Modeling the Adoption of Good Tech:

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Abstract: In this paper we extend the third evolution of the Technology Acceptance Model (TAM3) to incorporate warm-glow in order to understand the role this phenomenon plays on consumer adoption of ‘good tech’. Warm-glow is the feeling of satisfaction, pleasure, or both, which is experienced by individuals after they do something ‘good’ for their fellow human. Two constructs, perceived extrinsic warm-glow (PEWG) and perceived intrinsic warm-glow (PIWG), were incorporated into the TAM3 model to measure the two dimensions of user-experienced warm-glow, forming what we refer to as the TAM3+WG model. An experimental approach was taken to evaluate the suitability of the proposed model (i.e., TAM3+WG). A vignette was used to describe a hypothetical internet search engine solution designed to evoke participants warm-glow. Our TAM3+WG model was found to be superior to the TAM3 model within our context. Furthermore, the PIWG and PEWG constructs were found to be unique within the original TAM3 model. Our findings indicate that the factors that have the greatest influence on consumer decisions are (in decreasing order) PU, PIWG, SN, and PEWG. In other words, both extrinsic and intrinsic warm-glow play a prominent role in user decisions as to whether or not to adopt technology.

Keywords: warm-glow 1; technology adoption 2; TAM3 3; good tech 4

1. Introduction

Since the inception of the first technology acceptance model (TAM) developed by Davis [1], the exercise of modeling user technology adoption has continued to evolve, emerging as a prime area of study in the field of information system management [2]. Given the prominent and steadily increasing role technology has played in the activities of individuals and organizations, this practice has become more widespread. Accordingly, organizations find value in the ability to ascertain if a technology will be accepted by prospective users, which can afford those organizations a competitive advantage [3]. For over 35 years, the TAM model in particular, presently in its third evolution (TAM3), has been used to explain and predict consumer behavioral intentions to accept technology [2]. Designed to be flexible, the TAM3 model has been extended and adapted for a wide variety of cases to meet the needs of different technologies and the contexts in which they are used [4,5]. However, one aspect that is only now being explored within the context of the TAM3 model is with respect to the phenomenon of warm-glow.

One can trace the origins of the term “warm-glow” to the work of Andreoni [6], who reported that consumers may perceive such a feeling subsequently to having donated to the less fortunate and in consequence having “done their bit” for humanity. There are two dimensions to warm-glow which depend on the motivation of the consumer action: extrinsic or intrinsic. The first form, extrinsic warm-glow (EWG), representing the feeling derived by consumers for engaging in selfish (non-altruistic) behavior [7], Andreoni [6] explains that “people have a taste for giving: perhaps they receive status or acclaim”. The second, intrinsic warm-glow (IWG), representing the feeling derived by consumers when engaging in altruistic behavior [8], Saito describing it as “a willingness to benefit others, even at one’s own expense” [9]. We can see this feeling being evoked in consumers when making decisions for a form of technology which Saravanos et al [10] categorize as ‘good tech’ i.e., technology products that are perceived by users as ‘good’, and accordingly this
perception of goodness evokes in them a feeling of warm-glow. For example, a consumer who has a passion for the planting of more trees would regard the Ecosia product (a web-based search tool) to be ‘good tech’ and would accordingly experience a feeling of warm-glow [10].

The purpose of this study is to extend (and evaluate) the TAM3 model for the warm-glow phenomenon thereby offering insight as to the effect it (i.e., warm-glow) plays on consumer adoption decisions for ‘good tech’. Accordingly, in this paper, we do the following: (1) incorporate the warm-glow constructs (i.e., PEWG and PIWG) originally proposed by Saravanos et al. [10] to measure the two dimensions (i.e., intrinsic and extrinsic) of warm-glow into the TAM3 model; (2) validate this new enhanced model which we shall refer to as TAM3+WG; (3) confirm that the warm-glow constructs do not replicate the role of other (potentially duplicative) factors within the original TAM3 model; and (4) ascertain the relative magnitude of the effect that warm-glow plays in users’ decisions to adopt technology they perceive as ‘good’ in comparison to the original TAM3 factors.

2. Materials and Methods

In this section we describe the development of the hypothesis and model and then the data collection process that was utilized.

2.1. Hypothesis and Model Development

Technology adoption modeling finds its origins in the work of Fishbein and Ajzen [11] and their Theory of Reasoned Action, and later in their Theory of Planned Behaviour [12,13], which were both designed to predict the behavioral intentions of consumers with respect to adoption. Over time, two main strands of technology adoption modeling emerged, the TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT) line of models [14]. The TAM line emerged from Davis’ [1] attempt to adopt the Theory of Reasoned Action specifically for use with technology products, and, as mentioned in the introduction, this is currently in its third evolution [2], and is referred to colloquially as TAM3. The UTAUT model was the result of a comprehensive review and subsequent synthesis of several models that emerged over time as alternatives to TAM. For this work, we selected TAM3 as a theoretical foundation to develop our model and corresponding hypotheses for several reasons: TAM is described as “an established approach in research on the acceptance of new technologies” [15], is “somewhat of a gold standard” [16], and is more widely used than UTAUT [17].

Taking a confirmatory approach, our first step is to establish the model that we are proposing for consideration (illustrated in Figure 1). We begin with the inclusion of the relevant constructs from Venkatesh and Bala’s [2] original TAM3 model. At the core of the TAM3 model are three fundamental constructs that serve as determinants of customer acceptance of technology, referred to as “behavioral intention” (BI): “perceived ease of use” (PEOU), “perceived usefulness” (PU), and “subjective norm” (SN). BI is defined as “the degree to which a person has formulated conscious plans to perform or not perform some specified future behavior” [18]. The first of the determinants, PEOU, measures the effort that consumers perceive they will need to expend in order to use a particular technology, which we formally accept as “the degree to which a person believed that using a particular system would be free of effort” [19]. The second element, PU, measures the value that consumers perceive they will gain from using technology, which we regard as “the degree to which a person believes that using a particular system would enhance his or her job performance” [19]. The third, according to Venkatesh and Bala [2], is SN, which is “the degree to which an individual perceives that most people who are important to him think he should or should not use the system”. To these, we add two supplemental constructs proposed by Saravanos et al. [10] to reflect the two dimensions of end-user perceived warm-glow.

2.1.1. Extrinsic Warm-Glow
It has been shown that warm-glow influences the use the adoption of what we define as ‘good technology’, with the literature focusing primarily on environmentally sustainable technologies. With respect to the EWG aspect, the effects are illustrated in the work of Griskevicius, Tybur, and Van den Bergh [20], who observe that the use of green products is a way for some consumers to signal to others that they are affluent enough to consume products that have a positive benefit for society (and the environment), even though they may be of lower quality. Another similar study is offered by Griskevicius and Tybur [21], who illustrate that consumers’ quest for status can lead to the purchasing of products that are priced higher than their non-green counterparts. They draw the conclusion that consumer selection is not made on the merit of quality, the environment, or price, but rather because in contemporary western society, doing good often has a higher effect on an individual’s image than luxury does. Similarly in Dastrup et al.’s [22] article, the authors look at home electricity generation through solar panels and its effect on social status. While the authors do not explicitly link to the concept of (extrinsic) warm-glow and its perception, nor do they look explicitly at individual user perceptions, they do observe an effect. These examples justify incorporating a construct into our model to reflect consumer perceptions of EWG, “perceived extrinsic warm-glow” (PEWG), and the proposal of the following hypothesis:

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

2.1.2. Intrinsic Warm-Glow

With respect to the IWG aspect, there are several studies which illustrate its effect on adoption. Hartmann and Apaolaza-Ibáñez [23] examine the attitude and intention of consumers pertaining to green energy brands. One of the aspects they examine is that of (intrinsic) warm-glow incorporating a corresponding construct which reveals that it does increase consumer purchasing behavior. Ma and Burton [24], explore consumer decisions to purchase green electricity in Australia. The authors find that warm-glow does influence consumer decisions over the actual attributes of the competing products. More recently, we see these ideas applied in the work of Sun et al. [25] who utilize the “Theory of Planned Behaviour” [12,13] to explore the attitude displayed by consumers coupled with their intention to purchase installation of rooftop PV’s in Taiwan. Their warm-glow construct focuses exclusively on the intrinsic dimension of warm-glow, once again demonstrating how it can influence consumer attitudes, this time towards the installation of rooftop PV’s. Azalia et al. [26] build on this work looking at how individual concerns for the environment, warm glow, and financial factors influence the adoption of solar PV’s in Indonesia. In their paper, they like Sun et al. [25], also rely on the “Theory of Planned Behaviour” [12,13] and focus on the intrinsic dimension. They likewise find (intrinsic) warm-glow to have a statistically significant effect “in the motivation of using solar PV” [26]. Another example, is offered in the work of Bhutto et al. [27] who look at the adoption of energy-efficient home appliances (EEAs) in Pakistan (again by extending the Theory of Planned Behavior). The authors share that “warm glow benefits motivate consumers to pay premium prices for EEAs to feel moral satisfaction”. Tangentially we can look to the work of Karjalainen and Ahvenniemi [28]. They apply Tiger’s [29] framework to investigate pleasure (specifically, in the forms of physical, social, psychological and ideological) devised by those who adopt solar photovoltaic (PV) systems in Finland. Karjalainen and Ahvenniemi [28] describe (ideo) pleasure being derived from “the capability to produce own clean energy and reduce emissions”, as well as “the ability to provide clean energy for other energy users”. In essence they are reporting with respect to the intrinsic dimension of the warm-glow phenomenon. Accordingly, we incorporate a factor to reflect IWG perceptions held by consumers into our model, “perceived intrinsic warm-glow” (PIWG), and subsequently consider the following hypothesis:
H2: Perceived intrinsic warm-glow (PIWG) positively influences behavioral intention (BI).

2.1.3. The Influence of Warm-Glow on PEOU and PU

The existing literature is not explicit about the kind of influence the warm-glow phenomenon can have on the main antecedents of consumer BI (specifically, PEOU and PU). Nevertheless, studies have shown that external factors can influence the aforementioned antecedents of BI. Examples include a consumer’s image, anxiety about using technology, price, privacy, and trust [30,31]. Therefore, we postulate that such a relationship could exist between the two primary determinants of BI, PU, PEOU, and the warm-glow constructs, PEWG and PIWG. Consequently, we propose the following hypotheses:

H3: Perceived extrinsic warm-glow (PEWG) positively influences perceived ease of use (PEOU).

H4: Perceived intrinsic warm-glow (PIWG) positively influences perceived ease of use (PEOU).

H5: Perceived extrinsic warm-glow (PEWG) positively influences perceived usefulness (PU).

H6: Perceived intrinsic warm-glow (PIWG) positively influences perceived usefulness (PU).

2.1.4. Determining the Uniqueness of the PEWG and PIWG Constructs

Finally, we must account for the possibility that there may be factors in the original TAM3 model that could act as substitutes to the constructs of PEWG and PIWG. With respect to EWG, there are two factors in the current TAM model that could potentially serve as substitutes to our PEWG construct. The first is “image” (IMG), which Moore and Benbasat [31] define as “the degree to which an individual perceives that use of an innovation will enhance his or her status in his or her social system”. The second is SN. Therefore, we propose the following hypotheses:

H7: Perceived extrinsic warm-glow (PEWG) serves as a substitute to image (IMG) with respect to perceived usefulness (PU).

H8: Perceived extrinsic warm-glow (PEWG) serves as a substitute to subjective norm (SN) with respect to perceived usefulness (PU).

For IWG, there are two constructs in the model that measure pleasure and serve as possible competitors to PIWG. The first is “perceived enjoyment” (ENJ), which Venkatesh [32] defines as “the extent to which the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use”. Although a connection between the two constructs is not well-established, we can see hints of a relationship in the work of Kuruvatti et al. [33], who report “fun” to be one of the reasons people donate blood. The second factor to consider is that of “computer playfulness” (CPLAY), which Webster & Martocchio [34] define as “the degree of cognitive spontaneity in microcomputer interactions”. To investigate the relationship between perceived IWG and the existing factors of ENJ and CPLAY, we establish the following hypotheses:

H9: Perceived intrinsic warm-glow (PIWG) is a substitute to perceived enjoyment (ENJ) with respect to perceived ease of use (PEOU).

H10: Perceived intrinsic warm-glow (PIWG) is a substitute to computer playfulness (CPLAY) with respect to perceived ease of use (PEOU).

In addition to the variable PU, the factor of SN is also associated in the TAM through the variable BI. For completeness, it follows that we propose this final hypothesis as well:
Perceived extrinsic warm-glow (PEWG) is a substitute to subjective norm (SN) with respect to behavioral intention (BI).

**Figure 1.** Illustration of our proposed theoretical framework based on the work of Venkatesh and Bala [2].

### 2.2. Data Collection

To evaluate the proposed theoretical framework participants were presented with a hypothetical internet search engine which simulated the presence of extrinsic and intrinsic warm-glow, as described by Saravanos et al. [10]. All participants were first asked to confirm their willingness to participate. Next, those that chose to continue answered questions with respect to their gender, age, income, schooling, race, and prior experience with internet search technology. Subsequently, they were presented with a vignette which described the hypothetical technology product (see Saravanos et al. [10]). They then filled out a questionnaire to capture user perception of the product. This included the respective questions from Venkatesh and Bala’s [2] TAM3 instrument, which were adjusted for consumers rather than for a workplace context, along with the case of internet search technology, as demonstrated by Roy [50], as well as the warm-glow questions from see Saravanos et al. [10]. Lastly, we incorporated two questions from Abbey and Meloy [35], which we modified to gauge participant attention. All questions – those from the TAM3 instrument, the PIWG and PEWG constructs, and the attention check questions – were rated through a 7-point Likert scale ranging from “strongly disagree” to “strongly agree.” The vignettes and questionnaire were distributed through the use of the Qualtrics’ online survey platform.

We recruited our participants using the Amazon Mechanical Turk crowdsourcing platform, which has become quite popular for such studies [36]. To identify an appropriate minimum size for our sample we looked to the “10 times rule method”, which is “the most widely used minimum sample size estimation method in PLS-SEM” [37]. This approach states that the sample size “should be equal to the larger of”, “10 times the largest
number of formative indicators used to measure a single construct” [38]. Given we have, in the most conservative case, 8 formative indicators (i.e., for the BI construct), the sample should be over 80. We also recognize that while SEM-PLS is well suited for small sample sizes, researchers recognize the advantage of larger sample sizes, for example Chin and Newsted [39] recommend samples be above 150, which they then go on to describe as large. Accordingly, we collected a total of 405 responses where all participants were from the United States. Of those, 80 submissions were removed from the final dataset, as they failed to pass the attention checks or were incomplete, leaving 325 remaining responses. The breakdown can be seen in greater detail in Table 1. Almost all participants appeared to be frequent users of search technology, with 96.92% indicating that they use a search engine on a daily basis. The majority of participants (83.38%) indicated that their favorite search engine was Google, followed by DuckDuckGo (10.77%), followed by Bing (3.69%).

Table 1. Demographic Profile of Respondents

| Item            | Type                          | Frequency (n = 325) | Percentage (%) |
|-----------------|-------------------------------|--------------------|----------------|
| Gender          | Female                        | 128                | 39.38          |
|                 | Male                          | 193                | 59.38          |
|                 | Other                         | 1                  | 0.31           |
|                 | Prefer not to answer          | 3                  | 0.92           |
| Age             | 18-25                         | 16                 | 4.92           |
|                 | 26-30                         | 54                 | 16.61          |
|                 | 31-35                         | 80                 | 24.62          |
|                 | 36-45                         | 91                 | 28.00          |
|                 | 46-55                         | 51                 | 15.69          |
|                 | 56 or older                   | 30                 | 9.23           |
|                 | Prefer not to answer          | 3                  | 0.92           |
| Income          | Less than $10,000             | 9                  | 2.77%          |
|                 | $10,000 to $19,999            | 27                 | 8.31%          |
|                 | $20,000 to $29,999            | 29                 | 8.92%          |
|                 | $30,000 to $39,999            | 45                 | 13.85%         |
|                 | $40,000 to $49,999            | 32                 | 9.85%          |
|                 | $50,000 to $59,999            | 41                 | 12.62%         |
|                 | $60,000 to $69,999            | 35                 | 10.77%         |
|                 | $70,000 to $79,999            | 29                 | 8.92%          |
|                 | $80,000 to $89,999            | 12                 | 3.69%          |
|                 | $90,000 to $99,999            | 12                 | 3.69%          |
|                 | $100,000 to $149,999          | 28                 | 8.62%          |
|                 | $150,000 or more              | 19                 | 5.85%          |
|                 | Prefer not to answer          | 7                  | 2.15%          |
| Schooling       | Less than high school degree  | 4                  | 1.23%          |
|                 | High school graduate (high    | 41                 | 12.62%         |
|                 | school diploma or equivalent  |                    |                |
|                 | including GED)               |                    |                |
|                 | Some college but no degree    | 67                 | 20.62%         |
|                 | Associate degree in college   | 32                 | 9.85%          |
|                 | (2-year)                     |                    |                |
|                 | Bachelor’s degree in college  | 136                | 41.85%         |
|                 | (4-year)                     |                    |                |
|                 | Master’s degree (e.g. MA, MS) | 31                 | 9.54%          |
|                 | Professional degree (e.g. MBA| 6                  | 1.85%          |
|                 | , MFA, JD, MD)               |                    |                |
|                 | Doctoral degree (e.g. PhD,    | 5                  | 1.54%          |
|                 | EdD, DBA)                    |                    |                |
|                 | Prefer not to answer          | 3                  | 0.92%          |
3. Results

In this section we outline the analysis that we undertook and then report on the results.

3.1. Measurement Model

In the first stage, a measurement model was used to examine the relationship between the manifest variables and their corresponding latent variables. This was done to ascertain whether the manifest variables effectively measured the latent variables. To accomplish this, we assessed the measures of convergent validity, construct reliability, and discriminant validity using SmartPLS3.3.2 [40]. To test convergent validity, which reveals how items are related between reality and theory [41], we relied on the factor loadings and the average variance extracted (AVE). We removed any manifest variables with values lower than 0.7 from our model for both of these criteria, as prescribed by Chin [42]. Specifically, we removed in sequence, VOL1 (0.290), RES4 (0.440), PEC4 (0.488), CPLAY4 (0.569), and PEC1 (0.663). The remaining items were statistically significant (p < 0.05, t-statistics were obtained from bootstrapping with 7000 subsamples), reflecting that they possessed appropriate convergent validity (see Table 2). To test construct reliability, we used the measures of composite reliability (CR) and Cronbach’s Alpha. For both measures, we found values greater than 0.7 indicating overall good construct reliability, except for VOL, which had a Cronbach’s Alpha of 0.548 and a CR score of 0.556, representative of acceptable construct reliability (see Table 3). Finally, to test discriminant validity, we used the Fornell-Larcker criterion as well as cross-loadings. Regarding the Fornell-Larcker criterion, Fornell and Larcker [43] advise that the correlations between each construct should be lower than the square root of the AVE. Concerning the cross-loadings, Chin [44] advises that each cross-loading be lower than all of the indicator’s loadings. Since we satisfied both of these requirements, we concluded that our measurement model’s discriminant validity was satisfactory. Given that our TAM3+WG model had acceptable convergent validity as well as suitable reliability and discriminant validity we felt confident to apply the manifest variables in order to investigate the concurrent validity and sensitivity of our warm-glow constructs, as well as the ensuing structural model.

Table 2. Summary of Convergent Validity Testing

| Factor | Item | Loading | t-Statistic | AVE |
|--------|------|---------|-------------|-----|
| BI     | BI2  | 0.97    | 232.177**   | 0.938|
|        | BI3  | 0.967   | 191.694**   |     |
| CANX   | CANX1| 0.92    | 53.383**    | 0.850|
|        | CANX4| 0.924   | 66.114**    |     |
|        | CPLAY1| 0.83   | 6.984**     |     |
| CPLAY  | CPLAY2| 0.933  | 6.029**     | 0.796|
|        | CPLAY3| 0.911  | 6.5**       |     |
|        | CSE1  | 0.792   | 23.705**    |     |
|        | CSE2  | 0.858   | 46.671**    | 0.670|
|        | CSE3  | 0.789   | 24.723**    |     |
|        | CSE4  | 0.834   | 29.711**    |     |
| ENJ    | ENJ2  | 0.974   | 270.531**   | 0.942|
|        | ENJ3  | 0.967   | 145.771**   |     |
|        | IMG1  | 0.923   | 55.107**    | 0.881|
| IMG    | IMG2  | 0.944   | 92.759**    |     |
|        | IMG3  | 0.948   | 129.774**   |     |
| OUT    | OUT2  | 0.962   | 120.328**   | 0.929|
|        | OUT3  | 0.966   | 169.197**   |     |
| PEC    | PEC2  | 0.905   | 48.966**    | 0.834|
| Construct | Number of Items | Cronbach’s Alpha | CR |
|-----------|----------------|-----------------|----|
| BI        | 2              | 0.934           | 0.968 |
| CANX      | 2              | 0.823           | 0.919 |
| CPLAY     | 3              | 0.879           | 0.921 |
| CSE       | 4              | 0.836           | 0.890 |
| ENJ       | 2              | 0.939           | 0.970 |
| IMG       | 3              | 0.932           | 0.957 |
| OUT       | 2              | 0.924           | 0.963 |
| PEC       | 2              | 0.801           | 0.909 |
| PEOU      | 4              | 0.911           | 0.938 |
| PEWG      | 3              | 0.904           | 0.940 |
| PIWG      | 3              | 0.934           | 0.958 |
| PU        | 2              | 0.804           | 0.911 |
| REL       | 3              | 0.938           | 0.960 |
| RES       | 3              | 0.815           | 0.890 |
| SN        | 4              | 0.912           | 0.938 |
| VOL       | 2              | 0.548           | 0.814 |

* p<0.05; ** p < 0.01.

Table 3. Summary of Reliability Testing

3.2. Structural Model

In the second stage we employed partial least squares (PLS), which is a flavor of structural equation modelling (SEM), specifically to test our conceptual model, using once again SmartPLS3.3.2 [40]. The use of PLS-SEM has, according to Hair, Ringle, and Sarstedt
Table 4. Structural Model Results

| Path          | β    | t-statistic |
|---------------|------|-------------|
| EXP → BI      | 0.101| 1.836       |
| PEOU → BI     | 0.023| 0.603       |
| PEWG → BI     | 0.190| 2.906**     |
| PIWG → BI     | 0.220| 3.424**     |
| PU → BI       | 0.296| 5.221**     |
| SN → BI       | 0.211| 3.345**     |
| VOL → BI      | -0.106| 2.880**  |
| EXP * PEOU → BI | 0.071| 1.510       |
| EXP * SN → BI | -0.075| 1.281     |
| PEWG * SN → BI| 0.015| 0.529       |
| VOL * SN → BI | 0.052| 1.546       |
| CANX → PEOU   | 0.240| 4.061**     |
| CPLAY → PEOU  | -0.013| 0.286      |
| CSE → PEOU    | 0.193| 2.652**     |
| ENJ → PEOU    | 0.214| 3.456**     |
| EXP → PEOU    | -0.049| 1.293      |
| PEC → PEOU    | 0.359| 4.624**     |
| PEWG → PEOU   | -0.070| 1.143      |
Table 5. Hypotheses Testing Results

| Hypothesis   | Relationship         | Decision     |
|--------------|----------------------|--------------|
| H1           | PEWG → BI            | Supported    |
| H2           | PIWG → BI            | Supported    |
| H3           | PEWG → PEOU          | Not Supported|
| H4           | PIWG → PEOU          | Not Supported|
| H5           | PEWG → PU            | Supported    |
| H6           | PIWG → PU            | Not Supported|
| H7           | PEWG * IMG → PU      | Not Supported|
| H8           | PEWG * SN → BI       | Not Supported|
| H9           | PIWG * ENJ → PEOU    | Not Supported|
| H10          | PIWG * CPLAY → PEOU  | Not Supported|
| H11          | PEWG * SN → PU       | Not Supported|

Table 6. $R^2$

|   | $R^2$  |
|---|-------|
| BI| 0.677 |
| PEOU| 0.530 |
| PU| 0.598 |
| IMG| 0.295 |

With respect to PU, the model explained 59.8%, with significant factors (in order of decreasing strength) of “output quality” (OUT) ($\beta = 0.252; p<0.01$), PEWG ($\beta = 0.195$;
p<0.01) and SN (β = 0.150; p<0.05), PEOU (β = 0.139; p<0.01), IMG (β = 0.115; p<0.05), REL (β = 0.112; p<0.05). Interestingly, H6 was not verified. Therefore, we were unable to assume a relationship between the constructs of PIWG and PU. With respect to H5, we did find a statistically significant relationship between PU and PEWG. Therefore, the results indicated that a higher perception of EWG led to a higher perception of usefulness by using the technology. Lastly, with respect to IMG, SN (β = 0.544; p<0.01) explained 29.5% of the variance. Table 4 summarizes the results from the structural model and Table 5 the results from the testing of the hypotheses.

The existence of a substitutive relationship was considered by using moderators, following the approach of Hagedoorn and Wang [53] (see Tables 10 and 11). We found no statistically significant moderating role between PEWG and SN with respect to the dependent variable BI, or between PIWG and ENJ, or PIWG and CPLAY for the dependent variable PEOU. For the dependent variable PU, we found no statistically different moderating role between PEWG and SN or PEWG and IMG. Therefore, we were able to discount the possibility that the aforementioned independent variables could serve as substitutes for one another, supporting H7 to H11. In other words, the PIWG and PEWG constructs were unique to the model and enabled it to capture a new phenomenon. In short, within the TAM3+WG model, we found no substitutive relationship between PEWG and PIWG with existing similar constructs.

3.3. Explanatory Power, Predictive Ability, and Model Fit for BI

Concerning the dependent variable BI, the TAM3+WG model had an R² of 0.677, which can be described as substantial (as defined by Hair, Ringle, and Sarstedt [45]). We also explored whether the addition of the PIWG or PEWG independent variables influenced R² into the model, and whether those models were superior to our TAM3+WG model, which was 5.1% higher than the original TAM3 model (see Table 7). The findings revealed that for the dependent variable BI, the associated independent variables in the TAM3+WG model explained a larger proportion of the variance (than the original TAM3 model, the TAM3 model with the PIWG construct, and the TAM3 model with PEWG construct). Consequently, we were able to conclude that the TAM3+WG model had superior explanatory power. With respect to the predictive ability of the TAM3+WG model, as the Q² for BI was greater than 0 (see Table 7), we can assert that the latent factors associated with BI indeed have predictive ability [54]. Concerning model fit, all of the models in Table 7 had a Standardized Root Mean Square Residual (SRMR) value of less than 0.08, which is the minimum acceptable value according to Hu and Bentler [55]. This further indicated that the TAM3+WG model was a good fit [56,57]. Furthermore, amongst the two models compared, the TAM3+WG model had the lowest Akaike Information Criterion (AIC) value, with respect to the dependent variable BI (AIC = -344.489). According to Akaike’s [58] guidelines, this allows us to conclude that the TAM3+WG model had the best fit.

| Table 7. Comparison of Models For BI Factor |
|-------------------------------------------|
| Factor | TAM3 | TAM3+WG |
|--------|------|---------|
| R²     | 0.626| 0.677   |
| ΔR²    |      | 0.051   |
| Q²     | 0.570| 0.614   |
| SRMR   | 0.048| 0.047   |
| AIC    | -302.727| -344.489|

4. Discussion and Conclusions
Through this work we developed a new model (i.e., TAM3+WG), in principle an extension of the popular TAM3 model, to incorporate warm-glow. The goal being to understand the effect that warm-glow plays on consumer adoption decisions for ‘good tech’ as defined by Saravanos et al. [10]. We incorporated the PEWG and PIWG constructs, proposed by Saravanos et al. [10], into the TAM3 model to form an enhanced model, TAM3+WG, which now explicitly takes the warm-glow phenomenon into consideration. Our TAM3+WG model was found to be superior to the TAM3 model when determining users’ BI to accept ‘good tech’. Moreover, none of the potentially competing factors in the existing TAM3 model were found to be appropriate substitutes to the PEWG and PIWG constructs. The finding that warm-glow plays a prominent role in consumers’ BI to accept technology and can influence consumer decisions is not in of itself novel; rather it serves to support what is shared from earlier studies. Certainly, our work agrees with the findings of others who have explored the effect of EWG on technology in the past such as Griskevicius, Tybur, and Van den Bergh [20], Griskevicius and Tybur [21], and Dastrup et al. [22]. In addition, regarding studies that conclude that IWG influences adoption, our work corroborates that which is presented by Hartmann and Apaolaza-Ibáñez [23], Ma and Burton [24], Karjalainen and Ahvenniemi [28], Sun et al. [25], Azalia et al. [26], and Bhutto et al. [27].

Furthermore, our work offers insight as to the relative magnitude with respect to ‘traditional’ constructs that affect the adoption of technology products. Correspondingly, PIWG represents the second-largest effect (β = 0.220) in consumer decisions, preceded only by their PU of the technology (β = 0.296). PEWG played the fourth greatest role in determining consumer decisions, with relation to technology adoption (β = 0.190), slightly less than SN (β = 0.211) which played the third greatest role. Hence, we find that PIWG plays a greater role than PEWG in consumer decisions. Moreover, the combined magnitude of effects that each form of warm-glow had on determining consumer intention was similar and comparable to that of the technology’s PU. This would explain why warm-glow appears to play such a critical role in adoption decisions. Our study also sought to ascertain whether warm-glow can influence a consumer’s perception of how easy it will be to use a technology (reflected through the PEOU construct) and how valuable that technology will be (reflected through the PU construct). For the most part, we found that these factors, which traditionally serve as the primary antecedents of consumer BI to accept a technology, were not influenced by the presence of either form of warm-glow, except for the case of PU and PEWG. This finding is slightly surprising, given that an association between consumers’ BI to adopt a technology and other factors has appeared in several studies related to the topic of technology adoption. For example, in the case of biometric authentication, Lancelot-Miltgen et al. [30] demonstrated that trust can influence a user’s perception of the ease and effectiveness of using a technology. In their work, they found that if a user trusts a certain technology, they will perceive it as easier to use and of greater value. In our findings, consumers’ perceptions of the value of a technology was based on the presence of extrinsic warm-glow.

4.1. Implications

This study contributes to the general technology adoption literature by being, to the best of our knowledge, the first empirical study to extend the TAM3 model with warm-glow through the use of the PEWG and PIWG constructs to study the category of ‘good tech’. From the practical perspective, the results highlight the magnitude of influence that the respective forms of warm-glow had on user adoption decisions (i.e., second and fourth greatest roles). This finding can justify the creation of ‘good tech’ by providing evidence of the advantage it has over ‘traditional’ technology. As mentioned by Saravanos et al. [10], the warm-glow phenomenon, is known to lead to an “enhanced willingness to buy”, and that the “effects persist and play out in actual behavior” [59], to novel consumption patterns [60]. Indeed, it clearly demonstrates that for organizations, not only is doing the right thing ethical, it can also be strategic. Moreover, the findings offer insight to
marketers of ‘good tech’ as they identify what factors influence consumer decisions and have important, they are in those decisions.

4.2. Limitations and Future Research Directions

We conclude by highlighting the key limitations of this study, which also conjointly offer insight into how this research can be further developed. The first limitation concerns the model that we selected to extend, TAM3, and the recognition that outside of this particular model, there is a wide spectrum of different models available for the study of technology adoption [61]. In our work, we selected the TAM3 model for two reasons: first, the TAM line of models serve as the original line of dedicated technology adoption models; second, over time, they represent one of the most widely used technology adoption models [4,5,62]. That being said, other technology adoption models are indeed available [61], the most popular being UTAUT [61], and its latest version, UTAUT2 [63]. While this study serves as a strong starting point, we recommend that future work go on to examine the inclusion and evaluation of our proposed warm-glow constructs into these other models (such as UTAUT).

The second limitation concerns the possible influences that culture may play on consumer BI to accept technology. Indeed, there are a plethora of examples [64–69] within the technology adoption literature, where authors share findings that reveal culture influencing consumer BI. Similarly, as pointed out by Saravanos et al. [10] the social innovation literature reports that the extent to which warm-glow impacts user decisions varies based on the culture of those consumers [70]. Consequently, given that our data was collected exclusively in the United States, future research may want to investigate our model’s suitability for use with other cultures, and go on to explore possible ways to integrate cultural factors into the model.

The third limitation concerns the characteristics of the technology we used to test our model for this study, a generic (unbranded) internet search solution, which is a standard, easy-to-use technology frequently offered without charge. Products with different characteristics regarding familiarity, complexity, price, and brand may lead the model to behave differently. Furthermore, research investigating the interplay between these factors and the presence of warm-glow would provide valuable insight into end-user technology adoption behavior.

The fourth limitation is based on our work looking exclusively at user behavioral intention to adopt and not on their actual usage behaviors. Accordingly, further work is required to afford insight into how these behavioral intentions to adopt convert into such behaviors.

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