The Effect of Warm-Glow on User Perceived Usability and Intention to Adopt Technology: Extending UTAUT2

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Abstract: In this work we investigate the effect that warm-glow has on user’s perception of the usability of a technology as well as their intention to adopt within the context of the second version of the Unified Theory of Acceptance and Use of Technology (UTAUT2). The UTAUT2 model was extended for this purpose, incorporating two existing constructs designed to capture the two aspects of warm-low (extrinsic and intrinsic), forming the UTAUT2 + WG model. An experimental approach was then taken to evaluate this proposed model, where participants were exposed to a vignette describing a hypothetical technology which was designed to evoke a feeling of warm-glow. The collected data was analyzed using the partial least squares approach in order to evaluate our extended model. The results revealed that warm-glow does indeed influence user behavior and plays a prominent role. Warm-glow was found to influence user perception of the usability of a technology, where effectiveness is reflected through the factor of performance expectancy (PE), efficiency through the factor of effort expectancy (EE), and satisfaction through hedonic motivation (HM). Furthermore, warm-glow was found to influence user behavioral intention to adopt technology. The paper concludes by discussing the implications of these findings.

Keywords: warm-glow; perceived usability; technology adoption; UTAUT2

1. Introduction

Identifying the factors which influence user intention to adopt a technology and their respective magnitudes offers organizations valuable information to advise their practices. Technology acceptance modeling is a mature approach that enables the acquisition of such valuable insight; the most contemporary model and accompanying instrument being the second evolution of the Unified Theory of Acceptance and Use of Technology (UTAUT2) [1]. The model has been adapted for a spectrum of varying aspects (e.g., consumer vs. workplace), cultures (e.g., east vs. west), and technologies (e.g., mobile banking, biometric authentication). There are several studies that offer a more extensive list of the ways in which the model has been developed (e.g., [2]). However, one area that has yet to be extensively explored within the context of the UTAU2 model is technology which evokes in perspective users warm-glow.

Warm-glow being the positive feeling that is realized when one does something good for their fellow human, irrespective of motivation which may be selfish or altruistic in origin. The first being classified as extrinsic warm-glow (EWG) and the second as intrinsic warm-glow (IWG), respectively. Albeit, the phenomenon of warm-glow has been studied as it pertains to the adoption of technology through the use of the Theory of Reasoned Action, its progression, the Theory of Planned Behavior (e.g., [3]), and then the Technology Acceptance Model (e.g., [4]). Importantly, the first two, Theory of Reasoned Action and Theory of Planned Behavior, are generic models for understanding user adoption behavior (i.e., not specifically designed for use with technology). The third, the Technology Acceptance Model, being an adaptation of the Theory of Planned Behavior specifically for technology which led to a series of evolutions (TAM0, TAM1, TAM2, and TAM3).
Subsequently an attempt to consolidate these into one optimal model resulted in the cre-
ation of the Unified Theory of Acceptance and Use of Technology (UTAUT) which later
was revised to UTAUT2. Given that the UTAU2 model is the most contemporary of the
standard technology acceptance model investigating the warm-glow phenomenon within
that context is of interest to the information systems community.

Through this work we demonstrate how the UTAUT2 model can be extended to
take into account the phenomenon of warm-glow. Accordingly, we incorporate two fac-
tors PEWG and PIWG to capture the two dimensions of warm-glow, extrinsic, and intrin-
sic, respectively. We then rely on an experimental approach to evaluate the model and
identify the effect that warm-glow plays on the behavioral intention of users to adopt a
technology. The findings reveal that the proposed UTAUT2 + WG is superior with respect
to fit than the original UTAUT model. Moreover, we demonstrate how the model can be
used with technology that evokes warm-glow for use by those working with such tech-
nology (i.e., that evokes a feeling of warm-glow). It should be noted that what evokes
warm-glow in one user may not evoke warm-glow in another. The findings reveal that
(when looking the total effect) warm-glow plays a prominent role in user decisions, with
the perception of EWG having the second greatest effect. Intrinsic warm-glow is described
as “some people social approval may be a reason for charity donations whereas for others
it is an intrinsic warm glow feeling” [5]. Both appear in the following passage “intrinsic
warm glows are personal feelings of being a good person, like the ones expressed in the
dictator game. Extrinsic warm glows, on the other hand, function as social signals. Hu-
mans are social creatures and indicating to others that we are good plays an important
role in group stability.6 In this case, an extrinsic warm glow occurs from the act of donat-
ing: donors can signal their virtue to others, ranging from mentioning the donation to
wearing “I Donated” stickers, t-shirts, and social media posts about their deed” [6].

2. Materials and Methods

Given that the practice of technology acceptance modeling relies on a confirmatory
approach, our first step was to establish the proposed model, which we refer to as UTAUT
+ WG, and the corresponding hypotheses for evaluation.

2.1. Development of the Hypotheses and Model

2.1.1. The Effect of Warm-Glow on Behavioral Intention to Adopt

There is ample literature reporting on the positive effect that warm-glow has on user
behavioral intention to adopt a technology. We therefore propose the following hypothe-
ses:

H1: Perceived extrinsic warm-glow (PEWG) positively influences behavioral intention (BI).
H2: Perceived intrinsic warm-glow (PIWG) positively influences behavioral intention (BI).

2.1.2. The Effect of Warm-Glow on Perceived Usability

Previous research has looked at the effect of warm-glow on two of the criteria of per-
ceived usability with respect to warm-glow, perceived effectiveness and perceived effi-
ciency, finding that warm-glow positively influences perceived effectiveness [4]. Accord-
ingly, we propose the following hypotheses:

H3: Perceived extrinsic warm-glow (PEWG) positively influences effort expectancy (EE).
H4: Perceived intrinsic warm-glow (PIWG) positively influences effort expectancy (EE).
H5: Perceived extrinsic warm-glow (PEWG) positively influences performance expectancy (PE).
H6: Perceived intrinsic warm-glow (PIWG) positively influences performance expectancy (PE).
2.1.4. Confirming the Uniqueness of the PEWG and PIWG Factors

It is also sensible to consider whether the warm-glow factors that we are integrating into our model duplicate the purpose served by those constructs that already exist in the UTAUT2 model. In particular, we should examine whether SI is analogous to PEWG and HM is analogous to PIWG. Accordingly, we propose the following hypotheses:

\[ H7: \] Perceived extrinsic warm-glow (PEWG) is a substitute to social influence (SI) with respect to behavioral intention (BI).

\[ H8: \] Perceived intrinsic warm-glow (PIWG) is a substitute to hedonic motivation (HM) with respect to behavioral intention (BI).

2.3. Data Collection

A web-based experimental approach using the Qualtrics platform was taken to evaluate the proposed model. To that end a total of 279 participants successfully completed the experiment. According to the work of Chin and Newsted [23], the size of our sample is adequate, as it is higher than 150, which they describe as large. Each participant was asked to consent to taking part in the experiment. Subsequently, they were presented with a vignette (from Saravanos et al. [10]) describing a hypothetical technology product designed to evoke a feeling of warm-glow. Thereafter, each participant was asked to complete a survey which in addition to demographic questions asked participants to rate the technology. These questions were adapted from Venkatesh et al.’s [1] UTAUT2 instrument and incorporated the warm-glow questions proposed by Saravanos et al. [10] to measure the two dimensions of warm-glow. Outside of the demographic questions, the remaining questions utilized a 7-point Likert scale ranging from strongly disagree to strongly agree.

2.3. Data Analysis

To analyze the data which was collected we relied on Structural Equation Modeling (SEM). The approach is regarded as extending the traditional linear modeling techniques [24]. It is recognized for its ability to work with complex models and is “used to explain multiple statistical relationships simultaneously through visualization and model validation” [24]. There are two flavors of this approach, the first is Covariance Based (CB) and the other is Partial Least Squares (PLS). Hair et al. [25] offer guidance as to when each should be used, specifically, they note that when a study “is exploratory or an extension of an existing structural theory” one should use “PLS-SEM”. As we are attempting to extend an existing theory (i.e., UTAUT2 with warm-glow), we selected PLS-SEM for our analysis using version 3.3.2 of SmartPLS (developed by SmartPLS GmbH, Germany) [26]. The approach relies on two elements, a measurement model which “specifies the relations between a construct and its observed indicators”, and a structural model which “specifies the relationships between the constructs” [27].

3. Analysis and Results

3.1. Assessing the Reflective Measurement Model

In the first instance we assess our reflective measurement model (also known as the outer model [27]) to confirm the reliability and validity of our construct measures to ensure their suitability for inclusion into our structural model [28]. This saw us evaluate the reliability of our indicators (see Table 2), in other words examine “how much of each indicator’s variance is explained by its construct” [28]. Given that all the indicator loadings were above the 0.708 recommended cutoff prescribed by Hair et al. [29] we were able to establish that item reliability was acceptable. Subsequently we used Jöreskog’s [30] composite reliability statistic, rho, in conjunction with Chronbach’s alpha, as the conservative and liberal perspectives respectively per Hair et al. [31], to investigate international consistency reliability. The values of both statistics for all constructs (see Table 2) were within the range recommended by Hair et al. [31] (i.e., between 0.70 and 0.90), where “higher
values indicate higher levels of reliability” [28]. We then went on to investigate the convergent validity and discriminant validity of our constructs. With respect to convergent validity, we relied on average variance extracted (AVE) indicator which in all cases (see Table 2) was equal to or above the 0.50 threshold (see Hair et al. [29]). With respect to discriminant validity, we relied on: the Fornell–Larcker criterion [32]; cross-loadings (see Chin [33]); and the heterotrait-monotrait ratio of correlations (HTMT) as proposed by Henseler et al. [34]. In all cases the values demonstrated convergent validity. As our reflective measurement model met all the aforementioned requirements it was appropriate for additional analysis (i.e., evaluating the structural model).

Table 2. Summary of Internal Consistency Reliability and Convergent Validity Testing.

| Factor | Item | Loading | t-Statistic | AVE |
|--------|------|---------|-------------|-----|
| EE     | EE1  | 0.915   | 51.247 *    |     |
|        | EE2  | 0.891   | 34.222 *    |     |
|        | EE3  | 0.906   | 51.720 *    |     |
|        | EE4  | 0.840   | 14.808 *    |     |
|        | FC1  | 0.897   | 30.877 *    |     |
| FC     | FC2  | 0.875   | 28.740 *    | 0.794|
|        | FC3  | 0.901   | 45.124 *    |     |
| HM     | HM3  | 0.951   | 81.007 *    | 0.911|
|        | HT1  | 0.756   | 14.012 *    |     |
| HT     | HT2  | 0.820   | 20.771 *    | 0.640|
|        | HT3  | 0.822   | 21.636 *    |     |
| PE     | PE1  | 0.869   | 50.233 *    |     |
|        | PE2  | 0.907   | 61.404 *    | 0.798|
|        | PE3  | 0.904   | 59.013 *    |     |
| PEWG   | PEWG1| 0.930   | 109.861 *   |     |
|        | PEWG2| 0.921   | 81.981 *    | 0.855|
|        | PEWG3| 0.923   | 81.216 *    |     |
| PIWG   | PIWG1| 0.926   | 75.375 *    |     |
|        | PIWG2| 0.902   | 41.643 *    | 0.847|
|        | PIWG3| 0.933   | 70.535 *    |     |
| PV     | PV1  | 0.825   | 6.805 *     | 0.823|
|        | PV2  | 0.982   | 37.661 *    |     |
| SI     | SI1  | 0.973   | 182.263 *   | 0.947|
|        | SI2  | 0.973   | 157.781 *   |     |

* p < 0.01.

Table 3. Summary of Reliability Testing.

| Factor  | Number of Items | Cronbach’s Alpha | CR  |
|---------|-----------------|------------------|-----|
| EE      | 4               | 0.911            | 0.937|
| FC      | 3               | 0.871            | 0.921|
| HM      | 2               | 0.903            | 0.954|
| HT      | 3               | 0.719            | 0.842|
| PE      | 3               | 0.874            | 0.922|
| PEWG    | 3               | 0.915            | 0.947|
| PIWG    | 3               | 0.910            | 0.943|
| PV      | 2               | 0.827            | 0.902|
| SI      | 2               | 0.910            | 0.943|

3.2. Assessing the Structural Model
The evaluation of the structural model (also known as the inner model within our context [27]) “focuses on evaluating the significance and relevance of path coefficients, followed by the model’s explanatory and predictive power” [35]. Initially one needs to assess the level of collinearity, this is traditionally done through the use of the variance inflation factor (VIF), where “VIF values above 5 are indicative of collinearity among the predictor constructs” [36] with values of 3 or greater signaling “possible collinearity issues” [31]. We used 5 as the cutoff for this work and there were several manifest variables that were therefore redundant and accordingly removed: PE4, SI3, FC4, HMI, PV3, HT4, BI2, BI3.

With respect to explanatory power of our model to BI we find an $R^2$ of 0.67 (i.e., explains 67% of the variance) which indicates according to the benchmark established by Chin [37] as substantial (reflected by a value of 0.67 or higher). Chin’s guidelines are reaffirmed in the work of Henseler et al. [38] who writes “0.67, 0.33, and 0.19 in PLS path models as substantial, moderate, and weak”. However it is important to recognize that “acceptable $R^2$ values are based on the context and in some disciplines an $R^2$ value as low as 0.10 is considered satisfactory” [39]. For example, Hair et al. [40] write that “in marketing research studies, $R^2$ values of 0.75, 0.50, or 0.25 for endogenous latent variables in the structural model can, as a rule of thumb, be described as substantial, moderate, or weak, respectively”. The factors, in order of decreasing strength, which had a statistically significant direct effect in determining user behavioral intention to adopt were: PE ($\beta = 0.310; p < 0.01$), PIWG ($\beta = 0.258; p < 0.01$), HM ($\beta = 0.225; p < 0.05$), and gender ($\beta = 0.096; p < 0.05$). With respect to total effect, we find the factors, in order of decreasing strength, which were statistically significant to be: PIWG ($\beta = 0.394; p < 0.01$), PE ($\beta = 0.310; p < 0.01$), PEWG ($\beta = 0.303; p < 0.01$), HM ($\beta = 0.225; p < 0.05$), and gender ($\beta = 0.096; p < 0.05$). Therefore, H1 (PEWG $\rightarrow$ BI) and H2 (PIWG $\rightarrow$ BI) were confirmed.

With respect to explanatory power of our model to EE we find an $R^2$ of 0.202 (i.e., explains 20.2% of the variance) which indicates according to the benchmark established by Chin [37] as substantial and according to the benchmark of xx as moderate. The factors, in order of decreasing strength, which had a statistically significant direct effect in determining user behavioral intention to adopt were: PIWG ($\beta = 0.425; p < 0.01$). With respect to total effect, there was no difference to report. Accordingly, H4 (PIWG $\rightarrow$ EE) was confirmed but H3 (PEWG $\rightarrow$ EE) was not verified.

With respect to explanatory power of our model to HM we find an $R^2$ of 0.455 (i.e., explains 45.5% of the variance) which indicates according to the benchmark established by Chin [37] as substantial and according to the benchmark of xx as moderate. The factors, in order of decreasing strength, which had a statistically significant direct effect in determining user behavioral intention to adopt were: PEWG ($\beta = 0.499; p < 0.01$) and PIWG ($\beta = 0.248; p < 0.01$). With respect to total effect, there was no difference to report. Thus, H5 (PEWG $\rightarrow$ HM) and H6 (PIWG $\rightarrow$ HM) were confirmed.

With respect to explanatory power of our model to PE we find an $R^2$ of 0.477 (i.e., explains 47.7% of the variance) which indicates according to the benchmark established by Chin [37] as substantial and according to the benchmark of xx as moderate. The factors, in order of decreasing strength, which had a statistically significant direct effect in determining user behavioral intention to adopt were: PEWG ($\beta = 0.496; p < 0.01$), PIWG ($\beta = 0.248; p < 0.01$). With respect to total effect, there was no difference to report. Hence, H7 (PEWG $\rightarrow$ PE) and H8 (PIWG $\rightarrow$ PE) were confirmed.

| Path           | B (direct) | t-Statistic (direct) | B (total) | t-Statistic (total) |
|----------------|-----------|---------------------|-----------|---------------------|
| AGE $\rightarrow$ BI | 0.025     | 0.584               | 0.025     | 0.584               |
| AGE x EE $\rightarrow$ BI | 0.029     | 0.431               | 0.029     | 0.431               |
| AGE x FC $\rightarrow$ BI | 0.031     | 0.433               | 0.031     | 0.433               |
| AGE x HM $\rightarrow$ BI | 0.045     | 0.611               | 0.045     | 0.611               |
| AGE x HT $\rightarrow$ BI | 0.006     | 0.104               | 0.006     | 0.104               |
Table 5. Hypothesis testing results.

| Hypothesis | Relationship   | Decision   |
|------------|---------------|------------|
| H1         | PEWG → BI     | Supported  |
| H2         | PIWG → BI     | Supported  |
| H3         | PEWG → EE     | Not Supported |
| H4         | PIWG → EE     | Supported  |
| H5         | PEWG → HM     | Supported  |
| H6         | PIWG → HM     | Supported  |
| H7         | PEWG → PE     | Supported  |
| H8         | PIWG → PE     | Supported  |
We also explored the possibility that there were factors in the original model that were duplicative (i.e., substitutes) to the introduced warm-glow factors (i.e., PEWG and PIWG). To achieve this we applied the technique prescribed by Hagedoorn and Wang [41], through the use of moderators. The results indicated that there was no statistically significant moderating role between the PEWG and SI factors concerning the dependent variable BI. Thus, H9 was not supported. Likewise, no statistically significant roles was found between the factors of PIWG and HM, with respect to the dependent variable BI. Accordingly, H10 was not supported. In other words, we can conclude that the PEWG and PIWG factors are unique within our proposed UTAUT2 + WG model.

Table 6. $R^2$ and $R^2$ Adjusted Values by Factor.

| Factor | $R^2$ | $R^2$ Adjusted |
|--------|-------|----------------|
| BI     | 0.666 | 0.613          |
| EE     | 0.202 | 0.197          |
| HM     | 0.455 | 0.451          |
| PE     | 0.477 | 0.473          |

4. Discussion and Conclusions

With respect to direct effects, our findings indicated that the UTAUT2 + WG was superior in terms of fit when compared to the traditional UTAUT2 model for a technology that evokes in users a feeling of warm-glow. The behavioral intention of users to adopt the technology revealed that the perception of intrinsic warm-glow (i.e., PIWG) played the second greatest role in user decisions ($\beta = 0.258$), preceded by the perceived effectiveness of the technology (i.e., PE) which had the primary role ($\beta = 0.258$). It was followed by HM ($\beta = 0.225$), and gender ($\beta = 0.096$). When looking at the total effect we find that PEWG becomes statistically significant ($\beta = 0.303$), and plays the third greatest effect. We see PIWG ($\beta = 0.394$) playing the greatest role followed by PE ($\beta = 0.310$). These were followed by HM ($\beta = 0.225$) and Gender ($\beta = 0.096$). These findings in part mirror the work of Saravanos et al. [4] who reported that the perceived usefulness of technology played the greatest role in determining user adoption of a technology, followed by perceived intrinsic warm-glow, social influence and then extrinsic warm-glow.

The effect of warm-glow on the perceived usability of technology has been touched upon in the past. We would present as an example the work of Saravanos et al. [4] who found that the perception of extrinsic warm-glow influenced the perceived usability of the technology. In our work we accepted the definition that usability is evaluated through the criteria of effectiveness, efficiency, and satisfaction. We then looked to the corresponding factors within the model, perceived effectiveness, perceived efficiency, and hedonic motivation, respectively. The findings revealed that PE was influenced by both PEWG ($\beta = 0.496$) and PIWG ($\beta = 0.272$). Regarding EE, PEWG did not have a statistically significant effect, but PIWG ($\beta = 0.425$) did. Finally, HM was influenced by both PEWG ($\beta = 0.499$) and PIWG ($\beta = 0.248$).

Author Contributions: Conceptualization, A.S.; data curation, A.S.; writing—original draft preparation, A.S., D.Z., and S.Z.; writing—review and editing, A.S., D.Z., and S.Z.; supervision, A.S.; project administration, A.S.; funding acquisition, A.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded in part by a New York University School of Professional Studies Dean’s Research Grant.
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