Author's response to reviews

Title: Healthcare professionals' acceptance of BelRAI, a web-based system enabling person-centered recording and data sharing across care settings with interRAI instruments: a UTAUT analysis

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Abstract/Conclusions:
Critical influencing factors in stimulating the behavioural intention to use new technology are good-quality software, interoperability and compatibility with other information systems, easy access to computers, training facilities, built-in and online help and ongoing IT support. These findings can be used by policy makers to maximise the acceptance and the success of new technology initiatives. For researchers, the conclusions of the original UTAUT study with regards to the item and scale...
construction should not be copied blindly across different information systems. A bottom-up approach should be preferred when building upon the UTAUT model.

We are not relying on item selection of other studies; also not including constructs in advance may weaken the UTAUT model.

Endnotes

85 questionnaire items related to the UTAUT constructs were measured: Performance expectancy (PE), 24 items; Effort expectancy (EE), 10 items; Attitude towards using technology (ATUT), 14 items; Social influence (SI), 9 items; Facilitating conditions (FC), 11 items; Self-efficacy (SE), 10 items; Anxiety (ANX), 4 items; Behavioural intention (BI), 3 items.

Table 2

PE: Performance expectancy; EE: Effort expectancy; ATUT: Attitude towards using technology; SI: Social influence; FC: Facilitating conditions; SE: Self-efficacy; ANX: Anxiety; BI: Behavioural intention. All questionnaire items were measured using a 7-point Likert agreement scale ranging from “Strongly disagree” to “Strongly agree”. All constructs were modelled using reflective indicators. The items with an asterisk were selected for inclusion in the final UTAUT model in the study of Venkatesh et al. [46]. We refer to the same study for an explanation with regard to the abbreviations and the non-relevant items.

Table 3

In accordance with the study of Venkatesh et al. [46] we operationalised the constructs in our UTAUT model by using the highest-loading items from each of the respective scales.

Std Dev: Standard deviation; CR: Composite reliability; AVE: Average variance extracted.

Data analysis

Theoretical concepts such as attitudes, intentions and preferences, also known as latent variables, factors or constructs, cannot be observed or measured directly [74,75]. Constructs are measured indirectly through indicators (observable, measurable or manifest variables such as an item on a questionnaire) designed to elicit responses related to a construct [76]. Scaling techniques have been developed to study the complexity inside a system and to derive information on constructs from indicators. However, to overcome limitations of the first generation regression-based approaches such as regression, more and more researchers started using structural equation modelling (SEM) as an alternative [77].

In this study, data analysis was done using SEM. SEM is a ...

Specifically, for PLS, the generated weights and loadings are outer model parameter estimates, while the path coefficients are inner model parameter estimates.

To evaluate the measurement model, PLS performs a confirmatory factor analysis (CFA) by testing the mandatory [75] reliability and construct validity (factorial validity of the constructs). Reliability relates to the measurement within constructs and is thus independent of the status within other constructs; construct validity relates to the measurement between constructs [75,80].
The evaluation of the internal consistency of constructs (ICR) (e.g. Cronbach’s alpha (CA) to test the unidimensionality of a set of questionnaire items measuring the extent to which all the variables are related to each other) is one technique to assess reliability. Moreover, PLS analysis provides other coefficients attesting to the reliability of the survey instrument such as composite reliability (CR) and average variance extracted (AVE) for each construct. As a rule of thumb the cut-off for (CA) is 0.70 \cite{[83,84]}. The recommended respective thresholds for CR and AVE are 0.70 and 0.50 \cite{[85]}.

To establish construct validity \cite{[75]}, PLS examines convergent and discriminant validity of the scale estimating how well a variable measures what it is intended to measure \cite{[45]} or how well the measurement items relate to the constructs \cite{[80]}. Convergent validity is established when each measurement item of the model loads with a t-value above 1.96 (rejecting the null hypothesis of no effect) on its latent construct meaning that each measurement item correlates strongly with its theoretical pre-specified construct. The p-value of this t-value should be significant at least at the 0.05 alpha protection level \cite{[80]}.

Discriminant validity is established under two conditions: 1) the correlation of the latent variable scores with the measurement items needs to show an appropriate pattern of loadings, one in which the measurement items load highly (> 0.70) on their theoretically assigned construct and weakly (< 0.30) on other constructs (cross loadings); 2) establishing discriminant validity in PLS also requires an appropriate AVE analysis \cite{[75,80]}. With the latest version of PLS-Graph 03.00 build 1126 of 2003, AVEs are generated automatically using bootstrapping as a resampling procedure. The AVE measures the variance captured by a latent construct being the shared (or explained) variance. The square root of AVE of each construct should be much larger than its variance shared with any of the other constructs in the model and should be at least 0.50. Conceptually, it is equivalent to saying that the correlation between the construct and its measurement items should be larger than its correlation with the other constructs \cite{[45,76,80]}.

Having established reliability, convergent and discriminant validity of the constructs, the next step is to test the structural model for the hypothesised paths. To evaluate the structural model, PLS estimates path coefficients for each hypothesised path using bootstrapping, a non-parametric technique for assessing the precision of the PLS estimates \cite{[81,86]}. The corresponding t-values suggest significance of the coefficients (t-values > 1.96, significance level p < 0.05) \cite{[80]}. To ascertain how well the model fits the hypothesised relationship, PLS generates the square of the correlation coefficient (\(R^2\)) for each dependent construct in the model. Similar to regression analysis, \(R^2\) is interpreted as the percentage of shared (or explained) variance and thus represents the proportion of variance in the dependent constructs which can be explained by the independent ones \cite{[45,77]}.

We ran PLS-Graph ©, a software package which applies PLS \cite{[74,81,86]} for SEM. Statistical analysis system (SAS) 9.3 © was used for descriptive analysis and creation of PLS-Graph data files.

(4) The measurement model
To evaluate the measurement model, PLS tests the reliability and the construct validity. Reliability relates to the measurement within constructs. Construct validity relates to the measurement between constructs \cite{[75,80]}.

As in the original study of Venkatesh et al. \cite{[46]}, for practical analytical reasons the constructs were operationalised by using the highest-loading items\(^5\) from each of the respective scales (Table 2). Given this specific healthcare situation, these items did not always accord with the highest-loading items used to measure the core constructs in the original UTAUT: only the items with an asterisk were selected for inclusion in the final UTAUT model in the study of Venkatesh et al. \cite{[46]}.
Discussion

Although the use of the BelRAI application was mandatory, it is plausible that the behavioural intention of professionals is influenced by the short-term nature of this project. Simulating mandatory use of new information technology in a public healthcare setting is not straightforward. Therefore, since the future professional value of BelRAI is not guaranteed, performance expectancy may not have influenced behavioural intention. Similarly, effort expectancy may not have a significant relationship with behavioural intention because people tend not to exert great effort during a pilot project. Social influence may not have an impact on behavioural intention because of a difference in attitude between caregivers and typical technology users. Future study designs should disentangle these effects inside the UTAUT framework to understand user acceptance in the context of a permanent implementation. The measurement of behavioural intention to use new information technology could be expanded to take into account the emotional disposition of professional caregivers. Ultimately, when new information technology is implemented on a large scale, professionals should be looking forward to using it.