# MSIN0094 First Assignment Answer Sheet

Candidate Number: [TBDH9]

Self-reported word count: 1490 words

## 1. Market Analysis

1. (1) Conduct a situation analysis for Tom's new bubble tea shop. Discuss what each C is about in general terms, then further discuss each C in the context of bubble tea business.

Company

The business model focuses on freshly brewed, customisable bubble tea. The main channels include in-store sales, digital ordering, and online delivery (e.g. Deliveroo, UberEats). The short-term objective is to reach operational break-even; the long-term goal is to scale through digital performance tracking and brand partnerships.

Strengths include data-driven marketing skills, product knowledge, and a strong location with dense office and student traffic. Weaknesses include limited brand recognition, high costs, and little retail experience. Supply-chain risks for imported ingredients and packaging also remain a concern.

Customers

The main customers are office workers and students looking for quick, quality refreshments. The UK bubble tea market is expanding fast, reaching USD 63.99 million in 2023 and projected USD 118.95 million by 2032 (Fortune Business Insights 2024). Within Canary Wharf, key segments are quick-service weekday customers, social groups, and delivery subscribers. Customers value convenience and quality over price.

Competitors

Direct competitors include Bubbleology, YiFang, Heytea, and Chatime; indirect competition comes from Pret, Costa, and other cafés.

**SWOT:** Strengths – fast-growing market and strong customisation potential. Weaknesses – new brand and high costs. Opportunities – increasing demand for premium and sustainable drinks (The Guardian 2024). Threats – saturation in London, inflation, and tightening health regulations.

Collaborators

Core collaborators include ingredient suppliers, packaging manufacturers, and delivery partners. Collaboration with local offices, gyms, and coworking spaces can increase recurring orders and visibility. Sustainable suppliers and influencers can enhance positioning. Building stable relationships early will reduce supply risk and secure consistency.

Context (Climate PESTLE)

Political: post-Brexit import complexity may raise ingredient cost.

Economic: inflation drives expenses but Canary Wharf incomes remain high.

Social: bubble tea has become a social trend and lifestyle product in the UK

Technological: digital ordering and analytics allow precise marketing performance tracking.

Legal: compliance required for allergen labelling, food hygiene, and data privacy (ICO 2025).

Environmental: sustainability is both regulatory and marketing necessity (UK Food Standards Agency 2024).

1. (2) What would be the next steps in the marketing planning process?

STP should be conducted. The market needs to be segmented by profile and behaviour: the main target group should be high-frequency professionals with strong spending power. Positioning should focus on a modern, sustainable, and data-driven brand image. The next step is to apply the 4Ps: offer high-quality, customisable drinks (product), use value-based pricing (price), rely on both in-store and delivery sales (place), and promote through targeted digital ads and local partnerships (promotion). Performance should then be tracked by CAC, repeat rate, and customer lifetime value to guide marketing decisions.

2. Use R code blocks to compute the customer acquisition costs for the three customer acquisition methods.

```
## complete the code below
library(tidyverse)

── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0
──
✔ dplyr     1.1.4     ✔ readr     2.1.5
✔ forcats   1.0.1     ✔ stringr   1.5.2
✔ ggplot2   4.0.0     ✔ tibble    3.3.0
✔ lubridate 1.9.4     ✔ tidyr     1.3.1
✔ purrr     1.1.0
── Conflicts ────────────────────────────────────────── tidyverse_conflicts()
──
✖ dplyr::filter() masks stats::filter()
✖ dplyr::lag()    masks stats::lag()
```

```
ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```r
library(dplyr)

# first, we need to calculate cost per offer. To do this, it is needed
# to add printing price to labour price
print_cost <- 0.5
labour_cost <- 0.1
cost_each_offer_blanket <- print_cost + labour_cost
response_rate_blanket <- 0.02
# we have the response rate of 2% stated in the case study

CAC_blanket <- cost_each_offer_blanket/response_rate_blanket

## complete the code below
# for this, it is also needed to think of printing
# price per menu. First print, then post, and pay £0.60 per name
post_costs <- 0.10
name_costs <- 0.60
# we have print costs from case study
cost_each_offer_targeted <- post_costs + name_costs + print_cost
response_rate_targeted <- 0.05

CAC_targeted <- cost_each_offer_targeted/response_rate_targeted

## complete the code below
# here, only CPC and response rate are used.
# Cost is not for impressions/exposure,
# but for clicks only, hence the calculations
cost_per_click <- 0.5
response_rate_SEM <- 0.25

CAC_SEM <- cost_per_click/response_rate_SEM

# do not temper the below line of code; this is to print out your answer for TAs to check

print(paste0("Customer Acquisition Costs for blanket mailing is £", CAC_blanket))
```

```
[1] "Customer Acquisition Costs for blanket mailing is £30"
```

```r
print(paste0("Customer Acquisition Costs for targeted mailing is £",CAC_targeted) )
```

```
[1] "Customer Acquisition Costs for targeted mailing is £24"
```

```r
print(paste0("Customer Acquisition Costs for SEM is £", CAC_SEM))
```

```
[1] "Customer Acquisition Costs for SEM is £2"
```

3. Discuss the pros and cons of each of the three acquisition methods.

   Blanket mailing has proven to be the most expensive and the least effective way of marketing, with £30 CAC and only 2% success rate. The price is explained by the resources needed to print the menu and labor cost for distribution. While might seem ineffective in comparison to other methods, it can be useful to create the psychological sense of presence (Marketreach and WARC 2025), and is more effective impressions-wise, as covers vast numbers of people (JICMAIL 2024, 1-2).

   Basing on the calculations, targeted mailing proved to be more efficient with the response rate of 5%. Pros include higher response rate, as the users on the list are target audience more inclined to become customers (DMA, n.d). However, the response rate is still too low in comparison to the costs, as resources needed include printing and posting. Statistics show that 77% of people only look to mail ads and just 6% convert to purchase (JICMAIL 2024); some might even consider them spam.

   The SEM proved to be the most price- and response rate-efficient, with the cost of only £2 per click and the response rate of 25%. It has proven its efficiency as it has a specific target audience of interested people (those who look for this type of product specifically). Target ads have proven to be one of the most effective marketing tactics (Huang, Aral, and Brynjolfsson 2020, 1148-1150). However, it excludes some of the demographics due to being limited to digital space only, and has rather low exposure rate with only 0.5% web users seeing the ad.

4. Discuss which acquisition method Tom should choose under what circumstances and explain why.

It is suggested that marketing campaigns should target the volume and quality of leads. Building presence among competitors is essential in the early stage to make the business visible, whereas targeted ads attract a paying and interested audience. Campaign performance should be monitored dynamically through KPIs such as expected vs actual response rate, CAC, retention, and lifetime value.

Blanket mailing, despite its high CAC (£30) and low success rate (~2 %), may still serve a role during the pre-launch stage. Direct-mail response rates typically average from 4% to 6% in the UK (DMA UK 2023), which means that even small returns can generate early traction if the objective is exposure rather than conversion. However, because the conversion efficiency is low, it suits early-stage awareness only.

Targeted mailing becomes relevant once awareness exists and engagement is needed in key segments. It achieves higher response rates and works best for campaigns addressing nearby offices, coworking spaces, gyms, or university campuses. Although more expensive than digital alternatives, it increases legitimacy and conversion quality.

SEM should prevail in the long term, as it combines precision targeting with high intent: users are actively searching for relevant products. Research shows that 76% of intent-driven mobile searches result in visits within 24 hours (Embryo 2025). SEM also provides performance data, allowing dynamic monitoring and adaptation.

# 2. A Marketing Survey to Estimate Customer Metrics

5. Based on the case description, discuss any flaw(s) in the survey design and how would you improve the survey design

Conducting the survey outside Heytea only during weekday lunch hours makes it prone to location and timing bias. Reliable CLV requires samples that reflect the brand's wider catchment and different purchasing contexts rather than one-location intercepts (AAPOR 2021).

The first question is limited to a self-label of "foodie", measuring image instead of behaviour and encouraging bias. Without a graded scale, occasional buyers can misclassify themselves, therefore inflating CLV projections. Also, respondents misdate purchases and over-report how often they buy. The suggestion is to tie questions to the latest purchase, as longer recall produces inaccurate data. It would also be beneficial to know average prices for bubble tea to estimate not only how much they spend in total but also how many actual teas customers buy.

The final question asks for a decimal probability of buying next month, which is inappropriate for a standard respondent, as it requires prerequisite statistical understanding. Also, intention estimates tend to be over-optimistic and cannot be reliable in fact (Sheeran and Webb 2016, 278-280).

6. Load the survey_data.csv file into R. Report the summary statistics for each of the two customer segments (foodie vs non-foodie). Comment on any noteworthy observations you feel relevant for Tom.

Foodies buy more often, spend more per visit, and show stronger loyalty intentions – they drive repeat revenue and should be prioritised for retention and personalised offers. Non-foodies are more price-sensitive and less consistent in purchase behaviour, meaning low-cost tools such as loyalty stamps or short-term promotions can help turn them into regular buyers. Tom should allocate acquisition budget based on expected CLV – premium offers and community-style campaigns for foodies, and discount or awareness tactics for non-foodies. Before further modelling, missing or inconsistent data on spend and frequency should be corrected to secure reliable CLV estimates.

```r
# load the data.
survey_data <- read.csv("survey_data.csv")

# report the summary statistics
## Filtering the dataset to view the foodie segment
f_data <- survey_data %>% filter(foodie == 1)
```

```
## Then, filtering the dataset to view the non-foodie segment
nf_data <- survey_data %>% filter(foodie == 0)
summary(f_data)

  customer_id     purchase_frequency average_spend    retention_rate
 Min.   :  1.00   Min.   : 1.000     Min.   : 0.000   Min.   :0.7100
 1st Qu.: 97.25   1st Qu.: 6.000     1st Qu.: 4.000   1st Qu.:0.8200
 Median :193.50   Median : 8.000     Median : 6.000   Median :0.8500
 Mean   :193.50   Mean   : 8.057     Mean   : 5.974   Mean   :0.8502
 3rd Qu.:289.75   3rd Qu.:10.000     3rd Qu.: 8.000   3rd Qu.:0.8800
 Max.   :386.00   Max.   :19.000     Max.   :14.000   Max.   :0.9800
     foodie
 Min.   :1
 1st Qu.:1
 Median :1
 Mean   :1
 3rd Qu.:1
 Max.   :1

summary(nf_data)

  customer_id     purchase_frequency average_spend    retention_rate
 Min.   : 387.0   Min.   : 0.000     Min.   : 0.000   Min.   :0.5500
 1st Qu.: 540.2   1st Qu.: 3.000     1st Qu.: 2.000   1st Qu.:0.6700
 Median : 693.5   Median : 4.000     Median : 4.000   Median :0.7000
 Mean   : 693.5   Mean   : 4.021     Mean   : 3.993   Mean   :0.7032
 3rd Qu.: 846.8   3rd Qu.: 5.000     3rd Qu.: 5.000   3rd Qu.:0.7400
 Max.   :1000.0   Max.   :11.000     Max.   :12.000   Max.   :0.8600
     foodie
 Min.   :0
 1st Qu.:0
 Median :0
 Mean   :0
 3rd Qu.:0
 Max.   :0
```

7. Compute the average spending, average shopping frequency, and average retention rate for both foodie and non-foodie customer segments.

```
# Compute and report the required statistics

avg_spending_nonfoodie <-
avg_frequency_nonfoodie <-
avg_retention_rate_nonfoodie <-

avg_spending_nonfoodie <- survey_data %>%
  filter(foodie == '0') %>%
  summarise(avg_spending_nonfoodie = mean(average_spend, na.rm = TRUE)) %>%
  ungroup()

avg_frequency_nonfoodie <- survey_data %>%
```

```
  filter(foodie == '0') %>%
  summarise(avg_frequency_nonfoodie = mean(purchase_frequency, na.rm = TRUE))
%>%
  ungroup()

avg_retention_rate_nonfoodie <- survey_data %>%
  filter(foodie == '0') %>%
  summarise(avg_retention_rate_nonfoodie = mean(retention_rate, na.rm =
TRUE)) %>%
  ungroup()

avg_spending_foodie <- survey_data %>%
  filter(foodie == '1') %>%
  summarise(avg_spending_foodie = mean(average_spend, na.rm = TRUE)) %>%
  ungroup()

avg_frequency_foodie <- survey_data %>%
  filter(foodie == '1') %>%
  summarise(avg_frequency_foodie = mean(purchase_frequency, na.rm = TRUE))
%>%
  ungroup()

avg_retention_rate_foodie <- survey_data %>%
  filter(foodie == '1') %>%
  summarise(avg_retention_rate_foodie = mean(retention_rate, na.rm = TRUE))
%>%
  ungroup()

# This code block is for printing the results, pls do not modify
print("Metrics for foodie segment:")

[1] "Metrics for foodie segment:"

print(paste("The average spending is £", avg_spending_foodie))

[1] "The average spending is £ 5.9740932642487"

print(paste("The average frequency is", avg_frequency_foodie))

[1] "The average frequency is 8.05699481865285"

print(paste("The average retention rate is", avg_retention_rate_foodie))

[1] "The average retention rate is 0.850233160621762"

print("Metrics for non-foodie segment:")

[1] "Metrics for non-foodie segment:"

print(paste("The average spending is £", avg_spending_nonfoodie))

[1] "The average spending is £ 3.99348534201954"
```

```
print(paste("The average frequency is", avg_frequency_nonfoodie))

[1] "The average frequency is 4.02117263843648"

print(paste("The average retention rate is", avg_retention_rate_nonfoodie))

[1] "The average retention rate is 0.703241042345277"
```

# 3. Customer Break-Even and Lifetime Value

8. Use R programming to compute the CLV for foodie customers. Discuss whether or not foodie customers are profitable to acquire.

```
## Complete the code below
## Step 1. Defining CLV horizon for analysis
N <- 24       # 2 years but in months due to seasonality
COGS <- 0.45  # Cost Of Goods Sold from case study
c <- 0        # Tom has chosen SEM as primary marketing instrument,
# and it operates on CPC-basis, therefore, there is no fixed number
k <- 0.1/12   # discount rate converted to monthly
d <- 1/ (1 + k) # monthly discount factor
r_foodie <- as.numeric(avg_retention_rate_foodie) # monthly retention rate
from survey data

# The as.numeric function is used due to running into the issue of data frame
mixing up with vector

## Step 2. Calculating monthly profit per customer
# M = (avg monthly revenue) * (1 - COGS)
M_foodie <- avg_spending_foodie*avg_frequency_foodie * (1-COGS)

# g = M - c , - monthly net profit per customer
g_foodie <- M_foodie - c
g_foodie <- as.numeric(g_foodie)

## Step 3. Creating profit sequence for all months
# rep() function replicated g across 24 periods (months)
g_seq_foodie <- rep(g_foodie, N)
g_seq_foodie <- as.numeric(g_seq_foodie)

## Step 4. Applying retention rate
# Each months profit is multiplied by r^(t-1), where t is the
# time index for each month

g_seq_after_retention_foodie <- g_seq_foodie * (r_foodie)^(seq(1, N) - 1)

## Step 5. Applying discount factor
# Each months retained prodit is discounted
```

```
g_seq_after_retention_discount_foodie <-
g_seq_after_retention_foodie*d^(seq(1,N))

## Step 6. Compute CLV

CLV_foodie <- sum(g_seq_after_retention_discount_foodie)

# This code block is for printing the results, pls do not modify
print(paste0("The g_seq is ", g_seq_foodie[1:5]))

[1] "The g_seq is 26.4732811619104" "The g_seq is 26.4732811619104"
[3] "The g_seq is 26.4732811619104" "The g_seq is 26.4732811619104"
[5] "The g_seq is 26.4732811619104"

print(paste0("The g_seq_after_retention_discount is ",
g_seq_after_retention_discount_foodie[1:5]))

[1] "The g_seq_after_retention_discount is 26.2544937142913"
[2] "The g_seq_after_retention_discount is 22.1379581863399"
[3] "The g_seq_after_retention_discount is 18.666868917505"
[4] "The g_seq_after_retention_discount is 15.7400240912156"
[5] "The g_seq_after_retention_discount is 13.2720896839705"

print(paste0("The CLV for foodie customers is £", CLV_foodie))

[1] "The CLV for foodie customers is £164.651845501621"
```

9. Use R programming to compute the CLV for non-foodie customers; use comments #... to explain your steps. Discuss whether non-foodie customers are profitable to acquire.

```
## Step 1. Defining CLV parameters
# The majority of information is consistent with the previous code block
N <- 24       # 2 years but in months due to seasonality
COGS <- 0.45  # Cost Of Goods Sold from case study
c <- 0        # Tom has chosen SEM as primary marketing instrument,
# and it operates on CPC-basis, therefore, there is no fixed number
k <- 0.1/12   # discount rate converted to monthly
d <- 1/ (1 + k) # monthly discount factor
r_nonfoodie <- as.numeric(avg_retention_rate_nonfoodie) # monthly retention
rate from survey data

## Step 2. Calculating monthly profit per customer
# M will be calculated based on average monthly revenue of customers.
M_nonfoodie <- avg_spending_nonfoodie*avg_frequency_nonfoodie * (1-COGS)
# g = M - c , where M is profit and c is variable marketing costs.
g_nonfoodie <- M_nonfoodie - c
g_nonfoodie <- as.numeric(g_nonfoodie)

## Step 3. Creating profit sequence for all months
# G_sequence is a profit for all months, for which the rep()
```

```
# function is used to derive elements for a vector
g_seq_nonfoodie <- rep(g_nonfoodie, N)
g_seq_nonfoodie <- as.numeric(g_seq_nonfoodie)

## Step 4.Applying retention rate
# Each months profit is multiplied by r^(t-1),
# where t is the time index for each month
g_seq_after_retention_nonfoodie <- g_seq_nonfoodie * (r_nonfoodie)^(seq(1, N)
- 1)

## Step 5. Applying discount factor
g_seq_after_retention_discount_nonfoodie <-
g_seq_after_retention_nonfoodie*d^(seq(1,N))

## Step 6. Computing adjusted CLV
# Since non-foodies are targeted, it is essential
# to introduce CAC. Since the chosen strategy is SEM, it will be used.

CLV_nonfoodie <- sum(g_seq_after_retention_discount_nonfoodie) - CAC_SEM

# This code block is for printing the results, pls do not modify
print(paste0("The g_seq is ", g_seq_nonfoodie[1:5]))

[1] "The g_seq is 8.83217169412938" "The g_seq is 8.83217169412938"
[3] "The g_seq is 8.83217169412938" "The g_seq is 8.83217169412938"
[5] "The g_seq is 8.83217169412938"

print(paste0("The g_seq_after_retention_discount is ",
g_seq_after_retention_discount_nonfoodie[1:5]))

[1] "The g_seq_after_retention_discount is 8.75917853963245"
[2] "The g_seq_after_retention_discount is 6.10890629385074"
[3] "The g_seq_after_retention_discount is 4.2605292195146"
[4] "The g_seq_after_retention_discount is 2.97141719927995"
[5] "The g_seq_after_retention_discount is 2.07235292079106"

print(paste0("The CLV for non-foodie customers is £", CLV_nonfoodie))

[1] "The CLV for non-foodie customers is £26.944102785776"

# Non-foodie customers generate a low monthly profit and,
# after subtracting the £2 CAC, their CLV remains marginal.
# This suggests they are barely profitable to acquire and
# offer limited long-term return compared with foodie customers.
```

# 4. Loyalty Program for Tom's Bubble Tea Shop

10. Should Tom go ahead with the loyalty program for the bubble tea business? Explain your codes and calculations in detail.

To assess whether Tom should introduce the loyalty programme, CLV is compared for foodie and non-foodie customers before and after the scheme. The added cost equals £4 * (average frequency / 4) per month, while retention increases to 0.9 for foodies and 0.75 for non-foodies. CLV is recalculated over 24 months using the same discounting setup and retention structure as before.

```
# show your calcuations below;
# feel free to create your own variables for the calculation
## Step 1. Defining new retention rates under loyalty
r_foodie_loyal  <- 0.90
r_nonfoodie_loyal <- 0.75

## Step 2. Computing expected monthly cost of free drink
free_cost_foodie <- 4 * (avg_frequency_foodie/4)
free_cost_nonfoodie <- 4 * (avg_frequency_nonfoodie/4)

# Step 3. Adjusting monthly profit for loyalty
g_foodie_loyal <- (avg_spending_foodie * avg_frequency_foodie)*(1 - COGS) -
free_cost_foodie
g_nonfoodie_loyal <- (avg_spending_nonfoodie * avg_frequency_nonfoodie) * (1
- COGS) - free_cost_nonfoodie

# Step 4. Computing CLV for both segments under loyalty
g_seq_foodie_loyal <- rep(as.numeric(g_foodie_loyal), N)
g_seq_nonfoodie_loyal <- rep(as.numeric(g_nonfoodie_loyal), N)

g_seq_after_retention_discount_foodie_loyal <-
  g_seq_foodie_loyal * (r_foodie_loyal)^(seq(1, N) - 1) * d^(seq(1, N))
g_seq_after_retention_discount_nonfoodie_loyal <-
  g_seq_nonfoodie_loyal * (r_nonfoodie_loyal)^(seq(1, N) - 1) * d^(seq(1, N))

CLV_foodie_loyal <- sum(g_seq_after_retention_discount_foodie_loyal)
CLV_nonfoodie_loyal <- sum(g_seq_after_retention_discount_nonfoodie_loyal)

# Step 5. Comparing with existing CLVs
difference_foodie <- CLV_foodie_loyal - CLV_foodie
difference_nonfoodie <- CLV_nonfoodie_loyal - CLV_nonfoodie

# Step 6. If the programme needs or needs not to be launched, the return will
be TRUE or FALSE
launch_programme <- (difference_foodie > 0) & (difference_nonfoodie > 0)
launch_programme
```

```
[1] FALSE
```

11. Discuss how Tom can use CLV as a customer relationship management tool to guide his future marketing decisions

For a small business like Tom's bubble-tea shop, CLV works more as a control tool for strategic and financial decisions. CLV combines marketing, finance, and customer data to define which customers to attract, how much to spend on retention, and when to disengage from unprofitable ones (Dreze and Bonfrer 2008, 2-3).

At the financial-planning level, CLV sets the upper limit for Customer Acquisition Cost. Comparing expected CLV with CAC across channels such as search ads, influencer marketing, or local promotions ensures that marketing investment produces a positive return. Research shows that CLV-based budgeting increases long-term profitability and stabilises cash flows (Gupta et al. 2006, 141-145).

At the operational level, CLV supports segmentation and prioritisation. Customers differ not only by behaviour but by profit contribution, so it is highly helpful to understand as whether Tom should launch personalised offers and faster service for high-value regulars or low-cost digital contact for occasional buyers. Firms using CLV-based targeting achieve higher ROI than those using frequency or recency alone (Gupta et al 2006, 143). In practice, this means cutting blanket discounts and focusing on profitable retention through simple loyalty tools or small cross-sells that raise margin without lowering value.

CLV also acts as a monitoring system. Because it is calculated from discounted future profits, it reacts to shifts in retention, spend, or cost structure. Falling CLV indicates deteriorating customer economics before it appears in sales. Tom can read CLV trends as early signals of strategic risk, for example, loyalty schemes that raise cost faster than retention.

Aggregated CLV forms customer equity – the total present value of all customer relationships. Tracking total CLV each quarter shows whether marketing grows the underlying asset of the business, which is its customer base, or only short-term revenue.

12. What name would you give to the bubble tea shop ;-)

Dr Meow's Bubble-T. Slogan: *We are Always right with sugar %*

(T stands for Teacher :))

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