A Model of Visualised QS & QS Heptagon: A New way of Visualising Periodicity in Fitness data

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ABSTRACT
A holistic view on visualising personal informatics is currently missing in the literature. In this paper, I propose a model of visualised quantified self. The model is then used to develop a set of novel visualisations of physical activity data – a heptagonal view, *QS Heptagon*, facilitates periodic pattern discovery; scatter plot with a trendline shows global trends; a multi-faceted view of various data streams allows for new data interrelationship discovery. An evaluation plan to assess the effectiveness of the new visualisation is suggested.

INTRODUCTION
People's desire to record information about themselves has been documented in the past (e.g. Benjamin Franklin's virtues [16]) but it was not until the last decade that we have seen a proliferation of affordable personal tracking devices that allow the general public to engage in self-monitoring on a large scale [20].

The enormous amount of data generated by sensors must be translated into a "human-friendly" language – that is where data visualisation plays a key role [31].

It is, therefore, surprising that there is currently missing a holistic view on how to approach QS data visualisation in the literature. To address this, I conducted a thematic analysis of personal informatics related literature and developed a model of visualised QS. Using the model, an opportunity for novel visualisations was identified for (1) multi-faceted views, and (2) pattern discovery in periodic data. I developed several visualisations to illustrate a novel approach using a publicly available FitBit dataset.

LITERATURE REVIEW

Personal informatics definition
Li *et al.* [20] define *personal informatics systems* (also termed as *lifelogging* or *quantified self systems*) "as those that help people collect personally relevant information for the purpose of self-reflection and gaining self-knowledge". For a QS system to be effective, the information presented must be insightful and invite to be reflected upon.

Motivations for gathering QS data
People have different motivations for gathering personal data – from supporting reflective thinking and becoming more aware of one's behaviour [5] to facilitating better decision-making [11]. Some people monitor themselves simply out of curiosity [12]. Self-esteem plays an important role – recording personal achievements has been shown improve one's self-perception [29].

What people want to know from their data
Li, Dey and Forlizzi [21] conducted a study to understand what questions people want to get answered by QS data. Six themes were uncovered: (1) *Status* (checking current performance or progression towards a goal); (2) *History* (seeing data from a long-term perspective to discover trends), (3) *Goal* (setting appropriate goals, understanding what action to pursue to reach a goal); (4) *Discrepancies* (comparing goals with current status); (5) *Context* (looking for explanations for current state of events), (6) *Factors* (looking for factors of long-term trends).

This shows that a mixture of quantitative and qualitative data needs to be provided to the user in a format that is easily understandable and actionable.

Models of personal informatics
Several models of personal informatics life cycle and styles of tracking have been proposed:

Li *et al.* [20] identified five stages that people go through when engaging in personal informatics: *Preparation* (deciding what information to record and how), *Collection* (collecting the data), *Integration* (transforming and preparing data for reflection), *Reflection* (reflecting on collected information), and *Action* (deciding what actions to take). The authors advocate a *holistic* approach to QS by taking into consideration all stages when developing personal informatics systems. Li *et al.* also described barriers occurring in each stage which can cascade from stage to stage. For example, if a user does not collect data on certain days, it may later hamper the *Reflection* and *Action* stages.

Rooksby *et al.* [29] argue that the stage-based model is too technology focused and they offer their own view on personal informatics consisting of five styles of personal tracking: *directive* (working towards a specific goal or following a training program), *documentary* (documenting activities without the immediate aim of changing them), *diagnostic* (looking for factors that lead to a certain event or

Figure 1. Conducting thematic analysis of QS literature

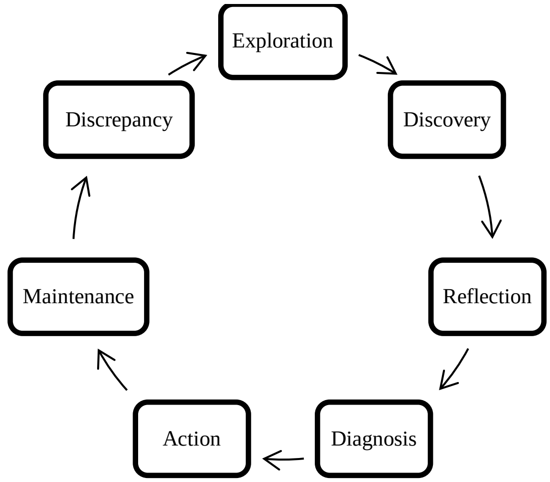


Figure 2. A model of visualised QS

state), c*ollecting rewards* (playing a game), and *fetishised* (being interested in technology and gadgets).

Epstein *et al.* [12] combined both of the above models into a stage-based model from a perspective of *lived informatics* [29]. Most notably they added *lapsing* and *resuming* to capture the reality of people forgetting using their devices or taking a break from them for some time.

QS and visualisations

Humans are very good at spotting patterns, trends and periodic events in large amounts data if it is visualised [10]. That is why QS data, especially physical activity data, have been visualised in many ways: from traditional charts (see Figure 3) to virtual companions (pets [23], plants [8,18], avatars [17,26]) to abstract informative art [28]**.**

The emotional attachment that some participants developed towards the virtual companions (VC) motivated them to continue improving. The same attachment, however, also caused distress – if participants did not engage in a physical activity, they knew their VC would be sad and they would avoid using the app [23]. This can be overcome by not explicitly punishing users for not progressing on their goals but conveying positive reinforcement through, for example, abstract representations of the progress [14].

Cuttone *et al.* [10] suggested following four design heuristics when visualising QS data for reflection: (1) *make data interpretable at a glance* (the authors suggest starting off with a simple visualisation but offering gradually more grained levels of detail); (2) *enable exploration of patterns in time series data* (trends and patterns are important for reflection – different visual representations of the data can facilitate discoveries); (3) *enable discovery of trends in multiple data streams* (allowing users to see multiple data streams at once can lead to finding new interrelationships); (4) *turn key metrics into affordances for action* (suggesting next steps and allowing users seeing the history of their actions and effects can aid decision making).

In the next section, I describe an identified gap in the literature and explain how I approached addressing it.

A MODEL OF VISUALISED QS & ITS USE IN A SCENARIO

After conducting the literature review, I started developing various scenarios to demonstrate my understanding of the connection between personal informatics and visualisations. However, although there are several models of personal informatics [12,20,29] and general design and visualisation heuristics for quantified self [10,24], I have not encountered a holistic model of how to approach visualising QS data.

Therefore, instead of presenting the QS and visualisation interrelationship in a set of scenarios that would be scattered since the literature does not provide a unified model, I conducted a thematic analysis [4] to uncover themes in the QS literature that are specifically related to what data in what stages should be served to a user in a visual form (see Figure 1). This model has formed a basis for my approach to a novel visualisation. Below, the model is presented.

A model of visualised QS

The model has seven stages: *Exploration, Discovery, Reflection, Diagnosis, Action, Maintenance,* and *Discrepancy* (see Figure 2). These are by no means clearly separated, however, they have distinct characteristics.

Exploration

Allow users to explore long-term time series data [20], it should be presented in the context of other QS data streams creating a coherent multi-faceted view [20,21] and avoiding data silos. Start with a simple view that can be gradually enhanced with more details on demand [10].

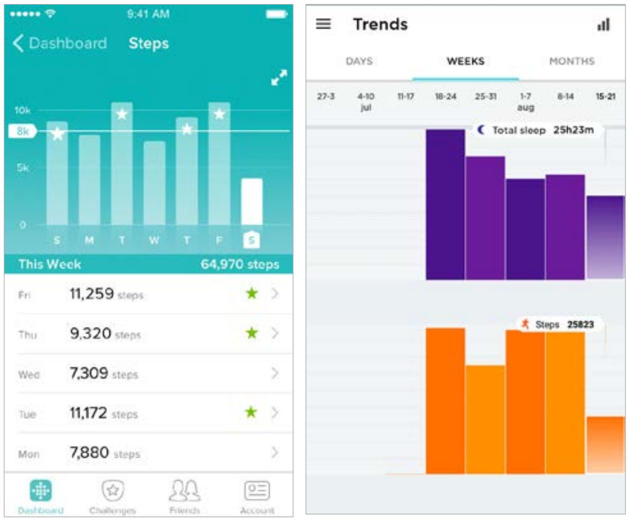


Figure 3. Left: FitBit daily step overview[1]; Right: Jawbone Trends (author's personal archive)

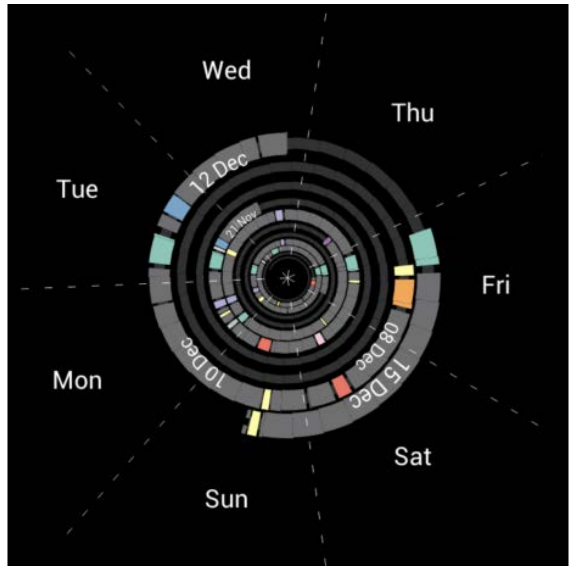


Figure 4. *QS Spiral* [19]

Discovery
Facilitate discovery by highlighting anomalies and discrepancies in the data [15]. Showing global trends, periodic patterns, and multiple visual representations of the same data enables new interrelationship discoveries [10,15]. User history, goals and contexts are all important factors that help seeing the data in new ways [21]. Make it easy to tag and annotate events to create a richer picture of the context surrounding an event – richer information can lead to uncovering hidden relationships [22].

Reflection
Support viewing results from different perspectives [2] by presenting surprising or puzzling facts – e.g. compare user performance with friends, family members or general public [2]. Bring past records into user's attention unexpectedly to promote reflection [15]. If possible, model and show alternative outcomes of different goal-achieving scenarios [15]. Present goals and key metrics set by the user to help them reflect upon data. Allow insights to be shared with friends or public and facilitate feedback from them.

Diagnosis
After exploring the data and reflecting on discoveries, the users are ready to diagnose the causes of discrepancies. Allow them to annotate the data and store the discoveries and insights they have made. Assist them in turning these into actionable points [10].

Action
Support users in adjusting, setting and achieving their goals [10,21]. Suggest next steps. Gamification can motivate action – e.g. collecting rewards [29], taking care of pets [23] or plants [8,18] or use of avatars [17,26] were shown to be an effective approach to behaviour change facilitation. Involvement of family members has been shown to improve chances of a positive change [25].

Maintenance
Display current status and make data interpretable at a glance [10,21]. Offer a simplified view but allow for gradual enhancement [10]. Use positive reinforcement – users do not want to see bad results [20] – abstract representations of the data may be perceived better than charts [14] or living metaphors [8,18,23]. Take into account that users will forget or skip measurements and do not punish them for it [12].

Discrepancy
Support users by notifying them about discrepancies between their current status and their goals [21].

Use of the model in a scenario
Here I present a simple scenario grounded in literature that shows how the recommendations of the above model are currently violated by commercial products:

A young professional, Alex, uses a fitness tracker most days, primarily for exploratory purposes. The associated smartphone app displays step counts without any additional information apart from meeting or not meeting a daily goal,

[1] https://www.fitbit.com/uk/app

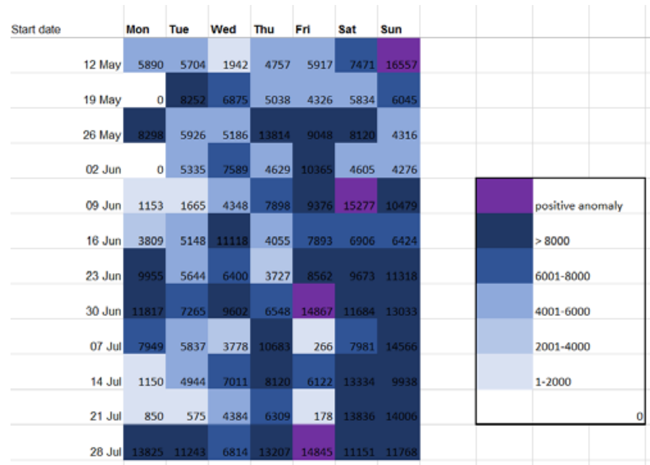
which she does not find very useful (reported in [20]; violation of *Exploration*, *Discovery* and *Reflection* stages).

Sometimes she forgets to wear the tracker, which skews her results and makes the data unrepresentative of her progress (reported in [20]; violation of *Maintenance* stage).

She also finds it hard to see the data in the context of other activities she has done (reported in [10]; violation of *Exploration* stage).

The app does not allow her to filter data to see several months at once (reported in [20]), which she would like to do to discover long-term trends and patterns (violation of *Exploration* stage).

All the violations are addressed in the *Prototype description* section.



Start date	Mon	Tue	Wed	Thu	Fri	Sat	Sun
12 May	5890	5704	1942	4757	5917	7471	16557
19 May	0	8252	6875	5038	4326	5834	6045
26 May	8298	5926	5186	13814	9048	8120	4316
02 Jun	0	5335	7589	4629	10365	4605	4276
09 Jun	1153	1665	4348	7898	9376	15277	10479
16 Jun	3809	5148	11118	4055	7893	6906	6424
23 Jun	9955	5644	6400	3727	8562	9673	11318
30 Jun	11817	7265	9602	6548	14867	11684	13033
07 Jul	7949	5837	3778	10683	266	7981	14566
14 Jul	1150	4944	7011	8120	6122	13334	9938
21 Jul	850	575	4384	6309	178	13836	14006
28 Jul	13825	11243	6814	13207	14845	11151	11768

Figure 5: Step count data clustered in a heat map – MS Excel

DESIGN FOCUS & RATIONALE FOR PROPOSED VISUALISATIONS

It is not feasible to focus on all the stages of the model described above within the limited space of this coursework. Given the presented scenario, I am going to focus on *Exploration* and *Discovery* phases to show how the use of the model can lead to a novel visualisation.

Especially the *Discovery* phase seems to be largely disregarded in the commercial products like FitBit[2] or Jawbone[3].

Young professionals are considered as primary target audience since most participants recruited through interest QS websites for Li *et al.*'s study [20] were 26-30 years old.

Jawbone and FitBit (see Figure 3) generally only offer one default view on the data and are largely uni-faceted, i.e. they take into consideration only one aspect of person's life, although participants in Li *et al.*'s study expressed a desire to see their data in the context of other activities [20].

There seems to be a gap in the literature around discovering periodicity in QS data despite the fact that young professional's life is, in some ways, inherently periodic. One of few attempts to provide a visualisation of this type has been Larsen *et al.*'s *QS Spiral* [19] (see Figure 4).

Spiral visualisations like the QS spiral [19,32] present an interesting alternative to traditional time-series charts. A continuous spiral timeline can allow users to discover repetitive or periodic patterns in their data.

Although looking promising, the QS spiral has not been tested with users and therefore its efficiency is not known. Judging from the provided pictures, it is not very easy and straightforward to navigate. Could there be a way to visualise data periodicity while making the visualisation easy to navigate?

PROTOTYPE DESCRIPTION

A mobile app is considered as a medium for the novel visualisation since smartphones are used as a primary display device for most commercial fitness products (e.g. FitBit, Jawbone).

To build a prototype several data sources were used – an open Fitbit dataset covering a period from Oct 2011 to Sept 2014[4], and my personal GPS tracking and banking data.

I started by exploring the FitBit dataset in *Microsoft Excel* and an R-powered data science tool *Exploratory*[5]. My primary aim was two-fold: (1) facilitate a better way to discover periodic patterns, (2) allow multi-faceted views.

QS Heptagon

A proposed visualisation for periodic pattern discovery, *QS Heptagon* (see Figure 6), builds upon the *QS Spiral.* Instead of a spiral, however, it uses heptagons to represent days of a week. Using seven line segments for seven week days seems to be a straightforward metaphor but it needs to be confirmed with users. The visualisation was developed by creating a heat map in Excel (see Figure 5) and then translating it to the proposed shape in Adobe Illustrator.

Let's imagine, a user sets her daily step goal to 8,000. Step-count data is clustered into 2,000-step intervals and each interval is assigned a colour – green for achieving the goal, shades of blue to represent underperforming, and bright pink for positive anomalies. To avoid punishment-like emotions emerging, underperforming is intentionally coloured in blue

[2] https://www.fitbit.com

[3] https://jawbone.com

[4] http://doi.org/10.5281/zenodo.14996

[5] https://exploratory.io/

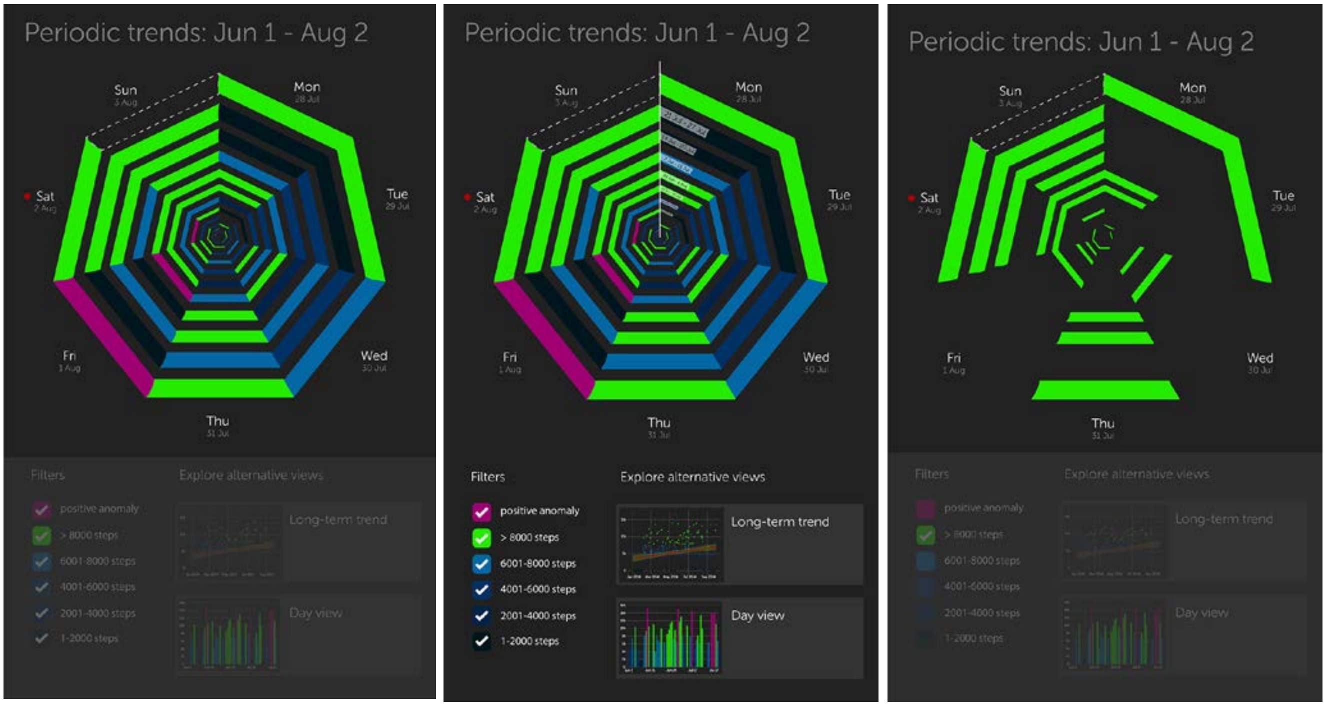


Figure 6. ***QS Heptagon*****: Left: Dimmed view facilitating focus; Centre: Active interaction view; Right: Applied filter**

Figure 7. Alternative step-count views. Left: Scatter plot with a trendline; Right: Bar chart.

that has been shown to be perceived as positively calming among young adults [27]. The worse the results, the more a segment blends with a background, making it less visible. To avoid punishment for skipping measurements, skipped days are coloured in the background colour, i.e. they are made invisible – similar method was used in [19].

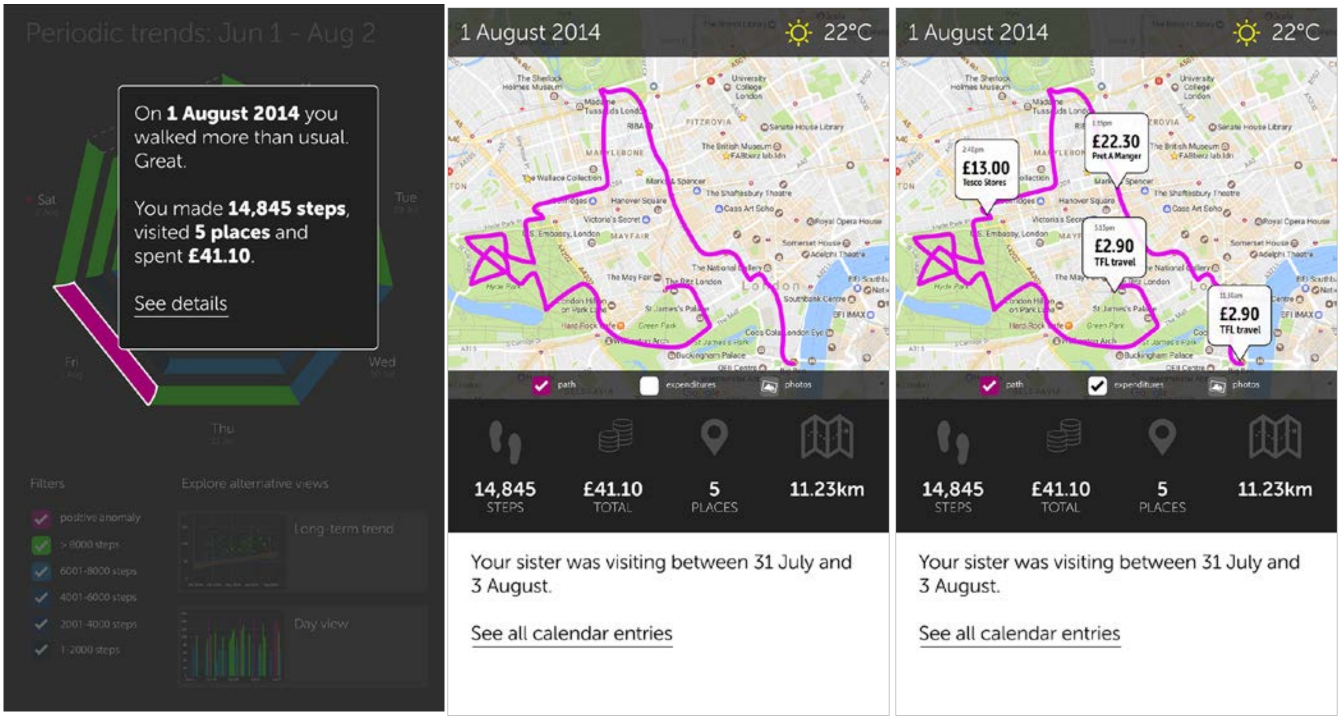


Figure 8. Multi-faceted views – Left: Information about a day provided on tap; Centre: Detailed view of a day; Right: Path and Expenditures filters ON

Figure 6 also shows examples of interaction with the visualisation. To let the user focus on the QS heptagon, other UI elements are dimmed (Figure 5 – left) until the user taps on them which makes them active (Figure 6 – centre). Discovery is facilitated by allowing users to filter data. In Figure 6 (right), we can see that the user walked more towards the end of the week (Sat, Sun).

Alternative views

To further support discovery, two alternative views are presented (see Figure 7) – a scatter plot is displayed with a trendline (linear regression) to show the user the overall global trend. Lastly, a bar chart view is also offered to allow for more precise comparisons - according to [7] differences in length are easier to perceive than colour differences and some more analytic users prefer this view [13]. These two charts were developed following Yau's method [33] – they were created in *Exploratory* using R scripts and then finished in Adobe Illustrator.

Multi-faceted view

Set of three visualisations (Figure 8) implements the *Discovery* stage recommendations by allowing users to gradually increase the granularity of the data. A user can click on a *QS Heptagon* segment to get more information (Figure 8 – left), this data is presented as a narrative which has been shown to be more engaging for users [30]. If „See details" is clicked, a new visualisation is presented (Figure 8 – centre) with a multi-faceted view. The user can see a map and select to show combinations of a path taken and expenditures (Figure 8 - right). This allows the user to discover new interrelationships. Two other data streams are suggested for future development –photos and calendar entries associated with a given day could further enhance contextual information.

EVALUATION PLAN

To assess the effectiveness of the proposed visualisations, I developed three research questions:

RQ1: Is the ***QS heptagon*** more effective in discovering periodic trends compared to traditional charts?

RQ2: Do the **two alternative views** of step-count data enhance discovery and reflection compared to traditional single views of commercial products?

RQ3: Does the **multi-faceted detail view** enhance discovery and reflection compared to traditional single views of commercial products?

Target audience as mentioned in the *Design focus* section, are young professionals. To ensure that participants will be familiar with traditional QS systems, a criterion of having used a fitness tracking device in the last year is added to participant screener.

Lab study

In a controlled setting, a usability testing should be conducted with a mix-method approach and at least 6 participants from the target group. For quantitative assessment, participants should be given a set of tasks to compare traditional charts and the proposed ones – task completion time and error rate should be recorded and statistically assessed.

For qualitative assessment, a researcher should elicit participants' views on the novel visualisations compared to traditional ones in a semi-structured interview.

Challenges: In a lab study, usability can be assessed but the QS data shown would not be likely generated by the participants themselves. They would therefore not have an emotional attachment to the data and would not be genuinely interested in discovering discrepancies. That is where a field study should help.

Field study

According to Ayobi *et al.* [1], there are currently two unaddressed research topics in personal informatics: (1) Understanding contextual an immediate experience (most QS studies rely on delayed self-report); (2) Long-term studies (to understand long-term benefits and challenges of using personal informatics systems).

To address Ayobi *et al.*'s research questions as well as RQ 1-3 of this study, ethnography and experience sampling method [3,6,9] should be used. To assess how the new visualisations compare to the traditional ones, participants (ideally at least 10 per group) should be randomly assigned to two groups. Each group would use traditional and new visualisations (in a different order for counterbalancing). To assess long-term benefit, the study would have to be run at least for two months – one month with traditional visualisations, one month with the new ones.

Challenges: Keeping participants engaged over long-term can be difficult, participants who are already motivated to gather QS data should be selected to decrease the risk of dropping off the study.

To truly assess the benefits, participants should be given an option to keep the new visualisations installed after the study has finished. A delayed assessment could be then conducted to see what proportion decided to use the new solution over the traditional one.

CONCLUSION

In this paper, I have presented a new *model of visualised QS* that aims to provide a holistic view on QS data visualisation, currently missing in the literature. I have also developed a new way of presenting time-series data for periodic patterns discovery, *QS Heptagon*, as well as alternative and multi-faceted views of QS data.

Limitations

Neither the model nor the visualisations have been evaluated with users. Although it was not a coursework requirement, it presents a limitation to the study contribution.

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