Received: 24 August 2021 | Revised: 29 May 2022 | Accepted: 12 June 2022

DOI: 10.1002/bse.3188

RESEARCH ARTICLE

Business Strategy and the Environment

WILEY

Doing good for society! How purchasing green technology stimulates consumers toward green behavior: A structural equation modeling–artificial neural network approach

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Funding information

This research was partially funded by Key Project of National Social Science Foundation of China (21AGL014); Natural Science Foundation of Guangdong—Guangdong Basic and Applied Basic Research Foundation (2021A1515011894); Guangdong 13th-Five-Year-Plan Philosophical and Social Science Fund (GD20CGL28); and Shenzhen Science and Technology Program (JCYJ20210324093208022).

Abstract

Many countries have recognized the urgent need to address environmental problems, such as air pollution, waste disposal, global warming, and natural resource depletion, through the application of green technology. ANT Forest is one such technological initiative that has gained academic attention for its potential to minimize adverse environmental impacts and promote sustainable green behavior by involving people in eco-friendly activities. We built an integrated framework to understand users' continuance intention (CI) toward ANT Forest based on the expectation-confirmation model (ECM) and the task–technology fit model (TTFM). Using structural equation modeling (SEM), we analyzed survey data from 353 ANT Forest users. We then included the SEM results as components of an artificial neural network (ANN) to understand users' CI toward ANT Forest. The results from the SEM analysis revealed a series of sequential associations: (a) green habit as an individual characteristic and perceived entertainment as a technology characteristic significantly affect perceived green task–technology fit (GTTF), (b) perceived GTTF strongly and positively influences confirmation and CI, (c) confirmation is positively associated with users' satisfaction and delight, (d) delight significantly impacts satisfaction, and (e) perceived usefulness (PU) and satisfaction are strong determinants of CI. An ANN analysis further confirmed these findings. The study discusses managerial implications along with future research directions.

KEYWORDS

ANT Forest, delight, ECM, green habit, perceived entertainment, TTFM

1 | INTRODUCTION

The world faces several environmental problems, and many of these seem to worsen with time (Balasubramanian et al., 2021; Begum et al., 2022; Kumar et al., 2021; Thakur et al., 2021). Among the main reasons for such problems are individuals' activities and habits—for example, high carbon emissions, which negatively impact the environment (Kumar et al., 2020; Mi et al., 2021; Yang et al., 2018). Because individual behaviors have such a significant impact on environmental quality, several experts have recommended that individuals alter their personal behaviors to reduce their negative environmental impact (Ali et al., 2020; Arun et al., 2021; Dhir et al., 2021; Du et al., 2020). A crucial factor in this regard is individuals' agreeableness to engage in pro-environmental behaviors, such as walking, traveling by public transport, and paying utility fees online (Ashfaq et al., 2022; Zhang et al., 2021). Green technology (also referred to as environmental technology or clean technology) offers viable solutions and is leading the way for individuals to work towards maintaining environmental sustainability (Khan et al., 2021; Yang et al., 2020)—for example, by assisting in waste and carbon footprint reduction as well as water conservation (Wang et al., 2019). Green technology is defined as "products, equipment, and systems used to conserve the natural resources" (Fernando et al., 2016, p. 210). Because green technology supports an eco-friendly environment, it offers practical implications for addressing the critical environmental problems scholars and practitioners have acknowledged globally.

We focus on one promising green technology in China: ANT Forest (a tree-planting mini-program developed by Alipay and available in the Alipay app), which enables users to earn "virtual green energy points" by making low-carbon lifestyle choices. The ANT Forest app aims to plant trees by encouraging users to become involved in eco-friendly activities and thereby take tangible steps toward environmental regeneration (Zhang et al., 2020). The eco-friendly activities included in the app can be organized into five main categories: (1) green travel (e.g., walking and subway travel), (2) recycling (e.g., second-hand recycling), (3) paper and plastic reduction (e.g., online payment, QR code shopping, and plastic reduction), (4) efficient energy saving (e.g., electronic toll collection payment), and (5) travel reduction (e.g., online appointment registrations and online bill or ticket payment; Mi et al., 2021). To participate in these pro-environmental activities through the app, ANT Forest account holders must collect "green energy" points by performing sustainable behaviors and activities. ANT Forest users begin growing a "virtual tree" by collecting green energy points. Upon collecting a definite number of points, users can exchange them to plant a real tree in China through Alipay (Ashfaq, Zhang, et al., 2021).

ANT Forest has become a highly popular green behavior phenomenon since its launch in August 2016 as a corporate social responsibility project. Statistics indicate that ANT Forest gained 500 million users, planted 122 million offline trees, and reduced 7.92 million tons of carbon emissions as of August 2019, which is equivalent to saving 373 billion plastic bags and 11.6 billion kWh of electricity (Ministry of Ecological Environment, 2019). ANT Forest was awarded the "United Nations Champion of the Earth Award" in 2019 for these contributions toward the good of society (Wang & Yao, 2020). While ANT Forest, by virtue of its gamification design features, has demonstrated great potential to minimize adverse environmental impacts in China, stakeholders and academic scholars have raised concerns about sustaining its growth trajectory (Ashfaq et al., 2022; Zhang et al., 2020). For example, gamified information systems (IS) typically have short-term effects (Du et al., 2020) and are dependent on material rewards (external motivational factors), such as money to promote users' continued behavior (Zhou et al., 2021). When users do not receive such external incentives, they often disappear, making it impossible to consistently entice them to engage in gamified activities (Zhou et al., 2021).

When Herrmann and Kim (2017) conducted an empirical study by tracking whether users continue using fitness apps (at months 1, 3, and 5), they found that only 73.4% of users had completed the post-test survey for the five-month study. In the environmental preservation setting, users' continual performance of pro-environmental behaviors is exceedingly crucial to the achievement of the campaign's objective in the long term (Du et al., 2020). ANT Forest is also a recent gamified information system (IS), which encourages individuals to perform pro-environmental activities without offering them material incentives (i.e., their involvement is voluntary) to fulfill their social responsibility toward an eco-friendly environment (Ashfaq et al., 2022; Yang et al., 2018).

Due to its possible extent of contributions, a valid concern is whether users' acceptance of ANT Forest and their intentions for its continued usage will continue in the long run. However, scholars have devoted surprisingly limited attention to investigating this issue in the current literature. In fact, most of the prior studies have focused on understanding the motivation to participate in ANT Forest (Chen et al., 2020), while some have studied the reasons for adopting ANT Forest (Ashfaq, Zhang, et al., 2021). To the best of our knowledge, only a few studies have empirically examined the factors affecting users' continuance intention (CI) toward ANT Forest (Yang et al., 2018; Zhang et al., 2020). This is a critical gap because the long-term success of any technology (such as ANT Forest) depends on its continued usage (Bhattacherjee, 2001). Thus, to address this gap, our study pioneers the investigation of users' CI for ANT Forest by formulating a research model grounded in the expectation-confirmation model (ECM; Bhattacherjee, 2001) and the task–technology fit model (TTFM; Goodhue & Thompson, 1995). We raise and answer three research questions (RQs) drawn from these theories and gaps indicated in past literature;

RQ1. *How do green habit (as an individual characteristic) and perceived entertainment (as a technology characteristic) affect perceived green task–technology fit, which in turn may lead to users' continuance intention?*

RQ2. *How does confirmation influence users' emotional state (user delight and satisfaction)?*

RQ3. *Are perceived usefulness and user satisfaction associated with continuance intention?*

To address these RQs, we propose a two-step model leveraging the antecedents of perceived green task–technology fit

(GTTF; e.g., green habit and perceived entertainment) from the TTFM (Goodhue & Thompson, 1995) and the consequences of perceived GTTF (such as CI) from the ECM (Bhattacherjee, 2001). We test the proposed two-step model using cross-sectional data from 353 Chinese ANT Forest users. Our findings offer three significant contributions to the existing body of literature: (i) extending the theoretical underpinnings of the literature by using a dual theory lens, (ii) empirically deciphering factors that could help to sustain ANT Forest's growth, and (iii) methodologically advancing the literature by applying two statistical techniques (e.g., PLS-SEM and ANN). In these ways, we advance the existing understanding of the nuances of the relationship among the proposed variables.

The next section (Section 2) of the manuscript briefly discusses the theories used in this paper. The arguments for the tested hypotheses follow (Section 3). Next, we discuss the methodology and results (Sections 4 and 5) and deliberate on the findings (Section 6). The paper culminates in a discussion of the study's implications and the scope for further research (Section 7).

2 | THEORETICAL BACKGROUND

2.1 | Expectation-confirmation model (ECM)

The current study draws primarily upon the ECM (Bhattacherjee, 2001), which is derived from the expectation-confirmation theory (ECT; Oliver, 1980) and the technology acceptance model (TAM; Davis, 1989). The ECM is a well-known research model that has been used to understand the CI of IS/technology (IT) users in the post-adoption phases (Talwar et al., 2020). According to the model, successful IS/IT adoption depends on users' CI rather their initial acceptance (Bhattacherjee, 2001). Within the ECM paradigm, users' confirmation of expectations from the initial use of a product/service is a crucial predictor of perceived usefulness (PU) and satisfaction. Additionally, PU and satisfaction strongly influence users' CI (Bhattacherjee, 2001).

We adopted the ECM for two primary reasons. First, traditional theories, such as TAM and the unified theory of acceptance and use of technology (UTAUT), are often criticized—particularly in the context of new technologies' acceptance—for neglecting potential changes in users' behavior during the pre-and-post adoption phases (Bölen, 2020; McLean & Osei-Frimpong, 2019). However, the ECM is a well-accepted theory that also addresses the post-adoption phase, thereby transcending the critiques to which TAM and UTAUT are subject. Moreover, numerous studies in the technological domain have concluded that the ECM has a stronger explanatory power than the TAM in understanding users' CI towards IS products and services (Hou, 2016; Liao et al., 2009). Second, the ECM has been broadly used to explain CI for various technologies, such as fintech (Belanche et al., 2019), smartwatches (Bölen, 2020), mobile payments (Talwar et al., 2020), and artificial intelligence (AI)-based chatbot services (Ashfaq et al., 2020). Moreover, Ambalov (2018) analyzed 51 studies using the ECM through meta-analysis and concluded that the ECM is particularly well-suited to studying users' CI in various contexts.

2.2 | Task–technology fit model (TTFM)

The TTFM is another well-regarded theory that includes five key variables: "task characteristics, technology characteristics, task–technology fit, utilization, and individual performance" (Goodhue & Thompson, 1995). The TTFM suggests that individuals are more likely to use a technology when they believe that it fits a particular task. The model identifies the characteristics (e.g., individual, task, and technology) that enhance TTF, which, in turn, increases utilization and performance impact (Goodhue & Thompson, 1995).

Scholars have employed the TTFM to study user adoption intention in various domains, including knowledge management systems (Lin & Huang, 2008), mobile banking (Zhou et al., 2010), and mobile social media use (Li et al., 2019). Several studies have demonstrated the possibilities for integrating the TTFM with other theories to explain users' behavior and choices regarding technology use. For example, previous scholars have used the TTFM with the ECM to understand users' CI toward a technology (Sun et al., 2016) while others have used it with the UTAUT to explore mobile banking users' adoption (Zhou et al., 2010). Dishaw and Strong (1999) asserted that the integration of dual models (e.g., TTFM and TAM) provides a better model than either model alone; nevertheless, they concluded that the TTFM was more effective in predicting technology adoption. Because TAM does not explain new technologies' adoption, we combined the TTFM and the ECM to understand users' CI toward ANT Forest (McLean & Osei-Frimpong, 2019).

2.3 | Adopting a dual theoretical lens: Applying ECM and TTF to develop our research model

We adopted the ECM to explicate the factors affecting users' CI toward ANT Forest. We utilized the original model proposed by Bhattacherjee (2001), which suggests that confirmation of users' expectations and PU are predictors of satisfaction while PU and satisfaction are predictors of CI. However, we extend the ECM by adding a relevant construct: user delight. User delight plays a decisive role in improving satisfaction (Ali et al., 2016; Foroughi et al., 2019) and developing long-lasting relationships with consumers in the hospitality and tourism domains (Ali et al., 2018; Lee & Park, 2019). While tourism and hospitality research has extensively studied delight (Ali et al., 2016; Ariffin & Yahaya, 2013; Foroughi et al., 2019), to the best of our knowledge, no empirical study has specifically investigated users' delight in the context of green technology CI. We expect this variable to significantly influence ANT Forest users' CI because their experienced delight during its use may increase their satisfaction with the app and subsequently induce CI.

We used the TTFM to conceptualize green habit, an individual characteristic, and perceived entertainment, a technology characteristic, as potential influencers of GTTF and subsequently ANT Forest users' CI. Green habit can be a fundamental factor in reducing negative environmental impacts and promoting sustainable development. For example, users with green habits may prefer more eco-friendly products and services, such as cloth bags over plastic bags, online payment over paper money, and public transport over heavy automobiles, which eventually leads them to maintain green habits. Such users are thus more likely to adopt eco-friendly products or services, such as ANT Forest. Consistent with this reasoning, we expect green habit to play an essential role in understanding ANT Forest users' CI.

Further, we believe that users' adoption of a new technology will be greater when the technology is more entertaining (technology characteristic; Ma et al., 2019), thereby inducing users to continue using it (Ashfaq et al., 2020). Our contention aligns with prior research, which has also argued that users' adoption level increases when they find a product or service entertaining (San-Martín et al., 2015). Thus, perceived entertainment as a technology characteristic may also serve as a critical factor enhancing users' perceptions of GTTF. Through the TTFM, moreover, we introduce a new concept of perceived GTTF, adapting the model specifically to the context of the green environment (e.g., ANT Forest). In the context of ANT Forest usage, we argue that GTTF is a vital construct—i.e., when ANT Forest provides features and support that "fit" the requirements of green tasks and activities (Goodhue & Thompson, 1995). To be more specific, we propose GTTF as the conduit between green activity requirements, individual abilities, and ANT Forest functionality. We further maintain that when ANT Forest meets users' green task needs (e.g., walking and green travel), the likelihood of its continued use will be high.

3 | RESEARCH MODEL AND HYPOTHESES

Figure 1 illustrates the research model testing the hypothesized associations, and Table 1 offers the operational descriptions of all study variables. As discussed in previous sub-sections, we investigate green habit and perceived entertainment as the antecedents of GTTF, which we expect to influence confirmation and CI for ANT Forest users. Furthermore, we include confirmation, users' delight, and PU as the antecedents of users' satisfaction, while we test PU and users' satisfaction as the antecedents of CI. Finally, consistent with prior studies (Ashfaq, Zhang, et al., 2021; Mi et al., 2021; Tandon, Dhir et al., 2021; Tandon, Kaur, et al., 2021), we control for demographic variables, such as income, age, and education, to account for their possible confounding influence.

3.1 | Individual and technology characteristics: Green habit and perceived entertainment

Individual characteristics can often influence how efficiently and effectively someone uses a specific technology (Erskine et al., 2019; Sun et al., 2016). The prior literature has determined the influence of several individual characteristics/traits on TTF and found such characteristics to be significant influencers of technology use behavior. For example, Erskine et al. (2019) reported the significant effects of individual characteristic or trait (self-efficacy) on TTF (through a multi-group analysis), which, in turn, enhanced individual decision-making performance. Similarly, Sun et al. (2016) observed the significant influence of individual trait (mindfulness of technology adoption) on TTF and post-adoption decision-making. Additionally, Lin and Huang (2008) found a positive association between self-efficacy (an individual trait) and TTF in the knowledge management context. Consistent with prior research, we argue that green habit as an individual trait will also affect perceived GTTF. Earlier studies in

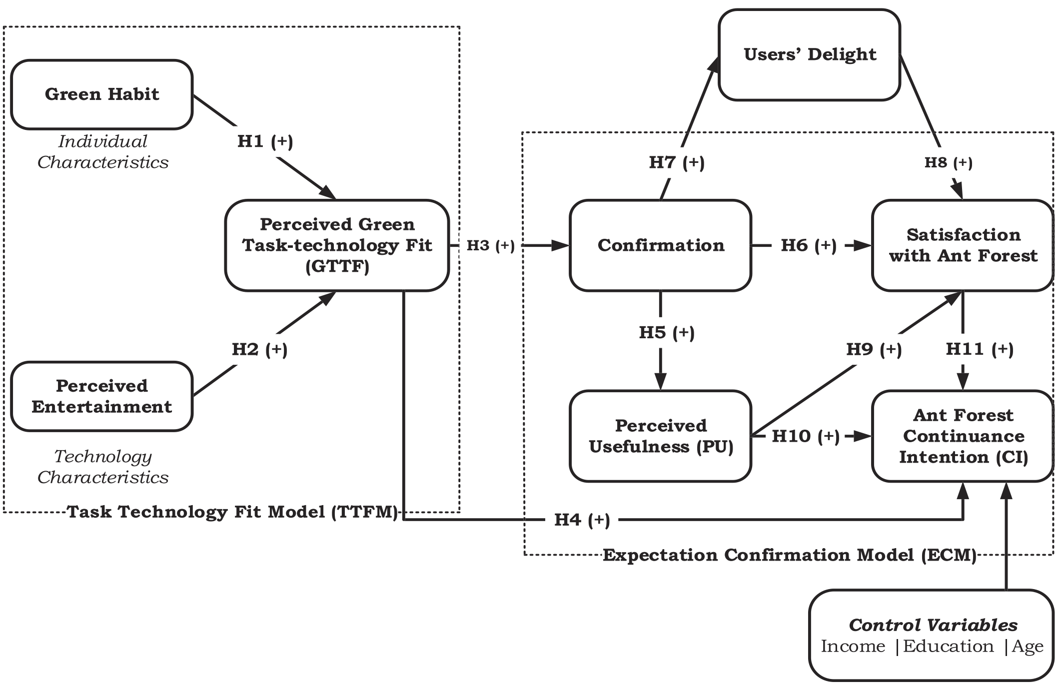

FIGURE 1 The hypothesized research model

TABLE 1 Operational description of variables

Variables	Operational description	Source
Green habit	Habit can be defined as "psychological dispositions to repeat past behavior."	(Neal et al., 2012, p. 492)
Perceived entertainment	Perceived entertainment is the capability to satisfy users' needs/desires for fun or amusement, anxiety relief, excitement, artistic enjoyment, or expressive pleasure.	(Ducoffe, 1996; Ma et al., 2019)
Perceived green task–technology fit	The degree to which ANT Forest green technology assists users in performing their green activities.	(Goodhue & Thompson, 1995)
Confirmation	The extent to which users' expectations are realized during the actual use of ANT Forest.	(Bhattacherjee, 2001)
Perceived usefulness	The extent to which ANT Forest users believe that their use of this green technology will enhance their contribution to environmental protection.	(Bhattacherjee, 2001; Chen & Lu, 2016)
User delight	An emotional response in which ANT Forest users are pleasantly surprised by the application's performance.	(Finn, 2005; Loureiro & Ribeiro, 2014)
Satisfaction	Satisfaction "refers to the user's overall feeling of the ANT Forest, based on one's own user experience."	(Zhang et al., 2020, p. 2)
Continuance intention	ANT Forest users' intention to continue using the application after its initial acceptance.	(Bhattacherjee, 2001)

technological settings suggest that when a specific technology is adequate to meet people's objectives, they adopt the technology as a habit (Veeramootoo et al., 2018; Wang et al., 2013).

Habit is an automatic response (Limayem et al., 2007), and individual's lives include myriad repetitive behaviors encompassing various habits (Wood & Rünger, 2016). For example, Wood et al. (2002) conducted an experimental study by recording what people did, thought about, and felt once per hour. They found that almost 43% of activities were carried out practically every day, and they were usually carried out the same way. In fact, people perform some behaviors habitually—for example, playing video games (Ventura et al., 2012), using blogs (Shiau & Luo, 2013) or mobile social apps (Hsiao et al., 2016), and wearing smartwatches (Bölen, 2020). Extrapolating from these studies, we argue that users with green habits will use ANT Forest habitually and perceive it to align with their inclinations to perform green activities. We therefore, propose the following:

> **H1.** Green habit is positively associated with perceived GTTF in the context of ANT Forest.

The TTFM postulates that technology characteristics (such as fun, mobility, and helpfulness) significantly influence TTF. The extant literature has found several technology characteristics to influence TTF. For example, Li et al. (2019) demonstrated the significant influence of mobility as a technological feature/characteristic for TTF in mobile social media use. Similarly, Lu and Yang (2014) noted the positive influence of Facebook's technological features (e.g., profiles, check-ins, messages, find friends, and likes) on TTF in the social media context. We adopt perceived entertainment to represent the technology characteristic of ANT Forest in the current study. We argue that when a user employs ANT Forest to promote a green environment, the user's pleasant experience can enhance his or her perceptions of GTTF. As an intrinsic motivation, perceived entertainment may also influence users' adoption of technologies (Ashfaq, Yun, & Yu, 2021) because users sometimes employ new technologies for entertainment rather than performance enrichment (e.g., PlayStation; Thong et al., 2006). For example, perceived entertainment is considered a crucial factor affecting social media adoption (Zolkepli & Kamarulzaman, 2015), news reading, and sharing on social media (Lee & Ma, 2012). Thus, extrapolating from existing research on technology users' behavior, we propose the following hypothesis:

> **H2.** Perceived entertainment is positively associated with perceived GTTF in the context of ANT Forest.

3.2 | Perceived green task–technology fit

Several authors have postulated that when technology functionalities and task requirements align, they enhance users' confirmation (Cheng, 2020; Sun et al., 2016) and adoption of the technology (Zhou et al., 2010). For example, scholars have determined the positive and significant direct association between TTF and confirmation among users of Robo-advisers (Cheng, 2020), e-learning systems (Lin & Wang, 2012), and cloud-based e-learning (Cheng, 2019). We extrapolate the findings of existing research to propose that perceived GTTF will be positively associated with confirmation. Thus, contingent on the ANT Forest's alignment of green task requirements (e.g., walking and cycling) and technology functionalities (e.g., online ticketing and bike-sharing), users will experience a high level of confirmation for the app. Thus, we hypothesize as follows:

> **H3.** Perceived GTTF is positively associated with confirmation in the context of ANT Forest.

We further contend that perceived GTTF will affect users' CI toward ANT Forest. TTF is an essential element linked to CI in the technological context (Kim & Song, 2021; Yuan et al., 2016). Prior research has highlighted that users with high TTF perceptions toward a particular technology will exhibit significantly higher CI (Kim &

Song, 2021; Lin, 2012; Yuan et al., 2016). For instance, Lin (2012) reported that TTF is an important antecedent of users' CI toward virtual learning systems. Likewise, Kim and Song (2021) found a strong association between TTF and CI in the context of massive open online courses (MOOCs). Consistent with previous studies that offer evidence for the relationship between TTF and CI, we assume that perceived GTTF will also enhance users' CI toward ANT Forest. Consequently, we propose the following:

> **H4.** Perceived GTTF is positively associated with CI toward ANT Forest.

3.3 | Confirmation

The ECM theorizes that the confirmation of users' expectations, that is, realizing the expected benefits from using a particular technology, will positively affect PU and users' satisfaction with the technology (Bhattacherjee, 2001). Prior research has supported this proposition in various instances of technology use. For example, Bölen (2020) reported that consumers' satisfaction with smartwatches is based primarily on the confirmation of their expectations. Furthermore, many previous studies on mobile instant messaging (Oghuma et al., 2016), social networking sites (Lin et al., 2017), fintech (Shiau et al., 2020), mobile learning (Al-Emran et al., 2020), and mobile wallets (Gupta et al., 2020) have revealed confirmation's positive relationship with satisfaction. Consistent with the extensive empirical support for the associations between confirmation, PU, and satisfaction, we propose that these relationships will be evident in the context of ANT Forest as well. Specifically, we believe that ANT Forest users' engagement in green activities and realization of the expected benefits of pro-environmental behavior will positively influence PU and users' satisfaction with the app. Hence, we postulate as follows:

> **H5.** Confirmation is positively associated with the PU of ANT Forest.

> **H6.** Confirmation is positively associated with users' satisfaction with ANT Forest.

Within the paradigm of expectancy-disconfirmation theory (Oliver, 1980), scholars have found that consumers are delighted when they are pleasantly surprised by their experiences (Ali et al., 2016). Delight is an emotional response toward customers' experiences (Finn, 2005; Verma, 2003), a reaction to pleasant surprises (e.g., joy, excitement; Kim & Mattila, 2013; Loureiro & Ribeiro, 2014), or simply a feeling of pleasure (Parasuraman et al., 2020). However, surprise is not a definitive threshold for delight, and research has shown that users' delight is contingent on the confirmation (Espejel et al., 2009; Kwong & Yau, 2002) as well as the transcendence of their expectations (Oliver et al., 1997) regarding a product or technology's use and performance. For example, scholars have argued that product or service marketers can increase user delight by managing users' expectations (Kwong & Yau, 2002). Consistent with prior research arguments, we propose that confirmation of ANT Forest users' expectations and the app's performance will be correlated with its users' delight. Accordingly, we propose the following:

> **H7.** Confirmation is positively associated with users' delight in ANT Forest.

Recent literature has devoted significant attention to the concept of delight (Ali et al., 2018; Parasuraman et al., 2020), highlighting its vital role in enhancing customer satisfaction (Ali et al., 2016), behavioral intentions (Foroughi et al., 2019), customer loyalty (Ahrholdt et al., 2017; Loureiro & Kastenholz, 2011), and repurchase intentions (Wang, 2011). A considerable amount of research has revealed that a high level of customer delight results in a higher level of customer satisfaction (Ali et al., 2016; Foroughi et al., 2019), which promotes long-term relationships with customers (Ali et al., 2018; Loureiro & Kastenholz, 2011). For example, Ali et al. (2016)) found a strong impact of passengers' delight on passengers' satisfaction with an international airport. In another study, Foroughi et al. (2019) reported the positive effect of customer delight on customer satisfaction with a fitness center. Consistent with these studies, we expect that users' delight will have a significant direct effect on users' satisfaction with ANT Forest and thus hypothesize as follows:

> **H8.** Users' delight is positively associated with their satisfaction with ANT Forest.

3.4 | Perceived usefulness

PU is a critical determinant of IS and IT-based systems' use (Boakye et al., 2014) and a primary element in technology acceptance behavior (Davis, 1989), technology service satisfaction (Ashfaq et al., 2020), and CI (Gupta et al., 2020; Talwar et al., 2020). Several studies have asserted that users' satisfaction with and perceived utility of technology are significantly associated with the likelihood that they will continue using it (Ashfaq et al., 2020; Bhattacherjee, 2001). Drawing on the ECM, the literature has determined that PU influences satisfaction and CI for technologies such as mobile payment (Talwar et al., 2020), AI agents (Ashfaq et al., 2020), and mobile wallets (Gupta et al., 2020). In addition, Koo et al. (2015) reported that the PU of smart green IT devices enhances users' intentions to continue using them. Consistent with the existing body of literature, we argue that the PU of ANT Forest will be positively associated with users' satisfaction and CI for this app and propose the following hypotheses:

> **H9.** PU is positively associated with users' satisfaction with ANT Forest.

> **H10.** PU is positively associated with users' CI toward ANT Forest.

3.5 | Satisfaction

Several scholars have reported that the long-standing profitable relationship between companies and users relies on users' satisfaction with and intention to continue using a technology (Bölen, 2020; Gupta et al., 2020). Satisfaction is indeed a core antecedent of users' behavioral intentions (Ashfaq et al., 2020), especially their CI for a technology (Bhattacherjee, 2001). In addition, it enhances customer trust (Konuk, 2018). For example, highly satisfied users of ANT Forest feel that their expectations are met, which leads them to continue using the app (Zhang et al., 2020). Thus, users' satisfaction with the technology determines users' CI (Bhattacherjee, 2001; Liébana-Cabanillas et al., 2019). Aligning with these prior studies, we hypothesize as follows:

H11. Satisfaction is positively associated with CI for ANT Forest.

4 | METHODOLOGY

4.1 | Measures

We used a 5-point Likert scale for all variables. To ensure that the items fit the study context, we made some adjustments to each item in the survey after soliciting the opinions of three academic experts (from the fields of human–computer interaction, psychology, and consumer behavior). Previous scales on TTF (Cheng, 2020; Zhou et al., 2010) and habit (Tam et al., 2018) were used and then modified carefully in our context. Perceived GTTF was measured using four items while green habit was measured using three items. We used seven items to measure perceived entertainment (Zolkepli & Kamarulzaman, 2015). Confirmation (Bhattacherjee, 2001), users' delight (Ali et al., 2016), and CI (Zhang et al., 2020) were estimated using three items while PU (Bhattacherjee, 2001) and satisfaction (Zhang et al., 2020) were measured using four items. Table 2 presents the items' means and standard deviations (SDs).

4.2 | Data collection

We employed WeChat and QQ to collect data from ANT Forest users in China through convenience sampling between January and February 2021. The questionnaire was designed on one of China's most commonly used platforms, that is, Wenjuanxing (Ashfaq, Zhang, et al., 2021). We sent the respondents' the link to the questionnaire using the afore-mentioned social network services (i.e., WeChat and QQ). The questionnaire included a screening question to ensure that only ANT Forest users answered the survey. To avoid respondent bias, the survey also communicated that respondents' participation was voluntary, they would receive no financial compensation for their responses, and we would protect their confidentiality. We sent the survey link to 578 potential respondents; of these, 375 completed the survey. After we removed 22 incomplete responses, 353 valid responses remained for the data analysis. We used the G*Power statistical tool to compute the adequate sample size (Erdfelder et al., 2009). G*Power analysis recommended a sample of 160 to test the model, and our working sample of 353 exceeded this recommendation. Of the participants in the sample, 172 were males, and 181 were females. The majority of the participants held a bachelor's degree (184 responses, 52.12%) while 19.45% held a master's degree (57 responses). The ages of most respondents (46.18%) fell between 21 and 30 years.

4.3 | Analytical tools

We used SPSS and SmartPLS 3 to analyze the data (Ringle et al., 2015). Specifically, we employed PLS-SEM and the artificial neural networks (ANN) approaches. Social science research frequently utilizes PLS-SEM to test complex models and the relationships among latent constructs (Sarstedt et al., 2017). In addition, this approach has several advantages over traditional techniques. For example, it is suitable for use with a small sample size (Sarstedt et al., 2017). More importantly, it allows researchers to determine discriminant validity (DV) using the heterotrait-monotrait (HTMT) ratio of correlations approach (Hair et al., 2019). We employed a two-step mechanism—the measurement model (for validity and reliability) and the structural model (for hypotheses testing)—for PLS-SEM (Chin, 2010; Hair et al., 2010).

According to Liébana-Cabanillas et al. (2017), the ANN is an important AI approach, and the extant literature reveals the increasing application of this technique in quantitative studies within the social sciences domain (Priyadarshinee et al., 2017; Raut et al., 2018; Siyal et al., 2020). The traditional linear statistical approaches, i.e., multiple regression analysis (MRA) and SEM, can only detect linear relationships; thus, they over-simplify complicated decision-making processes (Liébana-Cabanillas et al., 2017). Scholars have suggested using the ANN technique to address this issue and capitalize on ANN's advantages over conventional methods (Liébana-Cabanillas et al., 2017). For example, the ANN approach can detect both "linear and non-linear relationships" (Liébana-Cabanillas et al., 2017; Priyadarshinee et al., 2017). It also has a higher level of prediction than regression (Chiang et al., 2006). Although the ANN technique can identify "linear and non-linear associations," however, it cannot test hypotheses (Priyadarshinee et al., 2017). Thus, it is appropriate to use SEM for hypothesis testing and ANN for prediction (Raut et al., 2018; Siyal et al., 2020).

Various types of neural networks exist; these include multilayer perceptron (MLP) and radial basis function. However, MLP, which has proven to be a valuable tool for prediction, classification, and function approximation (Gardner & Dorling, 1998), is the most commonly used approach (Zafar, Shen, Shahzad, & Islam, 2021). This study employs the ANN approach using MLP through SPPS (version 25).

TABLE 2 Reliability and validity results

Variable	Items	Loadings	VIF	Mean	SD	Alpha	CR	AVE
Green habit						0.70	0.83	0.62
	GH1	0.76	1.48	3.22	1.30			
	GH2	0.87	1.65	3.30	1.30			
	GH3	0.72	1.22	3.41	1.22			
Perceived entertainment						0.92	0.93	0.67
	ENT1	0.83	2.67	3.24	1.08			
	ENT2	0.82	2.28	3.15	1.04			
	ENT3	0.83	2.52	3.20	1.09			
	ENT4	0.81	2.34	3.11	1.09			
	ENT5	0.85	2.66	3.18	1.10			
	ENT6	0.82	2.40	3.23	1.10			
	ENT7	0.75	2.00	3.16	1.12			
Perceived green task–technology fit						0.89	0.92	0.75
	GTTF1	0.90	2.95	3.45	1.07			
	GTTF2	0.88	2.48	3.46	1.11			
	GTTF3	0.88	2.51	3.38	1.12			
	GTTF4	0.80	1.97	3.37	1.13			
Confirmation						0.71	0.84	0.63
	CON1	0.79	1.35	3.42	1.25			
	CON2	0.80	1.43	3.46	1.27			
	CON3	0.80	1.40	3.38	1.21			
Perceived usefulness						0.75	0.84	0.58
	PU1	0.64	1.31	3.40	1.20			
	PU2	0.79	1.60	3.41	1.22			
	PU3	0.85	1.96	3.49	1.21			
	PU4	0.75	1.45	3.20	1.24			
Users' delight						0.72	0.84	0.64
	UL1	0.77	1.35	3.47	1.11			
	UL2	0.84	1.48	3.53	1.05			
	UL3	0.79	1.44	3.45	1.03			
Satisfaction						0.78	0.86	0.61
	SAT1	0.73	1.45	2.98	1.22			
	SAT2	0.87	1.85	3.10	1.30			
	SAT3	0.77	1.62	2.97	1.18			
	SAT4	0.74	1.47	3.00	1.20			
Continuance intention						0.71	0.84	0.65
	CI1	0.63	1.14	3.46	1.02			
	CI2	0.89	2.14	3.24	1.24			
	CI3	0.87	2.07	3.20	1.08			

5 | RESULTS

5.1 | Common method bias (CMB)

This study utilized two methods to check for CMB. Following recent studies (Bahta et al., 2021; Begum et al., 2021; Khan & Mir, 2019; Sadiq et al., 2021), we first employed Harman's single-factor test, which is a well-known and widely used technique (Harman, 1976). Podsakoff et al. (2012) posit that CMB can influence a study's results if a single factor accounts for more than half (>50%) of the variance. Second, we determined the variance inflation factor (VIF), which is another widely used approach (Kock, 2015). The literature holds that if the VIF for the indicators is less than 3.3, the model is free of CMB (Kock, 2015). The results showed that a single factor in our model accounted for 42.54% of the total variance—less than 50% (Harman, 1976). Further, all indicators reported a VIF of less than 3.3 (Table 2; Kock, 2015). Based on these results, we did not consider CMB to be a problem in our study.

5.2 | Reliability and validity

We confirmed the constructs' reliability with composite reliability (CR) and Cronbach's alpha (CA) values; according to Hair et al. (2019), values >0.70 are acceptable. As Table 2 shows, the values of CR and CA fulfilled the criteria. Next, we examined convergent validity (CV) to determine the constructs' validity using the average variance extracted (AVE) and factor loadings; Hair et al. (2019) recommend values of >0.50 for the AVE and >0.70 for the factor loadings. These values are adequate and satisfactory in our study (see Table 2). Finally, we evaluated the DV using the traditional Fornell and Larcker (1981) approach and the more recent HTMT ratio approach (Henseler et al., 2015). The traditional technique recommends that √AVEs exceed the constructs' inter-correlations, and the √AVEs in Table 3 successfully met the first criteria. The second approach proposes a cut-off value of 0.85 for HTMT, and as seen in Table 4, our values were less than the recommended threshold, thus meeting the second criterion (Henseler et al., 2015). Based on these results, our framework exhibited good validity and reliability.

TABLE 3 Discriminant validity

	1	2	3	4	5	6	7	8
Confirmation	0.80							
Continuance intention	0.25	0.80						
Perceived entertainment	0.15	0.47	0.82					
Green habit	0.11	0.30	0.21	0.79				
Green task–technology fit	0.40	0.62	0.60	0.25	0.86			
Perceived usefulness	0.05	0.33	0.23	0.53	0.17	0.76		
Satisfaction	0.21	0.42	0.36	0.28	0.50	0.24	0.78	
Users' delight	0.32	0.57	0.37	0.33	0.45	0.28	0.36	0.80

TABLE 4 HTMT analysis

	1	2	3	4	5	6	7	8
Confirmation								
Continuance intention	0.36							
Perceived entertainment	0.18	0.59						
Green habit	0.16	0.43	0.26					
Green task–technology fit	0.51	0.77	0.65	0.32				
Perceived usefulness	0.08	0.44	0.27	0.71	0.20			
Satisfaction	0.26	0.56	0.43	0.37	0.60	0.30		
Users' delight	0.44	0.81	0.45	0.47	0.55	0.37	0.46	

TABLE 5 Hypotheses testing

Hypotheses	β	*t* values	*p* values	Decision
H1: Green habit → Perceived GTTF	0.13	2.78	0.005	Accepted
H2: Perceived entertainment → Perceived GTTF	0.57	13.2	0.000	Accepted
H3: Perceived GTTF → Confirmation	0.40	8.15	0.000	Accepted
H4: Perceived GTTF → Continuance intention	0.53	9.77	0.000	Accepted
H5: Confirmation → Perceived usefulness	0.04 (ns)	0.82	0.409	Rejected
H6: Confirmation → Satisfaction	0.11	2.19	0.028	Accepted
H7: Confirmation → Users' delight	0.31	6.14	0.000	Accepted
H8: Users' delight → Satisfaction	0.28	5.21	0.000	Accepted
H9: Perceived usefulness → Satisfaction	0.15	2.78	0.005	Accepted
H10: Perceived usefulness → Continuance intention	0.21	5.10	0.000	Accepted
H11: Satisfaction → Continuance intention	0.14	2.78	0.004	Accepted

Abbreviation: ns, not supported.

5.3 | Hypotheses testing

We performed bootstrapping based on the 5000 subsamples to test the proposed hypotheses (Hair et al., 2019). All path coefficient results (except for confirmation → PU) were significant and supported. The results showed the significant influence of green habit ($\beta = 0.13$; $p = 0.005$) and perceived entertainment ($\beta = 0.57$; $p = 0.000$) on perceived GTTF, supporting H1 and H2. Further, the results revealed the significant effect of perceived GTTF on confirmation ($\beta = 0.40$; $p = 0.000$) and CI ($\beta = 0.53$; $p = 0.000$), while the relationship between confirmation and PU ($\beta = 0.04$; $p = 0.409$) was insignificant. Thus, we accepted H3 and H4 and rejected H5. As Table 5 shows, confirmation had a positive influence on satisfaction ($\beta = 0.11$; $p = 0.028$) and users' delight ($\beta = 0.31$; $p = 0.000$). Therefore, H6 and H7 received support. A closer look at Table 5 reveals that users' delight ($\beta = 0.28$; $p = 0.000$) and PU ($\beta = 0.15$; $p = 0.005$) significantly affected satisfaction, while PU ($\beta = 0.21$; $p = 0.000$) and satisfaction ($\beta = 0.14$; $p = 0.004$) significantly affected CI. Thus, H8, H9, H10, and H11 received support. As shown in Figure 2, the model explained 45% of the variance in CI, and there was no effect of any control variables on it.

5.4 | Effect size and predictive relevance

We employed Cohen's (1988) method to determine the effect size (F^2); an effect size can be small ($F^2 = 0.02$), medium ($F^2 = 0.15$), or large ($F^2 = 0.35$). The results showed that most paths had a small effect, while perceived entertainment and perceived GTTF had a large effect on the endogenous variables (Table 6). Next, we calculated Q^2 to measure the predictive accuracy of our model; while a $Q^2 > 0$ has predictive model relevance, a $Q^2 > 0.25$ indicates medium predictive accuracy, and a $Q^2 > 0.50$ represents high predictive accuracy (Hair et al., 2019). In our model, the Q^2 for all endogenous variables exceeded zero (Table 6), indicating acceptable outcomes.

5.5 | The artificial neural network approach

Importantly, we were only able to examine direct relationships wherein the dependent variable was considered the output and the predictors were integrated as inputs in the ANN approach. Having proposed a complex framework with many paths, we divided the model into multiple steps following the literature (Zafar, Shen, Shahzad, & Islam, 2021). In the first step, we treated the predictors of perceived GTTF (i.e., green habit and perceived entertainment) as input covariates. In the second step, we included the predictors of satisfaction (i.e., confirmation, delight, and PU) as input covariates. In the third step, we considered the predictors of CI (i.e., perceived GTTF, PU, and satisfaction) as input covariates. In the fourth and final step, we treated all variables in our model as input covariates to predict CI (see Table 7). Although we divided the model into four steps, Steps 1–3 were our primary focus because they included only those variables that, according to our research model, directly predict satisfaction or CI.

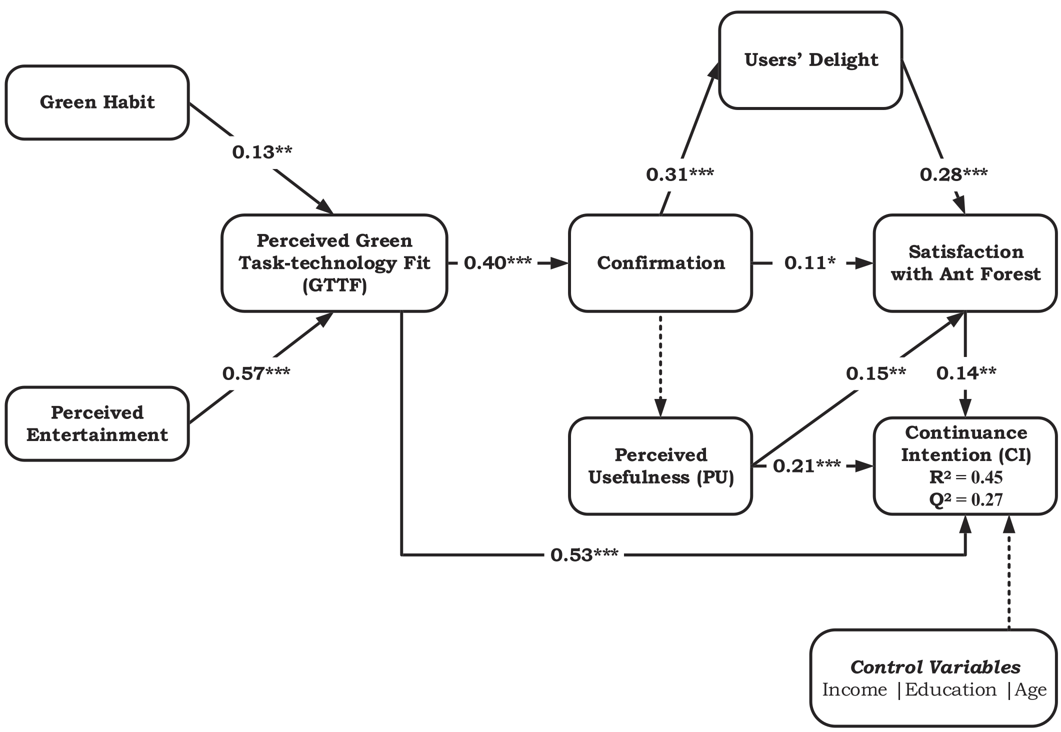

FIGURE 2 Results of the structural model. *Note*: Insignificant relationships are indicated with dotted lines.

TABLE 6 Predictive relevance and effect size

Endogenous variables	R^2	Q^2	Exogenous variables	Effect size (f^2)
Perceived GTTF	0.38	0.26	Green habit	0.03
			Perceived entertainment	0.50
Confirmation	0.16	0.10	Perceived GTTF	0.19
Perceived usefulness	0.02	0.00	Confirmation	0.00
Users' delight	0.10	0.06	Confirmation	0.11
Satisfaction	0.17	0.09	Confirmation	0.02
			Users' delight	0.08
			Perceived usefulness	0.03
Continuance intention	0.45	0.27	Perceived GTTF	0.38
			Perceived usefulness	0.08
			Satisfaction	0.02

TABLE 7 Validation results of ANN

	Step 1 Input covariates: GH, PE Output: GTTF		Step 2 Input covariates: CON, PU, UD Output: SAT		Step 3 Input covariates: GTTF, PU, SAT Output: CI		Step 4 Input covariates: GH, PE, GTTF, CON, PU, UD, SAT Output: CI	
Neural network	Training	Testing	Training	Testing	Training	Testing	Training	Testing
ANN1	0.1478	0.1695	0.1444	0.1482	0.1267	0.1236	0.1147	0.0858
ANN2	0.1552	0.1099	0.1406	0.1459	0.1210	0.1581	0.1096	0.0861
ANN3	0.1461	0.1601	0.1349	0.1404	0.1241	0.1006	0.1011	0.1231
ANN4	0.1494	0.1407	0.1409	0.1368	0.1304	0.1180	0.1077	0.1072
ANN5	0.1512	0.1564	0.1380	0.1295	0.1180	0.1573	0.1111	0.0896
ANN6	0.1505	0.1367	0.1427	0.1115	0.1277	0.1461	0.1114	0.0993
ANN7	0.1498	0.1315	0.1415	0.1137	0.1272	0.1021	0.1062	0.0996
ANN8	0.1437	0.1692	0.1433	0.1312	0.1225	0.1061	0.1082	0.0893
ANN9	0.1494	0.1503	0.1390	0.1523	0.1292	0.1447	0.0998	0.1043
ANN10	0.1485	0.1543	0.1307	0.1773	0.1294	0.1270	0.1084	0.1075
Average	0.1492	0.1479	0.1396	0.1387	0.1256	0.1284	0.1078	0.0991

Abbreviations: CI, continuance intention; CON, confirmation; GH, green habit; GTTF, perceived green task–technology fit; PE, perceived entertainment; PU, perceived usefulness; SAT, satisfaction; UD, user delight.

The MLP interface includes three sections: input, hidden, and output layers. We used a partition function to divide the data, with 90% of the data used for training and 10% for testing (Siyal et al., 2020). We employed the sigmoid function for both the hidden and output layers while conducting tenfold cross-validation to prevent the models from over-fitting with different nodes (Zafar, Shen, Shahzad, & Islam, 2021). As recommended by prior scholars, we calculated the root mean square error to assess predictive accuracy among the models (steps; Priyadarshinee et al., 2017; Raut et al., 2018; Siyal et al., 2020; Zafar, Shen, Shahzad, & Islam, 2021). The first step produced a 0.1492 value for training and a 0.1479 value for testing data for perceived GTTF. The second and third steps produced values of 0.1396 for training and 0.1387 for testing for satisfaction and 0.1256 for training and 0.1284 for testing for CI; these values are quite close and parallel, and the difference between training and testing results (average) is minimal. The results thus suggest that this study can confirm the model's satisfactory predictive accuracy (Zafar, Shen, Shahzad, & Islam, 2021). Table 7 provides the results for all networks along with the average outcomes.

5.6 | Sensitivity analysis

After the ANN analysis, we followed the literature (Yee-Loong Chong et al., 2015; Siyal et al., 2020; Zafar, Shen, Shahzad, & Islam, 2021) in performing a sensitivity analysis to calculate the average importance of the input covariate constructs and thereby predict the output for all 10 networks. Next, we checked the normalized importance by dividing each input covariate's importance by the highest importance value among the input constructs (Yee-Loong Chong et al., 2015). In our case, perceived entertainment had the highest normalized importance value for perceived GTTF; users' delight had the highest normalized importance value for satisfaction; and perceived GTTF had the highest normalized importance value for CI (Table 8, Steps 1–3).

In terms of outcomes, perceived entertainment was a strong predictor of perceived GTTF, followed by green habit (Table 8, Step 1). The second step revealed that users' delight was the strongest predictor of satisfaction, followed by PU. We found perceived GTTF to be a strong predictor of CI in the third step, followed by PU. We compared these results from the ANN analysis with the SEM results to determine whether these factors' importance, as reported in the ANN, were similar (Table 8 vs. Table 5). The results from the SEM analysis (Table 5) also indicated that entertainment ($\beta = 0.57$) had a stronger effect than green habit ($\beta = 0.13$) on perceived GTTF. Similar results were also found for all other relationships. Thus, the two analytical approaches, that is, SEM and ANN, offered similar results, which indicated that the associations among the variables proposed in our model were satisfactory.

6 | DISCUSSION

The results show that green habit (an individual characteristic) and perceived entertainment (a technology characteristic) positively influence perceived GTTF, which, in turn, strongly influences confirmation and CI; thus, our results support H1, H2, H3, and H4. Our findings are consistent with the extant literature on TTFM, showing that individual and technology characteristics influence TTF (e.g., Lin & Huang, 2008; Sun et al., 2016), which, in turn, leads to confirmation (Cheng, 2020; Lin & Wang, 2012) and CI (Lu & Yang, 2014; Yuan et al., 2016). The magnitude of the impact of perceived entertainment on perceived GTTF is greater than that of green habit. Similarly, perceived GTTF has a more substantial impact on CI compared to confirmation. The ANN analysis likewise supports these findings, which offer novel contributions to the existing knowledge regarding green technology (ANT Forest). These findings indicate that green technology users in China, particularly those with green habits, find the ANT Forest app to be entertaining and suitable for meeting their green task needs and securing the benefits they desire. If these conditions continue to be met, ANT Forest users in China may be inclined to continue using the app. The findings highlight the importance of considering individual and technology characteristics concurrently when examining the practical issues, such as loyalty and CI, that are vital for the parent organization's profitability and long-term growth in China.

Further, H5, H6, and H7 examined the impact of confirmation on PU, satisfaction, and users' delight, respectively. Consistent with the expectancy-disconfirmation theory, the ECM (Bhattacherjee, 2001), and existing ECM studies that have also reported a positive association between confirmation and satisfaction in various settings (Ashfaq et al., 2019; Gupta et al., 2020; Liao et al., 2009), the results supported H6 and H7 (Oliver, 1980). The ANN analysis likewise validates these findings, which make an important contribution by demonstrating the importance of users' expectations in promoting CI. The results indicate that these expectations are particularly related to the app's usefulness; therefore, ANT Forest users who have a greater expectation of confirmation in the post-adoption phase are likely to experience greater satisfaction and delight when using the app. These findings are especially significant because China is a technologically advanced country, and the findings can be applied to other green apps.

Contrary to Talwar et al.'s (2020) study, however, we did not find support for our hypothesis predicting a positive relationship between confirmation and PU (H5). Our findings, though, are consistent with a recent ECM-based study (Chauhan et al., 2021), which reported an insignificant association between confirmation and PU in the context of the digital classroom. We attribute our results to the fact that users may not focus on the personal benefits of ANT Forest's performance or productivity. Users may, instead, focus on ANT Forest's contributions to society and the environment and may thus emphasize the

TABLE 8 Normalized variable importance percentage

Predictors	Step 1 Input covariates: GH, PE Output: GTTF Normalized importance (%)	Step 2 Input covariates: CON, PU, UD Output: SAT Normalized importance (%)	Step 3 Input covariates: GTTF, PU, SAT Output: CI Normalized importance (%)	Step 4 Input covariates: GH, PE, GTTF, CON, PU, UD, SAT Output: CI Normalized importance (%)
GH	44.7	–	–	3.1
PE	100	–	–	22.8
GTTF	–	–	100	100.0
CON	–	44	–	7.1
PU	–	50.2	59.7	43.3
UD	–	100	–	95.0
SAT	–	–	26	13.4

Abbreviations: CI, continuance intention; CON, confirmation; GH, green habit; GTTF, perceived green task–technology fit; PE, perceived entertainment; PU, perceived usefulness; SAT, satisfaction; UD, user delight.

perceived delight and satisfaction they gain from contributing to environmental protection.

H8, which examined the positive relationship between users' delight and satisfaction, also received support from our SEM and ANN analyses. The findings here align with those of most past studies, including those in the tourism sector (Ali et al., 2016; Foroughi et al., 2019), which have noted delight's positive association with satisfaction. Our results thus confirm delight as a significant factor predicting users' satisfaction with ANT Forest, and our study raises important implications for further identifying the app-related components that may increase such delight. Further, the SEM and ANN results confirm a positive association between PU and satisfaction, thereby supporting H9. This finding, too, aligns with ECM theory and the relevant literature (Ashfaq et al., 2020; Bhattacherjee, 2001; Sun et al., 2016). The results suggest that PU is crucial for enhancing users' satisfaction and that positive post-usage experiences (e.g., high satisfaction) with ANT Forest are linked to the PU formed during the same stage (post-usage). These results highlight the need for a comprehensive outlook on the factors influencing consumer experiences across all stages of app usage.

Finally, our SEM and ANN analyses offer statistical support for H10 and H11, confirming the positive associations of PU and satisfaction with CI, respectively. These findings are consistent with the ECM (Bhattacherjee, 2001) and the extended ECM theoretical literature, especially in technological settings, including mobile payment (Gupta et al., 2020), AI-based digital service agents (Ashfaq et al., 2020), and mobile wallets (Talwar et al., 2020). Accordingly, the study findings suggest that higher technology PU and higher satisfaction levels may engender more positive CI toward the ANT Forest app. In our case (e.g., ANT Forest), these findings once again imply that post-usage PU and satisfaction drive users' CI toward ANT Forest.

7 | CONCLUDING REMARKS AND IMPLICATIONS

ANT Forest has been postulated as an innovative IT-enabled solution with great potential to promote sustainable green behavior by encouraging users to reduce their carbon footprints and, therefore, their detrimental environmental impacts. By integrating the ECM and the TTFM, we proposed a framework to investigate the factors that may influence users' CI toward this platform. Utilizing data collected from 353 ANT Forest users across China, we raised and answered three RQs by testing 11 hypotheses. Our findings provide statistical support for 10 of these hypotheses.

The findings from the present study confirm the significant positive associations of green habit and perceived entertainment with perceived GTTF, with perceived entertainment exhibiting a strong influence on perceived GTTF. In addition, the findings reveal the positive associations of perceived GTTF with users' expectation-confirmation and CI. Finally, the results demonstrate the significant positive associations of users' delight and PU with satisfaction, with PU and satisfaction further significantly predicting CI. The ANN analysis further supports these findings.

7.1 | Theoretical implications

Our findings raise several implications for theory. First, an essential contribution of our work is the concurrent application of the ECM and TTFM into an integrative framework to investigate the factors influencing the CI of ANT Forest users. Because theoretical grounding can increase the generalizability of research findings (Talwar et al., 2020), we believe that our study offers a foundational model for future scholars to explicate the nuances of users' behavior toward ANT Forest. We also posit that our framework can be extended to study users' experiences and CI for other ecologically-oriented mobile apps. Moreover, our consideration of new constructs (i.e., green habit, perceived GTTF, and delight) adds to the model's explanatory power, opening up ways to further adapt the theory to explore additional novel contexts and technologies.

Second, earlier studies of ANT Forest have primarily focused on the ways in which various gratifications, including social, environmental, and achievement gratifications (Mi et al., 2021), user experience (Ashfaq et al., 2022), and game elements, including game interaction and perceived cost (Zhang et al., 2020), affect users' adoption of the app. In contrast, we tested under-investigated antecedents of ANT Forest's CI (e.g., Ashfaq, Zhang, et al., 2021; Zhang et al., 2020), including green habit (an individual characteristic), perceived entertainment (a technology characteristic), and perceived GTTF. Thus, our work significantly extends the prior literature and adds to the current knowledge on CI for mobile apps and green technology.

Third, prior ECM studies have focused primarily on the associations among the constructs proposed in the ECM (e.g., Ashfaq et al., 2020; Gupta et al., 2020; Talwar et al., 2020). We extend this theory by including user delight, which has been identified as a critical influencer of user satisfaction in various contexts, including hospitality and tourism (Ali et al., 2018; Foroughi et al., 2019). To the best of our knowledge, however, scholars have not studied user delight as an antecedent to satisfaction in the context of green technology (e.g., ANT Forest). Thus, our findings extend the existing ECM literature by including this variable in the model and ascertaining its significant role.

Fourth, this study methodologically advances the literature by adopting two analytical techniques—ANN and PLS-SEM—and thereby offering a better understanding of the nuances of the relationships among the tested variables. Because ANN can generate a higher rate of prediction than regression (Chiang et al., 2006), our combination of ANN for prediction with SEM for regression (the most popularly used method in the extant literature) made our results more rigorous.

7.2 | Managerial implications

Our findings also provide critical practical implications for ANT Forest's mobile app developers and managers. First, recognizing that users with a higher level of green habits are more likely to utilize ANT Forest, app managers can introduce new green activities to attract new users and retain existing ones. For example, the app might reward users for visiting a professional service station to wash a vehicle with recycled water rather than washing the vehicle at home. Managers can also consider co-branding activities with other ecologically oriented businesses to generate additional opportunities for users to engage in green activities and habits. For example, ANT Forest users might receive coupons for restaurants that use recycled straws or packaging material.

Second, ANT Forest managers should focus on enhancing users' derived entertainment by introducing more exciting features to encourage the app's regular use, increase user delight, and improve perceived satisfaction. For example, providing official certificates and medals to users with the most activities could increase those users' satisfaction and delight levels (Ashfaq, Zhang, et al., 2021). Other features—for example, allowing users to donate energy to other users, co-plant with their favorite ones and assist family members, colleagues, and friends—may engage ANT Forest users socially and thereby increase their perceived entertainment.

Third, our study identifies confirmation, user delight, and PU as key drivers of users' satisfaction with ANT Forest. Therefore, ANT Forest managers and app developers should ensure that users' experiences and the service level the app provides continually exceed user expectations. Initiatives to this end might include gathering continuous user feedback via short surveys, analyzing comments on posts from various social media sites to understand users' needs (or problems), and devising novel solutions to fulfill (or solve) those needs (or problems).

Fourth, ANT Forest managers should ensure that the app is continuously useful in performing green activities to protect the environment. As users realize these green benefits, their CI for the app is likely to increase. Moreover, ANT Forest managers and research teams can conduct extensive user surveys to understand the specific factors that enhance user experience and satisfaction. Findings from these initiatives would be invaluable for enhancing the platform's affordances, introducing new green activities, confirming users' expectations, and creating delightful experiences.

Finally, we raise implications for ANT Forest's application to other developing economies, such as India and Pakistan, that are facing significant environmental problems. We cite these two counties as examples because Pakistan ranks third globally in air pollution (air quality index = 156) while India ranks fifth (air quality index = 151). These countries would thus significantly benefit from introducing green technology initiatives on a massive scale. Game developers in these countries can leverage our findings to develop new mobile apps similar to ANT Forest, thus encouraging green lifestyles and creating a platform that is beneficial for environmental sustainability.

7.3 | Limitations and future research scope

Despite our attempts to maintain a rigorous research approach, this study has certain limitations, which future scholars should address. First, we used convenience sampling, which is subject to certain biases. Scholars can address the limitations of our approach by employing more objective data collection methods, such as analyzing actual app usage patterns. Scholars can also utilize other forms of analysis (e.g., time lag analysis) to generate more objective findings while considering the stability of the associations over a specific period. Second, although our model explains a reasonable degree of variance in the data, scope exists for further improving the model's explanatory power. Future studies can add to the model by employing different theories or identifying additional relevant but uninvestigated variables via qualitative studies (e.g., interviews and focus groups). Finally, scholars can survey users who started but then stopped using ANT Forest to understand the factors and mechanisms influencing their decision to cease using the app (e.g., they can study discontinuance and use cessation factors). For example, researchers can employ the dual-factor model to concurrently understand the factors that hinder and enhance ANT Forest use (Tandon, Jabeen, et al., 2021). These exciting questions, which have yet to be explored, have the potential to add significantly to the current body of literature.

CONFLICT OF INTEREST

The authors report no conflict of interest related to this work.

AUTHOR CONTRIBUTIONS

Muhammad Ashfaq was responsible for the original study conceptualization and writing the first draft of the manuscript. Anushree Tandon was responsible for reviewing and writing the manuscript with the first author, revising the manuscript, and result interpretation. Qingyu Zhang was responsible for reviewing the manuscript drafts, revision, and formal data analysis. Fauzia Jabeen was responsible for formal data analysis, guiding the result interpretation and revising the manuscript drafts. Amandeep Dhir validated the data analysis and guided the manuscript writing in the original draft and subsequent revisions.

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How to cite this article: Ashfaq, M., Tandon, A., Zhang, Q., Jabeen, F., & Dhir, A. (2022). Doing good for society! How purchasing green technology stimulates consumers toward green behavior: A structural equation modeling–artificial neural network approach. *Business Strategy and the Environment*, 1–18. https://doi.org/10.1002/bse.3188