Interaction-driven User Interface Personalisation for Mobile News Systems

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I, Marios Constantinides, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the work.

“Family is where life begins and love never ends”— Anonymous

To my family

Abstract

User interfaces of mobile apps offer personalised experience primarily through manual customisation rather than spontaneous adaptation. This thesis investigates methods for adaptive user interfaces in the context of future mobile news apps that are expected to systematically monitor users' news access patterns and adapt their interface and interaction in response. Although mobile news services are now able to recommend news that a user would be likely to read, there has not been equivalent progress in personalising the way that news content is accessed and read. This thesis addresses key issues for the development of adaptive user interfaces in the mobile environment and contributes to the existing literature of adaptive user interfaces, user modelling, and personalisation in the domain of news in four ways. First, using survey methods it explores differences in how people consume and read news content on mobile news apps and it defines a News Reader Typology that characterises the individual news consumer. Second, it develops a method for monitoring news reading patterns through a deployed news app, namely Habito News, and it proposes a framework for modelling users by analysing those patterns; machine learning algorithms are exploited selectively in the analysis. Third, it explores the design space of personalised user interfaces and interactions that would be tailored to the needs and preferences of individual news readers. Finally, it demonstrates the effectiveness of automatic adaptation through Habito News, the prototype mobile news app that was developed, which systematically monitors users' news reading interaction behaviour and automatically adjusts its interface in response to their news reading characteristics. The results indicate the feasibility of user interface personalisation and help shape the future of automatically changing user interfaces by systematic monitoring, profiling and adapting the interface and interaction.

Impact Statement

In user interface research, a widely used paradigm is the "one-size-fits-all" in which all users of a system and across systems interact with the same user interface to optimise consistency and predictability. The inability, however, of this paradigm to address the particular needs of different users and the specific demands of different tasks, led to adaptation or personalisation of the user interfaces. Adaptation in user interfaces has been a longstanding interest with many successful applications demonstrating its effectiveness and desirability from users. Traditionally, the two paradigms of applying adaptation are the adaptable and the adaptive. Adaptable systems allow users to manually manipulate and configure their user interfaces based on their preferences. On the other hand, adaptive systems rely entirely on the system to build a user profile of the current user and exploit that profile to personalise the user interface without any explicit input from the user. This thesis investigates the use of adaptive user interfaces and explores its effectiveness in mobile news reading.

The domain of news is a challenging and relevant field for developing and investigating personalisation in user interfaces. Reading the news is a highly individual experience with marked differences in the ways people read and access the news. Although many news systems are able to help users find the right news by recommending stories they might want to read, their user interfaces do not respond to their habits, preferences and the particular ways of consuming the news content. This thesis delivers a concept demonstrator of an adaptive news application, coined Habito News, that learns users' interaction behaviour and adjusts its displays in response to those interaction patterns.

The thesis contributes in the research areas of User Modelling, Personalisation and the wider HCI. It suggests a News Reader typology that describes different kinds of news reading behaviour relating to news consumption patterns and habits. Furthermore, it proposes a framework that characterises the hierarchical relationship of abstracted factors relating to news reading behaviour with data that can be captured from monitoring users' news reading interaction behaviour. It explores different user modelling techniques and implements models that are capable of detecting the different kinds of news reading behaviour. The inferred models from users' interaction behaviour serve as the basis of adapting and reconfiguring the user interface to suit the individual ways of consuming news content. Different user interfaces are examined and proposed for different kinds of news reading behaviour.

In addition to its contribution to the academic research, this thesis has an impact in commercial news services and providers. The outcomes of this research can be incorporated in existing news services to model their users' interaction behaviour that would enable their service to provide a more personalised news experience, tailored to the individual user characteristics. The proposed News Reader typology can serve as a starting point in classifying different news reader types not only by the type of content they consume but also by the ways that content is consumed.

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List of Publications

The text of the thesis is partly based upon the following publications:

- M. Constantinides. ”Apps with habits: Adaptive interfaces for news apps. In *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems* (pp. 191-194). ACM, 2015.

- M. Constantinides, J. Dowell, D. Johnson, S. Malacria. Exploring mobile news reading interactions for news app personalisation. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services* (pp. 457-462). ACM, 2015.

- M. Constantinides, J. Dowell, D. Johnson, S. Malacria. A research tool to investigate mobile news reading. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct* (pp. 598-598). ACM, 2015.

- M. Constantinides, J. Dowell. User Interface Personalization in News Apps. In *UMAP Workshops*. ACM, 2016.

- M. Constantinides, J. Dowell. A Framework for Interaction-driven User Modeling of Mobile News Reading Behaviour. In *In Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization*, pp. 33-41. ACM, 2018.

- M. Constantinides, P. Germanakos, G. Samaras, J. Dowell. Your Digital News Reading Habits Reflect Your Personality. In *Adjunct Publication of the 26th Conference on User Modeling, Adaptation and Personalization* (pp. 45-48). ACM, 2018.

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Chapter 1

Introduction

The overarching goal of this thesis is to contribute to the systematic understanding of the design and evaluation of adaptive user interfaces for mobile news apps, and the broader area of modelling users' interaction behaviour in mobile contexts. This research work involves investigating news reading behaviour with mobile news apps, building user models that are capable of predicting news reading interaction patterns, developing variant user interface designs and interactions that would suit different kinds of news reading behaviour, and ultimately implementing and demonstrating an automated adaptive news app that personalises the user's news reading experience; the focus it goes beyond ***what*** content users access to ***how*** they access it and interact with. This Chapter presents the motivation for the research, highlights the research scope and questions, discusses the methodology followed throughout the research and provides an overview of the thesis structure.

1.1 Motivation

Today's smartphones might well be the epitome of personal computing. As of today, one third of the world's population owns a smartphone (Statista, 2016), and this number is expected to rise significantly in the next years (eMarketer, 2017). Mobile devices are now fully equipped personal computers with advanced capabilities of power processing that facilitate users' daily activities and tasks; from getting emails to editing documents to playing games to reading the news. The remarkable technological advancements that took place in the last decade (e.g. iPhone 2007) have established smartphones as the predominant device with which people interact on a daily basis. The paradox, however, is that smartphones' user interfaces have yet distinct limits in providing personalised service. In fact, the compound word 'smart-phone' encapsulates the notion of 'smart' or 'intelligent', which is yet to be accomplished in today's smartphones user interfaces. Mobile platforms in general do not learn about the users from their use of the device and they do not attempt to adapt to the users' habits and preferences.

In user interface research, a common paradigm for designing user interfaces is that of "one-size-fits-all", i.e., standardisation of the user interface for all users of an application and across applications to optimise consistency and predictability. Despite its wide adoption, research sometimes reached conclusions such as "one-size-fits-all may not in fact fit all" (McGrenere and Moore, 2000). As users, we interact with devices that were designed to meet the needs, habits and preferences of all. The inability to fit the specialised needs of different users and the specific demands of different tasks are well-known problems of this common approach in user interface design. A relaxation of this paradigm is the idea of customisable user interfaces, often referred in literature as adaptable. This paradigm enables personalised access through manual user interventions that allow users to manually tailor and adapt the user interface and interaction to meet their particular needs, tasks, habits, preferences, and context (Weld et al., 2003; Sears and Jacko, 2009). There is an abundance of apps on the Google and Apple marketplaces that provide personalisation by customising menus and configuring settings. Despite the plethora of customisable interfaces and their potential benefits in increasing users' performance (Findlater and McGrenere, 2004), they received criticism and many questions arose about their effectiveness. Users might never manually customise the interface themselves due to the additional effort and time needed to learn how to customise and use the interface effectively (Mackay, 1991; Weld et al., 2003), or simply they are not aware of what is optimal for them, at any given time and context; which might not be the case for a system to understand what is the optimal and design the interface, adapt or intervene to propose 'the optimal interface' (Oulasvirta, 2018).

A promising alternative to overcome these limitations is the idea of Adaptive User Interfaces (AUI), which aims to achieve the desirable automatic adaptation of the user interface without any user intervention involved in the process. A large body of research on AUIs introduced in late nineties and early the two-thousands (Sears and Shneiderman, 1994; Horvitz et al., 1998; Langley, 1999; Keeble and Macredie, 2000; Rothrock et al., 2002; Gajos et al., 2006; Cena et al., 2006), and praised their effectiveness. An AUI "autonomously adapts its displays and available actions to current goals and abilities of the user by monitoring user status, the system task, and the current situation" (Rothrock et al., 2002). AUIs employ automated procedures, often by utilising techniques and methods from the field of Artificial Intelligence (AI) to "build a user model based on partial experience with the user" (Langley, 1999), which in turn serves as the basis of adapting their displays and interaction, content or provide assistance to the user's current task. For instance, the classic example in menu systems by re-ordering frequently visited items to quicken visual search and selection (Gajos et al., 2006, 2008), provide clear evidence of the value of adaptivity for users and their preferences for it. Despite their potential benefit in assisting users with their task and enhancing their user experience, AUIs have also received criticism as they can create confusing inconsistency by constantly changing or optimising themselves (Weld et al., 2003). The biggest challenges, therefore, in developing such systems are the underlying algorithms that can accurately predict the user's behaviour and the right presentation of the user interface and interaction to reflect the user's behaviour that is delivered through the right channel at the right time. The aforementioned research works in AUIs have been conducted before the advent of today's smartphones and mainly focused on computer-based tasks and interactions, and, hence, the relatively limited exploration of adaptive user interfaces for mobile apps. The adoption of this paradigm in today's smartphones apps is yet an open question, as it has not been embraced as customisable (i.e., adaptable) interfaces. Delve into this problem, questions arise in relation to users' willingness to allow the system to decide the optimal design and interaction for them and users' unwillingness due to poor underlying intelligence, that fails to capture users' habits and preferences. For example, the predictability and controllability of AUIs are two critical aspects that lead to successful personalisation (Gajos et al., 2008). In fact, the technological explosion of recent years has transformed the ways users interact with devices. Users are now more sophisticated in using and interacting with technology; the traditional selection with a click of mouse has now been replaced with swipes and flicks; reading the news can now be anywhere and anytime (Westlund, 2008; Westlund and Färdigh, 2015), as well as most of the traditional desktop-based tasks. Evidently, the big volumes of data produced by users' interactions with smartphones in combination with advancements in AI and unconstrained power processing can help the idea of adaptive user interfaces flourish and ultimately achieve the desirable automatic adaptation in mobile apps user interfaces.

A relevant and rich domain to apply the idea of automatic adaptation in user interfaces is the domain of news. Until quite recently, reading the news was a niche use for smartphones, mostly for when users were 'on the go', as Westlund (2008) stated. Today, however, people have access to news through various channels and gateways, from print newspapers to online news portals to mobile news apps to social media platforms. Recent reports found that two in every three users of mobile devices in the United States regularly access news and as many as one in five read in-depth news articles on a daily basis (Pew Research Centre, 2012; Ofcom, 2014). Additionally, a report from Reuters Institute (2014) revealed that more than a third of online news readers across the globe use two or more digital devices each week to access the news and a fifth uses smartphones as their primary access point. Furthermore, social network platforms such as Facebook and Twitter are now established news gateways for news consumption. It is evident; therefore, that news is increasingly being accessed on smartphones and the use of mobile devices for news consumption continues to grow (Pew Research Centre, 2017a). While news is heavily consumed through different channels, predominantly via mobile news apps, it is also important to highlight the individual differences in the way people read and access the news. Prior studies have reported supportive results and findings in the individual nature of news consumption. Grzeschik et al. (2011) reported that influences on reading rate and concentration are posed by the individual reading behaviour of the person and by the nature of the text rather than by the reading devices. This might have implications to smartphone users who are likely to exhibit characteristic patterns of accessing and reading the news. For example, how much a person chooses to read of news articles or how they view and select them to read. In the digital world, a new kind of news reading behaviour has been found, named as 'the screen-based reading' (Liu, 2005). It is characterised "by more time spent on browsing and scanning, keyword spotting, one-time reading, non-linear reading, and reading more selectively, while less time is spent on in-depth reading, and concentrated reading".

Progress, however, in personalising the choice of news content has not been matched by progress in personalising the way that content is accessed and read. News apps such as Flipboard[1], BuzzFeed[2], Feedly[3], News360[4], web-based news portals such Google News[5] and Yahoo News[6], and research prototypes such as WebClipping2 (Carreira et al., 2004), Buzzer (Phelan et al., 2009), SmartMedia (Gulla et al., 2014), LumiNews (Kazai et al., 2016), PEN (Garcin and Faltings, 2013), Focal (Garcin et al., 2014) frequently do adapt to users' individual news interests through content recommendation services and many allow user customisation of news feeds (Billsus and Pazzani, 1999, 2000). Their user interfaces, however, do not adapt to how individual users characteristically select and read the news, as opposed to what news they are interested in reading. For example, the frequency and time spent reading news will vary considerably between people, as will their patterns of navigating news headlines and reading articles. This means that different users would likely be better served by different interfaces. For example, a user who likes to review all the headlines before choosing an article to read would be

[1] https://flipboard.com/
[2] https://www.buzzfeed.com/
[3] https://feedly.com/i/welcome
[4] https://news360.com/
[5] https://news.google.com/news/
[6] https://www.yahoo.com/news/

best served by a summary presentation of all headlines and a way of marking them as a reading list of articles. It might be expected that news app interfaces would benefit from personalisation to the same extent as the news content it provides access to. Moreover, the growing number of news apps available on marketplaces and the plethora of news portals justify users need for news consumption, but also creates the need for that access to be adaptive and personalised, which is yet an open question to news services.

1.2 Research Scope and Questions

The research scope and questions of this thesis ought to be set and clarified before proceeding with the presentation of the research work. This will clarify its contributions within the areas of Adaptive User Interfaces, User Modelling and Personalisation. The thesis aims to extend the state-of-the-art paradigm in news personalisation, which primarily focuses on news content recommendation, by developing user interface personalisation in news app interfaces. In particular, *"contemporary mobile news apps offer personalised news content recommendations and/or the ability to manually customise their user interfaces. The scope, however, of news personalisation needs to extend beyond **what** content users access and read to **how** that content is delivered, presented, and consumed."*

To address the high-level goal of this thesis requires an investigation of four research questions (RQ1-RQ4). The thesis is organised around the four RQs and the methodology followed to examine each question is provided below.

RQ1: *How do people vary in accessing and reading the news on smartphones? What are the stereotypical news readers profiles?*

RQ2: *How can smartphones news apps detect and learn individual user's news reading patterns of interactions?*

RQ3: *How can smartphone news apps exploit a news reader profile to adapt the interface and the interaction?*

RQ4: *How would different users benefit from different forms of a smartphone news* *app? To what extent the user interface personalisation is beneficial to different kinds of news reading behaviour?*

RQ1 is addressed in Chapter 3, which focuses on understanding news reading behaviour in order to reveal people's differences whilst reading the news on mobile devices. While many prior research works (Pew Research Centre, 2012; Reuters Institute, 2014; Fortunati et al., 2014; American Press Institute, 2014) have investigated users' news interests by examining, for example, socio-political factors, personality traits and so forth, no prior work, to the best of the author's knowledge, has been conducted in relation to the stereotypical behaviour of accessing and consuming the news. The study, therefore, presented in Chapter 3 does not attempt to repeat previous works, rather it focuses on patterns of interaction behaviour in relation to how users interact with mobile news apps interfaces to access and consume the news content. For example, it examines how people search through news headlines and choose articles to read and how they read the text of selected articles. The study utilises a survey method, in which participants responded in an online questionnaire aiming to investigate those news consumption behaviour differences. The results of the study serve as the foundation for defining a News Reader Typology for mobile news apps consumption. The typology describes three different kinds of news consumption behaviour, namely as *'Trackers'*, *'Reviewers'* and *'Dippers'*, and defines their characteristics. Statistical methods and an unsupervised clustering technique were used to form the typology and devise the definitions of the different kinds of news reading behaviour. It is important to note that the proposed News Reader Typology was utilised as the basis to explore the other research questions.

RQ2 is addressed in Chapter 5. Chapter 5 describes the User Modelling (UM) component and data collections through a dedicated news app, called Habito News. Both the UM component and the news app are part of the adaptive news research platform introduced in Chapter 4. Chapter 5 introduces models that learn to detect user's interaction behaviour patterns. It proposes a hierarchical framework for analysing mobile news reading interactions and explores two approaches of user model acquisition. Unlike previous research works that focused on modelling users' news reading interests, the two approaches attempt to model users' news reader type and users' news reading interaction factors, as originate from the News Reader Typology. It presents a descriptive statistical analysis on the interaction corpus collected with deployments of Habito News app through the Google Play platform and explains the implementation of machine learning algorithms utilised in the learning process.

RQ3 is addressed in Chapter 6 wherein the design space of variant user interface designs and interactions that would suit different kinds of news reading behaviour is explored. An iterative process for the design of user interface features was adopted and the Chapter reports the findings of two controlled laboratory studies (i.e., Phase I and Phase II) that aimed to assess the usability, user experience and satisfaction of different forms of Habito News user interface. User interface features were designed using Justinmind[7], a wireframe prototyping tool. Qualitative and quantitative methods were used to gather user's data during the two studies. The Chapter also introduces the Adaptation Mechanism (AM), another component discussed in Chapter 4, the component that is responsible to generate UI designs on-the-fly and adapt the user interface of Habito News.

RQ4 is addressed in Chapter 7. This Chapter puts together all the research strands discussed in Chapters 3, 4, 5, 6 and reports the results of a field evaluation study of Habito News, which aims to examine the effectiveness of automatic adaptation in news apps interfaces. The Chapter presents a layered evaluation study(Paramythis et al., 2010; Brusilovsky et al., 2001) in which the interaction assessment layer (i.e., user model acquisition) and the adaptation decision-making layer (i.e., adaptation mechanism and variant user interfaces of the news app) are examined. Qualitative data was collected through a daily email questionnaire and the AttrakDiff (Hassenzahl et al., 2003) questionnaire that administered twice before and after the adaptation. AttrakDiff measured user satisfaction and experience in four dimensions as follows: Pragmatic quality (PQ) measures the support for achieving a goal; hedonic quality stimulation (HQ-S) measures the perceived

[7]Justinmind: https://www.justinmind.com/

novelty and potential to grab users' attention; hedonic quality identification (HQ-I) measures the potential of identification, and; attractiveness (ATT) measures the perceived attractiveness. Quantitative data was also collected to examine users' engagement with the news app and evaluate the user model acquisition.

1.3 Thesis Contributions

This thesis addresses key issues for the design and development of adaptive user interfaces for mobile news apps and contributes into existing literature of Adaptive User Interfaces, User Modelling and Personalisation. The core contributions of the thesis are summarised below and elaborated in the Conclusions (Chapter 8).

1. A News Reader Typology for mobile news readers is defined along with six discriminating reading factors that reflect news readers interaction behaviour in accessing and consuming news on news apps.

2. Development of a method for monitoring and analysing news reading interaction patterns through a dedicated news app, called Habito News. The method defines the granularity of data being captured and proposes a hierarchical framework for analysing those patterns of news reading interaction behaviour. Rule-based and machine learning algorithms were implemented and compared for the user model acquisition.

3. Design of variant user interfaces that would suit the habits and preferences of different mobile news readers. Evaluation studies show empirical evidence of the proposed designs and their preferences from users.

4. A concept demonstrator of an adaptive news app, namely Habito News, that systematically monitors and models user's interaction behaviour pattern, infer models from those data, and adapts its displays in response to those models.

In addition to its core contributions, the thesis claims a technical contribution. It proposed an adaptive news research platform, implemented in a three-tier architecture, which facilitated the exploration of adaptivity in news apps.

1.4 Thesis Structure

The thesis comprises eight Chapters and is structured as follows:

Chapter 2 contextualises the research work and covers a literature review of the different research areas that the thesis draws and builds upon. It reviews research works within the areas of adaptive and adaptable user interfaces and user modelling that span across different application domains, including web and mobile, but also with a particular focus on the news domain.

Chapter 3 examines people's mobile news consumption patterns and introduces a News Reader Typology that reflects the different ways mobile news readers consume and access news content.

Chapter 4 presents the design and implementation of an adaptive news research platform that facilitates the exploration of adaptivity in mobile news apps.

Chapter 5 explores the user model acquisition. It proposes a hierarchical framework for analysing news reading interaction patterns and reports two approaches for modelling user interaction habits. It presents models that are capable of predicting users' news reader types and models that are capable of learning the individual reading characteristics that discriminate news reader types in order to construct an individual user profile. Rule-based models and machine learning algorithms were implemented.

Chapter 6 investigates the design space of adaptive user interfaces for news apps and provides empirical evidence through evaluation studies. It presents two controlled laboratory studies in which several designs were being tested and evaluated that suit the different kinds of news reading behaviour. It also describes the generation of adaptation rules that will be used during the adaptation process.

Chapter 7 presents the final evaluation study of the adaptive news research platform in which the effectiveness of adaptation is examined in a field deployment study with Habito News.

Chapter 8 provides an elaborated discussion of the findings of this research, reflects on the lessons learned over the course of the research and discusses future directions of this thesis.

Chapter 2

Background and Related Work

This Chapter surveys research works within the areas of adaptive and adaptable user interfaces, mobile context-aware systems and user modelling techniques. The review begins with an introduction to personalised systems in relation to adaptive and adaptable user interfaces and discusses the main challenges in developing such systems. It continues by identifying gaps in prior works that have motivated this research with a particular focus in the domain of news in the mobile environment. It then highlights the importance of user modelling and presents different approaches that have been used in modelling users' behaviour, interaction, and actions with user interfaces. The Chapter concludes with a discussion of the different lines of research works presented.

2.1 Adaptation and Personalisation

Adaptation and personalisation are commonly used terms in Human-Computer Interaction (HCI) literature, which are used to describe software systems that adjust or alter their behaviour or user interface to an individual or a group of users by leveraging information known about their users, context, platform and/or tasks (Gajos et al., 2010, 2006; Findlater et al., 2008; McGrenere et al., 2002; Kuflik et al., 2012). Although the terms may appear identical to the end user, in terms of the outcome, their practical usage and application is yet under controversy among the research community. In fact, researchers frequently use the terms interchangeably, however, there is a subtle difference between adaptation and personalisation. The following

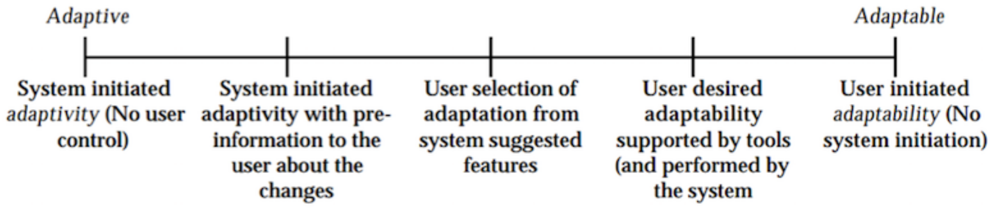


Figure 2.1: Spectrum of adaptation in computer systems (Oppermann and Rasher, 1997).

section examines their differences through an in-depth analysis and investigation of personalised systems proposed across different domains.

In computing, two kinds of computer software have been developed to support users with their tasks and enhance their experience interacting with computers; the adaptable and the adaptive. According to Oppermann (1994) terminology, the term adaptable is used for a system in which alterations or adjustments to its behaviour or user interface are explicitly performed by the user. The adaptive term is mainly used for systems in which personalisation of the system's behaviour or its user interface entirely relies on the system without any user intervention. Similarly, Weld et al. (2003) used the term customisation to describe an adaptable system in which personalisation is directly requested by the user and the term adaptation to describe an adaptive system in which personalisation is automatically performed by the user interface without explicit user directives. Building on previous definitions, Sears and Jacko (2009) have expressed adaptable systems as computer software that make changes to the content or the user interface only as a result of the explicit intervention of the user, whereas adaptive systems dynamically organise their contents to meet the perceived needs of the user without any direct user intervention. Certainly, apart from the two extremes, hybrid solutions have been proposed that combine principles of the two. Figure 2.1 depicts the whole spectrum of adaptation in computer systems.

Adaptable systems have been widely deployed. Most commercials systems allow users to manually change system parameters, provide individual interests and tailor the user interface to fit their needs or demands to complete specific tasks. Productivity software is a great example which illustrates the idea of manual adaptation. For example, Microsoft Word allows users to tailor toolbar items based on their preferences and tasks. McGrenere et al. (2002) showed that manual adaptation of the user interface found to be more appealing to users than automatic adaptation. Furthermore, web portals provide options through settings menus to specify the sorts of information users want to see. Mobile apps are now embedded with personalised mechanisms to provide the best possible experience to their users. Although adaptable systems are abundant in our everyday activity with computers and mobile devices, several issues arise about their feasibility and acceptability to users. The lack of the application domain, the additional effort and time to learn how to customise and use such systems effectively are barriers that prevent users from manually customising interfaces (Mackay, 1991). Even more, these kind of systems do not leverage the machine's capabilities to determine and learn about its users, instead they rely on user-initiated adaptation, which might be considered not the optimal form of adaptation.

Contrarily, adaptive systems are still quite rare (Findlater and McGrenere, 2010, 2004; Oppermann, 1994). However, the explosive growth in size and use of the World Wide Web and the advent of smartphones increased the demand for more adaptive services and interfaces. News web portals, online shopping and banking systems are example services that incorporate personalisation features in their systems. For example, Google News [1] generates recommendations using a collaborative filtering approach in which the learning process of producing recommendations is based on unobtrusively collected user and community data. Mobile news apps provide personalised content by pushing filtered articles predicted to match users' interests such as Flipboard, News360, BuzzFeed, Feedly, Pulse or research prototypes such as WebClipping2 (Carreira et al., 2004), Buzzer (Phelan et al., 2009), SmartMedia (Gulla et al., 2014), LumiNews (Kazai et al., 2016), PEN (Garcin and Faltings, 2013), Focal (Garcin et al., 2014). Further, mobile advertisements are now being targeted to specific users based on information about their context, social activity or other factors. In addition to the technological advancements, the

[1] Google News: https://news.google.com

target audience of those adaptive services is, often, the Millennials (also known as Generation Y).This younger generation, therefore, use technology differently than previous generations (Deal et al., 2010) and might be more receptive to systems that adapt or change functionality themselves without any intervention. For example, the Elastic News project (BBC RD, 2014) is an example of such a service that delivers news in a 'snackable' format and targets young people; a hard to reach and engage audience in news.

Apart from the two extremes, hybrid solutions in which the user's selects the adaptation from system suggested features. A prominent example of such system is the Amazon.com [2] platform, which acquires information about its users implicitly by monitoring previous purchases or the user's click-stream and explicitly by receiving the user's feedback and item ratings. For example, the different items that are being recommended at the top of the search result section might differ from one user to another.

2.2 Adaptive User Interfaces

Adaptive User Interfaces (AUI) literature is rich and diverse, spreading among multiple disciplines and different platforms and spans on two decades of accumulated research. Langley (1999) defined an adaptive interface as "a software artefact that improves its ability to interact with a user by constructing a user model based on partial experience with that user". An other definition given by Keeble and Macredie (2000) presented it as "One where the appearance, function or content of the interface can be changed by the interface (or the underlying application) itself in response to the user's interaction with it". Rothrock et al. (2002) have attempted to synthesise definitions of prior studies and considered it as a system that "autonomously adapts its displays and available actions to current goals and abilities of the user by monitoring user status, the system task, and the current situation". Later, Jameson (2009) defined a 'user-adaptive' system as the one that makes use of some type of information about the current individual, which performs some type

[2] Amazon.com: http://www.amazon.com

of learning and/or inference on the basis of the information obtained about the user in order to arrive at some sort of user model that will be used as the basis to adapt its behaviour to the user.

Adaptive user interfaces can also be classified based on the variables that influence the adaptation and the types of adaptation effects. An AUI can adapt in different ways in response to the following four variables (Cena et al., 2006):

(a) User: The AUI adapts to user's preferences, knowledge and skills, commonly known as user-based adaptation.

(b) Task: Adaptation is employed on user's current tasks and ensures that the adaptation is relevant and assists users completing efficiently their current activities.

(c) System: Adaptation takes place in the system level to adjust differing device capabilities and variables such as network connectivity, screen size, and many others. It is also known as platform-based adaptation in the context of mobile devices.

(d) Context: Adaptation is performed according to user's current context such as user's location.

2.2.1 Web-based and Desktop Environments

Adaptive user interfaces applications span on different areas such as menu systems for software programs, systems for disabled or elderly people, help and support in commercial software systems, shopping and news systems (Weld et al., 2003; Stephanidis et al., 1998; Connelly et al., 2006; Gajos et al., 2006; Horvitz et al., 1998; Preuveneers and Berbers, 2008).

Menu systems for computer software have gained attention, starting in the early 1990s, and resulting in interesting insight about design guidelines, challenges and other properties of adaptive user interfaces. Sears and Shneiderman (1994) first introduced the idea of Split Menu, which is a menu organisation wherein highly frequently viewed items are promoted to the top of the menu whereas the less frequent are relegated to the bottom. Evaluation studies showed that users were significantly faster using a Split Menu than alternatives such as alphabetical or logical order organisation menus. Although their work was promising at the time, it raises questions about consistency. The main criticism of that work was the confusion that adaptation might cause to the user by replacing or reordering menu items (Findlater and McGrenere, 2004). To cope with that, they proposed a variation of the initial Split Menu in which the high frequency items remained in their initial position but were also duplicated in the high frequency section. Duplication of menu items turned out to be beneficial to the user and ensured that users would locate the high frequent items regardless of the section they were browsing. Later, Shneiderman (2002) proposed an adaptive menu system that embodies the idea of multi-layer interface design to promote universal usability. He suggested a layered interface design for a word processor application in which users can begin with a limited set of features at the first layer and then can decide whether to remain at that level or move up to higher layers. He concluded that the idea of a multi-layer interface is a viable approach to empowering users of complex systems to begin to effectively manage their tasks at their own pace and needs.

Adaptive user interfaces have been deployed in systems to assist people with physical impairments or elderly people. Example systems include screen readers to help blind users, web-based applications that provide accessibility and high quality interaction to people with disabilities, dedicated accessible interfaces for elderly people and many others. The AVANTI project by Stephanidis et al. (1998) has focused mainly on addressing the interaction requirements of disabled people using web-based multimedia applications and services. The SUPPLE system proposed by Gajos et al. (2010) was capable of automatically generating interfaces tailored to a person's devices, tasks, preferences, and abilities. Their evaluation results showed that SUPPLE significantly improved speed, accuracy and satisfaction of people with motor impairments. Further, Connelly et al. (2006) have proposed two mobile applications that empower people to monitor their personal health. The first one, named DIMA, developed to assist dialysis patients in monitoring their diet (their fluid and sodium intake), while the second one, named Chick Clique, attempted to motivate teenagers to increase their physical activity with their friends' support. Likewise, Preuveneers and Berbers (2008) have explored the use of mobile phones as a tool to provide personalised health care assistance for individuals with diabetes.

Assistive technologies for computer software are another area in which adaptive user interfaces have been proven to benefit users' interaction and experience. The Lumiere Project proposed by Horvitz et al. (1998) is a great example of such a system that provides assistance to computer software users. Their goal was to build smart technologies that can observe a user interacting with a complex software interface and infer his goals/needs by providing valuable feedback and assistance if needed. Bayesian probabilistic models were used at the core of Lumiere to produce the inferences. Once the user model was constructed based on unobtrusive monitoring of user events, then a window displayed the inferred assistance when the deduced probability exceeded a specified threshold. Despite their work being promising and novel at the time, when they attempted to deploy it in the real world the results were not as expected. The Lumiere project was the predecessor of the Office Assistant in Microsoft Office suite '97, known as Clippy. Clippy continued to be part of the product until 2007 when it was permanently removed (Swartz, 2003). It was a very unpopular feature that many loved to hate because its help was often not relevant. The reasons that led to failure was simply because the Office team developed a simple rule-based system on top of the Bayesian query analysis system to infer the tips, instead of using the mathematically correct engine designed by Horvitz's team. Further explanation about this research work was conducted by Swartz (2003). A conclusion worth mentioning is that designing an effective user interface agent is difficult because many factors (task, situation, behaviour, appearance, label) co-exist and influence users' responses as Swartz stated.

2.2.2 Mobile Environment and Context-awareness

Adaptive user interfaces have been widely deployed in the mobile environment since the advent of smartphones. Undoubtedly, a large body of research has been conducted in relation to context, known as context-aware systems or applications.

Context-awareness, as first realised by Schilit and Theimer (1994), is defined as “the ability of a mobile user’s applications to discover and react to changes in the environment they are situated in”. Due to the broad scope of the aforementioned definition, they expressed it in terms of location, identities of nearby people and objects, and changes to those objects. A simpler definition given by Brown et al. (1997) presents context-awareness as the ability to change an application’s behaviour based on user’s context. Further, Abowd et al. (1999) added to previous definitions by defining context as any information that can be used to characterise the situation of an entity, where entity can be a person, place or object that is considered relevant to the interaction between the user and the application. Summarising the definitions given at different times, context-awareness is the ability of a computer system or a smartphone app to adjust its functionality or user interface in response to their ambient environment. A more detailed survey of context-aware mobile computing research was conducted by Chen et al. (2000) in which the authors discuss different approaches to sense and model the context, and list a number of context-aware application examples.

Today’s smartphones have a variety of embedded sensors that can be used to define users’ context. Numerous studies have used data derived from device sensors to reveal information related to users’ ambient environment. Brown et al. (2005) demonstrated a lightweight mobile system that allows city visitors to share their sightseeing experiences with remote users. Their work acknowledges the importance of context-aware techniques in supporting social activities. Böhmer et al. (2010) presented Appazaar, a prototype recommender system for mobile applications in which recommendations are produced based on the actual usage of the applications as relevance measure related to different contexts. In the same manner, Woerndl et al. (2007) incorporated context to recommend apps for train schedules in which recommendations are produced based on other users’ app usage at the user’s current location. The importance and the impact of relevant contextual information on recommender systems were highlighted by Adomavicius and Tuzhilin (2015) in their work. Context has been exploited not only in relation to recommendations but also in other topics. For example, Donohoo et al. (2012) exploited spatiotemporal and device context to dynamically predict energy-efficient device interface configurations. Xu et al. (2013) proposed a prediction framework for smartphone app usage that leverages user' environment as observed through sensor-based communication cues and other factors such as users' activities, app preferences and crowd-sourced shared patterns of app behaviour. Further, Noble (2000) proposed an approach that deals with turbulent environments (e.g. loss of network connectivity) to support mobile adaptive applications. Likewise, Capra et al. (2003) developed a middleware platform, which is capable of responding to context change.

2.2.3 Challenges of Adaptive User Interfaces

Previous usability studies on adaptive menus have mainly focused on evaluating the overall performance of an adaptive interface compared to some non-adaptive variant. However, none of these considered the fact that performance highly depends on the effectiveness of the underlying intelligent system. Users' trust and use of the system rely heavily on reliability of assistance provided by the intelligent system (LeeTiernan et al., 2001). A study reported by Tsandilas et al. (2005) focused on the impact of accuracy of the adaptive algorithm on users' performance and satisfaction. They compared two adaptation techniques that suggest items in adaptive lists and concluded that the effectiveness of different adaptation techniques may vary depending on the accuracy of the prediction mechanism. Gajos et al. (2006) have attempted to understand those aspects of adaptive user interfaces which make some of them successful and others not. They designed and implemented three adaptive graphical interfaces (Split Interface, Moving Interface and Visual Popout Interface) along with a non-adaptive baseline on top of Microsoft Word XP. They reported that Split Interfaces in which frequently used functionality is duplicated rather than moved, improved users' performance and satisfaction, offered medium to high benefits and avoided confusion. Specifically, they identified that spatial stability increases user satisfaction and performance. Spatial stability was achieved by only adapting a clearly designated separate adaptive area rather than by altering the familiar parts of the interface. It is worth mentioning that this strategy was later incorporated by Microsoft in Windows XP Smart Menus. Further, they reported that the frequency of interaction with the interface and the task complexity had a significant effect on the perceived value of adaptation. The behaviour of the adaptive algorithm, in terms of its accuracy and predictability, is another important factor. Based on their previous research, Gajos et al. (2008) reported the influence of accuracy and predictability of the adaptive algorithm on an adaptive toolbar user interface. Both properties affected users' satisfaction but only accuracy had a large impact on users' performance of the adaptive interface as they stated. Likewise, Findlater and McGrenere (2008) concluded that high accuracy influences performance and user satisfaction in an experiment comparing adaptive menus on small screens and regular desktop-sized displays. The factors of ease of use and learnability have also been explored in a study conducted by Paymans et al. (2004). They have attempted to overcome unpredictable interface adaptations, which might be a cause for the relative unsuccessfulness of some adaptive interfaces, by helping users to build adequate mental models of adaptive systems. However, it turned out that the provided support did improve ease of use but, unexpectedly, it reduced learnability. Therefore, the improvement of a user's mental model of an adaptive interface is not necessary to increase ease of use.

The aforementioned challenges apply to any kind of adaptive interface, but adaptive user interfaces for the mobile environment have some particularities that are worth discussing. The small screen size is an issue that all mobile devices have in common even today with high-resolution screens. The screen limitation has an immediate impact on the presentation of user interface elements. It can turn basic tasks such as reading or browsing into difficult ones, resulting in a significant drop in a user's performance (Jones et al., 2003) (e.g. how many interactions required to complete a task in terms of swipes, flicks or any other gesture). In addition, navigation in complex interfaces might be more difficult due to users' tendency to use mobile devices in contexts where their attention is very limited compared to desktop environments. For example, when users are in social contexts in which their attention span is limited or while they are commuting to work.

2.2.4 Evaluation of Adaptive User Interfaces

Evaluating Adapting User Interfaces is as important as designing and developing them. A widely used strategy to evaluate adaptive interfaces is a direct comparison between the adaptive version and some non-adaptive variant. Evaluation studies have been inconclusive in terms of the fundamental benefits of adaptivity. In some cases (Gajos et al., 2006; Greenberg and Witten, 1985) users performed faster and preferred the adaptive interface (menus, toolbars, etc), whereas other research work (Findlater and McGrenere, 2004; McGrenere et al., 2002) showed the opposite. Hence, adaptive interfaces benefits remain controversial among researchers and very few have been established in commercial software. Findlater and McGrenere (2004) study is an example where the adaptable interface dominated the adaptive. They compared static, customisable (adaptable) and adaptive versions of split menus using the original version in Sears and Shneiderman (1994) work where frequent items were promoted to the top location. They found that users were not faster using the adaptive in terms of performance, and the adaptable was more preferred in terms of satisfaction. Nevertheless, Jameson (2009) raised questions as to whether their findings were correct by attempting to explain their experiment methodology. He added that, under the conditions in which the experiment was conducted, there was not much chance of the adaptive variant providing any benefit simply, because adaptation could improve performance if users would execute the same commands several times in succession. Despite the strategy of comparing an adaptive to a non-adaptive version being widely used, he suggested that the interpretation and explanation of such studies should not be viewed as empirical tests, instead they should be seen as focusing on various aspects of adaptive and non-adaptive interfaces and on the effectiveness of these methods in certain conditions. An example of a study where the adaptive was in favour will be discussed in a subsequent section.

In addition to comparing the adaptive user interface to a non-adaptive variant, researchers have utilised other paradigms such as a layered evaluation. In this strategy the success of adaptation is addressed at two distinct layers, the user modelling or interaction layer and the adaptation decision-making layer. In the former, the researcher evaluates whether the user's characteristics have been successfully detected by the system and stored in the user model, while in the adaptation decision-making layer the assessment is on the adaptation mechanism and the user experience relating to whether the adaptation decision made are valid and meaningful to the end user (Paramythis et al., 2010; Brusilovsky et al., 2001; Weibelzahl, 2001; Masthoff, 2003; Gena, 2005)

2.3 News Consumption and Adaptation in News

As discussed earlier, adaptation has been applied and studied in various areas but a significant amount of research has been conducted in relation to news. This section presents research work in the domain of news that covers subjects such as understanding the news behaviour with particular focus on the mobile environment, examining factors and variables that affect news consumption and discussing important factors that should be taken into account when designing adaptive mobile news services.

2.3.1 News Reading Behaviour

News reading is being fundamentally changed thanks to digital news gateways, both web and mobile. The shift towards digital news services is perfectly justified by the move towards the mobile Internet platform by almost all the key players in the news industry including CNN, BBC, Guardian and others. The proliferation of 'smart' mobile devices and their indispensable nature in people's everyday lives indicates the significant role they play as platforms for cross-media news consumption (Chan, 2015). This rapid growth of mobile services is a key factor for transforming patterns of news consumption and, at the same time, a balanced readership appears between print and mobile news (Sasseen et al., 2013) that strengthens the trends moving in that direction. The fast growth of mobile news services is clearly evident. Data from Reuters Institute (2014) showed that more than a third of online news users across all countries use two or more digital devices to access the news and a fifth uses a mobile phone as their primary access point. Furthermore, a study from Pew

Research Centre identified that two in every three users of mobile devices in the US regularly access news, while similar findings appear in the UK according to an Ofcom (2014) report. It is evident that smartphones and tablets are beginning to become essential platforms in peoples everyday lives, not only as communication devices but also for a variety of different activities such as web surfing, news reading, playing games and others. It should be noted that a study from Pew Research Centre (2012) places news reading as the second most popular activity on smartphones after sending and receiving emails.

The future of news is yet continuing to evolve and the interest in mobile news services is rapidly growing. Mobile news services perfectly complement the 24-hour nature of digital news access by providing access to news stories anytime and anywhere. But, if users are now never out of range of the news, they need more than ever for that access to be adaptive and personalised. Personalised news services are already able to help people find news that is relevant to them, to recommend the right news to the right users, and to help users keep abreast of news by aggregation over multiple sources (Billsus and Pazzani, 2000). News recommendation engines, aggregators and others are already out there to provide a more personalised experience to mobile news readers. Of course, too much personalisation might create a 'filter-bubble' problem (Pariser, 2011), i.e., a state of intellectual isolation in which the personalised recommendation engine selectively guesses what information a user would prefer to see based on their information about that user. The user, therefore, might not be exposed to a diversity of content, thus the filter bubble. News apps frequently adapt to users' individual news interests and topics through recommendation engines and many allow user customisation of news feeds (Billsus and Pazzani, 2007). Their user interfaces do not, however, adapt to how individual users characteristically select and read the news, as opposed to what news they are interested in reading. Progress in personalising the choice of news content has not, however, been matched by progress in personalising the way that content is accessed and read. To put it differently, user interface personalisation in news apps has gained less traction than news content recommendation. Nevertheless, any kind of news personalisation requires a good understanding of the users, an analysis of users' behaviour, patterns of consumption, short- and long- term interests and preferences, and others. The remaining part of this section reviews work focused on examining patterns of news consumption and users' behaviour while reading the news on mobile devices.

The divergent use of mobile news services is explained by how different group ages consume the news, as well as the importance of gender and educational level. Westlund and Färdigh (2015) concluded that elderly people persist with legacy news media, while younger audiences (i.e., Millennials) predominantly shift towards the digital news consumption as well as use technology differently than previous generations (Deal et al., 2010). Similar findings are reported in another study (Wolf and Schnauber, 2015) with younger audiences 18-to-29 years old making up a greater proportion of smartphone and tablet news consumption. Education level was found to be another factor influencing how people follow news. A study by the American Press Institute (2014) showed that Americans with higher education levels are more likely to watch, read or hear the news on a daily basis or several times a week. Likewise, a cross-cultural study (Fortunati et al., 2014) amongst audiences from the most five populous and industrialised European countries including Italy, France, Spain, UK and Germany corroborated the importance of age and education level. Further, it revealed an interesting sociodemographic factor in which single people and housewives are less likely to access mobile news than people in relationships and employed people.

Apart from sociocultural and demographic factors the stereotypical behaviour, expressed in terms of navigational and reading behaviour, appears to have a great impact on news consumption. Empirical research has shown evidence that news reading is a very individual activity with marked differences in the way people read and access news stories. Grzeschik et al. (2011) reported that influences on reading rate and concentration are posed by the individual reading behaviour of a person and by the nature of the text rather than by the reading device. Mobile news readers are more likely to exhibit characteristic patterns of accessing and reading the news, for example, how much a person chooses to read of news articles or how they browse and select them to read. Furthermore, an interesting news reading behaviour has emerged thanks to digital news services, namely screen-based reading, as Liu (2005) reported. This news reading behaviour is characterised “by more time spent on browsing and scanning, keyword spotting, one-time reading, non-linear reading, and reading more selectively, while less time is spent on in-depth reading, and concentrated reading”. Evidently, the nature of today’s smartphones that are able to deliver news anywhere and anytime perfectly justifies this new reading behaviour.

In addition to the habitual and stereotypical behaviour that previous studies reported in people’s interactions with news services (Grzeschik et al., 2011; Liu, 2005), the emergence of social networks as platforms for delivering news stories reveals interesting insights into people’s ways of news consumption. Obviously one can observe that getting news feed from social networks such as Facebook or Twitter has gained traction over the last couple of years (Reuters Institute, 2015). Many apps leverage knowledge from users’ social activities to recommend and deliver targeted news feed. Pulse, for example, developed by LinkedIn, is an example of one such app that delivers personalised news from a user’s professional network. The way people use social networks seems to affect their way of consuming the news as a BBC RD (2014) study reported. It was found that users consume the news in a more ‘snackable’ format on mobile devices. Although, it is believed this behaviour was mainly observed in younger audiences. As more people use social networks this behaviour of consuming the news could extend to other age groups (BBC RD, 2014).

Contextual factors were also found to influence mobile news consumption (Cohen, 2015). In a situated study, Cohen investigated a range of contextual factors that are not accounted for in current ‘contextually-aware’ news delivery technologies, but they could be developed to better adapt such technologies in the future. Specifically, the study revealed contextual factors relating to four areas (a) triggers for reading the news, (b) conducive contextual factors, (c) negative contextual factors, and (d) barriers to use. Triggers for reading the news included specific reasons for consuming news in a particular situation such as break from study or work, the morning habit or breaking news via notifications and widgets. Conducive contextual factors were defined as those that have a positive effect on people's news consumption experience, leading to a more pleasurable experience. These factors are associated with people's alertness and mood, defined by how their emotional or cognitive capabilities in a given context are reflected in their likelihood to consume news. Negative contextual factors were defined as those that hampered the news reading experience such as connectivity issues (e.g. lack of internet), multitasking or suboptimal smartphone experience. Barriers to use were defined as those factors that lead to a situation where a user stops consuming news. For example, 'me time' was identified as a primary factor in this category in which participants reported that they did not want to engage in any form of news consumption but rather reserve this time as an opportunity for relaxation and introspection. News overload was also identified as a barrier not to consume news. The study findings suggest that news consumption is opportunistic and that the situation matters more than the physical location when consuming news. Additionally, the findings indicate that momentary needs are a primary driver for news consumption, described as a break or leisure activity in which they consume news to keep their mind busy or fill in 'dead time'. The exploration of contextual factors in that study demonstrates the role of interpretation and sense-making processes of how users interact with technology and the momentary nature of users' actions within a given context. Such results could serve as a starting point for future exploration of contextual factors and better understanding of their roles in the design of adaptive news access.

News consumption, from speed reading perspective, can be divided into three strategies based on the pace and the kind of reading that is being performed (Just and Carpenter, 1987). The three strategies are *'reading for comprehension'*, *'skimming'* and *'scanning'*. Skimming involves visual searching of the content to get the main idea or the gist of a news article. It is usually conducted at higher words per minute rates (i.e., 700 wpm and above) compared to reading for comprehension that occurs at lower rates around 200-230 wpm. Reading for comprehension is detailed reading that involves thorough reading of the news article to understand the details. Scanning occurs at higher rates than skimming in which the reader actively looks for information (e.g. specific facts or piece of information) without reading everything.

2.3.2 Personalised News Systems

Personalised news services are already able to help people find news that is relevant to them, to recommend the right news to the right users when they want it, and to help users keep abreast of news by aggregation over multiple sources. According to Billsus and Pazzani (2007) the adaptivity in news access is achieved through several methods:

- News content personalisation (refers to content): Push filtered articles predicted to match the user's interests.
- Adaptive news browsing (refers to the user interface and interaction): Change the order of categories of articles.
- Contextual news access (refers to the user interface and interaction): Offer users access to additional information related to the news they are reading.
- News aggregation (refers to content): Automatically identify main news topics emerging from multiple sources.

News consumption on the go has now become the priority for the leading news organisations (Kelion, 2015). The diffusion of smartphones has changed the way of news production and consumption. App marketplaces are already bursting with prominent apps for accessing news spanning the globe, delivering completely tailored news from multiple sources and offering the chance to share news content in social networks. Even more news portals and websites are optimised through responsive designs to support the mobile experience. A closer look at how smartphone apps and websites achieve personalisation, however, suggests that the majority of them, specifically news apps, allow users to manually create a personalised experience. For example, users can explicitly select topics of interest or specify system parameters on how they want the visual presentation of a story or how the stories are organised.

Surveying news apps from Apple's and Google's marketplaces that provide personalised experience will shed some light on adaptivity in this very specific domain. It will provide a better understanding of how personalisation is achieved and, of course, it will identify possible gaps that would inform the design of more personal user interfaces. The review reported in this section is based on online tech blogs including the DigitalTrends, the Wired, the BusinessInsider and the SimplyZesty. In addition to reviewing commercial news apps, the section reports research works and prototypes that have been proposed.

Leading news organisations such as BBC and CNN have already realised the need for personalization in their own news apps. For example, BBC news app provides a more personal news reading experience through customisations of the interface and other system parameters related to the content. Example features of the revamped app include the most read stories, an option to add a list of news stories a user follows, presentation settings of displaying and categorising the stories such as a compact layout or carousels and many others.

News aggregators are another breed of news apps in which the service mainly focuses on the aggregation and classification of news content from multiple sources. As more news sources are emerging with a tremendous number of stories spanning all over the world, news aggregators help users to identify news topics of interest easily and to access news topics from different news providers. Flipboard [3], for example, uses the metaphor of a 'personal magazine' by making the entire reading process stylish. It gives the sense of flipping a magazine page while navigating through news. Users curate and share their own mini-magazines with the app, drawing in stories on their preferred topics. Zite [4] is an intelligent magazine-like news app that recommends stories based on users interests and reading habits. The app learns users preferences through a thumbs-up or thumbs down button on each story.

[3]Flipboard: https://flipboard.com/
[4]Zite: https://medium.com/@meyerson/the-best-zite-replacement-is-5cfa44d94f70

Inside.com Breaking News [5] allows users to select news topics to follow and then provides 300-character summaries of relevant stories along with links to the original sources. Newsbeat [6] is another aggregator but one that creates ‘personalised radio news bulletins’. Users select their preferred text news sources from which stories are pulled each day. Summaries are created and in turn news podcasts are generated using text-to-voice technology. Feedly [7] aggregates news items, longer articles, blog posts, and quick videos into a single spot in an elegant way. Further, instead of providing a massive list of articles it breaks the content feed up into manageable chunks. News360 [8] differentiates from other aggregators by incorporating two ‘swipeable’ screens, in which the top part shows the most popular stories while the bottom displays the current article you are reading. Social networking platforms such as Facebook and Twitter are becoming distribution channels for news stories. Recently there appears to be a huge interest in such services with more people getting their news stories and updates from social networks; as numbers indicate (Reuters Institute, 2015). This kind of service, therefore, could be used to develop apps that pull or leverage knowledge from users’ social network activities. For example, Pulse, developed by LinkedIn, delivers personalised news from a user’s professional network. Phelan et al. (2009) proposed a system coined Buzzer, which recommends and ranks news articles by analysing real-time Twitter data. Further, LumiNews (Kazai et al., 2016) is another mobile app prototype that provides personalised content recommendations by leveraging Facebook and/or Twitter feed combined with a users current location to automatically infer that user’s news interests.

Apart from news apps, web portals such as Google News and Reddit aggregate news sources and/or recommend news articles to assist desktop end-users to find and read news more efficiently. These systems gather information about their users either explicitly, i.e. users give rates to articles, in the case of Reddit, or implicitly by observing user behaviour, i.e. track users’ activity, reading preferences, etc., in

[5]Inside.com Breaking News: https://inside.com/
[6]Newsbeat: http://www.bbc.co.uk/news/newsbeat
[7]Feedly: https://feedly.com/
[8]News360: https://news360.com/

the case of Google News (Liu et al., 2010).

Although a large proportion of news apps on marketplaces (Google and Apple) adopts the adaptable way of providing personalisation, the alternative is the use of adaptive principles. Adaptive systems attempt to overcome some of the limitations of adaptable systems by automatically personalising the user interface, without any manual user intervention. They mainly leverage prior knowledge about the user to infer their goals and needs to automatically alter the system's behaviour. However, despite these potential benefits of adaptive systems, news apps tend to adopt the adaptable principles by allowing users to manually customise the content or the interface. However, the evolution and adoption of technology (Pew Research Centre, 2017b) have transformed they ways users interact with user interfaces. Adaptive principles could possibly work better for today's smartphone user interfaces. Today's smartphones have much more advanced capabilities such as 4G connectivity (i.e., connected anywhere, that might increase user's experience when interacting with UIs), high-resolution screens, sophisticated interactions with the user interface (swipe, flick, scroll) and others.

Research-oriented prototypes for news personalisation have also been proposed over the last decade, mainly for web or desktop applications. A few properties these systems share are the aggregation of multiple news sources into one application, filtering and ranking of news articles based on users' feedback and finally recommendation of news articles based on users' interests and preferences.

Billsus and Pazzani (1999) developed NewsDude, a news recommendation system, aimed to recommend news articles for desktop users. News Dude relies on feedback from the user to automatically adapt to the user's preferences and interests. It uses a multi-strategy approach to model a user's interests in which a nearest-neighbour algorithm is used to model short-term interests and a Naïve Bayes classifier for long-term interests. Carreira et al. (2004) used interaction logs of mobile users of news services to implicitly capture user profiles as the basis for recommending articles of interest. Their prototype news application developed for PalmOS-based PDAs logged aspects of users' reading behaviour such as reading duration, estimated number of lines read, estimated reading speed as opposed to direct user feedback to infer interesting articles for a particular user. Another example of a personalised mobile news system was proposed by Tavakolifard et al. (2013), which efficiently delivers "tailored news in the palm of your hand", by leveraging temporal, locational and preferential information to provide news recommendations. Contrary to Carreria's mobile prototype, the work reported in this thesis is implemented on today's smartphones with all the advanced capabilities (e.g. 4G/5G connectivity and high-resolution screens) that discussed previously.

2.4 User Modelling

The ability of an adaptive system to adapt relies heavily on successful user modelling, construction and exploitation. User models are an integral part of any adaptive system; an intelligent agent that contains knowledge about their users, which in turn will be exploited to alter the system's behaviour. As software users differ in their interests, preferences, needs and tasks the need of user models in personalising a system's user interface or functionality is evident. Investigating these users' individual differences, therefore, is essential for implementing and applying personalisation in such systems Schiaffino and Amandi (2009).

Before explaining the process of user modelling in detail, a clarification about *user profile* and *user model* is needed. The two terms are often used in the literature interchangeably. A *user profile* is a collection of personal information associated with the user according to (Froschl, 2005) or a representation of users' cognitive skills, intellectual abilities and intentions, learning style or preferences (De Koch, 2001). The amount of information known and stored in a user profile determines whether a user can be modelled. De Koch (2001) defined a *user model* as the representation of the system's beliefs about the user. Similarly, Kobsa (1994) described it as system's assumptions about all aspects of the user. Despite the different definitions given in the literature, there is common ground among researchers that a user model is a distinctive feature of any adaptive system and an essential part necessary to provide the adaptation effect, i.e., to behave differently for different users (Brusilovsky and Millán, 2007). This section discusses the information that constitutes a user profile, the different ways in which user information is acquired and in turn the user profile construction and the different user profiling techniques.

2.4.1 User Model Contents

According to Brusilovsky and Millán (2007), the nature of information that is being modelled in adaptive systems distinguishes between models that represent features of the user as an individual and models that represent the current context of a user's work. The most popular and common features relating to an individual user are: the user's interests, the user's knowledge, background and skills, the user's goals and tasks and the user's individual traits such as personality.

User interests are facts about a user that mainly constitute a user profile in recommender systems, information retrieval and filtering systems, and information-driven adaptive systems such as museum guides and news systems (Brusilovsky and Millán, 2007). Interests can be anything from a specific web page to a hobby-related topic, classified either as short-term or long-term interest. For example, a user read a news article about the recent football match he attended, which can be considered as short-term while his favourite news category is politics, which can be considered as the long-term interest. Modelling users' news interests has also been demonstrated in news research prototypes such as the NewsDude (Billsus and Pazzani, 1999). The NewsDude learns users' interests in daily news by classifying recent events as short-term interests and general news preferences as long-term. Another example (Gulla et al., 2014) utilises articles views and preview time, clicks on news categories and information from Facebook and Twitter as implicit signals of a user's interest in particular articles. Further, Carreira et al. (2004) utilises total reading time, total number of the article's lines, number of lines read by the user and an approximation of the user's average line reading time to classify news articles.

Users' knowledge and skills are mainly application domain related information, which are vital in adaptive systems such as educational and tutoring systems to adapt in the optimal way. For example, systems categorise users based on their application domain knowledge into experts, intermediate and novices (Findlater et al., 2008; Shneiderman, 2002). Further, users' background is not directly related to the application domain, but it plays an important role. Background characteristics can be users' work experience, job or profession and many others. For example, Cawsey et al. (2007) proposed an adaptive healthcare information system that considers users' literacy and medical background to deliver information that is easy to understand.

Users' goals and tasks represent the user's objectives: simply what the user wants to achieve in the system. They may vary depending on the kind of system such as learning goals in tutoring systems or urgent information need in information access systems. Goals detection is a difficult and not trivial task. Goals are defined as target tasks or subtasks at the focus of a user's attention. For example, in the Lumiere project (Horvitz et al., 1998) utilised Bayesian probabilistic models to infer users' needs by considering their actions.

Individual traits consist of demographic information such as age, gender or human factors such as personality or cognitive factors. Individual characteristics are usually stable features of the user model, either cannot be changed at all or evolve over time. Personality could be regarded as one rather stable multidimensional factor referring to individual differences in preferences, behaviour, thinking and feeling (McCrae and John, 1992). The use of human factors, and more specifically Personality traits (i.e. Big 5 or FFM model) as proposed by Goldberg (1990), has been increasingly considered in recent years in various domains of recommender systems. Researchers acknowledge the fact that the potential to enrich user profiles and computational methods with intrinsic information about the users may lead to higher accuracy in the predictions of their algorithms thus successfully attaining their purpose. Hence, the related research focuses on correlating users' preferences and personality traits in groups (Tkalcic and Chen, 2015; Kompan and Bieliková, 2014), studying the personalisation potential on diverse levels based on the influence of personality types (Tintarev et al., 2013), personality and rating behaviour (Hu and Pu, 2013), recommendations in e-commerce based on personality (Bologna et al., 2013) correlations between personality characteristics and music (Rentfrow and Gosling, 2003), movies (Chausson, 2010), and others. In addition, personality traits could be regarded as domain-independent, thus learnings from personality models from one domain can be used efficiently in other domains to compensate on the cold-start problem (Cantador et al., 2013).

2.4.2 Building User Models

A user model is constructed through a User Modelling (UM) process wherein "unobservable information about a user is inferred from observable information from that user" (Frias-Martinez et al., 2005). Two techniques commonly used for collecting user information that can be used to build the user profile in adaptive systems: (a) *explicitly* through direct user intervention, and (b) *implicitly* through agents that monitor user activity (Gauch et al., 2007). Apart from the two edges, hybrid solutions are possible where a combination of both is used to build more accurate and reliable profiles.

Explicit user information collection, often called explicit user feedback, consists of any kind of information provided directly by the user such as forms and questionnaires. The data captured usually contains demographic information (i.e. age, gender, and profession), interests and/or preferences. Although the data collection this way will have greater reliability, the cost of users' time and the disruption to the user can be significant. Further, if the user is not willing to provide such information, this might be an obstacle of the data collection resulting in no profile being able to be built for that user. On top of that, users might not accurately report their own interests, preferences or demographic information, which could lead to an inaccurate profile construction and in turn to poor recommendations and/or adaptations. Example systems that explicitly capture user information include any social network portal, Google and Amazon services and many others. Of course, not only do such systems gather explicit user information to build user profiles, but they use a combination of both techniques to avoid profiles remaining static.

Implicit user information collection, often called implicit user feedback, requires unobtrusive data capture where an agent monitors users' activity and interaction to build the profile. An overview of the most popular techniques used to collect implicit feedback is reported by Kelly and Teevan (2003) and Kelly (2005). Techniques such as browser agents, web and search logs are mainly used for gathering user information in the desktop environment. For example, the study by Morita and Shinoda (1994) investigated how user behaviour, while reading articles from newsgroups, could be used as implicit feedback for profile acquisition. In the mobile environment, Carreira et al. (2004) used interaction logs of mobile users of news services to implicitly capture user profiles as the basis for recommending articles of interest. Their prototype news application logged aspects of users' reading behaviour such as reading duration, estimated number of lines read, estimated reading speed, etc. However, they logged interactions with news services on PDAs having much less advanced capabilities (neither 3G/4G nor high resolution screen). Further, interaction data capture with smartphones has been demonstrated in other contexts. For example, Oulasvirta et al. (2012) used logs of smartphone interactions to examine users' habits, in particular their habitual checking of their smartphone state and notifications. The data collected implicitly may vary, depending on the kind of the application and the interface (i.e. low-level interactions with the interface, mouse clicks, scrolling, reading time, etc.). Users may be more willing to take on this technique as opposed to the explicit technique.

Attempts at comparing both methods have found implicit data capture to be preferred by users. Implicit data capture yields larger amount of data, with some uncertainty, puts less burden and workload on the user, but it may result in more inaccurate profiles than ones created by explicit capturing or a combination of both (Gauch et al., 2007). Contrarily, White et al. (2002) reported no significant difference between profiles constructed using implicit and explicit feedback in a prototype system developed to improve search on the Web. Nevertheless, it is generally accepted that a combination of both methods could produce highly accurate and reliable user profiles.

2.4.3 Learning and Inferences

Adaptive systems often employ automated procedures that have their origins in the fields of Artificial Intelligence and Machine Learning to build a user model. These procedures and techniques enable a system to learn about individual users and make inferences and decisions about them. This section reviews several computation paradigms that have been employed in different systems, including classification learning, collaborative filtering, stereotypes (Jameson, 2009), and others.

2.4.3.1 Classification Learning

A broad category of machine learning techniques called classification learning, in the family of supervised learning algorithms in Machine Learning, has been employed in adaptive systems. A variety of methods have been developed that fall into this branch of learning, including decision trees, probabilistic classifiers, neural networks and others (Han and Kamber, 2001; Langley, 1996; Mitchell, 1997; Webb et al., 2001).

In a nutshell, in a classification problem - a classifier - attempts to identify a set of categories or sub-populations to which a new observation belongs, based on a training set of data that contains observations whose category membership is known (i.e. labelled data). The learning process starts with a set of training examples (i.e., features). To determine, for example, whether one's favourite genre is jazz, features could include the number of times visited to jazz bars, online activity searching for different genres and so forth. Each training example is classified, i.e. a label that corresponding to a specific category is assigned. For example, labels could be jazz or not jazz in a binary classification problem when predicting jazz genre, or jazz, rock or heavy metal in a three-class classification problem. Once the training set is generated, the process learns a classifier, which is a model capable of assigning a new item (new observation) to one of the same set of categories. The classifier, however, cannot be always certain about the assignment, thus some methods yield a set of probabilities for each category indicating degrees of certainty (accuracy, prediction and recall).

An example of a classifier, from the family of probabilistic classifiers, is the Bayesian network (BN). It represents probabilistic relationships among variables of interest (Heckerman, 1998). Simply, it relates the current probability to prior probability (i.e. express quantitatively how to update prior information given new evidence). Bayesian networks have been increasingly used to infer users' goals and model users' preferences and needs (Horvitz et al., 1998). An example of using the Bayes theorem for user profiling is the Lumiere project (Horvitz et al., 1998), which is described earlier in the related work. Another example is the work presented in (García et al., 2005) where BN used to detect and model students' learning styles in a Web-based education system. The Naïve Bayes classifier is a special case of Bayesian networks and has also been used for user profiling. It is based on the Bayes theorem with naïve independence assumptions between the features. The News Dude (Billsus and Pazzani, 1999), a news recommendation system, learns the long-term interest profile by using NBC. Other examples are the systems Syskill&Webert (Pazzani et al., 1996) and Personal WebWatcher (Mladenic, 1996), which use NBC to detect users' interests whilst browsing the web.

Another example of methods used in classification problems is decision trees. Decision trees, however, are known to suffer from the bias and variance tradeoff (i.e. large bias with simple trees and a large variance with complex trees). The bias is an error due to simplistic assumptions made by the algorithm during the learning process which in turn can lead to the model underfitting the data. The variance is an error due to too much complexity in the learning algorithm which can lead to the algorithm being over sensitive to high degrees of variation in the training data set, and thus can lead to model overfitting. It is important, therefore, to handle the bias-variance tradeoff. Ensemble methods have, therefore, been developed, which combine several decision trees to produce better predictive performance than utilising a single tree. They utilise a divide-and-conquer approach to improve performance by creating a group of weak learners that combine together to form a strong learner. Two general techniques developed to perform ensemble trees are: the bagging (or bootstrap aggregation) and boosting. A widely used classifier is the Random Forest (RF) (Breiman, 2001), which uses the bootstrapping method for training and testing, and decision trees for prediction. In other words, the algorithm 'overfits' a subsample of the training data set and then reduces the overfit by averaging the predictors. Another popular classifier is XGBoost (Friedman, 2002), which uses a boosting method wherein a new classifier is added at a time in order that the next classifier is trained to improve the existing ensemble.

Classification problems, however, cannot be employed under all circumstances. They require, first, that a labelled training set can be obtained and, second, that there is an adequate number of training examples available before the classifier begins to make inferences about new observations (Webb et al., 2001). Those two prerequisites in a classification learning method may be hard to fulfil in some cases. Alternative techniques such as expert labelling or methods that handle small datasets have been proposed to address those limitations.

A large body of research has also focused on modelling users directly from their actions with specific user interface elements, clickstream behaviour (Wang et al., 2016), usage patterns (Dev and Liu, 2017) and others, often without any prior knowledge about users. Sophisticated methods of user modelling involving supervised learning techniques have also been demonstrated in different research works. In the domain of news, for example, Billsus and Pazzani (2000) inferred users' news preferences from interaction data, specifically on desktop environments. In the mobile environment, research works have also been demonstrated in relation to search engines (Bertini et al., 2005), news articles preference (Carreira et al., 2004), and using function usage histories to refine menu displays (Fukazawa et al., 2009).

2.4.3.2 Collaborative filtering

The paradigm of Collaborative Filtering (CF) has been widely illustrated in recommender systems in a variety of domains including movies, music, news, and has been proven as an appropriate technique for recommending content. The principal idea of this paradigm lies on the automatic prediction (filtering) of a user's interests by collecting preferences to which other users have previously expressed an interest (collaborating) (Schafer et al., 2007; Das et al., 2007; Linden et al., 2003; Sarwar et al., 2001). A more detailed survey of CF techniques was conducted by Su and Khoshgoftaar (2009) in which they discussed the main challenges such as data sparsity and scalability and they presented three main categories of CF techniques: the memory-based, model-based and hybrid. A movie recommender system (Melville et al., 2002), for example, will generate recommendations based on how other users have rated movies rather than on the user's interests and preferences.

Although this idea is intriguing, collaborative filtering techniques suffer from the same problems as classification learning. For example, this method cannot be applicable if too few users have previously rated or annotated items with their preference. Further, if the other users' interests and preferences are fresh and relevant to the user now, they might not be relevant by the time the algorithm obtains enough responses from other users to generate recommendations. In a nutshell this is a major challenge in CF, known as the cold-start problem. The cold-start problem describes the difficulty of recommendations when the users or items are new. For example, it is difficult to initiate an accurate recommendation when no or very few interests/ratings are available to infer the interest/rating of a new user (Schein et al., 2002). To overcome these limitations many techniques have been proposed by employing additional information such as demographic information of a new user (Loh et al., 2009; Kim et al., 2010) or content information for the new item (Leung et al., 2008).

2.4.3.3 Stereotypes

The use of stereotypes in user modelling is one of the oldest paradigms that have been proposed but a less widely used. It has its origin in the works of Elaine Rich (1979, 1989), and in this approach an individual user is associated with a class of users and facts about the class are then attributed to the individual.

The general approach in the previous paradigms has been the acquisition (learning) of a user model at a feature-level. Significantly, this approach is entirely data-driven (i.e., bottom up) and makes use of virtually no "general knowledge about users, their goals, or the items that they are dealing with" (Jameson, 2009). An alternative, top-down approach is to use prior knowledge or theoretical models, to determine a category (stereotype) for a user. This approach enables inferences about other characteristics of a user such as task expertise and personality traits; it supports reasoning about adaptation of sets of interface features and sets of interface variants. It enables user interface adaptation based on matching complete user interface variants to particular user categories. Specifically, it provides a mapping of specific features or attributes to one of the stereotypes. The emphasis is less on sophisticated computation than on realistic specification of the content of the stereotypes and the rules for activating them (Jameson, 2009). This stereotypical approach has been applied to user modelling in natural dialogues (Carberry et al., 2012), accessible systems for users with disabilities (Stephanidis et al., 1998), digital guides for museum visitors (Kuflik et al., 2012). For example, Kuflik et al. (2012) in order to provide personalised information presentation in the context of mobile museum guides they monitored and modelled users' visiting patterns. The modelling was achieved using a known museum visiting style classification (Veron and Levasseur, 1983) in order to classify the visiting style of visitors as they start their visit. Another example is the Europeana project for cultural heritage that offers a typology of cultural heritage objects (Haslhofer and Isaac, 2011; Oomen and Aroyo, 2011).

This thesis explores the combination of top-down (stereotypes) and bottom-up (data-drive) approaches, and makes use of knowledge from stereotypes to inform the user modelling procedure.

2.5 Summary

The research works reviewed in this Chapter show the high potential benefit of adaptive user interfaces to the end user's experience and satisfaction. Adaptive user interfaces have been touted as potential solutions for problems such as learning to use complex systems, assisting disabled and elderly people providing help and support in commercial software application, enhancing users' experience in domains such as music and news, and many others. On the downside, they are faced with possible problems and pitfalls such as privacy issues, confusion, user control and freedom. Prior research works have shown mixed results in users' willingness to adopt adaptive user interfaces but clearly their potential is huge if the right presentation is given to the user at the right time and in the right context. An important element, of course, that may influence users' willingness to adopt such systems is the underlying intelligent mechanism in which an effective user model needs to be acquired for the users of a system. The recent technological advancements in terms of data availability, power processing and computational methods, open the door for effective user modelling acquisition and exploitation, which in turn can be transformed into a successful adaptive user interface.

In the domain of news particularly, while there is an abundance of literature in relation to news content recommendation, personalisation of the user interface of news services has received less attention. Due to the individual nature of consuming digital news, the need of more personalised news access is evident; personalisation that can be achieved by adaptive user interfaces. Today's news apps' user interfaces have limited personalisation, and if they have, it is achieved by manual user interface customisation (i.e. adaptable). Adaptive news interfaces that adapt 'automatically' to the way the individual user reads the news in a particular context are not found other than by re-ordering menus of headlines to take account of previous reading choices. Simply, this adaptation is restricted to what content users access. Nevertheless, it could be far more extensive and multi-dimensional, for example, to take account of users' idiosyncratic patterns of browsing news headlines or the different ways in which different users read news articles (Grzeschik et al., 2011; Westlund, 2008). Adaptive user interfaces for news apps have, therefore, the potential to transform the way people consume news including not only, *'what'* content they access, but also *'how'* they access it and interact with.

Chapter 3

Understanding Mobile News Reading Behaviour

The previous Chapter discussed related work and relevant literature from the areas of Adaptation and Personalisation, Adaptive User Interfaces and User Modelling. It reviewed literature from the broader area of Adaptive Systems, summarised challenges and difficulties in building such systems and established the gap that exist in mobile news apps personalisation. In summary, personalisation in news apps interfaces has received less attention as opposed to news content recommendation. Evidently, as discussed in Chapter 2, there is a lack of research around news apps that systematically monitor users' behaviour and adapt themselves in response to users' news reading behaviour. To reach the point where news apps could automatically respond to the specific needs of mobile news readers, requires a clear understanding of people's differences in mobile news reading.

In this Chapter we will present work conducted in the early stages of this research, which aims to explore people's differences and stereotypical behaviour whilst reading news on mobile devices. This Chapter addresses questions such as how people differ whilst reading the news on mobile devices, what factors discriminate mobile news reading behaviour and what mobile news reader stereotypes can be formed. Although many studies and reports (Institute, 2014; Reuters Institute, 2015; American Press Institute, 2014; Pew Research Centre, 2017a; Reuters Institute, 2014; Ofcom, 2014; Pew Research Centre, 2012) have been published over the years about mobile news consumption, the Chapter presents a study that differentiates from previous attempts as it places emphasis on categorising news readers and generating a News Reader Typology. Clearly all prior work have categorised news readers but it was a different categorisation for different purposes. The categorisation that this Chapter proposes is about the patterns of consumption of digital news on mobile apps rather than the content itself that is being consumed. Forming a mobile news reader typology, therefore, is essential in the scope of this research as it will drive the user model acquisition and construction that will be discussed in subsequent Chapters.

The Chapter begins with a discussion of related studies and conclusions that helped the design of this study. It then presents the design of an online questionnaire used in the study and then reports the analysis conducted as well as the findings of the study. The Chapter ends with a discussion of the findings.

The News Reader Typology presented in this Chapter has appeared in the Proceedings of MobileHCI '15. (Constantinides, M., Dowell, J., Johnson, D., Malacria, S. Exploring mobile news reading interactions for news app personalisation. In Proc. MobileHCI 2015.)

The exploration of domain-independent factors presented in this Chapter has appeared in Adjunct Publication of the 26th Conference on User Modeling, Adaptation and Personalization 2018. (Constantinides, M., Germanakos, P., Samaras, G., Dowell, J. Your Digital News Reading Habits Reflect Your Personality. In Adjunct Publication of UMAP.

3.1 Motivation

As discussed in Chapter 2, a significant amount of work has been conducted in the field of news focusing on different factors that affect news reading behaviour in the digital era and understanding the emerging challenges in consuming news on mobile devices. Previous studies (Pew Research Centre, 2012; Reuters Institute, 2014) have examined a diversity of factors ranging from contextual to sociodemographic. Even more, other studies have examined the relationship between print and digital news, providing interesting insights about the transfer from print to digital. Factors such as frequency of accessing news, platforms of news consumption, users' interest and preference in type of news were examined in a study conducted from Reuters Institute (2014), concluding with compelling evidence about the pace of the multi-platform revolution and use of smartphones and tablets as the preferred medium for news consumption. In addition to those findings, evidently, smartphones and tablets are now the epitome of mobile computing. People use them not only for their everyday communication but also for a variety of activities including entertainment, work, news reading and others. The proliferation of mobile news apps, as recent numbers show (Pew Research Centre, 2015), clearly indicates the shift towards mobile news and people's interest in consuming mobile news increases.

The aforementioned studies show people's differences in accessing and reading the news, which evidently makes room for personalisation in news apps in terms of the ways people access and interact with news. However, to the best of the author's knowledge, no previous studies have examined the pure navigation and reading behaviour in accessing and reading the news. For example, the frequency and time spent reading news will vary considerably between people, as will their patterns of navigating news headlines and reading articles. This means that different users would likely be better served by different interfaces, for example, a user who likes to review all the headlines before choosing an article to read would be best served by a summary presentation of all headlines and a way of marking them as a reading list of articles. Understanding people's differences, therefore, and forming a news reader typology that distinguishes people based on their navigational and reading behaviour would inform the design of an even more personalised access not only in terms of what news content people read but also how that content is accessed and consumed.

3.2 Online Questionnaire

To investigate people's news consumption patterns, the author designed a questionnaire to collect exploratory information about their mobile news reading behaviour.

The questionnaire aimed to identify stereotypical patterns of behaviour, to probe people's differences in reading the news on smartphones and tablets and, ultimately, through an analysis to propose a mobile news readers typology that describes people's news consumption patterns. In addition to its primary goal, questioning people about their behaviour provides an insight into the kind of data that is needed to be collected in a mobile news app that will automatically attempt to learn this behaviour and make changes in its interface and functionality accordingly.

The online questionnaire consisted of a total of 24 questions, mainly focused on news reading behaviour with questions probing the estimated daily time spent on news reading, the frequency of accessing the news, different browsing strategies and reading style and others. Supplementary questions were also asked about news type preference such as broadsheet or tabloid, i.e., distinguishing between papers for easy reading and serious papers, to examine whether this might have an effect on the consumption patterns. Questions relating to specific features of news apps such as scrolling preferences, headlines organisation, summary of the article and others, were also asked. In addition to the primary navigation and reading related questions demographics characteristics such as age, gender and level of education were collected. Demographics have been found to impact news consumption as discussed in (Fortunati et al., 2014), and thus it is worth examining the relationship between potential navigational and reading factors and demographics. Overall, questions were selected in such a way as to expose as clearly as possible the users' news reading preferences and tendencies. Table 3.1 and Table 3.2 summarise the selected questions by providing additional details of what each question examines as well as the category to which it belongs. There are four categories of factors navigational, reading, contextual, and demographics. Navigational refers to people's characteristics while browsing for stories in the news headlines organisation interface, reading refers to their actual reading behaviour once they select to read a news story, contextual refers to location and the context of reading, and demographics refer to age, gender and level of education.

The deployment of the questionnaire was conducted through an online crowd-

Question Number	*Questions*	*Description*	*Influences*
Q9	How often do you read news on your mobile device?	It refers to frequency of accessing the news throughout a day	Navigational & Reading
Q12	How much time a day do you spend reading the news on your mobile device?	It refers to the daily reading time spent on news apps	Navigational & Reading
Q11	Where do you often read news?	It refers to the location of reading the news	Contextual
Q14	How do you look for stories of interest?	It refers to the strategy used to browse for stories	Navigation
Q20	How do you read a story?	It refers to the strategy used to read a story	Reading
Q10	What time of the day do you prefer to read the news?	It refers to the time of day	Navigational & Reading
Q18	Some newsreader apps classify the stories in sections. Do you believe this helps you to find a particular story?	It examines the usefulness of organising stories in sections/categories	Navigational
Q19	How often do you look through all the stories of each section?	It supplements Q14	Navigational
Q15	What makes you decide to read a story?	It examines reasons why people choose to read a particular story	Navigational
Q17	What makes you decide to stop reading?	It examines reasons why people choose to stop reading a particular story	Reading
Q21	How much attention do you pay to a story's images?	It examines the usefulness of story's images	Reading
Q22	How much attention do you pay to image captions?	It examines the usefulness of image captions	Reading

Table 3.1: Selected questions related with navigational, reading and contextual factors.

sourcing platform, CrowdFlower[1] , but participants were also recruited through friends and colleagues and social network posts. The online questionnaire can be retrieved online here [2] and a copy of it can be found in the Appendix A. The inclu-

[1]CrowdFlower: http://www.crowdflower.com
[2]Online Questionnaire URL: http://goo.gl/HvoxBc

Question Number	*Questions*	*Description*	*Influences*
Q1	What is your gender?	It refers to the gender	Demographics
Q2	What is your age?	It refers to the age	Demographics
Q3	What is the highest level of education you have completed?	It refers to the level of education	Demographics

Table 3.2: Questions related with demographic information.

sion criteria required participants to be 18 years or above, use a mobile news apps to read the news at least a few times in their life, but preferably to read the news on a regular basis using a smartphone or tablet, so their digital news consumption habits could be gauged. Each successful completion was remunerated with a token of £0.40 and the study lasted for a month.

Two hundred and seventeen participants responded to the online questionnaire. Before conducting the analysis, a data cleaning was performed to drop duplicate responses and outliers due to there being no control on the online crowdsourcing platform from which we experienced some duplicate responses submitted using the same I.P. address. Further data pruning was conducted on some responses where participants responded that they do not read news on mobile devices, thus they had to be dropped from the analysis.

The final dataset comprised of one hundred and forty participants, fifty-four females and eighty-six males. Participants' ages ranged from 18 to 51 (M= 32, SD = 8, 72% participants aged between 18 and 35) and nighty-two participants (66% including Bachelor's degree or higher) hold higher education qualification. The geographical distribution of the responses came from four different countries including 34% from USA, 29% Cyprus, 25% United Kingdom and 12% Germany. Table 3.2 provides the questions relating to the demographic information. It is important to note here that the majority of respondents to the questionnaire are Millenials compared to other group ages, thus results should be interpreted carefully. But it is also aligned with previous works (Deal et al., 2010) that found this age group to be more receptive in technology adoption, a fact that it is important for the investigation of adaptivity in news app.

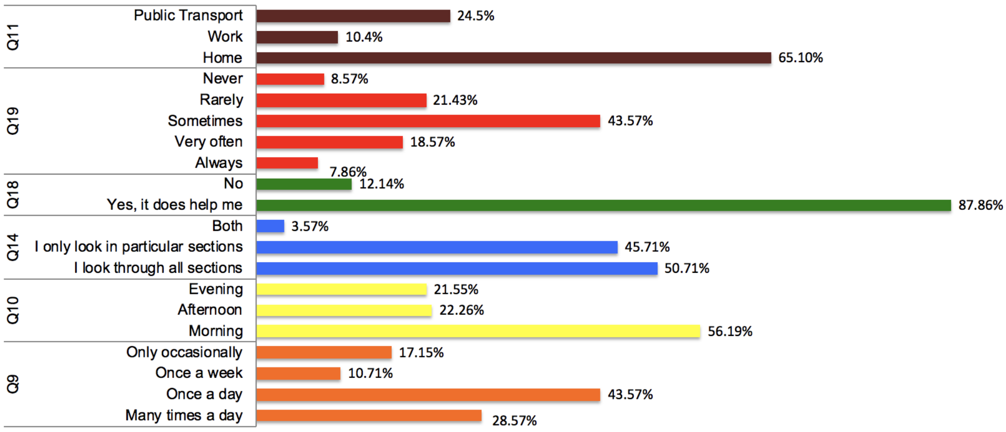


Figure 3.1: Descriptive statistics of the questions relating to navigation and context.

3.3 Questionnaire Analysis Descriptive Statistics

The questionnaire analysis was performed in two steps: descriptive analysis and formation of the news readers typology which included tests such as clustering, logistic regression, Kruskal-Wallis and Chi-square. This section presents the descriptive analysis and the preliminary analysis on potential navigational, reading and contextual factors, while the next section describes the procedure of clustering people and forming the news reader types.

To begin with, a descriptive analysis of the questionnaires' responses revealed interesting but also surprising tendencies in people's preferences on mobile news reading. Overall, respondents reported a preference to read the news once a day (43.57%), between 10 and 20 minutes (48.57%), preferably during the mornings (56.19%) and at home (49.29%). Regarding to their navigation and reading behaviour, there is no strategy that dominates. Respondents either navigate through all sections (50.71%) or to a specific section (45.71%), but of course there are those who use both techniques (3.57%). Likewise, skimming and scanning (46.43%) and reading for comprehension (45.71%) were the most popular reading strategies among respondents' answers, whereas reading the first sentence of each paragraph was not. A story's headline (90%) is mainly what makes them choose an article to read while the story's thumbnail (7.14%) does not seem to play an important role in their decision. To the question, what makes them stop reading, respondents varied

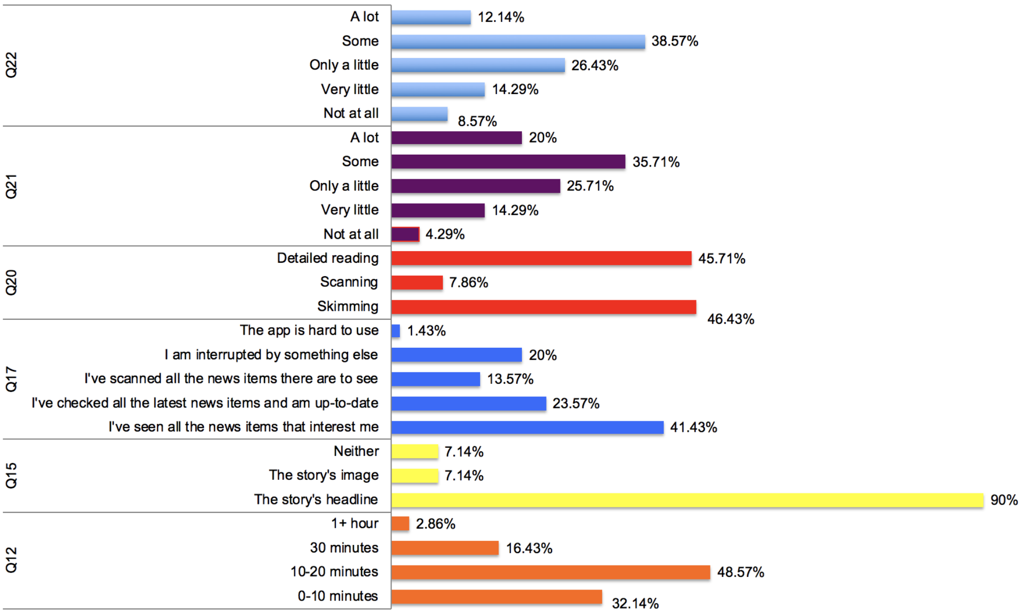


Figure 3.2: Descriptive statistics of the questions relating to reading.

in their answers from 'I have seen all the news items that interest me' (41.43%) to 'I am interrupted by something else' (20%). In regards to their news type preference broadsheet news (40%) dominates over tabloid (20%), and that could be explained by the respondents' level of education, if we assume that more highly educated people prefer to read broadsheet news. Finally, respondents reported reading at home with (65.1%), following with public transport, i.e. while commuting with (24.5%) and just 10.4% reported that they read the news at work. Figures 3.1, 3.2, depict the descriptive statistics of the questions related with navigational, reading and contextual factors (Table 3.1). At a first glance, it is evident that there are significant differences in people's behaviours. For example, as can be observed many people reported that they read once at home in the morning. The story's headline seems to be the most important factor they take into to account when they choose a story to read. Other factors will be discussed later in the analysis.

3.4 Mobile News Readers Typology

Having gained useful insights in the first part of the analysis, this section describes a rigorous statistical analysis in order to establish a typology for mobile news readers and identify factors that are related with mobile news reading behaviour. In particular, the analysis presented in this section included the following phases: (a) clustering, (b) feature extraction and (c) description of clusters.

3.4.1 Hierarchical Cluster Analysis

A Hierarchical Cluster Analysis (HCA) was conducted on the responses to all questions from all participants. The aim of HCA is to group similar objects into clusters where each cluster is distinct from each other cluster, and the objects within each cluster are broadly similar to each other. It provides, therefore, an objective way to measure the degree of similarity between people's responses across the 24 questions.

Agglomerative (bottom-up) and divisive (top-down) are the two approaches that the clustering algorithm groups similar objects into clusters. The agglomerative clustering starts with n clusters (n = number of observations), assuming that each of them is its own separate cluster, and then the algorithm finds most similar data points, groups them together and forms the clusters. Contrarily, the divisive clustering assumes all the n data points are one big cluster and repeatedly divides most dissimilar ones into separate groups. Due to the complexity (O(2^n) possible splits) of divisive clustering compared to (O(n^2) possible merges) in agglomerative clustering, the latter was favoured in this analysis.

Euclidean distance, which is the geometric distance between two objects was used to measure how similar cases are. An integer encoding was performed on the data to transform the nominal into numerical values. The Euclidean distance is defined as follows (where i first case and j second case):

$$d_{\mathrm{ij}} = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

Once the Euclidean distance is computed between cases, the next step is the choice of the method for grouping the cases together based on their similarity coefficients. Among the available methods, i.e., linkage methods (e.g. single, complete and average) and Ward's method, we have chosen a Ward's method. All linkage methods are based on a similar principle in which a chain of similarity exists that

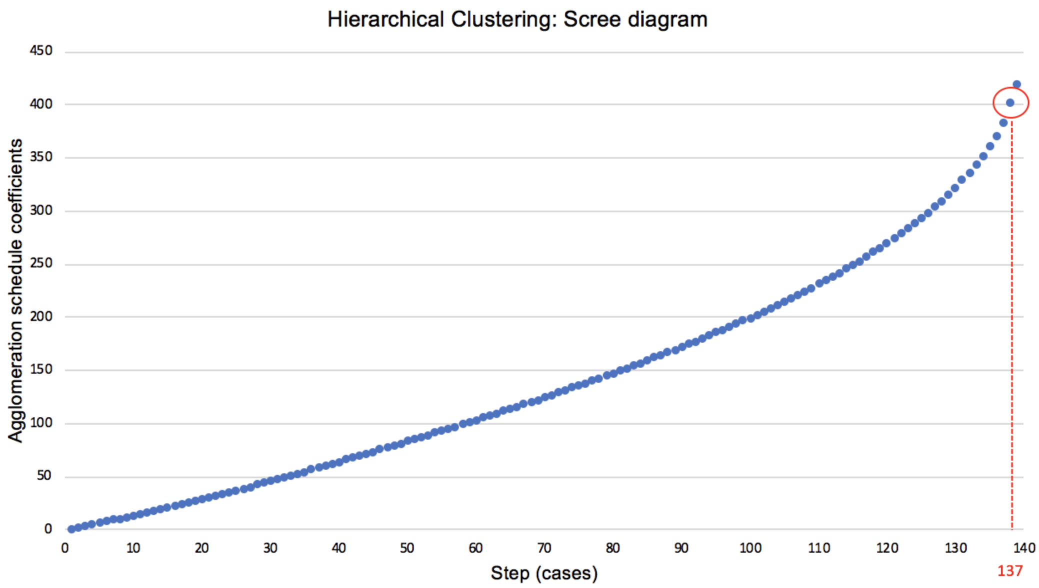


Figure 3.3: The scree diagram showing a big jump ("elbow") at 137$^{\text{th}}$ step.

leads to whether or not a case is added to a cluster. On the contrary, Ward's method joins cases into clusters such that the variance within a cluster is minimised. Specifically, it first calculates the means for all variables for each cluster and then the squared Euclidean distance is calculated for each case. All the distances are then summed for all the cases. In every step, two clusters that merge are those that result in the smallest increase in the overall sum of squared within-cluster distances.

To determine the number of clusters, the agglomeration schedule coefficients were plotted as depicted in Figure 3.3. By doing so, we investigate the bigger jump between two consecutive coefficients, which is the elbow point to select the number of cluster. As can be observed from the graph in the 137_{th} step it is the biggest jump, indicating that a number of clusters 3 is a good candidate (number of clusters = N cases - elbow point). Additionally, when we inspected the dendogram as shown in Figure 3.4 3 clusters can be formed at height equals to 12. The resulting clusters are formed as follows: cluster 1 (red) included 31%, cluster 2 (purple) 36% and cluster 3 (green) 33% of the 140 cases.

Figure 3.4 depicts the three clusters that emerged from the analysis. As can be observed, cluster 1 (red) included 31%, cluster 2 (purple) 36% and cluster 3 (green) 33% of the 140 cases. The dendrogram reveals the point where to cut the tree and

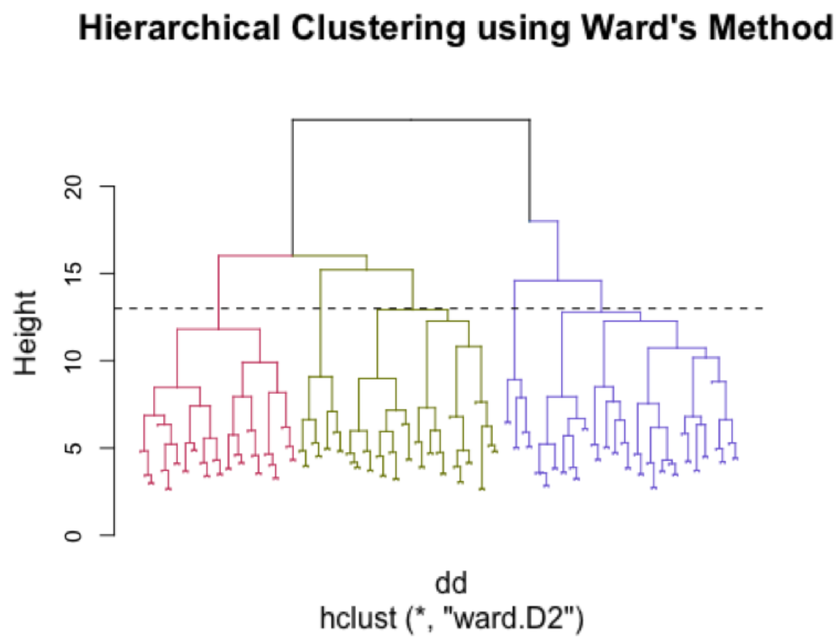


Figure 3.4: Dendrogram of Hierarchical Cluster Analysis.

decide about the numbers of clusters. The y-axis shows the value of the distance metric between the clusters, i.e. it provides information about the distance between clusters that are merged at a particular height. Therefore, the height of the cut to the dendrogram controls the number of clusters obtained. In this case, a good cut point would be at height 15, which reveals three clusters. Of course, a cut at a different level would produce a different number of clusters, but further analysis will show evidence why three clusters is a good solution here. In general, there is no definitive point this is more of an exploratory approach. In addition, the interpretation of the resulting clusters is context-dependent and often multiple solutions could be equally correct.

3.4.2 Features Extraction and Significant Factors

Having clustered people's responses into three homogeneity clusters with roughly equal distribution among clusters, the following phase of the statistical analysis was the extraction of the significant factors that are strong predictors for those clusters. This part of the analysis uses two different techniques to analyse each question due to mixed values, ordinal and nominal. The dependent variable in both cases was

	Q9	*Q12*	*Q19*	*Q21*	*Q22*
Chi-Square	21.533	9.463	2.345	.138	6.194
df	2	2	2	2	2
Asymp. Sig.	**.000**	**.009**	.310	.933	**.032**

Table 3.3: Kruskal-Wallis test results three significant factors.

the Ward's clustering method that consists of three categories and the independent variable were all the questions summarised in Table 3.1.

A Kruskal-Wallis test was selected for questions in which their answers were in ordinal form such as questions Q9, Q12, Q19, Q21 and Q22. As can be observed from Table 3.3, clearly Q9, Q12, and Q22 are statistically significant with the clustering method, meaning that the factors of Frequency, Daily Reading Time and Preference for Image Captions are strong predictors for the clusters. However, Image Captions might relate with the content itself and not included further in the analysis.

A Multinomial Logistic Regression model was fit in with the nominal features to extract the predictive power of this set of features. Apart from the nominal questions presented in Table 3.1, the model also made use of the demographics information as explained in Table 3.2. Although this set of features might not be part of the navigational, reading and contextual behaviour of mobile news consumption, previous studies (Institute, 2014) have shown they might influence the way people read and access the news, and thus they were selected to be part of the analysis. As can be observed from Table 3.4, Q10 and Q11 were statistically significant, meaning that the factors of Time of the Day and Location are strong predictors for the three clusters. Surprisingly though the questions Q14 (Browsing Strategy) and Q20 (Reading Style) have shown no statistical significance and a word of caution is appropriate here. Browsing strategy and reading style were found not to be good predictors, but further investigation is needed as these factors found in previous works (Liu, 2005) to play an important role in news reading behaviour. Section 3.6 further examines these two factors as part of another studied but also Chapter 5 validates them using behaviourial data from users' interaction logs.

	Model			*Likelihood*		
Effect	*AIC*	*BIC*	*Likelihood*	*Chi-Square*	*df*	*Sig.*
Intercept	207.079	412.994	67.079[a]	.000	0	.
Q14	200.535	394.684	68.535[b]	1.456	4	.834
Q2	202.521	390.786	74.521[b]	7.442	6	.282
Q3	193.123	369.621	73.123[b]	6.043	10	.812
Q15	201.617	395.765	69.617[b]	2.537	4	.638
Q16	199.573	393.722	67.573[b]	.494	4	.974
Q17	200.937	383.319	76.937[b]	9.858	8	.275
Q18	204.667	404.698	68.667[b]	1.587	2	.452
Q1	203.146	403.178	67.146[b]	.067	2	.967
Q10	**303.533**	**474.149**	**187.533[b]**	**120.454**	**12**	**.000**
Q11	**205.133**	**375.748**	**89.133[b]**	**22.054**	**12**	**.037**
Q20	199.700	393.848	67.700[b]	.621	4	.961

Table 3.4: Likelihood ratio of a Multinomial Logistic Regression.

3.4.3 Crosstabs Analysis and Demographics

In the final phase of the analysis we established the identity of the clusters by examining the pattern of factors associated with them. To do so, we conducted a crosstabs analysis in which the distribution of the factors emerged previously was examined over the three clusters. The crosstabs analysis provides a way of examining and comparing the results of one or more variables (the factors), with the results of another (the clustering method). Thereby, we can describe the three clusters by looking how participants responded to those factors.

Table 3.5 summarises the three clusters along with the values of each factor that emerged from the crosstabs analysis. Table 3.6 is a supplementary table that provides all the potential values for each factor. Furthermore, the two factors that do not show any correlation, i.e. Browsing Strategy and Reading Style (marked with ***), are both included in the typology and subsequent investigation will examine their relationship with news reading behaviour.

In addition to the seven factors, the distribution of demographics information was also examined with the three clusters. Table 3.7 shows the distribution of age, gender and education level within the three clusters.

It is observed that male population dominates Cluster 1, whereas the other two clusters have equal number of males and females. Regarding age, the age group

Factor	*Cluster 1*	*Cluster 2*	*Cluster 3*
Frequency	Many times a day	Once a day	Less than once a day
Total daily reading time	5-10 min	10+ min	0-5 min
Time of the day	Morning Afternoon Evening	Morning Afternoon	Morning Evening
Image Captions	Moderate Strong	Strong	Moderate
Location	Public Transport	Home	Home
Browsing strategy ***	Both	Through all sections	Particular section
Reading style ***	Skimming	Detailed reading	Scanning

Table 3.5: Mobile News Readers Typology along with the clustering factors (factors with *** will be further investigated).

Factor		*Possible Values*	
Frequency	Many times a day	Once a day	Less than once a day
Total daily reading time	5-10 min	10+ min	0-5 min
Time of the day	Morning	Afternoon	Evening
Image Captions	Weak	Moderate	Strong
Location	Home	Work	Public transport
Browsing strategy	Through all sections	Particular section	Both
Reading style	Detailed reading	Skimming	Scanning

Table 3.6: Factors and their potential values.

between 18 and 35 dominates all clusters with one exception - in Cluster 2 the age group between 36 and 50 also has a significant presence. This can be explained by the behaviour of people who form Cluster 2, which is considered to be more of a traditional reading behaviour. Hence, observing older people in this cluster rather than the others is an expected result. Much of the sample (60%) holds a higher education degree but it is also observed that for Clusters 2 and 3 a substantial proportion of their population did not complete higher education, whereas higher education dominates Cluster 1.

		Cluster 1	Cluster 2	Cluster 3	Total
Gender	Male	34	26	26	86
	Female	9	25	20	54
Total		43	51	46	140
Age	18-35	37	30	36	103
	36-50	4	16	9	29
	51+	2	5	1	8
Total		43	51	46	140
Education	Some high school, no diploma	1	2	2	5
	High school, no diploma	4	16	11	31
	Trade/technical/ vocational training	1	7	4	12
	Bachelor's degree	19	16	17	52
	Master's degree	13	9	10	32
	Doctorate degree	5	1	2	8
Total		43	51	46	140

Table 3.7: Age, gender and education distribution over the three clusters.

The relation of demographics with the seven factors was also examined. A chi-square test was performed to examine whether there is any significance among demographics and those factors, aiming to enrich our understanding on the news reader types and their characteristics. It was found that there is a statistically significant relationship between age and total daily reading time χ^2, (6, N=140) = 28.60, p=0.05, education level and reading time χ^2, (20, N=140) = 39.14, p=0.06 as well as age and reading style χ^2, (6, N=140) = 16.03, p=0.14. In fact, the relationships can be explained as one might expect different group ages to approach reading the news differently in the case of the relationship between age and reading style. For example, younger audiences are more likely to consume news in a more 'snackable' way (i.e. scan and skim) rather that elderly people as another study suggested (BBC RD, 2014). Likewise, the relationships between total daily reading time with age and education level can be explained. In the former case, one would expect the time that is reserved for news consumption to vary among different age groups, whereas in the latter people with higher or lower education background might spend more or less time consuming the news.

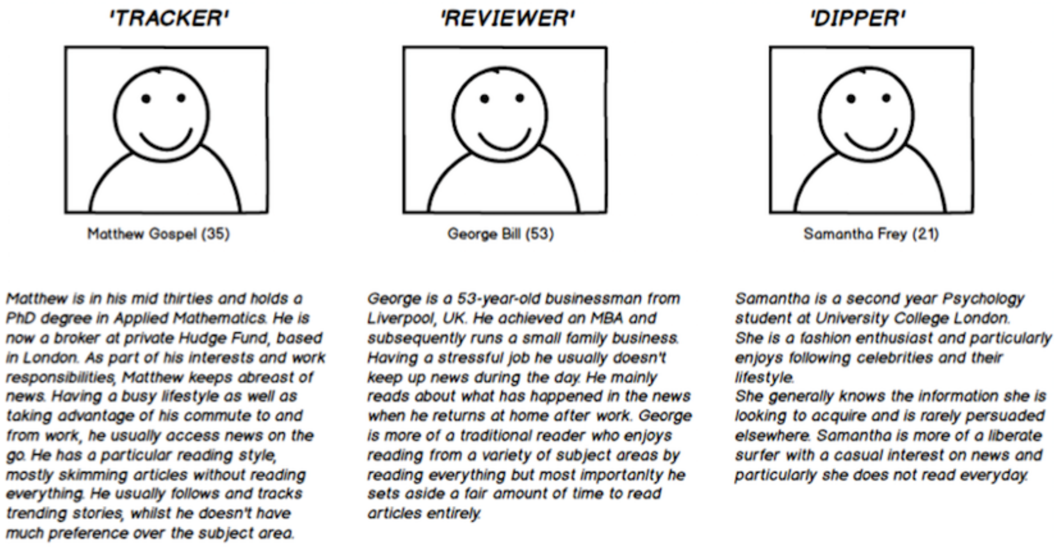


Figure 3.5: Mobile News Readers Personas.

3.5 Mobile News Readers Personas

Given the analysis presented in the previous sections, this section presents the three news readers personas which are a result of the interpretation of the analysis. In brief, the three clusters along with their characteristics (i.e., reading factors) were named as ***'Trackers'***, ***'Reviewers'*** and ***'Dippers'*** respectively. Figure 3.5 illustrates the three personas with fictional characters and a more detailed description and explanation of each type follows. For example, Reviewer defines a mid-age businessman as the dominant population compared to other two clusters comes from the range of 36-50 years old, as it is shown in Table 3.7. Similar procedure was followed to form all the reader personas, based on the crosstabs analysis over the three clusters.

A ***Tracker*** is a repetitive news reader. She is a person who likes to be informed about the latest stories and any updates to stories she is following. She usually reads the news for up to 10 minutes at a time and several times a day at intervals, for example, when travelling. Due to her limited time she prefers to extract the important bits of a story (i.e. reading by skimming).

A ***Reviewer*** is a daily routine news reader. She is a person who likes to catch up on the day's news, preferably at home. She likes an in-depth analysis of the stories she reads and will read at length to fully understand the story (i.e. a detailed reading). She usually reads the news once a day, spending more than 10 minutes to get through all the stories of interest and likes being informed on a variety of topics.

A ***Dipper*** is a liberate surfer news reader. She is a person with a casual interest in the news but likes to read news on specific topics such as sport. She always knows what she is looking for so does not spend more than 5 minutes accessing the news. She likes to browse particular sections to find stories and looks for specific facts or pieces of information without reading everything (i.e. reading by scanning).

3.6 Domain-independent factors

In addition to the specific news reading factors that reflect people's ways of interacting and consuming news content, a side investigation was carried out to examine domain-independent factors that could be incorporated in a user modelling component as discussed in Chapter 2 (2.4.1). The study presented in this section was conducted in the late stages of this research work. Although the work provided useful insights, it will be only discussed in this Chapter. At the same time, however, it paves the way to future directions of this work. This will be discussed in more detail in Chapter 8 (8.2).

3.6.1 Data and Methods

Having identified the six reading factors of Frequency, Reading duration, Browsing strategy, Reading style, Location/Context and Time of day, we developed an online questionnaire to survey individuals' digital news reading behaviour and their personality. Personality, as discussed in Chapter 2, is a domain-independent factor that is stable over time and can be incorporated in user modelling to better refine the model or even help to overcome the cold-start problem, which is common in personalised services.

The online questionnaire consisted of three parts: (a) details about age, gender and education, (b) questions relating to the six news reading factors, and (c) two standardised questionnaires that assessed the Big 5 personality traits (OpenPsychometrics) and the Need for Cognition (Cacioppo and Petty, 1982). The form of the questions relating to the six factors was based on the findings of the study reported previously in the Chapter, but is also listed below along with the response choices.

1. *Question:* How often do you read news on your mobile device?
   Response choice: [a. Many times a day b. Once a day c. Occasionally]

2. *Question:* How much time in a day do you spend reading news on your mobile device?
   Response choice: [a. 0-5 minutes b. 5-10 minutes c. 10+ minutes]

3. *Question:* How do you look for stories of interest?
   Response choice: [a. I look through all sections b. I look in particular section c. I utilise both techniques]

4. *Question:* How do you most often read a news story?
   Response choice: [a. Detailed reading b. Skimming c. Scanning]

5. *Question:* Where do you most often read news?
   Response choice: [a. Home b. Work c. Public Transport]

6. *Question:* What time of day do you usually read the news?
   Response choice: [a. Morning b. Afternoon c.Evening]

The survey also integrated the 50 questions comprising the standard BFI personality traits questionnaire (OpenPsychometrics). Additional questions were included to elicit the trait of Need- for-cognition (Cacioppo and Petty, 1982). The survey also included questions about the demographic factors of age, gender and extent of education. The questionnaire was developed in GoogleDocs (available here [3]) and distributed as an Amazon Mechanical Turk [4] task, a widely used platform to crowdsource user studies (Kittur et al., 2008). Respondents were paid a nominal sum for anonymous participation. Further, participation was restricted to those with good reputation as workers (95% HIT approval rate and 1000 HITs [5]

[3]Questionnaire: https://goo.gl/6AWk5b

[4]Amazon Mechanical Turk: https://www.mturk.com/

[5]HITs (Human Intelligence Tasks) represent the assignments a user has participated in on Amazon Mechanical Turk prior to this study

approved) in order to prevent any careless contributions. The survey ran for three separate 24 hour periods after which the data were retrieved and collated in spreadsheets. The results of 241 participants (96 female, Age M=30.89, Age SD=8.38) were recorded. Personality traits were computed from the answers using the standard protocol (OpenPsychometrics). A similar process was followed to compute the NFC score (Cacioppo and Petty, 1982).

3.6.2 Analysis

3.6.2.1 Correlations: News reading factors and Personality

Due to the gathered data were not normally being distributed, as assessed by the Shapiro-Wilk's test ($p<.05$), a non-parametric test was selected to examine the relationship between personality and the reading factors. We used the Spearman's rank correlation analysis to investigate potential correlations between the BFI, NFC and the Newsreader factors. All the significant correlations adhere to alpha levels of $p<.05$, as depicted in Tables 3.8, 3.9, 3.10.

Correlations were found between several news reading factors and personality traits (Table 3.8). People who told us they read the news several times a day (Frequency) are more likely to exhibit the trait of 'Openness-to experience' than those who read the news less than once a day. The more time people spend reading the news over a day (Duration), the more likely they are to exhibit both the traits of Openness-to-experience and Need-for-cognition. People who say they sometimes look at all headline categories and sometimes at just particular categories (Browsing strategy) are more likely to exhibit Openness-to-experience than those who always only look at particular categories of headline or always read all headline categories. People who read articles in detail word-for-word (Reading style) are least likely to exhibit a Need-for-cognition whilst those who read by scanning are most likely to exhibit this trait. People who read the news away from home (Location) are more likely to exhibit Openness-to-experience than those who only read the news at home. Correlations were also found between Newsreader factors and Demographic factors (Table 3.9). We find that women amongst our respondents are more likely than men to read the news several times a day (Frequency) whilst men are more

	Frequency	*Duration*	*Browsing Strategy*	*Reading Style*	*Location*	*Time of day*
O	**.033***	**.011***	**.036***	.548	**.032***	.621
C	.638	.659	.463	.403	.621	.934
E	.500	.331	.990	.206	.513	.284
A	.964	.138	.313	.187	.316	.840
N	.939	.702	.478	.231	.177	.255
NFC	.386	**.018***	.334	**0.01***	.409	.843

Table 3.8: Correlations between the news reader factors, Personality traits and Need-for-Cognition. Significant results in boldface adhere to alpha levels of $p<0.05$. (E: Extroversion, A: Agreeableness, C: Conscientiousness, N: Neuroticism, O: Openness-to-experience, NFC: Need-for-cognition.

	Frequency	*Duration*	*Browsing Strategy*	*Reading Style*	*Location*	*Time of day*
Age	.403	.084	**.006***	.189	.442	.127
Education	.367	.526	.648	.976	.895	.096
Gender	**.029***	**.044***	.687.	.561	.308	.855

Table 3.9: Correlations between Age, Education and Gender and Newsreader factors. Significant results in boldface adhere to alpha levels of $p<0.05$.

likely than women to read the news less than once a day. Women are likely to read the news for longer overall in the course of a day (Duration) than men. A correlation in news reading habits was found with education, where the more extensive a person's education, the more likely they are to browse all headline categories than just particular categories. No other correlations with education were found, not even Need-for-cognition. No correlations were found between newsreader factors and age, so older people amongst our respondents did not read digital news differently from younger people. Examining effects between the demographic factors reveals only that respondents who are older tend to have a more extensive education ($r=0.129$, $p<0.05$) but neither age nor education correlate with gender.

Finally, we look at relationships between Newsreader factors (Table 3.10). It is apparent that the more often people read the news (Frequency), the longer they do so over the day (Duration) and they will tend to view all categories of headlines each time they read the news (Browsing Strategy). It is also apparent that the longer respondents spend reading the news overall in a day (Duration), the more likely they are to view all categories of headline (Browsing Strategy) and to read news articles

	Frequency	*Duration*	*Browsing Strategy*	*Reading Style*	*Location*	*Time of day*
Frequency	-	**.002***	**.006***	.989	.121	.267
Duration	**.002***	-	**.001***	**.004***	.168	.434
Browsing Strategy	**.006***	**.001***	-	.756	.631	.617
Reading Style	.989	**.004***	.756.	-	.050	.567
Location	.121	.168	.631	.050	-	.409
Time of day	.267	.434	.617	.567	.409	-

Table 3.10: Correlations within the news reader factors. Significant results in boldface adhere to alpha levels of $p<0.05$.

by skimming the text for keywords rather than reading in detail or scan reading for meaning (Reading style). People, who read the news occasionally do so for the shortest overall time in a day but read the news articles they choose in detail. These people appear to be highly selective in what they read and when they do it as is reflected in their focused reading of the material. By contrast, people who read the news frequently in a day are in some sense trying to keep up with all the news as it happens and they will, as a consequence, be likely to skim read articles.

Relationships were also found between Demographic factors and Personality traits. With the exception of Extrovertism, all the personality traits are increasingly exhibited with age amongst our respondents. A more extensive education correlates with the traits of Agreeableness, Conscientiousness, and Openness-to-experience. Women are also more likely than men to exhibit Neuroticism, a finding reported previously elsewhere (Lynn and Martin, 1997). Finally, each personality trait was found to correlate with at least two other personality traits and in particular, Neuroticism correlated with all other traits.

The analysis finds that the way a person reads digital news reflects their personality; all but one of the Newsreader factors correlated with either or both of the traits of Openness-to- experience and Need-for-cognition. Other personality traits might well be found with more extensive testing (more participants more carefully sampled, etc), a more refined questionnaire instrument (inclusion of more consistency checking questions, a separate validation of the questions, etc), and a more controlled procedure (face-to-face interviews rather than a crowd-sourced task). The study found some evidence of differences in news reading habits with gender and education but none with age. Specifically it found that women read the news more frequently and extensively than men, and people with more education will browse more categories of headline. Demographic factors in news consumption are complex and this survey contained few questions to examine them. Other recent work on demographic factors affecting news consumption (Institute, 2014) finds that older people read the news more often than young people and enjoy doing it more, but young people are nevertheless interested in keeping up with the news, contrary to reports from other studies (Patterson, 2007).

Contrasting types of news reader are revealed by the correspondences between news reading factors and personality traits. People who read the news frequently tend to also review headlines broadly and skim read articles (e.g., read by keyword spotting. Relating this to the typology discussed earlier in the Chapter, this kind of reader can be characterised as 'Trackers' who try to keep up with the news; their personality will tend towards the traits of Openness-to-experience and a Need-for-Cognition; they are more likely to be women than men. By contrast, people who read the news occasionally will look at relatively few categories of headline and when they have chosen a news article to read, they will read it in detail, word-for-word. These readers can be characterised as 'Dippers' who only read the news that interests them and only read it when it suits them. Their personality will tend significantly less towards the traits of Openness-to-experience and Need-for-Cognition.

3.6.2.2 Examining sub-populations of news reader types

The intriguing possibility suggested by this analysis is that there may exist other user types within our data. In this section we report a clustering analysis that more exhaustively and systematically explore the existence of reader types. This was achieved by ingesting all the Newsreader factors and Personality traits into a clustering method. We explored whether clustering based on the Newsreader factors alone can be improved by the addition of Personality traits data. Given the correlations reported in the Section 3.6.2.1 between these two kinds of 'user fact', we

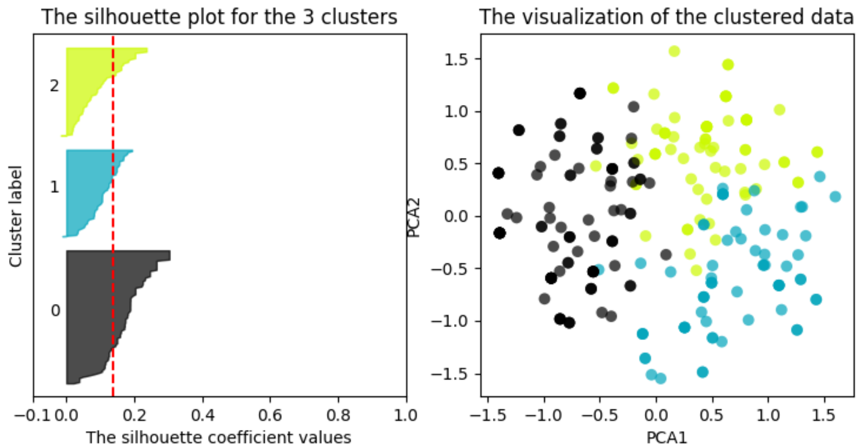


Figure 3.6: Silhouette analysis: k-means (n=3) clustering using the six factors.

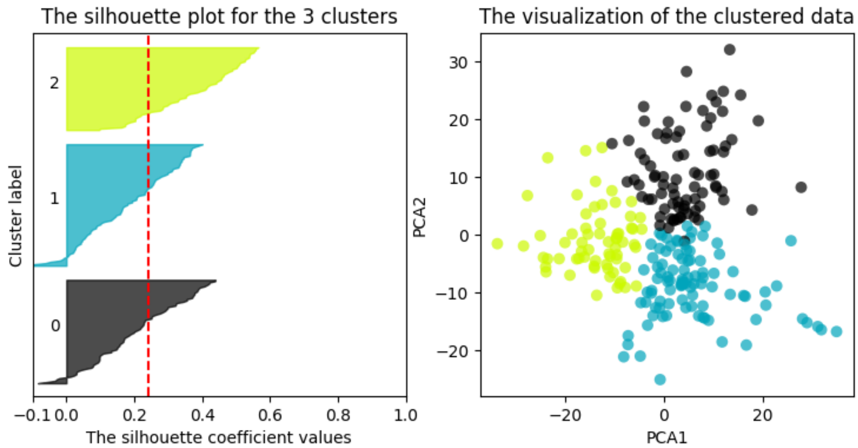


Figure 3.7: Silhouette analysis: k-means (n=3) clustering using the six reader factors and personality traits and NFC.

aim to examine whether the addition of personality traits data can improve the identification of the different news reader types. The promise is that user models can benefit from facts about an individual user's personality, ultimately supporting a more precise categorisation of the user within a particular domain of activity, and therefore a more accurately personalised user interface and interactive experience.

In the first part of the analysis, we seek to answer the question whether a person's personality and cognitive factors of their behaviour improve the identification of their news reader type. To examine that, we performed a clustering analysis on participants' responses. Feeding a clustering method with both the reading factors and traits enable us to (a) acquire evidence of the role of those specific human factors

#Clusters	*Six reading factors*	*Addition of Personality traits and NFC*	*%increase*
2	.139	.196	41%
3	**.137**	**.242**	**76.64**%
4	.139	.234	68.34%
5	.143	.236	65.03%
6	.133	.221	66.16%

Table 3.11: Comparison of silhouette coefficients for analyses of 2-6 clusters when only the reading factors are used and when the Personality traits and NFC are included.

in distinguishing news reader types, and (b) examine how those personality aspects are explained among the types, a required step before we fuse a recommendation framework for digital news reading.

The clustering method we used is k-means, which requires integer data whereas the six reading factors are categorical with the exception of Reading duration. The categorical data were encoded as nominal data labelled with integers. A one- hot encoding was applied to the duration data. Each integer- encoded variable was removed and a new binary variable was added for each unique category. The K-means method also requires the number of expected clusters to be declared. Three clusters were declared for illustrative purposes on the basis of three types of news reader (section 3.5) To evaluate the strength of the clustering effect, a Silhouette analysis was performed on each of the analyses and the results are shown graphically in the left side panel of each figure (Figures 3.6 and 3.7). The silhouette coefficient is a measure of the proximity of the points within the clusters and conveys the definition of the clusters overall. Table 3.11 summarises the analysis of silhouette clusters when the number of expected clusters increases from 2 to 6. In each case the coefficient is seen to increase substantially and for three clusters, an increase of 76.64% is returned, which also corroborates the initial choice of three clusters in the k-means algorithm.

Having acquired evidence that the inclusion of personality traits and NFC yields more clear clusters with increased consistency among the proposed features, the second part of our analysis attempts to describe the newly identified groups by utilising the Newsreader typology, as described earlier in this Chapter, and examin-

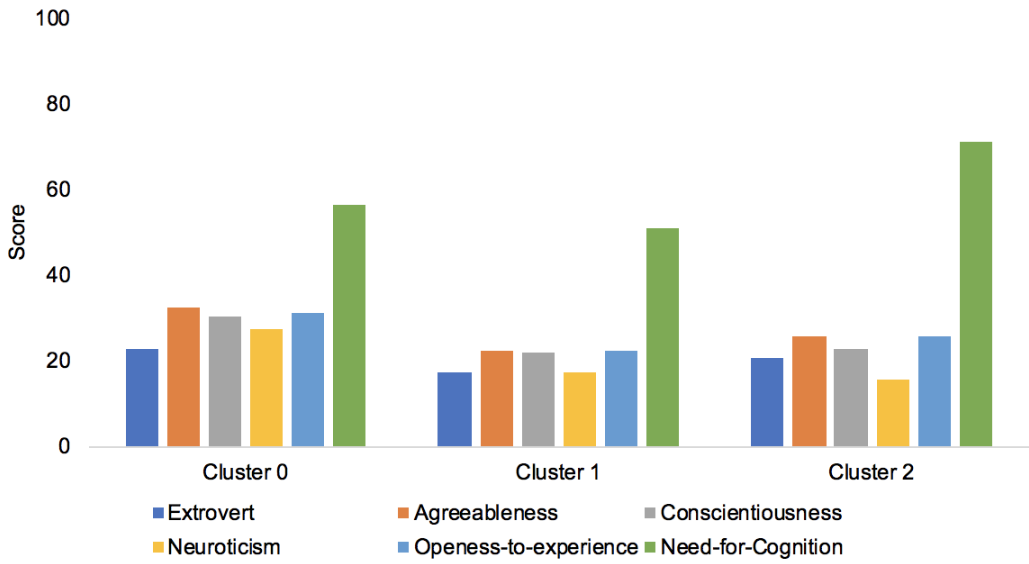


Figure 3.8: Personality traits (range between 0-40) and NFC (range between -72, 72) scores distribution.

ing the dimensions of personality and need for cognition.

A required step in our ad-hoc interpretation is to incorporate prior knowledge, by extracting a news reader label for each participant, that will enable us to describe each cluster with news reading characteristics, and in turn examine the personality and NFC dimensions. To extract the label we converted their answers to the six questions that correspond the reading factors into a complete logical coding using binary encoding. Therefore, for each reading factor we computed a binary vector (length=3) that corresponds the possible values one could assign to each factor (e.g. Frequency factor (a) many times a day, (b) once a day, (c) occasionally). Given the six reading factors and the three possible values that can be assigned to each factor, each participant's answers were converted into a binary vector (length=18). Similar transformation was conducted in the three stereotypical news reader types defined in Section 3.5. To compute the label we used a Cosine Similarity function, which is a measure of the similarity between two vectors derived from the cosine of the angle between them. We estimated the cosine similarity between each participant's coded responses and the three news reader types binary vectors. The label was then assigned to each participant using the higher cosine similarity amongst the three vectors. The final dataset that we used to describe the emerged clusters consisted,

#Clusters	*Reader type*	*Personality and NFC*
0	T: 45.6% R: 42.1% D: 12.3% Label: Tracker/Reviewer	O: 31.17% C: 30.48% E: 22.7% A: 32.43% N: 27.40% NFC: 56.65%
1	T: 49.5% R: 37.9% D: 12.6% Label: Tracker	O: 22.43% C: 22.05% E: 17.57% A: 22.45% N: 17.40% NFC: 51.09%
2	T: 47.7% R: 49.2% D: 3.1% Label: Reviewer/Tracker	O: 25.90% C: 22.86% E: 20.73% A: 25.78% N: 15.66% NFC: 71.26%

Table 3.12: Distribution of the computed news reader type, personality traits and NFC across the three newly formed clusters.

therefore, of the six reading factors, the five personality traits scores, the NFC score, and the computed variable of the news reader type.

To ad-hoc interpret the clusters, we ran a crosstab method that examined the distribution of the computed variable of news reader type and the six factors over the clustering method. As can be seen from Table 3.12, Cluster 1 only consists of pure Trackers whereas the other two clusters are a mix of Tracker and Reviewer behaviour. By retrieving the cluster membership we are able to observe how participants' responses clustered together and examine the distribution of the six reading factors across the three clusters. Cluster 1 is aligned with the characteristics of a Tracker type as, it is described by participants who responded that they access the news several times a day and skim through news stories. In clusters 0 and 2, though, there is a mixture of skimming and detailed reading, which cannot relate to pure behaviour of either type. It is also important to mention that the Dippers news reader type was not found in the dataset. A possible explanation could be that this behaviour was relatively less represented in our dataset, and hence news readers are grouped into two behaviours regarding their habits. Those who are compulsive/obsessive about accessing news (Trackers - Cluster 1) and those who are more traditional in-depth readers (Reviewers - Cluster 0 and 2). This claim could also be supported by the need for consuming news, particularly created from social media, that was absent in previous years. In the final step of the interpretation, we examined the distribution of the personality traits and NFC across the newly formed clusters (Figure 3.8 and Table 3.12). As can be observed participants who grouped in Cluster 0 (i.e. Tracker/Reviewer) scored higher across the five personality traits except for Extroversion. In relation to the other two clusters, BFI scores were lower, suggesting intermediate levels of each trait. The higher NFC score was observed in Cluster 2 (i.e., Reviewer/Tracker), a finding that is aligned with the definition of a Reviewer type (i.e., a person who seeks for an in-depth understand of news content) and indicates a tendency towards undertaking challenging activities.

3.7 Discussion

This Chapter examined people's mobile news consumption patterns and defines a News Reader Typology that reflects the different ways people consume and access news content. While previous studies have independently examined different factors that are associated with people's preferences and choices of news content, this study investigates news reading factors that are related with people's navigational, reading and contextual behaviour in relation to consumption habits.

An online questionnaire was designed and deployed with the aim of investigating people's mobile news reading behaviour. A descriptive analysis on people's responses revealed a news reading behaviour that is characterised by more time spent on browsing and skimming stories, one-time reading and less in-depth reading. Similar results were reported in a study conducted by Liu (2005) that attempted to investigate reading behaviour in the digital environment. The statistical analysis performed on the online questionnaire suggested a mobile news readers typology that is characterised by the factors of frequency, total daily reading time, time of the day, location, image captions preference. The factors of browsing strategy and reading style did not show statistical significance but further investigation is needed. Chapter 5 examines both factors with behaviourial data from users' interactions with a news app.

The News Reader Typology proposed in this Chapter contributes towards the ultimate goal of this research. Firstly, it establishes three news reader personas that are well defined and distinct, which is fundamental for applying personalisation in news apps user interfaces. The three news reader personas are (a) 'Trackers', people who follow the news throughout the day and skimming over them; (b) 'Reviewers', people who are daily routine news readers, mainly the traditional daily catch up of the news that sometimes tend to engage with an in-depth understanding of the news content; and (c) 'Dippers', people who are liberate surfer news readers, mainly described as casual readers who are looking for specific facts of information without reading everything through keyword-spotting. Secondly, having extracted factors that are statistically significant with news reading behaviour it can inform the design of a mechanism that collects such data from a dedicated news app, i.e. a news app that systematically monitors the seven significant factors from interacting with the news app's user interface. Additionally, aside from the Chapter's primary aim, an investigation of domain-independent factors (i.e. personality traits and need-for-cognition) in relation to the domain-specific news reading factors was carried out. The analysis showed the added value of personality traits and NFC in identifying a person's news reader type. Specifically, a Silhouette analysis showed an improvement of 76.64% increase when adding those domain-independent factors into domain-specific factors about news reading behaviour. Furthermore, we showed an ad-hoc interpretation of the newly formed clusters by relating them to the news reader typology. Finally, by analysing those factors, it would be possible to build a user model that is capable of detecting and recognising the user's stereotypical behaviour of news consumption.

Chapter 4

An Adaptive News Research Platform

The previous chapter investigated people's differences in the way they read and consume news on their mobile devices through an online questionnaire, which resulted in a News Reader Typology. The News Reader Typology defines three prototypical types of news readers characterised by six discriminating factors, mainly describing how people browse news headlines and how they read news stories.

This Chapter presents the design and implementation of an adaptive news framework that defines a research platform, which seeks to address questions on automatic detection of mobile news reading behaviour and adaptation of the user interface and interaction. The implementation of an adaptive news framework is essential towards the ultimate goal of this thesis, as it will provide the research platform to examine the research questions defined in the Introduction. Its ultimate goal is to facilitate the idea of extending beyond what news content people read and access on mobile news apps to how they read and interact with it.

The Chapter presents the architecture of the research framework and discusses its main components from a technical perspective. The framework was designed in a three-tier architecture. The well-known three-tier architecture was favoured in our research framework, mainly because it gives the ability to update the underlying technology of one tier without impacting other areas of the application stack, it provides an ease maintenance of the code base, as it keeps the presentation code separate from the business logic and the data, and it can easily scale up the application. The framework introduces all the components that in subsequent Chapters will tackle the research questions around adaptivity in news apps. Particularly, it discusses the components in relation to how the automatic detection of a user's news reader type can be achieved and the automatic adaptation of the user interface and interaction.

The Chapter begins with a motivation and explains the need for a research framework. It then presents the framework's architecture and highlights its main components through architecture diagrams and technical implementation details.

The architecture presented in this Chapter was presented in the Doctoral Consortium of CHI'15 and appeared to CHI '15 Extended Abstracts. (Constantinides, M. Apps with habits: Adaptive interfaces for news apps. In Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems (pp. 191-194). ACM)

Our prototype mobile news app, Habito News, presented in this Chapter has appeared to MobileHCI '15 as a demo. (Constantinides, M., Dowell, J., Johnson, D., Malacria, S. A research tool to investigate mobile news reading. In Proc. of MobileHCI Adjunct).

4.1 Motivation

The work presented in this Chapter introduces a framework as the research platform to investigate how personalisation on mobile news app can be achieved, and extend beyond, existing literature on news content recommendation to incorporate personalisation of the user interface and interaction with news services. It presents the framework that its main components seek to address; questions on automatic detection and recognition of mobile news reading behaviour and questions related to automatic adaptation of the user interface and the interaction.

4.2 Three-tier Architecture

The Adaptive News Framework is built on the basis of the well-known three-tier architecture (Schulte, 1997). Primarily, the decision of a three-tier architecture was

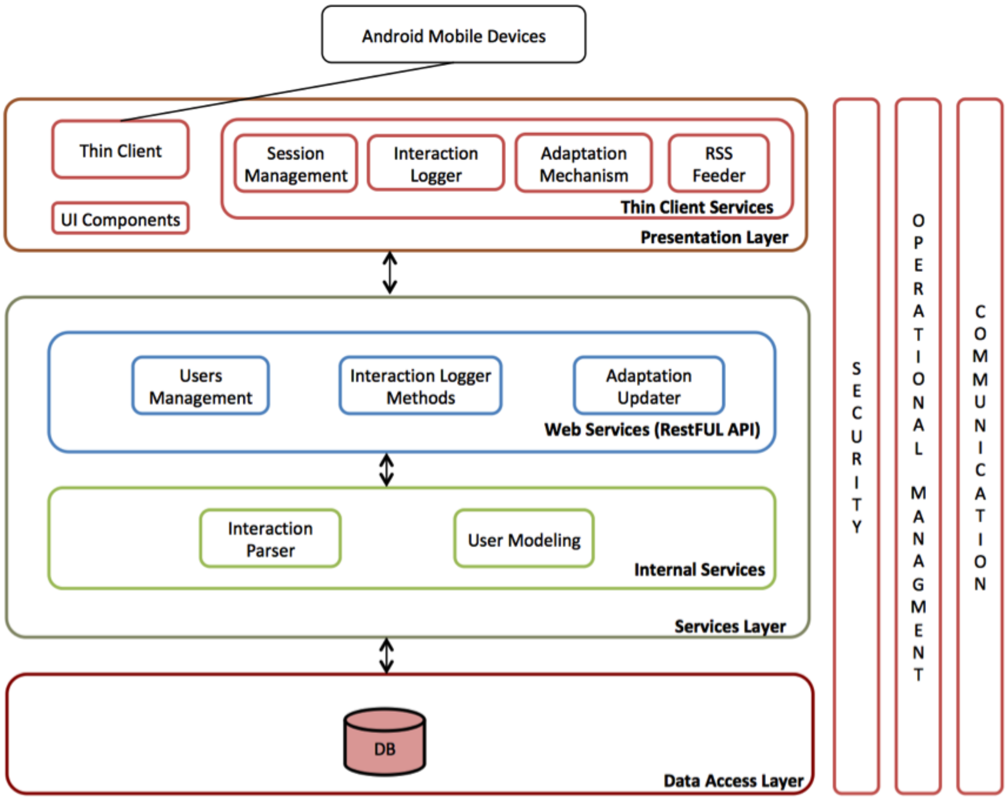


Figure 4.1: Layered Architecture View diagram. The three-tier architecture of the Adaptive news framework.

reinforced by the fact that it provides maintainability of the code, as it separates the presentation code from the business logic and the physical data layer. It can easily scale up to support more users, and it gives the ability to update the underlying technology of each tier without impacting other application areas in other tiers.

The communication between the tiers is achieved through a RESTful API, Representational State Transfer (REST). REST is an architectural principle in which the web services are viewed as resources and can be uniquely identified by their URLs. The fundamental characteristic of a RESTful Web service is the explicit usage of HTTP methods to denote the invocation of different operations. In addition, REST is considered to be considerably generic since it is based on HTTP and most of the devices support HTTP methods (POST and GET). Figure 4.1 depicts the RESTful API in the WebServices layer and explained in detail in Section 4.2.2. Figure 4.2 shows a flow diagram of how the components interact with each other.

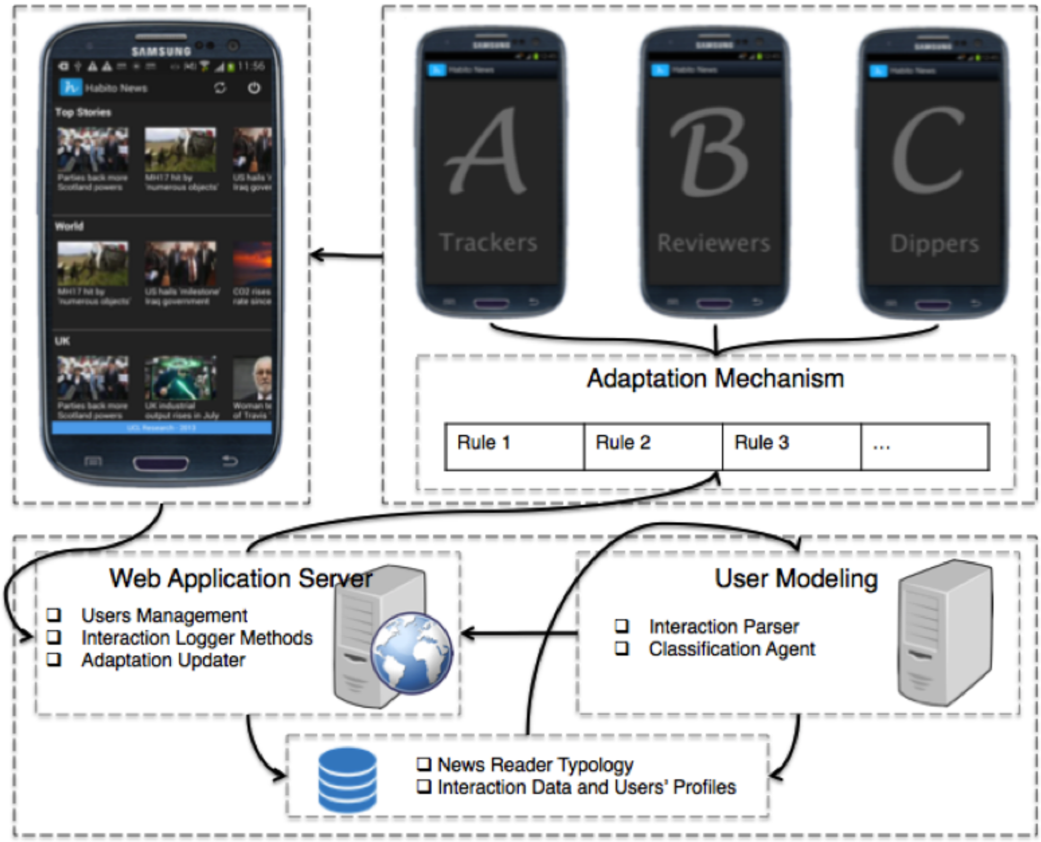


Figure 4.2: Framework components (arrows indicate the direction of communication between the components).

The three layers defined in our architecture are (a) the Presentation Layer, (b) the Services Layer, and (c) the Data Access Layer. Subsequent sections explain in detail the components and functionality in each layer.

4.2.1 Presentation Layer

At the top of the three-tier architecture is the presentation layer. It consists of a thin client, which is the Android mobile news app, named Habito News.

Habito News is a prototype mobile news app implemented in the Android platform with a twofold objective. First, it will be used as the research tool to explore news reading interaction by deploying it to collect users' interaction data that subsequently will be analysed to construct a user model. Second, it will be used to demonstrate an adaptive news app in which the user interface and interaction automatically adapt according to users' news reader type.

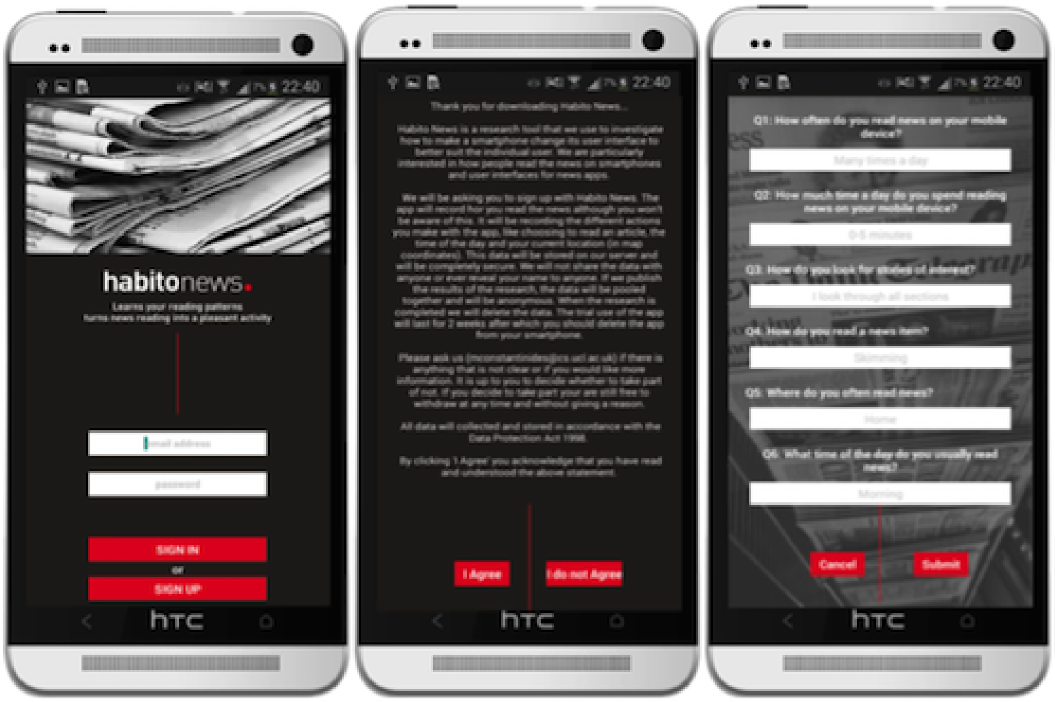


Figure 4.3: Habito News screens during the registration phase.

Habito News Baseline version : It mimics the BBC news app in terms of its layout organisation of headlines and news stories presentation. News stories are organised in rows of thumbnails and there are eleven news categories in which the user can select to read news. Primarily, the choice to mimic the BBC news app layout was because it is representative of news app interface designs and a widely used news app with more than five million downloads [1] on Google's marketplace. Figure 4.4 depicts how Habito News baseline version displays news headlines and the article's story compared to the BBC news app. Figure 4.3 depict the screens during the registration phase and information collected through a built-in questionnaire that will be discussed in Chapter 5.

All the development of the app was done on Android Studio version 2.3, with Java language for application programming and XML markup for displaying the user interface. All the communication between the presentation and service layer is achieved through a RESTful API, which exposes methods to retrieve and store data in the database (i.e. Data access layer). It defines the client's app five components

[1] https://play.google.com/store/apps/details?id=bbc.mobile.news.uk

Figure 4.4: Left: News headlines organisation, Right: News article presentation. Both compare Habito News to BBC news app.

as follows:

1. *UI Components:* A set of Android views and widgets responsible for rendering, manipulating and displaying the content (e.g. headlines, news content). Among the most popular views such WebViews and Adapters, a particular view, a ViewPager, was implemented, which allows more accurate scroll gesture directions to be obtained as opposed to a regular view component. This was important, as we are interested in capturing all possible interactions with the interface as accurately as possible.

   The horizontal rows of thumbnails are simply multiple ViewPager adapters that define placeholders for the article's thumbnails. Implementing it in that particular way allows us to locate which articles were browsed or seen (post interpretation and approximation based on the item reached in each horizontal ViewPager). It will be further discussed during the feature extraction process (Section 5.3.2.1 in Chapter 5).

2. *Interaction Logger:* A lightweight background service that collects data associated with users' interactions with the user interface and context related in terms of GPS coordinates and data from Google's Activity Recognition API (Note: All data collected will be discussed in Chapter 5). It stores the data in the Data access layer through the RESTful API, which defines methods that

are exposed in the web services layer (i.e. Interaction logger methods). As explained for the previous components, we are interested in low-level interactions with the user interface, and thus the logger captures from swipe events to precise scroll positions to open/close windows and others. The service also considers battery-life limitations of smartphones, and thus it was designed in a way for the impact on a phone's performance to remain negligible. It does not, therefore, send requests to a server frequently rather it stores data locally and transfer it in short bursts.

3. *RSS Feeder:* A component, which is responsible for retrieving the news feed from the public BBC API. It is an asynchronous background task that receives the news feed to and populates it in the UI components. The component is implemented asynchronously in order to be transparent to the user without interrupting user's news reading experience and not to block the user interface from displaying the news articles. It utilises an external open source library [2] that implements a SAX (Simple API for XML) parser, which is responsible for reading and interpreting the XML feed.

4. *Adaptation Mechanism (AM):* It is responsible for retrieving users' news reader type and generating on the fly an adaptive user interface based on a set of adaptation rules.

   The AM communicates with the API (Appendix D - Method #13) to retrieve a user's type, as it was inferred from the User Modelling component in the server side in a form of percentages. Chapter 6 explores two different approaches on how the set of adaptation rules were generated. A single rule is defined by a name, which is an identifier for the rule, the three news reader types percentages, represent how close/related it is with each news reader type and a list of features associated with that rule. The features represent a single user interface region/area, related within Navigation level features or Reading level features. The skeleton of a rule is an XML format is given below:

[2] https://github.com/ahorn/android-rss

```
<?xml version="1.0" encoding="utf-8"?>
<rule>
  <name></name>
  <trackerPercent></trackerPercent>
  <reviewerPercent></reviewerPercent>
  <dipperPercent</dipperPercent>
  <features>
    <feature></feature>
    <feature></feature>
    <feature></feature>
    <feature></feature>
    <feature></feature>
  </features>
</rule>
```

The user type is divided into three percentages representing the three types (e.g. Trackers 60%, Reviewers 25%, Dippers 15%) (it will be further discussed in Chapter 6). It defines methods for parsing those percentages and reading a rules.xml file in which the adaptation rules are stored. The adaptation rules are discussed in Chapter 6. At this point, as Figure 4.5 depicts, the AdaptInterfaceActivity class loads the list of features (Appendix D - rules.xml), setting flags and populated lists that will be used by the next Activity to be called. For example, depending on the main layout news headlines organisation in the feature list, the appropriate Activity is called, i.e., MainActivityTrackers, MainActivityReviewers or MainActivityDippers. The setting flags enabled the user interface generation to be dynamic, as the Activity loads the relevant View from the layout xml files and attaches it to the Activity view to construct the user interface. For example, a flag was used for the top static area for each of the three news headlines' organisation to indicate whether this user interface region should present tracked article, a search box feature, or no feature at all. Similar flags were used for other user

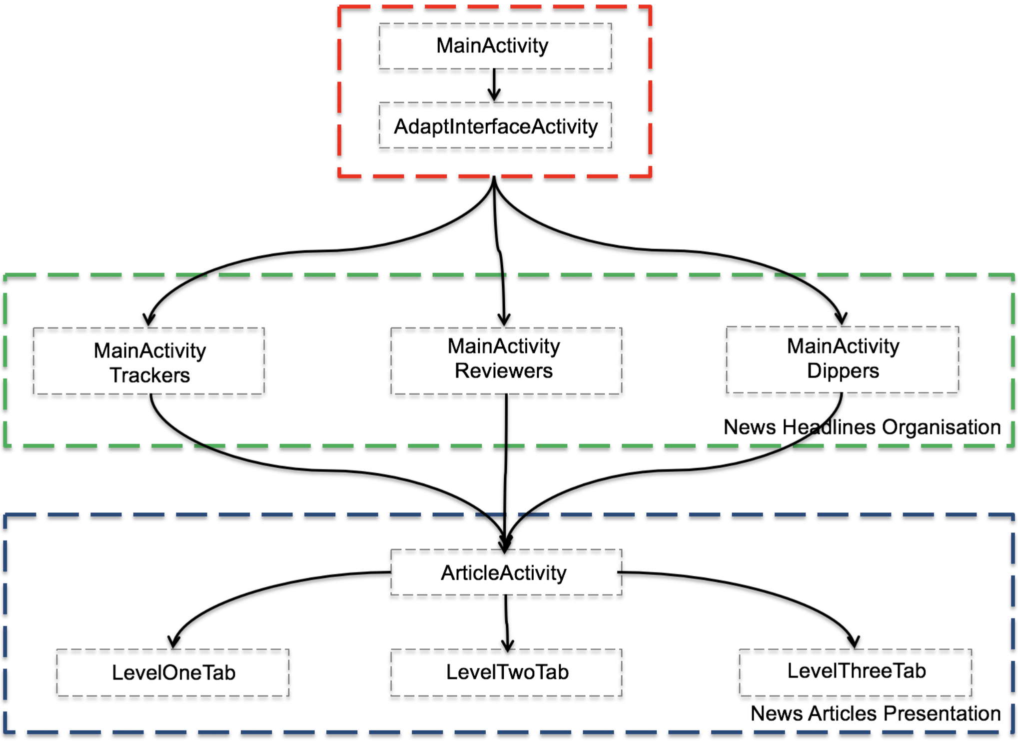


Figure 4.5: Adaptation mechanism Flow diagram of the automatic generation of the user interface (Initialisation stage in red, News Headlines Organisation in green and News Articles Presentation in blue).

interface regions. Chapter 6 discusses the design generation and the different user interface regions in detail.

Likewise, a handler was implemented in the ArticleActivity, which is responsible for matching user interface features in each reading level based on a user's news reader type. Details about the different user interface features are provided in Chapter 6. A news article is divided into three levels with each level presenting different information of the article (similar to the Elastic News project (BBC RD, 2014)). When the user clicks to read an article, the ArticleActivity is launched, which is different for each news reader type and reflects their characteristics. The activity displays a TabView that consists of three tabs implemented as Fragments (LevelOneTab, LevelTwoTab, and LevelThreeTab). The choice of fragments preferred, as multiple screens (levels) could be implemented under the same activity, thus makes the article activity more lightweight, as opposed to loading a new activity for each level. The HTML content of the news article (as loaded from the RSS feeder) is parsed into the correct format for the WebView present on all the three fragments while the tabs load. The three tabs correspond to the levels associated with the amount of the article's content displayed to the user (again, Chapter 6 presents the reading level features). For example, as the user progresses from one level to another, more of the article's story and different visualisation and features are applied to the content. The user also has the option to navigate back and forth tabs, not necessarily in a linear way, but any tab is enabled to be selected. Of course, the idea is to provide different visualisation and additional text as the user progresses through the tabs in order to facilitate a better reading experience.

It is also important to mention that different external APIs were used to implement different reading level features such as a summarisation API, keyword extraction, wordcloud, and an according-style presentation of background information related with the news article. All these features shared a common functionality, the HTTP request to the relevant API. An Android Volley tool was used to make the HTTP requests to external APIs as it allowed for multiple concurrent connections. For example, in the case of the accordion background information feature with the concurrent Wikipedia API requests. It adds a new request to the queue, populates the headers and additional API's parameters before making the call, and then provides a method to handle the response. Further, another common functionality between reading level features was the extraction of the news article's text. The JSoup library was used for that purpose, which provides an easy way to manipulate HTML content.

5. *Session Management:* It is responsible for managing user authentication and maintaining the continuity of news reading sessions. It generates a Universally Unique Identifier (UUID) that represents a 128-bit long value, which guarantees uniqueness across time and space. It therefore, provides a way to keep track of individual and unique news reading sessions. Further consider-

ations about a user's session needed to be taken into account based on how Android lifecycle works and the differences between home button and back button. By default, pressing the back button means that the destroy method will be triggered, whereas the home button pauses the activity, and thus it stays alive in background. Given this behaviour we reset a user's session only when the back button is pressed, whereas we treat home button as a pause and perhaps a continuation to the current reading session.

4.2.2 Services Layer

At the middle of the three-tier architecture is the services layer, which consists of two sub-layers, the web services and the core business logic. The services layer handles all the communication between the client side and the data access layer.

They reside at a UCL server, which is accessible at the following URL address: http://habito.cs.ucl.ac.uk (a landing page) and the Webserver is running at port 9000. The web services layer defines a set of methods through a RESTful API in order to be exposed to the client side for the storing of users' logged data and users' account management. The RESTful API is implemented in Tornado framework, which is a Python framework for building web applications and APIs and all the communication between the client-side is done using JSON. The full list of the implemented methods can be found in Appendix D. The core business logic layer defines methods that are used internally in the server side, such as the interaction parser and the user modelling component. All the core business logic components are implemented in Python. They are defined as follows:

1. *Users management:* It exposes methods that the client side uses to authenticate and manage users accounts. It ensures security through password encryption and other users sensitive data (Appendix D - Method #1-3).

2. *Interaction Logger Methods:* It defines a set of methods for storing users interactions and context related data in the data access layer. As previously discussed Habito News communicates through this set of API methods to store the interaction data (Appendix D - Method #4-8).

3. *Adaptation Updater:* It is responsible for notifying the presentation layer (i.e. Adaptation mechanism) when the interface needs to change. It communicates internally with the User modelling component (Appendix D - Method #13).

Another set of API methods was used to facilitate the final evaluation study (Chapter 7) in which the adaptive version of Habito News was deployed to investigate the effects of the adaptation.

The internal services layer components are defined as follows:

1. *Interaction parser:* It defines a set of functions that are running internally in the server and are responsible for interpreting and analysing the logged interaction data (it will be further discussed in Chapter 5. It also defines methods to retrieving the data from the data access layer. This will be discussed in detail as part of the User Modelling component in Chapter 5.

2. *User Modelling:* The User Modelling component is running periodically in the server and it is responsible for constructing a user model and predicting a user's news reader type. It communicates with the Adaptation updater component once the prediction is made. This will be discussed in detail in Chapter 5.

4.2.3 Data Access Layer

At the bottom of the three-tier architecture is the data access layer where a physical MYSQL database is hosted and stores all the data. The data being logged (detailed discussion in Chapter 5) with the app were well-defined and formed a schema, as they informed by the News Reader Typology in Chapter 3. The choice, therefore, of a relational database (RDBMS) over a NoSQL database was preferred. The database is completely structured, organised in tables that define the main entities of the application such as users, news reading, news navigation, context, questionnaires and others.

Another important decision that needed to be made for the database design was the use of stored procedures over hardcoded SQL statements in the application layer (presentation Habito News). The choice of stored procedures is reinforced by its nature to allow modular programming in which the emphasis is to separate the functionality of a program into independent and interchangeable modules, aligned with the three-tier architecture. Further, they allow faster execution, as they are pre-parsed statements checked syntactically and semantically thus reducing the time of execution. Finally, they can be used as a security mechanism in order to avoid any SQL injection vulnerabilities in the case of hardcoded SQL statements in the application.

In relation to users' sensitive data, anonymity was taken into consideration as passwords are hashed using an MD5 encryption method before being stored in the database. Location data is also treated as sensitive data and it will be explained further in detail in Chapter 5 in the section of feature extraction, how anonymity was ensured.

4.3 Discussion

This Chapter introduced the architecture of the framework that was used to address the research questions of this thesis. In particular, it presented a three-tier architecture that separates the presentation from the services and the data layer. The components of our framework aim to address questions relating to automatic detection and recognition of mobile news reading behaviour and the automatic generation of variant user interfaces and interactions that would suit different news reader types. Chapters 5 and 6 will discuss in detail the implementation of the User Modelling component and server side (Services layer) functionality as well as user interface components such as the adaptation mechanism and the variant user interfaces generation. Chapter 7 will present an evaluation study of Habito News in which all the components are being utilised in an attempt to demonstrate the application and examine the effectiveness of an adaptive mobile news app.

Chapter 5

User Modelling for Mobile News Reading Interactions

The previous Chapter outlined the architecture of the adaptive news research platform and presented its main components that facilitate the exploration of the overarching goal of this thesis.

This Chapter reports the construction and data acquisition of the User Modelling (UM) component, which is responsible for generating user models from users' interactions with Habito News. It presents studies wherein the app was deployed through Google Play ('in-the-wild'), and data analyses were performed in order to demonstrate the capability of automatically recognising patterns of news reading interactions and building models that are able to predict a user's news reader type, and subsequently, construct a user's profile.

The Chapter begins with presenting the data collection using Habito News app. In particular, it reports two deployment studies and discusses the data being collected. It then presents a hierarchical layered framework that was used to facilitate the analysis of those news reading interaction data collected from the app. The framework defines different levels of abstraction over the logged interaction data and incorporates knowledge from Chapter 3 (i.e. the news reading factors and the News Reader Typology - Section 3.5). The Chapter then explores two approaches of building user models; rule-based models and statistics-based models where the latter utilises machine learning algorithms. Finally, the exploitation of the user model in order to facilitate the automatic adaptation of Habito News app user interface is discussed.

The user model acquisition and the framework presented in this Chapter has appeared to UMAP ’18. (Constantinides, M., Dowell, J. A Framework for Interaction-driven User Modelling of Mobile News Reading Behaviour. In Proc. UMAP 2018.)

5.1 Motivation

This Chapter presents the development of the User Modelling component of the Adaptive News Research Platform. As discussed in Chapter 4, the User Modelling component is at the core of the platform and is responsible for the user model acquisition that will be used during the adaptation process. The Chapter seeks to investigate how behavioural data about user’s news reading interactions can be used to build a user model. In particular, it aims to address the research questions (RQ2 and RQ3 - Chapter 1). These are:

(a) “How can a smartphone app detect and learn individual patterns of news reading interactions?”

(b) “How can a smartphone news app exploit a user’s news reader profile to adapt its user interface and interaction?”

Motivated by people’s individual differences while reading news, this Chapter builds on and utilises the News Reader Typology proposed in Chapter 3 in order to propose a user modelling framework for mobile news reading interactions. The aim of the framework is to provide the methods and mechanisms for analysing and modelling news reading interactions in relation to the News Reader Typology. The Chapter explores different user model acquisitions and discusses how they can be exploited as part of the adaptive news research platform.

5.2 Data Collection with Habito News

As introduced in Chapter 4, we implemented a prototype Android mobile news reading app. called Habito News. Habito News’ baseline version served as the

Total number of downloads (users)	85
Mean and Std Age	M=29, SD= 5.58
Min and Max Age	Min=18, Max=47
Gender	Male=58, Female=27

Table 5.1: Statistics of the users who downloaded Habito News.

research tool to collect users' news reading interaction in order to be analysed and explore different approaches in generating the user model. Apart from delivering news stories using the BBC API, Habito News is also capable of logging low-level interaction data in relation to news reading behaviour. For example, the different interactions made while browsing (e.g. swipe left or right within a news category or scroll up and down to navigate across categories) news headlines or precise scroll positions while reading a news story (e.g. the offset of the Android View that user scrolled to or whether the scroll reached the end of the article). A full list of the low-level interaction data that was captured is provided in Table 5.3 and will be discussed further in Section 5.3 as part of the hierarchical framework.

5.2.1 Deployment studies and Participants

The first deployment study was conducted in 2014 (between April and September). A total of 31 participants (11 Female, Age: M=30, SD=3.94) downloaded and installed Habito News in their mobile devices. At the time the app was not listed on Google Play and participants were invited to download the app via email. The first version of the app was not capable of transmitting the data to our server, instead the device's SD card was used to store the data locally, and upon completion of the 2-week trial all users has sent the local files via email.

The second deployment study was conducted in 2016 (between June and November) to further increase the sample size. In addition a revamped version of the app was developed at the time of the second deployment. A total of 34 participants (11 Female, Age: M=29, SD=6.53) downloaded and used the newer version of the app. In the second deployment we released the app on Google Play [1] in which the improved version included features such as the automatic transmission

[1] Habito News: https://play.google.com/store/apps/details?id=com.ucl.newsreader&hl=en$_GB$

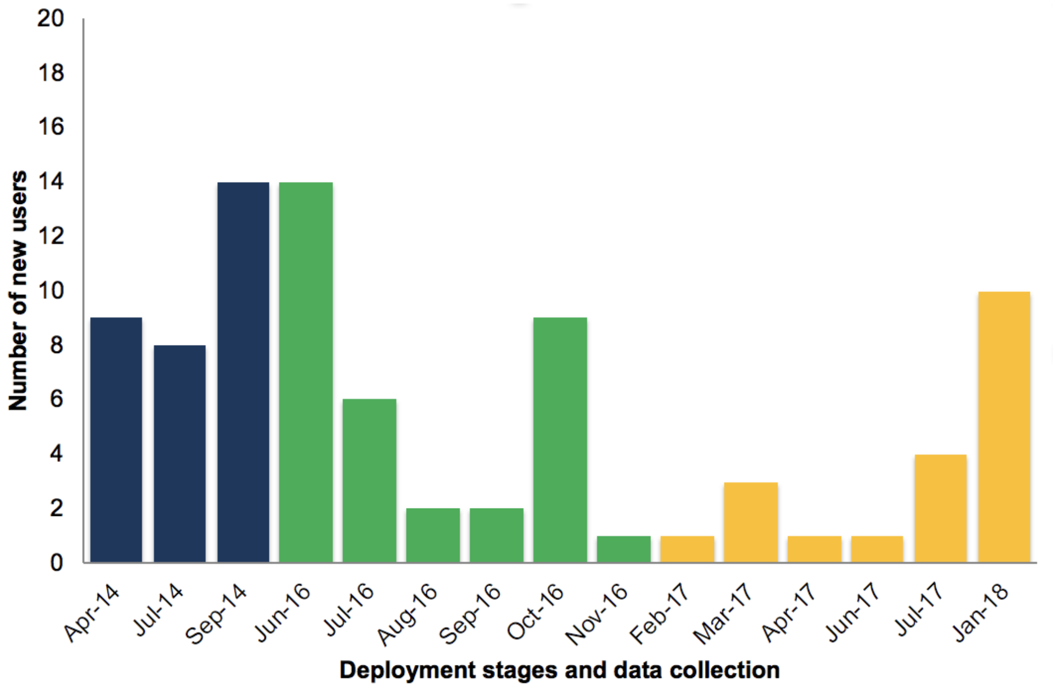


Figure 5.1: Deployment stages of Habito News and data collection (1st deployment in blue, 2nd in green and the 3rd in orange).

of the data to our server and a built-in questionnaire to collect participants' answers to those six questions relating to their news reading behaviour (as described in Chapter 3). During the six months that the app was publicly available it was kept up to date in line with updates on third-party API such as the BBC (e.g. parsing needed to change due to updates on the XML format of BBC API). There were also updates made to the Android platform and Google Play console (such as privacy policy statements) because the app had access to users' sensitive data. Participants were mainly recruited through university and social-network posts. Participants who were recruited through university posts (30 out of 34) entered a draw for a £50 Amazon voucher (Appendix A.2), whereas the rest who directly downloaded the app from the app store did not receive any compensation for their participation.

At the end of the second deployment we kept the app listed on Google Play with the aim of further increasing our data corpus. By January 2018, another 21 participants (5 Female, Age: M=27, SD=4.94) downloaded and signed up for Habito News. The final users' corpus is summarised in Table 5.1 and the deployments stages are depicted in Figure 5.1.

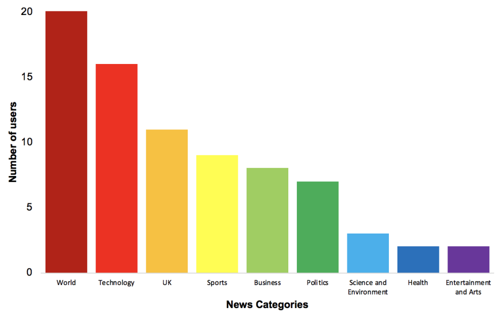


Figure 5.2: Number of users who read articles from different categories.

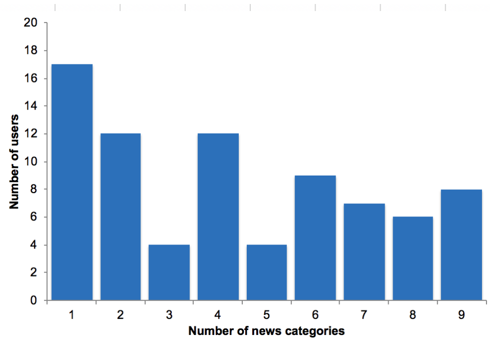


Figure 5.3: Number of users who read articles from unique categories.

The inclusion criteria for the two deployments as well as for everyone who directly downloaded the app from Google Play consisted of:

(a) Participants own an Android device running an operating system > 4.3

(b) Participants use the app as their primary news reading application for a period of 2-weeks

To ensure that participants used Habito News as their primary source, we logged the apps that were running in the background, while Habito News was open. At the same time we applied filters for the News & Magazines category to ensure privacy. We did not want to obtain any other information about users' running apps.

Of the eighty-five users who downloaded Habito News only seventy-three users are included in the descriptive statistical analysis presented in this section. Further data pruning was necessary as six users downloaded the app but did not use it at all, while another seven did not answer the six questions related to their news reading behaviour. The final dataset for the analysis included seventy-two users. Further data cleaning and pruning was required for the classification problem, but this will be discussed in Section 5.4.

5.2.2 Descriptive statistics on Habito News usage

A total of 1517 news articles were read through Habito News across nine news categories (Figures 5.2 and 5.3). The most popular news categories include World, Technology, UK and Sport. The UK category appeared in the most frequently be-

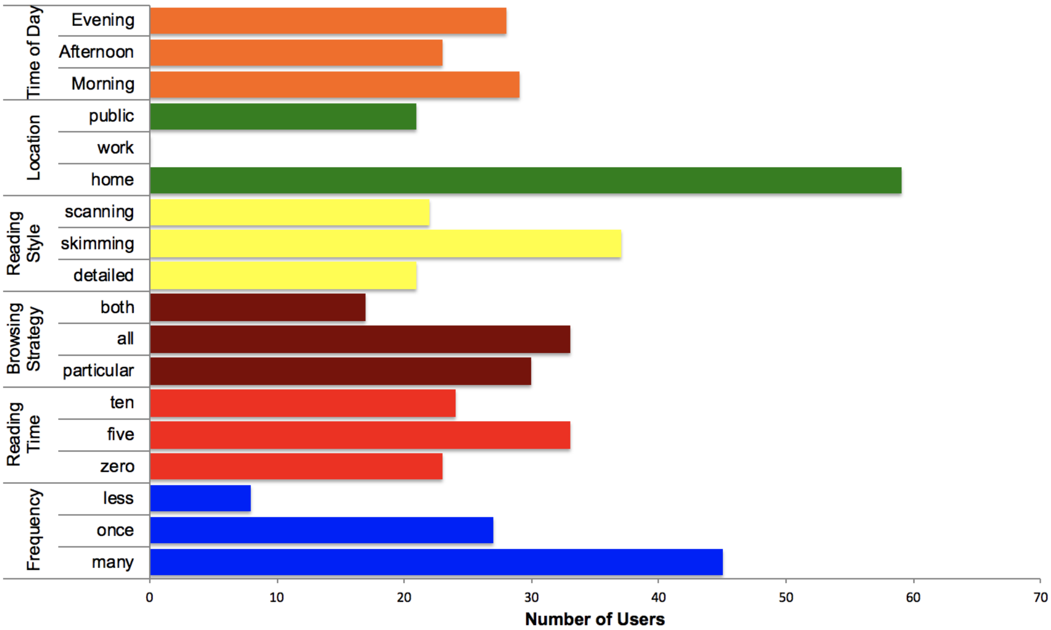


Figure 5.4: Distribution of users' answers to the six questions.

cause most participants were recruited from UK. Another interesting fact is that users on average chose to read articles from four or six unique categories, but there was also a large proportion of the sample who read just from one unique category.

5.2.3 Procedure

Upon download users signed up with Habito News. Before providing any data, users had to agree to a built-in consent (Appendix B.1) form disclosing the type of data that was being monitored as well as providing information relating to the setup of the study. The registration process consisted of two steps with data gathered using explicit methods through built-in questionnaires. Participants provided demographic information such as their age, gender and date of birth. They also answered six questions about their news reading behaviour. These six questions were originated from the News Reader Typology, as discussed in Chapter 3. The six questions along with the potential responses (users chose one answer for each question) are summarised in Table 5.2.

Figure 5.4 depicts how users responded to the six questions relating to their news reading behaviour. As can be observed, there is a tendency to read the news many times a day, throughout the day and their reading duration varied. With re-

S/N	Question	Possible Answer
1	How often do you read news on your mobile device?	(a) Many times a day (b) Once a day (c) Occasionally
2	How much time a typical day do you spend reading news on your mobile device?	(a) 0-5 minutes (b) 5-10 minutes (c) 10+ minutes
3	How do you most often look for stories of interest?	(a) Through all sections (b) In a particular section (c) Both techniques
4	How do you normally read a news story?	(a) Detailed reading (b) Skimming (c) Scanning
5	Where do you most often read news?	(a) Home (b) Work (c) Public Transport
6	What time of the day do you most usually read news?	(a) Morning (b) Afternoon (c) Evening

Table 5.2: Questions and possible answers related with news reading behaviour

gard to their browsing strategy and reading style, there was no dominant tendency between the two browsing strategies, whereas skimming reading style dominated the other two strategies. Regarding to the potential location of reading the news, there is a tendency to read at home and while they commute, as opposed to reading at work.

5.2.4 Low-level sensor and interaction data

In addition to delivering news, Habito News logged low-level interactions with the user interface in relation to the news reading activity.The choice of the low-level data was reinforced by the six reader factors that discriminate the News Reader

Data category	*Identifier*	*Description*
Navigation	Navigation Session	A unique identifier that indicates the navigation session
	Category Name	The category from which the user selected to read
	Order id	The order in which an article is selected within a session
	Swipe Direction	The swipe directions performed in each news category widget (e.g. left to right)
	Item Position	Article's position within the category (number 1-9)
Reading	Reading Session	A unique identifier that indicates the reading session
	Article id, name and URL	Information about the article
	Reading duration	Time in seconds that the user spent on reading an article
	Is Scroll used	Boolean value that indicates whether scroll was used while reading an article
	Scrolled end of the article	Boolean value that indicates whether the user scrolled until the end of the article
	Number of words per article	Number of words per article
	Scroll range and offset (precise scroll position)	Range: Scrollbar's total vertical range; Offset: Scrollbar's thumb vertical offset
Context	Context Session	A unique identifier that indicates the context session
	Latitude	Geographical coordinates
	Longitude	Geographical coordinates
	UserActivity and Activity Confidence Level	Google Activity Recognition API
	Running apps	App and package names as listed on Google Play

Table 5.3: Full list of logged sensor and interaction data with Habito News.

Typology (Chapter 3). We attempted to gather as much information as possible in terms of interactions by utilising different Android widgets and context related information through the devices' sensors. Table 5.3 lists the logged sensor and low-level interaction data.

5.3 A framework for analysing mobile news reading interactions

As discussed in Chapter 2, user profiles often contain a user's related information such as interests, knowledge, background and skills, goals and tasks (Brusilovsky and Millán, 2007). A domain-specific user profile for personalised news access will contain facts about a user's news interests (i.e. what news content they prefer to read) and facts about their news reading interaction patterns (i.e. how to access and interact with that content) (Figure 5.5). While many successful techniques for news recommendation (i.e. content-based, collaborative filtering or hybrid) have been developed (Hopfgartner and Jose, 2009; Liu et al., 2010; Gulla et al., 2014; Das et al., 2007; Billsus and Pazzani, 2007, 1999; Kazai et al., 2016), to the best of the author's knowledge, techniques for modelling users news reading interaction patterns have not been developed.

In Chapter 3, a News Reader Typology was defined that describes three news reader types, which are discriminated by interaction factors arising in the users news reading interaction behaviour. The proposed framework in this Chapter characterises the hierarchical relationship of these abstracted factors with data that can be captured from logging the user's interactions as well as their relationship with the three news reader types. The framework would then enable the analysis of mobile-sensing data in order to build the user profile.

The modelling approach aims to examine different techniques for the user model acquisition towards the same goal of inferring models of news reading interaction behaviour that will be used as the basis of delivering user interface adaptation. In particular, we examine two techniques as follows:

(a) Predict a user's news reader type (i.e., Tracker, Reviewer, Dipper)

(b) Build a user profile consisting of the six news reader factors

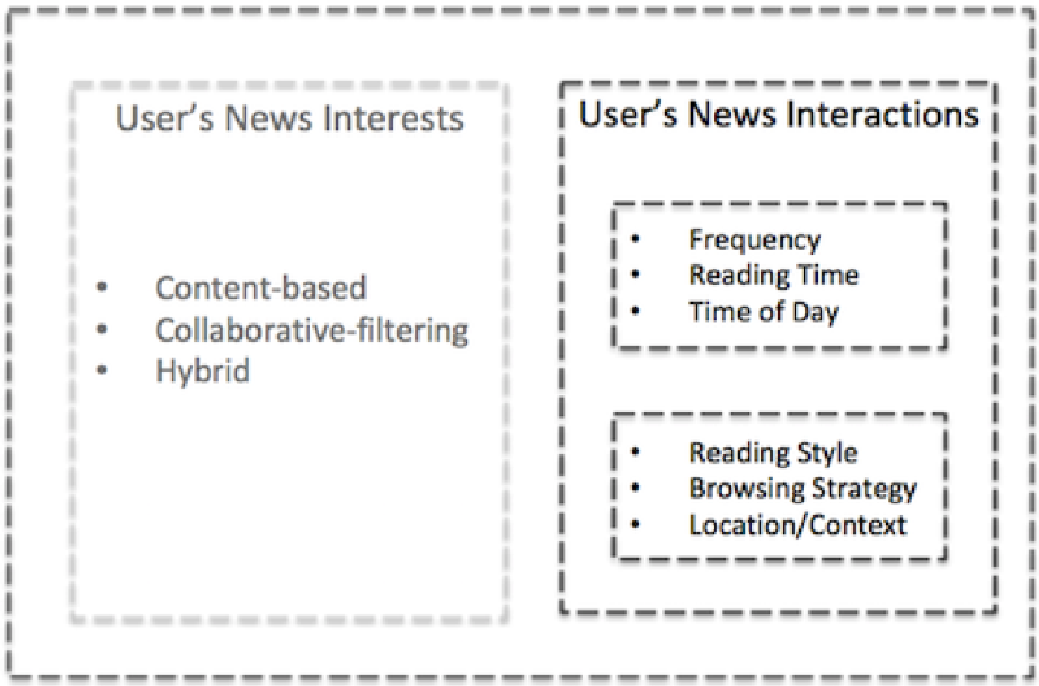


Figure 5.5: A conceptual diagram of a user profile for personalised news access. (left) A user profile that consists of users news interests (e.g. article preference) (right) A user profile that consists of users news reading interactions (e.g. reading style).

The framework characterises the raw interaction and sensor data collected from users' interactions with the news app and the layers of abstraction over the data that constitutes the user model, achieved by both bottom up and top down approaches. A similar layered hierarchical framework has been proposed by Mohr et al. (2017) to support the monitoring of the mental health of at-risk people from their low level interactions with their mobile phones. To the best of author's knowledge, such framework has never been proposed in analysing news reading interactions. The framework is fundamental to address the RQ2 and RQ3 (described in Section 5.1), as it enriches low-level interactions with high-level constructs of news reading behaviour. The framework consists of four layers (Figure 5.6). Layer 1 consists of low-level values related with sensors data and news reading interactions (e.g. GPS coordinates, scroll positions). Layer 2 defines functions for extraction and aggregation of raw data into low-level features. By doing so, we extract meaningful information from the raw data (e.g. daily reading sessions, swipes directions). Layer

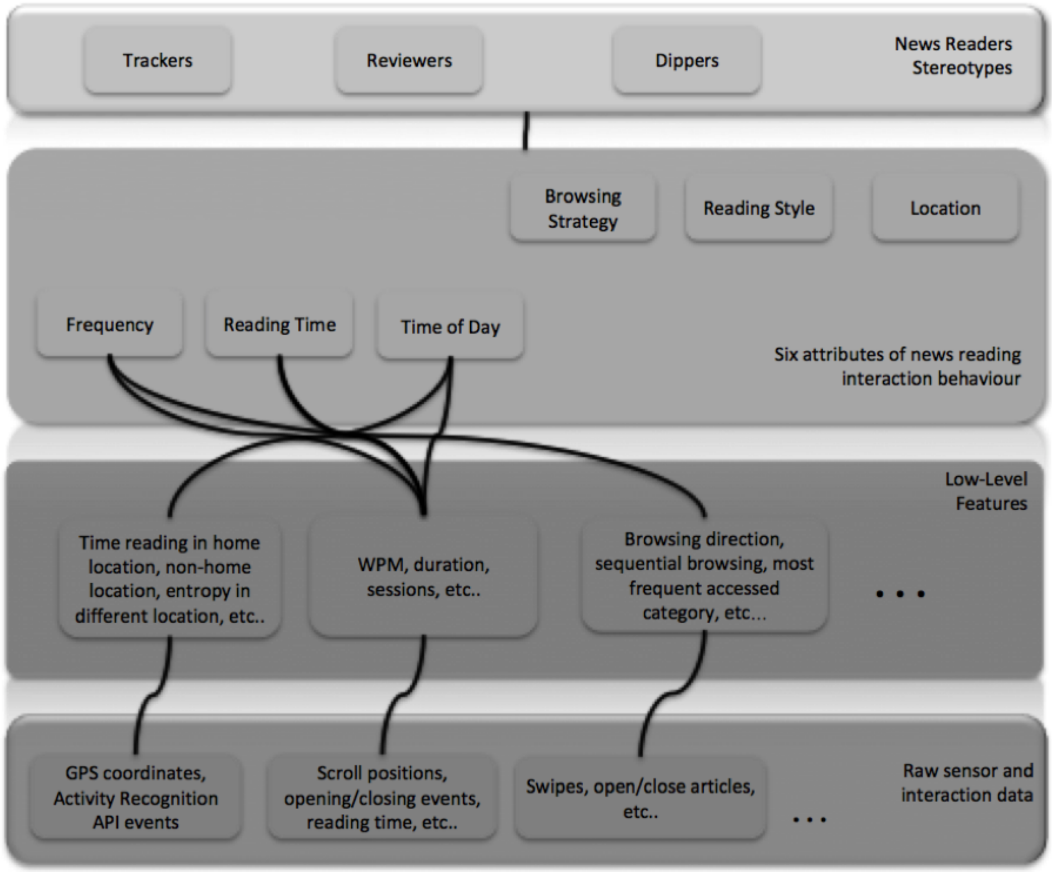


Figure 5.6: Mobile-sensing framework for analysing news reading behaviour.

3 defines transformation functions of low-level features into the six factors of news reading interaction behaviour. Layer 4 integrates the News Reader Typology into the framework. The framework defines the layers in relation to users' patterns of news consumption rather than the news content they consume.

5.3.1 Layer 1: Raw interaction data

Layer 1 defines the raw sensor data and low-level news reading interaction data collected using our prototype news app. The app logged different interactions made while reading articles, browsing to choose articles and context related data through the devices sensors. For example, a number of low-level events related with scroll positions that can determine how the user read an article, the trajectory of swipes and navigation behaviour for choosing articles to read. The app also utilised location services of the device as well as the Google's Activity Recognition API that allowed us to capture whether the phone was still or moving while reading.

5.3.2 Layer 2: Low-level features

Layer 2 of the hierarchical framework adds information to the low-level behaviourial and sensor data. It defines functions for extraction and aggregation of raw data into low-level features. For example, the different articles read on a day are aggregated into a low-level feature of number of daily articles read. The feature engineering is structured around three categories of features; the Reading, the Navigation and the Context related features.

5.3.2.1 Feature Extraction

The low-level features were chosen with the aim of revealing all aspects of news reading behaviour according with the six factors. All the features were aggregated on a daily level. Additionally, intra-daily features were computed, dividing a day into three periods (Morning: 4-11 TW1, Afternoon: 12-19 TW2 and Evening: 20-3 TW3). A Boolean value was also extracted that indicates whether a date falls into weekend or not. Combining all features (including the Boolean value of isWeekend), a set of 103 features was extracted.

5.3.2.2 Reading Features

Reading features refer to data relating to how users perform the reading task. We computed unique reading sessions, the number of unique articles read, articles that were read more than once, reading duration, the number of articles in which scroll was used, the number of articles that were read in whole (computed using scroll reaching the end of the window). We also computed spikes in reading that could be an indication whether they followed a constant reading fast scroll up and down vs. constant ascending scrolling, and words per minute in terms of how much of the article was exposed to the user divided by how much time was required to read it (min, max, mean, median and std were computed for these features). For all reading features we computed one value for their overall daily behaviour as well as three more values for the intra-daily behaviour, which resulted in 30 reading features.

5.3.2.3 Navigation Features

Navigation features refer to data relating to how users navigated and chose news stories to read. We computed unique navigation sessions, total news categories browsed, number of news categories in which all headlines were browsed (we use number of swipes of direction in order to find whether a user browsed all headlines of a particular category), number of non-sequential and sequential navigation (i.e. the trajectory of user's browsing across categories - e.g. a. [1, 3, 7, 2, 4]→non-sequential or b. [1, 4, 8 or 9, 7, 2]→sequential numbers indicate the category id), number of swipes left, number of swipes right, total number of swipes, time spent in browsing headlines, most frequent news story reached across categories. The final navigation features set including the overall daily and intra-daily values resulting in 40 features.

5.3.2.4 Context Features

Context features refer to data related mainly with users' location while they were accessing the news. We treated location as sensitive user data, thus we further pre-processed all location related data. All locations were obfuscated with unique identifiers (UUID) and a new identifier was generated if two locations were more than 10m away. By doing so, we ensure that users' location data will not be exposed to the researcher who performed the analysis. Further, data pre-processing consisted of determining a possible Home location for each individual. To compute the home location, we took the two most frequently appearing identifiers in TW1 and TW3 (in this case 5am-9am for TW1 and 10pm-4am for TW3) for each user session, under the assumption that people are more likely to be at their homes during those time intervals. Then, the most frequent identifier of the two was marked as home and subsequently all of a user's entries were marked as home or non-home locations.

The context features list consisted of unique context sessions, time reading at home and non-home location daily, ratio of time reading at home over non-home location, total movements while reading, entropy at non- home location (as a measure of the temporal dispersion of locations), entropy of different locations visited while reading throughout the day. Again, the final context features list including daily and intra-daily values resulted in 32 features.

5.3.3 Layer 3: The six factors

Our user modelling approach aims to build a user profile that consists of the six factors that reflect a user's news reading interaction behaviour. As might be seen, the factors of Frequency, Reading Time and Time of Day can be directly computed from users' usage of the news app without the need for a learning process. For example, one can track the sessions of opening/closing the app and compute whether a user is a frequent news reader or not. However, the factors of reading style, browsing strategy and location/context are more high-level behaviours and more complicated constructs to determine. We explain in Section 4 the different approaches in inferring, computing and learning these factors. The factors are defined as follows:

- Frequency: How often users read the news(many times a day, once a day or occasionally)
- Reading Time: The average daily time spent on reading the news(0-5 minutes, 5-10 minutes, or 10+ minutes)
- Time of Day: The period of the day when the user usually reads the news (morning, afternoon or evening)
- Reading Style: How people read a selected news article (i.e. detailed reading, skimming or scanning)
- Browsing Strategy: How people browse headlines and select news stories (i.e. scan headlines in a particular section, navigate through all sections)
- Location/Context: Where people read the news (at home, at work, public)

Having introduced the mechanisms to transform the raw sensor data and users' interactions into low-level features, Layer 3 defines functions that can transform the low-level features into the six factors that describe news reading behaviour. As previously explained the factors of Frequency, Reading Time and Time of Day can be directly computed from low- level features. The factors of Reading Style, Browsing

Strategy and Location/Context are more complicated but we defined transformation functions for this set of factors and as one of the approaches we examined making use of them.

5.3.3.1 Transformation Functions to compute Frequency, Reading Time and Time of Day

- 'Frequency': We aggregate the number of reading sessions on a daily basis to determine the frequency of reading. For example, if two or more reading sessions appear on the log of one particular day then we mark it as 'many times a day'.

- 'Reading Time': We compute the average daily reading time low-level feature and accordingly we mark it as 0-5 minutes, 5- 10 minutes or 10+ minutes.

- 'Time of Day': We compute the time spent in reading in the three time windows (TW1, TW2, TW3) and then we assign accordingly the output as 'Morning', 'Afternoon', and 'Evening' using the highest value among the three time windows.

5.3.3.2 Transformation Functions to compute Browsing Strategy, Reading Style and Location/Context

These factors involve interpretations of behaviour and therefore cannot be computed simply by aggregation over low-level features. The functions we created to compute these factors inevitably make several assumptions and simplifications. This section summarises those functions and explains the heuristics applied in each function.

- 'Reading Style': We estimate the user's pace of reading in words per minute (wpm) from approximating how much text of the article was exposed by the users scrolling actions and the period during which the article was opened. Different reading styles are associated with different speeds of reading: detailed reading as speeds up to 230 wpm; scan reading as speeds over 700 wpm, and; skim reading as speeds in between. The different reading styles were defined in Section 2.3.1.

- 'Browsing Strategy': We use low-level features such as the number of different categories of headlines browsed and the number of times headlines were browsed in a day as well as the total number of headlines categories browsed. We compute two ratios: (a) categories in which all headlines were browsed over different sessions which indicates whether a user has a preferred category, and (b) unique categories browsed over unique navigation sessions which indicates whether a user accesses most of the categories available. Given the nine news categories present in the news app we set a threshold for particular category browsing as 1 and for browsing through all categories as 6. Given the two ratios and the thresholds then a rule-based algorithm produces three possible outputs (a) 'both', meaning that the user on different occasions either only reads articles in a selected category or categories, and at other times chooses to view articles in all categories, (b) 'particular', meaning that the user navigates only in particular categories, and (c) 'all', meaning that the user navigates most of the cases through all categories.

- 'Location': A rule-based algorithm is used to determine whether the user is reading the news at home or in a non- home location. A location where the user spends more time than any other specific location is designated as home. The inference is modified by the time at which the news is read making the assumption that most people are at work in the second time window. We use entropy of location to describe the variability in different locations, meaning that if the user has a high entropy they are more likely to be in a public setting, while low entropy indicates a work environment.

5.3.4 Layer 4: News Reader Types

Layer 4 integrates the News Reader Typology from our previous work into the framework. It is used by one of the approaches we take to building the user profile through making inferences about the high-level behaviourial factors as an alternative to computing them directly from the low-level features.

5.4 User Model Acquisition

Having defined a framework that characterises the hierarchical relationship of the six abstracted factors with the low-level interaction data that was captured from logging the user's interactions, we explore, in this section, two user model acquisition techniques. The aim is to infer models from the interaction behaviour that will be used as the basis of the user interface adaptation. In this section, we report two different techniques towards this goals. First, we attempt to predict a user's news reader type (i.e. Tracker, Reviewer, Dipper) and secondly we aim to build a user profile that consists of the six news reader factors.

5.4.1 Data Pre-processing

Before exploring the two techniques we examine the ground-truth information that was used to evaluate our models and describe the data pre-processing that was conducted to prepare the datasets for the analysis. As explained in the Section 5.2, users provided answers to six questions in relation to their news reading behaviour during the registration phase with Habito News. Those questions originated from the News Reader Typology and were used as the ground truth information. In the rule-based approach those questions used to validate the algorithm, whereas in the supervised learning method used to train the algorithm. Furthermore, we used a label for each user that was derived from the six answers to evaluate the first technique (i.e. predicting a user's news reader type), whereas we used the exact answers to those six questions to evaluate the second technique (i.e. building a user profile that consists of the six news reader factors).

5.4.1.1 Target variable

The target variable in the first technique was the user's news reader type. Given the six answers to those questions we implemented a function (Algorithm 1) that uses Cosine Similarity to derive a label for each user. The Cosine Similarity function is a measure of similarity between two vectors derived from the cosine of the angle between them.

To extract the label we converted users' answers to the six questions into a complete logical coding using binary encoding. Therefore, for each reading factor we computed a binary vector (length=3) that corresponds to the possible values one could assign to each factor (e.g. Frequency factor (a) many times a day, (b) once a day, (c) occasionally) 5.2. Given the six reading factors and the three possible values that can be assigned to each factor, each users answers were converted into a binary vector (length=18). Similar transformation was conducted in the three news reader types, as defined in Chapter 3. This yielded three binary vectors, one for each news reader type. To compute then the label we used our function that relies on the Cosine Similarity. We estimated the cosine similarity between each user's binary vector and the three news reader types binary vectors. The label was then assigned to each user using the higher cosine similarity amongst the three vectors.

Algorithm 1 Convert six answers to a label

```
Input: answers [] = Answers A_n {n: (i) to (vi) answers}
Output: label = {Tracker | Reviewer | Dipper}
function ConvertSixAnswersToLabel(answers[])
    binary_answers ← []
    T_vector ← binary vector of Tracker
    R_vector ← binary vector of Reviewer
    D_vector ← binary vector of Dipper
    for answer in answers do
        coded_answer = code_binary(answer)
        binary_answers.append(coded_answer)
    cs_Trackers ← cosine_similarity(binary_answers, T_vector)
    cs_Reviewers ← cosine_similarity(binary_answers, R_vector)
    cs_Dippers ← cosine_similarity(binary_answers, D_vector)
    label ← max (cs_Trackers, cs_Reviewers, cs_Dippers)
    return label
```

5.4.1.2 Data Imputation and Cleaning

When it comes to mobile sensing data, the missing values represents a common problem. Despite the fact that Habito News was designed in such a way to minimise this problem, our dataset suffered from missing values. For example, it prompted the user to enable location services in order not to miss context related values. However, nothing could have been done for the other two categories of data as we did not want to intervene and force people to read under given instructions but rather let them perform it at their own pace and when they had the need to read the news. Therefore, there are cases in our dataset where values for some categories are missing (e.g. navigation is missing due to the user reading a few articles without performing any browsing). Contrary to other mobile-sensing data (e.g. proximity sensor, accelerometer, etc.), where common imputation strategies can be applied (such as inserting mean values if some of the data is present), for the these categories of data (i.e. navigation and reading) we could not apply it. Thus, the initial 72 users dataset reduced down to 42.

Apart from missing values, further data pruning was carried out in order to eliminate users with one-day usage. In particular the cleaned dataset of 42 users reduced down to 33 users. We treated this set of users as outliers as their behaviour could have added noise to the data due to them having downloaded the app and then after a day's usage opted-out. Therefore, we applied the feature extraction methods (from the framework), as discussed in Section 5.3.2 and this yielded 198 daily datapoints of those 33 users. This is the final dataset that will be used for the modelling techniques.

5.4.2 Identification of the three types through clustering

Before addressing the two fundamental questions (i.e. predicting a user's news reader type and building a user profile consisting of the six reading factors), this section reports a preliminary analysis in which we aimed to identify the three news reader types in the behavioural interaction data through clustering. By showing that the three news reader types can be found in the data we can then move to train models that are capable of predicting such types.

We conducted the analysis in three steps:

(a) Extract the low-level features (Layer 2 of the framework)

(b) Transform low-level features into high-level markers (Layer 3 of the framework)

(c) Cluster high-level markers (dataset formed from the previous step)

Reading factors	*Cluster 0*	*Cluster 1*	*Cluster 2*
Frequency	Once a day	Occasionally	Many times a day
Reading duration	0-5 min	0-5 min	5-10 min
Browsing strategy	Both	Particular section	Particular section
Reading style	Scanning Detailed reading	Scanning	Scanning Skimming
Location	All locations	Home/Work	Public Transport
Time of Day	Evening	Morning	Morning Evening

Table 5.4: Emerged clusters from behaviourial data.

First, we extracted the low-level daily reading, navigation and context features for each user as described in the Layer 2 of the framework (Section 5.3.2). Second, we transformed the low-level features into high- level markers (Layer 3 of the framework - Section 5.3.3) for each day of logging. An intermediate step was performed by aggregating their daily data into single values that represented user's behaviour for the whole period of the trial (i.e. two weeks). Therefore, the resulting dataset consisted of 33 users' averaged high-level markers (e.g. F1,.., FN:, where n = factor(s) described in the high- level transformation section). Thirdly, we ran a clustering method over the high-level markers to determine whether the three categories can be found in users' behavioural data.

Due to the fact that the high-level factors are categorical data we used a k-modes algorithm, a variation of k-means, as it uses simple matching dissimilarity measure (the notion of 'distance', for each data point and each centroid, is defined as the number of factors that are not the same) instead of Euclidean distance that is used by k-means. The k-means variation algorithm was preferred due to the prior knowledge (Chapter 3) in which 3 news reader types where identified. A cross tabulation method was then used to examine the distribution of the six factors over the three clusters. We then performed a post-hoc interpretation of the crosstabs (Table 5.4) in which we attempted to associate the emerging clusters with the canonical forms of the News Reader Typology.

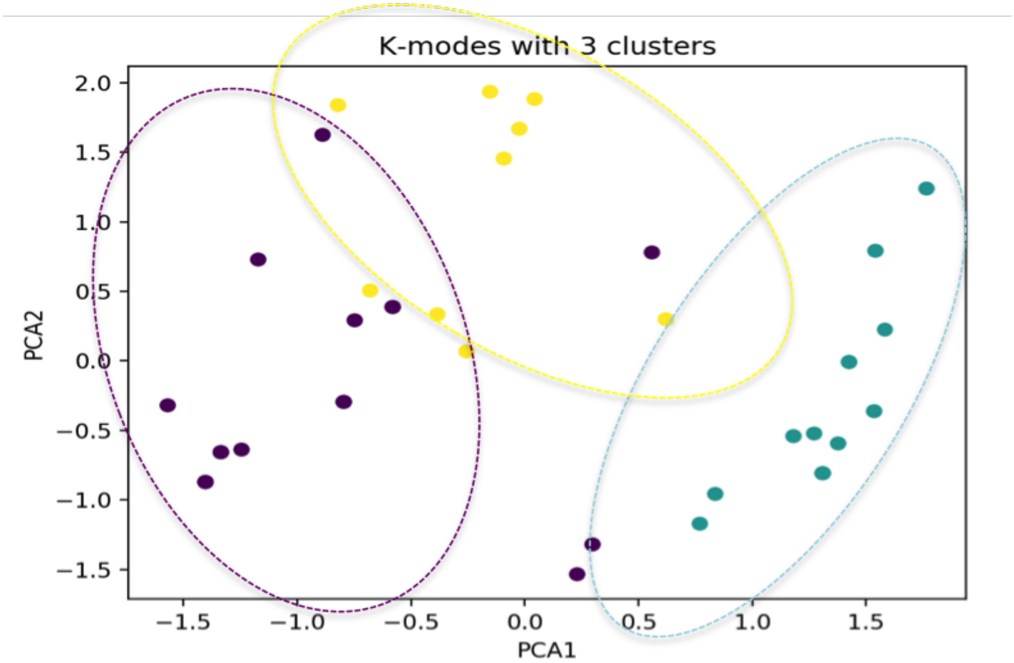


Figure 5.7: The two components explain 57.74% of point variability.

Table 5.4 shows the three clusters emerged from the behavioural data. At this point, we attempt to post-hoc interpret the emerged clusters having as a reference point the News Reader Typology that was proposed in Section 3.4 (Chapter 3). A Dippers type can be found purely in the behavioural data, as there is a one-to-one match. The Reviewers type differs only in two factors (Reading Time and Browsing Strategy), whereas Trackers differ on Browsing Strategy only. Therefore, Cluster 0 is more likely to be Reviewers, Cluster 1 to be Dippers, and Cluster 2 to be Trackers. Another interesting insight is that the factor of Frequency is found to be a strong discriminator of the three clusters as opposed to other factors, which discriminate one or two out of the three clusters. However, subsequent analysis showed that users behavioural data (see next section) was not normally distributed among the values of each factor. For example, no 10+ minutes class was found for the factor of Reading Time, with the majority of users behaving/reading news in 0-5 minutes. Figure 5.7 shows a visual of the three clusters after PCA dimensionality reduction in order to be plotted in a 2d space.

5.4.3 Classification Agent: Predicting a user's news reader type

As there were indications from the clustering analysis that the three news reader types were possible to be detected in the behaviourial data, the next part of the analysis focuses on building a classification agent that is capable of predicting a user's news reader type. As mentioned in Section 5.4.1.1 the ground information used to train the classifier originated from users' answers to the six questions related to their news reading behaviour. In addition to this source of ground truth, we examined another source of ground truth in which experts labelled the behaviourial data.

We implemented two types of models, namely *personalised* and *generic*. For testing the generic model, the cross-validation was performed by leaving one user out (i.e. leaving out all the instances that belong to the test user). In this way, a generic model correspond to a model that in practice would not require any prior information (i.e. training samples) about a user in order to predict their news reading type. On the other hand, in order to evaluate the personalised model we applied cross-validation by leaving one daily instance out, i.e., in the training set we were keeping all the available points from the other users as well as the test user except a test (daily) point for the test user. In practice, developing such model (referred to as personalised) would require some prior knowledge about the user, e.g. requiring a user's data for a few days and labelling news reading type before the model can be developed.

5.4.3.1 Target variable label using survey responses

At first, we developed a personalised model, for predicting the user's news reader type by mapping the extracted daily features to the classes defined from their answers to those six questions (i.e. extract the target variable Section 5.4.1.1).We implemented a Random Forest (Breiman, 2001) algorithm as it is proven to work well with small datasets. In addition, other algorithms have been tested such as Multinomial Logistic Regression, SVM, Decision Tree, but Random Forest outperformed them, thus the choice of Random Forest. The hyperparameters used were 100 estimators, 42 for random state and class weight was set to balanced that automatically

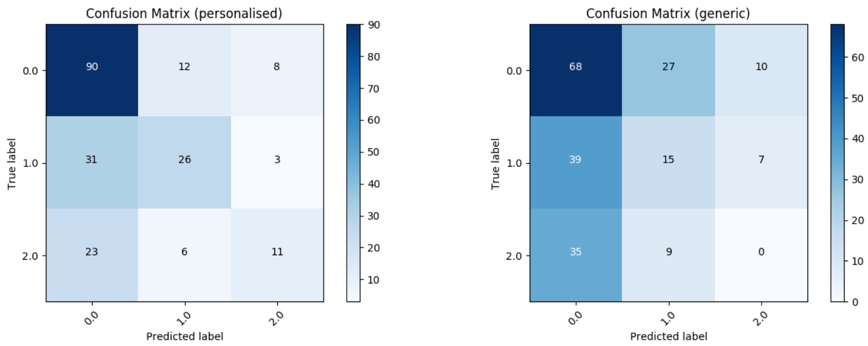


Figure 5.8: Averaged of 10-fold validation confusion matrices for the two approaches *using the label from users' responses to the questionnaire*. Left, shows the personalised model and Right, shows the generic model. (0 label corresponds to Trackers, 1 corresponds to Reviewers, and 2 corresponds to Dippers.

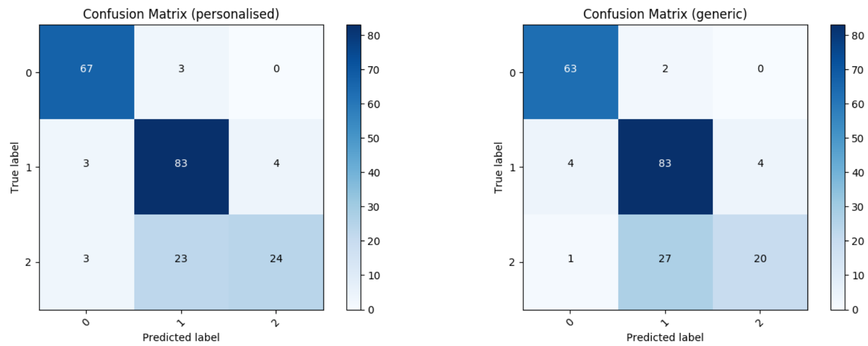


Figure 5.9: Averaged of 10-fold validation confusion matrices for the two approaches *using the label from the expert labelling*. Left, shows the personalised model and Right, shows the generic model. (0 label corresponds to Trackers, 1 corresponds to Reviewers, and 2 corresponds to Dippers.

adjust weights inversely proportional to class frequencies.

Random Forest resulted an overall accuracy of 59.04% (precision of 57.36%, recall of 58.57% and F1-score of 56.56%) (Figure 5.8 - Left), having an unbalanced dataset of distributions amongst the three classes as: Trackers 51%, Reviewers 28% and Dippers 21% (Table 5.5). We cross-validated the model (k-fold, k=10), as explained above, by leaving one instance out. Given the unbalanced dataset a good baseline model can be considered the majority class in the distribution amongst the classes. In this case the baseline model was set to the Trackers class (i.e. 51%). Although the overall accuracy outperforms the baseline model, this model cannot be deployable. In addition to the personalised model, we developed a generic model that was validated by leaving one user instance out from the cross-validation. The

Class	*Label* *Answers to six questions*	*Label* *Expert labelling*
Trackers	51%	31%
Reviewers	28%	46%
Dippers	21%	23%

Table 5.5: Baseline model. Distribution of the three classes.

accuracy has significantly dropped with poor performance of an overall accuracy of 39.52% (precision of 32.48%, recall of 39.52% and F1-score of 35.31%) (Figure 5.8 - Right).

Therefore, this method of labelling the data yielded models that slightly outperform the baseline (personalised model) and a model that performed worse than the baseline (generic model). The next section discuss an alternative way of labelling the data and re-training the models.

5.4.3.2 Target variable label using expert labelling

As both models did not work using the label derived from users' responses to the questionnaire, we examined an alternative labelling technique of the target variable (i.e., the label that indicates the news reader type). The expert labelling was conducted by 2 researchers independently. First, we explained the definitions of the News Reader Typology (i.e. the characteristics of each news reader type). Second, we provided the daily high-level behavioural data (in the form of F_1, .. , F_N: where F: reader factor) and their task was to provide a label for each row. Then this label was assigned accordingly on the low-level features. In the end the 2 researchers discussed the rationale behind their labelling and resolved any inconsistencies.

First, we developed a personalised model (Random Forest with same hypermeters as previously) using the labels form expert labelling this time. The distributions of the labels significantly improved with Trackers 31%, Reviewers 46% and Dippers 23% (Table 5.5) based on expert labelling. The new model resulted an overall accuracy of 82.85% (precision of 83.63%, recall of 82.85% and F1-score of 81.63%) (Figure 5.9 - Left). Same k-fold (k=10) validation was performed for this model by leaving one instance out (personalised model). Additionally to the personalised model, we also implemented a generic model, using the dataset with

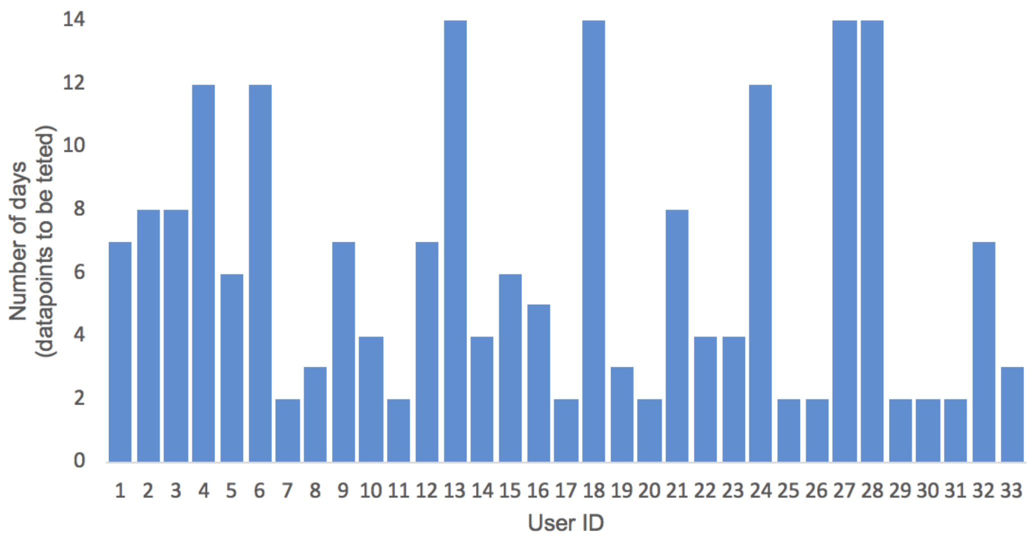


Figure 5.10: Generic model: Number of days required in order to learn to make predictions for user's news reader type.

expert labelling, in which the k-fold (k=number of users) validation was performed by leaving one user, meaning that the model can make predictions without having any prior knowledge about a particular user. Similar performance was observed in this model with an average accuracy of 81.37% (precision of 82.18%, recall of 81.37% and F1-score of 79.73%) (Figure 5.9 - Right) amongst all users, suggesting that our model can indeed predict a user's news reader type. Both models using the expert labelling outperformed the baseline model (Table 5.5) and yielded acceptable degrees of accuracies, which means that the models can be deployable. The generic model, therefore, was used in the app during the final evaluation study (Chapter 7) in which the validation was performed by completely leaving one user out, which in turn indicates that the real system does not require any user's knowledge beforehand, as opposed to the personalised model.

Another interesting insight that can be drawn from this analysis is the number of days required for the model to make a 'good enough' prediction. We selected users in which their accuracy was close (3-4%) to the average accuracy. We took the average of users' (20 out 33, 60% of the population) data points (days in which they produced interaction data) and resulted to 5.9 ˜6 days (Figure 5.10), meaning that in one week our model can make good enough predictions. Further, we examined

Factor	*Values*	*Distribution*
Reading Style	detailed	27.28%
	skimming	31.30%
	scanning	41.42%
Browsing Strategy	particular	28.79%
	all	49.49%
	both	21.72%
Location/Context	home	80.81%
	public	19.19%

Table 5.6: Distribution of the ground truth information for each reader factor.

the user (userID #28) in which the model performed badly (accuracy around 35% - Figure **??**) and we found that she used the app for the whole period of the trial (i.e. 14 days).

5.4.4 Classification Agent: Building a user profile with the six factors

The second approach of our user model acquisition aims to build a user profile that consists of the six discriminating factors. Although the previous model of predicting a user's news reader type performed with a good level of accuracy, we aimed to further examine the behaviourial interaction data and model the individual interaction factors.

The interaction factors of Frequency, Reading Time and Time of Day were computed directly from the low-level features using the transformation functions provided in Layer 2 of the framework. To model the interaction factors of Reading Style, Browsing Strategy and Location/Context we explored three approaches, (a) and (b) are rule-based approaches and (c) is a statistics-based approach:

(a) Inferences from the News Reader Typology

(b) Use of the transformation functions of Layer 3 of the framework

(c) Supervised machine learning method

Reader Factor	*Inferences from the Typology*	*Transformation functions*	*Supervised Learning*
Reading Style	36.36%	51.02%	59.5% (F1-score 58.72%)
Browsing Strategy	42.42%	24.74%	54.5% (F1-score 50.85%)
Location/Context	45.95%	36.86%	78.5% (F1-score 71.19%)

Table 5.7: Performance of inferring, computing and learning the three behaviourial factors. For inferences and computation cosine similarity was used, and accuracy for learning.

5.4.4.1 Inferences from the News Reader Typology

Given the computed factors of the Frequency, Reading Time and Time of Day, we derived the other three factors from the typology (Chapter 3) based on the characteristics of the stereotypical profiles. To derive Reading Style we used frequency and reading time, we used frequency for Browsing Strategy and we used frequency and time of day for Location/Context. The idea here is to use the prior knowledge (i.e., the News Reader Typology) to infer the labels for the factors of reading style, browsing strategy and location/context that cannot be computed directly. For example, the typology defines skimming as the reading style of a news reader type who reads the news many times a day. Likewise, it defines 'looking for particular section' as a browsing strategy of a news reader who reads the news occasionally. Table 5.7 shows the performance in inferring the three behaviourial factors.

5.4.4.2 Use of the transformation functions

The second approach we explored, made use of the transformation functions that are defined in Layer 3 of the framework to compute the factors of reading style, browsing strategy and location/context (Section 5.3.3.2). For example, to compute reading style we made the assumption that words per minute can be an indication of the pace while reading, and in turn can distinguish the different reading strategies (i.e. reading for comprehension from scanning or skimming). At first glance it may seem straightforward, but the factor of reading style might be more complicated and depend on other variables than simply words per minute.

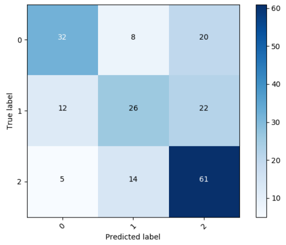


Figure 5.11: Confusion Matrix (Reading Style).

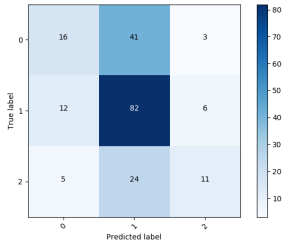


Figure 5.12: Confusion Matrix (Browsing Strategy).

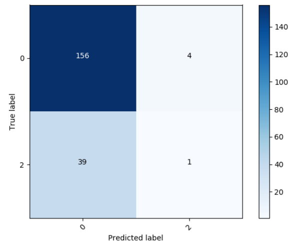


Figure 5.13: Confusion Matrix (Location/-Context).

5.4.4.3 Performance of rule-based approaches

We used a Cosine Similarity function in which we transformed the output of the derived (approach a) and computed (approach b) behaviourial factors into binary vectors and compared them with binary vectors of the ground truth. Table 5.7 shows the accuracy in computing the three behaviourial factors. The accuracies were below the baseline models except for the reading style that was computed using the function provided by the framework. For the location/context factor both algorithms completely failed. A possible explanation for that is the fact that these behaviourial factors might depend on different variables that the rule-based approaches failed to capture, and thus we examine a learning method in the next section.

5.4.4.4 Supervised learning method

Given that the results produced by the rule-based approaches did not outperform the baseline models for each factor, in the third approach we examined the use of a supervised machine learning method with the low-level features set as input, allowing the algorithm to learn and detect any hidden structure and associations between the low-level behaviourial features and the high-level factors.

We trained three Random Forest classifiers, one for each individual factor. The choice of Randrom Forest was informed by the fairly small dataset used to train the algorithm, as it is recognised for its accuracy and its ability to deal with small sample sizes. We tuned each individual classifier with 500 estimators (trees) and due to the imbalanced datasets we used a balanced class weight mode that automatically adjusts the weights inversely proportional to the classes distributions. To avoid over-

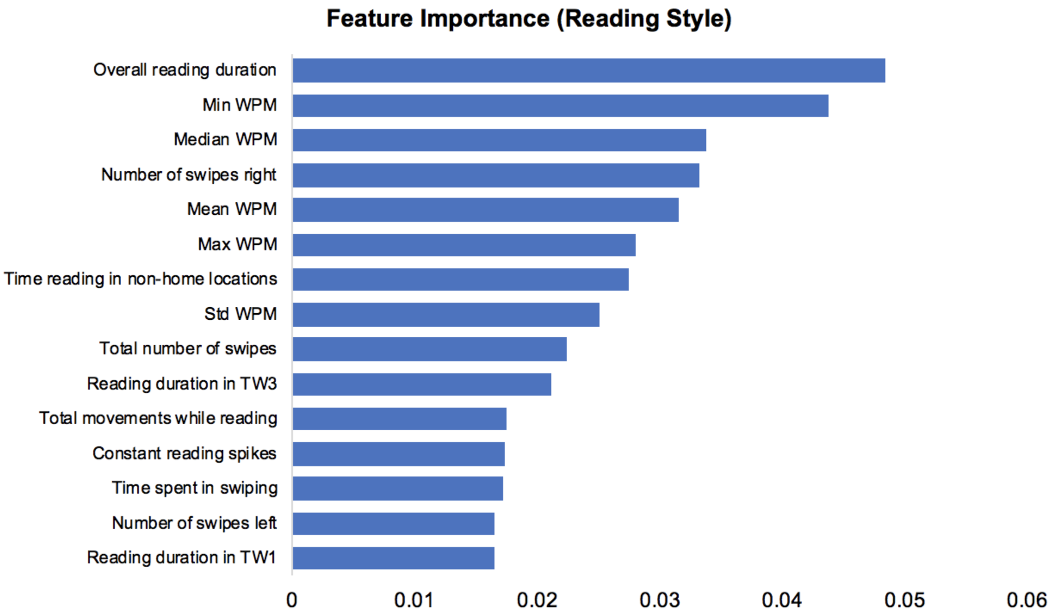
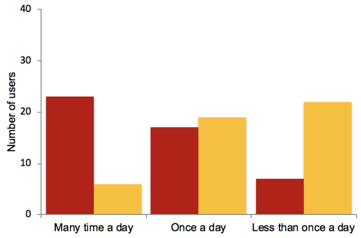


Figure 5.14: Most predictive features of the Reading Style classifier.

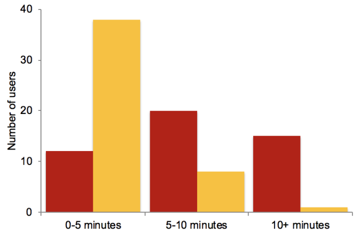
fitting of the algorithms, we ran a k-fold (k=10) validation by leaving one instance out. Table 5.7 shows the performance in learning the three behavioural factors and the confusion matrices for each predicted factor are shown in Figures 5.11, 5.12, and 5.13.

The learning method produced better results compared to the rule-based approaches, as all three learnt behaviourial factors exceeded the baseline values. The browsing strategy improved by 12.08%, reading style by 23.14% and location/context by 32.55% compared to the inferences approach. Further, the browsing strategy improved by 29.76%, reading style by 8.48% and location/context by 41.64% compared to the accuracies observed using the transformation functions.

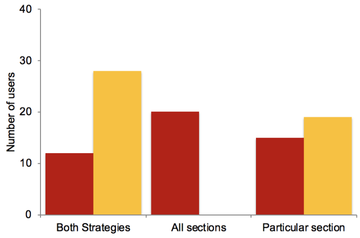
Another important insight that can be drawn from the learning method is the features' importance, which can be used to inform the heuristics and the design/refinement of the transformation functions or lead to better understanding of the behavioural factors. For example, the current transformation function of reading style (Section 5.3.3.2) uses an approximation of the words per minute. Among the 15 most predictive features (Figure 5.14) of the Reading Style classifier were the different statistics for wpm (max, min, median, std) and daily reading time, which



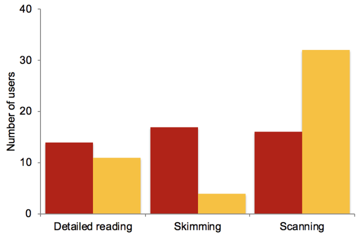
(a) Frequency



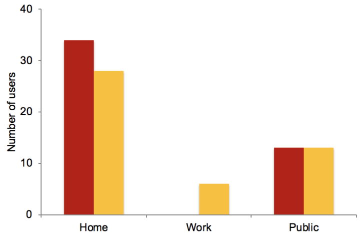
(b) Reading Time



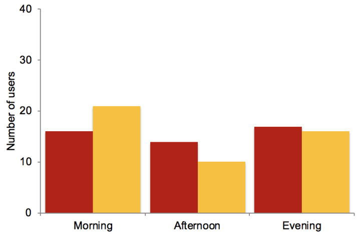
(c) Browsing Strategy



(d) Reading Style



(e) Location



(f) Time of Day

Figure 5.15: Comparison of users' responses (questionnaire) to the six questions related with the factors (in brown) and the high-level behavioural data (in orange).

currently the function makes use of, but also navigation related features (e.g. number of swipes, categories browsed) that the heuristics did not consider.

5.4.4.5 Descriptive analysis of behavioural and questionnaire data

A separate analysis examined whether there is a systematic relationship to what people say they are and to how they behave. This is important to investigate, as it can explain why the rule-based approaches did not work as well as the first model that we trained to predict user's news reader type (Section 5.4.3). Therefore, we compared users' questionnaire answers to those six factors and the six factors computed from their behavioural data using the transformation functions as described in Layer 3 of the framework. Contrary to the previous analysis in which we dropped users with one's day usage, for this analysis we restored the initial dataset of 42 (Section 5.4.1.2).

Figure 5.15 provides evidence that people might fail to assess themselves or they believe that they would behave in a particular way and actually their behaviourial data show otherwise. For example, with the factor of Frequency, users who claimed to be frequent news readers were the exact opposite. A similar picture was seen for Reading Time as one would expect since they spent less time in reading. Quite surprising is the fact that users mainly preferred scanning as their reading style as opposed to a balanced distribution amongst the three strategies that they reported. Likewise, the factor of Browsing Strategy followed the same pattern in which through all sections behaviour did not appear in the behavioural data. Regarding to where they read (Factor of Location) users did not report work at all, which contradicts their actual behaviour in which there were cases marked as work. As for the Time of Day it is the only factor that is aligned. Of course, this could be explained in some extent because 'humans do not remember experiences in a consistent and linear way, but rather recall events selectively and with various biases' (Allan, 1979; Hogan, 1978).

Apart from people's failure to accurately assess themselves another potential reason for the poor accuracy of the rule-based algorithms is the complexity of the high-level markers and might depend on more variables that our heuristics fail to detect. Therefore, we explain a different approach, data-driven in which we train machine learning algorithms to extract hidden structure and unveil any relationships between the variables that are related with each high-level marker.

5.5 Limitations and Alternatives

It is also important to highlight some of the limitations of the work presented in this Chapter. First, both approaches utilised a small sample size. Measures not to overfit the algorithms (i.e., cross-validation of the algorithms) were taken into account as well as the choice of Random Forest, as it works well with small datasets (Breiman, 2001). However, increasing the dataset might yield to better algorithms' performances. Second, the training datasets used for the learning methods were aggregated on daily-level. Alternatively, we could aggregate the data on user-level, but due to the small dataset it was decided not to do it. Despite the fact that an attempt was made to examine the dataset in users-level aggregation by (i) exploding the dimensionality and (ii) using high entropy encoding (e.g. min, max, mean, variance features) in order not to lose information from the low-level features, a dataset consisting of only 47 users would have been problematic. Penalisation techniques such as Lasso Regression (L1) and Ridge Regression (L2) regularisations were explored but their application in such small dataset did not yield any better results. Thirdly, the ground truth used to train the models was obtained through self-reported questionnaires. Despite the fact that it is a standard technique, it relies on people's ability to accurately assess themselves, which can be considered as a limitation, as discussed above. Alternatively, we could observe users interaction behaviour in a laboratory setting with video recordings in order to obtain the ground truth information. However, doing so implies that we lose ecological validity of our results, thus we aimed to investigate it in a field study to explore as much as possible users' natural behaviour while reading the news.

5.6 Discussion

This Chapter presented the development of the User Modelling component of our Adaptive News platform (Chapter 4). It proposed a hierarchical framework for analysing mobile news reading interaction data and explored two approaches towards the user model acquisition. Utilising the framework as the basis of the user model acquisition, it first presented models that are capable of predicting users' news reader types and second, models that are capable of learning the six reader factors that discriminate the news reader types.

In the first approach (i.e., predicting the user's news reader type), the model trained with the self-assessments (i.e., using the label from users' responses to the questionnaire) was able to categorise users slightly better than the baseline model (59.04% as opposed to 51% the baseline). The generic model, however, performed worse than the baseline with only 39.52% accuracy. Furthermore, the model utilised the labels from the expert labelling yielded significantly improved accuracies by achieving 82.85.52% for the personalised model and 81.37% for the generic model (Section 5.4.3). In the second approach (i.e. learning the six reader factors), the factors of Frequency, Reading Time and Time of Day can be directly computed from the low-level interaction data as explained in Section 5.3.3.1. To model the factors of Reading Style, Browsing Strategy and Location/Context, which are more abstracted factors, we employed three different techniques including two rule-based (i.e. inferences from the typology and using the transformation functions) and a statistics-based approaches (i.e. supervised learning method).The rule-based approaches did not yield good performances (below the baseline for each factor except the reading style in one of the approaches) but the learning method was able to learn and predict the high-level behaviourial factors (Section 5.4.4). The learning method outperformed the baseline models for each factor improved significantly the accuracies of predicting these factors compared to the rule-based approaches. In particular, learning the three reading factors of Reading Style, Browsing Strategy and Location/Context, the learning method improved by 12.0.8% for the browsing strategy, 23.14% for the reading style and 32.55% for the location compared to the inferences approach. Similarly, the improvement compared to the accuracies observed using the transformation functions was 29.76% for the browsing strategy, 8.48% for the reading style and 41.64% for location. Therefore, the results suggest that our learning method of learning the individual reader factors is feasible in principle and with further tuning and training of the algorithm is can be deployable.

Having explored two alternatives towards the user model acquisition, Chapter 6 will build on these ideas to explore the design space of different kinds of user interfaces and interactions that would suit different kinds of news reading behaviour. For example, having a model capable of predicting a user's news reader type means that the adaptation mechanism can generate variant user interfaces for the different news reader types. Further, having models capable of learning the six interaction factors means that the adaptation mechanism can generate compositional user interfaces in which particular user interface features are generated on the fly to construct a unique design for that individual user.

Chapter 6

Exploring the Design Space of Adaptive User Interfaces

In Chapter 4 we presented an adaptive news research platform that facilitates the investigation of adaptive user interfaces for mobile news applications. The main components of the research platform include the prototype mobile news app, Habito News, a web-server that handles all the communication between the app and the data access layer (i.e. loading the news feed, storing interaction data and others), and the user modelling component as presented in Chapter 5.

Building on the work reported in the previous Chapters, this Chapter aims to investigate different forms of Habito News user interface that would benefit different kinds of news reading behaviour. Having identified and defined different news reader types in Chapter 3, the focus of this Chapter is to develop different user interface features that would suit the different news reading characteristics of those news reader types. To achieve that, the two different user modelling techniques examined in Chapter 5 will serve as the basis of the user interface exploration. In the first modelling technique where the model is capable of predicting a user's news reader type, an adaptive interface variant form that corresponds to a user's news reader type can be developed. In the second modelling technique where the model learns the individual news reader factors and constructs an individual user profile, a compositional user interface can be developed.

The Chapter explores the design space of adaptive user interfaces through an iterative process. It presents two controlled laboratory studies in which the findings of the first informed the design of the second. The first study aimed to gather requirements for the design of the variant user interfaces and elicit users' preferences towards these designs. In particular, three variant user interfaces were designed for each news reader type and evaluated in interactive wireframes on Android devices. The results of the first study were mixed. One particular type did express preference and performed faster using the variant user interface designed for them, whereas the other two types found their variant design less useful compared to a baseline interface that was used as the reference point for comparison. The results of the first study, led us to further develop the interface and the interactions. The second study was aimed at resolving issues raised by participants during the first study as well as further enhancing the features of the variant user interfaces. The second evaluation study suggested user interface features that were preferred by users and revealed associations between news reading behaviour characteristics and those features. Upon completion of the second study, all the features were implemented and evaluated in the native app, as opposed to the controlled laboratory studies presented in this Chapter. The data obtained during the second study was also used to investigate the set of adaptation rules that are embedded in Habito News as part of the automatic generation of the adaptive variant user interfaces. The Chapter introduces the adaptation rules, discusses their integration with Habito News and explains how the mechanism could select features 'on-the-fly' to automatically generate a user interface and adapt.

The evaluation study "Experiment 1" presented in this Chapter has appeared to MobileHCI '15. (Constantinides, M., Dowell, J., Johnson, D., Malacria, S. Exploring mobile news reading interactions for news app personalisation. In Proc. MobileHCI 2015.)

6.1 Motivation

The work presented in this Chapter is motivated by the fact that mobile news readers differ in the ways of interacting and consuming news. The Chapter seeks to answer the research question (RQ4 - Chapter 1) in relation to:

(a) "How different users would benefit from different forms of a smartphone news app? To which extend the user interface personalisation is beneficial to different kinds of news reading behaviour?"

Having identified people's differences in news reading consumption and forming news reader personas in Chapter 3, in this Chapter we explore the design space of different user interface features and forms that would improve users' experience in relation to the news reading characteristics that describe the news reader personas (e.g. navigation and reading behaviour). We aim to answer this question through controlled laboratory studies that attempt to establish the effectiveness of user interface features with particular characteristics of news reading behaviour that discriminate the three news reader types.

6.2 Controlled Laboratory Study I

The aim of the first controlled laboratory study was twofold. First, it aimed to gather requirements for the design of the variant user interfaces, and second, it assessed the effectiveness of the initial designs that were implemented based on the requirements elicitation in a laboratory study. The study consisted of two Phases as follows: Having examined a wide range of commercial news apps (Section 2.3.2), the initial phase of the study attempted to elicit users' preferences and generate a user interface features pool and subsequently construct the three variant user interfaces for the news reader types. At Phase I, ten participants responded to a questionnaire and a follow up short interview. At Phase II, eighteen participants took part in a controlled lab setup to assess the designs using interactive wireframes deployed in Android devices.

6.2.1 Phase I: Requirements Gathering

To gather requirements for the design of the variant user interfaces and elicit users' preferences towards user interface features of news apps, we utilised a questionnaire and conducted a follow up interview. The questionnaire comprised of ten questions that were intended to capture high-level information of people's attitudes towards mobile news consumption such as their favourite news app, user interface features that were particularly liked in use and others. The full list of questions is provided in Appendix A.3. Upon completion of the questionnaire, participants were interviewed. The interview was broken down into two parts. First, a set of six questions was asked to identify participants' news reader type; the six questions originated from the News Reader Typology proposed in Chapter 3 that differentiated the three news reader types. Second, a mixture of closed and open-ended questions were asked as they allowed us to further question and elaborate on particular user interface features. In Phase I, a total of ten participants responded to the questionnaire as well as completed the interview. The participants were university students (4 female, M=24, SD=2.45) with an interest in news (as an initial screening was conducted to make sure participants previously used news apps and showed interest in mobile news reading).

The questionnaire served as the starting point to construct the interview questions wherein we had the chance to elaborate on interesting features which had emerged from reviewing existing news apps in Google's and Apple's marketplaces (Section 2.3.2). During the interview, participants were presented with screenshots and given explanations of features for which they were asked to state their preference (either like or dislike) in order to get an initial indication of potential 'good' features. Table 6.1 shows the features presented and screenshots can be found in Appendix C.1. The choice of a binary responses was due to the nature of Phase I as it was more focused on requirements gathering than evaluating the designs. To examine possible associations between news reader types and the user interfaces features, we first identified their news reader types. To identify participants' news reader type we followed the same technique that applied in Section 5.4.1.1. We assigned, therefore, a label (i.e. Tracker, Reviewer or Dipper) to each participant.

6.2.2 Phase I: Initial User Interface Features Pool

Having gained an initial insight into what user interfaces might be good candidates for each news reader type, we generated an initial features pool. The features pool

User Interface Feature	*News Reader Type*	*Likes*	*Dislikes*
Quickview	Trackers	7	3
Summarised articles	Trackers	8	2
Recently read category/ Frequently accessed	Trackers	5	5
Top stories news	Trackers	7	3
Related articles	All types	10	0
Custom category	Reviewers	3	7
Article tag searching	Trackers	3	7

Table 6.1: Initial interview - requirements gathering.

provides a mapping of different features with particular news reader types that will be evaluated in Phase II. The features are broken down into the three news reader types and presented in Table 6.1. Table 6.1 also depicts the baseline user interface for comparison purposes, as it was introduced in Chapter 4. Building on the descriptions of the three news reader personas that were created in Chapter 3, we provide the rationale of assigning different user interface features to the different news reader types.

Trackers Variant User Interface: Trackers received the latest stories or updates in the top static area for quick access and we replaced the horizontal organisation from the baseline user interface to a full-width layout due to the fact Trackers prefer to get a quick snapshot of the news. Further, we replaced the original form of the news story's text as it comes from BBC to a paragraph summary due to the fact Trackers prefer to skim while reading text. Put it differently, they tend to read faster without reading everything and aim to get the gist of a story, and thus the option of a summary would be reasonable.

Reviewers Variant User Interface: Reviewers appear to be more traditional news readers so we did not make significant changes compared to the baseline interface because it seemed that it almost met their needs. However, we introduced an accordion style organisation of news headlines with the aim of assisting them browsing news headlines. We reduced the visuals in the headlines organisation and controlled the stories that are, by default, open.

Dippers Variant User Interface: Dippers require a search functionality which

Variant User Interface	*User Interface Feature Elements*
Baseline (Figure 6.1 a)	• Horizontal rows of thumbnails to present news headlines • News story's text presented exactly as BBC layout (no change in the text presentation)
Trackers (Figure 6.1 b)	• Top static area for tracked articles • Full-width categories layout • Option of a summarised version of the story (summary in a paragraph)
Reviewers (Figure 6.1 c)	• No visuals, i.e. articles' thumbnails, in the layout organisation • Only top stories are kept open • Accordion to ease access categories
Dippers (Figure 6.1 d)	• Search functionality • Easy access to articles of a particular category (jump-to like functionality) • Option of a summarised version of the story (bullet point)

Table 6.2: Features of the variant user interfaces designed for each reader type

enables quick browsing of specific facts and jump-to category features allowing them to move between news categories faster. Further, Dippers received news story's text in the form of bullet points as they prefer to read at a faster pace and their reading behaviour is characterised by keyword spotting and identifying the important message of the story without reading everything.

(a) Baseline (b) Trackers (c) Reviewers (d) Dippers

Figure 6.1: The baseline user interface with the variant user interfaces for the three news reader types.

6.2.3 Phase II: Evaluation of the Variant User Interface Designs

Having generated a mapping of user interfaces features and the news reader types, we seek to explore whether the different variant user interface designs improve users' experience in consuming the news.

6.2.3.1 Participants

Participants for the evaluation study were recruited through friends, colleagues and social network posts. The inclusion criteria required participants to have considerable experience in using mobile devices, preferably Android devices, and that they read news on their mobile devices. A screening was performed to select the participants using a short questionnaire in which participants had to state whether they owned an Android device, the number of installed news apps and how long they, on average, read news on news apps. Eighteen university students aged 20 to 30 years old (M=23, SD=2.26) met the inclusion criteria of the study and were invited into the lab to take part. The participants comprised of 7 Trackers, 5 Reviewers, and 6 Dippers the news reader type determination was done as previously explained in Section 6.2.1.

6.2.3.2 Materials

The designs, as depicted in Figure 6.1, were developed as interactive wireframes using a prototyping tool called Justinmind [1]. The interactive wireframes are proven to be a helpful technique of rapid prototyping in which prototypes can be made faster compared to real development and deployment in a native app, and thus it increases the amount of testing and the amount of feedback and user data. We deployed the interactive wireframes on a Samsung Galaxy S3 running Android OS with a 4,8 inch screen and 1280x720 resolution.

Additional materials for the study included a video camera and a comparison questionnaire. Apart from the measurements (discussed in subsequent section) we utilised a video camera to record participants' interactions with the device to identify any interesting gestures or interactions that they performed that can be further developed in future design iterations. An adapted version of WAMMI questionnaire (Appendix A.4) used to measure participants' subjective preference between the user interfaces that were under evaluation (e.g. the baseline vs. the variant user interface for Trackers, and so forth). For example, participants interacted with two interfaces; a baseline user interface (Figure 6.1 a) and the variant user interface according to their news reader type. Therefore, the comparison questionnaire enables us to capture their overall preference towards an interface. The questionnaire scale ranged from Mostly A to Mostly B; with Mostly A indicating strong preference towards the first interface they were given as counterbalancing was used.

6.2.3.3 Procedure

At the beginning of the trial participants completed a questionnaire that would allow their news reader type to be determined. We used an identical questionnaire as in Phase I, in which the news reader type could be determined as previously explained using a Cosine Similarity function. Upon determination of their news reader type, participants were instructed to complete a set of predefined tasks on both user interfaces, the baseline user interface and the user interface that was designed for their news reader type. It should be noted that the tasks necessarily varied between news

[1] Justinmind: http://www.justinmind.com/

reader types, appropriate to their characteristic patterns of news reading. For example, each news reader type was given articles to find and read, which required browsing and reading reflecting the dependent variables that were measured for the experiment. The list of tasks and the instructions that were given to participants can be found in Appendix B.2. After completing the tasks with both user interfaces, participants completed the comparison questionnaire. Further, a short debriefing at the end of the experiment sought participants' views on how easily they were able to find and read articles with each interface and the specific features of each variant interface.

6.2.3.4 Study Design and Hypotheses

The experimental design for the evaluation study was a one-way within-subject design on User Interface type (baseline, variant) that conducted independently on each group of news reader type (Trackers, Reviewers, Dippers). The dependent variables were the time taken to find articles (browsing) and the time taken to read them (reading). The choice of the two metrics reflects the rationale behind the designs as they aimed to improve users' browsing and reading behaviour. Participants were not aware which user interface was the baseline and which was the variant user interface design. We formulated the following hypotheses for each variant user interface:

- H1: The variant user interface for Trackers improves their performance over the baseline UI.
- H2: The variant user interface for Reviewers improves their performance over the baseline UI.
- H3: The variant user interface for Dippers improves their performance over the baseline UI.

6.2.3.5 Results

An independent-samples t-test was conducted to compare the time taken to find and read stories in the baseline and the variant user interface for each news reader type.

Baseline vs. Variant User Interface for Trackers: There was a significant difference in the scores for the time taken to find articles in the baseline (M=21.42, SD=7.59) and the adaptive for Trackers (M=9.85, SD=4.37) conditions; t(12), p=0.004. There was also a significant difference in the scores for the time taken to read articles in the baseline (M=147.42, SD=62.05) and the adaptive for Trackers (M=77, SD=30.47) conditions; t(12) p=0.019. We therefore accept H1 the variant user interface for Trackers improved their performance over the baseline.

Baseline vs. Variant User Interface for Reviewers: There was not a significant difference in the scores for the time taken to find articles in the baseline (M=21.40, SD=5.77) and the adaptive for Reviewers (M=25, SD=10.12) conditions; t(8), p=0.509. No significant difference was found in the scores for the time taken to read articles in the baseline (M=199, SD=12.04) and the adaptive for Reviewers (M=221.60, SD=27.15) conditions; t(8) p=0.127. We therefore reject H2 the variant user interface for Reviewers did not improve their performance over the baseline.

Baseline vs. Variant User Interface for Dippers: There was not a significant difference in the scores for the time taken to find articles in the baseline (M=18.67, SD=5.98) and the adaptive for Dippers (M=25.50, SD=8.43) conditions; t(10), p=0.137. There was also not a significant difference in the scores for the time taken to read articles in the baseline (M=180.83, SD=79.17) and the adaptive for Dippers (M=117.33, SD=38.51) conditions; t(10) p=0.108. We therefore reject H3 the variant interface for Dippers did not improve their performance over the baseline.

Satisfaction and User Comments: In addition to the statistical test, which examined the measurement of performance in the set of predefined tasks, we analysed the comparison questionnaire and the users' comments during the short debriefing at the end of the experiment. The following Figures 6.2, 6.3, 6.4 depict the frequency distribution for each variant user interface compared to the baseline user interface. The post-experiment comments were used to further understand the success of those designs and help us refine any potential shortcomings in subsequent iterations.

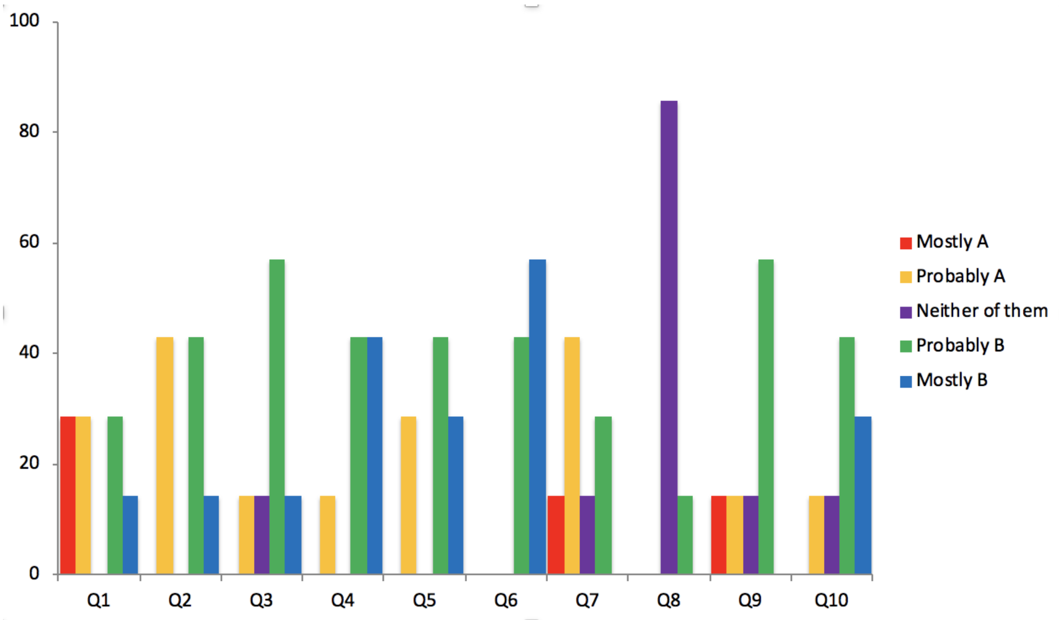


Figure 6.2: Trackers responses about their preference for the baseline (A) and their variant user interface (B).

Trackers: Nearly three quarters of Trackers (71%) preferred their variant user interface as easier to use overall (Q3) as well as for first time use (Q2). More than three quarters (85%) stated that their variant user interface would help them find news stories more quickly (Q4), 71% reported that this would help them to browse headlines more easily (Q5), and all Trackers found their variant user interface more suitable for reading (43% - probably, 57% - mostly) (Q6). Neither their variant user interface nor the baseline seemed to contain unnecessary features (85%), but surprisingly Trackers found the baseline user interface more visually appealing (57%) (Q1).

In their post-experiment comments, Trackers praised the possibility of switching between the full article and its summary, but also suggested extra features to support tracked articles, e.g. visually differentiating read articles and new ones - in the form of a notification when news articles have been read or are new since last visit. They strongly disliked, however, the menu structure; particularly the vertical scrolling for categories, due to the fact they want to be able to browse all categories with ease. They suggested horizontal scrolling through news categories might be more suitable.

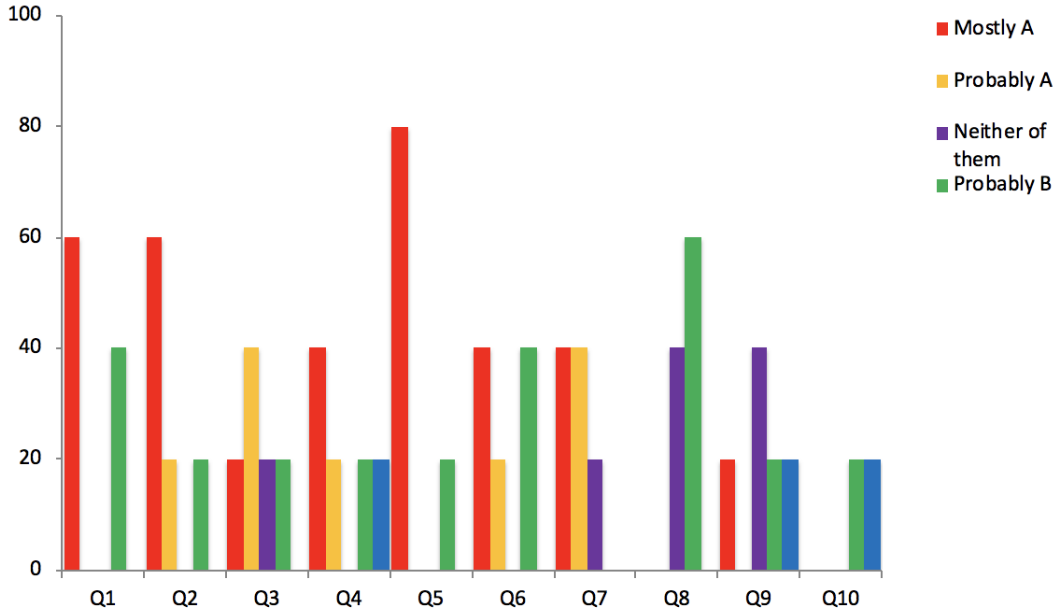


Figure 6.3: Reviewers responses about their preferences for the baseline (A) and their variant user interface (B).

Reviewers: Three-fifths of Reviewers (60%) preferred the baseline over their variant user interface as being easier to use overall (Q3). 80% expressed a stronger preference for this as the user interface that is easier to use for the first time (Q2). They slightly preferred baseline over their variant for browsing news stories quicker (60%) (Q3), and reading news stories more easily (60%) (Q6), and had an even stronger preference towards the baseline for browsing news stories more easily (80%) (Q4), Unlike Trackers, Reviewers found that their variant user interface did contain unnecessary features (60%) (Q8) as well as finding the baseline more visually appealing (60%) (Q1).

Overall, Reviewers found their variant user interface not particularly beneficial and expressed stronger preference for the baseline user interface instead. Their responses to the questionnaire were aligned with their post-experiment comments as they found their variant did not outperform the baseline. In particular, they suggested restoring the full access to news stories as opposed to the 'top stories kept open' method of organisation. They also praised a feature that indicates when news stories have been read. It should be noted that we did not receive any comments about the need for a news story's summary. This further corroborates that this news

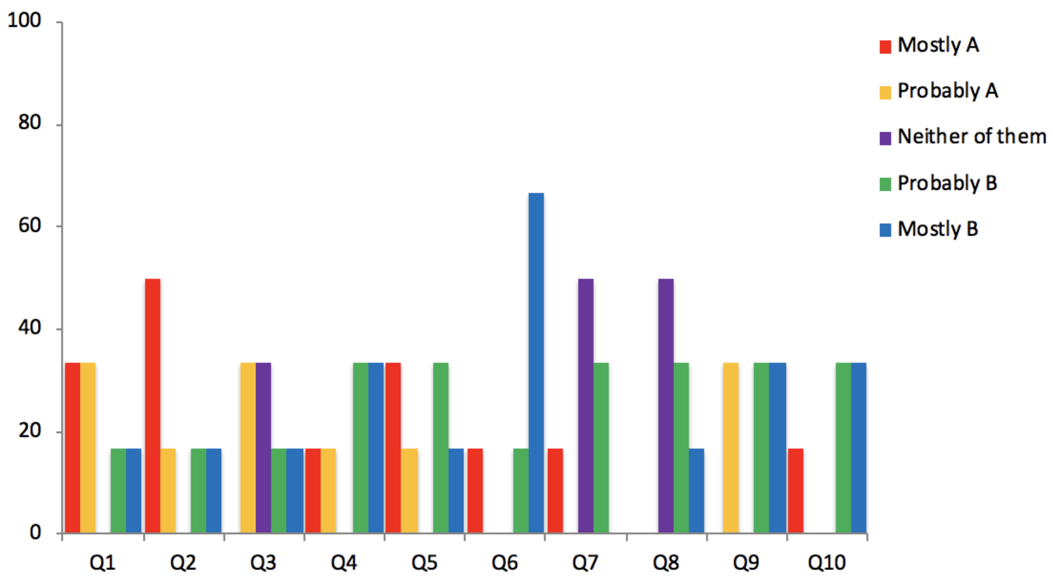


Figure 6.4: Dippers responses about their preference for the baseline (A) and their variant user interface (B).

reader type is different from the other two in terms of reading behaviour, and thus they tend to prefer the full article as opposed to the gist of it.

Dippers: Dippers stated neutral preference towards the user interface that is easier to use overall (Q3), but nearly two-thirds (67%) preferred the baseline as the user interface easiest to use for the first time (Q2). Dippers preferred their variant user interface for browsing news stories more quickly (66%) (Q4), they stated neutral preference for easier browsing (Q5), and strong preference (84%) for reading news stories (Q6). However, there was a small tendency towards their variant regarding unnecessary features (17%) (Q8). Overall they found the baseline user interface more visually appealing (66%) (Q1).

Overall, Dippers stated a neutral preference towards both user interfaces. They found the article summary very useful, but they also suggested that an option to view the full article if they were particularly interested would be a plus. They praised the jump-to-category feature, which enabled them to navigate between news categories and browse news headlines easier and quicker. In addition they recommended an option to view a summary within the menu (news headlines), i.e. being able to view more details about a news story without having to dive in. Finally, they suggested a mechanism to move faster once they reach the bottom of the menu organisation such as a return-to-top function similar to websites navigation.

6.2.4 Discussion

The Phase I of the design of Habito News Variant User Interfaces aims to gather requirements of each news reader's type variant user interface and evaluate them in a controlled setting.

The evaluation study demonstrated that it is feasible to construct a variant user interface particularly for a news reader type, that reflects on their characteristic ways of browsing news headlines and reading the news. In particular, the experiment showed that Trackers performed better with their variant user interface, whereas Reviewers and Dippers performed better with the baseline interface. Trackers also stated strong preference towards their variant user interface, whereas Reviewers did not. Dippers were neutral about their preferences, but also stated that they preferred their variant only for reading the news.

The findings of Phase I will serve as the basis for further exploration of the design space of the variant user interfaces. In particular, Phase II will focus on the users' comments and suggestions about features, especially, for Reviewers and Dippers. Reviewers, for example, did not praise the accordion style organisation for news headlines and thus the horizontal rows of thumbnails organisation could be restored. An additional feature of expanding news categories that provides an overview of the news stories in each category could be beneficial for them. Dippers suggestions such as the return-to-top functionality combined with a jump-to-category mechanism could be implemented as an accordion style organisation.

Overall, the findings of the evaluation study were mixed. The variants for Reviewers and Dippers were not successful but only the variant for Trackers outperformed the baseline user interface. However, this does not preclude that successful forms of their variant user interfaces could be created. The most significant finding of this evaluation study is that their needs and those of Trackers were not met by the same user interface and that an adaptive and personal user interface is desirable and preferred by users.

6.3 Controlled Laboratory Study II

As the results of Phase I were mixed, further exploration of the variant user interfaces was necessary in order to establish the variant user interfaces for each news reader type. The statistical result from this phase did show that one particular type preferred their variant (i.e., Trackers), but not the other two. In addition to that, participants' post-experiment comments and satisfaction responses suggested good features, but also new features and improvements that could be done in the interfaces, thus the Phase II will make use of those comments to refine the designs. Further, a new set of features, particularly for the reading layer, will be introduced in Phase II as the user interfaces features relating to how users perform the reading were only limited to presenting news story's summary with different visualisation. The aim is to examine further visualisations of news story's text in an attempt to facilitate and improve news reading. In addition to the primary goal, the data gathered in this phase will also be used to investigate potential adaptation rules that will be used during the adaptation process. Due to the fact that the new designs would be further enriched with features, potential relationships between features and the news reader types are expected to be revealed, which in turn will inform the generation of a set of rules for the adaptation process. The rule extraction and generation will be discussed later in the Chapter.

6.3.1 Revised User Interface Features Pool

Based on the insights gained from the first study and the users' suggestions (Section 6.2), a revised version of the initial user interface features pool was created including features relating to the reading layer such as a breakdown of news story presentation in different levels with different visualisation. Table 6.3 presents the revised features pool, while Table 6.4 explains the newly introduced reading-related features. All revised designs are depicted in Figures 6.5, 6.6, 6.7, 6.8.

The features (1-3) refer particularly to the three different layout organisations of the news headlines, whereas the features (4-13) refer to different ways of presenting a news story. The Trackers layout organisation remained the same as it was successful during the evaluation in Phase I, whereas the Reviewers layout restored

S/N	*UI Feature Name*	*Description*
1	Tracker Layout	News headlines organisation in which the nine most recent stories are visible in one page without the need to scroll left or right to browse all the stories within a category. The categories can be browsed horizontally
2	Reviewer Layout	News headlines organisation in which stories are organised in rows of thumbnails. News categories can be browsed vertically and stories horizontally. Each category has a button next to the heading that opens a popup window in which all stories of that category are visible.
3	Dipper Layout	News headlines organisation in which news stories are presented in an accordion of categories. The categories can be browsed by tapping on a category or scrolling up or down from other categories.
4	Tracked Articles	A top static area in the news headlines organisation in which the latest six stories that have been followed or have updates during the day are presented.
5	Paragraph Summary	Story's summary in a paragraph.
6	Bullet Point Summary	Story's summary in a bullet point list.
7	Highlighted Terms & Keywords	It highlights the important terms, names, and entities of a story to mark their significance.
8	Colour Gradient Text	Colour gradient on the story's text to guide the reader's eyes from one line to the next.
9	Accordion Background Information	It displays the important terms, names, and entities of a story in an accordion in which the reader can tap to reveal further information about a particular term/name/entity.
10	WordCloud	It presents the important terms, names, and entities of a story as a wordcloud.
11	Related Articles	Articles with the same topic/theme at the end of a story. External APIs were used from Mashape (Mashape, 2016)
12	Search Box	Search functionality at the top of a news headlines organisation.
13	Push Notifications	Receive updates in news stories of interest.

Table 6.3: Revised User Interface Features Pool.

News Reader Type	*Level 1 (Overview)*	*Level 2 (Richer Content)*	*Level 3 (Links to full story)*
Trackers	• Screen divided into two sections (F5) • Top section consists of the article's summary • Bottom section shows article's updates (if any)	• Original article displayed using colour gradient (F8)	• Original article
Reviewers	• Original text (extract important entities and highlight them) (F7)	• More info about the important entities shown in the previous level (F9) • Any other background info that would help the reader (F8)	• Related articles (F11)
Dippers	• Wordcloud of important terms and entities (F10)	• Bullet point summary (F6)	• Original article

Table 6.4: Reading level features (F# indicates the number of the feature from Table 6.3).

the horizontal rows of thumbnails and the Dippers layout introduced an accordion style organisation for presenting news headlines. With respect to reading layer features (F4-13), we adopted the idea of a three-levels of depth story breakdown in which each level utilised different visualisations to present the content. This idea was originally introduced in the Elastic News project (BBC RD, 2014) wherein the aim was to provide more content as the user progressed to the story. We turned this idea into different visualisations as the user progressed through in the different layers. Table 6.4 summarises the reading layer features.

As described in Chapter 3, Trackers are people who mainly skim and like to be

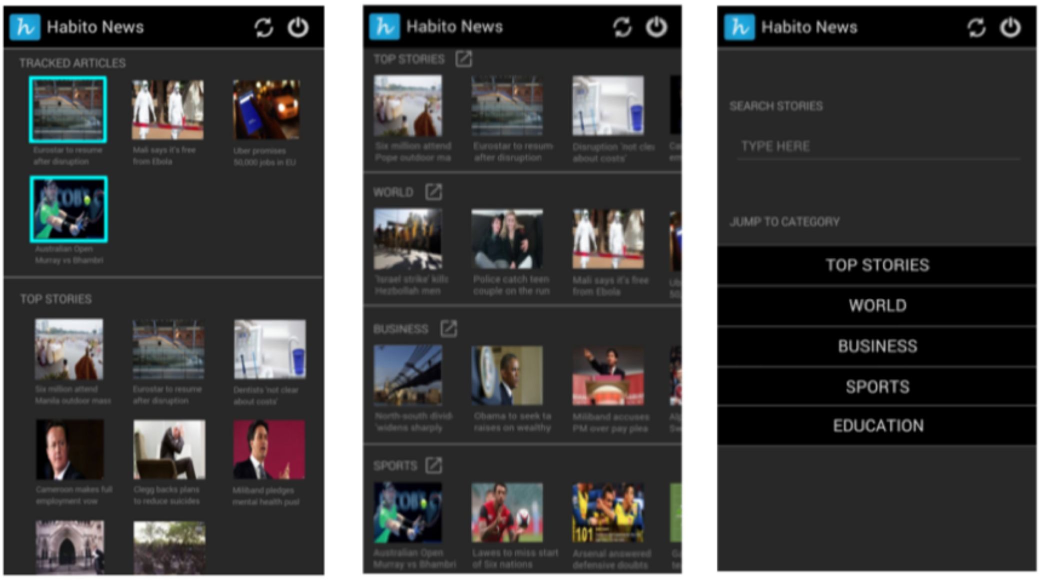


Figure 6.5: News headlines layout organisations - TrackersLayout, ReviwersLayout, DippersLayout (from left to right).

informed about the latest stories and any updates of stories they follow. In the first layer, we introduce a split window where they get the story's gist in the top area and story's updates as a list in the bottom area. In the second layer, the story's text is the same as the third layer (i.e. the original story's text) except colour gradient is being used. We took inspiration from BeeLine Reader (Reader, 2016), which uses colour gradient to guide the eyes from the end of one line to the beginning of the next. By doing so, it claims to help users read faster and with less eyestrain. We expect this to be a suitable feature for skimmers. In the third layer, we keep the original article in case Trackers want to read the article in more depth.

Reviewers are people who like to read in-depth and catch up on the day's news. They spend time going through all stories of interest and like being informed on a variety of topics. In the first layer, we extract the important entities and terms and highlight them in order to show the important parts of the stories that aid better understanding. In the second layer, we provide more information about the important entities that were previously extracted. We also present any other background information related to the story that would help the reader (e.g. Wikipedia links). In the third layer, we list all the related articles to the story in order to help them enhance

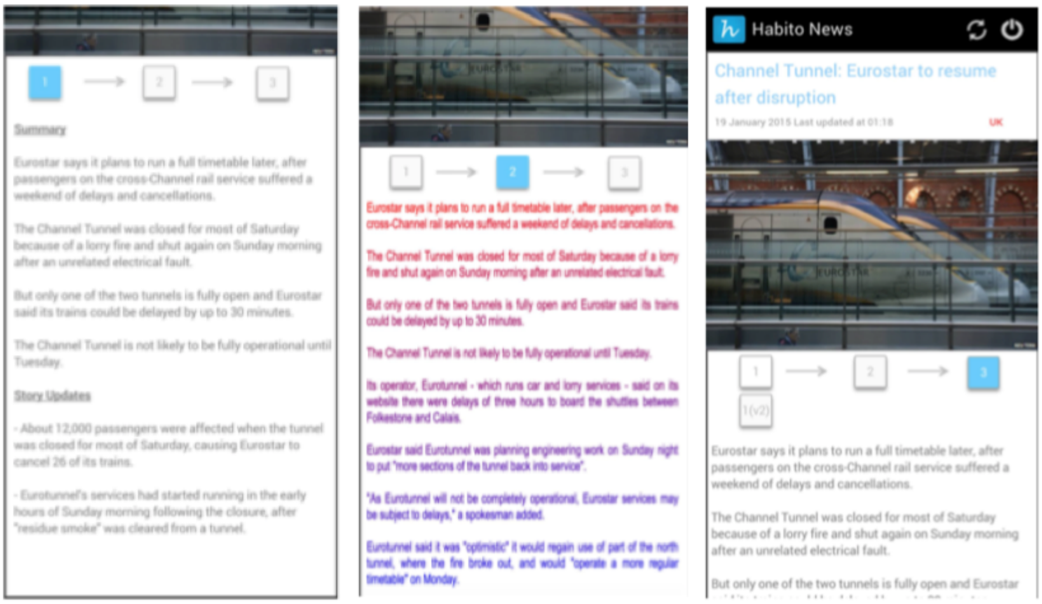


Figure 6.6: Trackers reading layer features

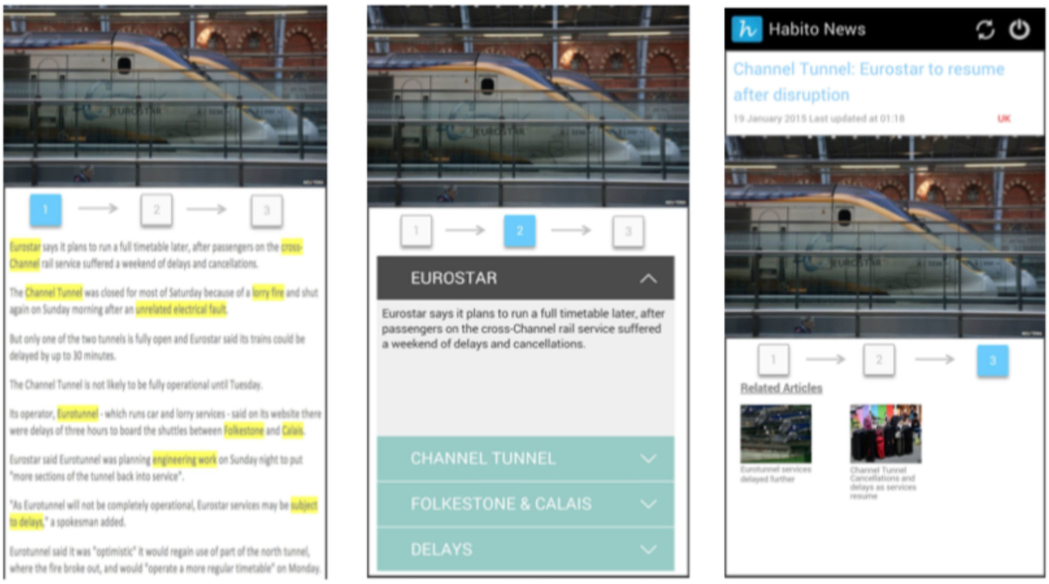


Figure 6.7: Reviewers reading layer features.

their knowledge.

Dippers are people with casual interest in news. They browse particular sections to find stories and look for specific facts or pieces of information without reading everything. In the first layer, we extract the main terms and entities and create a Wordcloud. We expect such visualisation to help them get an overview of the story as the individual words in the cloud will cue relevant facts. In the second

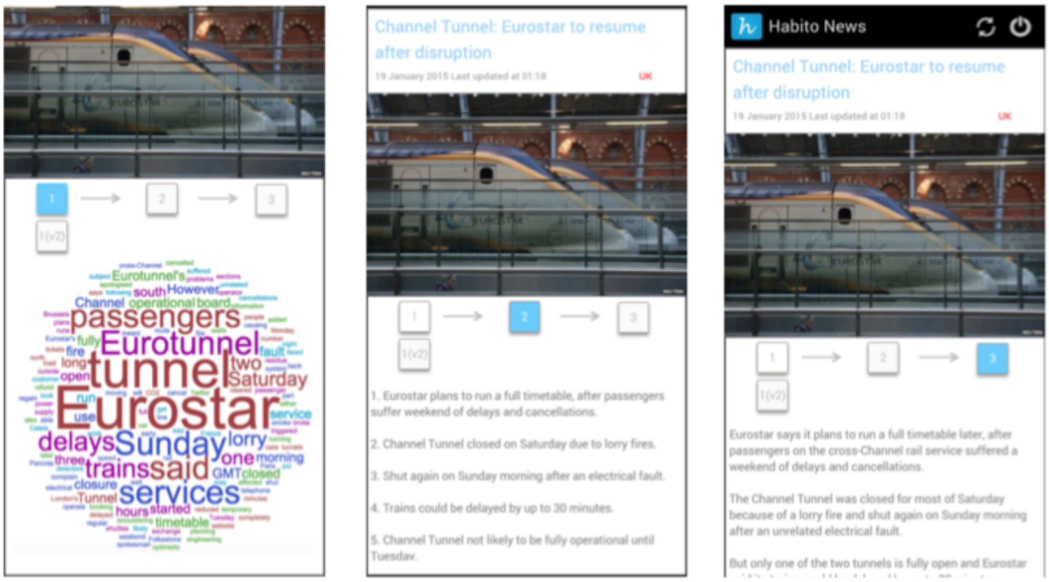


Figure 6.8: Dippers reading layer features.

layer, we present the article's summary in the form of bullet points. In the third layer, similar to the Trackers reading interface we provide the original article in case they want the article in more depth.

6.3.2 Participants

Participants were recruited through students in two university campuses. A total of twenty-seven participants were recruited, thirteen of them were MSc students from the UCL Computer Science Departments and the remaining fourteen were undergraduate students from University of Cyprus. The age range of these participants spanned between 21 and 28 years old. (M=23.07, SD=1.85). The prerequisite for participation was that users must have previously used a news app on their mobile devices. All participants took part in the experiment voluntarily. A note should be made here in relation to the cohort. Participants represent Millenials, but as stated in Chapter 2, this age group might be more receptive to systems that adapt and change their functionality without any manual intervention (Deal et al., 2010). Chapter 8 discusses future work, which includes a more diversified cohort of these studies.

6.3.3 Materials

Similar to the first experiment all the designs were implemented using Justinmind and deployed on 2 Samsung Galaxy S3 (4,8 inch screen, 1280x720 resolution, same specifications for both devices). We used the similar questionnaire with questions relating to the six factors in order to identify participants' news reader type. In addition, participants rated each feature in a Likert-type scale after the feature had been explained to them and they had the chance to interact with the interactive wireframe. Also, open-ended questions were asked at the end of the experiment for additional comments and suggestions for the candidate user interface features.

6.3.4 Procedure

The experiment consisted of two parts. In the first part participants responded to a questionnaire and in the second we walked them through the interface features (Figures 6.5, 6.6, 6.7, 6.8) in an interview-style process. The information sheet about the study can be found in Appendix B.3.

The first part of the experiment lasted approximately 10 minutes in which participants responded to a questionnaire consisting of three parts. The first part was mainly focused on general background information about the participant's age, gender, education and occupation. In the second part we included questions about participants' previous experience with mobile news apps such as the amount of installed news apps, their favourite news app, interface features they liked the most and others. In the third part, we utilised the same six questions that describe the News Reader Typology, as presented in Chapter 3, in order to use them as the basis for categorising participants into the three news reader types. For example, we asked them questions about their frequency of reading in a news app, how they browse to find news headlines, how they decide to read a story and others. The questionnaire can be found in Appendix A.5.

The second part of the experiment consisted of an interview with each participant and lasted approximately 30 minutes. The aim of the interview was to validate those features and identify potential associations of features and the news reader types. Each feature was shown to the participant in an Android phone as described in the previous section. During the interview each feature was explained in detail and then participants had the chance to interact with it using the Justinmind wireframes. Similar to Phase I, all the features were implemented as interactive wireframes and participants interacted with them in Android devices. A series of questions that explore themes such as usefulness, usability and understanding (visually clear) were provided for each feature. The questions were a mixture between open-ended by extracting participants' opinions on news app interactions, and close-ended by assessing/rating each individual feature in a Likert-style scale such as not useful at all to very useful. The interview material can be found in Appendix B.4.

6.3.5 Study Design

Unlike the first experiment in which participants interacted only with the interface design based on their news reader type, in this experiment all participants interacted with all features, even some features that were not intended to be used for their news reader type. We have chosen this study setup in order to establish that particular news reader type has a stronger preference towards some features than others.

6.3.6 Results

The analysis was conducted in two parts. In the first part, we examined how participants perceived each individual feature despite their news reader type, which could provide insights towards good candidate features. In the second part, we investigated potential associations between the user interface features and the news reader types as well as the relationships between individual high-level behaviourial (e.g. frequency, reading time, and others) markers and the user interface features.

In the first part of the analysis we investigated how users perceived the set of user interfaces features. As it can be observed from Table 6.5, there are features such as the wordcloud, colour gradient and the keyword list, which are below the average (participants assessed the usability, usefulness, and clarity in a Likert-scale of 1-5), but also there were features paragraph summary and related articles closer to 5, which indicates a greater degree of either usability/usefulness or clar-

Feature Name	*Usefulness*	*Clarity*
Wordcloud	1.96	3.04
Coulour Gradient	2.22	2.41
KeywordList	2.63	3.37
Accordion Background Information	3.26	3.81
Highlighted Terms & Keywords	3.33	3.81
Bullet Point Summary	4.15	4.37
Paragraph Summary	4.44	4.44
Related Articles	4.67	4.78
Feature Name	*Usability*	*Clarity*
Trackers Layout	3.78	4.26
Reviewers Layout	3.85	4.19
Dippers Layout	3.56	3.81
Feature Name	*Usefulness*	*Obtrusiveness*
Push Notifications	3.89	3.48

Table 6.5: Participants' assessments of user interfaces features: usability, usefulness, and clarity in a Likert-scale of 1-5.

ity. Although the majority of features were perceived as being good candidates for different visualisations of news headlines or content, some did not score highly. A possible explanation could be the fact that such features (i.e. wordcloud, colour gradient) do not frequently appear in existing news apps, and thus participants were faced with a new way of accessing and interacting with news content that was not familiar to them.

In the second part of the analysis, we examined two kinds of associations. First, we explored associations between user interface features and the news reader types, and second, we examined associations between user interface features and individual high-level markers that describe the news reader types (i.e. frequency, reading time, and others). To extract participants' news reader type we used similar method (using Cosine Similarity function), as previously explained in Phase I. We used a Chi-square test for both types of the analysis.

Association between UI features and News Reader Types: The news reader types was found to have an association with the Paragraph summary feature in Reading

Level 1 (p=0.047) as well as two other borderline associations were found on the features of push notifications (p=0.074) and related articles (p=0.058).

Association between UI features and Individual High-level Markers: Several individual answers regarding participants' individual news reading behaviour were found to have significance with individual user interface features. The reading style was associated with the idea of two-level story presentation (p=004), the frequency with keyword list (p=0.023), with dippers layout (p=0.018) and trackers layout (p=0.027), the time of day with highlighted terms (p=0.034) and the wordcloud (p=0.029). In addition, other suggestive associations were found. The browsing strategy found to be associated with dippers layout (p=0.077), the frequency with push notifications (p=0.061), the browsing strategy with reviewers layout (p=0.083), the location with wordcloud (p=0.73), and the paragraph summary reading level 1 (p=0.070), the reading style with reviewers layout (p=0.062).

6.3.7 Discussion

Phase II further explored the design space of variant forms of the user interface for the news app (Habito News) and aimed to evaluate a more enriched set of features compared to Phase I, particularly by adding more reading layer features such as the breakdown of a news story and improving the news headlines layout organisation.

The evaluation study found user interface features that were strongly preferred by participants, but also participants reported that features such as the wordcloud, colour gradient on the story's text and a keyword list might not be useful. An interesting finding, contrary to Phase I, is that all the three news headlines layout organisations were found to be preferred by users in terms of their usability and clarity. In particular, the Trackers layout (usability = 3.78, clarity = 4.26), the Reviewers layout (usability = 3.85, clarity = 4.19) and the Dippers layout (usability = 3.56, clarity = 3.81), all scored above the average in a scale of 1-5 (with 1 indicating low and 5 high). With regard to the features that scored low in participants' assessments, a possible explanation could be that those features do not frequently appear in news apps, and thus participants' were not familiar with them. In comparison those rated with a high score featured such things as related articles, summarisation and push notifications, which are concepts that do appear in existing contemporary news apps.

In addition to participants' preferences, the evaluation study found associations between the user interface features and the news reader types (as well as with high-level markers of news reading behaviour that describe the types). In particular, the reading style found to be strongly associated with the concept of the two-level presentation of a story (breakdown), indicates that people's characteristic way of reading affects the way the story is broken down and presented. Further suggestive associations were also found such as the browsing strategy with the news headlines layout organisations of two types, which indicates that people's way of browsing and looking for headlines affects the way headlines are organised.

Overall, the evaluation study found interesting insights about the user interface features and the news reader types. Despite, not all the features being found to be preferred or associated with people's news reading behaviour, we believe that another evaluation is required as this could have affected users' interaction and experience. The features will be implemented in the native news app and will be evaluated in a real setting, as opposed to interactive wireframes in a controlled setting in this evaluation study. Finally, the data obtained during this evaluation will be used to extract the set of adaptation rules, which will be discussed in the following section.

6.4 Adaptation Mechanism

While the two controlled laboratory studies presented in this Chapter aimed to explore the design space of the variant user interfaces for our news app, an important and core component in the process of adaptation is the Adaptation Mechanism (Section 4.2.1). The adaptation mechanism is the component that will generate the variant user interface automatically based on a set of adaptation rules. In this section, two alternative approaches of defining a set of adaptation are explored. The first is purely data-driven whereas the second is based on argumentation in order to form rules about the potential association between user interface features and the news reader types.

6.4.1 Approach I: Data-driven

The data obtained during the second controlled study (Section 6.3) used to explore potential adaptation rules. First, we used participants' responses to the six-item questionnaire that helps us identify their news reader type. The same technique, as discussed in previous section of this Chapter and introduced in Section 5.4.1.1 was applied in order to identify each participant's news reader type. Second, once we identified participants' news reader type we divided participants' skill spectrum into three parts. The first part comprises Novices, the middle is where Intermediates belong, and the third part is for Experts. We used this sub-type classification to help us discriminate types that are closer to the stereotypical type (as explained in Chapter 3). For example, an eighty percent Tracker differs with a fifty percent Tracker. Perhaps, an eighty percent Tracker shares stronger characteristics with the Tracker type, whereas a fifty percent might also share characteristics from other news reader types. The ranges were defined as 0-30 to refer as Novice, 31-70 to Intermediate, and 71-100 to the Expert. Given the three sub-type categories, a set of twenty-seven permutations was generated (three news reader types and three sub-type categories for each news reader type). At this point we aim to explore the whole spectrum of types and sub-types, thus the choice to examine all the possible permutations.

The new dataset generated consisted of a unique user identifier (UUID), the primary news reader type, the distribution among the three news reader types, and their responses to the interview questions wherein participants assessed the user interface features. The distribution among the three news reader types is the output of the cosine similarity function which identifies how close each user is to stereotypical type. For example, one participant could be seventy percent Tracker, ten percent Reviewer, and seven percent Dipper. The responses to the interview questions were also coded as 1-5 ranges, with 1 being not useful at all, 3 being neutral, and 5 being very useful. This helped us to identify the most useful feature for each

News Reader Type and sub-type category	*User Interface Features*
Novice Trackers (0-30)	Tracked Articles, Dipper Layout, Paragraph Summaries, Related Articles Bullet, Points Summary
Novice Reviewers (0 - 30)	Tracked Articles, Reviewer Layout, Push Notifications, Highlighted Terms, Related Articles, Bullet Points Summary
Novice Dippers (0-30)	Tracked Articles, Tracker/Reviewer Layout, Push Notifications, Paragraph Summaries, Related Articles, Bullet Points Summary
Intermediate Trackers (31 - 70)	Tracked Articles, Tracker Layout, Push Notifications, Paragraph Summaries, Related Articles, Bullet Points Summary
Intermediate Reviewers (31 - 70)	Tracked Articles, Tracker Layout, Push Notifications, Paragraph Summaries, Related Articles, Bullet Points Summary
Intermediate Dippers (31 - 70)	Tracked Articles, Reviewer Layout, Push Notifications, Paragraph Summaries, Related Articles, Bullet Points Summary
Expert Trackers (71 - 100)	Tracked Articles, Reviewer Layout, Highlighted Terms, Accordion/Bullet Points, Related Articles
Expert Reviewers (71 - 100)	Tracked Articles/Search Box, Dipper Layout, Paragraph Summaries, Accordion/Bullet Points, Related Articles
Expert Dippers (71 - 100)	Tracked Articles, Tracker Layout, Paragraph Summaries, Bullet Points Summary, Related Articles

Table 6.6: Features combinations with the sub-type category and news reader types.

user interface region, for each news reader type and sub-type category. The feature with the highest score was selected to represent that particular news reader type and sub-type category. Table 6.6 presents all the combinations of features with the news reader types and sub-type categories. Having extracted the most useful features for each type and sub-category, then all 27 permutations were generated. For example, a variant user interface could combine features from a Novice Tracker, Intermediate Reviewer and Expert Dipper as follows:

- **Novice Trackers (0 - 30):** Tracked Articles, Dipper Layout, Paragraph Summaries, Related Articles, Bullet Points Summary.
- **Intermediate Reviewers (31 - 70):** Tracked Articles, Tracker Layout, Push Notifications, Paragraph Summaries, Related Articles, Bullet Points Summary
- **Expert Dippers (71 - 100):** Tracked Articles, Tracker Layout, Paragraph Summaries, Bullet Points Summary, Related Articles

In the rare case of no commonalities for a particular user interface region the feature with the highest score was selected. Further, if the scores were equal, then the selection followed the pattern Expert>Intermediate>Novice.

However, the data-driven approach did not meet the expectations, as it did not result in enough distinct variant interface combinations and in turn it was very difficult to find a pattern where two news reader types could be matched to the same features, as everyone else would also be matched to same features. The main problem was the Expert overlap in the rules, with the majority of news reader types and sub-categories preferring the following set of rules:

```xml
<?xml version="1.0" encoding="utf-8"?>
<feature>trackerTop</feature>
<feature>trackerLayout</feature>
<feature>paragraphSummary</feature>
<feature>bulletPointSummary</feature>
<feature>relatedArticles</feature>
<feature>pushNotifications</feature>
```

This led us to abandon this approach and attempt to rationalise the problem by providing argumentation for each user interface feature in relation the News Reader Typology (Chapter 3).

6.4.2 Approach II: Theory-based

Unlike the previous approach, in this section we present argumentation for each user interface feature in relation to the News Reader Typology (Chapter 3). We followed the procedure as follows:

1. Select a feature from the feature pool as it is described in section 5.3.1

2. Develop a rationale for this feature (e.g. usefulness and suitability in relation to each type in the News Reader Typology)

3. Construct an argument about which news reader types could benefit from that feature and was more likely to prefer it to others. Unlike the sub-categorisation of novice, intermediate and expert, we analysed hybrid types (e.g. Tracker/Reviewer, etc..)

4. Repeat steps 1-3 for all the features in the features pool

5. Define a set of rules derived from these arguments

The aforementioned approach led to a significantly simplified set of five rules, i.e. one rule for each pure news reader type and one for the two hybrids. It is important to mention that a combination of Tracker/Dipper types could not be possible as it is against the initial News Reader Typology.

Rule Reasoning Navigation Level Features

Tracker Layout: *The Trackers Layout is designed with the aim of providing a quick view of the top nine stories throughout the day. We suspect this would be beneficial to news readers who follow and track stories during the day and want to see the latest popular stories without having to browse through other stories in the process.*

This layout is more likely to be preferred by Trackers. Trackers like to be informed about the latest stories, and so displaying the top nine most recent stories on the main page would allow them to navigate to these stories more quickly. Further, as Trackers prefer to read multiple times throughout the day, this layout would give them the option to keep track of the top stories. Reviewers would find this layout less useful as they read stories through all sections in the more traditional way of browsing through all categories. However, as this layout provides a quick way of catching up on the day's news, it could be suitable for a hybrid news reader type who is a mixture of Tracker and Reviewer. For example, it could be beneficial for a user who reads the news once a day and wants to be informed of the latest stories. As for Dippers they are more likely not to like this layout due to their preference to browse through particular categories of news stories.

Reviewer Layout: *The Reviewers' layout allows news readers to get a full view of all categories and stories within a category. It is more like to be beneficial for people who prefer to view sections in detail.*

This layout is more likely to preferred by Reviewers. Based on their navigation behaviour, which is described as browsing through all sections in detail, this layout's news headlines organisation matches the Reviewers news reader type. It would be less useful for Trackers as they prefer to browse for latest news stories along with stories that have updates. Likewise, Dippers prefer only to browse through particular sections so providing a view of all the sections would not be beneficial as it might confuse rather than help them.

Dipper Layout: *The Dippers Layout aims to help users view all the stories in a particular news category through clickable expanding categories organised in an accordion layout.*

This layout would be more useful for the Dippers news reader type. Dippers prefer only to read from particular news categories and sections, and thus being able to navigate to those stories faster would be beneficial and useful for them. Reviewers would be unlikely to find this layout useful as they like to browse through all sections so stories being hidden from them until the category is clicked on would not suit their behaviour. Likewise, this layout would not suit Trackers. Despite the fact that Trackers might utilise both browsing strategies (either navigating through all sections or in a particular section), they want to be informed of the latest stories, which this layout does not support.

Tracked Articles: *The Tracked Articles features is a section in the top of a layout that displays the six most recently read news stories and highlights the articles that* *have updates. This feature enables quick access to previously read stories or stories to keep following throughout the day.*

This feature would be more useful to Trackers. Trackers prefer to read the news many times a day and follow stories with updates, and thus this feature would be beneficial for them. Reviewers on the other hand are people who read the news once a day so might not find this feature useful as there would be no record of articles they had tracked. Similarly, Dippers read in less frequent bursts than Reviewers and this same argument can be made for them. Further, it can be argued that a person who is a mixture between Tracker and Reviewer might also benefit from this feature. For example, a user who reads the news multiple times a day utilising a detailed reading approach, would benefit from knowing when there have been updates to a story they have previously read in order to obtain more information about this story.

Search Box: *The Search Box allows users to search for a particular story by matching the keywords with the story's title.*

This feature is more likely to be beneficial for Dippers. Dippers prefer to read the news for a very short period of time, having in mind what they are looking for, and only reading stories in particular sections. This would, therefore, be significantly useful, as it would allow them to search for what they are looking for and access it immediately without having to browse through other stories. Reviewers, on the other hand, might prefer to spend a significant amount of their time looking and browsing through all news stories so having an option to quicken their search might be not so useful. Trackers might find this feature somewhat useful, if they occasionally want to search for particular stories but it might not be their priority if they tend to read the news many times a day.

Push Notifications: *The Push Notification allows users to be informed about any breaking news and story updates in the stories that they have been reading throughout the day. A push notification is sent once there is an update on a story that they have read during the day.*

This feature could be useful for Trackers, as they tend to read many times a day and like to be informed about news stories' updates. Reviewers and Dippers might not find this feature so beneficial as they do not express the compulsive behaviour of tracking the news as Trackers might do.

Rule Reasoning Reading Level Features

Paragraph Summary *The Paragraph Summary provides a summary of the story in a paragraph-style organisation and allows the reader to get a gist of the story while reducing the amount of time required reading the story thus making it easier for readers who tend to skim read.*

This feature would be useful for Trackers, as they generally prefer to skim the story's text and read for an average amount of five to ten minutes per reading session. Reviewers are more likely not to find this feature useful as they tend to read for a longer period of time and in greater detail. For this reason omitting parts of the text might discourage them from reading. A mixture of Tracker and Reviewer might find this feature appealing, for example, a user may read the news for a long period and browse through all sections, but skim the stories. This feature would allow the user to read much more content in a shorter period of time, thus would be useful for the mixture of Tracker and Reviewer. Further, Dippers may find this feature useful, as they do not spend much time reading (e.g. it enables faster reading, keyword spotting).

Colour Gradient: *The Colour Gradient allows users to guide their eyes from one line to the next more efficiently. The feature is designed in such a way as to aid the process of speed reading and is expected to help users read more stories in a shorted amount of time.*

Trackers may find this feature appealing, as their behaviour can be linked to speed-reading (e.g. skimming). Reviewers may also find this feature appealing as it presents the full text and allows them to read the whole story but at a faster pace. It may, therefore, be useful for a mixture of Tracker and Reviewer. Dippers on the other hand may not find it useful as they tend to scan the story's text and may not find this to be a satisfactory presentation of the whole story's text.

Highlighted Terms: *The Highlighted Terms feature is designed to draw the reader's attention to keywords or phrases that appear more frequently. The aim* *of this feature is to provide the key parts and messages of a story.*

Trackers may find this feature useful as it can again be linked to their reading style behaviour (i.e. skimming). Having the important terms highlighted would ensure that they read the key points while skimming, and thus get a better comprehension of the story. Likewise, it may apply for Reviewers, as they would still have the option of reading the full story but with the addition of the important details being highlighted. They might get a deeper understanding of the story by seeing which parts are key points to the text. It could also be argued that this feature may be useful for Dippers. Based on their reading style behaviour, (i.e. scanning), one could assume that the information for which they are looking for would be part of the key highlighted text so finding this information would become much easier and less time consuming during their short reading sessions.

Accordion Background Information: *The Accordion Background Information feature allows users to get a broader understanding of the story's context by providing further information of the key highlighted terms in an expandable accordion style organisation.*

This feature is more likely to be useful to Reviewers as they generally read for comprehension and in greater detail than the other news reader types. Reviewers would enjoy the ability to find more information about key parts of the story for a better understanding. Trackers and Dippers may not find this feature useful. Trackers tend to skim the news for general understanding of the context whereas Dippers tend to scan it in extremely short time. Both reading style behaviours would have no interest in understanding the details of a story, especially from outside sources.

Related Articles: *The Related Articles feature allows users to get more context around a particular story by providing access to other stories with similar topics or themes.*

Reviewers are more likely to find this feature beneficial as they read the news in detail to fully understand the context of the story. An option to enhance their understanding of a current news story by providing access to similar themes or topics would be useful. It can also be argued that Dippers may find this feature useful.

For example, Dippers tend to read the news for a very short time and only read in particular sections so providing related articles may allow them to navigate to stories within the same section in which they have shown interest. Further, a mixture of Reviewer and Dipper may find this feature useful; for example, a user who reads the news for over ten minutes at a time but only browses particular sections. On the other hand, Trackers are less likely to find this feature useful as they are not detail oriented and they utilise both browsing strategies to choose news headlines.

Word Cloud/Keyword List: *The WordCloud/Keyword List is designed in such a way as to provide a general overview of the story by presenting keywords and phrases alone without all the story's text, thus extending the information provided by the story's title.*

Dippers may find this feature beneficial. They do not spend as much time reading the news compared as the other types and they are looking for specific pieces of information. As this feature allows readers to view the important parts and key messages of the story in a relatively short period of time it would more likely be a suitable feature for this news reader type. On the other hand, Trackers and Reviewers, as they are characterised by skimming and detailed reading in terms of their reading style preference, would be unlikely to find this feature conducive for them. It can be argued, therefore, that this feature is not suitable for those two types.

Bullet Point Summary: *The Bullet Point Summary feature allows readers to gain a general understanding of the story by presenting the key messages of the story in bullet points, thus reducing the amount of text and reading time needed to get the gist of the story.*

Dippers may find this feature useful as they tend to read for a short period of time to utilise scanning while reading news stories. This feature would help Dippers quickly to gain an overview of the story while being able to scan for the important information more quickly due to the reduced text. Trackers may also find this feature beneficial as it is similar to the paragraph summary feature. The reduced amount of detail in the story may not be suitable for the reading style of skimming which characterises Trackers. On the other hand, Reviewers may not find this feature useful at all as they prefer an in-depth view of a story which can only be achieved through detailed reading; clearly bullet points cannot provide this level of detail.

6.5 Discussion

This Chapter investigated different forms of Habito News app user interface that would benefit different kinds of news reading behaviour. Building on prior knowledge (i.e. News Reader Typology in Chapter 3 and user model acquisition in Chapter 5), it proposed and evaluated different user interface designs for the different news reading characteristics.

The Chapter presented two controlled laboratory evaluation studies in which several prototypes were being tested and evaluated, as well as it described the generation of adaptation rules that will be used during the adaptation process. The results of the first controlled lab study were mixed wherein only the variant user interface for Trackers worked better than the baseline user interface. The designs for Reviewers and Dippers did not meet the expectations and further investigation was needed. The set up of the first study was aligned with the first modelling technique presented in Chapter 5, in which the model was capable of predicting a user's news reader type. By doing so, and having designed a variant user interface for a particular news reader type, we would be able to recommend this variant user interface to that particular type. In the second lab study, however, we aimed to further elaborate on our designs but also to attempt to associate individual user interface features with different news reading characteristics (i.e. the news reader factors that discriminate the News Reader Typology). By doing so, and having the model from the second modelling technique of Chapter 5 (i.e. learn the reader factors and construct a user profile), we would then be able to generate and construct a compositional user interface instead of a variant for a particular news reader type.

While the results of the two controlled lab evaluation studies found successful forms of the user interface and features that were preferred by the participants, a final evaluation study is needed. In particular, the final evaluation will evaluate the adaptive news research platform (Chapter 4) in an end-to-end user scenario in which all its components will be evaluated. Moreover, the user interface features that were proposed in this Chapter will be implemented in the native Android Habito News app (as opposed to interactive wireframes) as well as the adaptation rules will be integrated in the app. The end users, therefore, will be exposed to a fully adaptive version of Habito News wherein the model will unobtrusively monitor their behaviour and based on the modelling technique and the adaptation rules will adapt the app's user interface accordingly.

Chapter 7

Evaluation of the Adaptive News Research Platform

Chapter 4 introduced an adaptive news research platform that aims to facilitate the exploration of the research questions addressed in this thesis. Chapters 5 and 6 explored separately the individual core components of the research platform (e.g. User Modelling, Designs of adaptive forms of the app and the Adaptation mechanism). This Chapter aims to examine the effectiveness of adaptation in a final evaluation study in which all the components of the research platform will be evaluated in end-to-end user scenarios.

The Chapter begins with a motivation of the evaluation study presented. The study aims not only to examine the effectiveness of the adaptation process, but also to assess the adaptive research platform in its whole wherein all the components interact to each other and will be evaluated together. The Chapter continues by presenting the study protocol and presents an analysis of the data being collected. It concludes with a discussion of the findings.

7.1 Motivation

The work presented in this Chapter aims to evaluate the adaptive news research platform and all its core components in a final field evaluation study. Specifically, the primary aim of the Chapter is to assess, in a layered evaluation study, first the interaction layer and second the adaptation decision-making layer. As discussed in Chapter 2, according to the layered evaluation of adaptive user interfaces (Paramythis et al., 2010; Brusilovsky et al., 2001; Weibelzahl, 2001; Masthoff, 2003; Gena, 2005), the interaction layer assesses whether the user's characteristics have been successfully detected by the system and stored in the user model. The adaptation decision-making layer assesses the adaptation mechanism and the user experience relating to whether the adaptation decisions made are valid and meaningful to the end user.

The research questions that were individually examined in previous Chapters (i.e. RQ2, RQ3, RQ4 in Chapters 5 and 6), will be addressed in this Chapter where all the components of the research platform interplay in an end-to-end user scenario. Additionally, subsequent questions will be addressed including: (a) "To which extent Habito News users prefer the adaptive user interface over a baseline user interface", and (b) 'To which extent the adaptation effect is noticeable to the user".

Having addressed the research questions (RQ2-RQ4) individually in Chapters 5 and 6, an evaluation study of the whole framework is essential, as this will increase the ecological validity of our results and seek to address the overarching goal of this thesis, i.e. the automatic adaptation, purely interaction-driven, of news apps user interfaces.

7.2 Data and Methods

The final evaluation study was chosen to be a field study in which Habito News app was deployed through Google Play and we monitored participants' user experience throughout the trial using questionnaires. As explained in the previous section having participants use the app in their personal device in a real setting would increase the ecological validity (i.e. the extent to which the findings are able to be generalised to real-life settings) of our study.

7.2.1 Materials

Unlike the laboratory evaluation studies presented in Chapter 6, this study aims at a longitudinal study of self-determining news reading where patterns emerge from repeated behaviour. In addition, contrary to those previous evaluation studies, wherein participants interacted with the same Android device that were given in the lab, in this study we allowed participants to read the news on their own device. By doing so we enabled participants to have more freedom as they were able to read the news whenever they needed to without the need to come in the lab. In addition we expected them to interact in their natural way because they were using their own device. We also utilised questionnaires to assess participants' overall user experience and satisfaction. All these materials are discussed in Section 7.2.4.

7.2.2 Procedure

All participants who took part in the study were given instructions by email (Appendix B.5). First, participants downloaded and installed Habito News in the personal smartphone device. A similar process was followed as in the data collection studies reported in Chapter 5. Participants created an account wherein they had to agree, by way of a consent form, that their interaction data would be collected (the same consent form used here as in Chapter 5 in which Habito News collected participants' interaction data, Appendix B.1). As part of the registration phase participants responded through built-in questionnaires which provided demographic information and their answers to questions relating to the six reading factors. This is the same built-in questionnaire used in Chapter 5 during the data collection.

In addition to the built-in questionnaires during the registration phase, we implemented a built-in questionnaire that popped-up on a daily basis just before they were starting the reading session. The aim of the daily questionnaire was to probe participants' daily experience using Habito News. The daily questionnaire can be found in Appendix A.7.

Additionally, two more built-in questionnaires popped-up on the 3rd and the 6th day of the trial to examine participants' user experience and their satisfaction in using Habito News. We have chosen the SUS questionnaire (Brooke et al., 1996), a standardised questionnaire to measure a system's usability. This is a general-purpose questionnaire so we adapted the original 10-item questionnaire to reflect the purposes of news reading in a mobile news app. The adapted SUS version can be found in the Appendix A.6.

#P	*Age*	*Gender*	*#Days usage*	*#Days daily question-naire answered*	*SUS ques-tionnaire answered*
P1	28	Male	2	1	No
P2	28	Male	3	2	No
P3	16	Female	1	0	No
P4	29	Male	2	0	No
P5	28	Female	2	0	No
P6	27	Male	6	5	Yes
P7	26	Male	4	2	No
P8	28	Male	2	0	No
P9	28	Female	1	0	No

Table 7.1: Pilot study. Key participants information.

7.2.3 Pilot study

A pilot study was first conducted to simulate the study protocol in order to reveal any particular difficulties due to its complicated nature. Conducting studies ‘in the wild’ may reveal more complications than controlled laboratory study.

We conducted the pilot study in January 2018 in which nine participants (three female; aged M=26.4, SD=4) agreed to take part voluntarily. All participants were colleagues acquaintances of the author and live in United Kingdom and Cyprus. We aimed to have two different groups, a controlled and a test group. The controlled group would receive no adaptation throughout the trial whereas the test group would receive a tailored adaptive user interface after the 3rd day of use. By doing so we would be able to compare the two groups and examine whether the adaptation was beneficial.

As expected the pilot study revealed some problems in the current study protocol which was then refined. As can be observed in Table 7.1, only one participant (#P6) completed the trial in its entirety. Some participants dropped at different stages and two participants (#P3 and #P9) downloaded the app and opted-out from the first day. It is important to note that all participants received the instruction email and no follow-up contact was made. The idea was that participants would respond to the built-in questionnaires in the app without having the experimenter contact them on a daily basis. This could be the reason for the low participation rates. This can happen when you have no control over your participants. There were also participants who did not respond to the daily questionnaire at all; even the app prompted them to do so. We discuss, therefore, the revised study protocol in the next section.

7.2.4 Revised study procedure

Based on the insights gained from the pilot study we refined the study procedure as follows. The registration phase remained as is but we dropped the built-in daily questionnaire from the app. Instead, we created a Google form consisting of the same questions, that participants received via email every evening of the trial. It is also important to mention that participants were instructed to complete this whether they decided to read the news on that particular day or not. The complete version of the revised questionnaire can be found in Appendix A.8, as well as the revised instructions email to take part in the study in Appendix B.6.

Further, we decided not to utilise the SUS questionnaire due to its very general purpose. Instead a more appropriate tool was used to assess participants' overall user experience and satisfaction. We have chosen AttrakDiff (Hassenzahl et al., 2003), a questionnaire that measures the attractiveness of a system. The questionnaire measures four dimensions of a product being tested. It measures the pragmatic quality (PQ), which describes the usability of a product and indicated how successful users are in achieving their goals using the product. It distinguishes hedonic quality into stimulation and identity. Hedonic quality stimulation (HQ-S) indicates to what extent the product is interesting, contains stimulating functions, contents, interaction and presentation styles. The hedonic quality identity (HQ-I) defines the extent to which the product allows users to identify with it. Finally, the attractiveness (ATT) describes a global value of the product based on the quality perception. The full version of the questionnaire consists of 28 questions, each requiring scalar responses. The scales' poles are opposite adjectives (e.g. "complicated" "simple") and they are related to the four dimensions mentioned. For the purposes of this study, due to its complicated nature and to avoid overloading participants with additional questions, we chose to utilised the shortened version of the questionnaire which consists of 10 sets of words-pairs and combines the two hedonic quality dimensions into a single value.

We used the same days to send the questionnaire, i.e. the 3rd and the 6th day of the trial (before and after the adaptation). The questionnaire was sent through an online platform [1].

Finally, the choice initially made to have a control and a test group was not viable, as we did not have the resources to reach large audiences in order to be able to collect enough data for the purposes of statistical analysis. We preferred, therefore, a more qualitative nature of the evaluation study by including both close and open-ended questions in the questionnaires. In this alternative study design, the first 3 days would test the non-adaptive version, whereas the following 3 days of the experiment would test the adaptive variant interface.

7.2.5 Participants

For the main study, we recruited participants through colleagues, and university students at University College London and University of Cyprus (Table 7.2). It is important to highlight that the participants of the main study are completely different from the pilot study. The inclusion criteria required participants to use a smartphone running Android operating system 4.3+ (for purposes of Habito News compatibility) and to read the news on a regular basis using a digital device. All participants took part in the study voluntarily.

Ten participants were recruited, four female and six male and their ages ranged from 18 to 33 (M=26, SD=5). Four participants are currently living in London, UK, and six live in Cyprus. Six participants are professionals, and four are students.

7.3 Results

The analysis was conducted in two parts with the aim of examining whether the adaptation process was beneficial (i.e. improved their overall experience, the interactions required to find articles, the easiness to read them and others - refer to

[1] AttrakDiff: http://attrakdiff.de/index-en.html

#P	Age	Gender	Location	#Days did not read news
P1	28	Male	UK	2
P2	27	Female	Cyprus	1
P3	28	Male	Cyprus	2
P4	30	Male	UK	3
P5	19	Male	Cyprus	2
P6	26	Male	Cyprus	4
P7	23	Female	Cyprus	0
P8	18	Female	UK	1
P9	33	Male	Cyprus	1
P10	33	Male	UK	1

Table 7.2: Main study. Key participants information.

the Daily Questionnaire) to the participants and to which extent participants preferred the adaptive variant of Habito News that was tailored to them. In the first part of the analysis, we evaluated the adaptation mechanisms and the user experience with variant user interfaces. The central question of this analysis examined whether the adaptation decisions were valid and meaningful to the participants. In the second part of the analysis, we evaluated the user modelling component by examining whether the user model was able to successfully detect participants' news reading behaviour and predict their news reader type.

7.3.1 Daily Questionnaire

In the first part of the analysis we analysed the responses to the daily questionnaire. That allowed us to examine participants' preferences before and after the adaptation.

Initially, we aggregated all participants' responses into a single value for each question for the day before the adaptation and the days after the adaptation. All participants' responses to the six questions depicted in Figure 7.1 and Table 7.3 lists the Likert scale used for each question. Q3, Q4 assessed the navigation behaviour, while Q5 and Q6 the news reading behaviour. All these four questions are further categorised and analysed under the performance measure. Q2 and Q10 refer to the overall user experience and satisfaction of using Habito News before and after the adaptation.

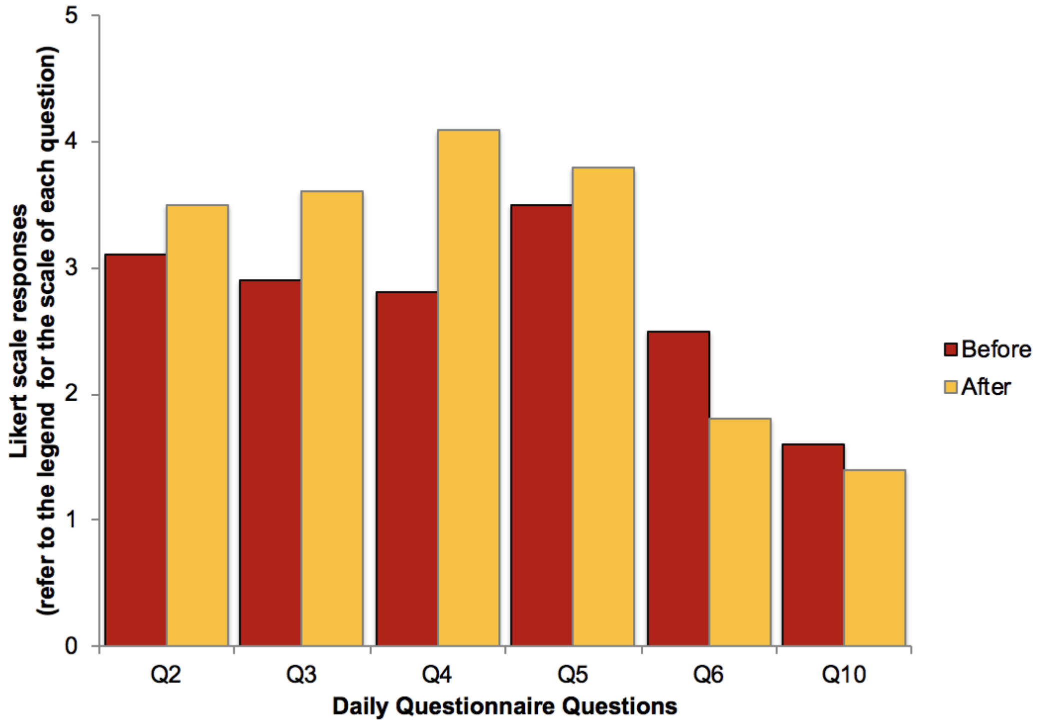


Figure 7.1: Participants' aggregate responses before and after adaptation for each question. Refer to Table 7.3 for the Likert-scale of each question.

As can be observed in Figure 7.1, all participants found the adaptive variant easier for browsing news headlines with fewer interactions needed (Q3 and Q4). Likewise, participants found the adaptive version of Habito News easier and quicker to read news articles (Q5) and with better organisation and structure of the article's content (Q6). Overall satisfaction and user experience was also improved using the adaptive version (Q2 and Q10). Although, at first glance, the results seem quite promising, we conducted a statistical test to establish whether the interface switch yielded better performance, increased user experience and satisfaction. We first discuss the results of a Wilcoxon signed-rank test (a non-parametric statistical test that compares two related samples), and then we dive into participants' individual responses for the first 3 days (non-adaptive) and the following 3 days (adaptive) in order to understand the reasons why adaptation was preferred and was beneficial or not. Figures 7.2 shows the aggregated responses of all participants for the 6 questions of the daily questionnaire in each day of the trial (in brown non-adaptive version, in orange adaptive variant interface).

A Wilcoxon signed-rank test showed that the interface change had a significant effect on participants' performance. The adaptive variant was easier to browse news headlines (Q1) ($Z = -1.985$, $p = 0.05$), the number of interactions required to do so was significantly reduced (Q2) ($Z = -2.670$, $p = 0.008$), and it was quicker for reading the story's content (Q3) ($Z = -2.136$, $p = 0.021$). In relation to an article's presentation (Q4) it was suggestive ($Z = -1.706$, $p = 0.088$) of an improvement in aesthetics. The effect size was computed by dividing the absolute standardised Z value by the square root of the number of pairs (N = #participants). The effect size to ease of easiness of browsing news headlines is 0.59, number of interactions is 0.84, quicker reading of the story's content is 0.73 and the article's presentation is 0.53. According to Cohen's classification (Cohen, 1988) of effect sizes, a value of 0.5 and above can be considered as a large effect.

7.3.1.1 Performance

Performance is defined in terms of navigation and reading behaviour. The four questions we investigate here are Q3, Q4 (navigation) that examine whether the adaptive was easier for browsing news headlines and reduced the amount of interactions required to do so, and Q5, Q6 (reading) that examine how quickly is the reading experience and the article's presentation.

As can be observed from Figure 7.2a participants' easiness level of browsing news headlines were significantly increased after the interface switched. Three participants stated that they did not notice any difference between the baseline and the adaptive (#P1, #P2 and #P10), whereas all others reported a significant improvement with #P5 and #P8 reporting from slightly easy in the baseline to very easy using the adaptive. One participant (#P7) who preferred the baseline for browsing the news headlines stated:

"I prefer the previous interaction. The interface needs arrows (right/left) to indicate the categories. Finally the tracked articles are necessary, but I want to see all articles that I read." #P7

In addition to how easily participants browsed news headlines, we examined the number of interactions required to do so. As can be observed in Figure 7.2b all

Question	*Likert Scale Responses*
Q3: How easily did you find the news headlines that interested you with Habito News?	1. Not easy at all 2. Slightly easy 3. Neutral 4. Very easy 5. Extremely easy
Q4: How many interactions (e.g. swipes, flicks) did you make to browse the news headlines that interested you with Habito News?	1. A lot 2. Quite a few 3. Neither a lot not a little 4. Not many 5. Very few
Q5: How quickly did you read the news articles that interested you with Habito News?	1. Extremely slow 2. Slightly slow 3. Neutral 4. Very quickly 5. Extremely quickly
Q6: The ways articles were presented made them easy to read?	1. Strongly agree 2. Somewhat agree 3. Neither agree nor disagree 4. Somewhat disagree 5. Strongly disagree
Q2: How did you feel about using Habito News app?	1. Not at all satisfied 2. Slightly satisfied 3. Neutral 4. Very satisfied 5. Extremely satisfied
Q10: Overall, did you find the experience: positive, negative or neither?	1. Positive 2. Neutral 3. Negative

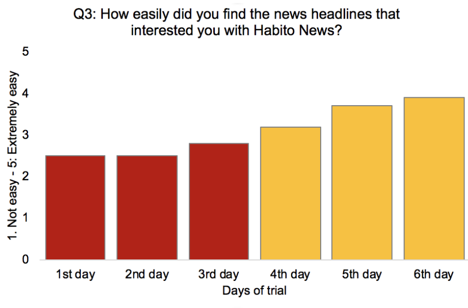
Table 7.3: Daily Questionnaire. Likert Scale for each question.

participants stated that the number of interactions (e.g. swipes and flicks) reduced with the adaptive variant (e.g. fewer swipes), except for participant #P6 which remained the same. Even #P7 who was the only one that preferred the baseline interaction over the adaptive stated a reduction in the number of interactions required from quite a few to neither a lot not a little.

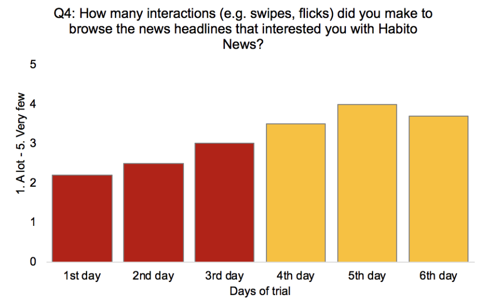
Similar picture found for Q5 and Q6, as participants were able to read faster news articles (Figure 7.2c) and the article's presentation (Figure 7.2d) was more preferred in the adaptive variant. Of course, reducing the number of time required to read articles might be desirable for news readers, but not necessarily for news providers as this might also reduce the engagement with the news app. This is a separate concern and it is not in the scope of this study. Unlike the previous results in relation to browsing, in this questions the results were mixed. Some participants stated an improvement, whereas others remained the same and only #P9 reported that it was slower reading the articles in the adaptive variant (Figure 7.2c). Reducing the amount of time required to read the article cannot, however, necessarily be considered beneficial, as it also depends on other factors such as the presentation of the news article and the content itself. Again, the current study examines the effectiveness of the presentation and not the content itself. For example, the content whether was interesting enough to the participant or not might have had an effect. Q6 examined the presentation of the story but the content is not subject to investigation in this study. Again, as can be observed in Figure 7.2d, all participants except #P7 strongly agreed that the presentation of the news articles contributed to the way they read them.

7.3.1.2 User experience and satisfaction

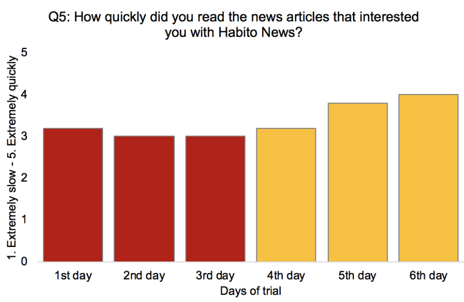
Participants' daily satisfaction, as depicted in Figure 7.2e, shows an increase using the adaptive variant over the baseline. Six out of ten stated an increase, two remained at the same level and two participants favoured the baseline (#P7 and #P10). Clearly, #P7 stated an overall preference towards the baseline over the adaptive, as her previous results suggest. The reason, however, for the decreased daily satisfaction of #P10 was due to the content rather the presentation and the interaction of



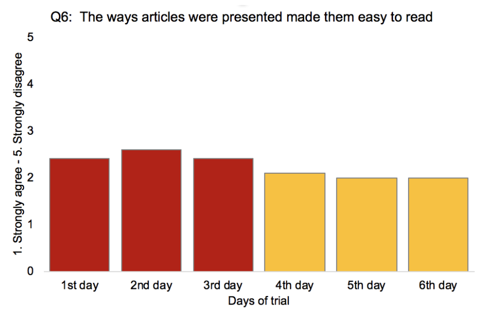
(a) Easiness of browsing



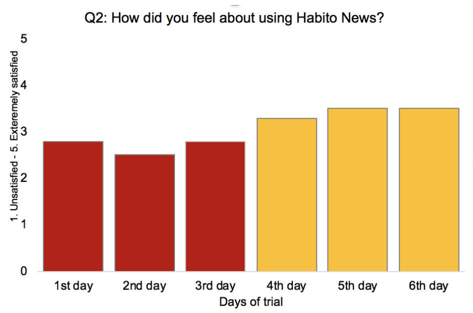
(b) Number of interactions in browsing



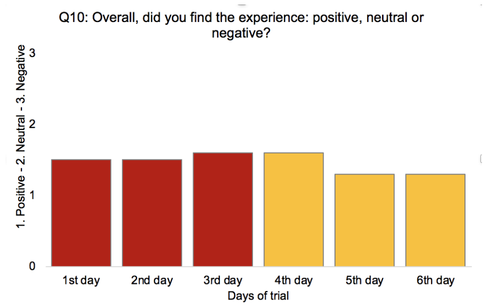
(c) Reading a news article - speed



(d) Reading a news article - presentation



(e) Overall user satisfaction



(f) Overall user experience

Figure 7.2: Daily questionnaire responses before and after adaptation.

news articles.

"The overall experience is good but today was slightly annoying as I couldn't find news that was of interest to me." #P10

Similar results were observed for Q10 (Figure 7.2f) in which no participant stated negative overall experience using the adaptive variant. Instead, overall they all found the user experience in the adaptive variant positive. This was not the case for the baseline as #P9 stated.

"Not so positive, the interaction was not so good." - #P9

7.3.1.3 Adaptation Noticeability

In addition to the performance and overall user experience and satisfaction, we examined whether participants did notice the change in the user interface and the new interactions that were proposed. All participants noticed the new user interface that was proposed to them, and no participant found the change obtrusive except #P2, who reported of the adaptive variant user interface that *"it was more slow"* - #P2. This is also supported from previous results of the same participant, as she was overall less satisfied using the adaptive variant over the baseline.

Looking more closely at other participants' responses there was a more general preference towards the adaptive variant (e.g. #P1 and #P3). #P1 praised the new articles' presentation features except the paragraph summary due to reduced spacing. However, such a problem could be easily tackled and fixed.

"Yes. I like the new interface and the features that come with it. First, I like the feature of "Tracked Articles" as it makes it easy to re-read an article of interest. Also, the new interface provides visibility of more articles, which makes it easy to read a few titles without the need to interact with the device (no swipes needed). After you click on an article, I noticed 3 versions of the same story: (1) Paragraph Summary, (2) Colour Gradient, and (3) Original Story. I do not like the version (1) because there isn't any paragraph spacing and makes it a bit difficult to read and keep track where you left off when you have to scroll. I like most the version (2) as it is clear and 'to the point'. Also, I like the fact that version (3) is supported for someone who wants to read the entire article in its original version." - #P1

A participant (#P3) stated that the new layout organisation of news headlines made it easier for him to track the stories he was following throughout the day as well as browsing more news headlines with the tailored design.

"Yes, the sections are now re-ordered. The articles I read are tracked at the top of the page, which is handy if I want to re-read them. Also, each news category provides more visible articles than before, which means that I can quickly scan many more titles at a glance. I like the new design because I don't have to scroll that much as I used to with the previous version." - #P3

Another participant (#P10) suggested that the adaptive variant that was delivered to him did not allow him to find the news topics in which he was interested, resulting perhaps in the slightly lower daily satisfaction after the adaptation. Indeed the new headlines layout organisation might have affected the news content, but still this could be further adapted by monitoring the topics of interest and further re-organising the news headlines.

"Yes. The interface changed but this time I could only access fewer news and not necessarily the usual topic (science/tech, finance, world) I look at." - #P10

7.3.1.4 Reasons for reading the news and stop reading the news

Another interesting insight that was gained from the dataset are the reasons that made participants decide to read the news but also what made them decide to stop reading it. It is important to examine these two questions (Q8 and Q9) in order to identify whether the adaptation gave them an additional boost and need to read the news or whether the adaptive user interface made them want to stop reading.

Participants, mainly, stated that they decided to read the news because they wanted to find out about what was happening in the world as well as for relaxation. The reasons, however, for making them stop reading were varying. Among the most popular were that they felt they "had enough news for that day" and "lack of free time". Quite interesting was the fact that some participants reported, "the app was slow" - #P2, and #P9 stated, "I got a bit tired and overwhelmed while interacting". Those two participants made similar comments in their overall user experience (Figure 7.2f Q10). Such a finding might suggest that for those two participants the adaptation was not beneficial. Additionally, other participants reported lack of relevant news content and interesting topics such as #P10 "I did not find interesting news to read as the interface was different". However, this may not necessarily be a problem because there was a chance that on that particular day there were no news stories of particular interest to that participant rather than that the interface did not present intersecting news headlines. As previously discussed, a mechanism could be implemented that tracks the topics of interests and reshuffle the news stories or load more topics from the BBC news feed API.

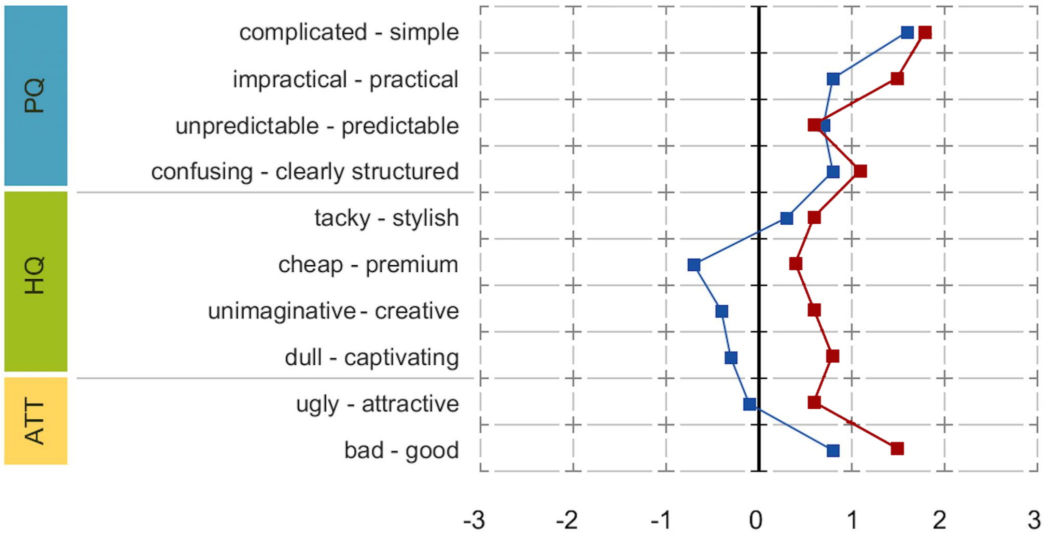


Figure 7.3: AttrakDiff word-pairs answers (e.g. -3 most complicated to 3 most simple, with zero as the neutral value between the anchors of the question). Baseline in blue, Adaptive in red.

7.3.2 AttrakDiff questionnaire analysis

In the second part of the analysis, we examined participants' responses to the AttrakDiff questionnaire; the instrument to assess Habito News attractiveness before and after the adaptation. Initially, all participants' responses to the word-pairs were aggregated (Baseline refers to the first 3 days, whereas Adaptive refers to the days after the adaptation, i.e., 4^{th} until the 6^{th} day) and are depicted in Figure 7.3. All AttrakDiff words-pairs are shown in the vertical axis, whereas the assessments in the horizontal axis. The values in the table represent the chosen option in the word-pair (-3 referring to the leftmost and 3 to the rightmost part of the scale).

As can be observed from Figure 7.3, in all three dimensions, pragmatic and hedonic quality as well as attractiveness, participants responded with higher values for the adaptive variant. Regarding the pragmatic quality, both the adaptive and non-adaptive versions of Habito News found to be successful for users to achieve their goals. An interesting finding, however, is in relation to the hedonic quality in which we can observe higher values in the adaptive than in the baseline. This may suggest that the adaptive variant was more interesting, contained stimulating

#P	*Tracker (%)*	*Reviewer (%)*	*Dipper (%)*	*Self-assessment of News reader type*
P1	**60.8%**	27.4%	11.8%	Reviewer
P2	**72%**	16.5%	11.5%	Reviewer
P3	**57.6%**	22.8%	19.6%	Reviewer
P4	**60.5%**	25%	14.5%	Dipper
P5	**45.66%**	**33.33%**	21%	Dipper
P6	**49.33%**	18%	**32.66%**	Dipper
P7	**52.33%**	28.33%	19.33%	Dipper
P8	**45.66%**	**40.33%**	14%	Dipper
P9	**39%**	**46%**	15%	Dipper
P10	**43.66%**	**34%**	22.33%	Tracker

Table 7.4: User Modelling component output on the 4th when the interface adapted. Last column shows participants' self-reported of news reader type during the Exit Questionnaire.

functions and contents, as well as interaction and presentation styles Likewise, the overall attractiveness showed an increase in the adaptive variant.

7.3.3 User Modelling evaluation

In addition to the evaluation of the adaptive mechanism and user experience before and after the adaptation, we evaluated the user modelling component. The central question of the user model evaluation was whether the user's characteristics were being successfully detected by the system and stored in the user model. In this analysis we compared the output of the user model with the information obtained during the registration phase (i.e. answers to the six reading factors) as well as the exit questionnaire (Appendix A.9) wherein participants were given descriptions of the three news reader personas and selected the one that best describes them.

Table 7.4 presents the output of the user modelling component in a form of probabilities (using the predict_proba() of the Random Forest algorithm [2]) in relation to the three news reader types that a user belongs to. It is important to note that the model was being trained from the data presented in Chapter 5 and no further training was carried out in this study all participants' daily data was being used to test the model. As can be observed the Dipper type, a person with a casual inter-

[2]http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html

#P	*Frequency*	*Reading time*	*Browsing strategy*	*Reading style*	*Location*	*Time of Day*
P1	Many	10+ min	Particular	Skimming	Home	Morning
P2	Many	10+ min	All	Scanning	Public	Morning
P3	Once	5-10 min	Particular	Skimming	Work	Morning
P4	Many	10+ min	Both	Scanning	Work	Morning
P5	Once	5-10 min	Both	Skimming	Work	Morning
P6	Less	0-5 min	Both	Scanning	Public	Morning
P7	Less	0-5 min	All	Detailed	Home	Evening
P8	Less	0-5 min	All	Skimming	Home	Morning
P9	Once	5-10 min	All	Skimming	Home	Evening
P10	Many	5-10 min	Particular	Scanning	Work	Morning

Table 7.5: Participants' responses during the registration phase.

est in the news, was less representative in the model output due to all participants reading the news almost all days of the trial (Table 7.2).

In Table 7.5 we show how participants responded to the six questions related to the six reader factors. By examining their responses we can observe that the model was able to detect some participants' behaviour. For example, #P6 has the most stereotypical Dipper characteristics (Table 7.4) and a closer look in Table 7.5 indicates that frequency of less than once a day, 0-5 minutes reading and scanning as the reading style are characteristics of that news reader type. Likewise, participants with frequency as many times a day, the model was able to assign higher values in the Tracker type as reading multiple times a day is a strong characteristic of that news reader type.

As a last step of the user model evaluation we examined how the different news reader types responded to the questions Q2 and Q10 of the daily questionnaire. This would allow us to draw some conclusions as to whether different kinds of news reading behaviour resulted in more satisfaction with the adaptation than others. In its simpler form, if we take the higher value of the three in Table 7.4, the model identified 9 Trackers and 1 Reviewer. However, this is a simplification of the real world as users might belong in between types and share characteristics among the types. Therefore, we can say the model detected 5 pure Trackers (#P1, #P2, #P3, #P4 and #P7), 3 Tracker/Reviewer (#P5, #P8 and #P10), 1 Reviewer/Tracker (#P9)

#P	*Q2 - Before*	*Q2 - After*	*Q10 - Before*	*Q10 - After*
P1	4	4	1	1
P2	2	3	1	2
P3	3	4	2	1
P4	2	4	2	1
P5	4	5	1	1
P6	3	3	2	2
P7	5	3	1	2
P8	2	3	2	1
P9	2	3	3	2
P10	4	3	1	1

Table 7.6: Q2 and Q10 of the daily questionnaire . Refer to Table 7.3 for the Likert-scale of Q2 and Q10.

and 1 Tracker/Dipper (#P6). As can be observed from Table 7.6, all except one pure Tracker stated more satisfaction using the adaptive variant. A similar picture was observed for Tracker/Reviewer except #P10, but the Reviewer/Tracker combination reported higher satisfaction using the adaptive as well as a more positive overall experience. The Tracker/Dipper combination reported neutral satisfaction and experience both before and after the adaptation. To some extent the results indicate that the adaptation did work for particular kinds of news reading behaviour. Of course, this could be related to how the initial model was trained and the limitations discussed in Chapter 5.

Another interesting result is how participants responded when they were given descriptions of the three news reader types and were asked to choose the one that best described them. Surprisingly, one out of ten chose the Tracker type (Table 7.4), a result that contradicts with their actual behaviour and how they utilised the news app for the period of the trial. Of course, it was previously discussed in Chapter 5 that these self-reported questionnaires rely on people's ability accurately to assess themselves, which sometimes can be considered unreliable.

7.4 Discussion

This Chapter presented the final evaluation study of the adaptive research platform proposed in this thesis and examined the effectiveness of adaptation. The aim of the layered evaluation study presented was twofold. First, it examined the adaptation decision-making layer in which the adaptation mechanism and the user experience with the variant user interfaces were evaluated. Second, it investigated the effectiveness of the user modelling and its ability to successfully detect users' news reading behaviour and build their news reader user profile.

The results of the adaptation decision-making layer suggest that the adaptation was desirable to participants, except one participant who stated otherwise. They show that the designs that have been implemented and evaluated in Chapter 6 were preferred compared to a non-adaptive version. This has implications to the design of news services, as participants reported higher levels of satisfaction when a tailored interface and interaction was proposed to them compared to a universal baseline interface that was designed for all. Designers and practitioners, therefore, should not only personalise the news content but also they should consider the interface and the interaction when they design news services.

The user modelling results also suggest that our modelling technique was able to build an individual user profile using their daily interaction activity. Different kinds of news readers' behaviour found to benefit more from the adaptive user interface than others. For example, pure Trackers stated more satisfaction in using the adaptive variant rather than the non-adaptive version. Furthermore, the limitations of the user modelling component (e.g. small sample size) highlighted in Chapter 5, were still present in this study and will be discussed in the Chapter 8 as part of future work.

In addition to the findings of the evaluation study, the Chapter also discussed the complicated nature of conducting field studies and maintaining participation throughout the trial. The pilot study presented in this Chapter showed the difficulty of running such a study with no control over the participants and how much data you could lose if you do not regularly stay in touch with them through reminders such as daily email or notifications.

Overall, the final evaluation addressed the research questions (Chapter 1 RQ2, RQ3, RQ4) in a real-life setting in which participants were given freedom to read the news under different circumstances and contexts in their daily life, away from the laboratory setting. In relation to RQ2, the final evaluation study showed the effectiveness of our user modelling approach in identifying the different kinds of news reading behaviour and learning from their interactions to classify users and construct an individual user profile. In relation to RQ3, the study showed that the adaptation mechanism (Chapter 6) did work and the adaptation rules that were generated served satisfactory individual user interfaces to the participants. Finally, in relation to RQ4, the analysis of the AttrakDiff and the Daily questionnaires, showed that participants stated a preference towards user interface personalisation and they praised the fact that they were given user interface elements to interact with that enhanced their user experience.

Chapter 8

General Conclusions and Future Directions

The goal of this research work has been the systematic understanding of the design and implementation of adaptive user interfaces for news services in mobile apps. The main objectives that were accomplished are; first that mobile news readers can be characterised within three primary news reader types and be discriminated by six reader factors that reflect their news reading habits; second, that it is possible for a news app to detect a user's news reader type and model the six reader factors by analysing their news reading interaction behaviour with a news app; third, that different kinds of news reading behaviour benefit from different forms of the news app user interface, and; fourth the ability of a concept demonstrator news app that systematically monitors and models users' behaviour in an attempt to recommend a better user interface and interaction that would suit their characteristic ways of consuming news content in news apps. Overall, the thesis has shown the feasibility of implicitly recognising news reading interactions patterns and adapting the user interface of a news app that matches users' news reading characteristics and reflects their ways of news consumption as opposed to what is being consumed.

8.1 Thesis Contributions

The main contributions of this thesis are (a) a News Reader Typology that characterises the different ways of how people consume news content, (b) the mechanisms for exploring and modelling news reading interaction habits, (c) the adaptive user interface designs for different kinds of news reading behaviour, and (d) a concept demonstrator of an adaptive news app.

8.1.1 A News Reader Typology

The thesis has proposed a News Reader Typology for mobile news readers. The typology defines three primary news reader types along with six discriminating reading factors. While there is a rich body of literature from media studies in understanding news consumption patterns, there is dearth of research on forming news reader types and personas that can explain different kinds of digital news reading interaction habits. The news reader typology is well defined and distinct, which is fundamental to applying personalisation in news apps' user interfaces. Although prior research has examined people's digital news reading behaviour, mainly in relation to what news people read, the proposed news reader typology investigated news reading habits in relation to how people consume and read the news. To the best of the author's knowledge such a typology does not exist. The potential value of utilising the proposed typology is that it could be used as the basis for modelling news reading behaviour, and further enriching user models with domain-independent factors such as personality traits or other cognitive aspects. Additionally, the news reader's persona characteristics could be associated with different forms of the user interface, providing a more tailored and refined interaction and experience to the end user.

8.1.2 Exploring and Modelling News Reading Habits

A fundamental component in any adaptive user interface is the User Modelling component. The User Modelling component defines mechanisms to obtain a user model that will be used during the adaptation process and, usually, relies on effective user models wherein observable information about a user is inferred from observable information from that user (Frias-Martinez et al., 2005). Chapter 5 of this thesis has demonstrated the mechanisms for obtaining a user model for news readers by exploring news reading interaction data that was obtained through Habito News, the concept demonstrator news app. The modelling mechanisms include rule-based methods (inferences from the typology and transformation functions) and machine-learning algorithms, in order to build models that are capable of predicting a user's news reader type and model the six reader factors that constitute a user's profile. In addition to the modelling mechanisms, the thesis proposed a hierarchical framework for analysing those patterns of news reading interaction behaviour. The framework defines different level of abstraction in the data and it was utilised during the exploration and implementation of the user models. In addition to its value in this work, the framework can be generalised to include more mobile-sensing and interaction data as well as enriched with domain-independent features such as personality traits that were examined in Chapter 3.

8.1.3 Design variant user interfaces for different kinds of news reading behaviour

The thesis has proposed three variant user interfaces for the three primary types, as defined in the News reader typology, along with a pool of user interface features that were used in order to provide a personalised user interface based on a user's profile. Some of the user interface features already exist in contemporary news apps but they are not tailored for each individual based on their characteristic way of reading the news. The evaluation studies presented in Chapter 6 show evidence that different news reader types, and subsequently different news reading behaviours, prefer to interact with different user interface elements in relation to how news stories are presented and the ways that the interface enables them to browse through news headlines. In addition to variant user interfaces, we explored the idea of compositional user interfaces wherein user interface elements are associated with different news reading characteristics, and based on a user's profile the system generates an individual user interface tailored to the individual user. Amongst the different user interface features that we implemented and evaluated (Chapter 6), there are features such as the wordcloud that do not appear in contemporary news apps. This particular presentation of a news article's text will facilitate liberal-surfer news readers that do not spend much time on reading the news quickly to get the gist of the story, as it provides slightly more information than the story's title. Empirical evidence about the desirability of adaptation was also obtained during the final evaluation study (Chapter 7). The results of the final evaluation study showed that participants preferred the tailored adaptive user interface compared to a non-adaptive. The tailored user interface reflected participants' individual news reading characteristics and participants praised the fact that they were given user interface elements to interact with that enhanced their user experience.

8.1.4 Habito News: A concept demonstrator of an adaptive news app

A concept demonstrator of an adaptive news app, namely Habito News, systematically monitors and models user's interaction behaviour pattern, infers models from that data, and adapts its displays in response to those models. The final version of Habito News, as presented and evaluated in Chapter 7, operates as an adaptive news app. In an end-to-end user scenario, the user downloads and registers with the app, while the user continues reading the news, the app unobtrusively gathers all their interactions and data related to the six reading factors. The user modelling component builds a user profile for that particular user, which is transmitted to the app. Once the app receives this information it generates 'on-the-fly' a unique user interface design that matches the user's profile characteristics.

8.2 Future research directions

The research work presented in this thesis opens the door for further research in the areas of User Modelling and Adaptive User Interfaces.

8.2.1 Large-scale deployment of the app

Besides the contributions to the scientific literature, this research work has implications in commercial news services. An immediate application and further exploration, therefore, would be that leading news organisation such as BBC embrace the knowledge gained in this thesis and apply it with larger audiences. Hence, collecting a larger pool of users we will be able to apply different machine learning algorithms, that we could not apply previously due to constraints of the limited sample sizes, and thus improve our model's accuracy. A similar process applies to the final evaluation study presented in Chapter 7 in which, with larger numbers, you would be able to include a control and experimental group as well as utilising mixed methods of data collection (both qualitative and quantitative) as opposed to the purely qualitative method as it stands in Chapter 7. Such an experimental design would require a group that would receive no adaptation throughout the trial (i.e., the controlled group) and the test group that would receive a tailored adaptive user interface (i.e., experimental group). This would allow to draw more concrete results on the effect of adaptation and eliminate any confounding variables. To implement this, an additional component needs to be implemented in the the app (in the Presentation Layer of the app - Section 4.2.1), which would divide the users into two groups and decide which user receives adaptation.

8.2.2 Generalisation of the Framework for Interaction-driven User Modelling

The framework for analysing news reading interaction habits (Chapter 5) can be considered as another line of future work. The framework that facilitated the user model acquisition, defines methods that enable the analysis of interaction data obtained while users interact with news content as well as mobile-sensing data, in order to construct the user profile. The framework, however, as it is defined in Section 5.3 serves a particular set of interactions that are associated with the user interface (i.e. rows of thumbnails layout; the design adopted from BBC). Future work includes the generalisation of our framework in order to provide generic methods that can translate news interaction patterns from different news apps and providers, other than the BBC. This would enable the integration of our framework in different news layout organisations and interactions, and thus it would enable the generation of extended news reader profiles for news consumption despite the different news apps layouts. In addition, further data collection and more diversified cohort would further improve the models reported in Chapter 5.

8.2.3 Further exploration of the design space of adaptive user interfaces

In Chapter 6 we proposed and evaluated different user interface features that were designed to suit the different news reading characteristics of news reading behaviour. Another direction of future work is the exploration of new user interface widgets or idioms that will further enhance user's experience and satisfaction. The existing set of features covered navigation, reading and context related features. In future, we could focus in refining and exploring alternatives in one of this categories of features such as exploring reading-related features. In combination with other research directions (Section 8.2.5) of this work, more advanced features for reading news articles can be developed.

8.2.4 Further exploration of domain-independent factors in relation to user modelling and the design of the adaptive user interfaces

In Chapter 3, domain-independent factors such as people's personality traits and need-for-cognition were found to be correlated with how individuals consume news. Additionally, the work reported in Chapter 3 suggested the added value of incorporating personality in a user model as this was corroborated by a clustering analysis that revealed more subtle clusters when adding personality. Hence, the user model acquisitions proposed in Chapter 5 could be extended to include facts about a user's personality and need for cognition. Those traits can be quantitatively measured, as there are numerical values for each of the factors which can easily be incorporated as features in the proposed classification agents.

Personality traits could be also examined in relation to the design of the adaptive variant user interfaces by investigating potential correlations with the pool of user interface features as proposed in Chapter 6. Given the findings discussed in Chapter 3 in relation to personality traits and the reading factors, these could be included in the adaptation mechanism that generates the personalised user interface. For example, a 'Tracker' has a tendency towards the characteristics of an extravert and openness to experience, while a ‘Reviewer’ presents high conscientiousness and NFC, in such a way that reflects the preferable ways on expanding and absorbing news content. Accordingly, adaptive user interface conditions could be created, containing navigation elements and presentation schemes that could leverage the algorithm’s outcome to benefit the user. For example, an extravert and openness to experience Tracker can be given features such as increased notifications or enriched content views with open access to reach as many news stories as possible. Likewise, a conscientious Reviewer can be provided with more structured viewpoints of the story, including related articles, and extended details.

8.2.5 Use of eye-tracking for better understanding of browsing strategy and reading style

Among the six reading factors that are discussed in Chapter 3 as part of the News Reader Typology and in Chapter 5 as part of the user modelling process, the factors of Browsing strategy and Reading style have some particularities compared to the other factors. Unlike the other reading factors that can be directly computed from users’ actions with the app (e.g. frequency of reading), these two factors involve interpretations of behaviour. Chapter 5 proposed functions to compute those factors but inevitably made several assumptions and simplifications. An alternative could be the use of eye-trackers that will provide more accurate metrics and better inform the design of the functions we proposed.

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Appendix A

Questionnaires for Main User Studies

A.1 Chapter 3: Online Questionnaire

Title: Habit-forming newsreader mobile app

This survey is part of a research project of my studies at UCL. The project aims to explore the effects of adaptation in the news domain on mobile devices. The survey is completely anonymous and the data collected will only be used for research purposes. For further information, feel free to contact me at: m.constantinides@cs.ucl.ac.uk

A. Demographics * Required

1. What is your gender? *
   - Male
   - Female
2. What is your age? *
   - 12-18
   - 19-35
   - 36-50
   - 51+
3. What is the highest level of education you have completed? *

- No schooling completed
- Some high school, no diploma
- High school graduate or diploma
- Trade/technical/vocational training
- Bachelor's degree
- Master's degree
- Doctorate degree

B. News Reading * Required

I. General questions about news reading

4. Do you read print newspapers? *
    - Yes
    - No
5. Do you prefer to read broadsheet (e.g. Times, Guardian, Telegraph) or tabloid (e.g. Sun, Mirror) newspapers? Answer this question if the answer in question 4 is Yes.
    - Broadsheet
    - Tabloid
    - Not applied
6. Do you read digital news? (Digital news is as any electronic form of news such as reading news on a newspaper website) *
    - Yes
    - No
    - Not applied
7. Do you read news on a mobile device? (smartphones, tablets) * If No, could you skip the following questions and submit the survey?

- Yes
- No

8. Which commercial newsreader app do you use? (Examples of commercial newsreader apps are BBC, Guardian, Times, etc.)

9. How often do you read news on your mobile device?

   - Many times a day
   - Once a day
   - Once a week
   - Only occasionally
   - Never

10. What time of the day do you prefer reading news?

    - Morning
    - Afternoon
    - Night

11. Where do you often read news?

    - Home
    - Work
    - Public Transport (train/bus)
    - Other:

12. How much time a day do you spend reading news on your mobile device?

    - I don't read news
    - 0-10 minutes
    - 10-20 minutes
    - 30 minutes

- 1+ hour

13. How much time a day do you spend reading a print newspaper?
    - I don't read news
    - 0-10 minutes
    - 10-20 minutes
    - 30 minutes
    - 1+ hour

II. Navigation in a news reader app

14. How do you look for stories of interest?
    - I look through all sections
    - I only look in particular section
    - Other:
15. What makes you decide to read a story?
    - The story's headline
    - The story's image
    - Neither
16. When you see a story you want to read, do you
    - read it immediately?
    - continue searching and come back and read it?
    - add it into a reading list and read it later?
17. What makes you decide to stop reading?
    - I've seen all the news items that interest me
    - I've checked all the latest news items and am up-to-date

- I've scanned all the news items there are to see
- I am interrupted by something else
- The app is hard to use

18. Some newsreader apps classify the stories in sections. Do you believe it helps you to find a particular story?
    - Yes, it does help me
    - No

19. How often do you look through all the stories of each section?
    (a) Always
    (b) Frequently
    (c) Sometimes
    (d) Seldom
    (e) Never

III. Reading in a news reader app

20. How do you read a story?
    - Scan and skim
    - Read the first sentence of each paragraph
    - Read the whole article

21. How much attention do you pay to a story's images?
    (a) Little
    (b) Somewhat
    (c) Much
    (d) A great deal
    (e) A lot

22. How much attention do you pay to image captions?
    (a) Little
    (b) Somewhat
    (c) Much
    (d) A great deal
    (e) A lot
23. Do you prefer stories that don't require scrolling to reach the end of the story?
    - Yes, I prefer not to scroll
    - No, I don't mind scrolling
24. If there was an option to see a summary rather than the whole text, would you use it?
    - Yes
    - No
    - Don't know

A.2 Chapter 5: Habito News deployment study

Title: Email Invitation to Participate in study with Habito News

Hello everyone,

If you read the news on a digital device and want a chance to win a 50 Amazon voucher download Habito News app today!

I am currently working on a project investigating how people consume news on their smartphones. We are interested to examine peoples' idiosyncratic patterns of accessing and reading the news in an attempt to make smartphone change its user interface to better suit the individual news reader. In this regard, we are looking for Android smartphone users running 4.4+ that would agree to monitor their interaction behaviour while reading the news using our dedicated app. The app will record how you read the news although you won't be aware of this. It will be recording the different actions you make with the app, like choosing to read an article, the time of the day, your current location (in map coordinates) and others. This data will be stored on our server and will be completely secure. All data are anonymous, and will be used for academic research purpose only.

To qualify for the £50 Amazon voucher draw you will have to use the app for a period of 2 weeks (at least) and enter a valid email address when register with Habito News. The app will be listed on Google Play until September 2016, so you can download it and use it any time you want. Please read carefully the consent form (it appears when you attempt to register) before you Agree to sign up with Habito News.

Download the app today: https://goo.gl/Z4I5gm

Read more about the research: http://habito.cs.ucl.ac.uk/

Thank you very much for your help! Please also share this e-mail with your contacts.

Kind regards,

Marios Constantinides

A.3 Chapter 6: Controlled Laboratory Study I: Requirements Gathering Questionnaire

1. What mobile news app(s) do you use?
2. How often do you use it/them?
3. How long do you spend in each sitting?
4. Do you tend to check the news at a particular time or place?
5. How in-depth do you generally read articles?
6. Do you have favourite subject areas you always check?
7. What's your favourite part about mobile news?
8. What's your least favourite part about mobile news?
9. Do your news apps have any significant strengths in your opinion?
10. Do they have any significant weaknesses or potential improvements in your opinion?

A.4 Chapter 6: Controlled Laboratory Study I: Adapted WAMMI Questionnaire

Adapted WAMMI Questionnaire: *It is used to compare the baseline and the variant user interface for each news reader type*

1. Which user interface design is more visually appealing?
2. Which user interface design is easier for the first time of use?
3. Which user interface design is easier to use overall?
4. Which user interface design helps you find interesting stories more quickly?
5. Which user interface design helps you navigate and browse all the news of interest more easily?
6. Which user interface design helps you read all the news stories of interest more easily?
7. Which user interface design makes it harder to remember at which point you are whilst browsing the news?
8. Which user interface design contains more unnecessary features?
9. Which user interface design makes you feel more in control while using it?
10. Which user interface design has better presentation of stories and organisation of menu navigation system that meets your news reading behaviour?

A.5 Chapter 6: Controlled Laboratory Study II: Background Information Questionnaire

Thank you for agreeing to participate in today's experiment. The first part of the experiment includes a questionnaire that probes your background information, previous experience with news apps and questions related with your news reading behaviour. The questionnaire takes 5 minutes to complete it. If you have any question please do not hesitate to ask the experimenter.

A. Demographics

1. Age
2. Gender
    - Male
    - Female
3. Occupation (If you are a Student provide your subject):
4. Level of education:
    - No schooling completed
    - Some high school, no diploma
    - High school graduate or diploma
    - Trade/technical/vocational training
    - Bachelor's degree
    - Master's degree
    - Doctorate degree

B. Previous experience with news apps:

5. How many news apps do you currently have installed in your smartphone?
6. How many news apps do you usually use?
7. From the news apps you currently have installed on your smartphone, which is your favourite?
8. Which interactions with the app's interface do you find the most useful when browsing to find news stories? Explain.
9. Which parts of the app's interface do you find the most useful when reading a news story? Explain.
10. Which parts of the interface do you most dislike from the news apps on your smartphone? Explain.

C. News reading behaviour (please circle one that best applies):

11. How many times do you access news on your smartphone?
    (a) Many times a day
    (b) Once a day
    (c) Occasionally
    (d) Never
12. What time of the day do you usually read the news on your smartphone?
    (a) Morning
    (b) Afternoon
    (c) Evening
13. How much time do you spend reading the news on your smartphone daily?
    (a) 0-5 minutes
    (b) 5-10 minutes

(c) 10+ minutes

(d) 20+ minutes

14. When do you usually access the news on your smartphone?

    (a) At home

    (b) At work

    (c) On the go (public transport, bus, etc)

15. How do you browse for stories of interest?

    (a) I only look through all sections

    (b) I only look at particular sections

    (c) Both

16. What reading strategy do you mainly use to read the news?

    (a) Skimming

    (b) Detailed Reading

    (c) Scanning

17. Does the context affect the way you browse for stories of interest?

    (a) Yes

    (b) No

18. Does the context affect the reading strategy you use to read a news story?

    (a) Yes

    (b) No

Date:

Participant Number:

Participant's Name:

Participant's Signature:

Experimenter Name: Marios Constantinides

A.6 Chapter 7: Final Evaluation Study: Adapted SUS Questionnaire

1. I would be happy to use Habito News as my primary source of online news.
2. Habito News is unnecessarily complicated as a way of keeping up with the news.
3. Habito News is easy to use both for checking and finding headlines and for reading news reports.
4. Habito News is not intuitive to use, you would really need to be shown what it does and how to use it.
5. The ways in which you can check and find headlines and read articles with Habito News are smooth and seamless.
6. Habito News is inconsistent in the way it displays similar kinds of things (headlines and articles, etc) in different ways and in the way you have to do the same kinds of activities (browsing, reading, selecting, etc) in different ways.
7. I would imagine that most people would quickly work out to use Habito News to check headlines and read news reports.
8. With Habito News it is awkward to browse headlines and choose articles to read.
9. I am always confident with Habito News that I know how to find the news I am interested in and how to do all the activities available to me.
10. I needed to work out quite a lot of things about Habito News before I could get going with it to check and read the news.

A.7 Chapter 7: Final Evaluation Study: Initial Daily Questionnaire

1. How did you feel about using the Habito News app today? Answers: 1 (Not at all satisfied) - 5 (Extremely satisfied)
2. How easily did you find news headlines that interested you with the Habito News app today? Answers: 1 (Not at all easy) - 5 (Extremely easy)
3. How easily did you read news articles that interested you with the Habito News app today? Answers: 1 (Not at all easy) - 5 (Extremely easy)

A.8 Chapter 7: Final Evaluation Study: Revised Daily Questionnaire

Email Address:

Name:

Date (current date):

1. Q1: Did you read the news with Habito News today? If ”No” please submit the form and skip the next questions and provide a reason why you did not read it.
    - Yes
    - No
2. If your answer in the previous question is ”No”, please provide a reason here. If ”Yes” leave it blank and proceed with the next questions
3. Q2: How did you feel about using Habito News app today?
    - Not at all satisfied
    - Slightly satisfied
    - Neutral
    - Very satisfied
    - Extremely satisfied
4. Q3: How easily did you find the news headlines that interested you with Habito News app today?
    - Not easy at all
    - Slightly easy
    - Neutral

- Very easy
- Extremely easy

5. Q4: How many interactions (e.g. swipes, flicks) did you make to browse the news headlines that interested you with Habito News app today?

    - A lot
    - Quite a few
    - Neither a lot nor a little
    - Not many
    - Very few

6. Q5: How quickly did you read the news articles that interested you with Habito News app today?

    - Extremely slow
    - Slightly slow
    - Neutral
    - Very quickly
    - Extremely quickly

7. Q6: The ways articles were presented made them easy to read.

    - Strongly agree
    - Somewhat agree
    - Neither agree nor disagree
    - Somewhat disagree
    - Strongly disagree

8. Q7: Did you notice any change on the user interface of Habito News today? If ”Yes”, how did you feel? (please explain if possible)

9. Q8: What made you want to read the news today with Habito News? (click all that apply)

    - For relaxation
    - Follow a story I'm interested in
    - Find out about what is happening in the world
    - Look something up I was thinking about
    - Other

10. Q9: Why did you stop reading? What made you stop reading? (please explain if possible)

11. Q10: Overall, did you find the experience: positive, neutral or negative? (please explain if possible)

A.9 Chapter 7: Final Evaluation Study: Exit Interview Questions

Email address:

Name:

Date (current date):

From the following three options that describe different news reader types, which one best describes you? If more than one option applies, please use the option 'other' but also state the order in which apply (e.g. Type A, Type B - means you believe that you are closer to Type A, and then Type B). *

Type A: I am an obsessive/compulsive news reader. I like to be informed about the latest stories and any updates to stories I am following. I usually read the news for up to 10 minutes at a time and several times a day at intervals, for example, when travelling. Due to my limited time I prefer to extract the important bits of a story (i.e. reading by skimming).

Type B: I am a daily routine news reader. I like to catch up on the day's news, preferably at home. I like an in-depth analysis of the stories I read and will read at length to fully understand the story (i.e. a detailed reading). I usually read the news once a day, spending more than 10 minutes to get through all the stories of interest and likes being informed on a variety of topics.

Type C: I am a liberate surfer news reader. I am a person with a casual interest in the news but also like to read news on specific topics such as sport. I always know what I am looking for so does not spend more than 5 minutes accessing the news. I like to browse particular sections to find stories and look for specific facts or pieces of information without reading everything (i.e. reading by scanning).

Appendix B

Consent Forms and Additional Material for Main User Studies

B.1 Chapter 5: Deployment Studies with Habito News: Consent Form

Thank you for downloading Habito News...

Habito News is a research tool that we use to investigate how to make a smartphone change its user interface to better suit the individual user. We are particularly interested in how people read the news on smartphones and user interfaces for news apps.

We will be asking you to sign up with Habito News. The app will record how you read the news although you won't be aware of this. It will be recording the different actions you make with the app, like choosing to read an article, the time of the day and your current location (in map coordinates). This data will be stored on our server and will be completely secure. We will not share the data with anyone or ever reveal your name to anyone. If we publish the results of the research, the data will be pooled together and will be anonymous. When the research is completed we will delete the data. The trial use of the app will last for 2 weeks after which you should delete the app from your smartphone.

Please ask us (mconstantinides@cs.ucl.ac.uk) if there is anything that is not clear or if you would like more information. It is up to you to decide whether to take part of not. If you decide to take part your are still free to withdraw at any time and without giving a reason.

All data will collected and stored in accordance with the Data Protection Act 1998.

By clicking 'I Agree' you acknowledge that you have read and understood the above statement.

B.2 Chapter6: Controlled Laboratory Study I: Experiment Instructions

Thank you for agreeing to participate in today's experiment. You are about to participate in an experiment of the evaluation of different user interface designs for a news app. The experiment will take place about 15 minutes. If you have a question or problem at any point in today's experiment, please do not hesitate to ask.

Identification of News Reader Type: Before we start the experiment, you will be asked to fill in a questionnaire to identify your news reader type. It will take up to 2 minutes to complete it.

Procedure: Your task today is to read news in an interactive wireframe. Before start the experiment, you will be asked to navigate in the user interface for 2-3 minutes to get familiar with. When you are ready, you will attempt to complete a set of tasks for two different user interfaces. Once you have completed the tasks on both user interfaces, you will be asked to fill in a user satisfaction questionnaire.

Trackers Instructions" Imagine you are commuting to work and just started reading the news on your smartphone. You like to keep yourself informed on the latest stories and any updates of the stories you follow. You also tend to read the news roughly up to 10 minutes several times a day in between activities, for example, in transit. Due to the limited time you prefer to gain only the general or main ideas of stories you read (i.e. skimming).

Please complete the following tasks:

1. You have three articles that you are following:

    (a) 'Eurostar to resume after disruption'

    (b) 'Uber promises 50,000 jobs in EU'

    (c) 'Australian Open: Murray vs Bhambri'

Please find and read each of them to get an overview.

2. Browse (but NOT read) ALL the articles on the app, and then tell the assistant the best three articles you would read.

Reviewers Instructions: Imagine it is a cold and stormy winter night, you are sitting on the sofa at home, having a cup of hot tea and reading the news on your smartphone. Catching up on the news for the day is what fascinates you at most. You like to get an in-depth analysis of the stories you read by performing an extensive reading to fully understand the story (i.e. detailed reading). You usually read the news once a day, spending more than 10 minutes to get through all of the stories that interest you. You also like being informed from a variety of topics. Please complete the following tasks: Read one article from each category and after each article tell the assistant briefly what it is about.

Dippers Instructions: Imagine you had a long week at work and you are now finally returning home. You are not a passionate news reader and you do not have much time to keep updated anyway. However you still like to find out news of your favorite interests. You are now opening your smartphone app to read the news and as you generally know what are you looking for you do not spend more than 5 minutes accessing the news. You like to browse to particular sections to find stories and look for specific facts or piece of information without reading everything (i.e. scanning). Please complete the following tasks:

1. Find and read the article 'Eurostar to resume after disruption'

2. Find and read the article 'Australia Open: Murray vs Bhambri'

3. Find and read the article 'Uber promises 50,000 jobs in EU'

B.3 Chapter6: Controlled Laboratory Study II: Information Sheet

Thank you for agreeing to take part in this study. Below is a detailed overview of the interview process. The interview will take approximately 30-40 minutes with all stages combined.

Stage 1 (10 minutes)

You will be given a questionnaire to fill out. There are three parts to the questionnaire. The first part asks general background information about your age, gender, occupation and education. The second part includes questions about your previous experience with news apps. You are asked about the news apps that you have installed on your smartphone, as well as your opinions on their interfaces for browsing and reading news stories. The third part of the questionnaire asks a series of multiple choice questions about your news reading habits. This is designed to categorise you into a news reader type. After you have completed the questionnaire, you will move on to the second stage of the study.

Stage 2 (30 minutes)

This is the main part of the study, and consists of an interview. This part will focus on your opinions of various user interface features in news apps. You will be shown each feature in the form of an interactive wireframe on an Android phone. They will be explained to you in detail by the experimenter, after which you will be asked a series of questions exploring themes such as usefulness, usability and understanding, as well as your general feedback on each feature. Your responses to these questions will be recorded for analysing each features suitability for a particular news reader type.

There will be a mixture of open-ended questions, which ask about your opinions on news app interactions, and closed-ended questions, which ask you to rate a particular interaction on a worded scale. These questions aim to understand whether a particular interaction with the interface is suitable for your reader type.

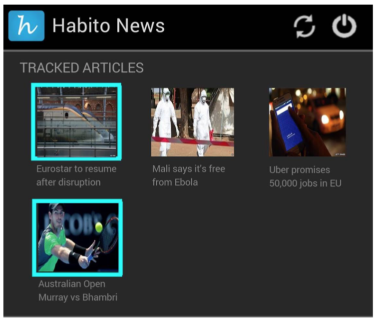
B.4 Chapter6: Controlled Laboratory Study II: Study Material

User Study Interview Questions and Materials

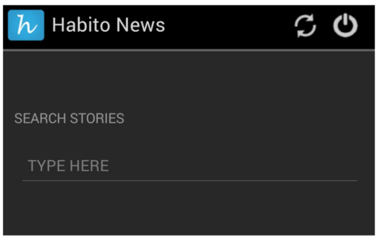
Navigation: These screens present various ways of browsing between different categories and stories.

Feature: Top Static Area

Trackers: This section shows the latest 6 stories that you have been following/tracking during the day. Stories with updates have a rectangle around them that indicates that there are updates.



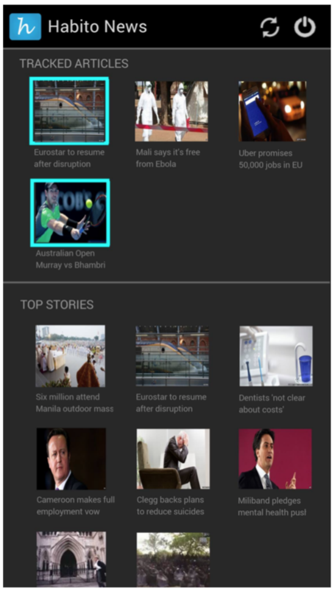
Dippers: This area contains a search box, so that you can search specific stories.



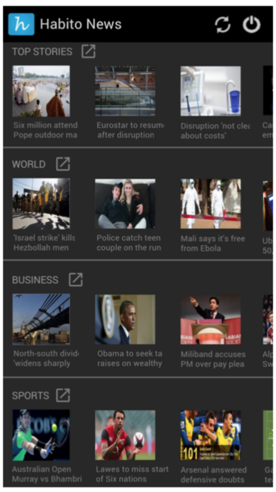
- How useful is this area in finding stories that interest you? [Not useful at all] [Not very useful] [Neutral] [Somewhat useful] [Very useful]
- Would you prefer to see something else there?

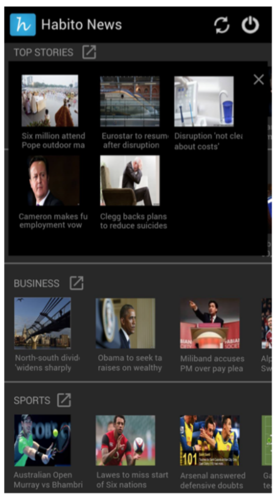
Feature: Headline Organisation

Trackers: In this headline organisation, the 6 most recent stories are visible in one page without the needing to scroll left or right to browse all the stories within a category. You can browse among categories horizontally.

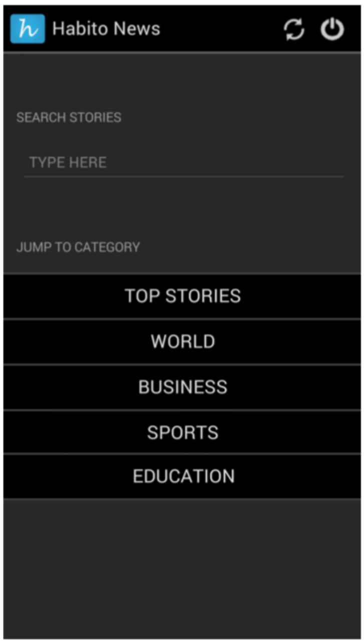


Reviewers: In this organisation, headlines are organised in rows of thumbnails. You can browse among categories vertically and there is also a button next to the heading of each category that opens a popup window in which all the stories of that category are visible.

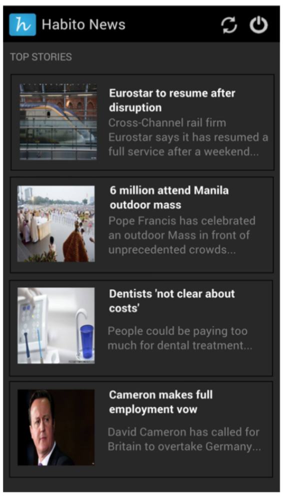


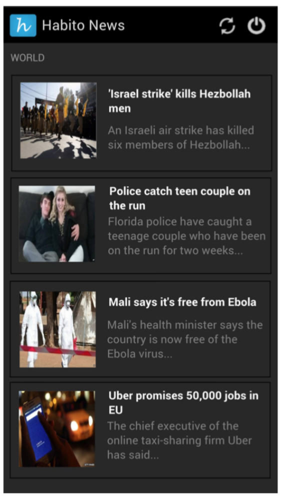


Dippers: This organisation presents the stories in an accordion of categories. You can tap on a category, which will immediately redirect you to that category, but you can also scroll up or down to browse headlines from other categories.



Dippers (Alternative): This headline organisation includes full-width stories. Each story block is split by a picture and some introductory text about the story. These stories can be browsed by scrolling up and down. You can swipe right or left to view the stories in a different category.





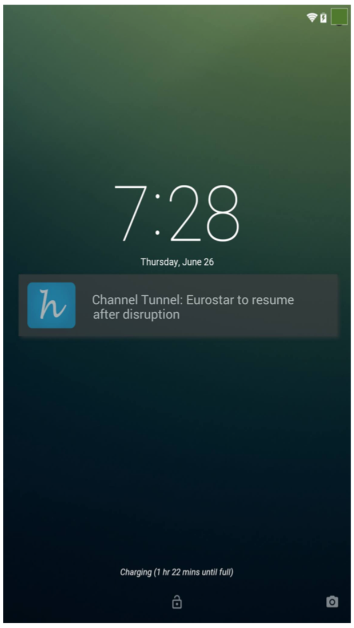
- How usable is this headline organisation for you? [Very hard to use] [Hard to use] [Neutral] [Easy to use] [Very easy to use]

- How clear is this headline organisation? [Very unclear] [Unclear] [Neutral] [Clear] [Very clear]

- Which headline organisation would help you browse categories more easily? Why?

Feature: Push Notifications

All reader types: These notifications will alert you to updates in stories you are interested in. When you click on them, you will be directed to the news story. The news app does not need to be open for you to receive these notifications.



- How obtrusive/annoying would these notifications be? [Very annoying] [Annoying] [Neutral] [Not very annoying] [Not annoying at all]

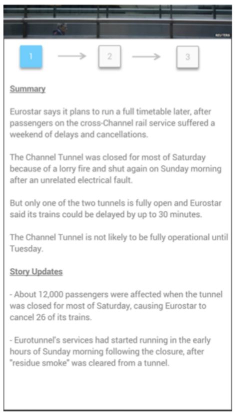
- How helpful would these notifications be to you? [Not helpful at all] [Not very helpful] [Neutral] [Somewhat helpful] [Very helpful]

Reading: For reading, there is a three-level presentation of each story. This is designed to deepen the user's understanding. So, as a user progresses from one level to another, more story content and different visualisations are applied, depending on the user's reader type.

- How would you imagine this feature in the app that you are currently using to read the news?

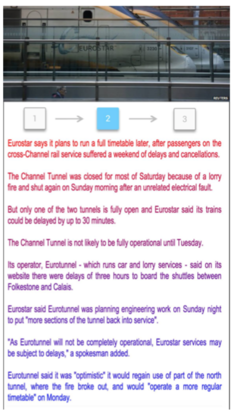
Feature: Paragraph Summaries & Story Updates

(Level 1 feature) The story is summarised and presented in short paragraphs. Below the summary, there is a section where you can view any updates on the news story.



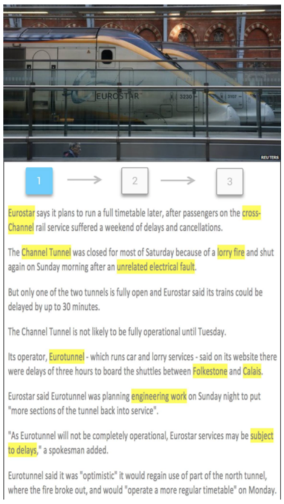
Feature: Text Colour Gradients

(Level 2 feature) A colour gradient is applied to all the text in a story. This allows you to guide your eyes from one line to the next.



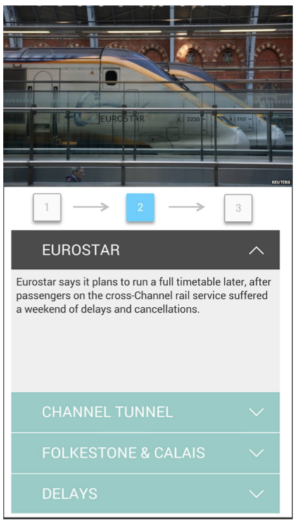
Feature: Highlighted terms

(Level 1 feature) Important terms, names and entities are highlighted in the original text of the story to mark their significance.



Feature: Accordion Background Information

(Level 2 feature) The important terms from the news story are presented in an accordion. When you tap on a term, the background information related to that term is shown.

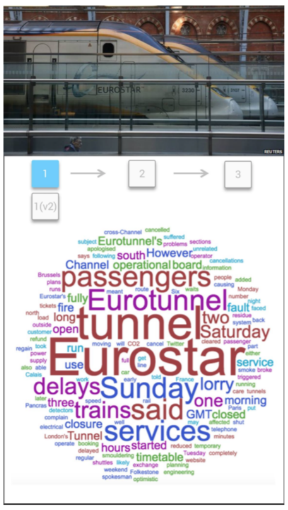


Feature: Related Articles

(Level 3 feature) If the original story has any stories/articles related to it, then these are displayed here in the form of thumbnails, which can be browsed vertically.

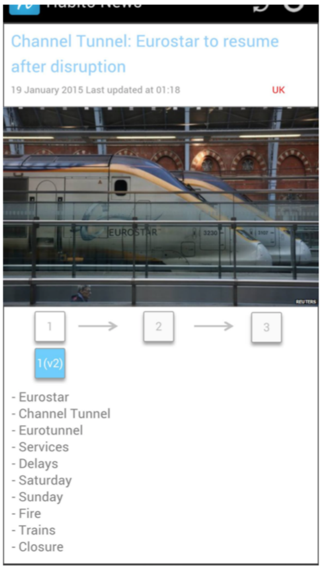
Feature: Word Cloud

(Level 1 feature) The important terms, entities and names in the news story are presented as a word cloud. The words vary in size. The larger the word, the more important it is in the story. The word cloud gives you a visual representation of how often a word is mentioned in an article.



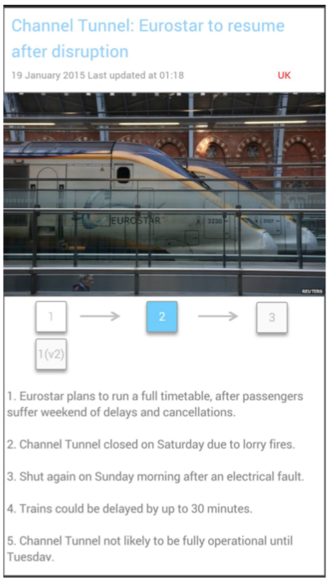
Feature: Keyword List

(Level 1 feature) The important terms, entities and names in the news story are presented as a list of key words, which can be browsed vertically.



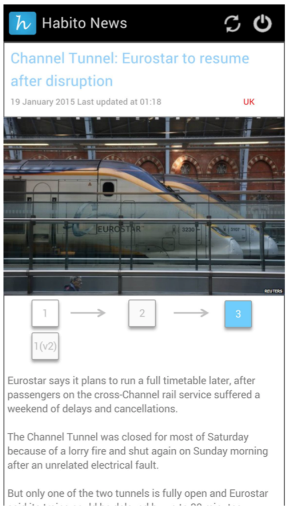
Feature: Bullet Points Summary

(Level 2 feature) The original story is summarised and presented as a bullet pointed summary to give an overview of the story.



Feature: Original Story

(Level 3 feature) The original story is presented without any modifications.



- How useful would this feature be in improving your news reading experience? [Not useful at all] [Not very useful] [Neutral] [Somewhat useful] [Very useful]
- How clear is this feature? [Very unclear] [Unclear] [Neutral] [Clear] [Very clear]
- Does this feature allow you to get all the information you want out of a story?
- Can you suggest any improvements on this feature?
- Is there a different way you would like to see the three levels presented?

B.5 Chapter 7: Final Evaluation Study: Instructions Email

Subject: Evaluation Study of Habito News An Adaptive News App

Body:

Habito News is an adaptive mobile news app that learns your news reading patterns and adapts its user interface and interaction to enhance your reading experience.

The app is part of an ongoing research project (http://habito.cs.ucl.ac.uk/) at University College London, which aims to investigate the use and application of adaptive user interfaces user interfaces that systematically monitor users interaction and behaviour and mutate their displays without any user intervention.

We would like your help to evaluate the effectiveness of our method. The inclusion criteria to take part in our study are as follows:

(a) Get your news on your smartphone on a regular basis

(b) Own an Android device that is running 4.3+ operating system

As a participant in this study you will be asked to:

(a) Download and install Habito News in your smartphone (https://goo.gl/q5kixX)

(b) Create an account (follow the sign-up button in the app)

(c) The study will take place seven (7) days and ideally we would like you to use it on a daily basis or when you feel you want to read news. You are free to use it as much as you want in each day. During the trial, the app will ask you to fill in couple of questionnaires, a short one on a daily basis and others during the study. It is important to note that as a participant you may use one user interface for the entire period of the trial. The app will decide whether an interruption will be made to adapt its user interface.

It is important when you download the app to do the following: Enable the Permissions manually. Go to Apps→Habito News→Permissions and make sure that all permissions are enabled. Particularly, Location and Storage.

The study has been reviewed and approved by the UCL Research Ethics Committee, University College London [Project ID No]: 4981/002 Companion app interfaces

Should you have any queries or require any further information about the study or how to install/use Habito News, please do not hesitate to contact Marios Constantinides at m.constantinides@cs.ucl.ac.uk.

Thank you very much for your help. Please also share this email with your contacts.

B.6 Chapter 7: Final Evaluation Study: Revised Instructions Email

Study Details - Please read carefully and adhere to the following instructions.

Habito News is an adaptive mobile news app that learns your news reading patterns and adapts its user interface and interaction to enhance your reading experience. The app is part of an ongoing research project (http://habito.cs.ucl.ac.uk/) at University College London, which aims to investigate the use and application of adaptive user interfaces user interfaces that systematically monitor users interaction and behaviour and mutate their displays without any user intervention.

We would like your help to evaluate the effectiveness of our method. The inclusion criteria to take part in our study are as follows:

(a) Get your news on your smartphone on a regular basis

(b) Own an Android device that is running 4.3+ operating system

We would like you to use Habito News as your primary news app and the length of the study is 7 days. You can read the news when you feel you want to and you are free to use it as much as you want each day. During the trial, you will interact with different user interfaces that the app will recommend for you and you will have to assess them (explained below).

TAKE PART IN THE STUDY:

Download the app and create account:

(a) Download and install Habito News in your smartphone (https://goo.gl/q5kixX)

(b) Create an account (follow the sign-up button in the app)

As a participant in this study you will be asked to:

(a) During the trial, we will send you an email every evening to ask you to fill in a short questionnaire about your daily experience with Habito News. It is important that you complete it, whether you decide to read news a particular day or not.

(b) In addition to the daily questions, you will receive two email invitations to answer 2 questionnaires online on the 3rd and 6th day of the trial. The email will be sent from eSURVEY service with subject lines:

    (i) 'Invitation to participate in AttrakDiff survey HabitoEvaluationA'

    (ii) 'Invitation to participate in AttrakDiff survey HabitoEvaluationB'

(c) Post interview at the end of the trial to share your experiences of using Habito News

The questionnaires will ask you to assess the usability and user experience of Habito News in different stages of the trial.

It is important when you download the app to do the following:

Enable the Permissions manually. Go to Apps-¿Habito News-¿Permissions and make sure that all permissions are enabled. Particularly, Location and Storage.

The study has been reviewed and approved by the UCL Research Ethics Committee, University College London [Project ID No]: 4981/002 Companion app interfaces Should you have any queries or require any further information about the study or how to install/use Habito News, please do not hesitate to contact me.

Appendix C

User Interface Designs

C.1 Chapter 6: Initial Designs for Requirements Gathering

1. Quickview

Figure C.1: It presents a quick snapshot of the article

2. Summarised articles

Figure C.2: It presents article's summary

3. Recently read category / Frequently Accessed

Figure C.3: A top static area for articles from the most recently accessed categories

4. Top stories news

Figure C.4: A top static area for the top stories

5. Related articles

Figure C.5: Related articles at the bottom of each story

6. Custom category

Figure C.6: View the articles from a custom category

7. Article tag searching

Figure C.7: Search based on article's tag

Appendix D

Development

D.1 Chapter 4: RESTful API

1. HTTP: POST

   Path: /users/login

   Description: Authorises user's credentials

2. HTTP: POST

   Path: /users/addUser

   Description: Stores users data including credentials in the DB

3. HTTP: GET

   Path: /users/isEmailUnique

   Description: Check whether the email address is unique

4. HTTP: POST

   Path: /newsbehavior/storeReadingBehavior

   Description: Stores in the DB the reading behaviour (e.g. frequency of opening news articles, reading duration, and others)

5. HTTP: POST

   Path: /newsbehavior/storeReadingScroll

   Description: Stores in the DB the reading scroll behaviour (e.g. trajectory of the scroll used while reading, whether the user scrolled until the end of the article, and others)

6. HTTP: POST

   Path: /newsbehavior/storeNavigationalMetaData

   Description: Stores in the DB the navigation meta data (e.g. actions while browsing news headlines, number of swipes, and others)

7. HTTP: POST

   Path: /newsbehavior/storeNavigationBehavior

   Description: Stores in the DB the navigation behaviour (e.g. the order in which news headlines were selected, time spent on browsing, and others

8. HTTP: POST

   Path: /newsbehavior/storeRunningNewsApps

   Description: Stores context related behaviour (e.g. longitude and latitude, information from Google's Recognition API about users' phone current activity tilting, still, and others)

9. HTTP: POST

   Path: /study/storeSUSQuestionnaire

   Description: This URI was used during the final evaluation study to store information about the Adapted SUS Questionnaire

10. HTTP: POST

    Path: /study/storeComparisonQuestionnaire

    Description: This URI was used during the final evaluation study to store information about the daily questionnaire

11. HTTP: POST

    Path: /study/storeStudyInformation

    Description: This URI was used during the final evaluation study to store information about the study (e.g. keeps users' session and days of usage)

12. HTTP: GET

    Path: /um/getNewsReaderType

Description: This URI was used during the final evaluation study to store information about the study (e.g. keeps users' session and days of usage)

13. HTTP: GET

    Path: /um/getNewsReaderType

    Description: This URI is being used by the Adaptation Manager to inform the generation of the user interface in the client side

D.2 Chapter 4: Adaptation Rules - rules.xml

```
<?xml version="1.0" encoding="utf-8"?>

<rules>
   <rule>
      <name>Tracker</name>
      <trackerPercent>100</trackerPercent>
      <reviewerPercent>0</reviewerPercent>
      <dipperPercent>0</dipperPercent>
      <features>
         <feature>trackerLayout</feature>
         <feature>trackerTop</feature>
         <feature>paragraphSummary</feature>
         <feature>colourGradient</feature>
         <feature>originalStory</feature>
         <feature>pushNotifications</feature>
      </features>
   </rule>

   <rule>
      <name>Reviewer</name>
      <trackerPercent>0</trackerPercent>
      <reviewerPercent>100</reviewerPercent>
      <dipperPercent>0</dipperPercent>
      <features>
         <feature>reviewerLayout</feature>
         <feature>highlightedTerms</feature>
         <feature>accordionInfo</feature>
         <feature>relatedArticles</feature>
      </features>
```

```xml
</rule>

<rule>
   <name>Dipper</name>
   <trackerPercent>0</trackerPercent>
   <reviewerPercent>0</reviewerPercent>
   <dipperPercent>100</dipperPercent>
   <features>
      <feature>dipperLayout</feature>
      <feature>dipperTop</feature>
      <feature>wordcloud</feature>
      <feature>bulletPointSummary</feature>
      <feature>relatedArticles</feature>
   </features>
</rule>

<rule>
   <name>Tracker/Reviewer</name>
   <trackerPercent>50</trackerPercent>
   <reviewerPercent>50</reviewerPercent>
   <dipperPercent>0</dipperPercent>
   <features>
      <feature>trackerLayout</feature>
      <feature>trackerTop</feature>
      <feature>paragraphSummary</feature>
      <feature>colourGradient</feature>
      <feature>originalStory</feature>
   </features>
</rule>
```

```xml
  <rule>
    <name>Reviewer/Dipper</name>
    <trackerPercent>0</trackerPercent>
    <reviewerPercent>50</reviewerPercent>
    <dipperPercent>50</dipperPercent>
    <features>
      <feature>reviewerLayout</feature>
      <feature>highlightedTerms</feature>
      <feature>accordionInfo</feature>
      <feature>relatedArticles</feature>
    </features>
  </rule>
</rules>
```