Cross impact analysis: an alternative way of qualitative data analysis of repertory grid technique

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Abstract: User research in understanding people's needs and expectations is a critical part of the design process. Researchers have sought to find methods that help them to collect data and lead the design process properly. To achieve this, several methods have been borrowed from other disciplines, one of which is repertory grid technique (RGT). While RGT has been widely used in user research, a common understanding of how the qualitative data of RGT should be analysed is still missing. This paper explores the qualitative and quantitative data analysis methods of RGT and suggests using cross impact analysis (CIA) for data analysis of qualitative data. It compares the results of suggested qualitative data analysis with the results of quantitative analysis. The paper further discusses the potentials of CIA and makes suggestions about usage of it.

Keywords: repertory grid technique; RGT; cross impact analysis; CIA; user research; data analysis.

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1 Introduction

Design is a dynamic process. It starts with a problem to be solved, followed by the designer's analysis and synthesis of the problem to generate possible solutions (Lawson, 2006). When the design problem is solved, the final solution is evaluated to see whether that solution is successful or it creates a new problem (Harper, 2008; Lawson, 2006). For a problem-driven design, the designer needs to learn about the potential users in order to understand their needs and expectations, mostly through hands-on-research, to have relevant knowledge that will be directly integrated into design process (Bruseberg and McDonagh-Philp, 2002; Cross, 2004; Stappers, 2006). The user research even starts before designing, to explore the potential values of users (Harper, 2008). Designer's hands-on research may depend on designer's unstructured observations. However, the most benefit can be taken from structured methods for this kind of research (Stappers, 2006). On the other hand, the evaluation of the final solution can require structured and guided research for a thorough understanding of the success of the solution (Squires and Byrne, 2002).

According to Squires and Byrne (2002), several methods can be used during discovery, definition and evaluation stages of design process. They suggest that during discovery process, the designer generally use generative methods such as contextual observation and open-ended interviews, while in evaluation process evaluative methods such as surveys and usability tests can be applied. On the other hand, in conducting user research, several theories, methods and techniques have been borrowed from psychology literature for knowledge elicitation. Most of these methods fit to user research very well as the main subjects of both psychology and user research is people. For knowledge elicitation, while qualitative and quantitative methods can be used separately, the current trend is using mixed methods as they have the opportunity to both generate and evaluate ideas.

Repertory grid technique (RGT) (Kelly, 1955) has been used for user research as it gives the ability to collect both qualitative and quantitative data (Fallman and Waterworth, 2010). In this technique, participants are asked to construct their personal criteria about predefined elements (Fransella, 2004; Kelly, 1955). The main idea in this technique is to collect people's constructs over a set of subjects. In psychology, while that subject can be other people, it becomes 'products' or 'systems' in design research.

RGT is a mixed data collection method. It can be utilised for both qualitative and quantitative data collection during the whole design process. During the discovery design process, it can be utilised to collect initial user preferences and needs by making people compare ideas or products. On the other hand, during the evaluation process, it can be utilised to understand through which qualities users evaluate the products or ideas. Moreover, RGT gives the researcher ability to statistically find out the products or ideas that users are in favour of.

The application and analysis techniques of RGT can vary and the designers can decide which type of analysis is required in relation to the aim of the research. Traditionally, RGT data is analysed through quantitative data. However, for designers, details of reasons behind people's needs and expectations have high importance. Analysing data only through quantitative data creates data reduction.

In this paper, I propose a new data analysis technique, cross impact analysis (CIA), for data analysis process of RGT. I propose this new method for data analysis of qualitative data of RGT and compare it with conventional data analysis of quantitative data of RGT. I do this to show that only statistical data analysis will cause the designers to lose high amount of data. I will discuss these through a research that has been conducted with conceptual wearable products. I further discuss the potentials of using this method in user research.

2 RGT as data collection method

RGT is based on the idea that people perceive the world with their own constructs (Kelly, 1955). The constructs have a bipolar nature which means that each construct have similarity-difference dimension. Each person's construct is different from others and can vary. For instance, while one can state 'simple-complex' as bipolar constructs, while other can stated ‘simple-powerful’ and those two bipolar constructs do not refer to the same dimension (Hertzum et al., 2011). Each person’s construct does not necessarily match with other people and that makes the RGT rich in terms of collecting wide variety of constructs.

Table 1 Bipolar RGT scale example*

Positive	*Product A*	*Product B*	*Product C*	*Product D*	*Product E*	*Negative*
Simple-pure	6	1	4	7	4	Overdone
New technology	5	1	6	6	2	Old technology
Technology that we are not used to	6	1	6	6	2	Technology that we are used to
Simple	7	1	6	7	4	Like jewellery
Practical	4	4	4	6	1	Not practical
Beautiful	4	2	6	7	3	Ugly
Esthetical	5	2	6	6	2	Not esthetical
Uses screen technology	3	1	7	6	2	Cannot give feedback
Easy to use	4	4	5	6	5	Hard to use
Has flexibility in usage	5	1	7	7	4	Is not flexible to use
Has effective form usage	5	1	7	7	2	Has stable form
Keyboard is easy to use	3	1	6	7	1	Has crowded keyboard
Has form unity	6	3	5	7	2	Has lots of parts
Hard to lose the parts	7	7	6	7	1	Easy to lose the parts
Technological	6	2	7	7	1	Not technological
Stylish	6	2	6	6	2	Not stylish
Has wide screen	5	1	7	7	2	Has small screen
Flexible screen	1	1	7	7	2	Stable screen
Has transparent material	1	2	7	3	1	Stable material
Has minimum number of functions	5	2	7	6	2	Has lots of functions
Slim in form	5	3	7	7	2	Thick in form
Has quality material	6	4	7	7	1	Looks cheap

Note: *Rating is out of 7.

Originally, the RGT application process consists of two major phases (Table 1) (Fransella, 2004; Kelly, 1955): contrast elicitation by comparing the elements, and rating the elements on the elicited constructs. Phase 1 aims at creating a bipolar scale which is constructed by each participant. The participant is introduced the elements to be compared and given the randomly selected ones. The aim is to make the participant "think of a way or dimension in which two of the elements are similar to each other and different from the other" (Fransella, 2004). Following that, the dimensions are asked to be labeled either positive or negative. When the participant states a positive dimension, the opposite dimension is asked, or vice versa. Each positive and negative dimension is noted to the bipolar scale (Table 1). After collecting data for the first set of elements, the interviewer randomly selects and presents another set of elements. In reference to other user studies (Hassenzahl and Trautmann, 2001; Tomico et al., 2009) each session ends when the subject finishes when the participant cannot find any differences or similarities between the subjects.

Phase 2 aims at comparing the elements in relation to participants' constructs. The constructed new scale is given to the participant, with a request of rating each element over the constructs elicited. The session ends when the subject finishes rating. There are three ways to conducting Phase 2 of RGT: Relating constructs to items by giving 1 (yes) or 0 (no) (Baber, 1996, 2005); rank ordering by ranking the elements in terms of constructs (ranking form 1–5) (Baber, 1996) and rating the elements (Cho and Wright, 2010; Fallman and Waterworth, 2010) and all these methods can be applicable in relation to the aim of the research.

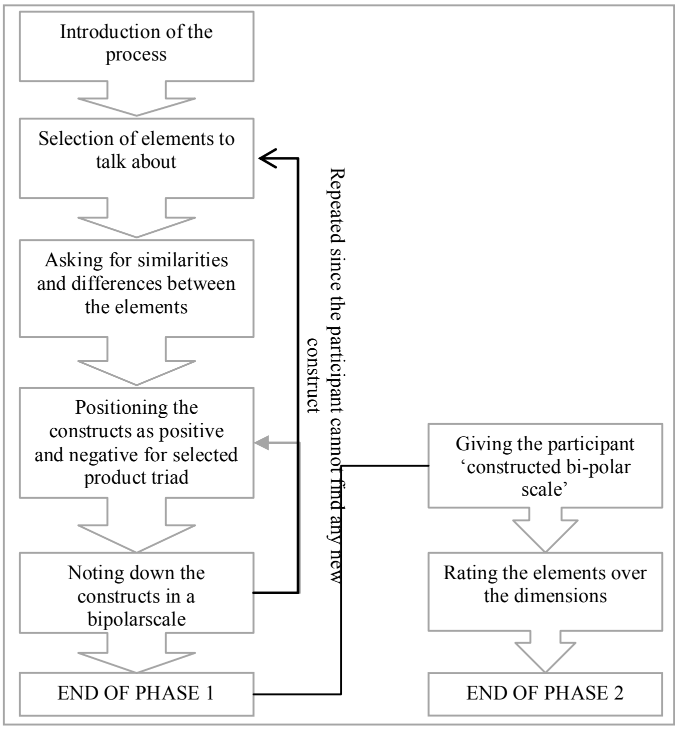
3 Application and analysis of RGT

When RGT is used for user research, people are asked to compare and contrast the given products, systems or concepts. The researcher notes down these comparisons and at the end ask the participant rate the elements over the constructs elicited. The procedure generally is applied with respect to the original RGT (Figure 1).

RGT has a potential to help researchers learn about the reasons behind people's comments such that people can further be asked to talk more about the dimensions elicited (Kuru and Erbug, 2013). Asking about the reasons can contribute to understanding the motives of positive and negative comments that can be critical to produce solutions for problems. As already been applied, laddering technique during the qualitative data collection of RGT gives valuable data about the rationale behind people's expectations (Crudge and Johnson, 2007). That is why, in Phase1, participants should be asked the reason of positioning a dimension either positive or negative, and they should be free to talk about any quality they wished. At this point, asking 'why' questions after the participants' preferences can help to clarify the relations between the constructs. This will make the results more powerful in reasoning the constructs with real user needs.

There are several approaches to analyse the elicited constructs. For instance, the researchers can do manual qualitative analysis to reduce the number of constructs to meaningful dimensions (Moynihan, 1996). While this can lead to bias results, it can be applied when the aim is to catch the general pattern within data. The process that is known as 'visual processing' can also be applied to see the similarities and differences between the elicited constructs. Those constructs are reorganised to put the similar constructs together and can help the researcher better explore the dimensions within data (Stewart, 2014). On the other hand, the general tendency in grouping the constructs is content analysis in which the data is coded and then grouped together to understand the dimensions behind the constructs (Edwards et al., 2009).

Figure 1 Typical data collection procedure



Source: Reproduced from Karahanoglu and Erbug (2011)

The constructs can be grouped by searching the participant's ratings to the elements. The data can easily be understood through focus algorithms and Princom Maps (Björkland, 2008; Fallman and Waterworth, 2010). Even though single participant data can easily be analysed statistically, "knowledge for interpersonal analysis of RGT data still lacks" (Karapanos and Martens, 2009). Single participant data statistical analysis is relatively easy to do in comparison to multiple participants. In doing statistical analysis of multiple users, the same graphs (focus algorithms and Princom Maps) also help to understand the patterns within the data. Still, quantitative data analysis of multiple participants is handy and requires at least two steps to be taken; analysis of single participant data and grouping the participants and then analysing the multiple participant data.

Data analysis methods of the original RGT is quite strict, but for designers, that stiffness can lead to losing genuine design ideas. In qualitative analysis, multiple users' data is analysed by content analysis, and researchers work for standardising construct names (Tomico et al., 2009). Analysing qualitative data also shows the patterns of constructs within "highly subjective and individual data" (Fallman and Waterworth, 2010). Fallman and Waterworth (2010) name this type of analysis as 'statistically blind'. On the other hand, in quantitative analysis of RGT data, the constructs of all participants are put together and iterative data analysis is made to arrive at the final factors within the data (Fallman and Waterworth, 2010; Grill et al., 2011). Fallman and Waterworth (2010) name this type of analysis as ‘semantically blind’. Even though there are examples that both qualitative and quantitative analysis were brought together, this paper offers a new method in order to form a reliable analysis that analysis qualitative data and quantifies the results through a new method.

4 Cross impact analysis

The analysis of RGT is either statistically or semantically blind and the approach that the designer chooses depends on the aim of the research; whether it is generative or evaluative. Still, grouping the constructs and finding the most dominant ones can be challenging for user research to understand what people mostly care for. In this paper, we suggest an alternative approach to qualitative data analysis of RGT. We propose that CIA can potentially show the most important construct groups within data. This analysis can be an alternative to the statistical analysis of RGT as it depends on the numerical relations between construct groups. In addition, it depends on the semantic analysis which saves the analysis from being totally ‘semantically-blind’.

CIA was first introduced by Gordon and Stover (1976) to first predict the future events through forecasting their possible interactions. Mainly, the method lists the events that could happen in the future, and the relationships and impacts between events are determined as the main predictors of future events (Gordon, 1994). The main strength of CIA is the cross impact matrix. A cross impact matrix can be utilised to define the influence of one factor on another (Bradfield et al., 2005; Huang et al., 2009; Spoerri et al., 2009; Wiek et al., 2008). It is the visualisation of the CIA and it allows the researcher to define the most influential variables and those variables that are impacted by the most other variables (Heuer and Pherson, 2010). In other words, through cross impact matrix, the mutual effect of variables can be defined. CIA is mostly used by futurists (Blanning and Reinig, 1999) however the cross impact matrix has the potential to be used in different research in which the interaction between variables matter.

Originally, in CIA, influence strength is defined by numbers placed at the cross-section cells of the variables. In the matrix, the qualities in the rows indicate their level of effect on other qualities, and the sum of the rows is called the ‘active sum’. Qualities in columns indicate the level of being affected by other qualities and their sum is called the ‘passive sum’.

Finally, by using the active and passive sum, cross impact chart can be formed. in the cross impact charts, the chart area is divided into five sections: active, passive, reactive, buffering and neutral, in relation to the variable’s activity-passivity level (Bang et al., 2008; Bradfield et al., 2005; Huang et al., 2009; Vester, 1988; Wiek et al., 2008). Each area represents the causal-affected position of the qualities: the critical area (pink) covers qualities with high activity (affected by others) and passivity (affect others); the active area (yellow) covers qualities with high activity (affected by others) but low passivity (affect others); the reactive area covers qualities with low activity (affected by others) but high passivity (affect others); the buffering area (orange) covers qualities with low activity (affected by others) and passivity (affect others) and the neutral area (gray) covers qualities with moderate activity (affected by others) and passivity (affect others).

Note that the X length of neutral area is 1/5 of all X length and the same applies to the Y length. These area length definition comes from the original CIA (Gordon and Stover, 1977). When the total length of X section of the square is 75, the X length of neutral area is 15. This also leads to define the X and Y lengths as multiplies of 5.

We use CIA to quantify the qualitative data analysis. In the following sections, we explain both qualitative and quantitative analysis of RGT data with an example, and further compare them for the purposes of user research. At the end, we discuss how quantitative data can reduce data, while using CIA to quantify qualitative data of RGT can lead to better guide.

5 Study

To discuss the method we propose for qualitative data analysis of RGT, we conducted a study with on-body interactive products. We applied the process that we explain in Figure 1. During the study, we explored the perceived qualities of on-body interactive products through RGT. We collected data from 30 participants, between the ages of 20 and 30 (12 were female and 18 were male). We showed participants the coloured print-outs of explanation posters of five conceptual on-body communication products. We asked them to compare and contrast the randomly selected three of the products. Once the participants gave the constructs, we asked whether it is positive or negative and why it is good or bad for them. We noted down the constructs in bipolar scales. At the end, we asked participants to rate the products over the constructs they stated. In total, the collected data consisted of 607 construct, changing from 17 to 30 from each participant.

5.1 Qualitative data analysis

To group the constructs, first, we did an initial content analysis. We analysed the grids of three participants by coding the constructs in a construct group. We also used the interview data to understand the reasons behind that construct and those reason were also coded. During this process, we named the construct of participant as 'affected quality' and reasons behind being good or bad as 'causal quality' as offered by CIA. In the below example, we show how we coded each construct. Here, the participant talks about how the flexibility of the product (causal quality) affects the perception of wearability (affected quality). The participant also explains why the product is not flexible by relating flexibility with wearability. During coding process, each code is used as both causal and affected quality as it one quality can both affecting and affected by other qualities.

> [Product D] wraps around my wrist (wearability), as it is more flexible (flexibility of form), but [Product B] is too rigid, since it is not flexible (flexibility). (Male10)

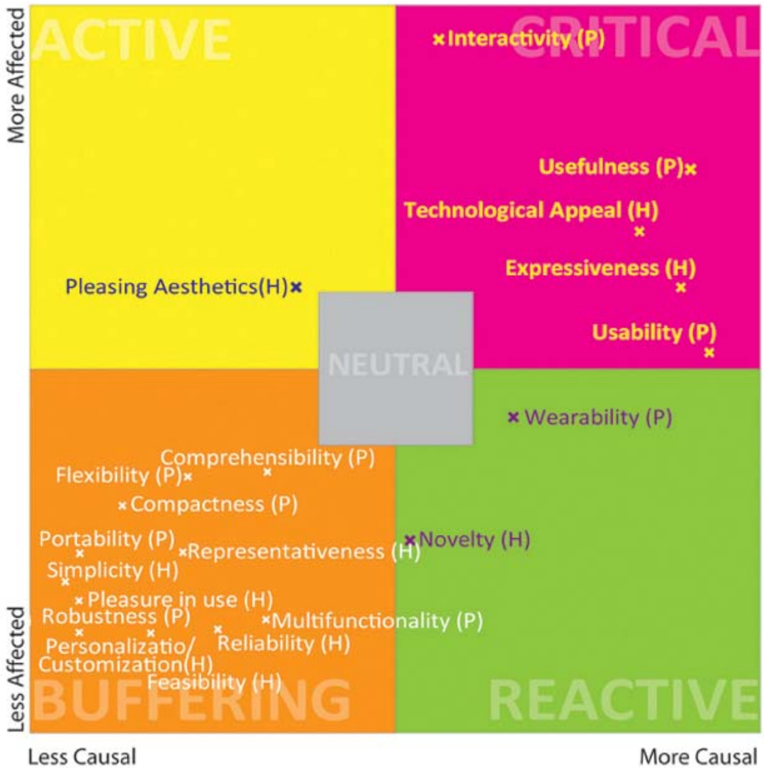
We then discussed these initial codes with a user research expert to arrive at final construct groups and their coverage. With this initial round, we noted approximately 20 main qualities. We also named each quality as either hedonic or pragmatic as offered by Hassenzahl (2003). To arrive at consistency, we created a glossary of terms and these terms were used throughout the content analysis process.

As explained in CIA section, we placed the main constructs (bipolar ones) noted by participants in the rows and the corresponding related constructs (the ones participants made to justify the bipolarity) in the columns. We then placed the total number of comments about the relations at the intersection cells of the constructs. For instance, for the example we gave above, we placed '1' in the intersecting cell of wearability and flexibility as shown below. Then the passive sum of wearability and the active sum of flexibility is counted as '1' (Table 2).

Table 2 Example of strength definition of constructs

Causal (reasons)	*Affected (constructs)*			*Passive sum*
	Usefulness	*Techonological appeal*	*Wearability*	
Expressiveness				
Feasibility				
Flexibility			1	1
Active sum			1	

Figure 2 Cross impact chart (see online version for colours)



Note: Axis represent: X = passive sum, Y = active sum

Source: Retrieved from Karahanoglu and Erbug (2011)

Table 3 Cross impact matrix (see online version for colours)

		Affected (constructs)																				
		Compactness	*Comprehensibility*	*Expressiveness*	*Feasibility*	*Flexibility*	*Interactivity*	*Multifunctionality*	*Novelty*	*Personalisation / customisation*	*Pleasure in use*	*Portability*	*Pleasing Aesthetics*	*Reliability*	*Representativeness*	*Robustness*	*Simplicity*	*Usability*	*Usefulness*	*Technological appeal*	*Wearability*	*Passive sum*
Causal (reasons)	Compactness		1									4					1			3		9
	Comprehensibility	2		2	1		5					1	1		1		1	5	3		2	24
	Expressiveness	1	5		1	1	4	2	3		2	3	17		3		3	1	12	7	3	68
	Feasibility		2			1	1		1		1				1	3		1			1	12
	Flexibility	1			1		1	1		4	1	2						1	4		1	17
	Interactivity		7		1	4		4	2		3		2		2	1	1	4	4	5	2	42
	Multifunctionality		1	2		4	8		2		1							2	3	1		24
	Novelty			1	4		8	2		1			5		3	2	1	3	4	5	1	40
	Personalisation/ customisation					2												1		1	2	6
	Pleasing aesthetics			3					2	1							5		5	11	1	28
	Pleasure in use			1		1							2				1			1		6
	Portability	2		1																2		5
	Reliability	1	3	2	1	2	2									1		2	1	3	1	19
	Representativeness			1			1		4		3		2					1	2		1	15
	Robustness																					0
	Simplicity				1								1						1			3
	Usability	3	4	4		3	12				1			1	3				12	5	9	57
	Usefulness	5	2	8		5	7		1	2		4	2	5	4	1		9		6	8	69
	Technological appeal	6	2	6		2	19		5	1		1	10	2		3	2	4	1		1	65
	Wearability	2		15		1	4	2		1	1	3	4	2	1			7	6	2		51
	Active sum	23	27	46	10	26	72	11	20	10	13	18	46	10	18	11	15	41	58	52	33	

Finally, we summed all the numbers in the rows and columns to find the strength of each construct in terms of affecting and being affected by other qualities. At the end, we had a 20 × 20 matrix (Table 3).

With the active sum and passive sum cells, each dimension is defined by a point in a square chart. For instance, flexibility is defined as (X = 17, Y = 26) and wearability is defined as (X = 33, Y = 51) within the chart. With each defined point, the matrix is then turned into a cross impact chart (Figure 2).

This final chart represents the importance of each quality for the participants.

This analysis shows us the hierarchy of the qualities. For instance, it is understandable that the ones in 'critical' area are the most important ones that designers need to consider while designing. The chart shows us that for an on-body interactive product, interactivity, usefulness, technological appeal, expressiveness and usability are the most critical qualities that the designer needs to focus on. However, this does not mean that other qualities that fall into active and reactive area are not important. The qualities that fall into reactive area also require emphasis as these affect the perception of other qualities more. In relation, the qualities that fall into active area are also important as they are affected by the design of other qualities. The 'buffering' area is a little crowded compared to other areas which show that these qualities are the drivers of other qualities and require less but still enough attention. Therefore, it should be noted that CIA chart is a 'balanced' chart; each quality has relations with other qualities; designer should not ignore any area during design process.

5.2 Quantitative data analysis of RGT

To compare these results with the conventional quantitative analysis of RGT, we also performed factor analysis with the data as suggested by Fallman and Waterworth (2010). We analysed the data by following the steps Fallman and Waterworth (2010) explains. To achieve this, we took the following steps:

5.2.1 Participant level analysis

At the beginning, we generated each participant's display, focus algorithms and Princom Maps to understand the data at participant level and to see whether there is any pattern or other kind of relations with the data statistically (Fallman and Waterworth, 2010). There are several programmes that can be used to manage this process. Within those, RepGrid is the software that is specifically designed and used for analysing RGT data statistically (Fallman and Waterworth, 2010; Tomico et al., 2009). In previous years, it was easy to access downloadable RepGridIV software, however, in recent years, RepGrid it is available only online under the name of WebGrid. To arrive at coherent results, we entered each participant's data to the system one-by-one and collected the graphs through online WebGrid system http://gigi.cpsc.ucalgary.ca:2000/.

First, we generated the 'display graphs' to see whether the data have been entered correctly. Following that, we generated 'focus' graphs to understand which of the constructs were grouped together and which of the products are found to be similar (Figure 3). In addition to these graphs, the 'Princom Maps' helped us to understand the position of each construct and element in two-dimension. After having each participant's graphs, all those graphs were printed out to understand the initial statistical pattern of the data.

Figure 3 Display and focus graphs of participant 05 (see online version for colours)

5.2.2 *Multiple participant data*

As the original method suggests, we put all the data of the participants and focus graphs that were created to catch the patterns within the data. Through this analysis, we tried to see if there are any similar patterns. While doing this, as explained in Fallman and Waterworth (2010), 85% similarity-threshold level was set to name the constructs as similar. However, as the referred article stated, not all the constructs can perfectly fit the construct group as the data is highly subjective and doing Factor Analysis is semantically blind. As they did, we excluded the constructs that semantically did not fit the construct group.

At the end, we found that 383 of the constructs fit well to the groups consisted. When turned back to the data, it was realised that these constructs are coming mainly from the participants who thought that products C and D highly are similar and A is relatively similar to those; but E and B are totally different. At the end, with 384 constructs, ten major groups were arrived at, eight of which have more than 15 constructs (is the half of the number of participants) and 2 of them have less than 15 constructs.

The construct groups arrived (namely the factors) could be explained by a combination of two interconnected factors we found in CIA including the sub dimensions (the ones we used to define the factor). Finally, we named each group constructed by factor analysis to compare the results with the results of CIA.

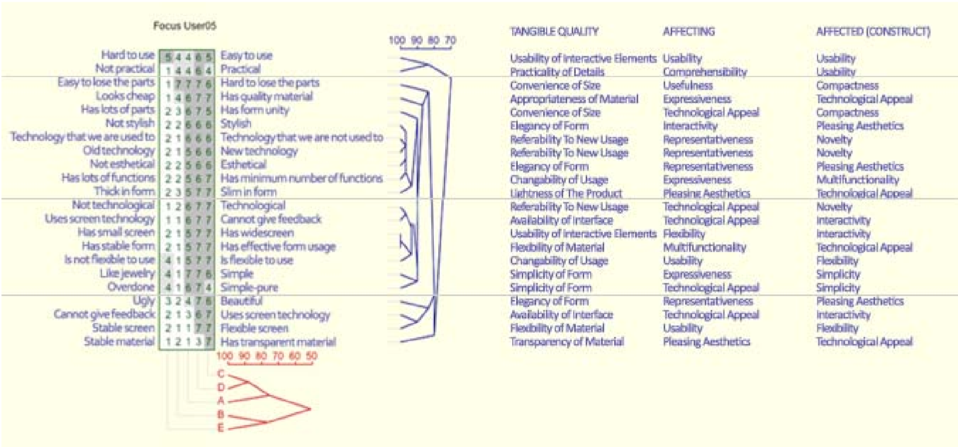
6 Comparison of qualitative and quantitative data analysis

Once we named the factors, we created comparison table to see how these factor analysis and content analysis differ or relate (Table 4). For that table, we turned back to the content analysis to explore how participants related the constructs with tangible qualities and the factors we listed in CIA.

6.1 Participant level analysis

We first explored each participant's data and compared the qualitative analysis coded with the participant level factor analysis results. We looked through each participant's data to see whether factor analysis results formed meaningful groups. The results showed that participant level analysis formed four groups for User5 while in the qualitative analysis, ten different codes were employed. This gave clues about how the multiple participant data results will lead to data reduction.

Figure 4 Comparison of factor analysis and qualitative analysis of participant 05 (see online version for colours)



Multiple participant data: When we combined all data, we realised that the first factor which was formed by factor analysis, consisted of 61 constructs, and it was a combination of sub dimensions such as appropriateness of colour, adaptability to daily life or practicality of interface. Once we looked at the CIA results, we found that those constructs were mainly related with technological appeal and usefulness. Therefore, we named this dimension of factor analysis as 'technological appeal + usefulness'. We followed the same procedure for the rest of the factors.

As a result, we can say that the factors we found by statistical analysis, overlaps with the ones we found by content analysis. On the other hand, these results are good examples for explaining how people can mentally connect more than two concepts together and this can form a 'factor'. With factor analysis we found 15 dimensions which is mainly a combination of eight main factors we found in qualitative analysis, on the other hand, in qualitative analysis we found 20 independent dimensions that play various roles in product design. As stated before, the factor analysis of RGT data is semantically blind. However, our results show that, doing solely with the results of factor analysis can result in overgeneralisation of the results.

Table 4 Factors of statistical (quantitative) and content (qualitative) analysis

Factors of statistical analysis	#	*Sub dimensions*	*Sub dimensions listed under factors of content analysis*
Technological appeal + Usefulness	61	Adaptability to daily life	Usefulness
		Appropriateness of colour	Technological appeal
		Appropriateness of material quality	Technological appeal
		Appropriateness of surface quality	Technological appeal
		Availability of interactive elements	Technological appeal
		Availability of multi-functions	Usefulness
		Convenience of product size	Technological appeal
		Feasibility of details	Technological appeal + Usefulness
		Practicality of interface	Technological appeal
		Resemblance to accessories	Usefulness
		Usability of interactive elements	Usefulness
Expressiveness+ Interactivity	36	Appropriateness to be used as body extension	Expressiveness
		Availability of interactive elements	Interactivity
		Availability of personalisation	Expressiveness
		Clarity of product language	Expressiveness + Interactivity
		Feasibility of details	Interactivity
		Novel impression	Interactivity + Expressiveness
		Quality impression	Expressiveness
		Usability of interactive elements	Interactivity + Expressiveness
Expressiveness + Wearability	40	Appropriateness of material	Expressiveness + Wearability
		Feasibility of details	Expressiveness
		Quality impression	Expressiveness
		Resemblance to accessories	Expressiveness + Wearability
		Simplicity of form	Expressiveness
		Usability of interactive elements	Expressiveness

Table 4 Factors of statistical (quantitative) and content (qualitative) analysis (continued)

Factors of statistical analysis	*#*	*Sub dimensions*	*Sub dimensions listed under factors of content analysis*
Technological appeal + Interactivity	25	Availability of interactive elements	Technological appeal + Interactivity
		Convenience of size/form	Technological appeal + Interactivity
		Flexibility of material	Technological appeal
		Visibility of feedback	Interactivity
Technological appeal + Novelty	9	Availability of interactive elements	Technological appeal
		Availability of size/form	Technological appeal
		Novel product impression	Technological appeal + Novelty
Technological Appeal + Expressiveness	38	Availability of personalisation	Expressiveness
		Availability to be used as body extension	Expressiveness
		Clarity of product language	Expressiveness + Technological appeal
		Convenience of size/form	Technological appeal
		Feasibility of details	Expressiveness + Technological appeal
		Referability to user group	Expressiveness
		Resemblance to other products	Expressiveness
Technological appeal + Usability	21	Adaptability to daily life	Usability
		Appropriateness of material quality	Technological appeal + Usability
		Appropriateness to anatomy	Usability
		Availability of interactive elements	Technological appeal
		Feasibility of details	Usability
		Ease of carrying	Usability
		Practicality of interface	Technological appeal
		Usability of interactive elements	Usability
Technological appeal + Wearability	17	Convenience of size/form	Technological appeal
		Ease of carrying	Wearability
		Practicality of interface	Technological appeal
		Resemblance to accessories	Wearability

Table 4 Factors of statistical (quantitative) and content (qualitative) analysis (continued)

Factors of statistical analysis	*#*	*Sub dimensions*	*Sub dimensions listed under factors of content analysis*
Pleasing aesthetics + expressiveness + Wearability	124	Adaptability to daily life	Wearability
		Appropriateness of material quality	Wearability + Pleasing aesthetics
		Appropriateness to anatomy	Wearability
		Availability of personalisation	Expressiveness
		Clarity of product language	Pleasing aesthetics + Expressiveness
		Elegancy of form	Pleasing aesthetics
		Lightness of product	Pleasing aesthetics
		Novelty impression	Pleasing aesthetics + Expressiveness
		Referability to user group	Expressiveness
		Simplicity of form	Pleasing aesthetics + Expressiveness
		Transparency of material	Pleasing aesthetics
		Usability of interactive elements	Expressiveness
Expressiveness + Usability	13	Appropriateness to be used as body extension	Usability + Expressiveness
		Feasibility of details	Expressiveness
		Simplicity of form	Expressiveness
		Usability of interactive elements	Usability + Expressiveness

7 Discussions

Product design is a multidimensional phenomenon and designers have to consider all related factors at the same time, as dimensions can affect the perception of others. For designers, every single construct coming from the users is valuable; therefore, in order to take each participant's constructs into account, it is vital to conduct content analysis for RGT data. In relation, while we were running conventional factor analysis for RGT data, we had to exclude some of the constructs of some of the participants. However, deleting those constructs can be failure for researchers who try to avoid data reductivity (Tore-Yargin and Erbug, 2012).

When we compared the results of content analysis and statistical analysis of RGT, we found that in statistical analysis, as literature also suggested, we had to exclude some of the constructs participants mentioned. However, this type of data reduction is not proper for the design process. On the other hand, with CIA, researchers can use all constructs, by naming the main construct as 'affected quality' and the reason behind that construct being positive or negative as 'causal quality'. This approach helps the researcher to build a cross impact matrix through which the CIA chart can be arrived at. This analysis method uses the number of comments as the main relation between various qualities, which also makes the analysis method appropriate for user research.

With CIA, we can define the constructs within construct groups, which is a kind of 'semantical' factor analysis. We think that the method we applied is a new perspective in understanding multiple participant analysis. It gives a more structured analysis than doing 'visual processing' to group the constructs while more meaningful groups that factor analysis does. Analysing qualitative data also shows the patterns of constructs within "highly subjective and individual data" (Fallman and Waterworth, 2010). On the other hand, we found that statistical analysis showed the main factors within the data, but with CIA it is possible to see the relations between minor and major factors. In addition to that, we can find the effect of each construct on other factors with the numbers we arrive at with CIA, which can reduce the statistically-blind effect of the RGT analysis.

It was easy to analyse repertory grids with CIA, as the constructs that people gave us was the final quality that people care for. With CIA, we were able to discover the most important factors that affect the design of on-body interactive products. With this analysis, we were able to lead the designers to focus on some of the qualities more, while also caring for the other influential of those qualities with a 'designerly' way of analysing data and reducing data reduction.

Another important point is that the CIA does not 'output' the main factors; instead it 'forms' these factors in relation to the constructs that the participants mention and relate each other. We tried to clarify the content analysis process by giving the cross impact matrix. As was shown, the active sum and passive sum of the 'factors' are different. It shows the number of constructs that are related to the factors (active sum) meanwhile it indicates the number of comments that participants mentioned while talking about that construct (passive sum). Therefore, the CIA does not only give the importance level of the factors, it also helps us to explain those in relation to the other factors that affect people's perception. Therefore, we are sure that CIA perfectly fits to the qualitative analysis of RGT when it is used for exploratory user research.

One drawback of CIA for RGT is that it is handy. Doing content analysis takes more time compared to the statistical analysis. In addition, creating a glossary of terms to code data can take time and it requires several researchers' agreement. However, we believe that CIA gives more detailed and valuable results when compared to statistical analysis. Therefore, CIA can best be benefited, when the aim of the study is to explore the product qualities and the relations between other qualities.

Another limitation of CIA is very similar to the limitations of the qualitative analysis. The meaning of the constructs can be named differently by different researcher. However, this limitation can be overcome by forming a glossary of terms at the beginning of the analysis. This can keep the consistency of the results when different researcher analyses the data.

In order to get the most benefit from RGT, the similarity of the products should be well considered. It is recommended that each product should have at least one similarity with each of the products. This similarity can either be the form, the colour or the way of usage. Otherwise, the participant will get lost and might think that the researcher is testing the participant rather than the products.

8 Conclusions

In this paper, we suggested CIA as a new data analysis method for RGT. We suggested that, in order to overcome the problems of 'statistically blind' analysis of RGT and reduce data reduction, CIA can be utilised. CIA facilitates the researcher to put the factors mentioned by the participants in a 'statistical' hierarchy order. This assists the design team to create a balance between those factors.

As stated before, RGT can be applied during the exploratory or evaluation phase of the design process and the analysis method can be selected in relation to the phase. On the other hand, we propose that the analysis method suggested for qualitative data of RGT can be utilised in either the exploratory or evaluation phase. In the exploratory phase, the results found with CIA can potentially lead the design team to focus on, e.g., critical qualities found through analysis. In the evaluation phase, the qualities that fall into the areas defined can be given weight (i.e., critical ones can be given 4 and buffering ones can be given 1) and the evaluation of participants can be multiplied with this weight. Then, the total weight of the constructs can be summed to find the most successful product at the end.

For the future researchers who would like to use RGT and CIA, we recommend to ask detailed questions about the participants' choices. Then the participants will give more detailed information about the reason behind their choices. With this type of data only, CIA can be applied. When the participant is not asked, CIA becomes hard to apply as it highly depends on the participants' choices (affected quality) and the reasons behind those choices (affecting quality).

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