Execution Using Big Data

**5.4 Conclusion and Future Studies**
Classroom or online learning about marketing must focus on using AI for real marketing activities. For the first time, we can have a single engine or environment (LLM) capable of using big data sets tuned to marketing activities covering the development of marketing strategies, recommendation of tactical sales and marketing programs, marketing analytics for measuring long and short-term marketing performance, auto correcting and writing copy with visual imagery for a new campaign, predict the campaign performance prior to execution.

Practitioner or learner uses several tools covering project management, analytics, email, CRM and content creation. Such tools exclude any automation of marketing strategy analyses as they are still nascent. However, with the advent of LLMs, the tool selection is no longer a limitation, with LLMs able to generate unlimited marketing analyses, develop software code, predict the impact of campaigns and execute at a button press on demand.

Here is the ideal yet universal marketing engine and tool for developing new pedagogical innovations alongside the AI-driven big data marketing curriculum, Not only aiding the development of AI marketers directly with marketing planning but helping a new generation of learning specialists grow through embracing the technology of LLMs in parallel with learners for teaching.

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