Jun 17th, 12:00 AM

Towards designing inclusion: insights from a user data collection study in China

Weining Ning
Tongji University

Hua Dong
Tongji University

Citation

Ning, W., and Dong, H. (2016) Towards designing inclusion: insights from a user data collection study in China, in Lloyd, P. and Bohemia, E. (eds.), *Future Focused Thinking - DRS International Conference 2016*, 27 - 30 June, Brighton, United Kingdom. https://doi.org/10.21606/drs.2016.230

DRS2016
Design + Research + Society
Future-Focused Thinking

2016 Design Research Society
50th Anniversary Conference
27-30 June 2016, Brighton, UK

Towards designing inclusion: insights from a user data collection study in China

Weining Ning and Hua Dong

Tongji University
donghua@tongji.edu.cn
DOI: 10.21606/drs.2016.230

Abstract: User data has been identified as one of the important knowledge bases for inclusive design. In order to explore the influential factors that may affect the reliability of data and then build up a more effective and efficient data-collection framework, we carried out an experimental study to collect data from older people (aged 50~70) in China, which included users' capability, psychological and social-cultural attributes. Users' actual product interaction performance was also investigated. Three issues were discussed based on the outcome of data analyses: a) mood states have significant effects on respondent's self-reporting results; b) compared with maximum settings, people may have a wider range of perceptions of "comfortable" settings and it is possible to predict the performance in a "comfortable " setting based on "maximum" data; c) social-cultural variables, vision, hearing, dexterity, cognition and psychological characteristics can predict successful product interaction tasks at different levels by using multiple logistic regression analysis.

Keywords: inclusive design; user data; capability

1. Introduction

Inclusive design focuses on making mainstream products and services usable by as many people as is reasonably possible, without requiring them to use specialized adaptations (Keates and Clarkson 2004). Dong et al. (2015) identified the important knowledge bases of inclusive design: a) theoretical models, b) user data, c) best practice exemplars, d) methods and tools and e) policy, standards and guidelines. Specifically, to address the knowledge needs of knowledge users (e.g. designers, manufacturers, policy-makers, charities, etc.) became an important research orientation in the practice of inclusive design (Clarkson and Coleman 2015).

Designers are an important group of the knowledge users of inclusive design (Dong, et al 2015). In order to understand the diversity of the population and design for the widest possible range of users, including the elderly and disabled people, inclusive design data is regarded as one of the effective means to ensure better design inclusion (Tenneti, et al 2012). An inclusive design database is expected to be an integration of anthropometric, capability, psychological and social-cultural data, with designer as the end user. It requires knowledge about the capabilities, needs and aspirations of potential users, meanwhile, it must also take wider psychological, social, and economic considerations, which would help designers gain a more accurate understanding of users' interactions with products and technology (Langdon, et al 2015). Consequently, it raises the requirement for collecting inclusive design user data for designers to make products and services accessible to the widest range of users, irrespective of their impairment, age or capability.

Some key issues in the research and practice of collecting inclusive design data have been identified (Johnson, Clarkson and Huppert 2010; Langdon and Thimbleby 2010):

- Comparison between self-report and performances;
- Measurement granularity: activities, tasks and component functions;
- Potential influences (such as psychological resources and physical context).

We conducted a study to collect end-user data that aimed to identify specific issues listed above. The study was initially derived from the project *Towards Better Design* (2010) done by the University of Cambridge. After the first round of adaptation and pilot studies, suggestions and principles of implementing such a data collection survey in China were proposed (see Ning and Dong 2015; Ning and Dong 2014; Huang and Dong 2015). Based on the findings from the pilot studies, the second round data collection was carried out to clarify emerging issues from empirical studies, including detecting the influence of mood states, exploring the relations between "maximum" and "comfortable" measurements, and verifying the feasibility of establishing predictive models of successful product interactions in the 50-70 years old user group.

2. Methods

A face-to-face survey was adopted in this study. The target respondents were set from age 50 to 70, the user group we defined as the "young-old", as they are experiencing the evolvement of new technologies like the Internet and mobile technologies. The data collected in this study included:

- Capability data (vision, hearing, dexterity and cognition);
- Psychological features (mood states, general self-efficiency and technical self-confidence);
- Social-cultural information (employment, education, income, living conditions);
- Product interactions (opening packaging and mobile phone operating tasks).

The specific survey items and methods applied are summarized in Table 1.

Table 1 Review of the survey items and methods.

Items	Methods
General health condition	Self-assessment (general)
Vision	Self-assessment (general and scenario-based), Visual chart test (acuity and contrast)
Hearing	Self-assessment (general and scenario-based)
Dexterity	Self-assessment (general and scenario-based) Grip strength test Picking up objects test
Cognition	Self-assessment (general and scenario-based) Icon cognition test
Psychological features	Self-efficiency scale Technical self-efficiency scale Mood state (POMS scale)
Social-cultural information	Self-report
Product interactions	Packaging opening test Mobile phone task test

2.1 Capability data

Different means were adopted to capture users' capability data, for example, self-report and performance test. In order to investigate more practical information in a product-using context, scenario-based questions (e.g. "What's the frequency of your missing a phone call because of not being able to hear the ring?") were incorporated with general self-reporting questions of capability assessment (e.g. "How do you assess your hearing capability?").

It should be noted that the capabilities of "mobility" and "reach and stretch" were not included for the reason that significant ceiling effects were found both in terms of self-report and performance tests in the first pilot study carried out earlier (Ning and Dong 2015). But for the future large-scale survey involving a wider age range, it is necessary to investigate these capabilities.

2.2 Psychological features

Mood state, general self-efficiency and technical self-confidence were applied to investigate the psychological features. In this study, we adopted a POMS (Profile of Mood State) scale to explore the effects of mood on respondents' reports and performance. The POMS scale is a checklist designed to measure the transient emotional states of tension-anxiety, depression-dejection, fatigue-inertia, vigor-activity, confusion-bewilderment and anger-hostility (McNair 1971). It has been proved as a reliable and valid measure of mood states in older adults (Gibson 1997). There are many adaptive versions of POMS scales that have been developed to fit different contexts. Due to time limits, we chose a short version that adapted from Grove and Prapavessis' work (1992).

A simplified version of self-efficiency scale was applied to measure self-efficiency. Self-efficiency describes an individual's perception of his or her capabilities to perform and complete a task. A person who has a high self-efficiency degree could be more active and confident in handling different issues (Bandura 1977).

Technical self-confidence is correlated with the performance of successful product interactions (Combe, Harrison and Dong 2013). In this study, the technical self-confidence questions were translated from an adaptive questionnaire (Combe, Harrison and Dong 2013), which was initially derived from the Subjective Technical Competence (STC) scale used by Arning and Ziefle (2007) and the Affinity to Technology scale (Wolters, et al 2010).

2.3 Social-cultural attributes

When collecting the user's data for inclusive design, in order to understand user profiles as much as possible, and their abilities of interacting with products and technology, it is necessary to draw wider considerations of users' information, including social and cultural background (Langdon, et al 2015). This kind of contextual data can help to clarify specific design context, and they are helpful in exploring influential factors that potentially affect users' report and performance when capturing user data. For instance, it proves that self-report measures (in terms of health and ability) can be affected by educational, cultural, language and social differences (Fors, Thorslund and Parker 2006). In this study, respondents' age, gender, educational qualifications, employment status, household income, living conditions (e.g. living alone or with the partner) and the size of living space were investigated.

2.4 Product interactions

A product interaction usually covers more than one specific capability, and it has been identified as an important component of collecting inclusive design data (Johnson, Clarkson and Huppert 2010; Langdon and Thimbleby 2010). Totally six product interaction tasks were involved in this study and the chosen tasks were all related to mobile phone operations. Mobile phones were selected for the basis of three primary considerations: a) mobile phones are popular among the target age group; b) multiple tasks can be performed and c) these tasks often cover more than one type of users' capabilities. Additionally, as a household survey, it can also help ensure a standardized test setting.

After two rounds of assessment, six interaction tasks were determined: 1) Sending pictures through social networking sites/APPs. In order to avoid floor effects, we chose Wechat in this study because it has been installed in more than 90% of smart phones in China and owned about 549 million users (Tencent Interim Report 2015); 2) Taking photos; 3) Texting and sending messages; 4) Making telephone calls; 5) Installing a SIM card and 6) Calling charges inquiry.

3. Findings and discussions

Respondents involved in this study ranged from 50 to 70. The mean age of the sample is 57(SD=5.2). In total, 130 valid samples from seven different cities and regions in China (South: Fuzhou, Shanghai, Nanjing, Nanchang; North: Lanzhou, Xianyang, and Yulin) were obtained and the investigations were carried out in different regions simultaneously during July and August 2015.The Basic information of the respondents was listed in Table 2.

Table 2 Review of the sample characteristics.

Age group	Percentage
50~54	34.6%
55~59	27.7%
60~64	26.9%
≥65	10.8%
Gender	Percentage
Male	46.2%
Female	53.8%
Education	Percentage
Primary school	3.1%
Junior middle school	23.1%
High school	38.5%
Secondary technique school	11.5%
Junior college	13.1%
Bachelor degree and above	10.8%
Living condition	Percentage
Live alone	3.1%
With partner	54.6%
With partner and children	36.9%
With children	3.8%
Other	1.5%
Employment	Percentage
Private	3.1%
The state-owned enterprise/ civil servants / research institutions	24.6%
Farmer	1.5%
Migrant workers	3.8%
Self-employed	50.8%
Retired	11.5%
Re-employment after retirement	4.6%

3.1 The effects of mood states

There is extensive evidence that affective state, such as mood or emotional state, can change people's perceptions, thoughts and behaviours (Forgas 2008). In the design context, a person's affective state will impact upon: a) users' perceptions of their own capability; b) their attitudes toward products/interacts; c) their actual capability with the products/interfaces and d) their actual capability with the product (Langdon, et al 2015; Norman 2002; Jordan 2000).

We adopted a short-version of POMS scale to measure respondents' mood states; the scale has been translated into Chinese and verified with good reliability (Zhu 1995). In our study, the results also show high reliability (Cronbach α=0.873). In this short Chinese POMS scale, eight modules (i.e. tension, depression, fatigue, confusion, anger, vigor and esteem) with 40 adjectives were presented to the participants and they were asked to choose the corresponding scores (1-5 points) that fit their mood states best in the latest week.

In the data analysis phase, the total mood disturbance (TMD) value was used to explore the effects of mood. TMD is a global estimate of affective state, calculated by first summing the scores for tension, depression, fatigue, confusion, and anger, then subtracting the sum of the scores for vigour and esteem-related effects, and finally adding a constant of 100（for the sake of eliminating negative values）. Thus, higher scores reflect a more negative emotional state (i.e. greater mood disturbance).

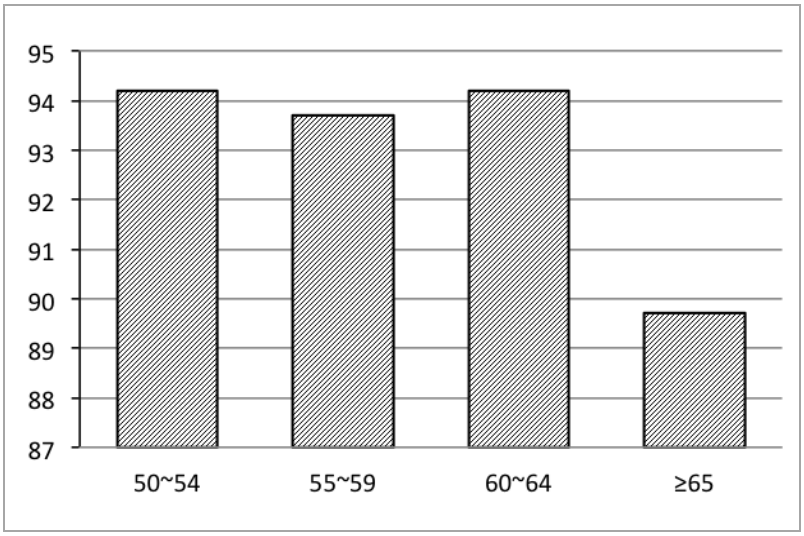

Figure 1 Comparison of TMD value in different age groups.

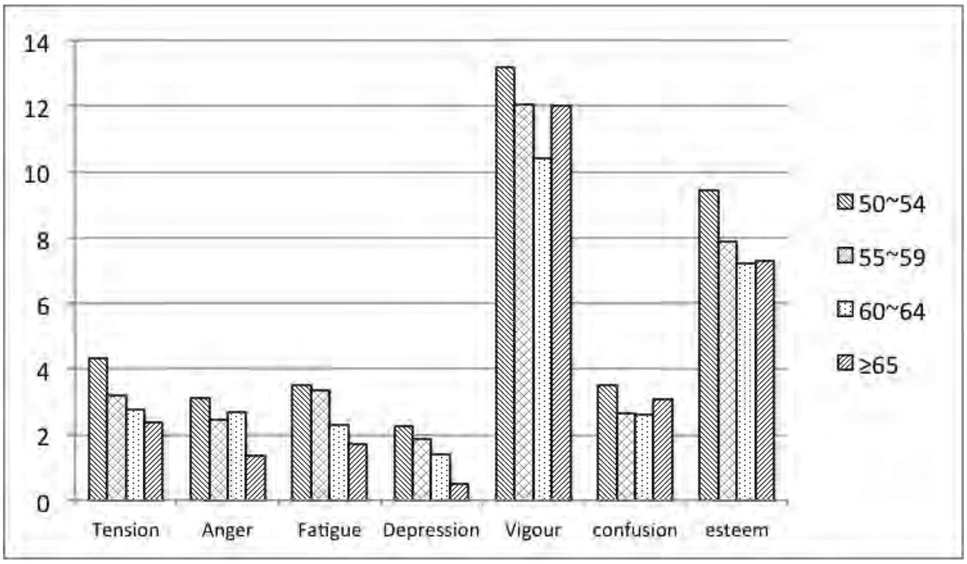

Figure 2 Comparison of seven modules of TMD values in different age groups.

As shown in Figure 1, the "≥ 65" age group shows lower TMD value than other groups; more specifically, older age groups reported higher scores in positive items and lower scores in negative ones (see Figure 2), which does not match the findings from other empirical studies (Gibson, 1997). This might be explained by the traditional family value of China: these people have entered the life stage of retirement and often enjoy taking some care of their grandchild. Much of the respondents in this group have shown higher satisfaction in their current lives and this could shed light on the lower TMD scores to some degree. The effects of mood states on the measurement of users' capability were investigated by analyzing different types of correlation coefficients in SPSS (Statistical Product and Service Solutions). The results show that mood states have significant impact on the older people's self-perceptions of their capability, more specifically, self-reporting results were significantly affected by the respondents' mood states. However, we did not observe significant impact of the mood states on older people's product interaction performances (in terms of whether the task was successfully completed or not), which are shown in Table 3.

Table 3 Correlation coefficients between mood states and self-reports/production interactions.

Self-reporting items	Correlation coefficients
Self-accessed health condition	- 0.35, p<0.01
Self-accessed vision	- 0.24, p<0.01
Self-accessed hearing	- 0.19, p<0.01
Self-accessed dexterity decline	0.20, p<0.05
Self-accessed cognition decline	0.23, p<0.05
Self-efficiency	- 0.25, p<0.05
Product interaction performance	Correlation coefficients
Installing a SIM card	-0.009, p=0.92
Making telephone call	0.013,p=0.88

Texting and sending message	-0.035,p=0.70
Taking a photo	-0.127,p=0.15
Sending a picture through Wechat	-0.201,p=0.22

It should be pointed out that in the product interaction performance task, we found that there existed many differences in the inquiring procedure among different regions of China, so “Calling charges inquiry” was removed from the final analysis to ensure a standardized test setting and credible results.

When considering the effects of mood states, the different results between self-reports and performance tests may imply that different mood states would influence users’ self-perception of their capability: better mood states indicate higher self-assessment of the capability, while mood states are not an influential factor upon the actual performance of product interaction based on the findings of our study.

3.2 Measurements of “comfortable vs. maximum” settings

In most cases, performance-based capability measures tend to provide an indication of maximum capability, which is not necessarily the most valid predictor of activities a person actually undertakes (Langdon, et al 2015; Porter, et al 2004; Simonsick, et al 2001). Datasets that establish on “comfortable” settings may help form more intuitive and accessible design guidelines. In our study, this issue was probed by asking respondents to perform the tests in both “comfortable” and “maximum” perceptions. Then the relations between users’ maximum and comfortable capability were explored by analyzing related data through SPSS. The differences were investigated by grip strength (in both dominant and non-dominant hand), visual acuity and visual contrast.

From the correlation coefficients analysis we can see that comfortable capabilities are correlated with maximum capabilities at different levels (Table 4). The maximum grip strength show moderate correlations with comfortable strength while comfortable visual capabilities weakly associated with the maximum ones.

Table 4 Correlation coefficients between maximum and comfortable measurements .

Testing items	Correlation coefficients
Grip strength (dominant hand)	0.61, P<0.01
Grip strength (non-dominant hand)	0.67, P<0.01
Visual acuity	0.43, P<0.01
Visual contrast	0.25, P<0.01

Additionally, there exist significant differences in the comfortable and maximum values between female and male participants (confirmed by nonparametric tests). In the grip strength tests, the mean value of comfortable grip strength is lower than the maximum and female shows lower performance than male. As seen in Figure 3, the variation ranges, determined by the minimum and maximum value, seem to be similar. However, in terms of the Std. and CV values (coefficient of variation), comfortable data show higher levels, indicating that the comfortable data has more dispersed distributions (Table 5). This may imply that the respondents have very different understandings of what is a “comfortable” condition. When capturing users’ capability data at a “comfortable” setting, it could be difficult to set up a consistent norm and to standardize users’ understanding of “comfortableness”.

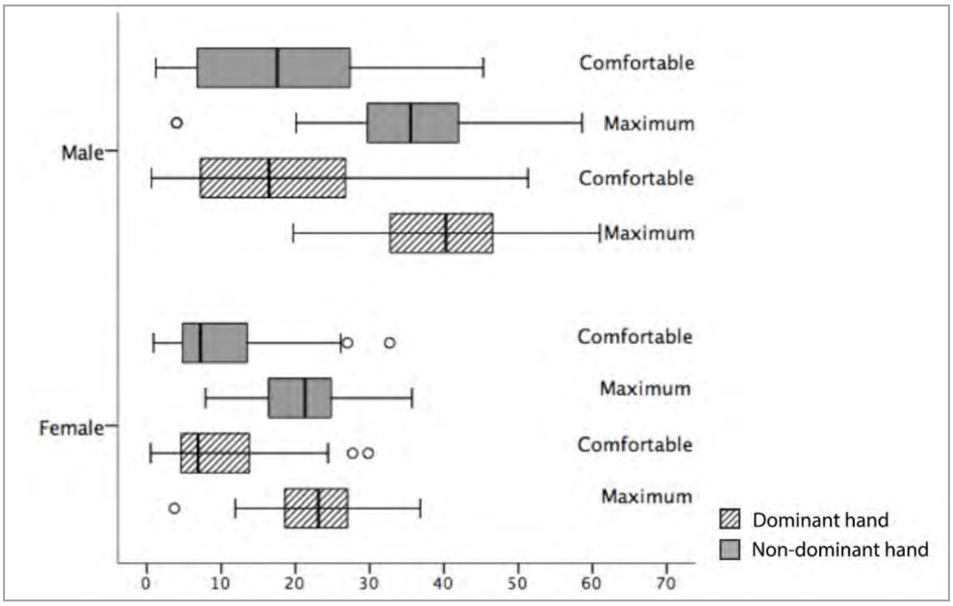

Figure 3 Mean grip strength of maximum and comfortable measurements.

Table 5 Comparisons of dispersion degrees of maximum and comfortable settings .

	Gender	Mean	Std.	CV
Dominant hand: Max	M	40.16	9.82	0.24
	F	23.05	6.49	0.28
Dominant hand: Comfortable	M	18.63	13.21	0.71
	F	9.82	7.30	0.74
Non-dominant hand: Max	M	35.08	10.94	0.31
	F	20.89	5.96	0.29
Non-dominant hand: Comfortable	M	18.49	12.08	0.65
	F	9.84	7.47	0.76

Since there are different perceptions and performances when measuring “comfortable” components, we conducted an exploratory analysis to find out whether there are valid relations between comfortable and maximum values. If any particular relations were verified, the models could be expected to be applied in current databases, which usually contain maximum measurements. Linear regression was conducted for female and male respectively, and the Enter model was used. Grip strength was adopted in the analysis and due to the weak correlations and the data type (ordinal scale), visual acuity and contrast measurements were not included.

As shown in Figure 4, for the comfortable grip strength of the dominant hand, the maximum grip strength value can predict the comfortable value at significant levels (male: $F=22.73$, $p<0.01$; female: $F=19.47$, $p<0.01$); for non-dominant hand, the linear model also account for the variance of comfortable values at significant levels (male: $F=25.36$, $p<0.01$; female: $F=26.86$, $p<0.01$). But it should be noted that the linear models could account for the prediction of comfortable values at moderate or even weak degrees (for the dominant hand, $R^2=0.369$; for the non-dominant hand, $R^2=0.452$). More effective predictive models are expected to be developed.

There is no consensus to inform respondents of what is the criterion of “comfortableness”: for example, in grip strength tests, some respondents may consider applying extreme slight force was “comfortable” while others held the view that as long as the force did not reach their limitations, it could be regarded as “comfortable”. These perceptions are in little accord with real product use scenarios. In addition, due to the moderate correlations between maximum and comfortable measurements, as well as the weak predictive power of linear models, it might be difficult to predict users’ comfortable states based on maximum datasets. Different approaches should be developed to capture users’ comfortable capability data. A future research direction may be to integrate the comfortable measurements into product interaction tasks. As combined performances of multiple functions, it may produce far better performance than summation of maximum capabilities would predict (Langdon, Persad and Clarkson 2010); at the same time, the relations (for example, valid analytical models) between “maximum” and “comfortable” yet to be explored for the reason that the measures of the component function on maximum settings are more reliable than measures of tasks or activities (Johnson, Clarkson and Huppert 2010).

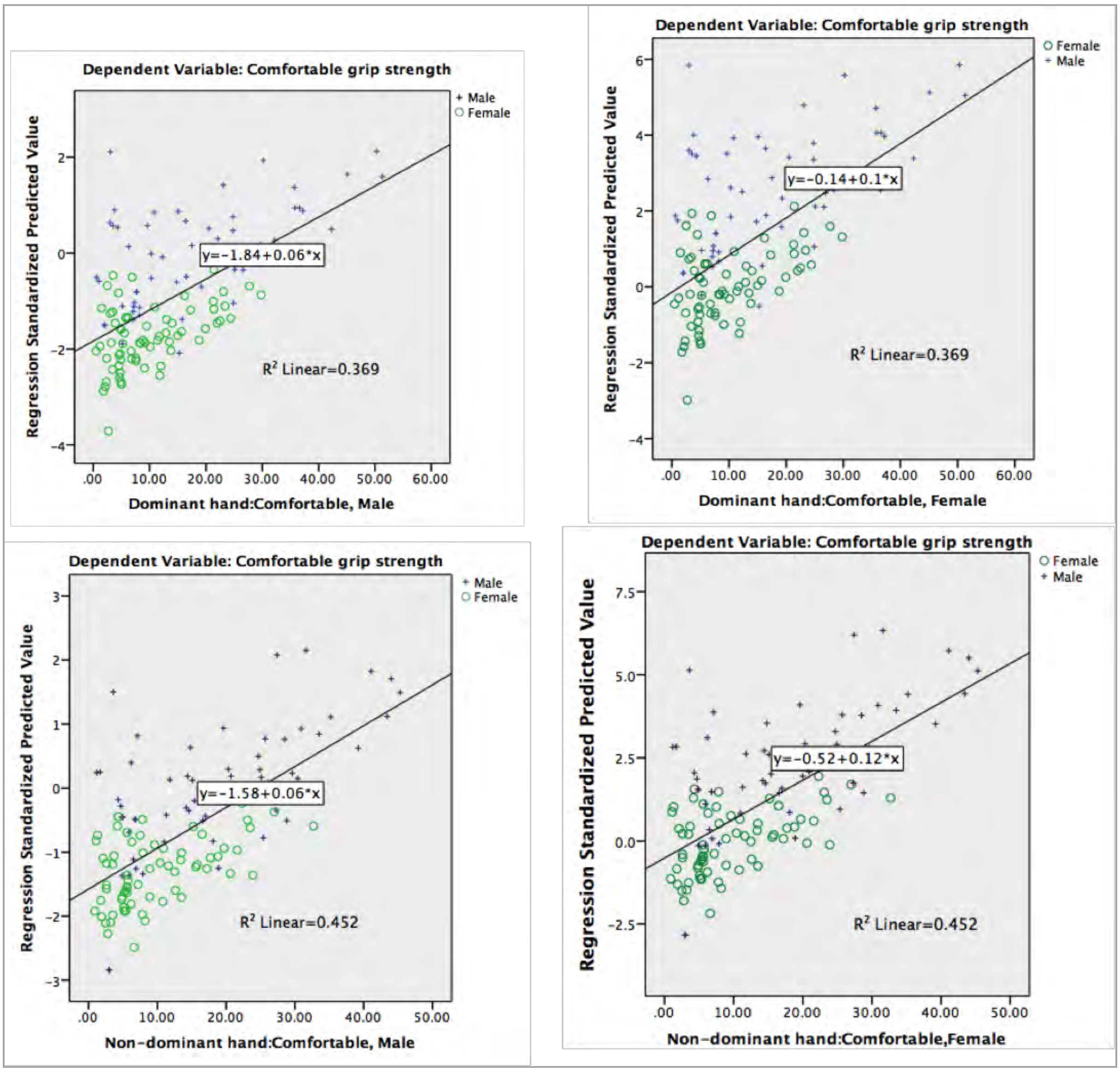

Figure 4 Linear regression analyses show that maximum grip strength could predict comfortable value at moderate levels.

3.3 Exploring predictive variables for product-interaction

As we are facing with ever-developing technologies, it will be unrealistic to develop a database that updates with the products and services change. Developing valid predictive models will significantly increase the feasibility and usability for offering guidelines to the design of a wider range of products, rather than the fixed products involved in this survey. Based on the data we have collected, an exploratory study was carried out to find effective predictors of different product interactions.

The analysis was executed in SPSS and the main methods were derived from the research conducted by Tenneti et al. (2012). In our study, we firstly divided all the variables into six modules, i.e. social-cultural data, vision, hearing, dexterity, cognition and psychological characteristics. And then, the results of product interaction tasks were processed: if the task was successfully completed, the corresponding result was encoded as “1”, and “0” if not. We did not count time taken as one criterion for the assessment of product interaction considering that “times are less useful in inclusive design than mainstream design, because people with limited capabilities often take longer to complete tasks” and “some older and less able users may prefer to take longer and be less rushed, and this does not necessarily indicate usability problems” (Goodman-Deane, et al 2014). Furthermore, time taken is not very useful because a short time could be a) due to the respondent completing the task quickly or b) due to the respondent finding they cannot do it at all and giving up quickly (Tenneti, et al 2012).

A multiple logistic regression approach was then conducted to find out significant predictors of successful product interactions. Forward model selection was used and odd’s ration value (“Exp (B) value” in SPSS) at a 5% significant level was adopted as the final selection criterion. All these five tasks were applied logistic regression analysis respectively and these six modules were used separately in every single analysis. Both odd’s ratio values and corresponding 95% confidence intervals were shown in Table 6. It can be seen that social-cultural variables, vision, hearing, dexterity, cognition and psychological characteristics can predict successful product interaction tasks at different levels.

Table 6 Significant predictors of successful product interactions at 5% significant level.

Product interaction task	Significant variables (at 5% significant level)	Exp(B)/OR	95% Confidence intervals
Sending pictures through SNS app (Wechat)	Age	0.83	0.76-0.95
	Income	1.53	1.13-2.06
	Self-assessed hearing	2.17	1.30-3.61
	Scenario-based report on hearing	1.50	1.07-2.07
	Self-assessed dexterity	0.40	0.20-0.80
	Self-reported frequency of computer use	0.60	0.37-0.98
	Self-reported frequency of Internet use	0.53	0.29-0.97
	Technical self-confidence	1.09	1.04-1.15
	Mood states	0.97	0.95-0.10
Taking photos by mobile phone	Age	0.81	0.70-0.93
	The size of living space	0.97	0.95-0.99
	Self-assessed hearing	2.14	1.28-3.60
	Self-reported frequency of mobile phone use	0.35	0.20-0.62
	Technical self-confidence	1.09	1.03-1.16
Texting and sending	Age	0.88	0.81-0.95

message	Performance-based visual acuity on “comfortable” set	1.55	1.03-1.30
	Performance-based visual contrast on “maximum” set	1.34	1.05-1.72
	Grip strength on “comfortable” set	1.05	1.02-1.09
	Self-reported frequency of computer use	2.17	1.25-3.78
	Self-reported frequency of Internet use	0.19	0.09-0.38
	Self-assessed cognitive ability decrease	0.51	0.31-0.84
	General self-efficiency	1.08	1.01-1.15
Making telephone call	Age	0.76	0.63-0.91
	Performance-based visual contrast on “maximum” setting	1.47	1.07-2.02
	Scenario-based report on hearing	2.27	1.27-4.07
	Self-reported frequency of mobile phone use	0.20	0.08-0.53
	Technical self-confidence	1.11	1.01-1.22
Installing SIM card of mobile phone	Gender	0.17	0.06-0.47
	Living condition	2.41	1.15-5.05
	The size of living space	1.02	1.00-1.03
	Performance-based visual contrast on “maximum” setting	1.27	1.03-1.57

Age is a significant predictor of four tasks in this survey and both self-reports and performance tests can effectively predict successful product interaction rates. It seems that the frequencies of technology products use could be significant predictors (in the tasks of “sending pictures through SNS app”, “taking photos by mobile phones”, “texting and sending message” and “making telephone calls”) which may imply that by investigating users’ frequencies of using products, users’ ability of conducting related interactions could be indicated.

In the task of “texting and sending messages”, the results of logistic regression show that the testing results of vision acuity (OR=1.55) and vision contrast (OR=1.34) could predict the task result at significant levels. It may due to the reason that the respondents usually tend to spend more time in observing and reading the information on the interface.

In addition, psychological variables show good predictive power, for example, the technical self-confidence in the tasks of sending pictures through SNS app (OR=1.09), taking photos by mobile phones (OR=1.09), making telephone calls (OR=1.11) and general self-efficiency in texting and sending messages (OR=1.08). Social-cultural variables appear in the analysis results of sending pictures through SNS app (income, OR=1.53), taking photos by mobile phones (size of living space, OR=0.97) and installing the SIM card (living condition, OR=2.41 and The size of living space, OR=1.02). It is interesting to note that factors thought to be correlated with the abilities of interacting with products, such as educational status, did not prove to be significant in this study.

Table 7 Significant predictors of successful product interactions at 1% significant level.

Product interaction task	Significant variables (at 1% significant level)	Exp(B)/OR	99% Confidence intervals
Sending pictures through SNS app (Wechat)	Age	0.85	0.75-0.91
	Income	1.70	1.22-2.60
	Self-reported frequency of Internet use	0.35	0.16-0.73
Taking photos by mobile phone	Self-reported frequency of mobile phone use	0.32	0.14-0.73
Texting and sending messages	Age	0.89	0.79-1.00
	Grip strength on “comfortable” set	1.06	1.01-1.12
	Self-reported frequency of Internet use	0.33	0.16-0.68
Making telephone calls	Self-reported frequency of mobile phone use	0.17	0.05-0.57
Installing the SIM card	None		

Finally, all the significant predictors of each task were analysed through logistic regression to find the strongest ones. A 1% significant level with 99% confidence intervals was used and forward model was adopted. Age and the frequencies of technology product use are retained and there is no significant predictive variable for installing the SIM card at 1% level.

The study suggests that we can make use of different types of user data by using the low-level functional capabilities to predict high-level task performance. Although it is difficult to measure user’s capability of interacting with products directly, it may be predicted by other factors. Furthermore, existing databases and data that collected for non-design purpose could also be taken into use.

4. Conclusion

In order to make design address the needs of a wider range of users, collecting end user data to support more inclusive products and services has become one of the primary research topics in the inclusive design research field. The findings from this study may help clarify some issues when capturing user data. Firstly, we find that the respondents’ mood states have positive effects on their perceptions of capabilities; better mood states indicate higher levels of self-report results, but no significant correlations were observed between one’s mood states and his/her actual product interaction performance. Secondly, data measured in "comfortable" settings were compared with those in "maximum" settings. The results show that, for grip strength, respondents may have dispersed perceptions of what is a "comfortable" condition. The linear regression analyses show that maximum values can predict the comfortable values at moderate levels. Lastly, we used multiple logistic regression analysis to explore some significant predictors for successful product interaction tasks. The results show that social-cultural variables, vision, hearing, dexterity, cognition and psychological characteristics can predict successful product interaction tasks at different levels. These predictive variables identified may offer references for the collection of new datasets in the future.

5. References

Arning, K., & Ziefle, M. (2007). Understanding age differences in PDA acceptance and performance. *Computers in Human Behavior*, 23(6), pp. 2904-2927.

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *Psychological review*, 84(2), pp. 191.

Clarkson, P. J., & Coleman, R. (2015). History of inclusive design in the uk. *Applied Ergonomics, 46*, pp. 235-247.

Combe, N., Harrison, D., & Dong, H. (2013). Designing Technology for Older People–The Role of Technical Self-confidence in Usability of an Inclusive Heating Control. In Design, User Experience, and Usability. *User Experience in Novel Technological Environments* (pp. 49-56). Springer Berlin Heidelberg.

Dong, H., McGinley, C., Nickpour, F., Cifter, A. S., & Inclusive Design Research Group. (2015). Designing for designers: Insights into the knowledge users of inclusive design. *Applied ergonomics*, 46, pp. 284-291.

Forgas, J., 2008. Affect and cognition. *Perspectives on Psychological Science* 3 (2), pp.94-101.

Fors, S., Thorslund, M., & Parker, M. G. (2006). Do actions speak louder than words? Self-assessed and performance-based measures of physical and visual function among old people. *European Journal of Ageing*, 3(1), pp. 15-21.

Gibson, S. J. (1997). The measurement of mood states in older adults. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 52(4), pp. 167-P174.

Goodman-Deane, J., Ward, J., Hosking, I., & Clarkson, P. J. (2014). A comparison of methods currently used in inclusive design. *Applied ergonomics*, 45(4), pp. 886-894.

Grove, J. R., & Prapavessis, H. (1992). Preliminary evidence for the reliability and validity of an abbreviated profile of mood states.*International Journal of Sport Psychology, 23*(2), pp. 93-109.

Huang, S., & Dong, H. (2015). Capturing Older People's Cognitive Capability Data for Design. In *Human Aspects of IT for the Aged Population. Design for Aging* (pp. 44-52). Springer International Publishing.

Johnson, D., Clarkson, J., & Huppert, F. (2010). Capability measurement for inclusive design.*Journal of Engineering Design*, 21(2-3), pp. 275-288.

Jordan, P., 2000. *Designing Pleasurable Products*. Taylor and Francis.

Keates, S., & Clarkson, J. (2004). Countering design exclusion. In *Countering design exclusion: An introduction to inclusive design (*pp.140-156). Springer London.

Langdon, P., & Thimbleby, H. (2010). Inclusion and interaction: Designing interaction for inclusive populations. *Interacting with computers*, 22(6), pp. 439-448.

Langdon, P., Johnson, D., Huppert, F., & Clarkson, P. J. (2015). A framework for collecting inclusive design data for the UK population. *Applied ergonomics*, 46, pp. 318-324.

Langdon, P., Persad, U., & Clarkson, P. J. (2010). Developing a model of cognitive interaction for analytical inclusive design evaluation. *Interacting with Computers*, 22(6), pp. 510-529.

McNair, D. M. (1971). Manual profile of mood states. *Educational & Industrial testing service*.

Ning, W., & Dong, H. (2014). Adapting a Capability Survey to Collect Chinese Old People's Data for Designers: A Pilot Study. Proceedings of *the 5th International Conference for Universal Design*, Fukushima & Tokyo,Japan,pp. 135-142.

Ning, W., & Dong, H. (2015). Collecting Old People's Data for More Accessible Design: A Pilot Study. In *Human Aspects of IT for the Aged Population. Design for Aging* . Springer International Publishing. pp. 84-93

Norman, D., 2002. *Emotion and design: attractive things work better*. Interactions Magazine ix, pp. 36-42.

Porter, J. M., Case, K., Marshall, R., Gyi, D., & neé Oliver, R. S. (2004). "Beyond Jack and Jill": designing for individuals using HADRIAN. *International Journal of Industrial Ergonomics*, 33(3),pp. 249-264.

Simonsick, E. M., Kasper, J. D., Guralnik, J. M., Bandeen-Roche, K., Ferrucci, L., Hirsch, R., ... & Fried, L. P. (2001). Severity of upper and lower extremity functional limitation scale development and validation with self-report and performance-based measures of physical function. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 56(1), pp. 10-19.

Tencent Interim Report. (2015) . http://tinyurl.com/zz5fg8t (Accessed 6 March, 2016, in Chinese)

Tenneti, R., Johnson, D., Goldenberg, L., Parker, R. A., & Huppert, F. A. (2012). Towards a capabilities database to inform inclusive design: experimental investigation of effective survey-based predictors of human-product interaction. *Applied ergonomics*, 43(4), pp. 713-726.

Towards Better Design.(2010). http://tinyurl.com/hmszyj4 (Accessed 6 March)

Wolters, K. M., Engelbrecht, K. P., Gödde, F., Möller, S., Naumann, A., & Schleicher, R. (2010). Making it easier for older people to talk to smart homes: the effect of early help prompts. *Universal Access in the Information Society*, 9(4), pp. 311-325.

Zhu, B. L. (1995). Brief introduction of POMS scale and its model for China. Journal of Tianjin University of Sport, 10, pp. 35-37. (In Chinese)

About the Authors:

Weining Ning is a MA student at the College of Design and Innovation, Tongji University, China. His research interests focus on inclusive design and particularly collecting user data for inclusive design.

Hua Dong is a professor at the College of Design and Innovation, Tongji University. She has extensive experiences of cross-cultural and interdisciplinary design research in the fields of inclusive design, healthcare, and co-design.