Integration of User Schedules into Health-Monitoring Apps: Current Practice and Possible Implementations for Adaptive Electronic Partners

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In the modern world, health-monitoring applications are widely used by individuals seeking to track and enhance their physical well-being. The success of these applications largely depends on their capacity to adapt to user needs and preferences. This study investigates how extensively and in what ways current health-monitoring apps integrate user schedules into their user models.

This research involved a detailed analysis of health-monitoring apps selected from the top free apps in the 'Health & Fitness' categories of major app stores. The study reveals that most apps feature custom scheduling functionalities, allowing users to set specific times and days for receiving reminders. However, none of the apps integrates with external calendar services, highlighting a reliance on in-app scheduling mechanisms.

The advantages and disadvantages of these current approaches are discussed. Findings indicate that while custom scheduling is straightforward and user-friendly, it lacks adaptability and integration with broader scheduling systems. Alternatives, such as integration with external services and using advanced machine learning models for personalised reminders, are also explored.

This research concludes that while current health-monitoring apps effectively provide basic scheduling functionalities, there is significant potential for enhancement through integrating external scheduling platforms and more sophisticated user modelling techniques. Future work should consider including apps that utilise dedicated wearables and the development of prototypes to gather direct user feedback.

Additional Key Words and Phrases: user schedule integration, health-monitoring applications, personalised health suggestions, behavioural support technology, mobile health apps

1 INTRODUCTION

In the digital age, health-monitoring applications have become commonly used tools for individuals striving to monitor and improve their physical health. These applications promise to elevate the personal health management experience by using technology to track, analyze, and correct user behaviour. However, the effectiveness of these tools heavily depends on their ability to integrate personal user information into their user models. Health-monitoring apps can greatly enhance user experience if the data collected is used correctly. On the other hand, lack of personal information, such as user schedule, can result in irrelevant and mistimed suggestions, which demotivate users [23]. This research explores how current health-monitoring apps collect and use users' schedules.

1.1 Goals and motivation

The primary objective of this research is to explore the ways and extent to which current health-monitoring apps collect and use the users' schedules in their models to provide meaningful suggestions and give reminders. Another goal of the research is to reason about the advantages and disadvantages of the current approach and provide alternatives to the present practice based on the findings from the initial analysis and insights drawn from the literature review. Health-monitoring applications were selected for this study due to their similarities with socially adaptive electronic partners (SAEP) described in the literature [25]. The first similarity with SAEPs lies in their intended daily use. Secondly, in the ideal world, these applications should be highly flexible to support users' individual differences. Adaptability is crucial for health-monitroing applications, as differences in fitness level, daily habits, and physical parameters are crucial for providing relevant health advice. In addition to the resemblance, health-monitoring applications are widely used by broad audiences of various ages, backgrounds, and fitness levels, which makes this research potentially valuable. The factors presented above make health-monitoring applications ideal candidates for examining their current schedule integration and comparing their adaptability to SAEPs.

1.2 Research question

Based on the objectives of the research, the following research questions were formulated:

- **RQ1** To what extent and in what ways do health-monitoring apps integrate user schedules into their user models?
- **RQ2** What are the advantages and disadvantages of the current approaches used for integrating user schedules into health-monitoring applications?
- **RQ3** What are the alternatives to the current approaches for user schedule integration in health-monitoring apps?

2 RELATED WORK

Recent studies by the CoreSAEP project have delved into various aspects of socially adaptive agents, which are engineered to enhance daily user experiences by utilising user-specific information [14, 15, 24, 25]. The integration of such agents into fitness applications would be a significant achievement, as it would allow users to receive personalised suggestions on how to improve their health. The research from 2018 highlights the need to recognise user values and context to implement SAEP [22], though it poses considerable challenges.

Within the realm of health-monitoring applications, user values manifest in three primary forms: hedonic and eudaimonic needs, qualitative goals, and quantitative goals [17]. A systematic review of 51 studies on goal-setting within health apps shows a predominant focus on quantitative objectives, such as step counts, whereas qualitative goals, like promoting an active lifestyle, are less commonly addressed [7]. The presence of quantitative goals in the majority of the apps provides an excellent opportunity for goal personalisation

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and automated adaptation to user's needs. As an example, recommended sporting activities can be dynamically adjusted based on the free time available and the amount of sleep the user had last night.

The concept of 'context' is less studied and remains a significant hurdle due to its inherent complexity. Context can be any circumstance which affects the value of the performed action [22]. As an example, when speaking about physical activity, the context can include weather, time of the day, amount of sleep, energy level and others. Taking into account all of these aspects is quite challenging, so only the user's schedule was considered in this research, as it can provide significant insight into the user's condition without an overwhelming number of nuances.

Users' schedules can be incorporated into user models by collecting information related to the timings of their daily activities and adjusting various app aspects based on it. There are several options for information collection. It is either performed automatically or requires manual input from the end user. Manual data collection can involve users specifying their availability and filling in a questionnaire about health-related tasks. The questionnaire can include questions about preferred times for health-related activities. Automated schedule incorporation can use data from existing calendar apps, which are present on the majority of modern phones. By extracting busy time slots and task types (like work, family activity, and leisure) from scheduling applications, the apps can provide highly personalised suggestions. Additionally, combining these approaches and extending the questionnaire to inquire about situations which should be avoided (for example, high-intensity training before work meetings) and some other constraints (for example, travel time to and from work is 30 minutes, so this time should not be considered as free) flexibility of adaptive electronic partners can be extended even further.

The idea of using the calendar as the key component of an intelligent life assistance app was explored during the creation of the research app called SuperCaly [30]. This app combined various data sources to simplify daily life planning. SuperCaly demonstrated how the integration with an external calendar can enhance app functionality and create a better user experience. A similar approach for the health domain was proposed in the PRO-Fit framework, which also suggests that the user's schedule is one of the main aspects that should be considered when optimising the functionality of health-monitoring apps [5].

Building on the theoretical groundwork outlined above, this research examines how users' schedules are integrated into existing health-monitoring apps and seeks to narrow the gap between theoretical study and practical application.

3 METHODOLOGY

3.1 Selection of apps

Initially, the leading smartphone app stores for both iOS and Android (App Store and Play Store, respectively) were examined. The top 50 free apps from the 'Health & Fitness' category—25 from the App Store and 25 from the Play Store—were downloaded. Duplicates were removed. Each app was then assessed to determine if it qualifies as a 'health-monitoring app'. The evaluation criteria were set to be as follows: to be considered a 'health-monitoring app', the application must track at least two health metrics from different categories listed in Table 1. The table is based on health and fitness app analysis [13] and preliminary app inspection. This selection criteria allowed focusing the research on applications that are facing the challenge of balancing various health goals. It is essential to mention that goals were assumed to be present in the absolute majority of the apps, based on the previous research [7]. So goal-setting practices and functionalities were not examined.

Table 1. Health aspects tracked by the health-monitoring applications.

Category	**Possible metrics**
Diet monitoring	Calories consumed Amount of water consumed
Activity monitoring	Step count Active time Training records
Sleep monitoring	Sleep duration
Weight monitoring	Weight Body fat percentage Body mass index
Cycle monitoring	Cycle length Cycle length variation Cycle symptoms
Vital sign monitoring	Heart rate Blood pressure Blood oxygen Blood sugar

In case the number of apps meeting this criterion would be below 15, an additional 10 apps (5 from each store) could be downloaded and subjected to the same selection process. This procedure could be repeated until the necessary number of eligible apps for the study is selected.

It is important to note that some apps are designed to function in combination with dedicated wearable devices, such as fitness trackers. These applications were excluded from the study due to the absence of such devices, which are necessary for their operation.

3.2 App analysis

For the app analysis, each selected app was thoroughly examined, and any schedule-related functionalities were noted. Based on examination results, apps were categorised based on their scheduling capabilities: no scheduling functionality, custom scheduling within the app, and integration with existing scheduling platforms. The presence of schedule-related features in these apps contributed to answering RQ1. The specifics of how scheduling is utilised within each app were documented, and these findings, together with the categorization mentioned before, also contributed to addressing RQ1.

3.3 Analysis of current practices and alternatives

The results from the previous sections answered the question about current practices. After that, RQ2 and RQ3 regarding the advantages and disadvantages of the current methods and their alternatives were answered. To do so, further review of the literature concerning the benefits and limitations of current health-monitoring apps, such as untimely notifications about physical activity deficits [17], was conducted. Finally, the alternatives were assessed, and conclusions were drawn.

4 RESULTS

4.1 Selection of apps

The initial evaluation of the 50 apps, following the specified methodology, yielded the following findings. Firstly, 5 applications were found to be present in both the top 25 lists in the 'Health & Fitness' category in the App Store and Play Store. For these apps, each app was considered only once, and its duplicate from the other store was excluded from further consideration.

In addition to the duplicates, 3 apps were specifically designed for use with dedicated wearable devices, which made them unsuitable for this study focused on standalone health-monitoring applications.

Further examination revealed that 13 apps had functionalities that were entirely unrelated to health monitoring, making them unsuitable for this study. Moreover, another 13 apps did not meet the required diversity criteria defined in the methodology section, disqualifying them from inclusion in this research.

After applying all these criteria, a total of 16 apps were identified as eligible and selected for further analysis. The complete list of the selected apps is available in Table 2. These applications met the requirement of tracking at least two health metrics from different categories (Table 3).

4.2 App analysis

The thorough examination of the selected apps revealed insightful results concerning their scheduling capabilities. Among the 16 apps analysed, a significant majority, 15 apps, featured custom scheduling functionalities within the app itself. The custom scheduling mechanism found in these apps allows users to manage their health reminders by specifying the precise times and sometimes days of the week when they want to receive notifications reminding them to take measurements or perform activities. Implementation of this method is shown in Figure 1. This functionality is a stand-alone feature and does not impact the other functionalities of the app, which is quite different from the ideas discussed at the beginning of the paper.

While examining the apps that fell into this category, a few interesting tendencies were noted. Two of the analysed apps had a dedicated reminder that presented an overview of daily activities, which was displayed once per day. Only two apps featured reminders for each metric tracked. Another two apps allowed users to set fully customisable reminders not tied to specific metrics, enabling users to specify the title of the reminder as well as the regular time and date as shown in Figure 2. The remaining apps offered reminders for a subset of features tracked. On average, 56% of the metrics tracked by the app had dedicated reminders (Table 5).

In contrast to the previous category, only 1 app was found to lack any scheduling functionality. This app did not provide users with any mechanism to integrate or set reminders based on their

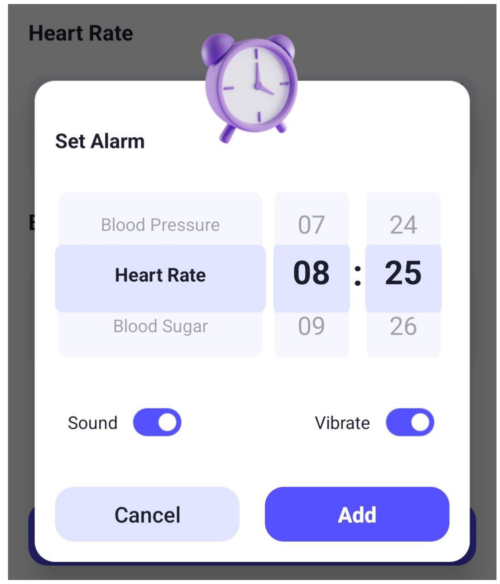

Fig. 1. Screenshot from the app (ID 3 from Table 2) with most common reminder type

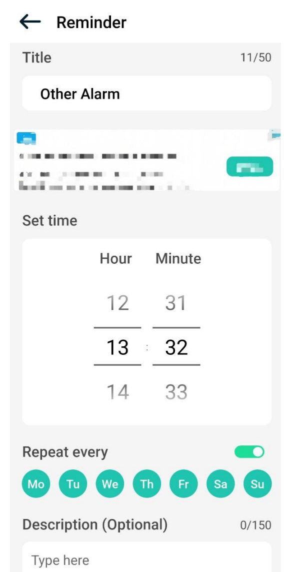

Fig. 2. Screenshot from the app (ID 8 from Table 2) with fully customisable reminder

schedules without any apparent reason, which could be considered a limitation.

Interestingly, none of the analysed apps utilised external calendar or scheduling services. This absence indicates that these apps are designed to operate independently of other tools, relying solely on their in-app features to manage user schedules. To explore integration with third-party scheduling applications, additional application exploration was performed by explicitly looking for apps on the internet in the 'Health & Fitness' domain that are integrated with calendar applications, using keywords such as 'health monitoring with calendar integration'.

As no apps with third-party scheduling integration were discovered during the app review, the targeted search was performed to verify that such integration exists. During the targeted search, an app for importing events from Apple Health to the calendar was discovered ('Import health into calendar' app); however, that is the sole functionality of this application. Additionally, various apps, such as 'ABC Trainerize' and 'Everfit', meant for fitness coaches and their clients, were found. These apps allow exporting training schedules into calendars of choice. However, these apps are better classified as business management platforms specifically designed for the 'Health & Fitness' domain.

These results demonstrate the following tendency among health-monitoring apps. Current health-monitoring applications rely on custom scheduling functionalities directly within the app rather than integrating with external scheduling platforms. Roughly half of the metrics the app tracks have specific reminders. This trend can be explained by users being expected to frequently engage with the app to add health data records. This can be seen in Table 6, which shows that, on average, only 33% of the metrics tracked by these applications are automatically measured. The user should manually enter the remaining measurements. Thus, the additional value of automated schedule tracking is minimised, as it would not contribute much to the autonomy of the applications.

Nevertheless, there are health-related apps that utilise external schedule integration. However, these are either limited to exporting health-monitoring-related events or are aimed at achieving goals other than adaptive health monitoring (such as fitness business management). This trend, along with its pros and cons, will be explored further in the subsequent subsections.

4.3 Literature review

In this subsection, the results of the literature review are presented. The review was performed with the aim of identifying the strengths and weaknesses of the current methods for incorporating users' schedules into health-monitoring applications. Analysis of apps revealed that the most common approach is using customised reminders for health-related activities.

Additionally, findings from previous research on alternative approaches are considered. These approaches include integration with external scheduling applications and collecting data about user interactions with their phone. The advantages and disadvantages of these methods are also examined.

4.3.1 Customisable reminders. Reminders are a common feature in various types of apps, including health-monitoring apps. In the past years, they have been extensively researched across multiple domains and use cases.

The primary advantage of using customisable reminders in health-monitoring apps is their ease of implementation. While there is no direct research comparing the implementation difficulties of various app features, there is indirect evidence supporting this claim. For instance, studies have shown that users receive a substantial number of notifications daily, ranging from 20-50 to 50-100 per day [10]. Another study reported that users receive an average of 63.5 notifications per day [19]. Of course, these studies examined all types of notifications, which are not necessary reminders created by the health-monitoring apps considered in this research. Nevertheless, based on my personal experience in mobile app development and the data presented, it is reasonable to infer that adding reminders to the app and allowing users to modify the timing of these is a relatively simple task. Another advantage of reminders is their effectiveness. Reminders were proven to promote positive changes in users' health behaviour [11, 21]. In addition to that, the effect of reminders on the consistency of self-monitoring of metrics relevant to health-monitoring apps, such as activity and weight change, was studied. These studies have shown that reminders are effective in the health-monitoring domain [8, 9, 20].

However, reminders also have potential drawbacks if certain factors are not considered. These effects include increased willingness to uninstall the app [29], stress [16], annoyance, anxiety [2] and others. Various studies have emphasised the importance of context when receiving notifications [12, 29] to minimise possible negative effects and increase effectiveness. As discussed previously, context can be approximated by using various combinations of the user's location, current activity level, social messaging, pre-defined time and schedule. Nonetheless, as uncovered during app analysis, the majority of health-monitoring apps are delegating the task of finding the appropriate timing for notification to the user. This delegation introduces a trade-off between adaptability and user involvement, particularly for users with inconsistent schedules who must either frequently adjust reminder settings or accept reminders at inconvenient times.

To conclude, the current approach of using customisable reminders aims to balance implementation complexity and effectiveness. However, it lacks adaptability, which leads to increased user burden and has negative side effects, such as increased stress and annoyance. The current functionality could be enhanced by integrating third-party services. Such integration would also allow these apps to expand their functionality and become SAEPs.

4.3.2 Alternatives. During the literature review on alternatives, two main alternative options for user schedule integration were discovered. The primary benefit of both approaches is the availability of extended context information, the importance of which was previously discussed.

The first method includes recording phone data when a notification is clicked and then building a classifier that learns user patterns based on the information collected [18]. As discussed in the paper, the use of this system increased the average click rate by 23%. A similar study in the domain of fitness also demonstrated that it is possible to enhance user response to reminders using this approach [27]. However, it is essential to note that the same study found that a good time for a reminder is not necessarily appropriate for the action the user is reminded about. This conclusion leads us to the next approach, which requires gathering more data but can further improve health-monitoring applications.

The second method is the use of external services for user schedule integration. This relatively new approach has not yet been studied extensively, but several important points about it have still been identified in the literature. Integrating third-party services, particularly calendars, into health-monitoring apps allows for extended functionality beyond adaptive reminders. These extensions include better activity organisation, the discovery of hidden life patterns [30], and the simplification of the workout scheduling process [6]. Automated scheduling of events around existing calendar records has been previously explored and found to provide satisfactory results [26]. The same research lists important requirements that must be considered if real-life applications utilise the underlying algorithm. The list of events to be scheduled can be automatically generated by the app using health and activity goals. A questionnaire could be employed to gather additional information about user preferences [4]. Additionally, the functionality of previews and adjustments of the schedule should be made available. An obvious advantage of such a system is its autonomy, reducing the need for user input during daily usage.

However, this schedule integration strategy also has significant disadvantages. Increased complexity is a major concern. Current applications are fully self-contained and are, therefore, easier to implement and maintain. Additionally, added complexity will likely impact the developers financially, as more resources will be required to create an app. Moreover, using models for intelligent schedule analysis could require significant computational power, which might be unavailable for some applications. From a user experience perspective, it is important to consider scenarios where users utilise multiple scheduling applications, such as one for personal use and another for work. Finally, integrating with third-party services introduces additional security concerns [3].

Moreover, both alternatives presented require gathering and processing additional personally identifiable information. This could prevent users who are cautious about sharing their private information from downloading the app [1]. It means that in order to attract users, highly personalised and valuable services should be provided by the app [28].

To conclude, it is clear that the more data available, the more adaptive and valuable the app can become. Nevertheless, identified alternatives - learning user patterns using phone data and integration with external scheduling services, introduce a trade-off between ease of implementation and functionality. The advantages of such an approach include increased user engagement, better activity organisation and more effective workout scheduling. However, proposed alternatives introduce complexities related to their implementation, maintenance, computational power requirements, and potential security concerns. The collection of extra data may also be undesirable for some users.

5 CONCLUSIONS

This study investigated how health-monitoring applications integrate user schedules into their user models, revealing several significant findings with important implications for developers, researchers, and end-users.

The analysis of 16 health-monitoring apps demonstrated that the majority (15 out of 16) rely on custom in-app scheduling functionalities. These applications allow users to set reminders for health-related activities at specific times and days. While straightforward and easy to implement, this approach places the burden of reminder customisation on the user, which may not always align with their varying schedules and contexts.

Detailed examination of the scheduling features within these apps revealed that some apps provide a daily overview of activities. In contrast, others allow fully customisable reminders that are not tied to specific health metrics. This flexibility can partially cover diverse user preferences, but the lack of integration with external calendar services limits the potential for more dynamic and context-aware reminders.

The literature review on the current practice of customisable reminders and alternatives revealed that more complex user schedule integration techniques, such as user pattern learning and third-party service integration, can allow apps to extend their functionality past context-aware reminders. But that would come at the cost of an increased system complexity with all the implications.

These findings are significant for several reasons. Firstly, they highlight a gap in the current market for health-monitoring apps: the absence of integration with external scheduling platforms. This gap presents an opportunity for developers to enhance user experience by creating more adaptive and contextually relevant reminders, potentially improving user experience and adherence to health routines. Such integration could transform health-monitoring apps into more sophisticated socially adaptive electronic partners (SAEPs), offering personalised health advice based on a comprehensive understanding of the user's daily activities and commitments.

End-users, particularly those with busy and irregular schedules, stand to benefit the most from these advancements. More adaptive health-monitoring apps could reduce the cognitive load associated with managing health reminders, making it easier for users to maintain healthy habits and achieve their health goals. Moreover, by reducing the need for manual input and adjustment, these apps could enhance user satisfaction and long-term adherence.

In conclusion, while current health-monitoring apps effectively use custom in-app scheduling functionalities, there is a clear potential for improvement through the integration of external scheduling services. This advancement could lead to more personalised, effective, and user-friendly health-monitoring solutions.

6 LIMITATIONS AND FUTURE DIRECTIONS

This study has several limitations that should be acknowledged. First, the analysis was restricted to a relatively small number of apps, focusing exclusively on free applications. This limitation may have excluded potentially relevant paid apps that could offer different or more advanced scheduling integration features. Second, the study primarily relied on app examination rather than extended practical use. Testing the apps over a prolonged period would provide more comprehensive insights into their effectiveness and usability in real-world scenarios.

To build on the findings of this study, future research could focus on several aspects relevant to this research. Firstly, researchers could explore health-monitoring apps designed for use with dedicated wearable devices. These apps are typically more autonomous and require less user intervention, potentially offering more sophisticated schedule integration features. Secondly, future studies could develop a prototype that integrates advanced scheduling features and gathers feedback from actual users. This would allow for the evaluation of its impact on user engagement, health outcomes, and overall app usability compared to literature-based analysis. Finally, the quality of dynamic schedule creation by previously explored algorithms and large language models could be compared to determine which technology should be used for health-monitoring applications.

By addressing these limitations and pursuing these future directions, researchers can gain a deeper understanding of how to effectively integrate user schedules into health-monitoring apps, ultimately improving their usability and effectiveness.

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A APP ANALYSIS DETAILS

Table 2. Apps selected for the research

App ID	App name	Store
1	Google Fit: Activity Tracking	Play Store
2	Step Counter – Pedometer (1)	Play Store
3	Health Kit	Play Store
4	Step Counter – Pedometer (2)	Play Store
5	Blood Pressure	Play Store
6	Weight Loss for Women: Workout	Play Store
7	Health Tracker: BP Monitor	Play Store
8	Health Tracker	Play Store
9	Step Tracker - Pedometer	Play Store
10	Samsung Health	Play Store
11	Lose Weight App for Men	Play Store
12	Pacer Pedometer & Step Tracker	App Store
13	MyFitnessPal: Calorie Counter	App Store
14	Calorie Counter by FatSecret	App Store
15	YAZIO Calorie Counter & Diet	App Store
16	JustFit: Lazy Workout	App Store

Table 4. Assigned scheduling categories of selected apps

App ID	Scheduling Category
1	Custom scheduling
2	Custom scheduling
3	Custom scheduling
4	Custom scheduling
5	Custom scheduling
6	Custom scheduling
7	Custom scheduling
8	Custom scheduling
9	Custom scheduling
10	No scheduling
11	Custom scheduling
12	Custom scheduling
13	Custom scheduling
14	Custom scheduling
15	Custom scheduling
16	Custom scheduling

Table 5. Features and reminders of selected apps

App ID	Number of features tracked	Number of features with reminders	Percent of features with reminders
1	16	1	6%
2	4	1	25%
3	4	4	100%
4	3	2	67%
5	3	1	33%
6	2	1	50%
7	6	4	67%
8	6	5	83%
9	3	2	67%
10	-	-	-
11	4	2	50%
12	4	4	100%
13	5	2	40%
14	3	2	67%
15	4	3	75%
16	6	1	17%

App with ID 10 was not considered in the metric analysis as the app was determined to have no scheduling functionality (Table 4).

Table 6. Automatically tracked features of selected apps

App ID	Number of features tracked	Number of automatically tracked features	Percent of automatically tracked features
1	16	3	19%
2	4	2	50%
3	4	1	25%
4	3	1	33%
5	3	0	0%
6	2	1	50%
7	6	2	33%
8	6	2	33%
9	3	1	33%
10	6	3	50%
11	4	0	0%
12	4	1	25%
13	5	2	40%
14	3	3	100%
15	4	1	25%
16	6	1	17%

Table 3. Features tracked by selected apps

App ID	Diet monitoring	Activity monitoring	Sleep monitoring	Weight monitoring	Cycle monitoring	Vital sign monitoring
1	✓	✓	✓	✓	✓	✓
2	✓	✓		✓		
3				✓		✓
4	✓	✓		✓		
5				✓		✓
6		✓		✓		
7	✓	✓		✓		✓
8	✓	✓				✓
9	✓	✓				
10	✓	✓	✓	✓		
11	✓	✓		✓		
12	✓	✓		✓		✓
13	✓	✓	✓	✓		
14	✓	✓		✓		
15	✓	✓		✓		
16		✓				✓