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ORIGINAL RESEARCH

Green Information System (GIS) Model in the Conference Sector: Exploring Attendees' Adoption Behaviors for Conference Apps

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Introduction: Academic conferences are carbon-intensive. Conference travel by air contributes to huge amount of global greenhouse gas emissions, which can be reduced by adopting green information systems (green IS or GIS). This study aims to investigate attendees' behaviors for adopting green IS (such as conference apps) from an ecological perspective.

Methods: For this research, a survey method was used. Survey instrument had 29 items adapted from existing scales. Data was collected using Mturk's panel of respondents on online Qualtrics. Exploratory and confirmatory factor analysis were conducted on 403 responses for data analysis and validation of the results using SPSS AMOS ver. 24.

Findings: This study provides empirical evidence to add ecological beliefs as a key predictor of green IS adoption models. Findings demonstrate that attitudes and ecological beliefs play an essential role in conference app adoption, in comparison with performance expectations, social impacts, and facilitation conditions, as presented in the traditional technology acceptance literature. Findings assist conference owners develop essential communication strategies for green attendees.

Keywords: conference app, mobile app, ecological beliefs, green IS adoption, technology adoption model, unified theory of acceptance and use of technology, UTAUT

Introduction

The conference industry has witnessed impactful economic growth¹ and technological revolutions in recent years^{2,3} and is the fastest-growing segment within the hospitality sector with a highly positive impact on the economy.⁴ The industry contributes to transportation, dining, business design, as well as providing high economic output from tourism.^{5,6} Recent reporting from the Events Industry Council indicates that 252.6 million people in the United States participated in business events in 2017, resulting in direct spending of more than \$325 billion (USD), with participants spending an average of \$1287.⁷ Employment for an event, convention, meeting, and planner is expected to increase by 8% between 2019 and 2029, with a steady demand persisting over time.⁸ However, with all of these positive outcomes, there are also negative externalities that come with them. There exists criticism towards the conference industry due to the resource intensity of the sector and their participation in practices that damage the environment.⁹

A recent survey shows 88% of United States citizens believe caring for the planet is an important issue, and 52% believe the government should take action.¹⁰ Because of growing environmental concerns among consumers who want to promote sustainability,^{11,12} minimizing these negative impacts is required in order to attract them to an event. People have increased density of carbon dioxide by more than 33% through urbanization, deforestation, automobile emissions, fossil fuel burning, and manufacturing.¹³ A growing consumer base is dedicated to reducing this percentage out of altruistic needs. Since consumers have a growing demand for environmentally friendly practices, having a green venue would improve international competitiveness in the marketplace and increase profitability.⁶ The use of paper for packets and pamphlets during conferences

adds to the damage mentioned. About 419.72 million metric tons of paper and cardboard made up the global production in 2018; almost a third of production is attributed to graphic paper, with 421.88 million metric tons being consumed globally.¹⁴

Academic conferences are carbon-intensive.¹⁵ Conference travel by air contributes to huge amount of global greenhouse gas emissions. Ewijk and Hoekman¹⁶ analyzed travel emissions for three global conferences and found that travel emissions were 722–955 tCO₂e per conference and averaged 1.3-1.8 tCO₂e per attendee. They suggested ways to reduce emission by shifting to land transport for short flights (reduction by 5%) and carbon tax of 100\$/t CO₂e (reduction by 4–14%). The downside is that students will face financial burden. The authors explained that if 10% of attendees who travel furthest attend the conference virtually will reduce emissions by 20–30% and multi-site conference with two or more video-linked locations (reduction of 25–50% up to 46–75% or more up to 82% by shifting to land transport). Finally, authors suggested that virtual conference would yield zero travel emissions.¹⁶

Hiltner¹⁷ was pioneer in suggesting a carbon-neutral conference model that combines pre-recorded talks and interactive online Q&A sessions. Covid-19 especially led to many such virtual conferences, which are worth reading (see¹⁸). Additionally, COVID-19 pandemic has highlighted many disadvantages associated with in-person conferences and demonstrated the advantages of virtual conferences. Virtual conference is cost-effective for organizers and attendees, helps in dissemination of knowledge and scientific exchanges of information accessible to low-income countries and poorly funded institutions who could not afford to pay for travel to in-person conferences, provides access to attendees who could not attend otherwise because of personal circumstances such as healthcare or childcare needs, pregnancy,¹⁹ and people hesitant to speak in public, and helps increase representation from various parts of the world by providing accessibility. Thus, virtual conference improves diversity by having speakers from remote and distant locations in the world. Availability of on-demand recordings and parallel-running sessions further improves value and accessibility.¹⁵ Overall, virtual conferencing has huge positive impact on natural environment.²⁰

Arsenault et al²¹ found that average travel distance (majority by air) is 8525 kms per year with a high of 33,000 kms per year causing significant negative impact on the environment. The average CO₂ emission from an attendee at an international conference is 849 kg, which may be as high as 1891 kg for attendees from more isolated regions.^{20,22} Emissions for a single conference trip amount to about 7% of an individual's total CO₂ emissions. Guldbrandsson and Malmodin²³ studied the carbon dioxide emission savings from three different videoconferencing meetings between Stockholm and Dallas. They found savings of about 215-ton CO₂e/year, which is almost 170 times less than in-person meetings that include plane travel. Similarly, Quack and Oley²⁴ found that substituting in-person meetings by videoconferences reduces carbon emissions by up to 90%. Finally, in a most comprehensive study by Ong, Moors, and Sivaraman²⁵ carbon footprints for the in-person meetings were found to be 3533 kgCO₂e (plane), 2900 kgCO₂e (train) and 3317 kgCO₂ e (car), while only 4 kgCO₂e (via laptop) and 215 kgCO₂e (via desktop and other computer peripherals) for videoconferencing. Finally, a recent study on telemedicine delivered to 1200 patients found savings of almost 40,000 kg CO₂e equivalent to 22,400 km of travel. In other words, emissions arising from telemedicine were only about 0.5% as compared to the emissions by travel, leading to significant amount savings of greenhouse gas emissions in the environment.²⁶

It is important here to mention about emissions from data centers as they have direct relationship to virtual conferencing. Past studies predicted that data centers would become world's largest users of energy consumption.²⁷ Researchers postulated that emissions from data centers in the US alone are equivalent to Argentina²⁸ and that the global data center consumption in 2012 was 270 billion kWh.²⁹ Good news is that contrary to the previous studies, Liu et al³⁰ found that because data centers are now being established in the Pan-Arctic region the energy consumption is reduced significantly. Authors postulated that by 2030, emissions from global data centers will be reduced by about 301 billion kWh and 720 million tons CO_2 .³⁰ Thus, it is safe to say that virtual conferences will significantly help to reduce carbon footprint^{20,31,32} and increase accessibility and inclusivity.^{33,34} The future is positive. Many academicians have chosen to reduce or eliminate air travel in order to align their practices with the reality of climate change.³⁵

Unfortunately, conference industry has been slow to engage with both hybrid and virtual conferencing and skeptical in embracing digital communication technology for conference delivery.³⁶ Also, adopting virtual conferencing entails a number of challenges, including logistics and unified acceptance,³¹ which we argue can be overcome by understanding attendees' motivations towards technology adoption and developing appropriate strategies to influence behavioral change.

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of carbon dioxide (CO2) emissions.³⁷ Despite the eco-friendly aspects of such apps, their adoption rate is low, resulting in a bottleneck in this sustainability effort. Since mobile apps are usually free for personal use, factors that influence the app adoption may differ from general information pertaining to Information Systems (IS) adoption.³⁸ Thus, this study concentrates on understanding technology (green IS) adoption behavior from ecological perspective taking the example of conference apps.

a conference app, "UNEA-2". This effort saved \$30,189 (USD), approximately 1.4 million prints/copies, and eight tons

In order to understand the technology adoption behavior for green IS, it is important to comprehend the elements that influence a conference attendee's adoption behavior. In addition, it is important to understand how attitudes towards green IS mediates the relationship between influence elements and behavior intent. As mentioned in the literature, a person's ecological perspective, or ecological beliefs, plays a vital role in the attitude needed for green IS adoption. The premise of promoting sustainability is altruistic by nature, as it is focused on the benefits of helping the environment at the forefront of adoption rather than promoting self-interest. In the context of conference, marketers could influence the rate of adoption by appealing to a conference attendee's ecological beliefs, which would have an effect on attitude, influencing behavioral intention.

An interesting fact from the literature reveals that users are reluctant to adopt not so attractive technologies.³⁹ In other words, users adopt technologies that provide direct benefit and utility to them. This has support from economists' rational-actor model, which assumes that people have a high self-interest value; this is evident from traditional theories of technology adoption that draw from theories of behavioral based on the rational-actor approach. An issue of conference apps in context, though, is that the presence of other substitutes, such as websites or emails, would naturally reduce the attractiveness of a conference app. Therefore, several scholars have recommended a combination of interventions and penalty strategies to change behavior.^{40–42} For instance, Darby⁴³ proposed social commitment and feedback, encouraging contextual changes, and introducing a penalty, or fee, that would break negative habits. However, it is hypothesized that the adoption of green IS such as conference apps will be influenced by altruistic values, such as ecological beliefs and attitude since they benefit the environment and community. Thus, this research extends the Modified Unified Theory of Acceptance and Use of Technology (UTAUT-2) to understand the adoption behavior for not-so-attractive technologies, such as green IS (or conference apps).⁴⁴

Conceptual Framework

Adoption Behavior

UTAUT states that there are three decision-making factors of an individual's adoption intention to new technology in an organizational environment (ie, effort expectations, social impacts, and performance expectations) and two decision factors of the actual use of the technology (ie, facilitation conditions and adoption intention). While the UTAUT framework is a promising start to the Green Information Systems (IS) Adoption Model, it needs further expansion. UTAUT-2 is on the basis of the original UTAUT,⁴⁵ which is considered the most elaborate theory in technology literatures.⁴⁶ UTUAT-2 expands upon the UTAUT model, adding consumers' perspective and voluntary settings, as well as new three determinants of behavioral intention: habit,⁴⁷ hedonistic motives,⁴⁸ and price value.⁴⁹ UTAUT-2 is relevant to the research, rather than TAM or the original UTAUT, because the modified model is developed with the consumer's viewpoint in mind. In this research, *Behavioral intention* (BI) to utilize a conference app was to evaluate the strength of the conference attendees' adoption intention of the conference app. The intentions to act in good faith in regard to the environment is suggested to be an expression of actual behavior and, as such, it can be predicted that conference participants with a high behavior intent have more possibility to adopt an app over the alternatives mentioned previously.

Performance Expectancy (PE)

PE was defined as the extent to which a conference attendees believe that the use of a conference app improves their performance in conferences and at work. According to UTAUT, when people trust that the use of technology will assist them increase benefits in performance, their behavior is affected by this concept.^{45,46} This was derived from a reasoned

and cognitive behavioral perspective. Unlike UTAUT, in this context, it was intuitively assumed that green IS (conference apps) do not offer sufficient personal benefits to affect behavior; the benefit of using green IS is altruistic. They benefit the environment rather than the self. Thus, it could be assumed that PE would not affect BI.

H1: PE does not have a significant impact on BI to use a conference app.

Effort Expectancy (EE)

EE was designated as the degree of easiness in using the conference app. According to UTAUT, behavior is affected by faith about how easy it is to use a technology.^{45,46} It is supposed that people, generally speaking, have experience in using apps, given that they are a common technology available on smartphones. In this sense, green IS was a relatively easy technology to use. Thus, it was assumed that EE would affect BI.

H2: EE has a positive and direct impact on EI to use a conference app.

Facilitating Conditions (FC)

FC was identified as the extent to which conference attendees believe they are receiving infrastructure support (both organizational and technical) for using a conference app. When people trust that infrastructure or support was provided to promote the technology use, their behavior was affected by these beliefs.^{45,46} Some problems with the context of conference apps relate to the duration of smartphone battery life and the availability of wi-fi or charging stations in the facilities that promote conference app usage. However, because conference organizers usually support using their apps, participants would feel positive in using them. Thus, it was assumed that FC would affect BI.

H3: FC have a positive and direct impact on BI to use a conference app.

Social Influence (SI)

SI was identified to the extent that individuals perceived that important people think that they should use a conference app. "The function of social influences in technology adoption decisions is complicated and affected by an extensive contingencies".⁴⁵ Similar views were made by previous scholars.⁵⁰ In addition, SI was discovered to have a greater impact on behavior in mandatory situations than in involuntary settings. SI has ambiguous results and is considered the least understood predictors of behavior since it is difficult to pinpoint the exact reason for the direct effect of SI on BI, since everyone has a different influence to adopt technology in a social environment, such as family, friends, religion, superiors, etc.^{51–53} However, conference app usage was mostly voluntary. Thus, it was assumed that SI would not affect BI.

H4: SI do not have significant impact on BI to use a conference app.

Habit (HB)

HB was identified as the extent to which the conference attendees instinctively behave in regard to conference app use as a consequence of training from prior app usage. Habit is distinct from experience, as in the span of three months, individuals may form different habits depending on technology use. In terms of a value perspective, in the same time span, different individuals will have either a high or low habit depending on values towards using technologies regardless of how much time is put into using the technology. It has been found that feedback from previous use of technology or past experience influences future behavioral intentions.^{54,55} Similarly, automatic behaviors resulted from regular use of technology have been discovered to have a direct impact on behavioral use.^{46,47} Thus, the HB was assumed to affect BI.

H5: HB has a positive and direct impact on BI to use a conference app.

Hedonic Motivation (HM)

Hedonic motivation was known as gaining a fun and pleasurable feeling from a conference app use.⁵⁶ When the technology use offers excitement and enjoyment to users, it generally affects user's future behavior intention. Conference apps, in the

context, HM depends on the characteristics available in the conference app, such as social media connectivity or gaming, or acquiring new information from the app may provide enjoyment through the novelty and innovation of green IS. In addition, the personality of the individual using the conference app would also influence their outlook towards the app's features. Hedonic motivations or pleasures have been found to positively affect behaviors in past studies.^{46,57,58} Thus, it was assumed that HM would influence BI.

H6: HM has a positive and direct impact on BI to use a conference app.

Price Value (PV)

PV was not included in this study as the conference app does not generate revenue from users. Prices would be a given if organization were to be insistent on using conference apps since the organization would have to pay for Internet connectivity or the cost of the phone user's data plan if the organization does not have a way to connect to the Internet.

Attitude Toward Conference App (ATCA) and Ecological Beliefs (EB)

Two new constructs, such as ATCA and EB, were added to the model, the *Green IS Adoption Model* (GISAM), as hypothesized in this study (Figure 1). ATCA was defined as the sentiment of conference attendees towards the conference app (favorable or unfavorable). It is based on the definition of "attitude toward any concept" as the favorableness or unfavorableness of an individual's feeling for that concept.⁵⁹ From the beginning of behavior aspect research, it has been known that attitudes influence behaviors. People with a favorable attitude to concept tend to act positively toward that behavior, and vice versa.⁵⁹ Therefore, ATCA was assumed to affect BI.

H7: ATCA has a positive and direct impact on BI to use a conference app.

EB referred to the salient beliefs about the consequences of using a conference app. It is based on⁶⁰ the definition of values as criteria "for guiding action [and] for developing and maintaining attitudes toward relevant objects and situations." GISAM draws from the *Value-Belief-Norm* (VBN) environmentalism theory.⁶¹ It indicates that human value influences their belief, which affects an individual's norms and attitudes.⁶² The difference of the value orientations (altruistic, biospheric, and egoistic

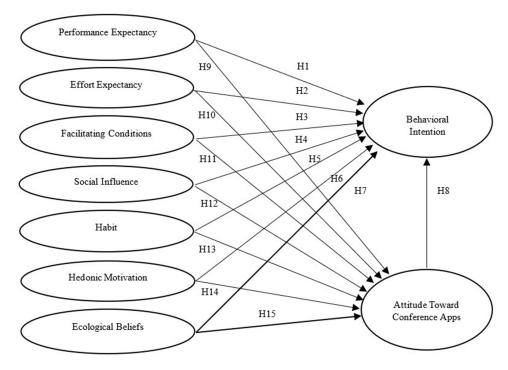


Figure I Proposed model.

values) in forming attitudes is emphasized. The model is in line with the recent work of,⁶³ which shows biospheric value as a core element in forming behavioral intentions. For over a decade, TAM, TRA, and other theoretical and experiential works have shown sufficient evidence that beliefs affect behavior intentions.⁶⁴ From an environmental behavior perspective, the impact of values and beliefs, including biosphere beliefs, on behavior has been empirically verified.^{61,65} Therefore, EB was assumed to affect BI.

H8: EB have a positive and direct impact on behavioral intention to use a conference app.

Mediating Effect

Previous studies using TRA and TAM suggest that each individual develops an intention to engage in behaviors with positive attitudes.^{50,66} In addition, other research has compiled empirical evidence for attitudes as mediators between various beliefs and BI.^{67–70} Therefore, ATCA was assumed to mediate the relationship between behavioral intent and all factors in this context.⁴⁴ Each factor is referred to as an individual hypothesis below:

H9: PE do not have a significant impact on BI to use a conference app through ATCA.

H10: EE has a positive and indirect impact on BI to use a conference app through ATCA.

H11: FC have a positive and indirect impact on BI to use a conference app through ATCA.

H12: SI do not have a significant impact on BI to use a conference app through ATCA.

H13: HB has a positive and indirect impact on BI to use a conference app through ATCA.

H14: HM has a positive and indirect impact on BI to use a conference apps through ATCA.

H15: EB have a positive and indirect impact on BI to use a conference app through ATCA.

Research on environmentalist behavior supports the notion that values, beliefs, and attitude factors are essential for establishing settled behavior patterns. EB help shape attitudes among consumers by developing biospheric values.⁶¹ These consumer beliefs, such as performance expectancy, are postulated to be higher than consumption level factors, which act as a prime indicator of environmentalist behavior.^{71,72} Therefore, EB and attitude combined with UTAUT-2 variables will forecast adoption behavior in green IS adoption model (GISAM), as shown in Figure 1.

Methodology

A survey method was used in this research. The survey instrument had 29 items (see <u>Supplementary Materials</u>) adapted from existing scales (eg, UTAUT-2). The instrument was tested using pilot data of 111 respondents before the final survey. The final survey was created on an online Qualtrics. In addition, the data was collected from Mturk's panel of respondents. The selection criterion for panel members was anyone living in the United States, who is more than 18 years old. Furthermore, the person who has participated in at least one conference using a mobile app in the last two years. Data were screened, cleaned, and prepared for analysis using univariate and multivariate techniques. Further, all assumptions for structural equation modeling (SEM) were checked before the final analysis. Invalid responses were eliminated. Mean, standard deviation, skewness, and kurtosis were calculated for descriptive analysis (EFA and CFA) were performed for inferential analysis as recommended by Yoon and Uysal.⁷³ To investigate the relationship between variables and hypothesis testing, SEM using maximum likelihood estimation method was used. Robustness tests to avoid confirmation bias and to maintain statistical precision were performed using an equivalent model and bootstrapping analyses⁷⁴ using SPSS AMOS ver. 24.

Results and Findings

Respondent's socio-demographic or sample characteristics are shown in Table 1. The key sociodemographic characteristics show that respondents were mainly male (68.20%), and the majority were between 18 and 30 years of age (57.6%). Table 2 provides the descriptive statistics for data collected via an online survey (eg, Mean, Standard Deviation, Kurtosis, and Skewness). The descriptive statistics reveal that the data is slightly skewed. Therefore, standardized scores were used for analysis.

Factor Analysis (EFA and CFA)

The results from exploratory factor analysis were found to be satisfactory looking at the factor loadings and reliability scores of each dimension or the pre-determined constructs used in the model.⁷⁵ Cronbach's alpha above 0.70 is considered an acceptable value indicative of high internal consistency of the scale.⁷⁶ Further, the covariances and correlations between constructs were examined for acceptable scores and significance at the 0.01 level (p < 0.01). Next, confirmatory factor analysis was performed to ensure that the hypothetical measurement model for predicting the behavior of conference attendees towards green IS appropriately fit the observed data. Confirmatory factor analysis was executed using structural equation modeling procedures in AMOS ver. 23. The measurement model confirmed the reliability and validity of the constructs, while the structural model confirmed the hypothesized structural paths using the model fit indices.

Measurement Model

The hypothesized measurement model consisted of nine factors: BI, PE, EE, FC, SI, HB, HM, EB, and ATCA. The goodness-of-fit index presented the marginal fit for the data, CMIN or χ^2 (29, N = 403) = 899.67, $\chi^2/df = 2.64$, p < 0.001, RMSEA = 0.06, CFI = 0.91, GFI = 0.86, NFI = 0.86, and TLI (or NNFI) = 0.89, which was re-specified using modification indices as suggested by Kline.⁷⁴ No item was removed to enhance the model fit. The alternative or the respecified measurement model showed substantial improvement in the goodness-of-fit index indicating that the data fit the model reasonably: CMIN or χ^2 (29, N = 403) = 810.34, $\chi^2/df = 2.41$, p < 0.001, RMSEA = 0.06, CFI = 0.92, GFI = 0.87, NFI = 0.88, and TLI (or NNFI) = 0.91.

| Characteristics of | N | Percent | |
|--------------------|----------------------|---------|-------|
| GENDER | | | |
| | Male | 275 | 68.20 |
| | Female | 128 | 31.80 |
| AGE | | | |
| | 18–30 years | 232 | 57.60 |
| | 31–40 years | 134 | 33.30 |
| EDUCATION | | | |
| | Bachelor's Degree | 228 | 48.10 |
| | Graduate Degree | 81 | 28.50 |
| INCOME | | | |
| | Less than \$30,000 | 141 | 35 |
| | \$30,001 to \$50,000 | 109 | 27 |
| RACE | | | |
| | Asian | 177 | 43.90 |
| | White | 156 | 38.70 |
| USAGE | | | |
| | I–2 Hours | 152 | 37.70 |
| | 2–3 Hours | 110 | 27.30 |
| | Less than I Hour | 44 | 10.90 |

 Table I Sample Characteristics

| Variables | Non-Standardized | | | | |
|--|------------------|----------------|----------|----------|-------|
| | Mean | Std. Deviation | Skewness | Kurtosis | |
| Performance Expectancy (PE) | PEI | 5.33 | 1.14 | -0.58 | -0.10 |
| | PE2 | 5.48 | 1.12 | -0.70 | 0.26 |
| | PE3 | 5.46 | 1.19 | -0.78 | 0.28 |
| Effort Expectancy (EE) | EET | 5.50 | 1.10 | -0.76 | 0.62 |
| | EE2 | 5.58 | 1.14 | -0.72 | 0.08 |
| | EE3 | 5.48 | 1.17 | -0.79 | 0.44 |
| Facilitating Condition (FC) | FCI | 5.51 | 1.18 | -0.83 | 0.33 |
| | FC2 | 5.63 | 1.09 | -0.67 | 0.03 |
| | FC3 | 5.54 | 1.11 | -0.61 | 0.24 |
| | FC4 | 5.30 | 1.33 | -0.91 | 1.00 |
| Social Influence (SI) | SH | 5.12 | 1.31 | -0.81 | 0.70 |
| | SI2 | 5.16 | 1.30 | -0.69 | 0.45 |
| | SI3 | 5.22 | 1.32 | -0.75 | 0.59 |
| Habit (HB) | HBI | 5.11 | 1.34 | -0.89 | 0.84 |
| | HB2 | 4.69 | 1.56 | -0.59 | -0.38 |
| | HB3 | 5.34 | 1.15 | -0.58 | 0.21 |
| Hedonic Motivation (HM) | HMI | 5.21 | 1.34 | -0.68 | 0.35 |
| | HM2 | 5.24 | 1.33 | -0.81 | 0.55 |
| | HM3 | 5.28 | 1.34 | -0.7 I | 0.30 |
| Behavioral Intention (BI) | BH | 5.50 | 1.19 | -0.55 | -0.25 |
| | BI2 | 5.28 | 1.34 | -0.62 | 0.18 |
| | BI3 | 5.32 | 1.33 | -0.64 | 0.41 |
| Attitude Toward Conference Apps (ATCA) | ATCAI | 5.89 | 1.10 | -1.15 | I.40 |
| | ATCA2 | 5.74 | 1.06 | -0.75 | 0.42 |
| | ATCA3 | 5.70 | 1.11 | -0.86 | 0.69 |
| | ATCA4 | 5.86 | 1.05 | -0.89 | 0.82 |
| Ecological Beliefs (EB) | EBI | 5.53 | 1.22 | -0.78 | 0.07 |
| | EB2 | 5.43 | 1.22 | -0.76 | 0.19 |
| | EB3 | 5.52 | 1.21 | -0.65 | -0.08 |

Table 2 Mean, Standard Deviation, Skewness, and Kurtosis

Construct Validity and Reliability

The next stage was to evaluate the construct validity and reliability of the latent constructs. Construct validity was established by the intensity of factor loading, significance of t-values (t > 1.96 for p < 0.05 and > 2.33 for p < 0.01), and average variance extracted (AVE).⁷⁷ Their magnitudes verified the intensity of factor loadings with shared variances (ie, squared multiple correlations [SMC or R²]). Convergent and discriminant validity was assessed using composite reliability (CR), AVE, and the correlations among the latent configurations. Composite reliability (>0.70) was rated as acceptable.⁷⁶ Table 3 indicates correlations and construct reliability, in some cases AVE as low as below 0.50⁷⁸ but considered acceptable since their respective Composite reliabilities were above 0.70.⁷⁷ Discriminant validity was estimated by comparing AVE and cross-correlation factors that must be lower than the square root of AVE.⁷⁷ Some discriminant validity issues are shown in Table 3. However, the scores were accepted based on the literature about inflated scores due to self-reported data and shared method variance.⁷⁹

Structural Model

Structural paths were stated instead of factorial covariance of the model to investigate the goodness-of-fit of the hypothesized structural model. In contrast to traditional technology acceptance models, as shown in the hypotheses section, some factors may not directly affect BI in the case of green IS. Therefore, while EE, FC, SI, HM, HB, EB, and ATCA were assumed to have a direct impact on BI, PE and SI were assumed to have no impact on BI. Because of the

| | CR | AVE | FC | PE | EE | SI | НВ | НМ | EB | ATCA | BI |
|------|------|------|------|------|------|------|------|------|------|------|------|
| FC | 0.74 | 0.41 | 0.64 | | | | | | | | |
| PE | 0.73 | 0.47 | 0.94 | 0.69 | | | | | | | |
| EE | 0.76 | 0.52 | 0.90 | 0.92 | 0.72 | | | | | | |
| SI | 0.85 | 0.65 | 0.56 | 0.64 | 0.57 | 0.81 | | | | | |
| НВ | 0.70 | 0.44 | 0.55 | 0.66 | 0.61 | 0.88 | 0.67 | | | | |
| нм | 0.83 | 0.61 | 0.54 | 0.61 | 0.62 | 0.80 | 0.87 | 0.78 | | | |
| EB | 0.78 | 0.54 | 0.75 | 0.80 | 0.73 | 0.58 | 0.47 | 0.53 | 0.74 | | |
| ATCA | 0.82 | 0.54 | 0.76 | 0.79 | 0.79 | 0.66 | 0.69 | 0.69 | 0.75 | 0.73 | |
| BI | 0.76 | 0.52 | 0.76 | 0.79 | 0.82 | 0.71 | 0.89 | 0.81 | 0.72 | 0.87 | 0.72 |

Table 3 Correlations and Construct Reliability

Notes: Correlations were found significant at 0.01 level (p < 0.01).

complexity of the model that increases with the pairwise covariance between exogenous factors (not shown in Figure 2), the key results show standardized regression weights from structural model analyses (Figure 2). All covariances are shown to be significant at the 0.01 level. The results of the model fit index support the GISAM model because it fits the data well, CMIN or χ^2 (29, N = 403) = 137.03, df = 48; χ^2/df = 2.86, p < 0.001, RMSEA = 0.07, CFI = 0.97, GFI = 0.95, NFI = 0.96, and TLI (or NNFI) = 0.95.

One of the significant findings is that attitudes can describe differences in BI by up to 44%. In other words, adoption of a conference app requires attendees to develop an attitude based on their beliefs (ie, enjoyment, ease of use, and environmental effect) about the apps. These results are consistent with Aluri and Palakurthi,⁶⁷ who postulated that various types of beliefs affect behavior through attitudes. As a result of bootstrapping analysis, it was confirmed that attitude mediates the association between five factors and the behavioral intention. Equivalence model and bootstrapping analysis confirmed the robustness of the model.

Equivalent Model Test

After the final model was chosen, equivalent versions should be deliberated to prevent confirmation bias of the model.^{74,80,81} Equivalent models have equal degrees of freedom; however, they have dissimilar path configurations

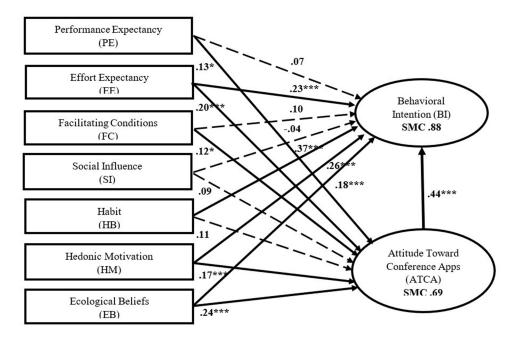


Figure 2 Conceptual model assessment results.

between the same variables. In this study, Lee-Hershberger's substitution rule number 12.2 for the structural model was used.⁸² Rule 12.2 suggests that if two endogenous variables have the same cause and the relationship is unidirectional, the paths can be reversed to evaluate effects and model validation. Thus, pathways between BI and ATCA were switched to evaluate the impact on the model (ATCA \rightarrow BI: BI \rightarrow ATCA).

Bootstrapping Analysis

As mentioned in the previous section, the bootstrapping technique was utilized to verify the consequences of structural equation modeling and to validate the model. In this study, significance bootstrap test of significance using the biascorrected percentile method was utilized in this study looking at the CIs, which is considered robust for model confirmation.⁷⁴ When "zero" falls out of bounds, the hypothesis should be dismissed. Bootstrap outcomes are related to direct, indirect, and overall impacts, as well as providing associated p-values and confidence intervals. The overall impacts discovered from the bootstrapping consequences are shown in Table 4, which confirms that ATCA was the most powerful direct predictor variable of BI to use green IS (0.44***). In addition, Table 5 shows the consequences to assist the hypotheses and to explain the effect of each of the crucial predictor in GISAM. Summary of the results, as shown in Table 5, provide support for the hypotheses.

| Hypotheses | | | Standardized Total Effects (β) | 95% Confidence Interval | | p-value | Results |
|------------|----|------|--|-------------------------|-------------|---------|------------|
| | | | | Lower Bound | Upper Bound | | |
| ATCA | -> | BI | 0.44*** | 0.25 | 0.67 | 0.004 | Support |
| EB | _> | BI | 0.18*** | 0.07 | 0.30 | 0.004 | Support |
| EE | _> | BI | 0.23*** | 0.11 | 0.33 | 0.004 | Support |
| FC | _> | BI | 0.10 | -0.02 | 0.22 | 0.096 | No Support |
| НВ | _> | BI | 0.37*** | 0.23 | 0.49 | 0.004 | Support |
| НМ | _> | BI | 0.26*** | 0.15 | 0.38 | 0.004 | Support |
| PE | _> | BI | 0.07 | -0.07 | 0.20 | 0.243 | No Support |
| SI | _> | BI | -0.04 | -0.17 | 0.08 | 0.496 | No Support |
| EB | _> | ATCA | 0.24*** | 0.13 | 0.34 | 0.004 | Support |
| EE | _> | ATCA | 0.20*** | 0.08 | 0.32 | 0.004 | Support |
| FC | _> | ATCA | 0.12* | 0.01 | 0.24 | 0.043 | Support |
| НВ | _> | ATCA | 0.11 | -0.04 | 0.27 | 0.163 | No Support |
| НМ | _> | ATCA | 0.17*** | 0.06 | 0.29 | 0.004 | Support |
| PE | _> | ATCA | 0.13* | 0.02 | 0.27 | 0.022 | Support |
| SI | _> | ATCA | 0.09 | -0.04 | 0.22 | 0.244 | No Support |

Table 4 Structural Equation Modeling Results

Notes: ***Hypothesis is support at p < 0.01 level. *Hypothesis is support at p < 0.05 level.

| Hypoth | eses | | Total Effect | Direct Effect | Indirect Effect | Results | |
|--------|---------------|----|--------------|---------------|-----------------|---------|--|
| ATCA | \rightarrow | BI | 0.44 | 0.44 | | Support | |
| | | | 100% | 100% | | | |
| EB | \rightarrow | BI | 0.18 | 0.08 | 0.10 | Support | |
| | | | 100% | 43% | 57% | | |
| EE | \rightarrow | BI | 0.23 | 0.14 | 0.09 | Support | |
| | | | 100% | 61% | 39% | | |
| НВ | \rightarrow | BI | 0.37 | 0.32 | 0.05 | Support | |
| | | | 100% | 87% | 13% | | |
| НМ | \rightarrow | BI | 0.26 | 0.18 | 0.08 | Support | |
| | | | 100% | 71% | 2 9 % | | |

Table 5 Summary of the Results

Discussion

This study discovered the conference app adoption behavior of conference attendees from an ecological perspective. Previous studies on technology adoption show that performance expectations are significant predictors of behavioral intentions. However, this study provides empirical evidence of ecological beliefs and attitude being a more significant key influencer in adopting Green IS, which contradicts results from other well-established theories/models that show technology's characteristics are crucial factors in determining the model type to assess the adoption behavior. Performance expectancy has shown to indirectly influence BI through ATCA; the direct effect of performance expectancy is of little significance. The logical reason is that attendees make a direct correlation between attending conferences to their work performance but conference app usage is not viewed as a necessity. Social influence, one of the least perceived characteristics to understand a technology adoption behavior,^{50,51} did not significantly affect behavioral intention. None of the three mechanisms that affect social influence: compliance, identification, and internalization⁸³ seem to work in the adoption of a conference app. For example, using a conference app does not essentially give people memberships or status to belong to a group as on LinkedIn. Using conference apps does not help people achieve leadership positions or recognitions within social groups, as confirmed in the previous research.^{84,85} Facilitating conditions, the third key concept, play an important role in traditional adoption models but play no significant role in the green IS context. Conference apps depend on users' resources over other resources, and apps generally have this dependency. Therefore, individuals would not anticipate facilitation assistance in using apps.

Attitude and ecological beliefs are two new predictors for green IS adoption that is found in GISAM.⁴⁴ The attitude was one of the earliest predictors of behavior and was proved in various contexts.⁵⁹ It is appropriate to mention the original TAM $model^{86}$ making attitude a direct prerequisite for behavioral intention, which was later removed. Davis et al⁵⁰ insisted that people in organizations shape intentions for actions rather than emotions, which lead to job performance because they make rational decisions that provide rewards (eg, high wages). The positive effect is not activated by the behavior (means-end) over time that was previously associated with performance-conditional rewards.⁸⁷ In the absence of effect, attitudes were excluded from the TAM because attitudes may not capture the effect of performance considerations on intentions. Enough evidence is given to accept the need for a green IS adoption model, where a rational-decision-based approach to technology adoption is not assumed. The Theory of Reasoned Action and Value Based Norm theory support attitude as a mediator between EB and BI.⁶⁷ Lastly, ecological beliefs were shown to have a significant impact on BI to adopt green IS. Both direct and indirect effects on BI to choose green IS were initiated. It was shown that the direct impact (43%) was lower than the indirect impact (57%). Though ecological beliefs did not directly influence behavioral intention, it is indirectly affected through attitude. This indicates that individual behaviors can be affected indirectly by affecting the EB that are held by a conference attendee. This finding can have high implications for marketing managers as it suggests that strategies, such as communication and promotional strategies, can be directed towards ecological beliefs to influence decision-making. The conference industry is directly influenced, as conference app adoption is proportional to profits. Finally, it is proven by the empirical results that assessment of green IS technology adoption differs from non-green technology, contrary to traditional technology adoption models. These results suggest that to adopt technologies, which are aimed at benefiting the wellbeing of others (eg, environment and community), individuals' ecological beliefs and attitude are key influencers in decision-making.

ATCA was discovered to be the most powerful predictor variable of BI, followed by HB, HM, EE, and EB.⁴⁴ Thus, conference organizers of managers may develop appropriate marketing strategies to trigger biosphere and altruistic values among consumers rather than self-interest values. In the past, companies have successfully motivated the altruism of customers to choose their products over their competitors due to there being elements of sustainability or renewability in the product or in a product's development.⁸⁸ Managers and event organizers can highlight the environmental benefits of converting to conference apps over the use of paper in advertisements as a marketing tactic to motivate customers to adopt the technology. Such green marketing tactics will paint a positive light on the organization in the minds of customers for their contributions to the greater good of the environment, which would generate profit. Not only would customers be motivated to adopt conference apps via green marketing but this would also place a necessity on rival companies or organizations to have sustainable practices in order to compete on the same level as green organizations.^{10,89}

In conclusion, the traditional technology adoption theories (eg, TAM and UTAUT) may not be sufficient in predicting green IS adoption in their current form. This is consistent with previous studies suggesting an extension of technology adoption model⁹⁰ and the inclusion of beliefs and values⁶⁷ to predict behavior. Furthermore, this study validates that context (conference) and product characteristics (green IS) are significant for understanding behavior, as suggested by.⁹¹

Limitations and Future Research Arena

This research concentrated on recognizing the link between crucial elements of UTAUT-2 in the context of green IS and extending them by supplementing EB and attitude. The recent study ignored difference among individuals between populations by looking at moderators (eg, age and gender). The moderating effects of experience, voluntariness, age, and gender as suggested by UTAUT^{45,46} were not assessed. It was suggested to test the effectiveness of the moderators in later studies to help exploit a theoretical understanding of actions on technology adoption from a green IS perspective. Additionally, "environmental concern" was proved to have a high interactive impact in environmental behavioral research,⁹² which is also recommended to be included in future research on this topic. This may help develop appropriate communication and marketing strategies by categorizing the conference organizer's profile and conference attendees. Thus, this research provides an understanding of why conference attendees have adopted conference apps, but does not provide a solution. Researchers should concentrate on establishing and testing relevant communication and marketing strategies about positive ATCA. For instance, when conference attendees are convinced that using conference app will help the natural environment appropriate persuasive message appeals,⁹³ it will have a huge direct impact on the conference and meetings industry.

Ethical Statement

The present research was conducted according to the guidelines of the Declaration of Helsinki and approved by the research program committee of Clarion University (IRB Proposal No. 37-19-20 from Clarion University).

Informed Consent Statement

Informed consent has been obtained from all subjects involved in this study to publish this paper.

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This paper was uploaded to the Iowa State University repository as a thesis in 2019 (March 26). <u>https://dr.lib.iastate.edu/</u>entities/publication/b6c1bb03-da33-40eb-a9ec-2b98fe148ea6.

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