A Service-oriented User Interaction Analysis Framework Supporting Adaptive Applications

Mohammad Hashemi
MaREI Centre, Beaufort Building, ERI
University College Cork, Ireland
Email: m.hashemi@cs.ucc.ie

John Herbert
MISL, Western Gateway Building
University College Cork, Ireland
Email: j.herbert@cs.ucc.ie

***Abstract*—A comprehensive user model, built by monitoring a user's current use of applications, can be an excellent starting point for building adaptive user-centred applications. The BaranC framework monitors all user interaction with a digital device (e.g. smartphone), and also collects all available context data (such as from sensors in the digital device itself, in a smart watch, or in smart appliances) in order to build a full model of user application behaviour. The model built from the collected data, called the UDI (User Digital Imprint), is further augmented by analysis services, for example, a service to produce activity profiles from smartphone sensor data. The enhanced UDI model can then be the basis for building an appropriate adaptive application that is user-centred as it is based on an individual user model. As BaranC supports continuous user monitoring, an application can be dynamically adaptive in real-time to the current context (e.g. time, location or activity). Furthermore, since BaranC is continuously augmenting the user model with more monitored data, over time the user model changes, and the adaptive application can adapt gradually over time to changing user behaviour patterns. BaranC has been implemented as a service-oriented framework where the collection of data for the UDI and all sharing of the UDI data are kept strictly under the user's control. In addition, being service-oriented allows (with the user's permission) its monitoring and analysis services to be easily used by 3rd parties in order to provide 3rd party adaptive assistant services. An example 3rd party service demonstrator, built on top of BaranC, proactively assists a user by dynamic predication, based on the current context, what apps and contacts the user is likely to need. BaranC introduces an innovative user-controlled unified service model of monitoring and use of personal digital activity data in order to provide adaptive user-centred applications. This aims to improve on the current situation where the diversity of adaptive applications results in a proliferation of applications monitoring and using personal data, resulting in a lack of clarity, a dispersal of data, and a diminution of user control.**

I. Introduction

Increasingly users are interacting with a wide variety of digital devices. This extends beyond using apps on smartphones to using various devices such as watches, activity monitors, cameras, heating systems, house alarms, household appliances that can be digitally controlled and internet-enabled. An interaction with a device that provides a digital effect and can be recorded digitally is called a user digital activity (e.g. turning a coffee-maker on at 7.30). Creating a comprehensive record of a user's behaviour is the basis for learning about a user and their habits [1]. As users increasingly live a 'digital life', involving digitally enabled activities, recording a user's digital activities together with associated context provides the basis for learning about a user and building a personalised user model. This model can support user analysis and the design of adaptive user assistance applications. An adaptive design can be used to provide a service based on both the user's context and user's personal model. The context changes over time and a good design needs to adapt to the changes in order to provide a good service to the users. On the other hand, a user's preferences and habits are constantly changing over time. The model needs to be created for a user and dynamically updated based on the user's behaviour and changing preferences.

BaranC is a service-oriented, user monitoring and data analysis framework based on re-engineering and extending a previous interaction monitoring framework [2], [3]. BaranC transparently, efficiently, and implicitly records a user's activities and context data. It analyses the collected data, extracts information and knowledge from the raw data, and enables other applications to use the user information in order to provide better (e.g. personalized) services to the user. BaranC collects the user's interaction and the context information about the interaction (e.g. application name, event, action, etc.), distinguishing this framework from pre-existing ones. BaranC is constructed as a service-oriented framework, and 3rd party services (e.g. adaptive services) can be built on top of it. BaranC's user model (the UDI) contains the user digital activity data and associated context data, and 3rd party services can request access to the user model. Full user control of the data collection and sharing is provided, so that the user explicitly controls any monitoring, and the user explicitly permits a 3rd party service to access specific data and for a specific period. The framework is implemented using Amazon's AWS, also supports IBM BlueMix, OpenStack and Azure, and can be extended to other cloud service providers. BaranC provides data collector services for Android devices and Windows servers and desktops. The data collector allows sensors to supply context information and send collected data securely to a cloud service. To reduce the burden on developers, BaranC provides a library so they can work easily with the framework. This paper describes the framework architecture and presents two demonstration applications to show the use of the framework for personal analysis and adaptive application design.

II. Background

The main related topics of research are context-based frameworks and user behaviour recording and modelling. Hermes [4] is a context-aware application development framework and Toolkit for the mobile environment. It is designed as a middle-ware to collect and provide context data to the applications. It does not collect the user's interaction which is a key advantage of our work. It also does not seem to provide the user with access to the collected data and to consider the privacy of the users. Contory [5] is another middle-ware framework that provisions context using multiple context provisioning strategies. It lets applications request context data through a query-based interface. The method of providing a simple query-based interface to other applications is well-designed. SCM (Service Context Manager) [6] is a framework that gathers context and provides processing, analysis and reasoning. CoBra(Context Broker Architecture) [7] is a context-aware and agent-based system for smart spaces. It provides a context broker as an intelligent agent to maintain models and share them. Frappe [8] is a context-aware mobile application recommender system. It, similarly to our work, records how frequently a user uses an application. It collects context data such as location, time, and the application category. It processes the collected data and recommends to a user what application they may likely want to use based on the current context. It seems that the work is designed specifically for mobile application.

Some of the above frameworks focus on data collection, and some on data sharing. However, they usually don't consider a user's UI interactions as part of context, and do not enable users to control the data collection and sharing. In work such as ours, recording a user's activities (in our case, digital device interactions) is a key part of constructing a comprehensive and rich user model. The available context (at the time that the user interacts) is important in building a rich user model. Several projects employ a user behavioural model in order to better understand, and provide adaptive and personalized services, to a user [9], [10], [11], [12]. For instance, a software system, MoodScope [13], infers the user's mood based on their smart-phone usage.

Our work aims to have a wider scope, and it develops a general service-oriented solution where users control their data and models, and 3rd party services can use a user's data (if permission is granted by the user) to provide assistive and adaptive user services. BaranC provides a wide-ranging solution that lets any device anywhere monitor the digital interaction of a user or record any relevant context, and contribute to constructing a model of a user. We call this user model, the User Digital Imprint (UDI). The UDI is a general hierarchical model containing raw data and derived information. While the raw data is the foundation of the user model, recording it alone is not sufficient for building a rich model [1]. The raw data needs to be processed and transformed to higher level information. Thus, while the raw data is the foundation for building the UDI, the data analysis services of BaranC are the foundation for transforming the data to higher level information which then gets added to the UDI model.

III. BaranC Framework

BaranC is a service-oriented user monitoring and analysis framework with various supporting services that reimplements and expands the scope of a previous interaction monitoring system [2], [3]. BaranC has a data management service to keep the data in containers for further usage. The data analysis

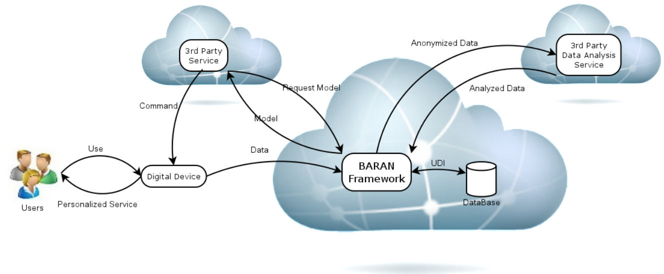

Fig. 1. The Overview of the BaranC Framework

service contains several software agents that process the data in order to analyse and extract useful information and knowledge out of the data. The data analysis is not limited to the framework data analysis services. BaranC lets 3rd party services contribute to data analysis. As the framework is responsible for collecting the data and delivering it securely to 3rd parties, there is a security service that takes care of de/encryption. Figure 1 provides an overview of the BaranC framework and how its components work together. It shows a digital device that supplies data to BaranC, how a 3rd party service can use a user's data in order to provide personalized services to the user (e.g. by sending a command to the device) and how a 3rd party can access anonymised data in order to contribute to data analysis. The current implementation provides an Android and a Windows data collector service that collects User Interface (UI) interaction and all available contextual data from internal and external sensors. It aggregates the data and sends it to the BaranC cloud service for processing and analysis (Figure 2). BaranC provides different security methods for data en/decryption that can be selected by the user. BaranC lets users manage who, how, and what information is collected. The framework explicitly informs a user about the data that is shared with 3rd parties. The user chooses what data and level of access to grant to a 3rd party.

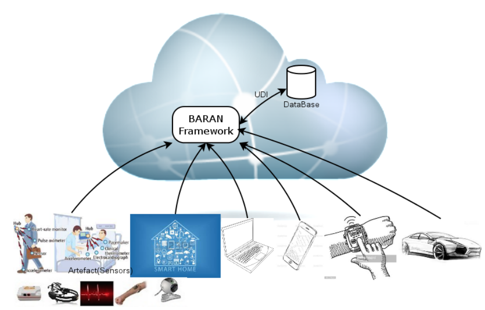

Fig. 2. The Data Flow to the BaranC Framework

A. User Digital Imprint (UDI)

The User Digital Imprint (UDI) is the user model that underlies BaranC. It is a model with a manageable, flexible, and scalable data structure that holds various types of data and information. The main focus of the UDI is to record the user's *digital imprint* and by that we mean to record dynamic user interaction with digital devices. While the interaction with a smartphone, tablet or desktop computer are obviously important elements in this, the UDI also contains dynamic information from any relevant sensors both in user devices (e.g. smartphone accelerometers) and in the environment (e.g a smart coffee-maker or a door sensor). Thus as well as the direct user interaction, we are also recording in the UDI the context of the interaction. Analysing the UDI enables better understanding of a user [1] and provides the basis for personalized services [14], [13]. The UDI can, therefore, be a valuable basis for many applications such as recommender systems [10], [11], games, adaptable services [9]. They can use a user model or presence in order to change their services and systems behaviour. The UDI model hierarchy contains three levels, *Data*, *Information*, and *Knowledge* (Figure 3). The basic values collected from devices provide the lowest level, data. Knowing the meaning of these values allows us to have information, e.g. information about user physical activity from the raw data values from accelerometers. Knowledge is a meaningful combination of information.(Figure3).

Consider a scenario where Bob likes to drink a cup of tea at home on Saturday mornings. In this example, the raw sensor values are at the data level, the fact that this corresponds to making tea is at the information level, and the pattern that the user, Bob, engages in this activity at home on Saturday mornings is at the knowledge level. A company has a tea maker product that can analyse a user's data and make a cup of tea depending on a user's habits. Once the product is installed by a user, it requests the user's data from BaranC. The user's UDI will be shared with the company's analysis service (if permission is granted by user). The service then analyses the data and the product can pro-actively service the user based on his/her habits. For instance, if today is Saturday, it is morning, and Bob is home, then the tea maker service would command the tea maker to prepare a cup of tea for Bob.

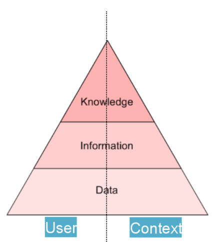

Fig. 3. The UDI Hierarchy

IV. BaranC Framework Architecture

In this section, the architecture of the framework is briefly described. Figure 4 shows how the components and services of BaranC cooperate internally. BaranC has three important utility services that are responsible for sending/receiving, encryption/decryption, executing a request. A summary of how they work is shown in Figure 5.

- ***Communication Utility Service***
  The Communication Utility Service is the lowest layer of the hierarchy and has two main functions: sending and receiving data. BaranC provides a library of APIs for communication but BaranC needs information about nodes (devices or 3rd parties which it interacts with) in order to communicate with them.
- ***Command Management Utility Service***
  The Command Management Utility Service is responsible for executing the commands such as sending, receiving, storing to DB, analysing, etc. It controls the routing of requests to the appropriate services.
- ***Security Utility Service***
  This utility service has two main functions, encryption and decryption. This service fulfils the security requirements of the framework. It makes sure that the data going out from the framework will be encrypted and the data coming in to the framework will be decrypted. This service runs on any target device and is responsible for collecting the data and sending it to the BaranC framework. BaranC provides different data collection services for different devices such as smart-phone, tablet, computer, smart TV. It also provides different versions to support different operating systems.
- ***Data Collection Service*** This service runs on any target device and is responsible for collecting the data and sending it to the BaranC framework. BaranC provides different data collection services for different devices such as smart-phone, tablet, computer, smart TV. It also provides different versions to support different operating systems.
- ***Data Management Service*** The Data Management Service is responsible for storing and retrieving UDIs to/from data storage. All UDIs sent to the framework should be properly stored. This service is the key to providing an efficient reliable service to the users and 3rd parties. It has to manage storing and retrieving very large amounts of data. In the current implementation of BaranC in Amazon AWS, we use S3 blob storage in order to store the UDIs.
- ***Data Analysis Service*** The Data Analysis Service is the heart of the framework. There are several software agents that are responsible for processing the UDI, mining patterns, extracting information and deriving knowledge. For example, the numbers recorded from an accelerometer sensor themselves have no meanings, but a software agent could convert them to meaningful information about movement such as standing still, walking, running. The Data Analysis Service also allows a 3rd party service to analyse anonymised data. A number of methods and algorithms have been proposed to derive frequent user behaviour patterns from a user's activities and interactions [15], [16]. As well as collected data, 3rd parties can also request a prediction model for a user. A software agent will then be assigned to retrieve (or construct) the model. A 3rd party needs to have user permission to access the requested data that is explained in [17].

V. Demonstration Applications

There are various ways in which BaranC and the UDI can be used to provide useful services for the user. The general user-controlled mechanism for allowing 3rd parties to provide services based on the UDI is innovative and will be the focus of the demonstrators. Two simple proof of concept demonstrations are presented as examples of 3rd party services that are implemented on top of the BaranC framework, and operate without directly collecting or accessing any user data. The first demonstration is a 3rd party service that uses the user's data in order to find useful patterns. The second demonstrator shows how a 3rd party service can access a user's data, request a prediction model, and provide a useful service to the users by cooperating with BaranC. In this work we designed a 3rd party service, Next-App, that uses the user's data in order

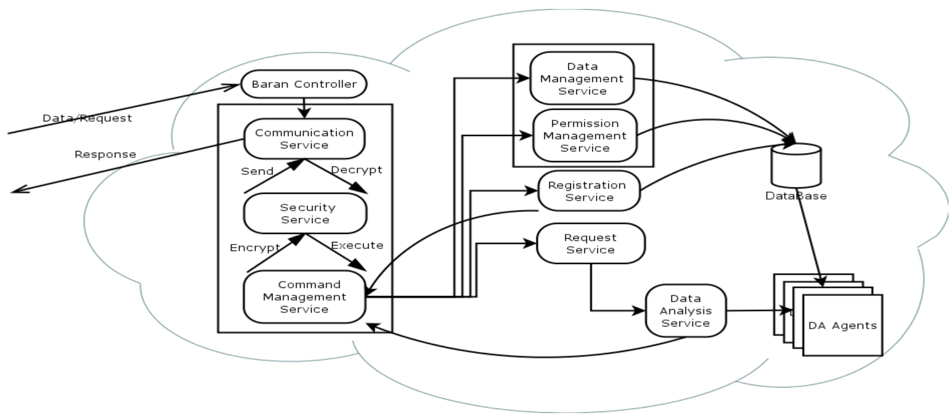

Fig. 4. BaranC Framework Cloud Architecture

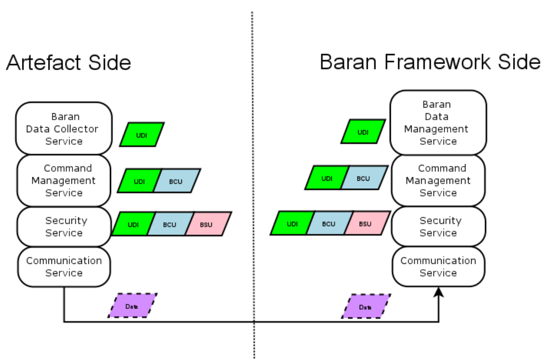

Fig. 5. The UDI Life-cycle from the Artefact to the BaranC Framework

to predict the next application a user is likely to use. Other research indicates the importance of next application prediction [18], [11]. Prediction of the next user action can be used in recommender systems, adaptive services, and context-aware applications [14].

A. Smartphone Use Pattern Analysis Service

A useful starting point for user centred design is to have an analysis of the current patterns of user digital interaction. This scenario involves a service (that uses BaranC) where the purpose is to monitor a user working with an Android smartphone, and to learn their patterns of application use at various levels of detail. The patterns for a single user can be used to analyse a user's day-to-day interactions with digital devices and also to compare user-to-user behaviour. The service is designed to access a user's data (provided the user gives this permission to the service), process it, and generate reports summarizing usage and frequent patterns. The service is built on top of the BaranC framework and needs to communicate to BaranC through BaranC's provided API libraries. For this case study we have collected two months of data from six users. BaranC's data collection service is installed on their devices, and it monitors their activities, collects context data, and sends the data to the BaranC cloud server. The users did not report any loss in performance or extra battery usage because of running the BaranC monitoring service. For the users in the case study, we found that the maximum load on the CPU of the service was less than 3%, and average battery usage per

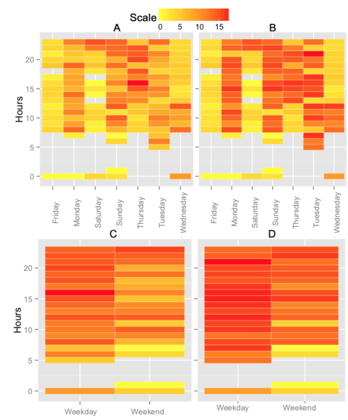

Fig. 6. Day/Hour Pattern of User A (A and C:Usage Frequency B and D:Duration)

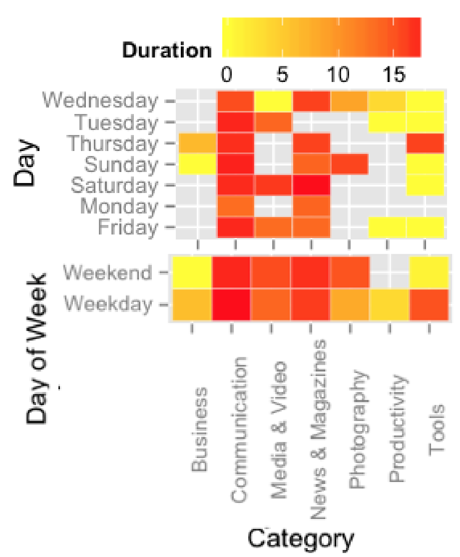

Fig. 7. The amount of time user A spends on different application categories

day was less than 4%.

In this example, the information summaries and patterns are sent by the service back to the BaranC framework where they can be accessed by the user. The following overview presents some of the service-generated results. Figure 6 shows how frequently and how long a user uses a device. The heat map

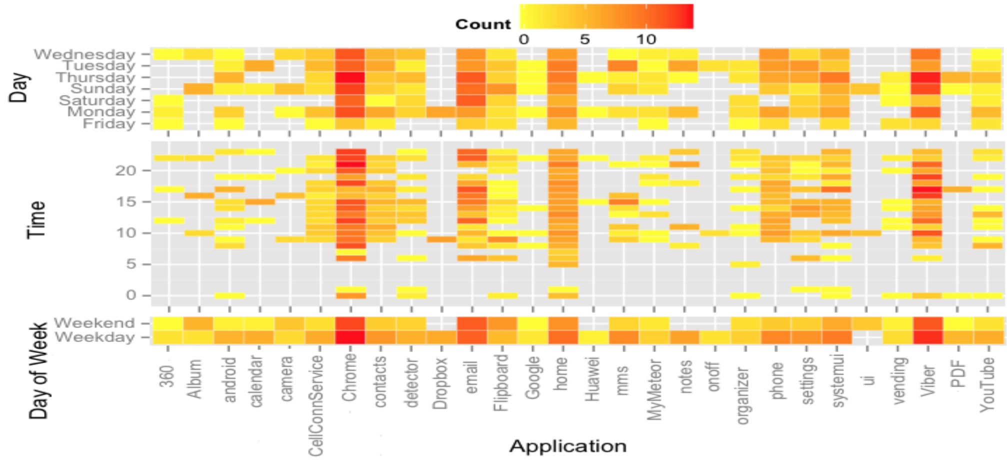

Fig. 8. Frequency: Application Usage Pattern of User A

shows the most frequent days and times of day users interact with their devices. It helps a service to be prepared to provide services at an appropriate time or do their heavy computing when users are not usually working with their devices. Figure 6 shows how frequently user A uses their device (top-left graph) during the days of the week. It also shows the same analysis for the weekend and weekdays (bottom-left graph). Another helpful pattern is that based on the classification categories of the applications. Figure 7 shows the amount of time user A spends on different application categories. It show that applications in the Communication and News&Magazines categories are used more than other categories especially in the morning, and that the Tools category is used on the weekdays more than weekend. The pattern of use of individual applications is shown in Figure 8. Google Chrome, Email, and Viber are the most frequently used applications. Finding what time of day, what day, or what part of a week a user works with an application can be very useful for a user or a 3rd party. In this demonstrator example, the 3rd party service generates some general summaries and patterns that provide insight into a user's habitual behaviours. It demonstrates how the raw data of the UDI can be transformed into useful high level information. The high level information, in this instance, is sent to BaranC where it can augment the UDI and is available for future use by the user or other 3rd parties (with the user's permission). This high-level information can support user-centered design through off-line browsing by a designer or through incorporation into an automated adaptive application.

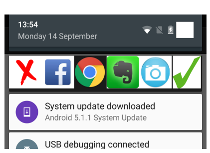

Fig. 9. Next-App Notification User Interface Showing Four Predictions

B. Adaptive Recommendation Service

A service is designed to make a predictive model, based on the user's UDI, of what application is likely to be used next based on the current context. An android application (Next-App; Figure 9) is implemented to use this service. Once a user starts using Next-App, and provides it with the

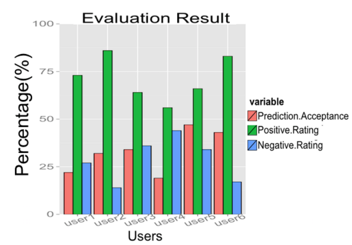

Fig. 10. Service Evaluation Result

required permissions to access their data, Next-App can start requesting the user data (UDI) from the BaranC framework. Machine learning is used for prediction. The Association Rule technique [19], [20] is selected to make a predictive model. This technique makes use of a set of rules and a predictive class for a set of rules. The service creates a set of rules from the history of application usage of the user by considering the context data as the observers of the classification. A predictive model is then built for a user. The predictive model can be used by Next-App in order to predict the top N applications the user is most likely to use next, based on their previous patterns and also the current context. For instance, if a user regularly uses an alarm application between 8.00 PM and 11.00 PM, then the Next-App application recommends the alarm application at that time. The Next-App application is a notification based service. It pro-actively predicts and shows a notification containing a list of recommendations. In this work we used the patterns of the Pattern Analysis Service to pro-actively predict the next application a user will probably use. At the times that a user usually works on the device, the algorithm predicts in a more frequent cycle, and vice versa, to save battery life, it generates predictions less frequently when the user doesn't usually use the device. For evaluating the predictions of the Next-App service and to demonstrate that a 3rd party service can work with the Baran framework, we used two months data for two of our users. We used the data to create the user's model and evaluate the Next-App service as a part of this work. The amount of collected data various between two to eight weeks. Six users were requested to use the Next-App service in order to evaluate the prediction accuracy. As the service is designed to use a user's model (UDI) for prediction, an assumption is that the participants already have a UDI model in BaranC. Our users have two months data in the BaranC framework. Next-App pro-actively predicts the top most likely applications based on the current context and provides the recommendations in the notification bar (Figure 9). We count how many times a user uses our prediction to open an application. The application also has an in-app rating service that lets a user like or dislike the list of recommendations. Figure 10 reports the acceptance rate of the predictions, the positive (number of likes) and negative (number of dislikes) rating recorded by the in-app rating. It shows an overall positive reaction, where the users take 30% of the predictions on average, and they give a strong positive rating for the app.

VI. Conclusion

An interaction-centred user monitoring framework, BaranC, based on a comprehensive dynamic user model, the User Digital Imprint (UDI), has been presented. The UDI is a record of the user's digital activities and associated context, and can be used to better understand a user for user-centered design, and can provide a basis for adaptive personalized user services. BaranC is implemented as an open cloud-based service-oriented framework that supports 3rd party services, and two demonstrator 3rd party services have been presented. A 3rd party demonstration service provides summaries of patterns in the user smartphone interactions, such as patterns of daily app use. This can be used off-line to inform user-centered design or can provide the basis for automated adaptive user services.. A second 3rd party service, Next-App, provides adaptive assistance to a smartphone user. Next-App predicts the next application a user is likely to use based on the current context and user model, and assists the user by making the top predications easily available. These demonstrators also show the interactions involving BaranC, the user and the 3rd party service, emphasising the user control of the monitoring and use of personal data.

Monitoring and analysing user behaviour is an important element in many companies efforts at being adaptive to the user. BaranC aims to improve on the current situation where a multitude of applications monitor, store and analyse a user's digital activities leading to inefficiencies, dispersal of user data, lack of clarity and reduced user control. In contrast BaranC provides a novel, unified, general purpose solution supporting collection and analysis of all available user digital activity data, supporting all kinds of adaptive 3rd party service, and all explicitly under the user control.

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