Inter IIT Tech-Meet 11.0

Cognitive Garage-Easy Automation of Complex Decision Making

Primary Team ID - 55

Index

IDEA IN BRIEF		
PROBLEM	**CAUSE**	**SOLUTION**
Inefficiency and lack of personalisation in consumer incentive design	• Inefficient handling of vast library of parameters • Lack of robustness against noise in consumer data for incentive analysis	• Use of 3 layered buckets i.e. consumer, product purchase and consumer centric parameters in a bayesian network • Incentive is presented under 4 sections: type, value, when in consumer journey to deliver, platform (where to deliver)

1. Understanding the Use Case: Incentive design for Consumers

Incentive in simple terms is something that **encourages** a person or organization to do or achieve something. It is something that incites or has a tendency to **incite a determination**. Incentive design for consumers refers to the creation of financial or non-financial incentives that encourage consumers to make **certain decisions, purchase certain products, or adopt certain behaviors.**

Incentive design can take many forms, such as **discounts, loyalty programs, reward points, cashback,** etc. For example, a retailer might offer a discount on a product to encourage consumers to purchase it, or a mobile phone company might offer a loyalty program with rewards for customers who make a certain number of purchases or refer new customers.

The goal of incentive design is to **align the interests of consumers and organizations** by providing rewards that incentivize desired behaviors. It can also be used to **encourage environmentally sustainable behavior**, such as recycling, energy conservation, and reducing carbon emissions.

1.1 Why is Consumer Incentive design a decision worth automating?

Incentives are not only methods in which to draw new audiences, but they also **lie at the heart of loyalty programs**. The case for **creating, sustaining, and even ramping up** a loyalty program is evidenced by the fact that 40% of revenue comes from **returning or repeat purchasers.** Incentive design can be an effective way to **change consumer behavior**, but it must be **carefully designed** to ensure that the incentives are **well understood** and that the benefits to consumers are clear. Additionally, incentive programs must be designed in a way that is **fair, transparent, and sustainable** for both consumers and organizations. Some of the key benefits of **designing the right incentives** for consumers are:

- **Incentives Are Necessary to Compete in Today's Market:** As of the last Incentive Federation tally, 84% of U.S. businesses were using non-cash incentives. Amazon found only **7% of** consumers **could not be swayed** to a brand after receiving an incentivized offer.
- **Incentives Boost Conversion Rates**: Previous customers who have signed up for a rewards program are primed and ready to purchase. The **chance of selling** to an existing customer is 60-70%, compared to **5-20% for a new customer.**
- **Incentives Generate Reviews and Referrals:** Positive reviews are crucial to the success of businesses these days, considering **90% of shoppers** read at least one review before making a purchase. After receiving a brand incentive, 75% made another purchase, and **50% discussed** their experience with others (referrals!).
- **Incentives Drive Engagement and Cultivate Long-Term Brand Loyalty:** Rewards transform the way shoppers interact with brands. After receiving a reward, 70% visit the brand's retail locations, **40% follow them** on social media, and **35% go on to view** other branded content.
- **Incentives Make it Easier to Collect Data and Personalize Content:** Typically, a shopper **may be wary** of giving out personal information, such as demographic-related details, address, phone number, email address, or preferences. However, when incentivized to do so, 87% of loyalty members and more than **50% of general consumers** don't think twice about it because they know providing this information will result in a **reward, tailored recommendations, and better customer service.**

As evident from the findings above, it is clear beyond doubt that **designing incentives** for **consumers** specifically will work as a better use case given the **complexity of the decision involved** and the **magnitude of impact** automating it stands to create.

1.2 Why consumer incentive design for digitally native brands?

A digitally native brand is a business that originated online. In contrast to beginning as brick-and-mortar businesses, these brands started online and grew their brand through their online store experience. For digitally native companies that **forge a data-backed**, **D2C model**, personalization isn't just how they market, it's how they should operate.

Advantages of using digitally-native brands

- **High customer relationship:** DNBs own product development and customer transactions lead to great strength in customer receptivity
- **1st party data:** Customer decisions at DNB are driven by 1st party data which powers decision making leading to more empathetic incentives

Impact of increase in revenue by the personalization-driven incentive structure

- Companies without direct relationship(eg, CPG): 5-10%
- Brick and mortar(eg, grocery, apparel): 10-20%
- **Digitally native brands(eg, e-commerce): *25%***

"I really liked the idea of automating the incentive design system and also the list of parameters seems pretty exhaustive. There is a growing need for personalization of incentives in the industry and if implemented and bring about a significant impact, especially for retention of customers. "

-**Prof. Anuj Kapoor, IIM-A**.Expert in Quantitative Marketing)

2. Current Market

2.1 Market Analysis

- **45% of consumers** **made one to three** purchases because of incentives in the past year while **18%** of consumers say incentives always **sway them to choose one brand** over another, even if they're loyal to the brand without rewards.
- The size of the consumer incentive design market has been **steadily growing**, driven by **increased demand for personalized** and **technology-driven** incentives.
- According to a report by Markets&Markets, the global market size of the consumer incentives market is expected to reach **USD 42.14 billion by 2023**, growing at a **CAGR of 7.6%** from **2018 to 2023**.
- The **growth potential** of the consumer incentives market is driven by factors such as the increasing need for **customer retention and engagement,** the **growth of e-commerce**, and the growing importance of **data-driven decision-making** in business.

2.2 Types of Incentive Design Methodology:

a. **Based on the segmentation of consumers:**

   i) Cohort based:

   - This approach groups customers into cohorts based on **similar characteristics**, such as **age, location, or purchase history**.
   - Incentives are then designed to **target** the specific **needs and motivations of each cohort**.

   ii) Personalized:

   - This approach focuses on **tailoring incentives** to individual customers based on their **unique characteristics**, such as their **past behaviour, demographics, or preferences**.
   - Personalized incentives are designed to address the **specific needs and motivations** of each customer, which can result in **increased customer engagement and loyalty.**

   Research has shown that **personalized incentives** are **more effective** than cohort-based incentives in **driving customer behaviour**. For example, a study by Accenture found that personalized incentives increased conversion rates by an **average of 14.5%,** while cohort-based incentives only increased **conversion rates by 4.5%.**

b. **Based on the desired outcome:**

   i) Push incentives:

   - Push incentives are designed to encourage intermediaries, such as wholesalers and retailers, to carry and promote a product.

- These can include Trade discounts and allowances Marketing and advertising support, Point-of-sale promotions, Joint marketing initiatives, and Co-op advertising programs.

ii) Pull incentives:

- Pull incentives, on the other hand, are designed to directly encourage consumers to purchase a product.
- These can include Coupons and rebates, Loyalty and reward programs, Contests and sweepstakes, Sampling and trial programs, Referral programs, etc.
- The choice of which type of incentive to use depends on various factors, such as the **target market, product positioning, and marketing objectives.**
- Pull incentives are typically used when there is a need to **generate immediate demand**, while push incentives are used when there is a need to build **long-term demand** through intermediaries.

3. Identifying complex decisions involved in the incentive design process

Given, the emphasis of digitally native brands over the consumer funnel to categorize activities and drive sales through it. The understanding of decision-making aspects can be derived from considering caveats of the consumer journey.

3.1 Analysis of the existing consumer user journey

We have analyzed what gaps exist between the expectations of the customers and the service provided by the company for each mode in the customer journey and how to overcome them.

Mode	Customer Needs	Gaps Identified	Company's offerings
Discovery (Automated) **Incentive**: Trials/Demo	Consumer expects a **seamless onboarding process** with exclusive rewards for use		No incentives; **Trials on services** not relevant to consumer
Exploration (Semi-Automated/Cohort) **Incentive**: First Buy Offer, Coupons, Discounts, BOGO	Expects personalized incentives on **relevant product categories** based on **personal interest** and needs		**A one-size-fits-all approach** which may hit its mark with some users but misses it with most
Purchases (Semi-Automated/Cohort) **Incentive**: Free Shipping, Cashback, Points	Wishes to get **free shipping**, points or cashback during purchase based on user psychology		Offerings vary because of industries/brands with no consistency in incentives being provided
Loyalty (Semi-Automated/Personalized) **Incentive:** Loyalty Programs, Tiered rewards. Gift cards	Expects his loyalty to be rewarded in kind by **preferential offers** and exclusive membership		**Unstructured and unempathetic** Loyalty programs offered
Advocacy (Automated/Cohort) **Incentive:** Referrals	Longs for rewards for **prolonged association** and promotion of select brands and the company		Provides referral programs even from the first stage of the user journey (Discovery)

Lack of Personalization (Incentives offered; User Experience)

Increased Time Complexity

Not in line with Company's goals and financials

Ineffective Adaptability to market trends

Improper Incentive Placement

3.2 Gaps identified in the incentives offered by the company

1. **Lack of personalization in incentives offered and user experience.**
    - The **surge in online interactions** since the onset of the pandemic escalated expectations—giving consumers **more exposure to the personalization** practices of e-commerce leaders and raising the bar for everyone else.
    - Over three-quarters of consumers **(76%)** said that receiving **personalized communications was a critical factor** in prompting their consideration of a brand, and **78%** said such content made them **more likely to repurchase**.
    - Companies tend to **neglect the personalization aspect** often across various points in the product life cycle, due to its complexity, while providing incentives and providing the **same incentives** to a large group of consumers leading to **low conversion** rates.

2. **Analyzing customer data to make minor decisions is time-consuming.**
    - For small companies, creating a simple discount program may only take a few hours to develop and implement, while large companies may spend **months or even years** planning and launching a comprehensive loyalty program.
    - Large companies especially digitally native brands have to **analyze large chunks of data** to analyze consumer behaviour and history to devise personalized incentives which is an **extremely time-consuming** and tedious process.

3. **Incentives not in line with the company's goals:**
    - Company's finances:
        - Before providing incentives it becomes imperative for companies to access their marketing budget and decide how much they can afford to shell out on incentives.
        - Consumer incentive provided by the company is **beyond** what the company **can afford** and leads to **overspending on irrelevant incentives** that might lead to losses.
    - Company's goals:
        - Knowing **exactly why** you need a consumer incentive program matters greatly while devising the right incentives. Does the company want to boost your sales? Does the company want to promote specific products or services? Does the company want to win consumers back from the competition?
        - Brands often **fail** to have a **clear understanding** of the same and end up providing the **same old generic incentives** irrespective of their goals.

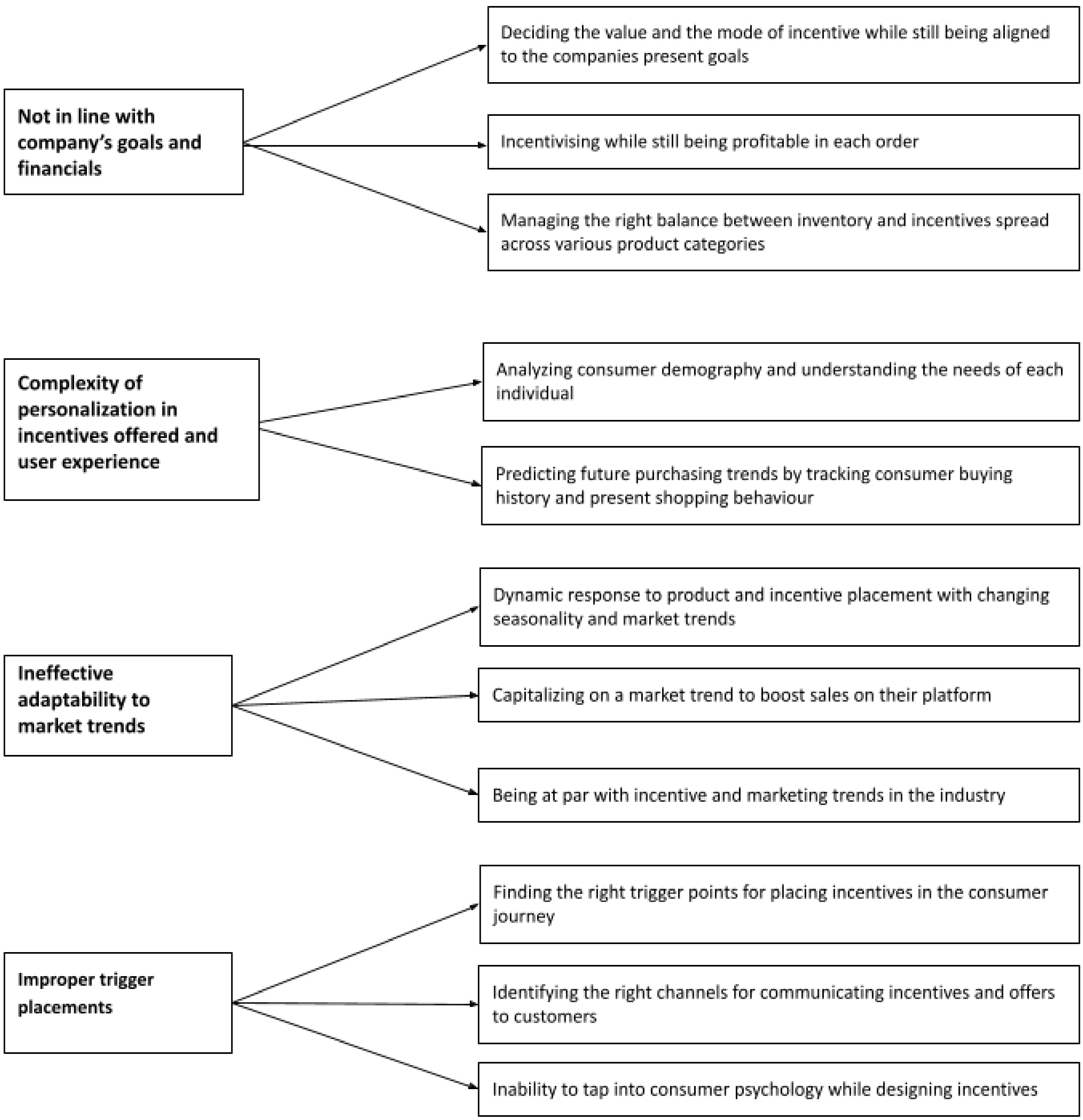
4. **Improper trigger placement and incentives not designed to tap into consumer psychology**
    - Placing triggers at the wrong stage of the user journey where customers are unlikely to respond hinders the effectiveness of the incentive program leading to low participation among consumers and a lack of return on investment
    - If the message of the incentive design is not being conveyed properly to the consumers, it can lead to failure making the timing and relevance of the incentive provided extremely crucial.

5. **Ineffective Adaptability to Market trends**
    - Companies are unaware of the trends currently in the market and hence, end up providing incentives that are not in line with the present time leading to a waste of resources
    - **82%** of Marketing executives believe that it is important for companies to follow the market trends to roll out adequate products and incentives for consumers.

"There are certain gaps in the current incentive design system which makes it inefficient and this model can work very well to bridge this gap. Also, the use of pseudo-variables is very important as some information like the customer income cannot be asked directly ".

-**Ratnakar Pandey, Data Science and Analytics for Customer Experience, Amazon**.

3.3 Complex decisions involved in the gaps identified across the product lifecycle



3.4 What makes these decisions complex?

Companies are often under the **misconception** that their consumers would be pleased **by any token** of appreciation. In reality, everyone, including their competitors, is doing some form of incentive or loyalty marketing to attract and retain customers. To truly get the **most value out of a consumer incentive program,** you need to have certain fundamentals in place. Simply putting together “points for purchase” or “refer a friend” social media promotion isn’t going to win new customers or influence existing consumers to stay. Thus, companies have to consider a lot of parameters and take certain **complex decisions**(identified above) before they can arrive at the right incentive. Let us take a look at what makes these decisions such complex:

1. **The company’s objectives:**
    - Knowing **exactly why** you need a consumer incentive program at this point is an important question company must have the answer to before designing any incentive.
    - Identifying **what their goals are** and **what kind of incentives** will best help them achieve these goals is a complex decision that will be **influenced by a magnitude** of parameters such as **company performance, market trends, consumer behaviour, historical data on the success of marketing campaigns,** etc.

2. **Their target audience**:
    - To design a successful incentive program, it's important to have a deep **understanding of the target audience**, including their **needs, preferences, and behaviour**. This can involve conducting research and gathering data on **demographics, buying habits, and motivators**.
    - Designing a personalized consumer incentive program can be a complex task, as it involves several **interrelated factors** that need to be **considered and balanced**.

3. **Understanding user journey and consumer behaviour:**
    - **One mistake** that many companies make is keeping the **focus** on the **customer’s destination** (conversion) **rather** than their **journey** (process).
    - Brands must be aware that **closing a sale in urgency** should not come at the **cost of a seamless customer experience.** Customers may get irritated easily if products and services are forced down their throats.
    - To avoid this, companies must **map out customer motivations** in advance and know their pain points carefully and incorporate the incentives at the **right point of the user journey** to improve their overall experience.

4. **Product or services being offered:**
    - The type of incentive provided to a consumer will also depend on the **kind of products and product categories** they are interested in.
    - There are a lot of variables that come into play when we talk about designing incentives for specific product categories such as the **value chain of the product, availability, market trends,** etc.
    - It becomes imperative to consider all these factors while devising the **right incentives for the right products** for the consumer thus making it a complex decision again.

5. **Performance of existing incentives:** Companies need to keep monitoring their consumer incentive program stats to see what is working and what is not. Some key insights that can be derived from this include: Enrolment – by geography or demographics
    - Program usage – beyond enrolment, who participated in the program?
    - What behaviour did they exhibit?
    - How soon did the participants respond after receiving the incentive

4. Impact of Automating these complex decisions in Consumer Incentive Design

a. **Companies' Perspective**

- **Reduce Time Complexity:** The average time required to process a consumer incentive reduces by **70% through automation** of the design process and can **increase operational efficiency** by up to **60%** as per a study by Mckinsey.
- **Improved Efficiency**: A survey by KPMG revealed that companies that have adopted automation for consumer incentive design have reported a median improvement of **20% in efficiency, accuracy, and speed**.
- **Optimum resource utilization:** According to a Mckinsey report, automation can lead to a **10% to 15% reduction in costs** for consumer incentive design and management. Once companies have identified the specific incentive **relevant to their user,** it will help them **avoid wasting their resources** by running multiple promotions and incentives on multiple platforms with **low conversion rates**.
- **Increased brand loyalty:** **79%** of consumers say loyalty programs make them **more likely to continue doing business** with brands**.** Automating the process **improves customer loyalty** overall as they get access to better **more personalized incentives** as a result.

b. **Consumers' Perspective**

- **Increased Personalisation:** A survey by Accenture found that **90% of consumers** find **personalization appealing** and **84% of consumers** are **more likely to buy** from a retailer that offers personalized experiences. Automating the complex decision of personalized incentive design will help consumers get more **personalized, more relevant incentives** across the consumer funnel.
- **Improved user experience:** According to Salesforce, personalizing the customer experience can lead to an **increase in customer lifetime value by as much as 15%.** Consumers don't find **irrelevant incentives and advertisements** at every point in the user journey and have a more seamless user experience.
- **Consumers get more value for money:** Apart from **monetary benefits, customers get reward points, personalized discounts,** and offers means customers can get **more value for money** by purchasing regularly from the company rather than their competitors.

5. Use Case and Knowledge Model Description:

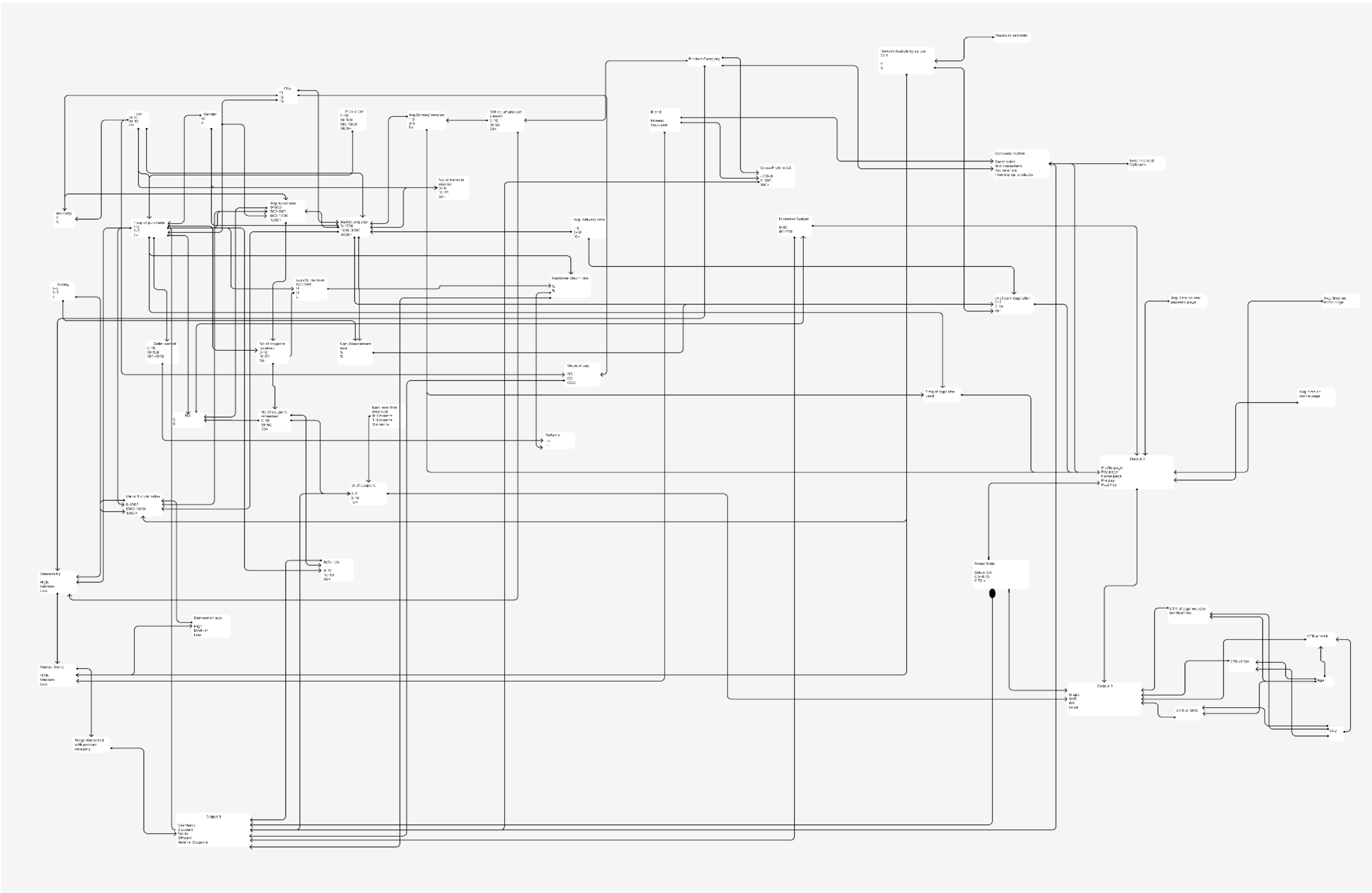
"Automating the complex decision of personalized consumer incentive design for digitally native brands across the consumer funnel."

- Our use case involves building a **knowledge model** that would first **rank the best incentive (value** and **category-wise)** for a given consumer based on the **probability score** obtained from the model after inputting **50+ parameters** that we have identified to be relevant to this decision.
- Further, the model would also output **when in the user journey** the identified incentives should be provided and **through what mode** must it reach the user.
- This will thus help automate the **end-to-end process of incentive design** right from choosing what incentive to offer to which consumer to where and when they should offer it.

"This is indeed a very good use case for a complex decision that can be automated using a model like a Bayesian network as there exist several dependent and independent variables influencing the final decision of which would be the right incentive to provide to a given consumer".

-**Prof. Karthik Sriram, IIM-A**.
(Expert in Bayesian Statistics and Quantitative Methods)

Inference Graph



[Bayesian Knowledge Model (Hyperlinked here)]

6. Understanding the Parameters

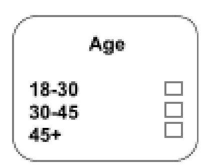
Two categories of parameters were involved in the knowledge track: ones in the **input direction** and those in the **output direction**. The input parameters were classified into **three** significant baskets of **Consumer, product purchase, and company-centric metrics** that can help quantify the impact all these should have over incentive design as a process.

6.1 Input Parameters

1) Consumer-Centric Basket

1.1)Demography

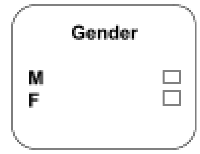
1.1.1) Age



- ***Motivation***: Age is an important demographic parameter that affects a **user's buying behaviour**, as people grow their needs change. The needs of consumers also differ from **generation to generation**.
- ***Affected By***: Age is an independent Parameter
- ***Affects***: Age directly affects buying patterns like **frequency of purchase**, frequency of app/site used, average ticket size, average basket size, **current order value**, and mode of payment and it has a crucial influence on the final output directly
- ***Data Source***: The age of a consumer can easily be collected from the signup page or the consumer's google account.

1.1.2) Gender

- ***Motivation***: [Several](#)things differ between male and female consumers and these differences like different needs and attitudes affect their buying choices. **Decision-Making patterns** also differ vastly.
- ***Affected By***: Gender is an independent Parameter
- ***Affects***: Gender directly affects buying patterns like **frequency of purchase**, frequency of app/site used, **average ticket size**, and the number of items in the wishlist, and it has a crucial influence on the final output directly
- ***Data Source***: The gender of a consumer can easily be collected from the signup page or the consumer's google account.



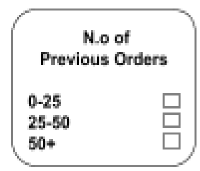
1.1.3) Consumer location of residence

- ***Motivation***: [People](#), whether located in a tier-1 city, tier-2 city, tier-3 city or village, buy products and consume them. They are all consumers. However, the locale has an influence on their buying behaviour and some dissimilarities have been noticed in their purchase, decision-making process and use of the products
- ***Affected By***: Location is an independent Parameter
- ***Affects***: Location directly affects buying patterns such as **average ticket size**, **frequency of purchase**, mode of payment and the number of items in the wishlist, and it has a crucial influence on the final output directly
- ***Data Source***: The location of a consumer can be mapped from their order location or the signup page.

1.2) Buying Behaviour

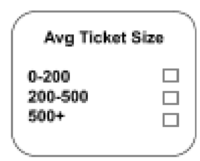
1.2.1) Previous Orders from the company's site/app

- ***Motivation***: The number of previous orders from the company's site is a crucial factor as it helps us quantify the **loyalty of a customer** with the company and gives us an idea of the willingness of the consumer to do business with the company
- ***Affected By***: Previous Orders is an independent Parameter
- ***Affects***: Previous orders affect the frequency of purchase
- ***Data Source***: The company always tracks the number of orders from a consumer account



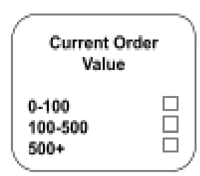
1.2.2) Average Ticket Size

- ***Motivation***: Average ticket size is the sum of the price of the consumer's previous buys divided by the total number of purchases, this helps us determine the **buying capacity** of the consumer
- ***Affected By***: It is affected by Age, Gender, Location of the consumer, basket average size, and warranty on products
- ***Affects***: It affects our important metric,i.e., Current order value and also affects the number of incentives received till now by the consumer
- ***Data Source***: Can be tracked by the transaction history of the consumer

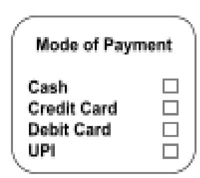


1.2.3) Current Order Value

- ***Motivation***: This parameter helps us quantify the **amount** of the incentive that should be rewarded to the consumer
- ***Affected By***: It is directly affected by **frequency of purchase**, **seasonality**, market trends, product rating, basket average size, product availability as per cart requirement, and **average ticket size**
- ***Affects***: This is a very crucial metric as mentioned above and this affects the final output directly and helps us quantify the incentive amount to be given
- ***Data Source***: Can be tracked by the current transaction

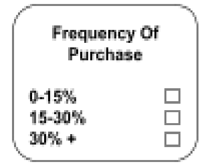


1.2.4) Mode of Payment



- ***Motivation***: [The mode of payment] affects the type of incentives that can be given out, eg:- more than 50% of credit card users use credit cards only because they can earn loyalty points
- ***Affected By:*** It is affected by customer demographics like age and location of the consumer
- ***Affects***: It directly affects our final output
- ***Data Source***: Easily accessible by transaction modes

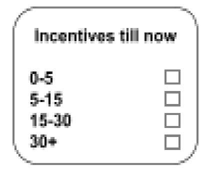
1.2.5) Frequency of Purchase



- ***Motivation***: Helps us track how often a consumer uses our site/app to shop
- ***Affected By:*** Demographic factors like age, location, and gender. It is also affected by factors like the number of previous orders, and seasonality
- ***Affects***: **Current order value**, order cancellation rate, whether a consumer is a loyalty member or not, number of incentives received till now, **return on investment**, number of referrals
- ***Data Source***: Easily accessible by transaction modes

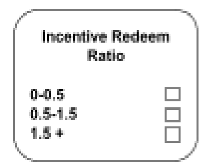
<u>1.3) Incentive History</u>

1.3.1) Number of Incentives received till now



- ***Motivation***: This parameter helps us **track customer loyalty** and also the reciprocation token of the company to the consumer
- ***Affected By***: Directly affected by **frequency of purchase**, **average ticket size**, and whether the consumer is an existing loyalty member or not
- ***Affects***: Number of incentives redeemed till now
- ***Data Source***: The company can track this data from the user's account, where past incentives are accumulated

1.3.2) Number of Incentives redeemed till now



- ***Motivation:*** This parameter helps us track whether the incentives given by the company create an **impact** on the consumer or not, it is the ratio of the number of incentives redeemed by a consumer divided by the industry standards of incentive redemption for 1 consumer
- ***Affected By***: Directly affected by the number of incentives received till now
- ***Affects***: delta t of incentive redeem, number of referrals, return on investment for a consumer
- ***Data Source***: The company can track this data from the user's account, where past incentives are tracked whether they are redeemed or they are expired

1.3.3) Delta T of coupons redeemed*

- ***Motivation***: This parameter tells us how much time the consumer redeems the given incentive, it helps us track the **relevance** of the incentive according to consumer needs
- ***Affected By***: Directly affected by the number of incentives redeemed till now and the last incentive received time
- ***Affects***: Directly affects the output
- ***Data Source***: The company can track this data from the user's account, where past incentives are tracked whether they are redeemed or they are expired.

***** *"Since incentive design is highly sensitive to the previous reaction of consumer for the same category of incentive, the average time taken to redeem an incentive could be a parameter to consider"*

- Bhavik Shah, CRM Expert, ex-Amazon

1.3.4) Last Incentive Received time

- ***Motivation***: This parameter helps us track the **frequency** of incentives issued to the customer, so helps us decide when to give an incentive and when not, hence cutting down the incentive budget
- ***Affected By***: Independent parameter

- ***Affects***: Directly affects delta t of incentive redemption rate
- ***Data Source***: The company can track this data from the user's account, where past incentives are accumulated.

2) Product Purchase Basket

<u>2.1) Directly affecting product purchase</u>

2.1.1) Basket Average Size*

- ***Motivation***: Basket Average Size helps us identify the range and variety of products in which the consumer is interested
- ***Affected By***: Directly influenced by demographic factors like age, gender, and location, apart from these also affected by **average screens per session**, the average delivery time of products, and the number of items in the wishlist
- ***Affects:*** Average ticket size, cart abandonment rate, and delta t of cart stagnation
- ***Data Source*****:** Companies easily track the cart contents of a consumer account

***** "*The conversion of product basket addition to purchase is an important standard metric in the industry and would have a sensitive relationship to the category of incentive provided*"

- Vaishnavi Tiwari, PM at Swiggy

2.1.2) Stocks to Sell Ratio

- ***Motivation***: It is the ratio of the quantity of an item available divided by the sold quantity of the item, given **inventory management** is a constraint to purchasing a product, we need to include this metric to assess this limitation
- ***Affected By***: Independent Parameter
- ***Affects***: Product Availability as per Cart Requirement
- ***Data Source***: Companies maintain their inventory data

2.1.3) Delta T of Cart Stagnation*

- ***Motivation***: It tells us for how long a cart in the consumer account is stagnated,i.e., products are added but have not been purchased, this will help us to affect the output which tells us **where** in the **user journey** the incentive should be given
- ***Affected By***: Directly affected by average delivery time, product availability as per cart requirement, cart abandonment rate, and basket average size
- ***Affects***: Directly affects the output that where in the user journey should the incentive be given
- ***Data Source***: Account Cart tracking

***** "*In due conversion for every purchase, a long incentive journey mapping is done which also consists of understanding how long has the consumer held the product in the basket and not purchased*"

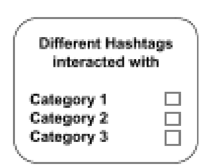
- Vaishnavi Tiwari, PM at Swiggy

2.1.4) Average time on the pre-payment page

- ***Motivation***: Helps us track how many consumers bounce out from the pre-payment page(i.e. Final review page where the final bill is displayed), so affects the user journey output(output 2)
- ***Affected By***: Independent Parameter
- ***Affects***: Phase of time for delivery of incentive
- ***Data Source***: By capturing the timestamps when a user enters and exits the pre-payment page

<u>2.2) Indirectly affecting product purchase</u>

2.2.1) Social Media hashtags*

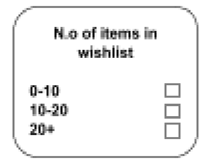


- ***Motivation***: By tracking the social media activity of the consumer we can figure out the **consumer activity** related to different types of products to which they are inclined, this can be quantified by the number of hashtags with which the consumer engages
- ***Affected By***: Market Trends
- ***Affects***: Final output, as helps us decide what type of incentives should be given and which type of products
- ***Data Source***: By tracking social media activity through APIs

* "*Digitally native brands have a high affinity for tracking consumer activities that do not lead to purchase but display behaviour towards brands, for instance, you can look into how many social media tags related to a product or company has the consumer interacted with in terms of likes and comments*"

- Saamir Gupta, India Nodes Lead at Accenture

2.2.2) Number of items in the wishlist*

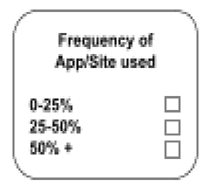


- ***Motivation***: Helps us track the **interest** of the consumer, hence can increase the impact of incentives for a consumer
- ***Affected By***: Demographic factors like Age and Gender
- ***Affects:*** Basket Avg size
- ***Data Source***: Track the wishlist of a consumer account

***** "*Instead of just looking at basket size in terms of the monetary value of items added, you can understand the intent for buying of any consumer through the number of items in the wishlist*"

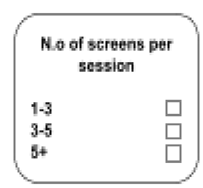
- Rishabh Kohli, PM at Flipkart

2.2.3) Frequency of App/Site used



- ***Motivation***: This metric will help us in tracking the **user engagement** with our app/site and we will be able to calculate how often the user uses to buy an item and how often uses it just for viewing products, this would help in the user journey incentivization
- ***Affected By***: Frequency of purchase and demographic factors like age, gender and location of the consumer
- ***Affects***: Phase of time for delivery of incentive
- ***Data Source***: Companies track the frequency of customer views of their app/site

2.2.4) Number of screens per session

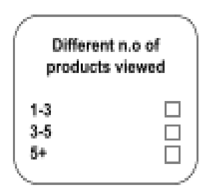


- ***Motivation***: This metric helps us identify where exactly the user exits our app/site,i.e., after switching how many screens
- ***Affected By***: Different number of products viewed
- ***Affects***: Number of items in the wishlist
- ***Data Source:*** Can be tracked using google analytics

* "*Within app/site searches can yield statistics for different number of products viewed for every consumer which will give insight into whether he has an intention to make a purchase or not, thus can affect the choice of the distribution network that the incentive needs*"

- Rishabh Kohli, PM at Flipkart

2.2.5) Different Products Viewed*



- ***Motivation***: Helps us track the interest of the user and also the **taste of the consumer**, i.e., colour biases and such factors
- ***Affected By***: Seasonality and Product Category
- ***Affects***: Average Screens per session

- ***Data Source***: Can be tracked by using user search history in the app/site

2.2.6) Product Rating

- ***Motivation***: This metric affects consumer buying behaviour a lot, hence we know which product to incentivize and which not to
- ***Affected By***: Independent Parameter
- ***Affects***: Current Order Value and Cart Abandonment Rate
- ***Data Source***: Customer Reviews

2.2.7) Average time on the home page*

- ***Motivation***: Helps us to track **time spent** on the home page and dropout rate from the home page
- ***Affected By:*** Independent Parameter
- ***Affects***: Phase of time for delivery of incentive
- ***Data Source:*** Track account activity

***** *"To understand the phase at which any particular consumer is in the consumer funnel, channel the average time spent by the user of different pages. For instance, the home and profile pages"*

- Shivam Jalotra, AdTech at Flipkart

3) Company Basket

<u>3.1) Surface Metrics</u>

3.1.1) Seasonality

- ***Motivation***: This will help us know whether the season going on currently is suitable for buying a product or not
- ***Affected By***: Product Category
- ***Affects***: Market Trends, Different number of products viewed, Current order value, and frequency of purchase
- ***Data Source***: Calendar purchase history

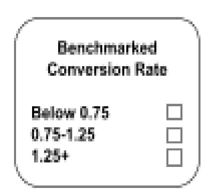
3.1.2) Market Trends

- ***Motivation***: Helps us identify how much a specific product is trending in the market
- ***Affected By***: Seasonality and type of brand
- ***Affects***: Hashtags and Demand for the product on our app/site
- ***Data Source***: Purchase History of the industry in that particular season, and financial reports of the companies in that space

3.1.3) Order Cancellation

- ***Motivation***: Helps us track the customer buying behaviour
- ***Affected By***: Frequency of purchase
- ***Affects***: Refunds
- ***Data Source***: Consumer account tracking

3.1.4) Benchmarked Conversion Rate*



- ***Motivation***: Keeps us in the **competition** and by analysing the competition we can use incentives as a brownie point to get ahead of the competition, it is the ratio of the company's conversion rate divided by the industry standards of conversion rate

- ***Affected By***: Independent parameter
- ***Affects***: Company Motive
- ***Data Source***: Industry analysis

***** *"Looking into conversion rate as a metric to judge the efficiency of the model seems rational, however, you can benchmark it against the industry standards to come up with slabs for different intents in incentive design"*

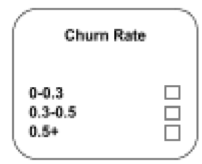
- Usmita Pareek, Data Scientist at MasterCard AI Garage

3.1.5) Number of in-house brands searched divided by total brands searched

- ***Motivation***: Helps us track that are consumers interested in our **in-house products** or **out-house products**, so accordingly we can promote in-house products
- ***Affected By***: Independent parameter
- ***Affects***: Final output helps us to score various incentives, quantify them and also scores various touchpoints in the user journey where incentive should be given
- ***Data Source***: Consumer Search History

<u>3.2) Internal Metrics</u>

3.2.1) Customer Churn Rate

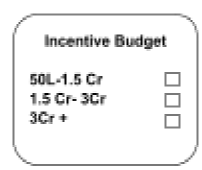


- ***Motivation***: It tracks the number of consumers that stop using our app/site, so this metric is very crucial for **customer retention** using incentives
- ***Affected By***: Frequency of purchase, Refunds, and whether a consumer is a loyalty member or not
- ***Affects***: Directly affects the output and helps us in choosing the type of customer who should be incentivized
- ***Data Source***: Companies track their churn rate regularly

3.2.2) Company Motives

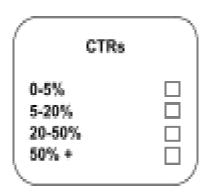
- ***Motivation***: A company's motive concerning a certain product helps us identify the amount you want to spend on a customer either for acquisition or retention.
- ***Affected By***: Type of brand and Product Category
- ***Affects***: Directly helps us in scoring different types of incentives, helps in quantifying them and also helps suggests exactly on which platform the user should be incentivized
- ***Data Source***: Company

3.2.3) Incentive Budget



- ***Motivation***: Tells us how much can the company spend on incentives
- ***Affected By***: Return on investment on customers
- ***Affects***: Directly helps us in scoring different types of incentives, helps in quantifying them and also helps suggests exactly on which platform the user should be incentivized
- ***Data Source***: Company

3.2.4) Click-Through Rates*



- ***Motivation***: Helps us track **consumer engagement** across **different platforms** so that we can precisely know where to provide the incentives
- ***Affected By***: Demographics like Age and location of the consumer
- ***Affects***: Our final output that where should the incentive be given
- ***Data Source***: Google Analytics

6.2 Output Parameters

Now, let's look at the **output for incentive design** and what linkages would majorly influence these parameters,

The complex decision involved an **end-to-end approach** across major incentive characteristics. Here, output parameters would answer the following questions basis personalization:

- What kind or **category** of incentive?
- What is the **value** of the incentive to the user?
- Where should incentives be placed across the **user journey** to boost **conversion?**
- How can you spread **awareness** regarding these incentives?

Let's look into each of these one by one:

1) Type and value of Incentive

1.1) Category and value of Incentive

- **Motivation**: The variation in how users interact with the app is immensely based on **demographics**, **buying behaviour**, and **user interactions not leading to direct purchase**. This requires an exhaustive set of incentives that serve different purposes for the company to **pull** the consumers. Some common buckets are
    a. **Cashbacks:** The most general form of incentive that provides users with a gift card or offers for a **fixed value or percentage** of the purchase made. Their value can be increased **2-3 folds** just by placing them through personalization
    b. **Discounts:** The buying behaviour can be influenced by introducing discounts at pivotal junctions basis personalisation. Discounts will be broken down into **fixed** and **percentage** variants, and the buy one get one free (**BOGO**) offer. This can be pushed through carefully curated personalised user flows enabling increase in **ticket size**.
    c. **Referrals:** Incentivised referrals for both sides are significant for promoting **brand awareness**. Types include **in-app points/coins** earning referrals, **free shipping referrals** and discounted referrals.
    d. **Monetary storage cards:** Monetary storage cards are gamified coupons, **in-house gift cards**, loyalty membership and points/coins. It enhances user experience by gamifying it through sensory biases of achievement and creating scarcity.
- **Affected by:** As corroborated by multiple primary user and expert interactions, **value** will be affected by
    a. Identified consumer demographics (Age, gender and city),
    b. Previous response on incentives (time taken to redeem the last coupon, no. of coupons received, referrals made),
    c. Product choice (product category, availability, stocks to sell ratio (inventory) and ROI from the incentive),
    d. Externalities through consumer-centric spaces (Consumer churn rate, brand or product hashtags interacted with on social media and current order value) and
    e. Internal metrics of the company (incentive budget, gross profit in unit economics and company motives for incentive).

    These would have a primary linkage to the output parameter, however, some other factors that also influence the incentive choice significantly would be linked to these via a secondary or tertiary node, like surface metrics (market trends, order cancellations, industry benchmarked CVR and average number of screen per session) and buying behaviour (frequency of purchase, average basket price))
- **Affecting:** None
- **Sources of data and structure:**
    a. **In-house surfing** of users and tracking their activity throughout their surf period.
    b. Out-of-application usage/site tracking, financial reports, **PRD**, and **investor pitch decks**.

1.2) Positioning of incentive across the consumer funnel

- **Motivation:** Incentive positioning is done to maximise influence on:
    a. the **purchasing intent** of the consumer
    b. the trust or belief that consumer has in the particular platform
    c. pushing the consumer to **increase his spending** on the platform

As validated by our experts, major customer touchpoints of a user are the Profile page, the home page, pre/post payment pages, search bars and the cart/wishlist window

- **Affected by:**
  a. how much time a **particular user spends on respective windows**
  b. average time spent on the profile, home and payment page depicts time spent by user on specific segments
  c. consumer demography (age, gender, city)
  d. relation to cart stagnation (understanding how dynamics in the cart would affect consumer's purchase behaviour)
  e. **internal metrics of the company** (incentive budget, gross profit in unit economics and company motives for incentive).

  ***Internal metrics** have a direct linkage with the output parameter, given the gravity of influence that they have. Other factors would only be highlighted through a secondary node and will also affect the output.*
- **Affecting:** Positioning of incentive
- **Source of data and structure:**
  a. highlighted tracking of CVR and a can be done by analysing in-app/site through **heatmaps** and other structures
  b. **internal metrics** and data available to the company

  *Structures were derived through **customer engagement experts'** analysis of which factors affect the time of the user journey at which an incentive should be delivered to the user*

1.3) Where to promote the incentive for a consumer

- **Motivation:** Given the overall impact of incentives, deciding where to promote these incentives would also be very relevant in terms of developing an end-to-end incentive design solution.
- **Affected by:**
  a. **click-through rates** for different outreach schemes as these quantify actions **not directly leading** to purchase
  b. time taken before the consumer uses the incentive for that category
  c. consumer demography and buying behaviour
- **Affecting:** None
- **Source of data and structures:** CTRs and time taken to use the incentive for that category can be tracked through in-house reports and data analysis

***** *"Given the feedback mechanism necessity of the marketing field, Click through rates (CTRs) can provide a steady response to where the incentive needs to be delivered and how effective that is"*

- Shivam Jalotra, AdTech at Flipkart

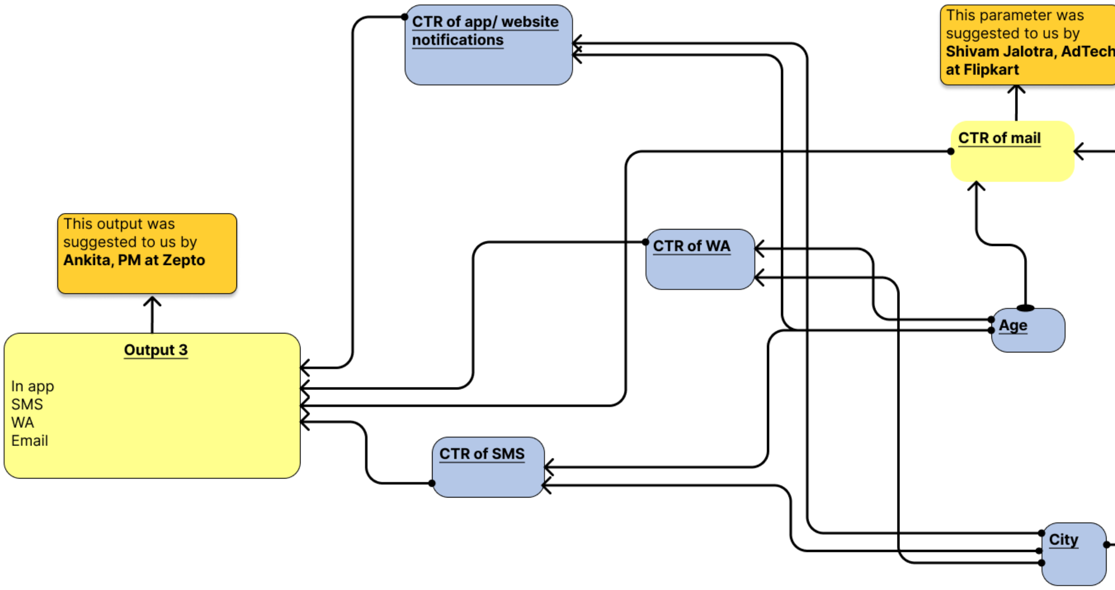
6.3 Chains and dilution of parameters

The intricacies in the knowledge model can be explained through two ways, one is through a detailed analysis of the nodes of the model, their bucketing based on similarities and their interplay. The other is through a thorough perusal of the decision-making chains that in sync with one another map out the entire inference graph and lay out all the inferences. We shall now look at these chains

A. Non-payment-related consumer activities and incentive distribution:

Motivation: Since there are distinct consumer activities that do not lead to any purchase but are avid indicators of **behavioural insights** needed to educate the consumer about the incentives or distribution of the someone. These input parameters are depicted above, i.e. **CTRs** (of app/website notification, Whatsapp advertisements, SMS and emails) and **Consumer demographics** (age and city) which directly affect the output of where to place the incentive for optimum return on investments.

Dependency on other parameters: This is mostly an independent decision block having limited influence on other parameter buckets



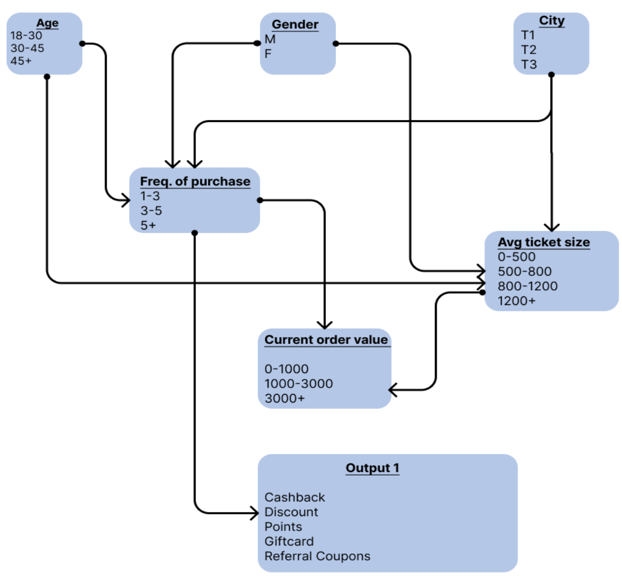
B. The primary purchasing behaviour of the consumer and type of incentive

Motivation: The type of incentive as a parameter is significantly dependent on direct consumer buying behaviour structured across **3 layers to factor** and categorise the dependence.

- First, the **consumer demography** i.e. age, gender and city would affect the classification of consumers for better personalisation
- Second, the **purchase history** is characterised by the frequency of purchase and average ticket size which depicts what and how has the consumer purchased till now to get directly into primary buying behaviour
- Looking into the **current order value** of the consumer to channel the aspects of dynamics in buying behaviour of the consumer

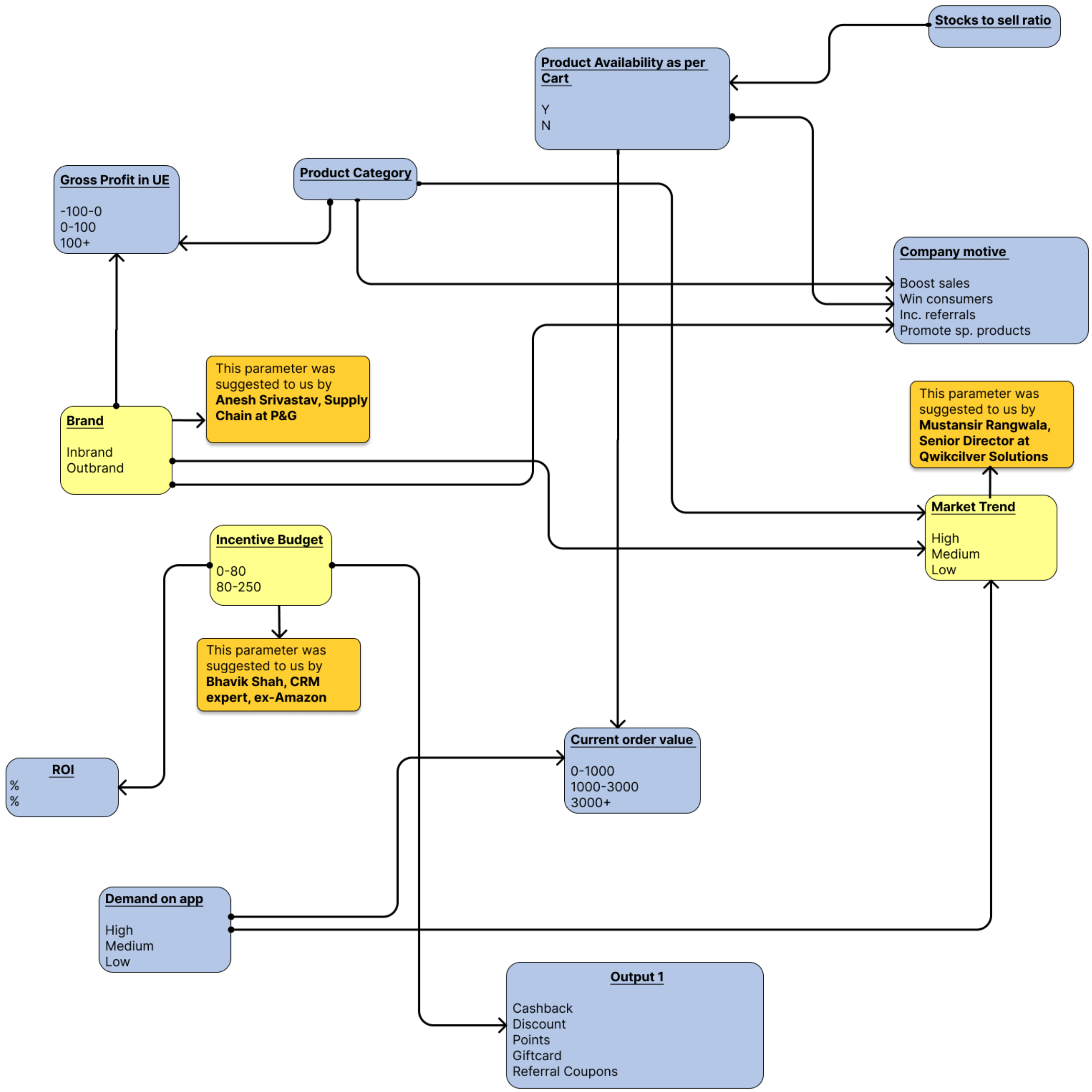
Now, these parameters directly influence the output for the type of incentive to be given to the consumer.

Dependency on other parameters: Other than buying behaviour the type of incentive is dependent on internal, surface company parameters and product intricacies involved.



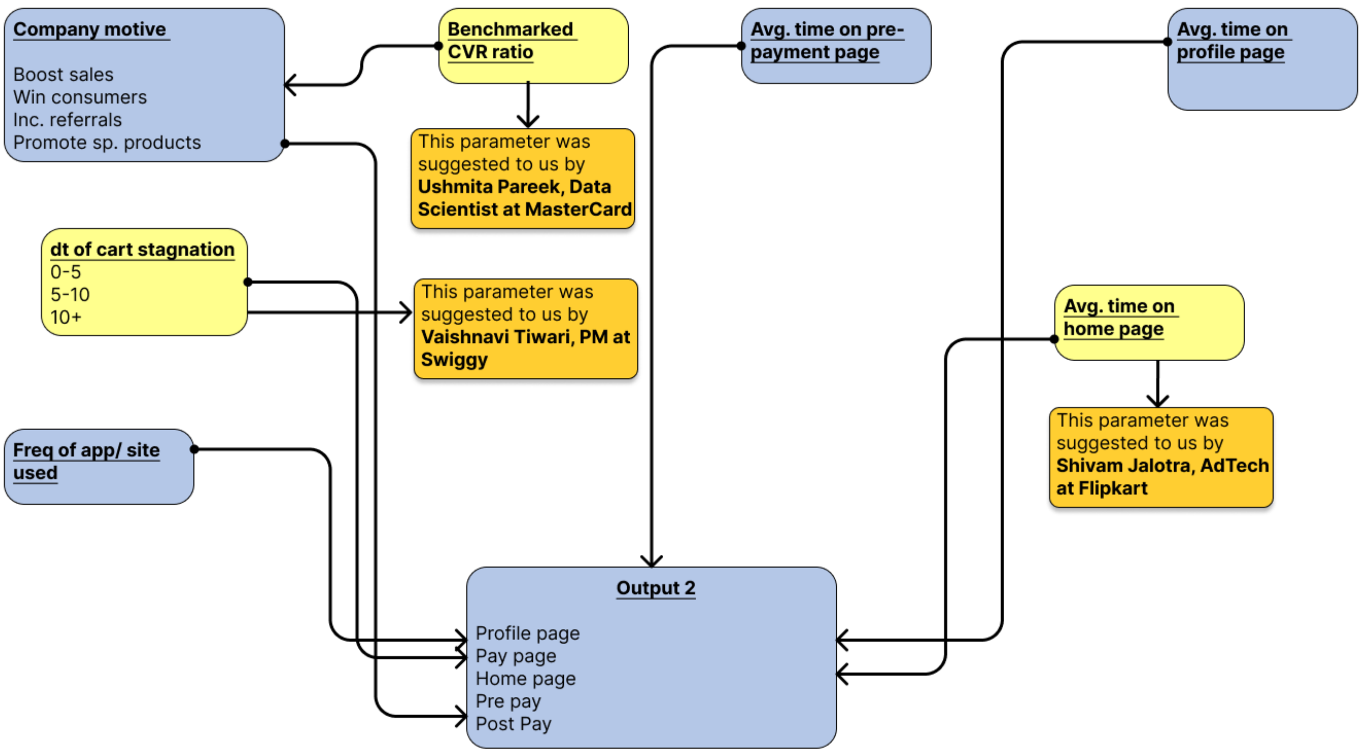
C. Company and product purchase parameters influencing the type of incentive

Motivation: The back-end factors that put boundary conditions to the dynamic equations in the prediction of the type of incentive.
Here primarily, **Internal company factors** put an **upper bound** to the incentive throw, which are gross profits in unit economics, Incentive budget, return on investment and company motives.
Then, moving to **product technicalities** that in static nature affect the choice of incentive chosen. Which are product category, availability, stocks-to-sell ratio, in/out brand characterization and demand for the product. In addition to this these technicalities, **current order value** has to be considered to benchmark these parameters in terms of consumers buying behaviour.
Dependency over other parameters: This is an exhaustive direction and not many parametric buckets affect the same.



D. **Non-Purchase related activities of consumers, the company's internal metrics and the phase of delivery of incentive**

Motivation: Given the effect of non-purchase-related activities of the consumers as the governing equations to determine the **phase of delivery of incentive**, factors such as average time spent on pre-payment, profile or homepage, cart stagnation time and frequency of app/site use. In addition to these, **internal driving factors** like industry benchmarked CVR ratios and company motives will be primary factors affecting the phase of delivery of incentive.
Dependency on other parameters: This also depends on the consumer demography (age, gender and city) to cater for the classification for consumers over buckets where the consumer funnel comes into play.



Dilution: These display the structure of the knowledge model in detail and its dependence and sensitivity to certain types of parameters, however since certain parameters would have many linkages between the final output and itself, the dependence will get **diluted**. To account for this, we have **introduced direct linkages** with them to emphasize the **sensitivity of dependence**.

7. Example use cases to depict implementation and feasibility

The generic model caters to most of the parametric directions that any company would require in the decision-making process for incentive design, however, certain additions or tweaks according to the company can improve the accuracy by many folds. To understand how for every specific company, the **generic model can be tweaked** to optimize the value coming from it, we shall look into 2 cases and what are particular **directions where certain intricacies** can be involved in the model.
To elaborate on the same, we shall look into what s**pecific indirect modes of value creation** these brands have and how that affect the incentive design in terms of the **tweaks** that can be made in the generic model.

A. Nykaa

India's biggest omnichannel for beauty destinations, Nykaa has a strong network of people that it caters to and engages through its extensive library of products and services. It has developed a strong social community for beauty discussions and extensive consumer data on the name of routine personalisation giving it the liberty to customize the incentive design according to every consumer.

Strong right to win:

a) **Strong social network** that can be converted into tons of data and can be an integral element in incentive design
b) **Distinctive data from routine planners** and history of beauty advice in the space to customise and sell products and design incentives according to the need of consumers
c) **High-frequency activities** that do **not lead to purchase** can be leveraged into understanding consumer psychology and provide relevant incentives

Indirect Value Creation	Tweaking the generic model
• **Nykaa Networks**: Interactive platform keeping in mind the user generated content, where subscribers can chat with other beauty buffs, and ask and answer all beauty-related answers. • **Beauty Advice**: Customizing and providing beauty advice through consumer profiling with given data - Beauty Book - Nykaa TV - Buying guide - Routine Finder	**Parameters** (Nykaa Networks): 1. Average Length of a discussion threads 2. Frequency of use of the feature 3. Identifying common trends of products from discussion threads **Parameters** (Beauty Advice): 1. Frequency of use of all 4 features 2. Tracking the concerned bucket in routine finder

B. G-pay

Google pay is a mobile payment service that has competitive leverage with regards to its excellent set of data available for every consumer and can be moulded to create a stronger consumer funnel, given the sensitive dependence this has on consumer retention for the fintech industry.

Strong right to win:

a) **Extensive purchase history** for every consumer to deliver depth in **personalisation** for incentives and product offering
b) **Vast network of In-house brands** for cross-selling models and brand pushing through incentives
c) **Strong classification capabilities** for every purchase made for creating value in terms of better predictions made

Indirect Value Creation	Tweaking the generic model
• **Payment History:** The library of extensive payment history for every consumer giving more liberty and space for personalization. • **Brand Pushing:** Pushing brands that are in collaboration with Google Pay or are in-house by giving them competitive leverage	**Parameters** (Payment History): 1. Purchasing Patterns 2. % of Category Payments: Impulse, Top-up. Stock-up **Parameters** (Brand Pushing): 1. Coupons Redeemed (In-house Brands/Total) 2. % of transactions involved in partner/In-house brands

8. Pitfalls and their Workarounds

Pitfalls	Workarounds
1 Lack of Feedback Mechanism	✓ Companies can incorporate A/B testing method to identify more efficient parameters ✓ Auto-adjustable parameter weights and conditional probabilities
2 Extraneous Noise (Inaccuracy in consumer data)	✓ Incorporating sufficient 60+ parameters divided across 3 funnels
3 Increased Technological Costs	✓ Taking into consideration the incentive budget of the company, complexity of model would be adjusted
4 Barrier for outsourcing incentive design	✓ Providing End-to-end incentivization across product lifecycle ✓ Transitioning to personalized incentives from cohort based system

9. Future Prospects

Tapping into incentive design for offline marketplaces

- **Prospect:** Given the fact that DNBs are our target market, many of the brands in this space are eventually also moving into *offline markets*, so if we can win their trust over our online incentive design model, then eventually we can also tweak our model and get into the offline marketplace. We'll also employ structures like heat mapping and Computer Vision for tracking data enabling **in-store design**
- **Relevance to our model:** The exhaustive set of input parameters in our model broadly covers most of the parameters that are required for an incentive design model for the offline marketplace, so just little tweaks would be required here and there, and we can jump into this space with ease

Foraying into incentive design for employees

- **Prospect:** *Employee satisfaction* is a very crucial aspect of any company's success, so this process of **giving timely useful incentives** to employees is a great way to maintain the satisfaction level of employees.
- **Relevance to our model:** Parameters, in this case, will change significantly, but the good thing is that the **basic structural framework** of the model will remain the same, so we can explore synergies to tap into this market.

Helping banks identify potential partners to sell their incentives

- **Prospect:** Currently, banks find it difficult to find the *right partners* in various industries like retail, FMCG, e-commerce, etc.
- **Relevance to our model:** We can help them find the right partners as through our model we thoroughly analyse the consumer buying behaviour and our input parameter **Mode of Payment** will be the game changer here, it will help us accurately predict the right partners.