Perceptions of Professional Chemical Engineers toward Immersive Virtual Reality in Health and Safety Training

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Abstract
Following the rapid advancement and growing market of immersive virtual reality (IVR), it is important to understand the impacts caused by these technological innovations. Research on feasibility, reliability, and ease of use of IVR has received considerable attention, but little is known about the specific factors weighing in the decision to adopt IVR in the health and safety (H&S) training setting. Since the success of implementing IVR in H&S training depends on the individuals willing to use it, this paper investigates the interrelationship between influential factors and behavioural intention to adopt IVR among different professional groups. To understand this, a conceptual framework was developed by adaptation of the Unified Theory of Acceptance and Use of Technology (UTAUT2). Data were collected using an online survey from professional chemical engineers. Partial least squares structural equation modelling (PLS-SEM) based on SmartPLS 3 was used to analyse the intention of the population sampled to adopt IVR, followed by multi-group analysis (MGA) to explore the differences between groups of professionals. The findings from this study contribute to the literature of the UTAUT2 model on IVR adoption and inform stakeholders in formulating appropriate strategies to improve the adoption of IVR in different group settings.

Keywords: Virtual Reality, UTAUT2, Multi-group analysis, Professional Training Chemical Engineering Education

Introduction

The chemical process industry is a large, dynamic, and complex sector. Due to these intricacies, professionals in the chemical plants face additional challenges since erroneous interpretations, or assumptions made during operation, may transform small near misses into serious accidents (Nazir, Totaro, Brambilla, Colombo, & Manca, 2012). To cope with the rapid evolution of a digitalized world, universities and chemical industry started to implement new teaching and training methods to upskill their employees (Patle, Ahmad, & Rangaiah, 2014). For instance, books are turned into e-books, while manual engineering calculations/design operation move towards desktop Virtual Reality (VR) software. However, making more people use the above-mentioned examples without changing the content, format, or teaching method has drawbacks. In addition, these formats are insufficient for situations encountered in highly automated chemical plants since desktop VR does not give a real feel of the process and e-learning *per-se* is not sufficient to develop practical skills (Arkorful & Abaidoo, 2015; Colombo, Nazir, & Manca, 2014). Recently, there has been a major shift from non-immersive to immersive virtual reality (IVR) technologies. These technologies were found to be effective in enhancing professional skills and they create a paradigm-shift in several fields including education and training (Ferjencik, 2007; Isleyen & Duzgun, 2019; Manca, Brambilla, & Colombo, 2013). Such new technology provides the users with a full immersive and safe 3D training space where their knowledge is constructed through trial and error approaches reflecting actual situations (Fällman, Backman, & Holmlund, 1999).

IVR technology using serious games and/or simulations is considered to be a good vehicle to improve higher order thinking competencies, including problem-solving and decisions-making skills (Voorhis & Paris, 2019). For instance, aside from the ability to create dynamic, immersive, and 3D simulated chemical plant environments where professionals can interact and move freely, IVR also allows users to have a better understanding of the schematics of the process/plant which are abstract at the representation level (e.g. 2D diagrams) (Nazir et al., 2012). IVR simulations or games that focus on improving problem-solving and decision-making skills are realistic, safe, and reliable tools for new professionals.

However, to achieve the abovementioned objectives for health and safety (H&S) training, it is important for the new learning experience to be accepted and used by the professionals. According to the critical mass theory, sufficient numbers of individuals (i.e. the critical mass) who are willing to try and use readily available new technology is necessary in order to achieve a self-sustaining rate of adoption and to create network-like benefits (Markus, 1987). Thus, the more people that adopt and use this kind of technology, the more valuable it will be.

Several models can be used to assess the acceptability and usability of technology (Sharma & Kumar, 2012; Venkatesh, Morris, Davis, & Davis, 2003). In particular, the UTAUT model has been used by many researchers over a decade (Sharma & Kumar, 2012). UTAUT model has been compared and validated using within-subject longitudinal data from different organizations and it is important in information technology (IT) user acceptance research (Venkatesh et al., 2003). According to Venkatesh et al. (2003), the UTAUT model considers four key factors: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). The model also includes four moderators: age, gender, voluntariness and experience. Both the key factors and the moderators are considered to affect the behavioural intention (BI) and/or use behaviour (USE). In this model, the key factors PE, EE, and SI affect the behavioural intention, while the key factors FC and BI influence the use behaviour. Vankatesh et al. (2012) established a new model called UTAUT2 to address a new context of consumers. This model employed hedonic motivation (HM), price value (PV), habit (H), and facilitating condition (FC) as additional key factors that influence BI compared to the original UTAUT model. Moreover, habit also influences USE (Venkatesh, Thong, & Xu, 2012).

It is paramount to understand professionals' concerns about IVR since it will affect their decisions whether to use IVR or not. Previous studies focused on the effect of different constructs towards IVR adoption intention and attempted to develop theoretical models of IVR adoption intention (Hartl & Berger, 2017; Shen, Ho, Ly, & Kuo, 2019). However, the abovementioned studies only focused on the IVR adoption intention of an identified single population sample. Interpretation of results from a lone population could be misleading so to minimize misinterpretation of results it was proposed to assess data by adding more subgroups of data into the model (Sarstedt, Henseler, & Ringle, 2011). Hence, incorporation of socio-demographic data, such as IVR prior experience, into the UTAUT2 model was done.

In order to explore the influencing factors within different professional group in IVR adoption intention, the current study combines the PLS-SEM with the multi-group (MGA) or between-group analysis method. Such a combination is beneficial since it can provide valuable insights about the similarities as well as differences between the groups. Additionally, the current study can provide support for future research by addressing the IVR adoption needs of specific professional groups and by widening the applicability of PLS-SEM and MGA to studies of IVR.

Methodology

Research model

Since the chemical industry training research barely uses the applied theories on technology acceptance, this may be the first reported application of the UTAUT2 model which helps in understanding one's perception toward IVR adoption in H&S training. As this study focused purely on perception, the UTAUT2 model was modified as demonstrated in figure 1.

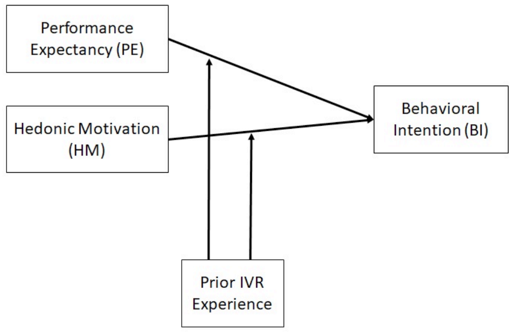

Figure 1: The modified UTAUT2 model.

Venkatesh et al. (2003) defined *"performance expectancy (PE) as the degree to which using a technology will provide additional benefits to individuals in job performance"*. This construct is one of the core predictors of the intention to adopt technology (Venkatesh et al., 2003). Previous studies showed positive results using various technologies such as VR glasses (Hartl & Berger, 2017), social media for health (Puspitasari & Firdauzy, 2019), and e-learning (Ramírez-Correa, Arenas-Gaitán, & Rondán-Cataluña, 2015). Since IVR enables professionals to learn certain H&S procedures more quickly and/or efficiently, the test hypothesis adapted and modified from Venkatesh et al. (2003) proposed in this study is:

H1: *Performance Expectancy will have significant influence on Behavioural Intention to adopt IVR for H&S learning.*

In UTAUT 2, additional key factors were added from original UTAUT model that influence behavioural intention. One of these key factors is hedonic motivation (HM). According to Venkatesh et al. (2012), *"hedonic motivation refers to the fun or pleasure derived from using technology"*. Previous research has proposed this construct and tested the perceived enjoyment as a positive influence on different context such as an e-scooter VR service (Huang, 2020), health apps (Yuan, Ma, Kanthawala, & Peng, 2015), and business simulation games (Wang, Wang, & Jian, 2019). To test this relationship within the context of the IVR adoption intention in H&S training, the following test hypothesis adapted and modified from Venkatesh et al., (2012) is proposed:

H2: *Hedonic Motivation will have significant influence on Behavioural Intention to adopt IVR for H&S learning.*

In addition, since the current study is interested on measuring the differences in attitudes across different populations with the aim of understanding the acceptability of introducing an IVR in chemical operation H&S training, it is important to establish the effects of prior experience of IVR upon the key constructs of UTAUT2 for its adoption. Therefore, the following test hypothesis adapted and modified from Venkatesh et al., (2012) is proposed:

H3: *There is a statistically significant difference between prior experience and without prior experience in the relationships between variables of the IVR adoption.*

Measures of the Constructs

A two-part survey was used in data collection; first part consisted of fourteen closed ended questions used to determine socio-demographic variables using a nominal scale, the latter part involved adapted and modified questions from the UTAUT2 mode that fits the purpose and population under study. Lastly, a 6-point Likert scale was used to measure every item in the questionnaire.

The items included in the study were adapted from already existing documents from other studies that were verified valid and reliable. The words used were modified to better fit the use of IVR games in educational settings. Face validity checks were carried out by academics in the field. Moreover, pilot studies were conducted with postgraduate chemical engineering students and practicing engineers in chemical industry volunteers to check for misconceptions in the formulation of the questions. Changes in wording and grammar were made based on feedback in order to improve questionnaire clarity.

Data collection procedure

Before sending out the questionnaires, ethics approvals were obtained from the university's ethics committee. All expected ethical procedures were followed in the development and administration of the questionnaires.

A non-probability sampling method (convenience sampling) was used to recruit participants as the population size was unknown and the contact list was made confidential by the relevant authority due to privacy issues. Professionals were invited to voluntarily take part in the survey if they were employed as professional chemical engineers at the time of the research. The data were collected over a three-month period. One hundred and forty professional chemical engineers completed the questionnaire but only 35.71% of them have tried IVR (e.g. head-mounted display VR).

The manual inspection done showed no data missing, no inconsistencies nor straight-lining answer behaviour, hence, all answer sets were used in further analysis.

Data Analysis

Data collected were analysed using PLS-SEM algorithm employed in SmartPLS 3 (Ringle, Wende, & Becker, 2015). Compared to covariance-based structural equation modelling (CB-SEM), PLS-SEM required a smaller sample size and can accept non-normally distributed data (Hair, Hult, Ringle, & Sarstedt, 2017). The minimum sample size was determined using the inverse square root method (Kock & Hadaya, 2018).

In order to identify differences in hypothetical relationships between groups, MGA analysis using PLS-SEM was carried out. According to Matthews (2017), running MGA in PLS-SEM involves a three-step approach: (1) creation of data groups based on the categorical variable of interest; (2) use of three-step procedure to analyse the measurement invariance of composite models (MICOM); (3) assessment of the results from the statistical tests for multi-group comparisons using Henseler PLS-MGA procedure.

Results

Measurement invariance for composite models

Since the creation of groups based on prior experience of IVR was established beforehand, the MGA then continued by testing measurement invariance (Matthews, 2017). Measurement invariance is required in order to ensure that a given measure is interpreted in a conceptually similar matter across specified population (Horn & Mcardle, 1992). In PLS-SEM, measurement invariance can be tested using MICOM procedure which includes configural invariance, compositional invariance, and equality of composite mean values and variances (Henseler, Ringle, & Sarstedt, 2016).

To assess the configural invariance, the measurement models for all groups need to be evaluated to determine if the same number of indicators and the same variance-based model estimation were used and if all the indicator data were treated equally across the specified groups (Henseler et al., 2016). Here, reliability and construct validity were calculated to assess the configural invariance across the groups. As the results reveal in Table 1, both groups have item loadings greater than 0.708, average variance extracted (AVE) greater than 0.5, composite reliability (CR) and Cronbach's alpha greater than 0.6 (Hair et al., 2017). Moreover, as shown in Table 2, both groups have Heterotrait–Monotrait (HTMT) values below the threshold of 0.90 (Hair et al., 2017). Thus, the configural invariance is confirmed since both groups indicate adequate reliability, convergent validity, and discriminant validity.

Table 1. Internal consistency reliability and convergent validity analysis for professionals with and without prior experience to IVR.

Constructs	**Items**	**Factor Loading**	**Cronbach's Alpha**	**CR[a]**	**AVE[b]**
Performance Expectancy	PE_1	0.896 (0.919)	0.862 (0.920)	0.916 (0.949)	0.783 (0.862)
	PE_2	0.880 (0.931)			
	PE_3	0.880 (0.935)			
Hedonic Motivation	HM_1	0.965 (0.939)	0.881 (0.845)	0.942 (0.928)	0.890 (0.865)
	HM_2*				
	HM_3	0.921 (0.921)			
Behavioural Intention	BI_1	0.937 (0.944)	0.884 (0.901)	0.928 (0.938)	0.813 (0.835)
	BI_2	0.937 (0.951)			
	BI_3	0.826 (0.841)			

Note: * - Removed due to the lack of outer loading reliability (< 0.7)
[a] - Composite Reliability
[b] - Average Variance Extracted
Numbers in bracket - Values for without prior experience to IVR group

Table 2. Discriminant validity analysis using Heterotrait-Monotrait (HTMT) ratio for professionals with and without prior experience to IVR.

	Performance Expectancy	Hedonic Motivation	Behavioural Intention
Performance Expectancy			
Hedonic Motivation	0.157 (0.597)		
Behavioural Intention	0.762 (0.783)	0.235 (0.509)	

Note: The numbers indicate the pairwise correlations between variables
Numbers in bracket - Values for without prior experience to IVR group

In order to assess whether the composite scores are formed across the subpopulations (i.e. compositional invariance), permutation analysis with 5000 resamples was performed in SmartPLS 3 (Henseler et al., 2016; Ringle et al., 2015). The correlation between composite scores between professionals with and without prior experience is close to 1 and above the 5% quantile, and it is shown in Table 3. Thus, compositional invariance is shown for all subpopulation groups.

Table 3. Measurement Invariance Assessment (MICOM) test for professionals with and without prior experience to IVR.

Construct	Step 1		
	Configural Invariance		
PE	**Yes**		
HM	**Yes**		
BI	**Yes**		
Construct	**Step 2**		
	C = 1	5% quantile of C_u	Compositional invariance
PE	1.000	0.999	**Yes**
HM	0.999	0.983	**Yes**
BI	1.000	0.994	**Yes**
Construct	**Step 3 (a)**		
	Difference	Confidence Intervals – Mean Value	Equal mean value
PE	0.019	[-0.336, 0.337]	**Yes**
HM	0.108	[-0.350, 0.344]	**Yes**
BI	-0.094	[-0.338, 0.348]	**Yes**
Construct	**Step 3 (b)**		
	Difference	Confidence Intervals – Variance	Equal variance
PE	0.333	[-0.731, 0.777]	**Yes**
HM	-0.447	[-0.534, 0.618]	**Yes**
BI	0.118	[-0.476, 0.546]	**Yes**

Note: PE = Performance Expectancy; HM = Hedonic Motivation; BI = Behavioural Intention

The final step is the assessment of the equality in composite mean values and variances. Permutation results allowed examination of differences in the mean values and variances calculated between the constructs score of professionals with and without prior experience. Since the differences on the mean values and variance both fall on the 95% confidence interval, full measurement invariance is established which makes comparison of professionals with and without prior experience possible and providing a more detailed comparison between the two groups (Henseler et al., 2016).

Assessment of the results of the statistical tests for multi-group comparisons

In order to assess whether having prior IVR experience or not are different in terms of the key constructs, multi group analysis (MGA) was done in SmartPLS (Ringle et al., 2015). PLS-SEM has significant advantage in relation to multiple linear regression (MLR), which works with observable variables, since the software is made more specific for composite measurement model.

As suggested by Matthews (2017), the MGA procedure begins by analysing the group separately to determine if there are group-specific similarities and differences. As shown in Table 4, both groups supported H1, which suggested significant relationships between performance expectancy and behavioural intention. However, both groups did not supported H2, which suggested significant relationships between hedonic motivation and behavioural intention.

Table 4. Structural model results for professionals with and without prior experience to IVR.

Hypothesis	With IVR Experience	Result	Without IVR Experience	Result
H1: Performance Expectancy → Behavioural Intention	0.658**	Supported	0.673**	Supported
H2: Hedonic Motivation → Behavioural Intention	0.206	Not Supported	0.022	Not Supported

Note: Significance level: * p < 0.05 ** p < 0.001

After analysing the group-specific similarities and differences, the significance of any differences between the groups was determined. The result of the PLS-MGA *p*-values in Table 5 showed that there were no significant group differences between professionals with and without prior experience in IVR. Therefore, H3 (statistically significant differences between prior experience and without prior experience exist in relationships between variables of the IVR adoption) is not accepted.

Table 5. Results of SEM multi-group analysis (MGA) for professionals with and without prior experience to IVR.

Hypothesis	│Path Coefficient Differences│	PLS-MGA p-value	Result
H3: Performance Expectancy → Behavioural Intention (Group Difference)	0.015	0.917	Not Supported
H3: Hedonic Motivation → Behavioural Intention (Group Difference)	0.078	0.609	Not Supported

Note: Significance level: * p < 0.05 ** p < 0.001

Discussion

The current study provides meaningful insights for available literature on IVR adoption based on the UTAUT2 model. This research demonstrate that, integrating PLS-SEM and MGA approaches works well since these methods are not only useful for analysing IVR adoption behaviour of the population sampled, but also for determining group differences (Matthews, 2017).

The results of MGA showed that there were both contrasting and common aspects in the relationships investigated in the current study from professionals with and without prior IVR experience. Performance expectancy is significantly related to IVR adoption intention for both groups. However, upon comparing the difference between the path coefficients for professionals with and those without IVR experience, there is no significant difference between the two groups according to MGA. This means that regardless of prior experience, as long as the IVR technology can create a reality-like H&S training experience and contribute meaningfully in enhancing user health and safety skills, he/she may be favourably willing to use it.

On the other hand, both groups did not support hedonic motivation toward IVR adoption intention. This implies that most professionals (with or without prior IVR experience) do not perceive a very high level of entertainment or pleasure that could be derived from using IVR for H&S training since they already perceived IVR itself as highly entertaining and additional enjoyment did not seem to influence their acceptance any further.

The observations show that professionals have different needs and demands in terms of IVR. Understanding the different factors that lead to IVR adaptation could prevent mismanagement of the available resource and provide information on the differences among professionals. Hence, it is important to create an appropriate strategy that satisfies the need of the professionals. For instance, the program should be focused on utilitarian factors (i.e. PE) rather than hedonic factors (i.e. HM) since the target population is professionals and not students.

Conclusion

In conclusion, the current study modified the UTAUT2 model on IVR adoption intentions consisting of performance expectancy, hedonic motivation, and prior IVR experience. Using this model, the IVR adoption intention of professionals with or without prior IVR experience were analysed using PLS-SEM and multi-group analysis (MGA) with SmartPLS 3.0. Although the study shows no statistically significant differences between professionals with and without prior IVR experience according to the model tests, the MGA approach is effective in understanding the intentions of multiple groups. The current study provided suggestions for the researchers and developers in formulating suitable strategies to improve IVR adoption based from the measured groups.

Although this research provides meaningful insights for researchers and stakeholders, it is important to bear in mind that the perception of professionals with respect to the adoption of IVR in H&S training may change over time. For instance, at this early stage, professionals may have answered questions based only on their prior experiences with IVR. Thus, it is important for the future research to reinvestigate the adoption of this technology considering other key constructs at various timeline of professional's IVR acceptance process through longitudinal studies.

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