Exploring behavioural patterns in interaction data from the "Your Fertility" website

Master's Thesis

Presented by

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Author's Declaration

Hereby I, Ngoc Cat My Tran, certify that this work does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any university; and that to the best of my knowledge and belief it does not contain any material previously published or written by another person except where due reference is made in the text.

Signed	**Date**
Ngoc Cat My Tran	Adelaide, 11 June 2021

Abstract

Understanding user's behavioural patterns while using a certain website can lead to improved website design with more personalized features, or more precisely targeted marketing campaigns. Various papers have been conducted to find the user's behavioural patterns in the online health platforms, but the majority of them just focus on totally or partially offline behaviours. This study focuses on exploratory data analysis to identify behavioural patterns in using an interactive tool on a fertility education platform (the "Your Fertility" website). A dataset of 4245 people (84% women and 16% men) who voluntarily accessed the online Healthy Conception Tool (HCT) on the "Your Fertility" website was analysed. Depending on the types of variables, the paper used certain statistical techniques including Pearson correlation coefficient, Scatter plot, Chi-Squared Test, Bonferroni correction, One-hot encoding, and Point Biserial Correlation. The paper indicated that the modified profile (the last input of users) has a greater number of correlations than the initial profile (the first input of users), which supports the "linear slider format" issue. Besides, this analysis shows the significant gender differences in behaviours related to age and weight directions, between people having children and no children, and between people having STI (Sexually transmitted infections) test and not. Also, Principal Component Analysis and K-means clustering were applied to figure out the user's behaviours in groups.

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TABLE OF CONTENTS

AUTHOR'S DECLARATION 2

ABSTRACT 3

ACKNOWLEDGEMENTS 4

TABLE OF CONTENTS 5

LIST OF FIGURES 6

LIST OF TABLES 7

LIST OF ABBREVIATIONS 8

1. INTRODUCTION 9

1.1 MOTIVATION 9
1.2. RESEARCH QUESTIONS 10
1.3. RESEARCH OBJECTIVES 10
1.4. STRUCTURE 10

2. BACKGROUND STUDY AND RESEARCH 12

2.1 INTRODUCTION OF "YOUR FERTILITY" WEBSITE AND HEALTHY CONCEPTION TOOL (HCT) 12
2.2. THE IMPORTANCE OF UNDERSTANDING ONLINE USER'S INTERACTIVE BEHAVIOURS 13
2.3. REVIEW ON USER'S BEHAVIOUR IN ONLINE HEALTH EDUCATION PLATFORMS 14

3. DATA DESCRIPTION 17

3.1. DATA COLLECTION 17
3.2. ORIGINAL DATA 19
3.3. DATA FOR PAIR-VARIABLE ANALYSIS 20
3.4. DATA FOR GROUP-VARIABLE ANALYSIS 22

4. METHODOLOGY 24

4.1. PAIR-VARIABLE ANALYSIS 25
4.2. GROUP-VARIABLE ANALYSIS 28

5. ANALYSIS AND RESULTS 32

5.1. PAIR-VARIABLE ANALYSIS'S RESULTS 32
5.1.1. The modified profile and the initial profile 32
5.1.2. Behavioral differences between men and women 39
5.1.3. Previous Children and Weight change behaviour 41
5.1.4. STI Test and Completion (%) 41
5.2. GROUP-VARIABLE ANALYSIS RESULTS 42

6. DISCUSSION AND FUTURE WORK 45

REFERENCES 48

APPENDIX 53

List of Figures

Figure 1. The questions in Page 1 in the HCT (Fertility Coalition, 2012) 17

Figure 2. The questions in Page 2 in the HCT (Fertility Coalition, 2012) 18

Figure 3. The hierarchy visualisation of data division 21

Figure 4. The general process for data analysis 24

Figure 5. The flowchart of pair-variable analysis 25

Figure 6. Chi-square tests using the Bonferroni correction between Gender and Age changing behaviours in the modified profile 27

Figure 7. The flowchart of the group-variable analysis 28

Figure 8. The PCA visualisation with the target Completion rate 29

Figure 9. An example for PCA visualisation without the target variable. 30

Figure 10. Data allocation by K-means with centroids after training the model 30

Figure 11. Correlation coefficient between features and user's initial health profile (the first value) 34

Figure 12. Correlation coefficient between features and user's modified health profile (the last value) 35

Figure 13. The scatter plots of Smoking and its Mean-Median between the initial profile and the modified profile 36

Figure 14. The scatter plots of Alcohol Consumption and its Mean-Median between the initial profile and the modified profile 37

Figure 15. The scatter plots of Trying Month and its Mean-Median between the initial profile and the modified profile 37

Figure 16. The scatter plots of Sex Frequency and its Mean-Median between the initial profile and the modified profile 38

Figure 17. The histogram charts for 7 numerical variables of the initial profile 38

Figure 18. The histogram charts for 7 numerical variables of the modified profile 39

Figure 19. The small set of heat map for correlations between the categorical variables in the modified profile and numerical behavioural patterns 42

Figure 20. The PCA visualisation of PC6 and PC9 with K-means for assigning data to clusters 43

Figure 21. The correlation coefficient between Clusters and the inputted variables in PC6 and PC9. 43

Figure 22. The PCA visualisation of PC7 and PC8 with K-means for assigning data to clusters 43

Figure 23. The correlation coefficient between Clusters and the inputted variables in PC7 and PC8 44

Figure 24. The linear slider format is used on the website for numerical answers 46

List of Tables

Table 1. The description of attributes in the original dataset 19

Table 2. A dataset of one visitor ID that captures all the changes of the user’s input. 20

Table 3. The summary of the expanded dataset 21

Table 4. The data classification of behavioural patterns 22

Table 5. The description of 5 data groups after feature engineering....................23

Table 6. The statistical techniques applied in the analysis depending on the types of variables 25

Table 7. The Sex Right Time after the one-hot encoding process 26

Table 8. The number of principal components per each scenario with the cumulative variance over 80%29

Table 9. The number of relationships in pair-variable analysis 32

Table 10. The list of correlations between numerical variables of user’s profiles and their mean and median (p < 0.001) (bold numbers are over 0.5) 36

Table 11. Behavioural differences between men (n=669) and women (n=3461) in two profiles and two types of directions....................40

Table 12. The percentages of men and women in Age direction in the modified profile between the last input and the first input....................40

Table 13. The percentages of men and women in Height direction in the initial profile between the last input and the first input....................41

Table 14. The percentages of men and women in Weight direction in the modified profile between the last input and the first input....................41

Table 15. The percentages of people who have previous children and not in Weight directions in the initial profile 41

Table 16. The percentages of people who having previous children and not in Weight directions in the modified profile 41

List of Abbreviations

BMI	Body mass index
HCT	Healthy Conception Tool
HISB	Health Information-Seeking Behaviour
ID	Identification/Identity/Identifier
MAC	Mean Age at Childbearing
PC	Principal Component
PCA	Principal Component Analysis
PCOS	Polycystic ovary syndrome
RRI	Robinson Research Institute
STI	Sexually transmitted infections
VARTA	The Victorian AssistedReproductive Treatment Authority
VAS	Visual analog scale

1. Introduction

1.1 Motivation

The Internet is becoming more and more popular for providing health information and access to health care (Hinchliffe and Mummery, 2008). In fact, information retrieved from the Internet is the most commonly referenced source of patients before consulting with clinicians (Rew et al., 2018). To improve fertility awareness, the "Your Fertility" website has been developed since 2011 by The Fertility Coalition with the fund from the Australian Government (The Fertility Coalition, 2012b). Besides other interactive tools such as ovulation calculator, animations, quiz, etc., the Healthy Conception Tool (HCT) is published in 2016 on the website to promote the modifiable factors that can reduce the possibility of having a baby (Raymond J. Rodgers et al., 2020). The tool provides information about these factors through the interactive questions and captures the data inputted by users for analysis and development (Raymond J. Rodgers et al., 2020).

However, there are certain barriers in IT systems to meet user's demands (Kerr et al., 2009) while the user's behaviours on fertility websites are limited in the previous studies. Various papers were conducted to find the user's behavioural patterns in the online health platforms, but the majority of them just focus on completely or partially offline behaviours (Guillory et al., 2014, Wall, 2007, Bujnowska-Fedak and Węgierek, 2020, Van Dijk et al., 2016, van Woerden et al., 2014, Bauerle Bass, 2003, Anderson, 2018, Graffigna et al., 2017, Mills and Todorova, 2016, Spoelman et al., 2016). In the number of studies analysing online user's data, most of them analysed to predict the general trends or figures (Ojala et al., 2017, Rampazzo et al., 2018) and to portrait user's profile or preferences (Starling et al., 2018, Raymond J. Rodgers et al., 2020), not to analyse the user's behaviours to understand their implicit needs.

Moreover, understanding user's behaviours can assist website operators to improve a user's experience by designing the website based on user's expectations and preferences as well as providing better performance, personalized features, or more precisely targeted marketing campaigns (Wang et al., 2016). Notably, one of the causes that lead to project failures is user's dissatisfaction (Anthopoulos et al., 2016, Pinto and Mantel, 1990, Imamoglu and Gozlu, 2008).

Meanwhile, there is no existing research in the Your Fertility program related to online user's behaviours, except the analysis of user's demographics and characteristics (Raymond J. Rodgers et al., 2020). Therefore, exploring behavioural patterns on the "Your Fertility" website is a currently active research domain, which can be the initial reference for further research and website development to succeed in meeting user's expectations.

1.2. Research Questions

The research topic is conducted with the purpose of exploring the interactive data from the "Your Fertility" website and its potential findings on understanding users as well as improving the user's website experience. The dataset with a great number of variables is very large, which is complex to comprehensively analyse to figure out all potential behavioural patterns. In the scope of an 18-unit thesis undertaken by one student, the paper focuses on answering the following questions:

- Is there any significant relationship between user's behaviours and user's health profiles in the "Your Fertility" website's context?
- What are these relationships?

1.3. Research Objectives

The main aim of the paper is to improve the health website quality for a better user experience by finding behavioural patterns of visitors to "Your Fertility" website by statistical techniques. These findings can also optimise the website design, especially the HCT not only to increase user's satisfaction but also to reduce the potential factors of data quality. Also, marketing and communication strategies can be beneficial because of the findings of user's preferences and behaviours. It is also hoped that the research will aid the development of measurable metrics for the healthcare professional to understand the concerns and needs of the relevant population based on data provided by visitors to the website.

1.4. Structure

The research report is divided into the following sections.

1. *Introduction*

The section provides the context and motivation for conducting the topic and the main research questions and primary goals. The structure of the paper is also provided in the section.

2. *Literature review*

The introduction about the "Your Fertility" website and the Healthy Conception Tool (HCT) is mentioned in the section. Additionally, the section provides the importance of understanding user's interaction in online health sites through its benefits and applications. Also, literature on current research of user's behaviours on healthcare websites in general and on fertility websites, in particular, will be discussed. The limitation and recommendation from the previous research papers will be concluded to explain why the topic should be chosen.

3. *Data Description*

The section will give a brief introduction about how the dataset is collected. It provides the classification of data in two phases of the analysis including pair-variable analysis and group-variable analysis as well as and summary of data description in each stage.

4. *Methodology*

The analytical design and statistical methods applied in the analysis will be discussed in the section. The flowcharts are illustrated for visualisation of the analysing process. Also, a brief explanation for each technique is also mentioned.

5. *Analysis and Results*

The results from undertaking the analysis will be illustrated in this section. Following is the explanation and interpretation of the results.

6. *Discussion and Future Work*

The section concludes key findings from the analysis with explanation by literature review. The suggested application and recommended approaches for future studies are mentioned.

2. Background Study and Research

2.1 Introduction of "Your Fertility" website and Healthy Conception Tool (HCT)

Your Fertility program established in 2011 is a government-funded fertility health promotion program with the purpose of awareness improvement related to fertility-affected factors that can assist people to make the best possible decisions regarding childbearing (Hammarberg et al., 2017a). The program is developed by the Fertility Coalition which is a partnership between, the Robinson Research Institute (RRI) at the University of Adelaide, Healthy Male, Monash University, and Jean Hailes for Women's Health (The Fertility Coalition, 2012b).

Due to the impact of the Internet on Health Information-Seeking Behaviour (HISB) (Diaz et al., 2002), as a part of Your Fertility program, Fertility Coalition built a website (www.Your Fertility.org.au) in 2012 for evidence-based information and resources related to fertility health education (Hammarberg et al., 2017a). The "Your Fertility" website is mobile-friendly with up-to-date information focusing on common factors that affect fertility and reproductive outcomes (Hammarberg et al., 2017a). For 5 years from its public launch, the website attracted over 10 million web page views and more than 5 million users (Hammarberg et al., 2017a).

Besides other interactive tools such as ovulation calculator, animations, quiz, etc., in 2016, the Healthy Conception Tool (HCT) is published on the website to promote the modifiable factors that can reduce the possibility of having a baby (Raymond J. Rodgers et al., 2020). The tool provides information about these factors through the interactive questions and captures the data inputted by users for analysis and development (Raymond J. Rodgers et al., 2020).

The HCT's questions are arranged in two pages. Page 1 has 5 questions including genders, age, weight, height, alcohol consumption, cigarette consumption while Page 2 has questions related to contraceptive intention, trying months, children, STI test, menstrual cycle regularity, frequency and timing of intercourse. The list of questions has changed for website update to provide the latest and useful information. For each answer, the HCT displays the basic recommendations and color degree in response to the user's inputs (i.e., green colour means positive effects or red colour means negative effects on fertility). The recommendation for each answer is the basic facts based on the evidence. After answering all questions, the user can select the 'View Summary' button to view a summary of all answers and the facts for each question.

2.2. The importance of understanding online user's interactive behaviours

The Internet is becoming more and more popular for providing health information and access to health care (Hinchliffe and Mummery, 2008). Health care's intensive information can be collected, processed and accessed online without barriers of the offline world (Helen et al., 2012). In fact, information retrieved from the Internet is the most common use of online medical information technologies (Rew et al., 2018). Moreover, the Internet of Things (IoT) has a significant impact on the way of data collection and analysis (Zou et al., 2020).

The user's interactive data on the website can provide user's insights and their needs (Zou et al., 2020), even their implicit behaviours and approaches (White et al., 2002). Understanding user's behaviours can improve user's experience by delivering personalised features, better targeted marketing campaigns, and higher performance (Wang et al., 2016). The purpose of user's analysis is to design a website for user's diverse needs, preferences and behaviours (Pang et al., 2016). Lacking adequate user's insight analysis can lead to project failures because of not meeting user's expectation (Anthopoulos et al., 2016, Pinto and Mantel, 1990, Imamoglu and Gozlu, 2008).

User's expectations and preferences role an important play in their feeling about the trustworthiness of the health websites. In an experiment among 15 women in England, many participants ignored high-quality content websites simply on the poor design and trusted fewer websites because of their preferences (Sillence et al., 2007). Another similar finding is found in the study by Marin and Marin (1990), in which identity preferences are highlighted as a motivation for users to trust those websites because of the self-verification theory (Swann Jr and Read, 1981). It means a number of medically credible websites can be rejected because users cannot find their social identity in the content of those sites.

However, user's interactive behaviours in online healthcare platforms are underestimated. In developing public health websites, according to an Australian survey by Kerr et al. (2009), several health websites seem to be developed without enough attention to the growing needs of end-users. Similar findings were reported by Hinchliffe and Mummery (2008) and White and Raman (1999), in which, many organisations pay little attention to evaluations when implementing a website. The reason is that understanding user's behaviour is not easy and the process can be taken significant time and costs (Wang et al., 2016). Remarkably, user's expectations can differ for each feature, such as providing particular feedbacks for recommendations, or accuracy for forecast functions (Su et al., 2020). By pilot survey among 1,000 women with either currently using fertility apps or future intention, Starling et al. (2018) noticed the user's demand for science-based content and personalized information under their circumstances while most of the participants are not satisfied with their used apps. Moreover, in the quality evaluation by Huang et al. (2005) among 266 fertility websites, they generally have low quality scores in all three sections: ownership, content and website navigation. These results raise the importance of evaluation about the expectations and satistication of current users who are using the health care platforms.

When more and more users demand interactive tools instead of traditional information format (Helen et al., 2012), not many healthcare websites collect behavioural and contextual data because they mainly focus on delivering healthcare information for a large number of users more than increasing the existing user's experience on sites (Zou et al., 2020). These types of mentioned data are vital for developing machine learning technologies, which can offer personalised features and behavioural predictions to increase user's engagements and experience (Goldenberg et al., 2021).

2.3. Review on user's behaviour in online health education platforms

Despite the large number of research related to behaviours in online environments, the studies on user's behavioural analysis in online healthcare platforms are limited, especially in fertility health education websites.

Many studies identified the relationship between offline factors and online health platform's behaviours. For example, Guillory et al. (2014) examine the impact of marital status and social support on HISB among 1,329 pregnant women by logistic regression models. They concluded that women with less social support may seek less healthcare information than women who already had social support. In the studies by Bauerle Bass (2003), Anderson (2018), Graffigna et al. (2017), and Mills and Todorova (2016), other factors affecting patient's HISB are listed including, but not limited to, user's self-efficacy, behavior, health status, knowledge, attitude, offline healthcare, and severity of an illness. Furthermore, the role of health promotion websites in user's health behaviours and decisions is significant in the studies by Wall (2007), Bujnowska-Fedak and Węgierek (2020), Van Dijk et al. (2016), and van Woerden et al. (2014). Additionally, the effectiveness of healthcare websites in offline healthcare usage and healthcare costs is investigated by interrupted time series analysis by Spoelman et al. (2016).

The analysis of online user's behaviours in healthcare channels mainly gives attention to user's behaviours on general health areas or suggestions for specific groups of the population. One of the studies analysing the online user behaviours within a health education website is presented by Pang et al. (2016). They analysed the navigation flows of users in the Better Health Channel (http://www.betterhealth.vic.gov.au) to figure out the HISB from user's journey. Their findings show that users tend to explore more topics of health information instead of one single topic. Their recommendation is that the health education website should develop interactive tools to satisfy user's needs and HISB.

Studies by Nguyen et al. (2020) and Nguyen et al. (2018) using the data on health-related websites found that if users can adjust the mode of information's presentation to be suitable for their preferences, characteristics, beliefs, etc., it will lead to the better user's satisfaction and increasing health information recall ability. The results can be applied in a new development process, but they cannot find the challenges or barriers of users in the current website.

The comprehensive analysis by Watfern et al. (2019) for health platform's design and implementation figured out the list of factors affecting user's engagement in the Healthy Mind website based on user's surveys. The findings can be useful to find out the website's problems and revised suggestions. The limitation of the study is that the health websites providing e-mental information assist people with intellectual disability, so their behaviours and insights may be different to the general population who would like to seek for fertility-related information.

A website evaluation research conducted by Ownby and Czaja (2003) presents the overview of design challenges in healthcare website for the elderly. These challenges are visual, motor and cognitive. They concluded that the poor design of websites can be difficult for users and decrease their ability to receive health information. Usability guidelines are provided for website designers to improve user's usability. Although the research's participants are people who are above 50 years old, the research's conclusion may open a potential domain to figure out if the younger people have any challenges related to usability in healthcare websites.

In the fertility field, the volume of studies is inadequate while most of them use online data to analyse for the general prediction or to portrait user's profile and preferences. For instance, Ojala et al. (2017) developed predictive models with 75% of the variance relating fertility for regional variation and trends by combined data from Google Correlate and Google Trends as well as identified the social status based on user's search keywords. Although the dataset of the study is standard and general without sub-groups, the findings still open further directions for analysis with online user's interactive data. A similar method is applied in the study by Rampazzo et al. (2018) when they built a simple regression model to estimate the Mean Age at Childbearing (MAC) for countries having no fertility data by finding a strong relationship between MAC based on Facebook and on traditional data using data from Facebook's Advertising Platform. To define the user's demographics and characteristics, Raymond J. Rodgers et al. (2020) use the interactive data in HCT of the "Your Fertility" website to validate the target audience. The engaged users are 84% of women while the target audience is equally direct to men and women. Giving the fact that men's fertility knowledge often less than women's (Daniluk and Koert, 2013), the communication campaigns of the website can deliver strategies for more concentration on targeting men.

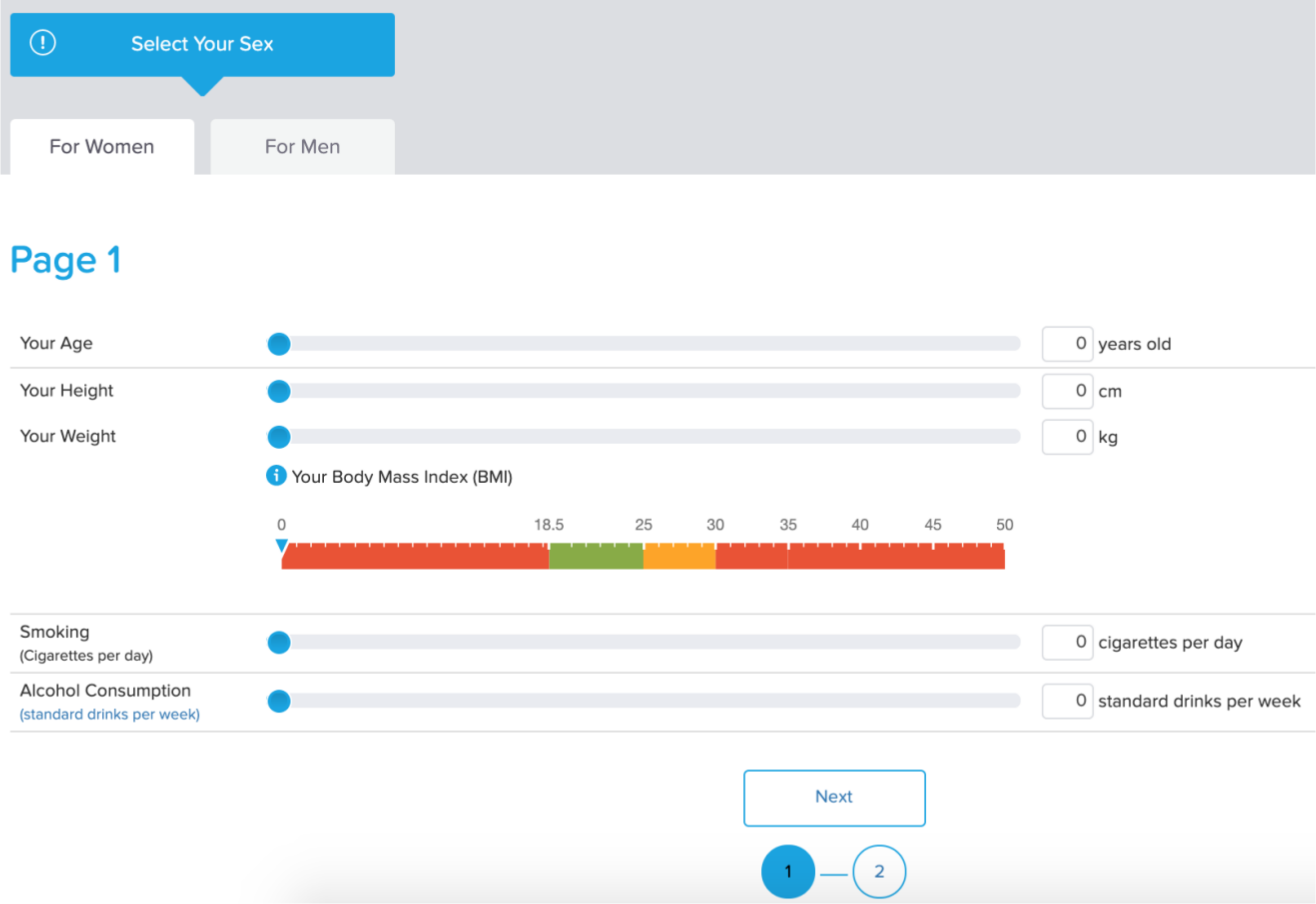
Finally, the Your Fertility program conducted several research projects including fertility-related factor’s awareness (Hammarberg et al., 2013), fertility knowledge and HISB in the general population (Hammarberg et al., 2017b), the HISB of healthcare nurses (Hammarberg et al., 2016), and user’s demographics and characteristics from data of HCT in the “Your Fertility” website (Raymond J. Rodgers et al., 2020) but there is no research in online user’s behaviours or interaction. Therefore, exploring user’s behaviours in an online fertility education platform in general, and the “Your Fertility” website in particular, is an open research domain not only to identify the user’s behavioural patterns but also, to find insights related to user’s challenges, barriers or issues when they interact with an interactive tool like the HCT.

3. Data description

3.1. Data collection

Data used in this paper is collected from 12th June to 31st August 2018 by HTC which is an interactive tool on the "Your Fertility" website. The dataset is non-identifiable and stored in software developed by goAct (http://goact.co/). To derive metrics, Piwik Analytics Platform software (https://matomo.org/) integrated with Your Fertility website was used. The privacy statement is available in the Appendix.

The HCT is an interactive tool with several questions about fertility-related factors such as age, weight, height, smoking, alcohol consumption, conceptive intention, trying months, etc. Due to regular version updates, since 2018, the list of questions in the HCT in June 2021 has changed. In particular, the questions related to conceptive intention and contraception are removed to replace by other modifiable factors' questions including folic acid and iodine, physical activity, chemical exposure, and medication. Because the previous user's interface in 2018 was not available, Figure 1 and Figure 2 are the latest user's interface in June 2021.



Your Age 0 years old

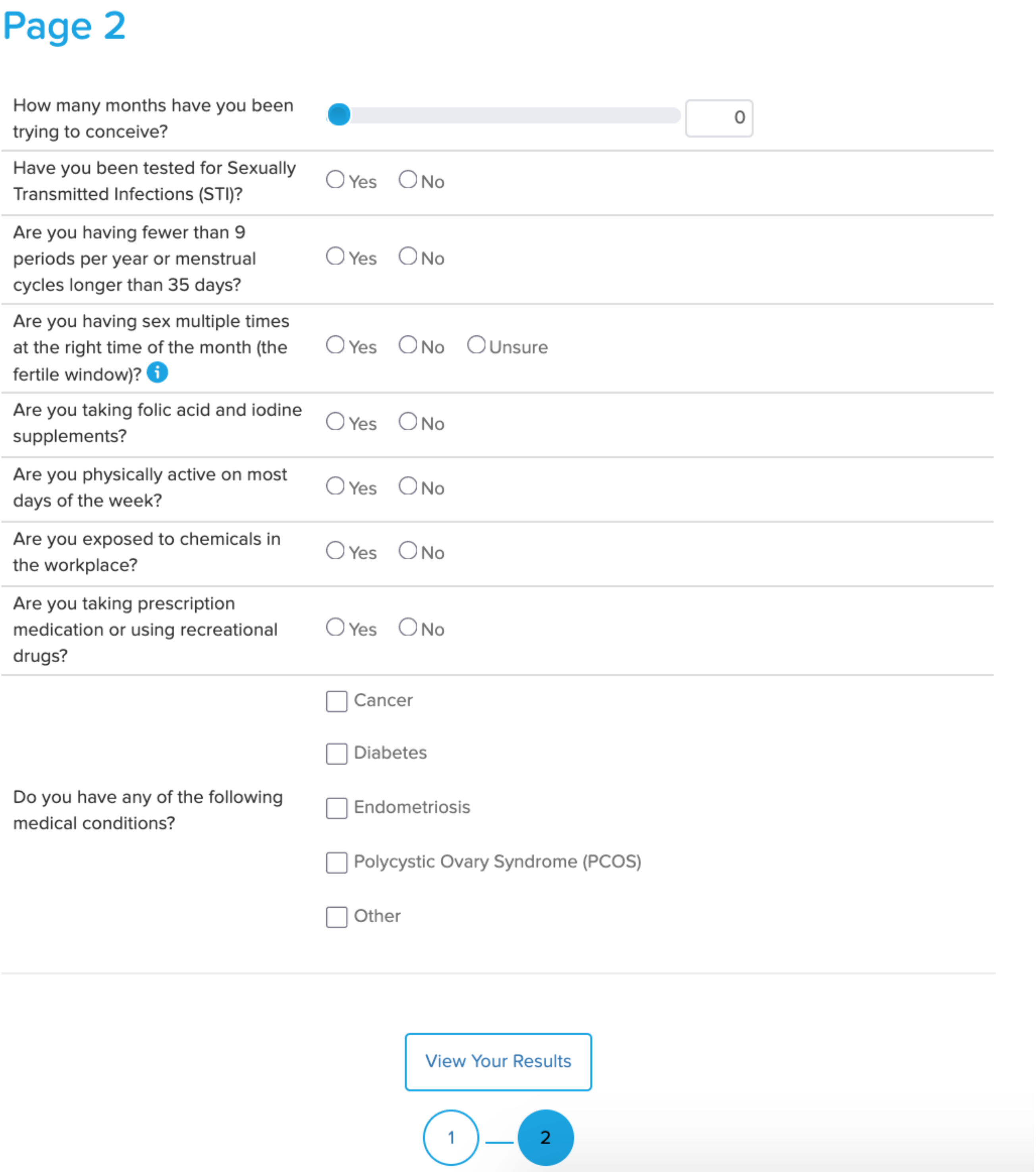
Your Height 0 cm

Your Weight 0 kg

Smoking (Cigarettes per day) 0 cigarettes per day

Alcohol Consumption (standard drinks per week) 0 standard drinks per week

Figure 1. The questions in Page 1 in the HCT (Fertility Coalition, 2012)



Page 2

How many months have you been trying to conceive?	0
Have you been tested for Sexually Transmitted Infections (STI)?	○ Yes ○ No
Are you having fewer than 9 periods per year or menstrual cycles longer than 35 days?	○ Yes ○ No
Are you having sex multiple times at the right time of the month (the fertile window)? ⓘ	○ Yes ○ No ○ Unsure
Are you taking folic acid and iodine supplements?	○ Yes ○ No
Are you physically active on most days of the week?	○ Yes ○ No
Are you exposed to chemicals in the workplace?	○ Yes ○ No
Are you taking prescription medication or using recreational drugs?	○ Yes ○ No
Do you have any of the following medical conditions?	□ Cancer □ Diabetes □ Endometriosis □ Polycystic Ovary Syndrome (PCOS) □ Other

Figure 2. The questions in Page 2 in the HCT (Fertility Coalition, 2012)

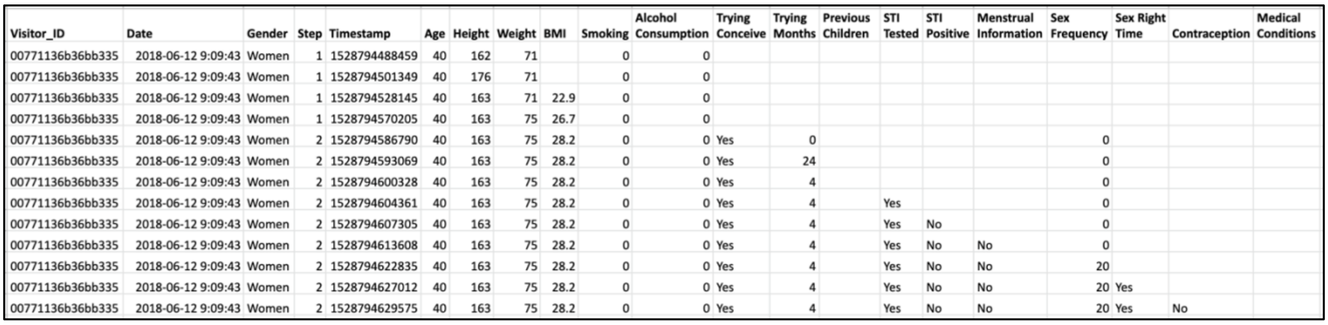
During the data period, 19,277 users visited the HCT while 22% of them interacted with the tool. Of the viewers, 12.5% entered the HTC directly while the rest came from other pages of the "Your Fertility" website. Although the "Your Fertility" website is originated in Australia, the country that has the highest percentage of users is the United States of America (38%). The following countries are Australia (21%), the United Kingdom (10%), Indian (6%), Canada (5%) and others (2%). Clearly, the majority of countries are from English-speaking countries.

3.2. Original data

The original dataset records all changes of inputs from 4245 users in the interactive tool on the "Your Fertility" website. The original dataset has 20 variables described in Table 1. The provided data is by date, which means that one day has one separated file contained a list of users and their changes in the HCT.

	Variable name	Description	Type of input	Type of data
1	Visitor ID	The unique code generated by the system for each user visited the website	Unique code	N/A
2	Gender	The state of being male or female of the user. The user selects the gender on the top of the tool.	"Women" or "Men"	Categorical
3	Step	The page at the user's input. The user has to answer the age, height, and weight questions to move to the next page (the second page). The total pages of the tool are 2.	"1" or "2"	Categorical
4	Timestamp	The time at the user's input. The system will automatically record the time of the user's inputs.	Unix timestamps	N/A
5	Age	The age of the user. The user input by either the slider scale or input text box	Number with the range of 0-45 for women and 0-60 for men	Numerical
6	Height	The height of the user. The user input by either the slider scale or input text box	Number with the range of 0-210	Numerical
7	Weight	The weight of the user. The user input by either the slider scale or input text box	Number with the range of 0-150	Numerical
8	BMI	The user's BMI calculated by the system.	--	Numerical
9	Smoking	The number of cigarettes per day. The user input by either the slider scale or input text box	Number with the range of 0-20	Numerical
10	Alcohol	The number of standard drinks per week (Drinkwise Australia, 2021). The user input by either the slider scale or input text box	Number with the range of 0-20	Numerical
11	Trying Conceive	Intention for trying to conceive	"Yes" or "No"	Categorical
12	Trying Month	The number of months that the user tries to conceive. The user input by either the slider scale (range: 0-20) or input text box	Number	Numerical
13	Previous Children	The situation of having children	"Yes" or "No"	Categorical
14	STI Tested	The situation of the test for Sexually transmitted infections (STI)	"Yes" or "No"	Categorical
15	STI Positive	The result of the STI Test	"Yes" or "No"	Categorical
16	Menstrual Information	The question is "Are you having fewer than 9 periods per year or menstrual cycles longer than 35 days?"	"Yes" or "No"	Categorical
17	Sex Frequency	The number of sex frequency per month. The user input by either the slider scale (range: 0-20) or input text box	Number	Numerical
18	Sex Right Time	Having sex at the right time of the month (the fertile window)	"Yes" or "No" or "Unsure"	Categorical
19	Contraception	Using the contraception method	"Yes" or "No"	Categorical
20	Medical Conditions	The user can tick multiple options: cancer, diabetes, endometriosis, Polycystic ovary syndrome (PCOS), and other	Name of conditions	Categorical

Table 1. The description of attributes in the original dataset



Visitor_ID	Date	Gender	Step	Timestamp	Age	Height	Weight	BMI	Smoking	Alcohol Consumption	Trying Conceive	Trying Months	Previous Children	STI Tested	STI Positive	Menstrual Information	Sex Frequency	Sex Right Time	Contraception	Medical Conditions
00771136b36bb335	2018-06-12 9:09:43	Women	1	1528794488459	40	162	71		0	0										
00771136b36bb335	2018-06-12 9:09:43	Women	1	1528794501349	40	176	71		0	0										
00771136b36bb335	2018-06-12 9:09:43	Women	1	1528794528145	40	163	71	22.9	0	0										
00771136b36bb335	2018-06-12 9:09:43	Women	1	1528794570205	40	163	75	26.7	0	0										
00771136b36bb335	2018-06-12 9:09:43	Women	2	1528794586790	40	163	75	28.2	0	0	Yes	0					0			
00771136b36bb335	2018-06-12 9:09:43	Women	2	1528794593069	40	163	75	28.2	0	0	Yes	24					0			
00771136b36bb335	2018-06-12 9:09:43	Women	2	1528794600328	40	163	75	28.2	0	0	Yes	4					0			
00771136b36bb335	2018-06-12 9:09:43	Women	2	1528794604361	40	163	75	28.2	0	0	Yes	4		Yes			0			
00771136b36bb335	2018-06-12 9:09:43	Women	2	1528794607305	40	163	75	28.2	0	0	Yes	4		Yes	No		0			
00771136b36bb335	2018-06-12 9:09:43	Women	2	1528794613608	40	163	75	28.2	0	0	Yes	4		Yes	No	No	0			
00771136b36bb335	2018-06-12 9:09:43	Women	2	1528794622835	40	163	75	28.2	0	0	Yes	4		Yes	No	No	20			
00771136b36bb335	2018-06-12 9:09:43	Women	2	1528794627012	40	163	75	28.2	0	0	Yes	4		Yes	No	No	20	Yes		
00771136b36bb335	2018-06-12 9:09:43	Women	2	1528794629575	40	163	75	28.2	0	0	Yes	4		Yes	No	No	20	Yes	No	

Table 2. A dataset of one visitor ID that captures all the changes of the user's input.

A dataset of one visitor ID that captures all the changes of the user's input is illustrated in Table 2. In other words, every time the user makes a change using a control on the web page, it is recorded in the data set. For example, in line 6, the user changed their value for Trying Months from 0 to 24, and in line 7, she changed it from 24 to 4.

The challenges of the original dataset are mentioned below:

1. The gender selection on the website may have been difficult for users to notice and is disable when being on page 2 of the Tool. Therefore, the default gender as "Women" affected the user's changes.
2. BMI calculated by the system is not accurate because of the system delays.
3. Smoking and Alcohol Consumption is default 0 from the beginning even the user does not slide or input.
4. Trying Months and Sex Frequency is default 0 when the user moves to page 2 even if the user does not slide or input.
5. No users answer the question of "Medical Conditional" so there is no data in the attribute.
6. Because each row captured a new change of users, each row is unique with its time of changes. However, there are many duplicated rows when joining datasets of all days from 12th June to 31st August 2018 together. After investigation, the reason is that certain datasets by date included a few of users and their changes, who were from the previous day because they made changes at 12 AM or they returned tomorrow. The system captured all changes of visitors until 12 AM of that day but if their last change was made the next day, the system would export the user's changes from the first change in the previous day to the last change in the current day.

3.3. Data for pair-variable analysis

After the duplicate removal, the data has 4,130 people with 3461 women (83.8%) and 669 men (16.2%). Then, the data was removed from the "0" default value and 2 attributes including BMI and

Medical Condition. A reason for BMI removal is because of system inaccurate calculation while no user answered the Medical Condition question (the attribute with no data).

For the user's profile, because of the large change frequency from the user's inputs, it is hard to conclude which input is to represent on behalf of users. Thus, the paper extracted the first user's input value of each attribute as the **initial profile** and the last user's input value of each attribute as the **modified profile**. The pair-variable analysis is applied for both profiles to figure out which profile has more meaningful information.

The process of feature engineering is applied to create the user's behavioural patterns. Hence, the dataset is expanded into 119 variables (excluding visitor ID) with two profiles: the initial profile and the modified profile. Table 3 shows the summary of the expanded dataset while Figure 3 illustrates the hierarchy visualisation of data division. Also, the detail of behavioural patterns is described in Table 4.

Type of variables	Sub-classification	Types of data
Independent (32)	Users' input (16 variables per profile)	Numerical (14) / Categorical (18)
Dependent (87)	Mean, median, number of changes and time spent for each input (45)	Numerical (45)
	Value differences and directions (42)	Numerical (14) / Categorical (28)

Table 3. The summary of the expanded dataset

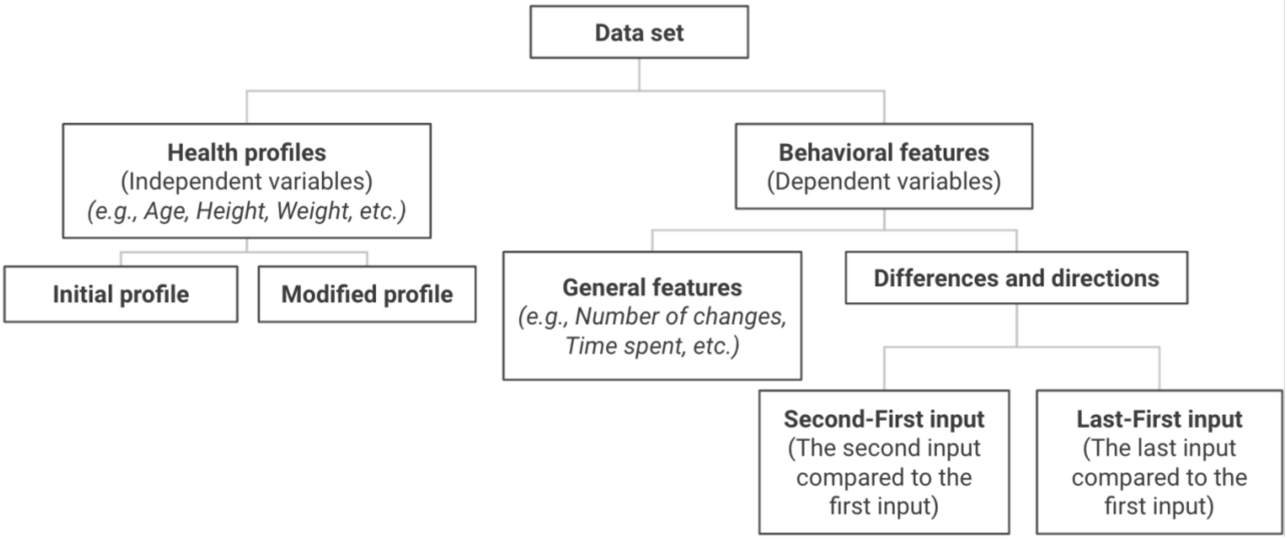

Data set
Health profiles
(Independent variables)
(e.g., Age, Height, Weight, etc.)
Behavioral features
(Dependent variables)
Initial profile
Modified profile
General features
(e.g., Number of changes, Time spent, etc.)
Differences and directions
Second-First input
(The second input compared to the first input)
Last-First input
(The last input compared to the first input)

Figure 3. The hierarchy visualisation of data division

The behavioural group	The behavioural pattern	Type of data
General (45 patterns)	Page Change: Number of page changes	Numerical
	Steps: The total frequency of changes made by users	Numerical
	Duration (milliseconds): Total user's time spent	Numerical
	Completion (%): The rate of the user completing the tool based on the number of completed questions	Numerical

	The change frequency for each attribute	Numerical
	The mean value for each numerical attribute	Numerical
	The median value for each numerical attribute	Numerical
	The time spent on each question	Numerical
Differences (14 patterns)	The difference between the second input's value and the first input's value	Numerical
	The difference between the last input's value and the first input's value	Numerical
Directions (28 patterns)	The change direction between the second input's value and the first input's value for each attribute	Categorical
	The change direction between the last input's value and the first input's value for each attribute	Categorical

Table 4. The data classification of behavioural patterns

In the analysis between categorial variables and numerical variables, the one-hot encoding (also called dummy coding) to transform the categorial variables with more than 2 values into numerical variable based on the value of categorial. For example, Sex Right Time with 3 values including "Yes", "No", and "Unsure", after one-hot encoding, the variable will be transformed into 3 variables: Sex Right Time with the answer "Yes", Sex Right Time with the answer "No", and Sex Right Time with the answer "Unsure". Each variable has two values: 0 means No and 1 means Yes. As result, 29 categorical variables with more than 3 values are transformed into 87 binary variables, which leads to 177 variables in total.

3.4. Data for group-variable analysis

From the result of pair-variable analysis, only the modified profile is applied in the group-variable analysis. To ensure the variable's independence in clustering, the behavioural patterns exclude the mean and median of numerical attributes (14 variables). The group-variable analysis just works well with numerical variables, so 177 variables after one-hot coding are applied in the group-variable analysis.

Because of the large number of variables, the dataset is divided into 5 groups (Table 5) when selecting variables into Principal Component Analysis (PCA) in order to limit the number of components and easily detect the clustering.

	Type of variables	**Description**
1	Original attributes (16)	Users' input
2	General features (31)	Number of changes and time spent for each input
3	Difference (14)	Two types of value differences: (1) between the second input and the first input, and (2) the last input and the first input
4	Change directions between the second input and the first input (42)	Three types of change directions: Positive (input's value increase for numerical variables or from No/Unsure to Yes for categorical variables), No change (the difference of value is 0), and

		Negative (input’s value decrease variables or from Yes to No/Unsure Yes/No for categorical variables)
5	Change directions between the last input and the first input (42)	Three types of change directions: Positive (input’s value increase for numerical variables or from No/Unsure to Yes for categorical variables), No change (the difference of value is 0), and Negative (input’s value decrease variables or from Yes to No/Unsure Yes/No for categorical variables)

Table 5. The description of 5 data groups after feature engineering

4. Methodology

The general process for data analysis is shown in Figure 4 as following steps.

- **Data cleaning:** The process of fixing and removing inaccurate, duplicate, wrong format data within the provided dataset.
  - Removing duplicates: identify and remove 115 duplicate rows of data in 4245 (2.7%) to maintain the data quality.
  - Removing the default value "0": Smoking, Alcohol Consumption, Sex Frequency and Trying Month attributes have the default value of 0, which affects the count of the user's change frequency. Thus, the default value of 0 is removed and the dataset is counted the first changed value as the first input of the user.
  - Format conversion: The timestamp in the original data is in Unix time format which is represented as an integer. It is necessary for Unix time conversion to the readable date/time format.
- **Feature engineering:** The process of transforming raw data into new features to represent the behavioural patterns of users. In this process, 87 behavioural patterns are extracted from the original attributes.

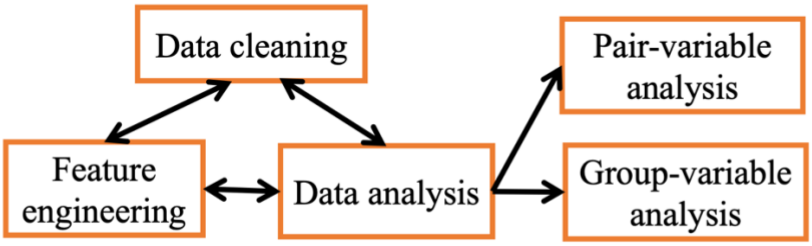


Figure 4. The general process for data analysis

- **Data analysis:** the process of discovering meaningful information or useful findings to answer the research questions. The process includes two separate sub-phases: pair-variable analysis and group-variable analysis.

Because of the unclear and unspecific requirements and expectation from project owners, the three processes are in an iterative circle, in which one process can support other processes during the data exploration to take advantage of what was learned in the previous stages.

All processes are used by Python programming language on Google Collaboratory (a Python development environment that runs in the browser using Google Cloud) with Python libraries. For data cleaning and feature engineering, the Python libraries include Pandas for data structures and operations; and NumPy for n-dimensional arrays. The data analysis process requires more Python libraries including Pandas, Seaborn, Matplotlib, Scipy, and Scikit Learn.

4.1. Pair-variable analysis

The pair-variable analysis is the data analysis to find a relationship between 2 variables. The paper conducted the comprehensive data analysis of 1-1 relationship between user's profiles and user's behavioural patterns, which means there are 2588 relationships for identification and significant testing. Table 6 shows the statistical techniques applied in the analysis depending on the types of variables. Also, the flowchart of pair-variable analysis is illustrated in Figure 5.

		Dependent variables	
		Numerical	**Categorical**
Independent variables	**Numerical**	Pearson correlation coefficient Scatter plot diagrams Histograms	Point Biserial Correlation One-hot encoding/Dummy coding
	Categorical	Point Biserial Correlation One-hot encoding/Dummy coding	Chi-Squared Test Bonferroni-adjusted p-value method

Table 6. The statistical techniques applied in the analysis depending on the types of variables

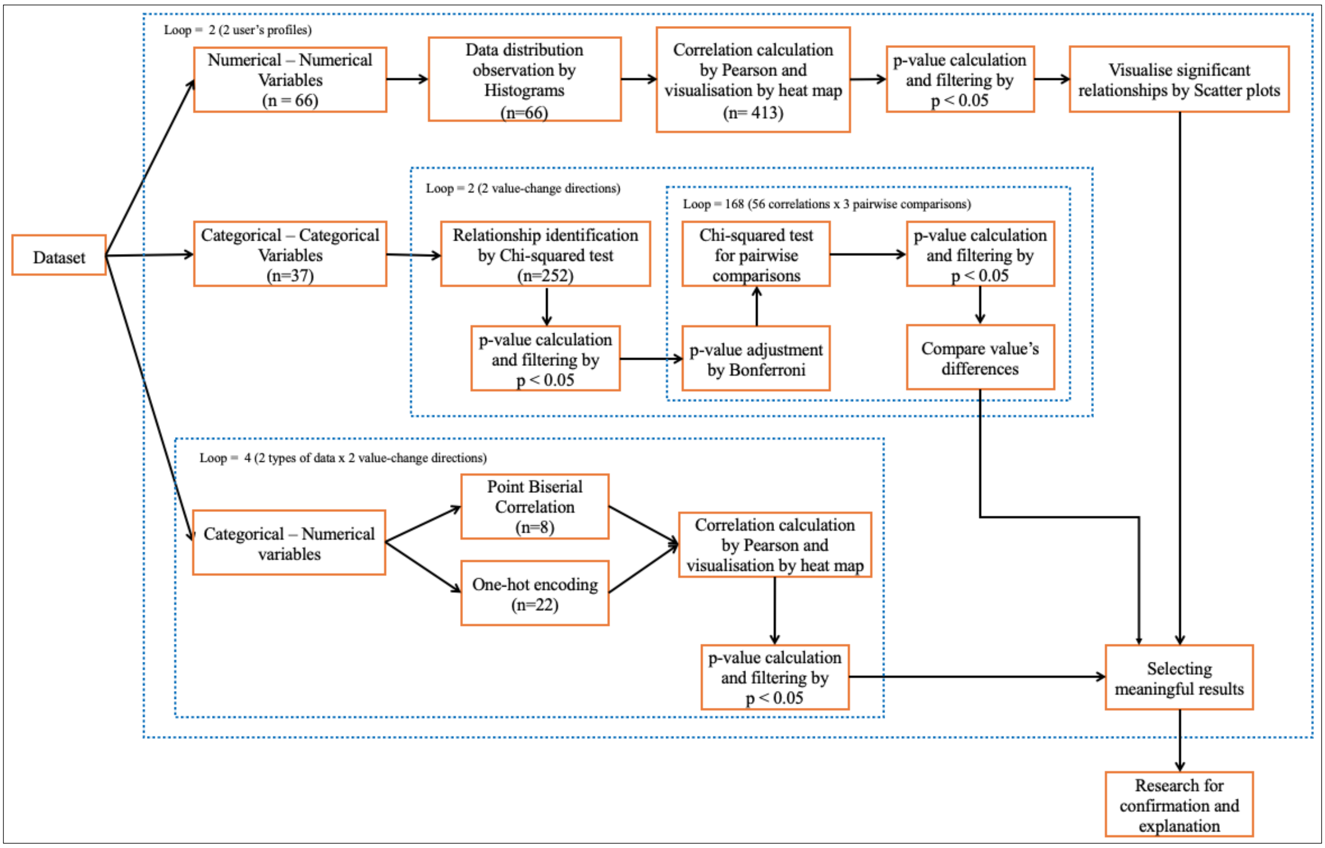
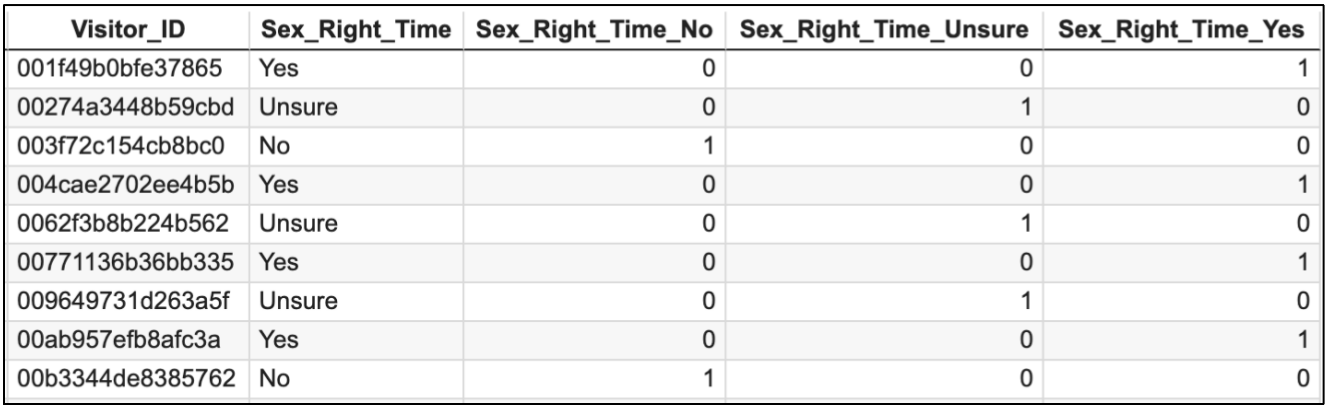

Loop = 2 (2 user's profiles)
Dataset
Numerical – Numerical Variables (n = 66)
Data distribution observation by Histograms (n=66)
Correlation calculation by Pearson and visualisation by heat map (n= 413)
p-value calculation and filtering by p < 0.05
Visualise significant relationships by Scatter plots
Loop = 2 (2 value-change directions)
Loop = 168 (56 correlations x 3 pairwise comparisons)
Categorical – Categorical Variables (n=37)
Relationship identification by Chi-squared test (n=252)
Chi-squared test for pairwise comparisons
p-value calculation and filtering by p < 0.05
p-value calculation and filtering by p < 0.05
p-value adjustment by Bonferroni
Compare value's differences
Loop = 4 (2 types of data x 2 value-change directions)
Categorical – Numerical variables
Point Biserial Correlation (n=8)
One-hot encoding (n=22)
Correlation calculation by Pearson and visualisation by heat map
p-value calculation and filtering by p < 0.05
Selecting meaningful results
Research for confirmation and explanation

Figure 5. The flowchart of pair-variable analysis

The brief introduction and application of statistical techniques are described below:

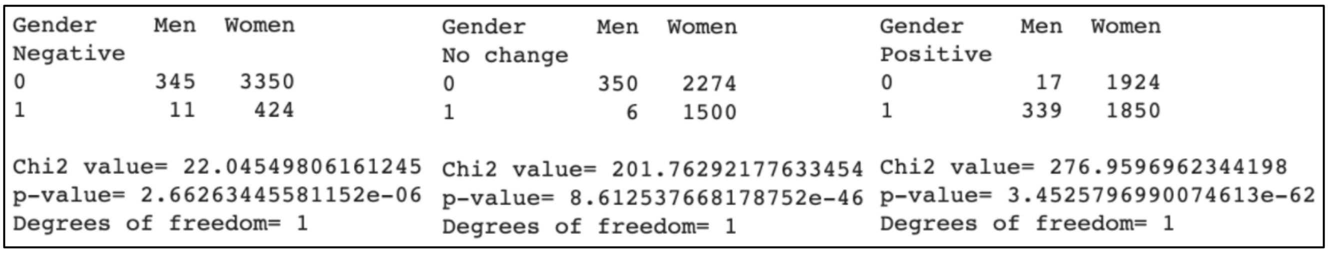
- **Pearson correlation coefficient**: it is a standard method for measuring the correlation and linear dependence between paired-data variables, which are numerical variables (Pearson, 1895). The value is ranged from -1 to +1, where ±1 means the strongest linear relationship, and 0 means no linear relationship (Pearson, 1895). The statistically significant value used in the paper is less than 0.05 ($p \leq 0.05$). The correlation coefficient values are illustrated in the heat map as a visually appealing way.
- **Scatter plot diagram**: the representation of data points for two numerical variables. The diagrams are used as the following steps after correlation calculation for observing the data trend (close or far to the trend line) between 2 variables.
- **Histograms**: the display of data distribution by its occurrences/frequencies for each bin. The histograms are used as supportive information to compare between two profiles (Figure 17 and Figure 18).
- **Point Biserial Correlation:** a technique for correlation calculation for categorical variables with only two values (i.e., Yes/No). The categorical values can be assigned to numerical values. In the paper, “Yes” is transformed into “1”, and “No” is transformed into “0”. After transformation, the Pearson technique can be applied to find the relationships between paired-data variables.
- **One-hot encoding/Dummy coding**: a process to transform a variable with *n* values into *n* variables with two values (0 and 1), where 1 means the presence of the value and 0 means the absence of the value (an example in Table 7). There are 30 categorical variables with 3 values per each in the dataset (2 variables in 2 user’s profiles and 28 variables in user’s behavioural features), which will be transformed into 90 binary variables with 0 and 1 values.



Visitor_ID	Sex_Right_Time	Sex_Right_Time_No	Sex_Right_Time_Unsure	Sex_Right_Time_Yes
001f49b0bfe37865	Yes	0	0	1
00274a3448b59cbd	Unsure	0	1	0
003f72c154cb8bc0	No	1	0	0
004cae2702ee4b5b	Yes	0	0	1
0062f3b8b224b562	Unsure	0	1	0
00771136b36bb335	Yes	0	0	1
009649731d263a5f	Unsure	0	1	0
00ab957efb8afc3a	Yes	0	0	1
00b3344de8385762	No	1	0	0

Table 7. The Sex Right Time after the one-hot encoding process

- **Chi-Squared Test:** a statistical hypothesis test for categorical variables to see their dependence by converting categorical variables into a frequency table. The significant relationship between variables in the Chi-squared test should meet three conditions: the Chi-squared value over the critical value for the Chi-squared statistic by degrees of freedom, all expected frequencies over 5 and p-value below 0.05. The Chi-squared tests applied two times in the pair-variable analysis: (1) between two categorical variables to find the significant relationship with original p-value 0.05; (2) between values across two identified variables with Bonferroni-adjusted p-value 0.017.
- **Bonferroni-adjusted p-value method**: a post hoc test for testing the significant differences between values within variables because the Chi-square test is an omnibus test. This means the Chi-square test can identify the relationship between 2 categorical variables but cannot interpret the particular result such as predictions or trends. Bonferroni correction is used for p-value adjustment by the number of planned pairwise comparisons, where the p-value is the integer division of the original test p-value and the number of planned pairwise comparisons. In the paper, the original test p-value is 0.05 and the number of planned pairwise comparisons is 3, so the Bonferroni-adjusted p-value is 0.05/3 = 0.017. Figure 6 shows the example of three Chi-square tests using the Bonferroni-adjusted p-value between Gender and Age changing behaviours in the modified profiles. In this case, all 3 planned pairwise comparisons are significant with the p-value < 0.017 so the comparison across the cells within the Chi-square test table can be interpreted.



```
Gender      Men   Women
Negative
0           345    3350
1            11     424

Chi2 value= 22.04549806161245
p-value= 2.66263445581152e-06
Degrees of freedom= 1
```

```
Gender       Men   Women
No change
0            350    2274
1              6    1500

Chi2 value= 201.76292177633454
p-value= 8.612537668178752e-46
Degrees of freedom= 1
```

```
Gender      Men   Women
Positive
0            17    1924
1           339    1850

Chi2 value= 276.9596962344198
p-value= 3.4525796990074613e-62
Degrees of freedom= 1
```

Figure 6. Chi-square tests using the Bonferroni correction between Gender and Age changing behaviours in the modified profile

Besides the programming language, environment and libraries mentioned in the Methodology section, the pair-variable data analysis requires more Python tools and libraries for statistical techniques including, but not limited to, Pandas for data structures and One-hot encoding/Dummy coding; Seaborn and Matplotlib for data visualisation (heatmaps, scatter plots, and histograms), Scipy for Chi-square test and Point Biserial correlation calculation; and Scikit Learn for Pearson correlation coefficient measurement.

4.2. Group-variable analysis

The group-variable analysis is the data analysis for finding a relationship between more than 2 variables using clustering methods. The main methods are used for group-variable analysis in the paper are PCA, K-means and Pearson correlation coefficient. The process of the group-variable analysis is described in Figure 7.

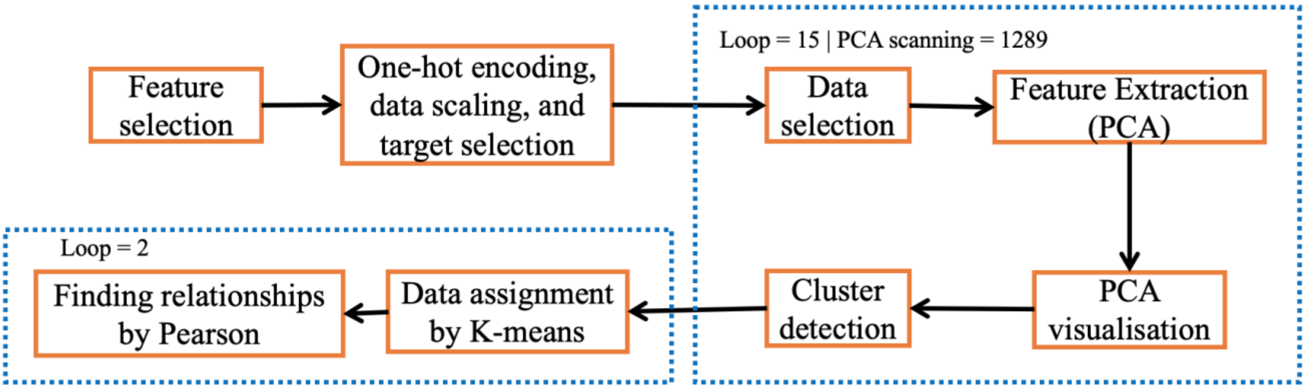

Feature selection
One-hot encoding, data scaling, and target selection
Loop = 15 | PCA scanning = 1289
Data selection
Feature Extraction (PCA)
PCA visualisation
Cluster detection
Loop = 2
Data assignment by K-means
Finding relationships by Pearson

Figure 7. The flowchart of the group-variable analysis

The description of each task as following:

- **Feature selection:** To ensure the variable's independence in clustering, the behavioural patterns exclude the mean and median of numerical attributes (14 variables).
- **One-hot encoding:** a process to transform a variable with *n* values into *n* variable with two values (0 and 1), where 1 means the presence of the value and 0 means the absence of the value. The PCA just works well with numerical variables, so 177 variables after one-hot coding are applied in the group-variable analysis.
- **Data scaling:** The variables have a different range of measure, so the data needs to be scaled into the same unit length.
- **Target selection:** The chosen target variable is Completion (%) to figure out the impact of the empty data (incompleted questions) on the dataset.
- **Data selection:** Due to a large number of variables, the dataset is divided into 5 groups when inputting into PCA in order to limit the number of components and easily detect the clustering.
- **Feature extraction using PCA:** The result from the PCA with Completion (%) is that there is a difference between below 50% completion rate and over 50% completion rate (Figure 8), which may be because the blank data should be replaced by the mean of each variable. To ensure the data quality, the dataset with a completion rate below 50% is removed in the group-variable analysis. The PCA runs with the loop of 15 times including 3 scenarios (1 with the target variable and 2 without the target variable: all dataset and dataset with a Completion rate

above 50%) multiply with 5 groups of data. The number of principal components for each data group depends on the cumulative variance (Table 8), which is set 80% as the minimum to cover the characteristics of the dataset.

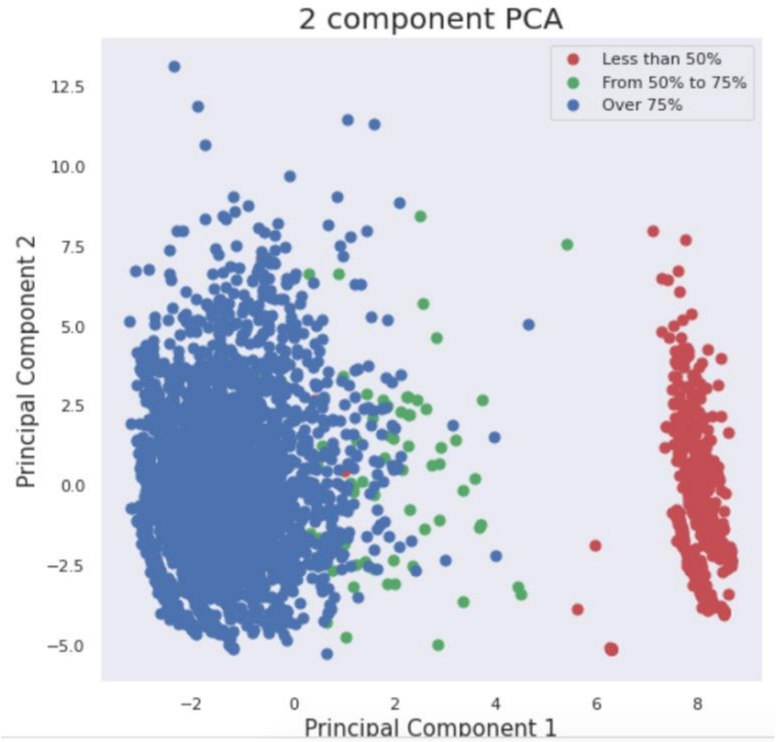
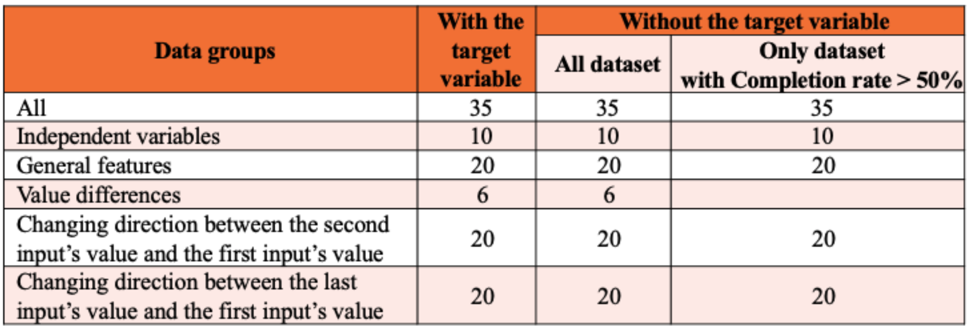


Figure 8. The PCA visualisation with the target Completion rate



Data groups	With the target variable	Without the target variable	
		All dataset	Only dataset with Completion rate > 50%
All	35	35	35
Independent variables	10	10	10
General features	20	20	20
Value differences	6	6	
Changing direction between the second input's value and the first input's value	20	20	20
Changing direction between the last input's value and the first input's value	20	20	20

Table 8. The number of principal components per each scenario with the cumulative variance over 80%

- **PCA visualisation:** The visualisation between principal components is a method to detect the distinguished clusters. An example for PCA visualisation without the target variable is illustrated in Figure 9. However, due to time limitation, the visualisation just focuses on the two main scenarios (without the target variable). Because of 2D visualisation illustrated only 2 components, the number chart for scanning is 1289.

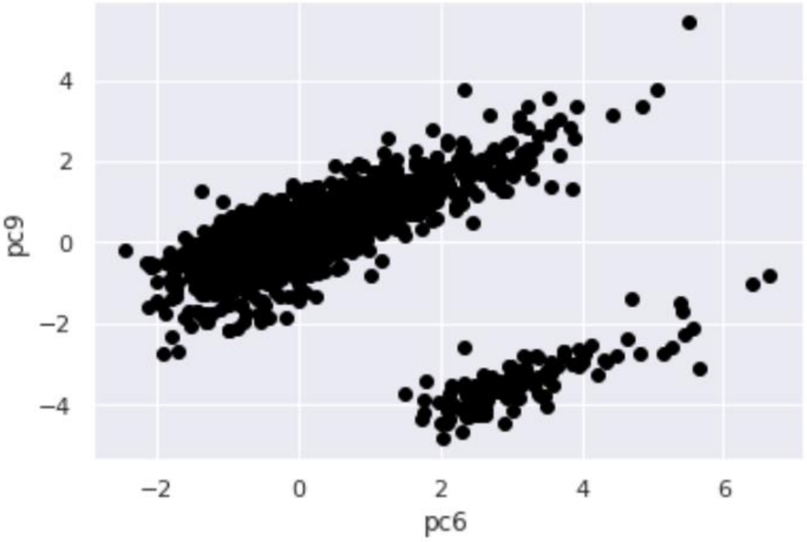


Figure 9. An example for PCA visualisation without the target variable.

- **Cluster detection**: From PCA visualisation (1289) charts, the task is to manually examine and observe to find if there are separated clusters. In the paper, two examples among several clustering charts are shown to discuss.
- **Data assignment by K-means:** Using the K-means algorithm is to extract the clusters as separated datasets. In other words, K-means are used to assign single data points into the nearest cluster's centroid and label them (Figure 10).

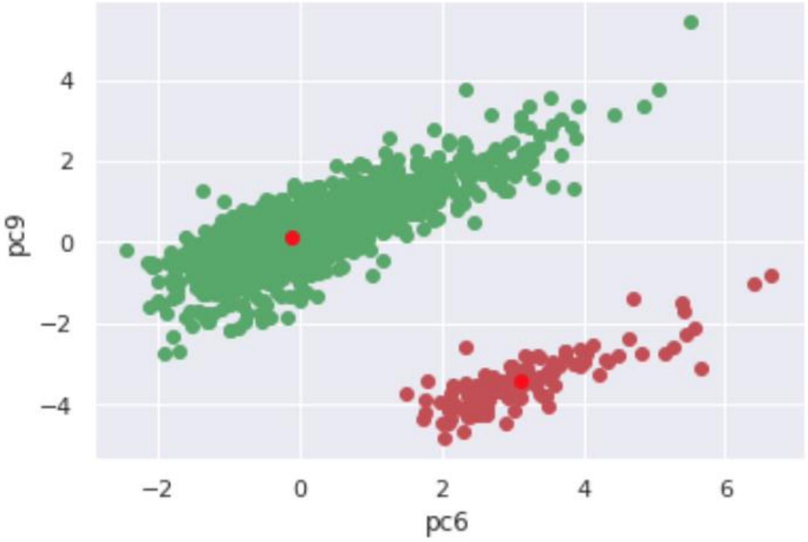


Figure 10. Data allocation by K-means with centroids after training the model

- **Finding relationship by Pearson**: After cluster extraction by K-means model, the average value between two variables is calculated, which is compared with the inserted variables of PCA by Pearson correlation coefficient to find the characteristics of each cluster.

The group-variable data analysis uses Python libraries including, but not limited to, Pandas for data structures, operations and One-hot encoding/Dummy coding; Seaborn and Matplotlib for data visualisation; Scikit Learn for PCA, K-means, and Pearson correlation coefficient.

5. Results and Analysis

5.1. Pair-variable analysis’s results

The paper conducted the comprehensive data analysis of 1-1 relationship between user’s profiles and user’s behavioural patterns, which means there are 2588 relationships between 1-1 variables and 666 times of planned pairwise comparisons (3 planned pairwise comparisons for each of 222 significant relationships after Chi-squared test) for identification and significant testing. After analysis with significant tests and post hoc tests, 58 significant relationships are identified, then, 31 meaningful relationships are pointed out and described in the paper. Table 9 shows the detail of the relationship’ number in each stage of the pair-variable analysis.

The analysis stage	**Total a pair of variables**	**Number of insignificant relationships** ($p \geq 0.05$)	**Number of significant relationships** ($p<0.05$)	**Number of meaningful relationships**	**Description**
Numerical vs Numerical	826	800 ($-0.5<r<0.5$)	26 ($r<-0.5$ or $r>0.5$)	22 (exclude dependent relationships, i.e., value differences and user’s initial inputs)	- 14 for the user’s modified profile and its Mean/Median - 8 for the user’s initial profile and its Mean/Median
Categorical vs Numerical	1314	1295 ($-0.5<r<0.5$)	19 ($r<-0.5$ or $r>0.5$)	1 (exclude dependent relationships, i.e., page and page changes; or value directions and user’s input value)	1 for STI testing and Completion Rate
Categorical vs Categorical	448	226	- 222 after Chi-squared test - 13 after Bonferroni correction post hoc test and have different trends	8 (exclude relationships with small differences)	- 4 for gender and Age directions in 2 profiles - 1 for gender and Height directions - 1 for gender and Weight directions - 2 for Children status and Weight directions

Table 9. The number of relationships in pair-variable analysis

5.1.1. The modified profile and the initial profile

Figure 11 and Figure 12 are heat maps based on the correlation coefficient value between 2 variables in the initial profile and the modified profile. From the heat maps, there are significant relationships between variables and their Mean or Median. Therefore, Table 10 compares between two types of profiles, which indicates that the modified profile has a greater number of relationships than the initial profile, especially the relationships between the modified profile and all variables' mean and median have a very strong positive correlation ($0.93 \leq r \leq 1$) with p-value < 0.001.

In detail, the scatter plots for Smoking (Figure 13), Alcohol Consumption (Figure 14), Trying Month (Figure 15), and Sex Frequency (Figure 16) are illustrated. Even the initial profile has a strong relationship between those variables and their Mean or Median ($0.58 \leq r \leq 0.91$), the graphs are observed that many value dots are disjointed while the scatter plots of the modified profile are displayed most dots near the 45-degree line, where the value and its Mean/Median are equal.

As the result, while Smoking, Alcohol Consumption, Trying Month, and Sex Frequency histograms have the nearly same shape in both profiles, Age, Height, and Weight histograms between profiles are observed the different shapes (Figure 17 and Figure 18). As can be seen, the modified profile's histograms have data distribution more normal than the initial profile.

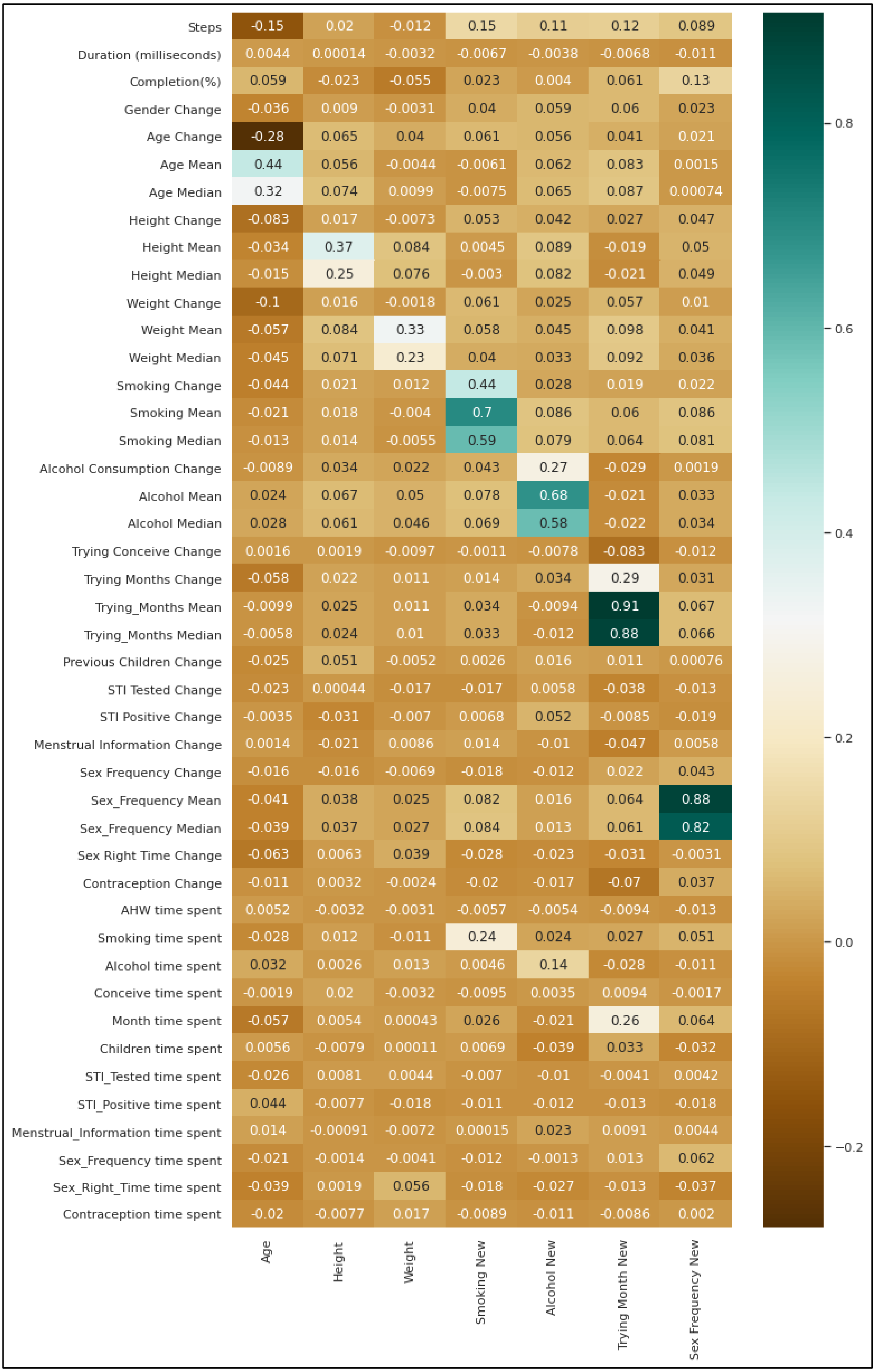


Figure 11. Correlation coefficient between features and user's initial health profile (the first value)

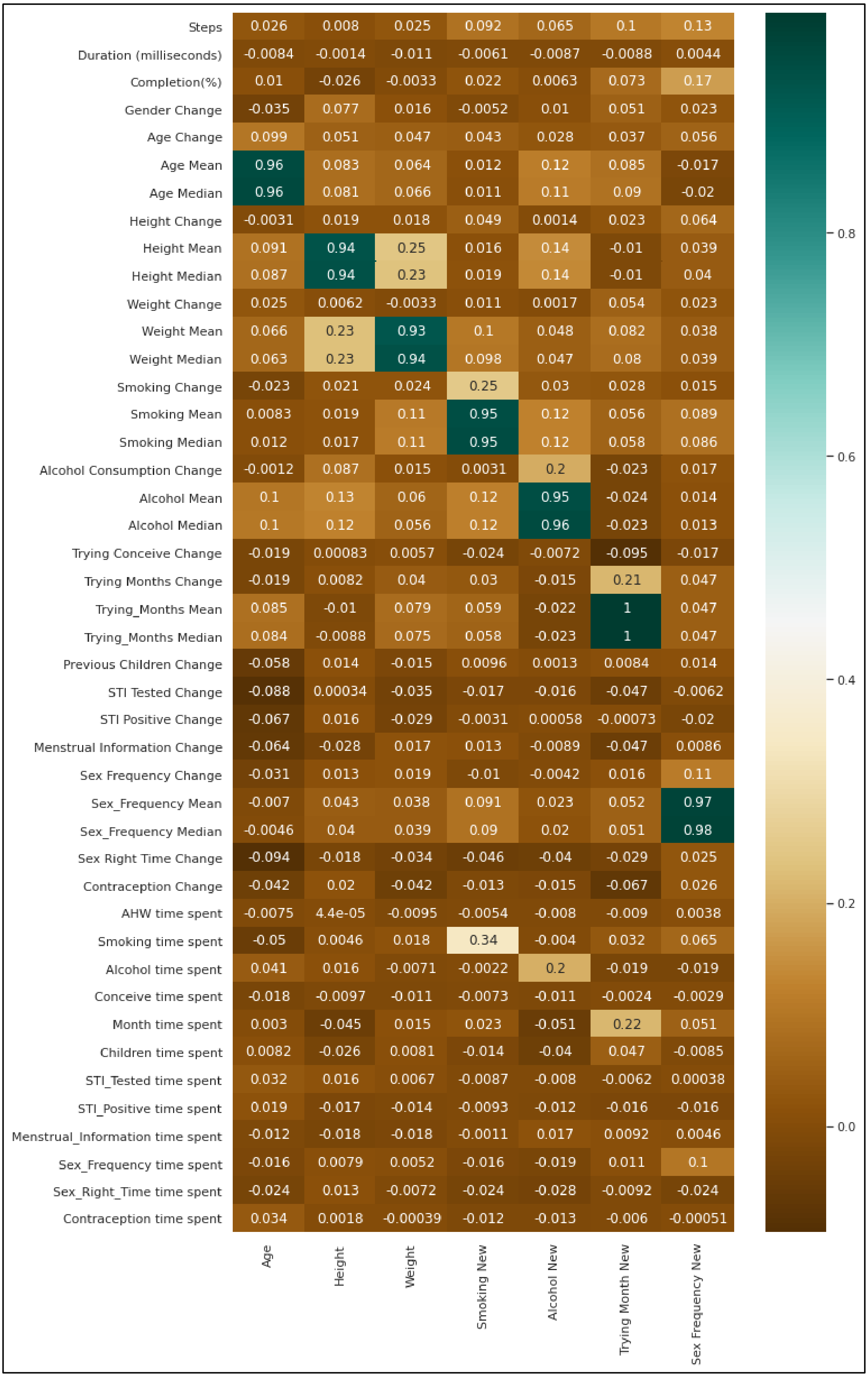


Figure 12. Correlation coefficient between features and user's modified health profile (the last value)

A pair of variables	**Correlation coefficient**	
	The initial profile	**The modified profile**
Age - Age Mean	0.44	**0.96**
Age - Age Median	0.32	**0.96**
Height - Height Mean	0.37	**0.94**
Height - Height Median	0.25	**0.94**
Weight - Weight Mean	0.33	**0.93**
Weight - Weight Median	0.23	**0.94**
Smoking - Smoking Mean	**0.7**	**0.95**
Smoking - Smoking Median	**0.59**	**0.95**
Alcohol Consumption - Alcohol Consumption Mean	**0.68**	**0.95**
Alcohol Consumption - Alcohol Consumption Median	**0.58**	**0.96**
Trying Month - Trying Month Mean	**0.91**	**1**
Trying Month - Trying Month Median	**0.88**	**1**
Sex Frequency - Sex Frequency Mean	**0.88**	**0.97**
Sex Frequency - Sex Frequency Median	**0.82**	**0.98**

Table 10. The list of correlations between numerical variables of user's profiles and their mean and median (p < 0.001) (bold numbers are over 0.5)

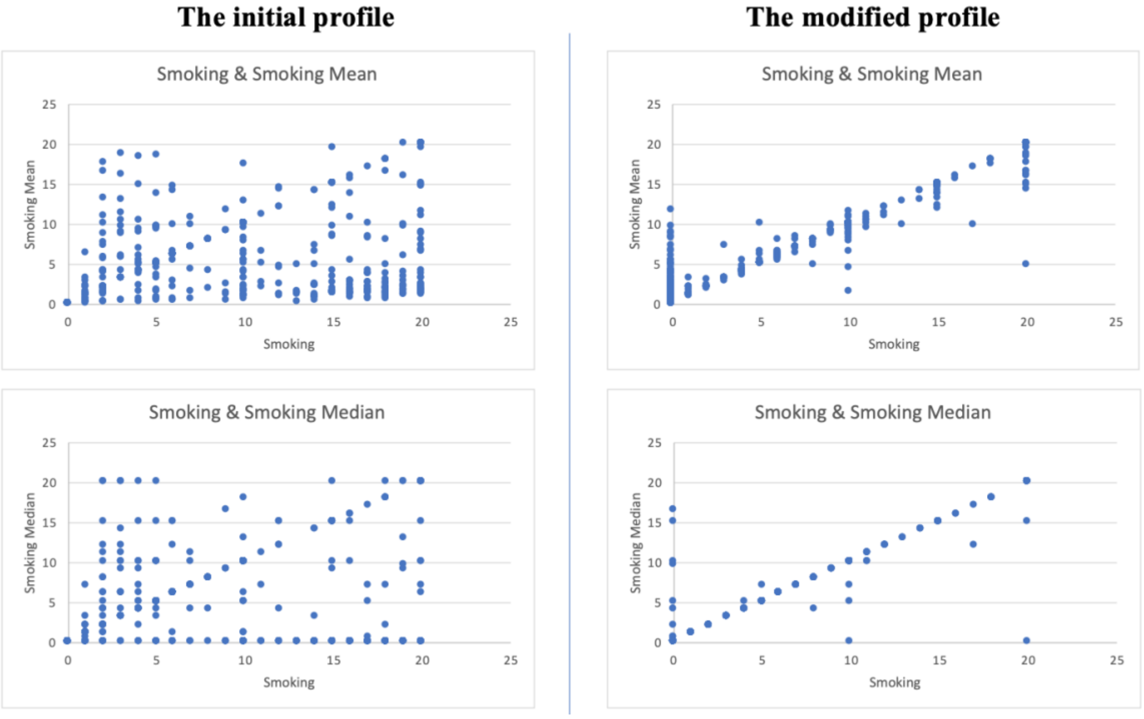
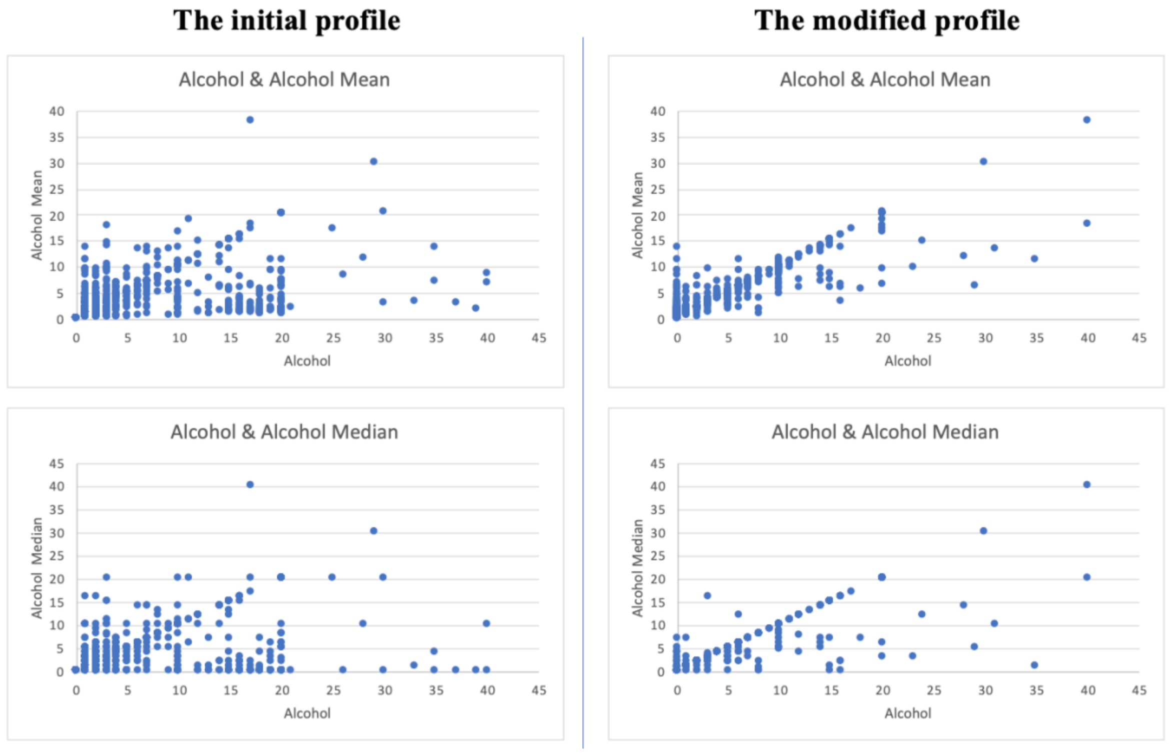


Figure 13. The scatter plots of Smoking and its Mean-Median between the initial profile and the modified profile



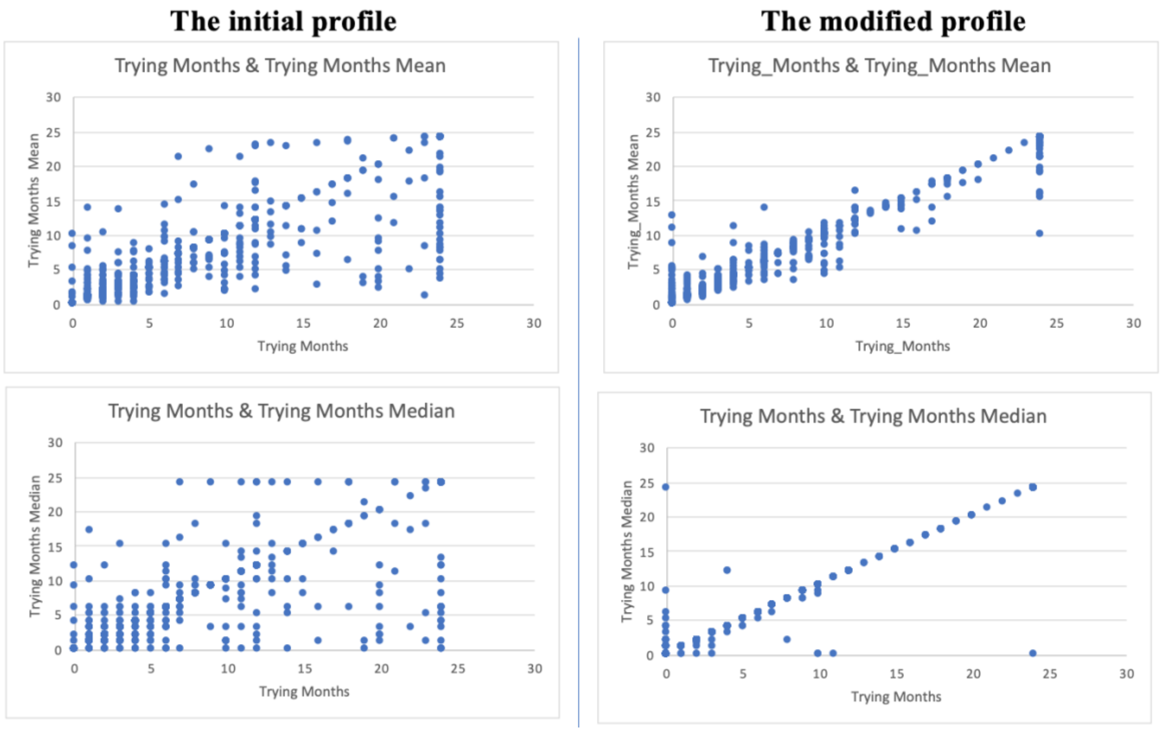
The initial profile

The modified profile

Alcohol & Alcohol Mean

Alcohol & Alcohol Median

Figure 14. The scatter plots of Alcohol Consumption and its Mean-Median between the initial profile and the modified profile



The initial profile

The modified profile

Trying Months & Trying Months Mean

Trying_Months & Trying_Months Mean

Trying Months & Trying Months Median

Figure 15. The scatter plots of Trying Month and its Mean-Median between the initial profile and the modified profile

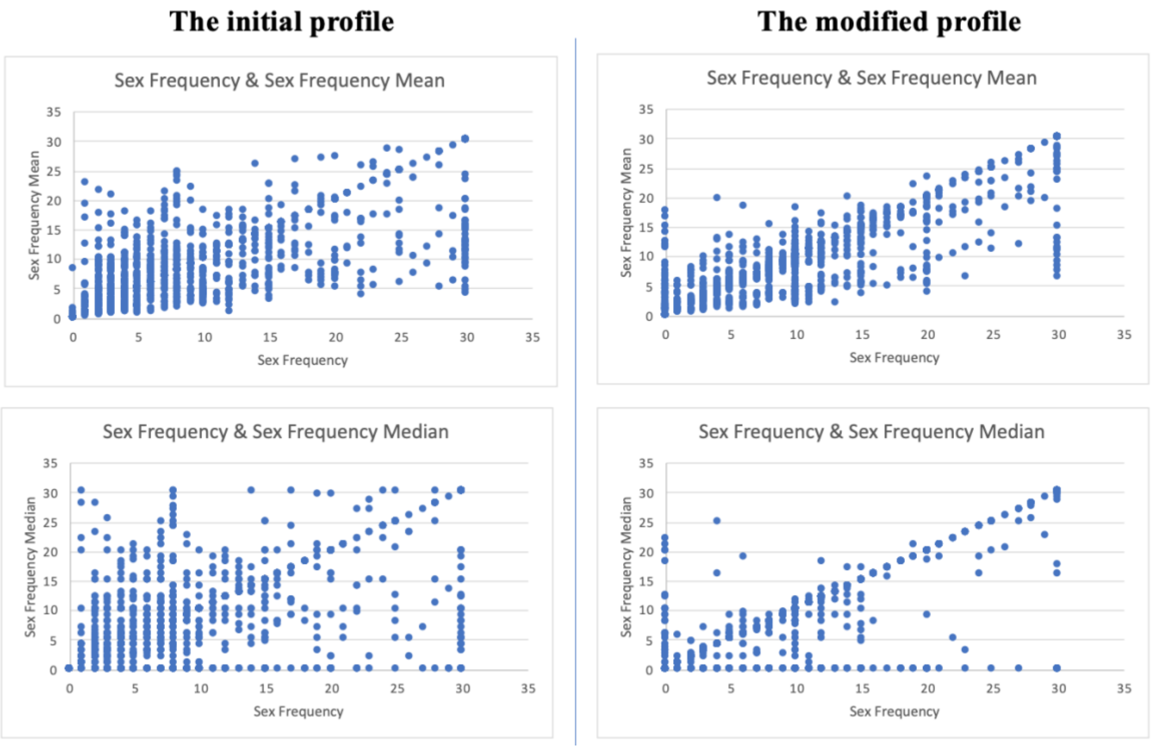


Figure 16. The scatter plots of Sex Frequency and its Mean-Median between the initial profile and the modified profile

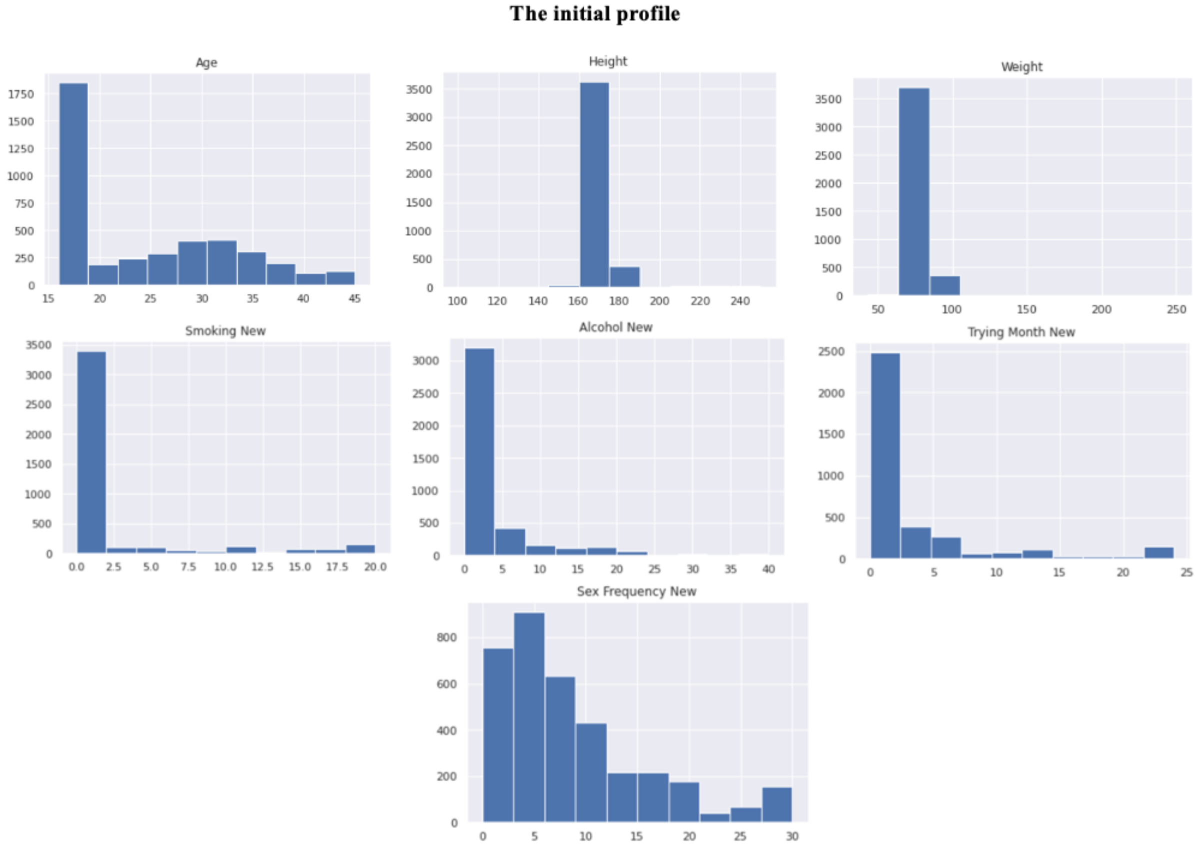


Figure 17. The histogram charts for 7 numerical variables of the initial profile

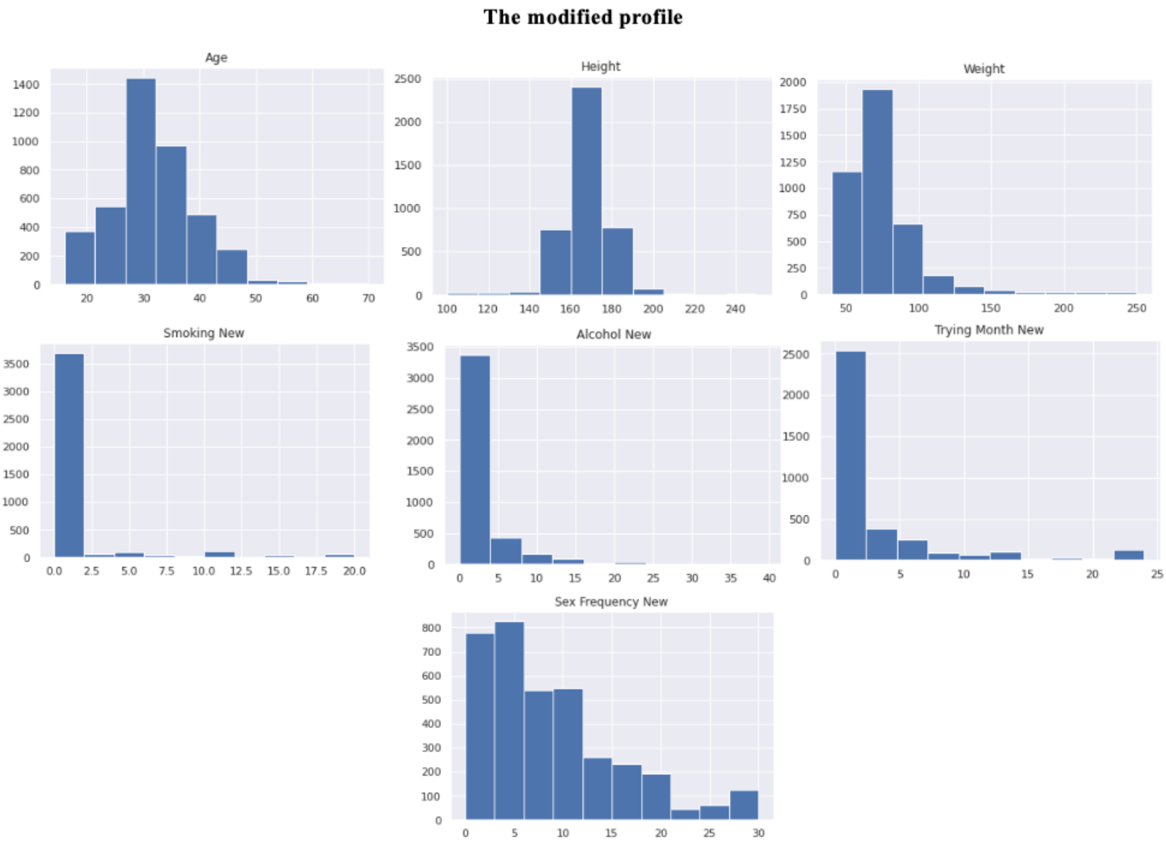


Figure 18. The histogram charts for 7 numerical variables of the modified profile

5.1.2. Behavioral differences between men and women

In the analysis between categorical variables, gender is a variable that has the largest number of relationships in both profiles. The results are demonstrated the gender differences in two profiles and two types of directions in Table 11.

For the pair of Gender and Age direction, in the initial profile, the analysis indicates that gender affects the volume of proportion but has no impact in behavioural directions while in the modified profile, the behaviours between women and men are different in both quantity and directions. From a case of Gender and Age direction in the modified profile between the last input and the first input (Table 12), more men decrease their age value than women while women tend to increase or keep the same value.

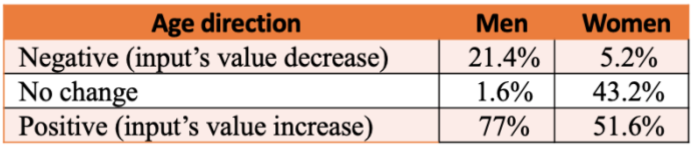
For the pair of Gender and Height direction, there is a gender difference in only the initial profile between the last input and the first input (Table 13), which found that the highest proportion (44.4%) of men has the height value decrease while the highest proportion (53.4%) of women has the height value increase.

For the pair of Gender and Weight direction, men tend to increase their weight value while women tend to decrease their weight value (Table 14). All correlations between two variables have the p-value <

0.05 and the significant differences in 3 planned pairwise comparisons, which are comparisons in each value of categorical variables, have the p-value less than 0.05/3 = 0.017.

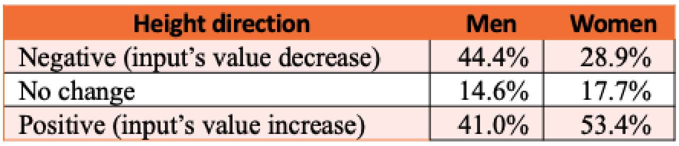
Profile	The initial profile		The modified profile	
The direction between	**The second input and the first input**	**The last input and the first input**	**The second input and the first input**	**The last input and the first input**
Gender - Age direction	The percentage of men who increase their age's value (95.2%) is higher than women's (49%).	The percentage of men who increase their age's value (96.6%) is higher than women's (51.9%).	More percentage of men increases and decreases their age (64.4% and 33.9%, respectively) while women tend to increase and keep the same age value (50.8% and 43.2%, respectively)	More percentage of men increases and decreases their age (77% and 21.4%, respectively) while women tend to increase and keep the same age value (51.6% and 43.2%, respectively)
Gender - Height Direction	Only ⅔ planned pairwise comparisons are significant but there is no gender difference.	The highest proportion (44.4%) of men has the height value decrease while the highest proportion (53.4%) of women has the height value increase.	Only ⅔ planned pairwise comparisons are significant but there is no gender difference.	All 3 planned pairwise comparisons are significant but no gender difference.
Gender - Weight direction	Only ⅔ planned pairwise comparisons are significant but there is no gender difference.	Only ⅔ planned pairwise comparisons are significant but there is no gender difference.	Only $^{1}/_{3}$ planned pairwise comparisons are significant but there is no gender difference.	The majority of men increases their weight (60.2%) while the highest proportion of women decreases their weight (55.4%)

Table 11. Behavioural differences between men (n=669) and women (n=3461) in two profiles and two types of directions



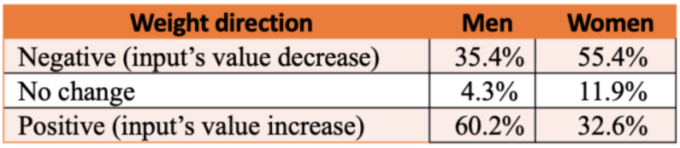
Age direction	Men	Women
Negative (input's value decrease)	21.4%	5.2%
No change	1.6%	43.2%
Positive (input's value increase)	77%	51.6%

Table 12. The percentages of men and women in Age direction in the modified profile between the last input and the first input



Height direction	Men	Women
Negative (input's value decrease)	44.4%	28.9%
No change	14.6%	17.7%
Positive (input's value increase)	41.0%	53.4%

Table 13. The percentages of men and women in Height direction in the initial profile between the last input and the first input

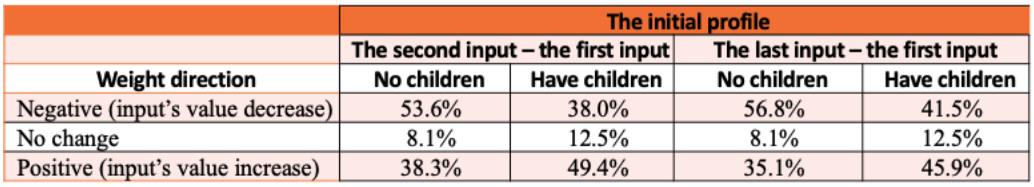


Weight direction	Men	Women
Negative (input's value decrease)	35.4%	55.4%
No change	4.3%	11.9%
Positive (input's value increase)	60.2%	32.6%

Table 14. The percentages of men and women in Weight direction in the modified profile between the last input and the first input

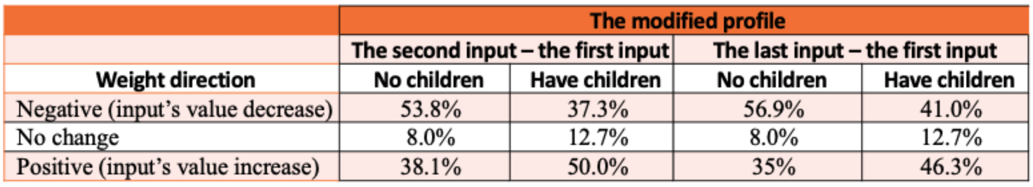
5.1.3. Previous Children and Weight change behaviour

Similarly, Weight change direction is different between people who have previous children and those who have no children. Specifically, having-children people (n=1138) tend to increase their weight value while weight value decrease is the behaviour of people having no children (n=2363). The finding is consistent among two profiles with two ways of directions (the second input or the last input compared to the first input of the user). Table 15 and Table 16 show that the nearly same proportion between two profiles for each direction and a few people (3.1%-3.7%) tends to decrease their weight value during the second input and the last input.



	The initial profile			
	The second input – the first input		The last input – the first input	
Weight direction	No children	Have children	No children	Have children
Negative (input's value decrease)	53.6%	38.0%	56.8%	41.5%
No change	8.1%	12.5%	8.1%	12.5%
Positive (input's value increase)	38.3%	49.4%	35.1%	45.9%

Table 15. The percentages of people who have previous children and not in Weight directions in the initial profile



	The modified profile			
	The second input – the first input		The last input – the first input	
Weight direction	No children	Have children	No children	Have children
Negative (input's value decrease)	53.8%	37.3%	56.9%	41.0%
No change	8.0%	12.7%	8.0%	12.7%
Positive (input's value increase)	38.1%	50.0%	35%	46.3%

Table 16. The percentages of people who having previous children and not in Weight directions in the modified profile

5.1.4. STI Test and Completion (%)

In the analysis between categorical variables in the modified profile and numerical behavioural patterns, there is a strong positive relationship between STI Test and Completion (%) with r = 0.61 and p < 0.001

described in Figure 19. In other words, people who already tested STIs (Sexually transmitted infections) tend to complete more questions than people who did not test STI. However, there is no strong relationship between variables in the initial profile and no linear relationship between the STI test with the positive results and the rate of completion.

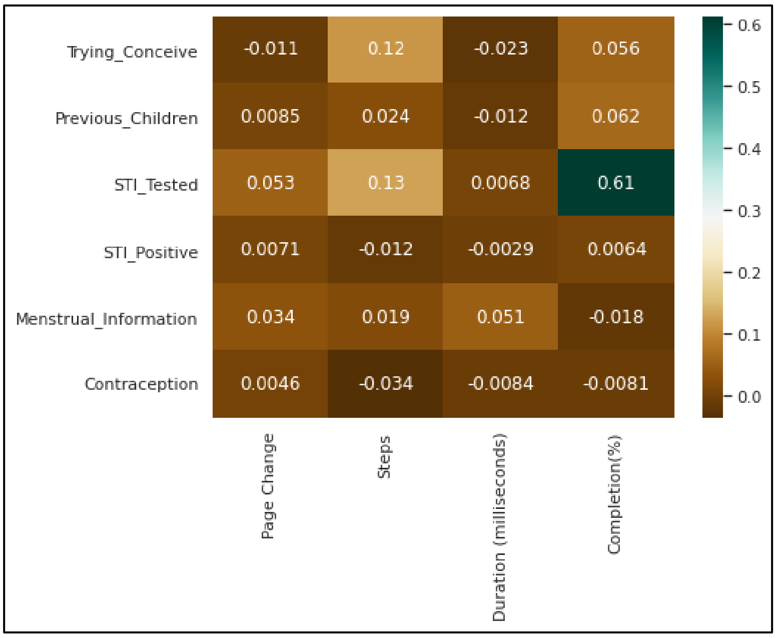


Figure 19. The small set of heat map for correlations between the categorical variables in the modified profile and numerical behavioural patterns

5.2. Group-variable analysis results

Using the PCA for dimension reduction, the analysis identifies that there are several clusters based on principal component (PC) visualisation. With the time constraint, the paper just illustrated two examples of clustering after scanning 1289 charts. The variables inputted in the PCA of examples are the original variables (user's inputs) with the completion rate above 50%.

In the first example of PC6 and PC9 (Figure 20), Cluster 2 has a stronger negative correlation with Height (r=-0.31, p=0.02) and a more significant positive correlation with Smoking (r=0.74, p<0.001) than Cluster 1 (Figure 21).

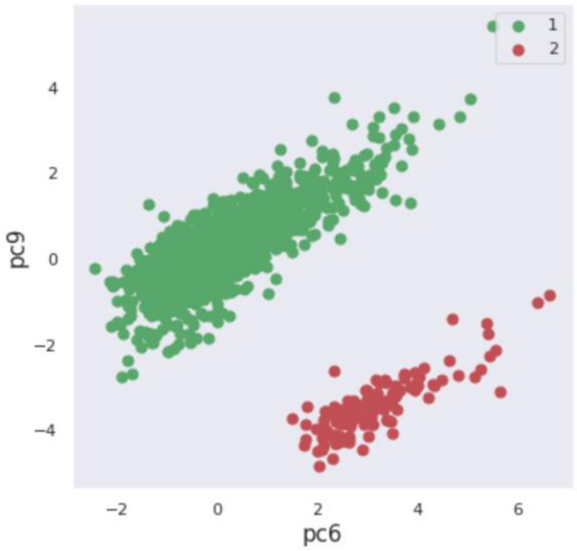
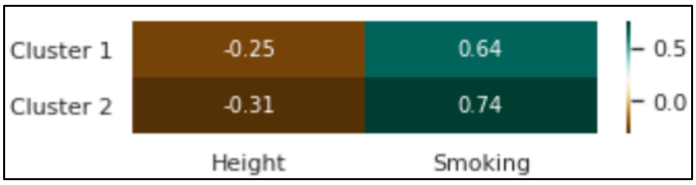


Figure 20. The PCA visualisation of PC6 and PC9 with K-means for assigning data to clusters



	Height	Smoking
Cluster 1	-0.25	0.64
Cluster 2	-0.31	0.74

Figure 21. The correlation coefficient between Clusters and the inputted variables in PC6 and PC9.

In the second example of PC7 and PC8 (Figure 22), Cluster 1 has more significant positive correlations with STI Test (r=0.72, p<0.001), and with Sex Right Time with the answer “Yes” (r=0.32, p=0.02), as well as has a stronger negative correlation with Sex Right Time with the answer “Unsure” (r=-0.4, p=0.008) than Cluster 2 (Figure 23).

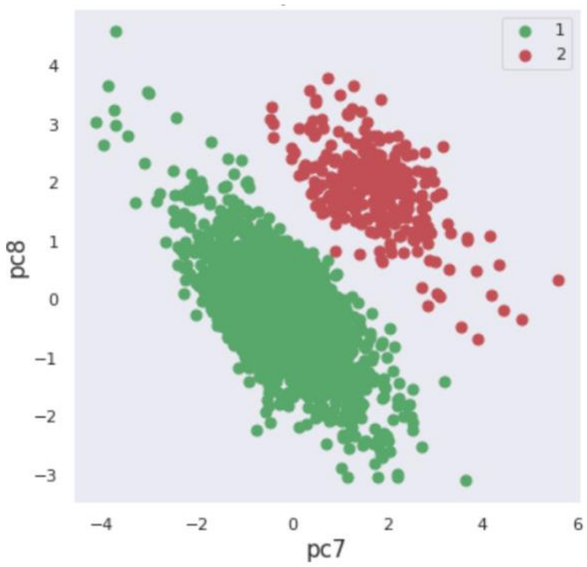


Figure 22. The PCA visualisation of PC7 and PC8 with K-means for assigning data to clusters

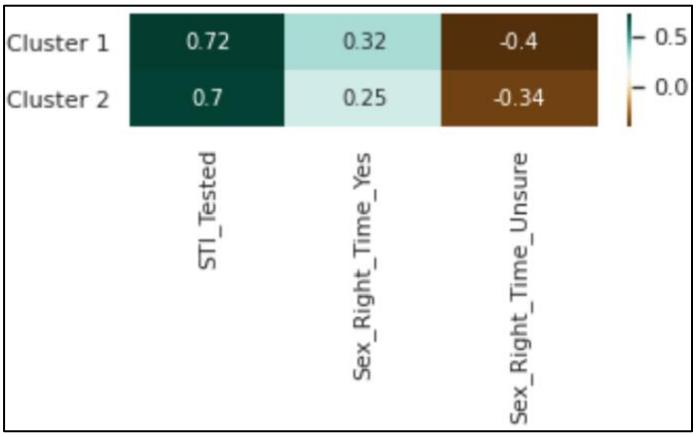
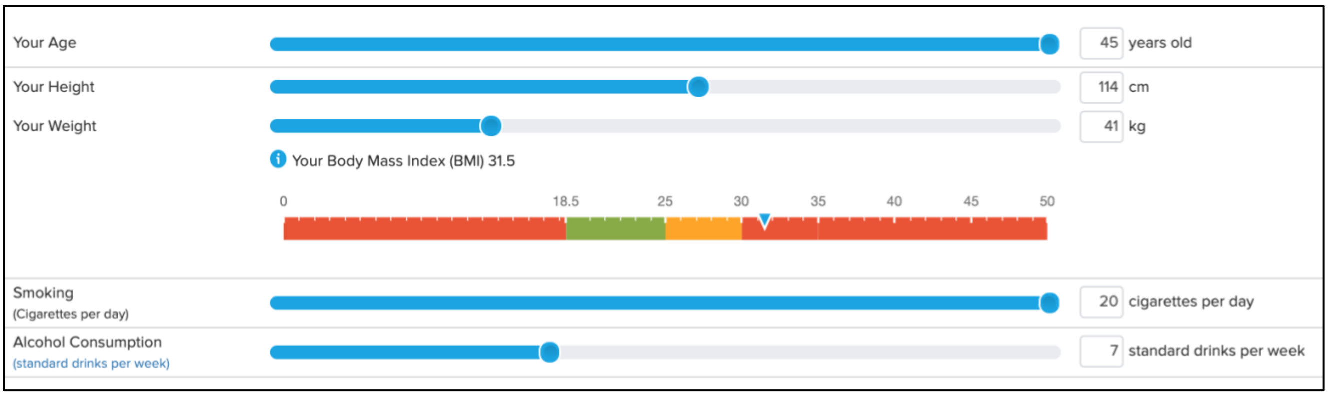


Figure 23. The correlation coefficient between Clusters and the inputted variables in PC7 and PC8

6. Discussion and future work

Understanding user’s behaviours can improve a user’s experience by providing better performance, personalized features, or more precise targeted marketing campaigns (Wang et al., 2016). While lacks of user satisfaction can lead to project’s failures (Pinto and Mantel, 1990), many fertility platforms fail to meet user’s satisfaction (Starling et al., 2018). Thus, the paper is to analyse the data captured by the HCT on the “Your Fertility” website with the aim of understanding user’s behaviours, exploring user’s insights and identifing user’s barriers when using an interactive tool. The key findings of the analysis show the differences between user’s initial profile and modified profile, and the significant differences in behaviours between men and women related to age and weight directions, between people having children and no children, and between people having STI (Sexually transmitted infections) test and not. Also, Principal Component Analysis and K-means clustering are applied to figure out the user’s behaviours in groups.

In detail, the result indicated that the last inputs of users may have a more informative value than the first answer of users because the modified profile has a greater number of relationships/correlations than the initial profile. Especially, the relationships between the modified profile and all variables’ mean and median have a very strong positive correlation ($0.93 \leq r \leq 1$) with the p-value < 0.001. The finding is supported by scatter plots and histograms between two profiles. The finding can be explained by the linear slider scale disadvantage. Even if there is a traditional text box at the end of the slider scale, human’s reading behaviour is from left to right (Holmqvist and Wartenberg, 2005). The linear slider or slider scale, which is a visual analog scale (VAS) that requires users to drag the slider and move to the desired numeric point, is used on the HCT for all numerical inputs (Figure 24). While the slider scale can increase user’s engagement (Stanley and Jenkins, 2007, Sikkel et al., 2014), it may reduce data quality and accuracy (Derham, 2011, Couper et al., 2006) and response time because it is not as easy to understand as the traditional format (Stanley and Jenkins, 2007, Sikkel et al., 2014, Couper et al., 2006). Moreover, the slider scale’s quality depends on the device users used, i.e., mouse or touch screen (Roster et al., 2015, Chyung et al., 2018, Buskirk, 2015). The slider scale is usually used for the rating question with no more than 11 values (Chyung et al., 2018) but evaluations for other questions are scarce. A comparison between slider scale and other input formats by Buskirk (2015) shows more disadvantages than advantages for using slider scale. The suggestion is that a user’s survey or an evaluation can be conducted to validate the finding in order to improve user’s experience and increase data quality.



Your Age 45 years old

Your Height 114 cm

Your Weight 41 kg

Your Body Mass Index (BMI) 31.5

Smoking (Cigarettes per day) 20 cigarettes per day

Alcohol Consumption (standard drinks per week) 7 standard drinks per week

Figure 24. The linear slider format is used on the website for numerical answers

Another finding in the analysis is that there are differences between women and men in two profiles and two types of directions. For the pair of Gender and Age direction, in the initial profile, the analysis indicates that genders affect the volume of proportion but have no impact in behavioural directions while in the modified profile, the behaviours between women and men are different in both quantity and directions, which shows that men tend to increase and decrease their age value while women tend to increase or keep the same their age value. For the pair of Gender and Weight direction, men tend to increase their weight value while women tend to decrease their weight value. Similarly, Weight change direction is different between people who have previous children and those who have no children. Specifically, having-children people tend to increase their weight value while weight value decrease is the behaviour of people having no children. The findings can suggest personalised features such as value recommended, adjustable range of slider scale, or false answer detection based on their behaviours.

The relationship between the STI test and completion rate is an interesting finding of the paper. The analysis presents that people who already tested STIs (Sexually transmitted infections) tend to complete more questions than people who did not test STI. It may be because people who already tested STI have more reproductive health than the rest, so they have the higher motivation to answer the relevant questions. While infertility is a strong motivation for STI testing (Denison et al., 2017) because STIs can cause infertility (Deyhoul et al., 2017), the relationship between STI testing and fertility awareness or information-seeking behaviours is a potential area for research.

Using the PCA for dimension reduction, the analysis combined groups of variables identifies several clusters based on principal component (PC) visualisation with the completion rate above 50%. Due to the time constraint, the paper just illustrates two examples of clustering after scanning 1289 charts. These findings can inspire further personalised functions for different user's groups or the development of machine learning models to detect the groups of correlated variables.

The limitations of the paper should be mentioned and discussed for further research. Firstly, the data were collected only from the HCT on the "Your Fertility" website, so the user's behaviours on the other websites can be varied. The default value in certain attributes of the original dataset also may affect the results. The dataset was collected in 2018 and a few questions in the HCT are changed, which can lead to the different user’s behavioural patterns. Because of time constraint, the analysis just shows the results in data exploration without evaluation and sets aside compounding variables such as the user’s activities before and after entering the HCT or the context of users (i.e., the operating system, browsers, date and time, countries, etc.). The groups of data in the group-variable analysis are not comprehensive to identify the relationships between user’s profiles and user’s behavioural patterns. Further data collection groups based on user’s origins, countries, or religions may provide further interesting insights based on data segmentation.

References

Anderson, A. 2018. Online health information and public knowledge, attitudes, and behaviours regarding antibiotics in the UK: Multiple regression analysis of Wellcome Monitor and Eurobarometer Data. *PloS one,* 13**,** e0204878.

Anthopoulos, L., Reddick, C. G., Giannakidou, I. & Mavridis, N. 2016. Why e-government projects fail? An analysis of the Healthcare. gov website. *Government Information Quarterly,* 33**,** 161-173.

Bauerle Bass, S. 2003. How will Internet Use Affect the Patient? A Review of Computer Network and Closed Internet-based System Studies and the Implications in Understanding How the Use of the Internet Affects Patient Populations. *J Health Psychol,* 8**,** 25-38.

Bujnowska-Fedak, M. M. & Węgierek, P. 2020. The impact of online health information on patient health behaviours and making decisions concerning health. *International journal of environmental research and public health,* 17**,** 880.

Buskirk, T. D. 2015. Are sliders too slick for surveys? An experiment comparing slider and radio button scales for smartphone, tablet and computer based surveys. *methods, data, analyses,* 9**,** 32.

Chyung, S. Y., Swanson, I., Roberts, K. & Hankinson, A. 2018. Evidence-based survey design: The use of continuous rating scales in surveys. *Performance Improvement,* 57**,** 38-48.

Couper, M., Tourangeau, R., Conrad, F. & Singer, E. 2006. Evaluating the Effectiveness of Visual Analog Scales: A Web Experiment. *Social Science Computer Review - SOC SCI COMPUT REV,* 24**,** 227-245.

Daniluk, J. C. & Koert, E. 2013. The other side of the fertility coin: a comparison of childless men's and women's knowledge of fertility and assisted reproductive technology. *Fertility and sterility,* 99**,** 839-846.

Denison, H. J., Bromhead, C., Grainger, R., Dennison, E. M. & Jutel, A. 2017. Barriers to sexually transmitted infection testing in New Zealand: a qualitative study. *Australian and New Zealand journal of public health,* 41**,** 432-437.

Derham, P. A. 2011. Using preferred, understood or effective scales? How scale presentations effect online survey data collection. *Australasian Journal of Market & Social Research,* 19.

Deyhoul, N., Mohamaddoost, T. & Hosseini, M. 2017. Infertility-related risk factors: a systematic review. *Int J Womens Health Reprod Sci,* 5**,** 24-29.

Diaz, J. A., Griffith, R. A., Ng, J. J., Reinert, S. E., Friedmann, P. D. & Moulton, A. W. 2002. Patients' use of the Internet for medical information. *Journal of general internal medicine,* 17**,** 180-185.

Drinkwise Australia. 2021. Available: https://drinkwise.org.au/standard-drinks-calculator/# [Accessed 19/4/2021].

Goldenberg, D., Kofman, K., Albert, J., Mizrachi, S., Horowitz, A. & Teinemaa, I. Personalization in Practice: Methods and Applications. Proceedings of the 14th ACM International Conference on Web Search and Data Mining, 2021. 1123-1126.

Graffigna, G., Barello, S., Bonanomi, A. & Riva, G. 2017. Factors affecting patients' online health information-seeking behaviours: The role of the Patient Health Engagement (PHE) Model. *Patient Education and Counseling,* 100**,** 1918-1927.

Guillory, J., Niederdeppe, J., Kim, H., Pollak, J., Graham, M., Olson, C. & Gay, G. 2014. Does social support predict pregnant mothers' information seeking behaviors on an educational website? *Maternal and child health journal,* 18**,** 2218-2225.

Hammarberg, K., Collison, L., Nguyen, H. & Fisher, J. 2016. Knowledge, attitudes and practices relating to fertility among nurses working in primary health care. *Australian Journal of Advanced Nursing, The,* 34**,** 6-13.

Hammarberg, K., Norman, R. J., Robertson, S., Mclachlan, R., Michelmore, J. & Johnson, L. 2017a. Development of a health promotion programme to improve awareness of factors that affect fertility, and evaluation of its reach in the first 5 years. *Reproductive Biomedicine & Society Online,* 4**,** 33-40.

Hammarberg, K., Zosel, R., Comoy, C., Robertson, S., Holden, C., Deeks, M. & Johnson, L. 2017b. Fertility-related knowledge and information-seeking behaviour among people of reproductive age: a qualitative study. *Human Fertility,* 20**,** 88-95.

Hammarberg, K. P. D., Setter, T. M. P. H., Norman, R. J. M. D., Holden, C. a. P. D., Michelmore, J. D. E. & Johnson, L. D. E. 2013. Knowledge about factors that influence fertility among Australians of reproductive age: a population-based survey. *Fertil Steril,* 99**,** 502-507.

Helen, H., Joseph, M. & Sumayya, B. 2012. Australian Online Public Information Systems:An Evaluative Study of an Evolving Public Health Website. *AJIS. Australasian journal of information systems,* 17.

Hinchliffe, A. & Mummery, W. 2008. Applying Usability Testing Techniques to Improve a Health Promotion Website. *Health Promotion Journal of Australia: Official Journal of Australian Association of Health Promotion Professionals,* 19**,** 29-35.

Holmqvist, K. & Wartenberg, C. 2005. The role of local design factors for newspaper reading behaviour–an eye-tracking perspective. *Lund University Cognitive Studies*, 127**,** 1-21.

Huang, J. Y., Discepola, F., Al-Fozan, H. & Tulandi, T. 2005. Quality of fertility clinic websites. *Fertility and sterility,* 83**,** 538-544.

Imamoglu, O. & Gozlu, S. The sources of success and failure of information technology projects: Project managers' perspective. PICMET'08-2008 Portland International Conference on Management of Engineering & Technology, 2008. IEEE, 1430-1435.

Kerr, D. V., Bryant, K. & Tsai, N. 2009. A Survey of Current e-Business (E-Government). *AJIS. Australasian journal of information systems,* 15.

Marin, G. & Marin, B. V. 1990. Perceived credibility of channels and sources of AIDS information among Hispanics. *AIDS education and prevention: official publication of the International Society for AIDS Education*, 2**,** 154-161.

Mills, A. & Todorova, N. 2016. An integrated perspective on factors influencing online health-information seeking behaviours.

Nguyen, M. H., Bol, N. & Lustria, M. L. A. 2020. Perceived Active Control over Online Health Information: Underlying Mechanisms of Mode Tailoring Effects on Website Attitude and Information Recall. *Journal of health communication*, 25**,** 271-282.

Nguyen, M. H., Smets, E. M., Bol, N., Loos, E. F. & Van Weert, J. C. 2018. How tailoring the mode of information presentation influences younger and older adults' satisfaction with health websites. *Journal of health communication,* 23**,** 170-180.

Ojala, J., Zagheni, E., Billari, F. & Weber, I. Fertility and its meaning: Evidence from search behavior. Proceedings of the International AAAI Conference on Web and Social Media, 2017.

Ownby, R. L. & Czaja, S. J. Healthcare website design for the elderly: improving usability. AMIA Annual Symposium Proceedings, 2003. American Medical Informatics Association, 960.

Pang, P. C.-I., Harrop, M., Verspoor, K., Pearce, J. & Chang, S. What are health website visitors doing: insights from visualisations towards exploratory search. Proceedings of the 28th Australian Conference on Computer-Human Interaction, 2016. 631-633.

Pearson, K. 1895. Note on Regression and Inheritance in the Case of Two Parents. *Proceedings of the Royal Society of London,* 58**,** 240-242.

Pinto, J. K. & Mantel, S. J. 1990. The causes of project failure. *IEEE transactions on engineering management,* 37**,** 269-276.

Rampazzo, F., Zagheni, E., Weber, I., Testa, M. R. & Billari, F. Mater certa est, pater numquam: what can Facebook advertising data tell us about male fertility rates? Proceedings of the International AAAI Conference on Web and Social Media, 2018.

Raymond J. Rodgers, Heidi Long, Michael J. Davies, Nicole O. Mcpherson, Louise Johnson, Renee D. De Silva, Karin Hammarberg, Sarah A. Robertson & Bidargaddi, N. 2020. Development of a web-based preconception health-optimisation tool and characteristics of its users. *Human Reproduction.*

Rew, L., Saenz, A. & Walker, L. 2018. A systematic method for reviewing and analysing health information on consumer-oriented websites. *Journal of Advanced Nursing*, 74**,** 2218-2226.

Roster, C. A., Lucianetti, L. & Albaum, G. 2015. Exploring slider vs. categorical response formats in web-based surveys. *Journal of Research Practice*, 11**,** D1-D1.

Sikkel, D., Steenbergen, R. & Gras, S. 2014. Clicking vs. Dragging: Different Uses of the Mouse and Their Implications for Online Surveys. *Public Opinion Quarterly,* 78**,** 177-190.

Sillence, E., Briggs, P., Harris, P. R. & Fishwick, L. 2007. How do patients evaluate and make use of online health information? *Social Science & Medicine,* 64**,** 1853-1862.

Spoelman, W. A., Bonten, T. N., De Waal, M. W., Drenthen, T., Smeele, I. J., Nielen, M. M. & Chavannes, N. H. 2016. Effect of an evidence-based website on healthcare usage: an interrupted time-series study. *BMJ open,* 6**,** e013166.

Stanley, N. & Jenkins, S. Watch what I do: Using graphical input controls in Web surveys. Challanges of a changing world. Proceedings of the Fifth International Conference of the Association for Survey Computing, 2007. 81-92.

Starling, M. S., Kandel, Z., Haile, L. & Simmons, R. G. 2018. User profile and preferences in fertility apps for preventing pregnancy: an exploratory pilot study. *Mhealth,* 4.

Su, Z., Figueiredo, M. C., Jo, J., Zheng, K. & Chen, Y. Analyzing Description, User Understanding and Expectations of AI in Mobile Health Applications. AMIA Annual Symposium Proceedings, 2020. American Medical Informatics Association, 1170.

Swann Jr, W. B. & Read, S. J. 1981. Self-verification processes: How we sustain our self-conceptions. *Journal of Experimental Social Psychology,* 17**,** 351-372.

The Fertility Coalition. 2012a. *Privacy statement* [Online]. Available: https://www.yourfertility.org.au/privacy-statement [Accessed 14/12/2020].

The Fertility Coalition. 2012b. *Your Fertility* [Online]. Melbourne, VIC (Australia): The Fertility Coalition (AU). Available: https://www.yourfertility.org.au/ [Accessed 9/9/2020].

Van Dijk, M. R., Huijgen, N. A., Willemsen, S. P., Laven, J. S., Steegers, E. A. & Steegers-Theunissen, R. P. 2016. Impact of an mHealth platform for pregnancy on nutrition and lifestyle of the reproductive population: a survey. *JMIR mHealth and uHealth,* 4**,** e53.

Van Woerden, H. C., Ashton, K., Garlick, C., Hurley, A., Cooper, A., Willson, A., Henry, R., Kiparoglou, V. & Potter, C. 2014. Evaluation of a web based tool to improve health behaviours in healthcare staff. *International archives of medicine,* 7**,** 1-9.

Wall, A. F. 2007. Evaluating a health education website: The case of AlcoholEdu. *NASPA journal,* 44**,** 692-714.

Wang, G., Zhang, X., Tang, S., Zheng, H. & Zhao, B. Y. Unsupervised clickstream clustering for user behavior analysis. Proceedings of the 2016 CHI conference on human factors in computing systems, 2016. 225-236.

Watfern, C., Heck, C., Rule, C., Baldwin, P. & Boydell, K. M. 2019. Feasibility and acceptability of a mental health website for adults with an intellectual disability: qualitative evaluation. *JMIR mental health,* 6**,** e12958.

White, C. & Raman, N. 1999. The World Wide Web as a public relations medium: the use of research, planning, and evaluation in web site development. *Public Relations Review*, 25**,** 405-419.

White, R. W., Ruthven, I. & Jose, J. M. The use of implicit evidence for relevance feedback in web retrieval. European Conference on Information Retrieval, 2002. Springer, 93-109.

Zou, N., Liang, S. & He, D. 2020. Issues and challenges of user and data interaction in healthcare-related IoT. *Library Hi Tech*.

Appendix

The privacy statement of Your Fertility web site says ‘The Fertility Coalition also collects data through Google Analytics and/or Piwik Analytics designed to track the number of unique users, time and date of visits to the site and behaviour of users on the website, such as page visited, clicks and referral sources. The information collected by Google Analytics and/or Piwik Open Analytics does not identify a user. This information is used for statistical purposes and to ensure our web site is providing information relevant to our users. The Fertility Coalition may distribute aggregated statistical information for statutory reporting purposes, but only in a form that will not identify any person individually’. (The Fertility Coalition, 2012a)