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When East meets West: Understanding residents' home energy management system adoption intention and willingness to pay in Japan and the United States

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ABSTRACT

A Home Energy Management System (HEMS) is a system for increasing energy efficiency and demand flexibility. Despite the steady advances in HEMS technology, there are still several barriers impeding its acceptance. This paper investigates the multifaceted factors influencing residents' willingness to adopt and pay for HEMS in New York (N.Y.) and Tokyo areas. Our findings suggest that perceived usefulness, a favorable attitude toward HEMS, and social norms are positively associated with adoption intention in both areas. While lacking perceived behavioral control is a barrier for adoption intention in Tokyo, privacy and cybersecurity concerns are barriers for N.Y. residents. The majority of residents indicate a strong or moderately strong adoption intention even when their cost concerns are great. Cost concerns, however, are associated with low willingness to pay (WTP) in both areas, as is perceived ease of use. Technology anxiety only negatively affects WTP in Tokyo. Positive attitudes, social norms, and perceived usefulness are positive predictors of WTP in both areas. Younger and higher-income were associated with higher WTP only in N.Y. Unexpectedly, trust in utilities is not a significant predictor of adoption intention or WTP. Finally, this study provides useful policy recommendations for promoting HEMS in two distinct cultures.

1. Introduction

A Home Energy Management System (HEMS), or a "Smart Home," is a system that enables consumers to manage energy use more efficiently by changing their behavior. HEMS products generally combine both hardware and software to monitor energy use and provide feedback to consumers [1]. HEMS hardware typically consists of sensors and controllers (e.g., smart thermostats, smart outlets, smart switches), while software features may include a monitoring system, notifications, automated control, demand response (DR), security protection, and data analysis/visualization [2]. HEMS can use advanced intelligent monitoring and controls to optimize energy use while maintaining consumer comfort [3,4]. When connected to the power grid, HEMS allows for two-way communication between energy providers and customers [5]. A smart meter is essential for enabling HEMS to employ these features [6,7]. A critical benefit of HEMS is its ability to facilitate DR programs. DR refers to customers using less energy during high-demand/high-price periods (i.e., peak hours) or shifting their energy use to off-peak hours in order to lower electricity costs or receive financial rewards [8]. HEMS can help change customer electricity-use patterns by keeping them apprised of different time-dependent pricing schemes such as time-of-use (TOU), critical peak pricing (CPP), and real-time pricing (RTP) [8,9]. HEMS' utilization of DR programs means it can better automate and optimize energy use at home, lower the wholesale price of electricity, ensure the stability of the power grid [8,10], and improve energy efficiency [10]. Feedback from HEMS may also induce more environmentally-conscious behavior [11]. In the wake of the Great Kanto Earthquake and Tsunami of 2011, Japan has taken extensive measures to make its energy system more resilient and efficient, including subsidizing HEMS as a means of reaching these goals. As a

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result, Japan has seen a measurable reduction in energy consumption since 2011 [12].

Due to its benefits, the HEMS market is expected to grow exponentially in the coming years. At the present time, however, although a majority of households may be interested in the benefits of HEMS, most are still not willing to pay for it. Willingness to pay (WTP) is a term coined in economic literature [13], and as some research highlights, it does not always coincide with adoption intention [14]. Consumers express low WTP for smart home-related technologies due to high-cost concerns [15,16], but scholars have found that the two strongest predictors of WTP for smart meters are concerns about data protection and intention to change consumption behavior [16]. In addition, the perceived benefits must clearly outweigh perceived risks before consumers will actually take actions [17]. Researchers have also found that socio-demographic characteristics have little to no influence on the decision to invest in smart home capabilities, with the sole exception of household income [15]. While WTP for renewable energy sources is related to income, it is also positively related to residence size, energy consumption, and previous experience of electricity shortage [20,21]; it is negatively related to the price of green electricity [21,22]. Other studies report that general energy knowledge [18], knowledge of renewable energy resources [19], and belief in climate change [18] increases WTP.

Despite its technical, economic, and environmental benefits, many users are still unwilling to switch to these systems; therefore, researchers need to address the various factors inhibiting consumers from adopting or paying for HEMS. These concerns include reliability, privacy and cybersecurity concerns, potential loss of control, lack of trust in energy providers, anxiety about using technology, concerns about changing habits, and a lack of WTP, as well as some other, more peripheral concerns [21]. As an added obstacle, many people live in older properties that are incompatible with smart technologies. With these potential barriers in mind, this paper attempts to address residents' willingness to adopt and pay for HEMS from a multi-dimensional social-technical perspective, with a special focus on cultural differences in technology adoption. In this study, we compare the differences in HEMS adoption intention and WTP in one urban center of Western culture (New York) and one of Eastern culture (Tokyo). Other researchers have compared WTP for various commodities in Tokyo and New York, and notable differences between the two cultures have been found [22]. Based on the previous literature, we propose that these two regions will react differently toward HEMS technology based on how culture shapes thoughts, attitudes, perceptions, and behavior.

2. Theoretical framework

This paper proposes an integrative approach to addressing the multi-dimensionality of technology adoption and WTP, with an emphasis on the interactions among technology attributes, users' attitudes, and social influence. Existing theories, especially the theory of planned behavior [23] and the technology acceptance model [24], have had considerable success in predicting behavior in specific domains. All models, however, have thus far struggled to consistently predict behaviors in disparate domains. Combining existing theories, therefore, would seem to be the most promising approach to building a model which can explain patterns of technology adoption [7,25] and pro-environmental behaviors [26] in diverse areas. Integrating all potential predictors into one model can also help decision-makers and planners who are considering all relevant aspects when designing strategies for behavioral intervention [27].

Recently, researchers have proposed the importance of merging the technical aspects of energy systems with concepts from the social sciences to form a socio-technical perspective that better reflects consumer engagement [28–31] and promotes the transitions away from fossil-fuel-based energy systems [32,33]. Modifying consumer habits to encourage more efficient energy use is a complicated process, requiring systematic changes to the way society thinks about technology, infrastructure, energy systems, governance, culture, and practices [32,33]. Although we are not directly addressing the energy technology transition, increased focus on consumers' perceptions and attitudes toward technology can potentially impact consumption habits and, eventually, society itself. This social-technical view considers HEMS as the next stage of development in the ongoing electrification of everyday life [33]. It emphasizes how the use and integration of technologies are socially constructed rather than based only on functional benefits. Here, the focus is not on how new home appliances can be controlled, nor on specific examples of user-technology interaction, but rather on the ways in which HEMS can affect pre-existing relationships between the structural (e.g., utilities and power systems) and agency (e.g., users' attitudes) levels. Through this framework, HEMS' impact on broader social-technical mechanisms can be highlighted. Before outlining our integrated framework, we will introduce the original three theoretical frameworks for explaining technology adoption which serve as its basis, as well as the related cultural differences which inform them.

2.1. Theory of planned behavior, technology acceptance model, and technology acceptance framework

The first theory we incorporate into our integrated model is Ajzen's (1991) theory of planned behavior (TPB) [23]. The TPB, a rational decision-making framework, is one of the best-known theories of how social-psychological factors influence behavioral intention and behavior itself. The TPB argues that an intention is formed by weighing attitudes (positive or negative evaluation of a behavior), subjective norms (expected approval from significant others), and perceived behavioral control (PBC, perceived difficulty or ease in performing a behavior). The more substantial the intention, the more likely the behavior is to be executed. The TPB is widely used in predicting technology adoption [40] as well as a variety of pro-environmental behaviors [34], such as energy conservation [35–37] and carbon reduction [38–40]. Although the evidence behind the TPB is valid, scholars have emphasized that the traditional TPB has limitations in predicting both repetitive behavior (e.g., habits) and the impact that the objective situational constraints of behavior can have on PBC [27]. In fact, there is an extended TPB model which has been shown to have better explanatory power and perform better at predicting the adoption of smart homes [41] and other renewable energy technologies [42]. By extending the TPB, scholars have found that factors such as mobility, security and privacy risk, and trust in service providers do, in fact, influence behavioral intention to use smart home technology [41].

The second theory is the technology acceptance model, or TAM. The TAM was initially proposed for information technology (IT) and is now considered one of the most useful models for explaining the factors which influence technology adoption and usage [43–45]. The TAM states that beliefs about usefulness and ease of use are the primary determinants of individuals' attitudes toward using a particular technology or system, which in turn impacts their intention to use the technology [24]. Perceived usefulness (PU) and perceived ease of use (PEOU), however, may not fully explain users' motives or attitudes, especially with the present tendency toward rapid introduction of increasingly complex new technologies [43]. Accordingly, additional factors such as habits, enjoyment, motivation, computer self-efficacy, social influence, and demographics have been proposed as supplements to give the model more nuance [43–45]. A number of scholars have integrated several related theories to enhance the efficacy of TAM. For example, one study [46] combined the TAM with Schwartz's norm activation model (NAM) [47] to examine customers' acceptance of smart grid technologies across several European countries, and discovered that adding personal norms to the TAM increases the explained variation in the rates of customer acceptance. After finding that attitudes mediate the relationship between the TAM variables, researchers of another study [48] combined TAM and TPB, creating an integrated model with increased explanatory power. Researchers have also begun to develop more holistic models for smart energy technology acceptance based on frameworks established by the TPB, the TAM, and the NAM [49].

The third theoretical model is Huijts, Molin, and Steg's technology acceptance framework (TAF), which can be used to explain sustainable energy technology acceptance [50]. The TAF incorporates elements of the TPB and the NAM, along with other social-psychological variables based on a review of psychological theories and empirical studies on technology acceptance. Specifically, the TAF proposes that the intention to accept sustainable energy technologies is influenced by attitudes, PBC, and both social and personal norms. Attitudes are affected by perceived costs, risks and benefits, positive and negative feelings in response to technology, trust, and procedural and distributive fairness [50]. Personal norms are affected by perceived costs, risks and benefits, outcome efficacy, and awareness of the unfavorable consequences, which may arise from not accepting the new technology. Based on the TAF, Chen, Xu, and Arpan performed a study which found that perceived usefulness, privacy risk, awareness of consequences, and trust in utility companies all influence residents' intention to adopt smart meters in the U.S. [7]. Huijts and colleagues [51] adopted the TAF to explain the psychological determinants of Dutch citizens' likelihood to accept hydrogen fuel station implementation, and found that personal norms, positive affect, and perceived positive effects of the technology are the three most influential factors determining acceptance.

Basing our approach on the TPB, the TAM, the TAF, and empirical studies in technology adoption, we propose an integrative technology-perception-system framework which highlights three dimensions: (1) technology attribute interaction, (2) attitudes, behavior, and social influence, and (3) system and infrastructure expectations. In addition, we have adopted a theoretical framework which addresses the cultural difference in technology adoption.

2.2. Dimension one: technology attribute interaction

The first dimension emphasizes the process of interacting with technology attributes and impacting individuals' likelihood of adopting HEMS. It includes the TAM variables of PU, PEOU, and two additional variables: perceived cost concerns and technology anxiety.

2.2.1. PU and PEOU

The TAM suggests that users' behavioral intentions, attitudes, PU, and PEOU influence users' actual use of a technology system. PU refers to an individual's subjective assessment of the new technology in a specific task-related context in terms of its ability to enhance job performance [52]. Similarly, PU in the TAF is conceptualized as the benefit of the new technology, which is predicted to be positively associated with technology acceptance. PEOU is the degree to which an individual believes that using a particular technology system will require little to no effort [24]. Therefore, the easier a system is to use, the more it can help users. Both PU and PEOU have been shown to directly impact residents' intention to accept smart grid technology in Korea [49]. In Denmark, Norway, and Switzerland, Toft and colleagues [46] have found that individuals are only likely to accept smart grid technology if they believe it will have a positive social and environmental impact. Another study in the U.S. also found that PU had a strong direct effect on support and willingness to adopt smart meters [7]. Regarding HEMS acceptance, both PU and PEOU positively influence the intention to accept; PU has a higher impact than PEOU, and PU and PEOU are positively correlated [53].

Unlike many previous studies, we investigate the variable of PU in respect to a specific technology function instead of its general usefulness. Since one important function of HEMS is automation, and automation has been widely accepted in smart homes in recent years [54], we examine PU in relation to the automatic control of household appliances without human interventions. Luor and colleagues suggested that when participants perceive the automation of smart homes as useful, they exhibit a positive attitude toward using these functions [54]. However, automation is not always perceived as a positive feature. Some interviewees reported that automation requires a new form of labor to save energy, contradicting the common belief that customers essentially equate automation with increased convenience [55]. Other concerns were discovered in a qualitative study which suggests that automation can cause consumer concerns related to losing personal control due to increased dependence on smart home technology, as well as the interruption of daily household routines and negative health effects resulting from the reduced physical activity that accompanies automation [21]. From such findings, it would seem that the influence of automation control on HEMS acceptance requires further investigation.

2.2.2. Technology anxiety

It is generally agreed that anxiety about technology can influence an individual's decision to use that specific technology while lowering overall satisfaction [56]. Gelbrich and Sattler found that technology self-efficacy influences technology anxiety, which, in turn, influences PEOU and overall intention to use [57]. Anxiety has been widely studied in relation to the adoption of computer technology, and evidence shows that computer anxiety significantly affects individual attitudes toward computers [58]. Anxiety levels also vary based on residence location, education, income level, prior computer use, length of computer use, and computer availability in the home [59]. The bulk of the technology anxiety literature focuses on computer technology, with little focus on how it impacts the adoption of HEMS, even though anxiety has been shown to be a barrier to adopting other technologies [21,53,55]. In our research, we were only able to find a single article explicitly outlining anxiety about HEMS [60]. HEMS is still considered a new technology by most households, and scholars suggest that those with lower computer literacy and the elderly might experience higher anxiety due to their lack of related experience [61]. For our purposes, technology anxiety is defined as a feeling of worry, nervousness, or discomfort while using HEMS and interacting with its interface and functions. This paper is interested in determining if technology anxiety will affect adoption intention and WTP.

2.2.3. Cost concerns

In classical economics, value maximization is a key assumption for predicting willingness to adopt a new technology or pay for a service [62]. Recently, some researchers have extended the TAM by including perceived cost (or price value) as an additional predictor of acceptance [45]. The TAF also recognizes the influence of costs, both monetary and non-monetary, on technology acceptance [50]. Cost concerns are common among consumers, and they can negatively influence consumers' perceptions, attitudes [63], and intention to adopt a new technology [64]. In the realm of HEMS literature, customers express concerns about potentially high front-end investment, maintenance, and additional service costs. Some potential users are concerned about several types of costs including installation, repair, maintenance, and rising electricity prices [65]. With such concerns in mind, this study focuses on monetary concerns related to the use and maintenance of HEMS services.

2.3. Dimension two: attitudes, behaviors, and social influence

The second dimension in our framework focuses on the concepts of attitudes, energy-related behaviors, and social influence. We include the three main TPB variables: attitudes, PBC, and social norms (indicating social influence) alongside energy-efficiency behaviors.

2.3.1. Attitudes, PBC, and social norms

We focus on attitudes, PBC, and social norms as the key personal and social factors behind HEMS adoption and willingness to pay. An attitude is an essential antecedent of intention to perform a behavior based on the TPB and the TAM. Empirically, attitudes are an essential factor influencing the intention to adopt smart meters [7], renewable technologies [48], and smart homes [41,54]. One study has indicated that positive attitudes towards the entertainment and automation functions of smart homes is negatively related to perceiving the cost of utilizing a smart home as a problem [54]. Additionally, attitudes have been found to be a stronger predictor of using a smart home service than subjective norms or PBC; PBC has the weakest effect of the three, but is still significant [41]. Other researchers have found a positive relationship between PBC and intention to use technology such as smart meters [7] and smart home services [66]. Moreover, PBC has a positive influence on the intention to adopt photovoltaic systems [67].

Social influences, such as norms and social expectations, are widely established as essential factors which influence consumers' intention to support or purchase a new technology [40,41,52,68,70]. Ajzen has incorporated social influence into the research model by including subjective norms, which is defined as perceived social pressure from the majority of significant others or beliefs about how significant others expect an individual to behave in a given situation [69]. Studies have shown that subjective norms are critical to both encouraging and discouraging investment in energy-efficient technologies [70] and smart home service adoption [41]. As for the adoption of renewable energy technologies, social norms and underlying social motives also play an essential role. For example, subjective norms (perceived pressure from significant others) have been shown to accurately predict the intention to oppose wind farms [71]. Similarly, the purchase of PV systems by peers and neighbors has been shown to be a positive motive for individuals to subsequently purchase their own PV systems [67]. Subjective norms also predict consumers' likelihood to adopt solar hot water heaters and alternative fuel vehicles [40]. Since the HEMS market is still in an early stage, potential users may be motivated to accept HEMS as a result of important referents' opinions or attitudes. Therefore, this study proposes that subjective norms affect the intention to buy and use HEMS.

2.3.2. Energy efficiency behavior

Given that the success of HEMS systems is dependent on energy-related habits and behaviors that users form around these technologies, the end user's experience and daily practices related to HEMS are of critical importance. Practices or prior experiences with technology can influence users' attitudes toward technology and future adoption behaviors [45]. Studies also suggest that models which include consumers' previous energy habits can improve the predictive power of projected future energy usage [73,74]. Additional research indicates that past behaviors and habits serve as a precursor to continued pro-environmental actions [73]. Since the majority of our participants have had no previous experience with HEMS, which is only one type of energy-efficiency technology, we have tried to gauge consumers' likelihood to be positively inclined towards HEMS based on previous energy-efficiency behaviors, including the previous purchase of energy-efficient light bulbs and appliances.

2.4. Dimension three: system and infrastructure expectations

2.4.1. Trust in utilities

This study considers utility companies and power providers as essential to the public-service power infrastructure. Unlike regular organizations, utility companies are subject to several forms of public control and regulation, from the policies of local community-based groups to the mandates of statewide government. Therefore, this study treats the relationship between utilities and customers as the nexus of interaction between the system and the individual. This study defines trust in utilities as the extent that HEMS users believe utilities or energy providers are honest, dependable, and can reliably provide quality services. Trust is one of the central constructs in Huijts et al.'s TAF, and is generally recognized as influencing perceived benefits, risks, costs, and affect, which in turn shape an individual's attitudes and personal norms and, as a result, influences adoption intention [50]. Trust is considered critical in determining whether a consumer will adopt a cyber system environment and energy programs promoted by utilities because this trust helps consumers "overcome perceptions of uncertainty and risk" and makes them more likely to participate in "trust-related behaviors" [74]. Trust has been shown to be very effective in attenuating the risk perception in novel technologies like CO2 storage [75]. Specifically for our case, if a user has a high level of trust in the utility provider, he/she is less likely to worry that the provider may violate its obligations, thus reducing their risk beliefs [76].

Lack of trust in energy suppliers poses a sizable threat to the acceptance of HEMS [2] and smart homes [2,76], as well as smart grid technologies and smart meters [7,21,41,49,77]. Chen and her colleagues went as far as to suggest that customers, even those who do not understand smart meter technology, are more likely to adopt the meters if they trust their utilities [7]. Further, trust can influence perceptions of other technological attributes (e.g., perceived costs, risks, and benefits) [7] and attitudes, subjective norms, and PBC [41,54], mitigating concerns regarding other aspects of the technology. When customers regard them with trust, they are more willing to offer personal information to utilities [54], whereas mistrust makes customers question the motives of energy suppliers' energy-saving campaigns and causes other serious issues [21,76]. Overall, the evidence indicates that potential users not only focus on the technological aspects but also on subjective impressions of institutions and systems.

2.4.2. Privacy and cybersecurity concerns

With an increasing amount of personal information being collected and communicated through wireless networks, concerns about privacy and cybersecurity have increased. Featherman and Pavlou defined privacy risk as "the potential loss of control over personal information, such as when information about an individual is used without that person's knowledge," and concerns about this issue have been demonstrated to be an important aspect of risk perception, which, in turn, reduces PU in TAM and discourages adoption [78]. The present study considers privacy and cybersecurity risk within the system infrastructure. Security issues typically deal with the cryptographic techniques used to secure communication channels by ensuring message integrity, confidentiality, and authenticity [79], and consumer trust issues generally involve perceived risks related to the collection, storing, distribution, and use of personal information [79]. From a psychological perspective, privacy and security concerns are significant deterrents to smart meter and smart home adoption [7,21,33,77,78]. In one study, the majority of participants expressed privacy concerns, unprompted [81]. If consumers do not trust their energy suppliers, their concerns about the privacy of personal data are likely to be even greater, suggesting a close link between trust and privacy concerns [77]. Privacy concerns have been shown to be the most important antecedent of risk beliefs, which in turn predict smart meter adoption [82]. In other words, perceived cyber insecurity is one of the key barriers to implementing smart grid technology because of consumers' reservations regarding data collection and concerns about power consumption data leakage [49]. Moreover, the fear of personal data falling into the 'wrong hands' or the system being hacked by criminals can make users leery of smart home services [41]. Customers have also expressed concerns about criminals breaking into their houses, utilities misusing personal information, law enforcement surveilling residences, etc. [73,79–81]. One risk-analysis study states that if a more robust security and privacy model were incorporated into the HEMS design, then many consumer concerns could be mitigated [83].

In sum, the majority of non-technical studies relating to HEMS and smart homes focus on privacy concerns in personal data linkage or misuse of personal information. Our research focuses on privacy and cybersecurity risks, including concerns about data privacy, misuse of data, and system hacking. More importantly, this study explores cultural differences in individuals' attitudes toward privacy and cybersecurity based on Hofstede's cultural dimensions (see more discussion in 2.5; [84–87]).

2.4.3. Influence of socio-demographics

Socio-demographic factors including age, gender, and income, along with culture, can impact an individual's willingness to adopt new technology [7]. For instance, Tucker found that young people are generally more likely to adopt new technologies, with over fifty percent self-identifying as major adopters of new technologies [88]. However, Sanguinetti et al. reported that adopters of smart home technology are more likely to be older, male, and have relatively high incomes [89]. These findings suggest that the effect of age on technology adoption may depend on the specific type of technology. Additionally, the motivation for men and women to adopt new technology has been found to be very different, with PU of the technology driving men's adoption but PEOU and subjunctive norms being the primary indicators of women's adoption [52]. Income also plays a significant role. One study found that farmers in China who adopted new technologies had incomes roughly 15% higher than non-adopters [90]. A positive relationship has also been found between income and residents' intention to adopt smart meters in the U.S. [7]. Another study discovered that low-income households in India were less willing to spend money to adopt renewable energy systems, probably because they have less disposable income in the first place [91].

2.5. Theoretical framework of cultural differences in technology adoption

A key aspect of this paper is to investigate how cultural differences between the U.S. and Japan can influence the impacts of the aforementioned variables in our three-dimensional framework. Scholars have long suggested that culture can be seen as a sort of "mental software" that shapes much of our individual thinking and behavior [85]. This paper uses Hofstede's cultural dimensions as a framework to propose our hypotheses. Among Hofstede's cultural dimensions, the most studied and relevant to our research are power distance (PD), uncertainty avoidance (UA), femininity vs. masculinity (MF), collectivism vs. individualism (IDV), and long-term orientation (LTO) [89–92]. PD is a measure of the interpersonal power, as well as the gap between a superior and a subordinate. In low PD cultures, employees believe the inequity should be minimized, whereas in high PD cultures employees believe that even large inequities are natural and acceptable [85]. The UA dimension relates to anxiety and the need for security. It determines the degree to which individuals feel threatened by ambiguous situations and attempt to minimize or avoid them by developing formal rules and rejecting deviant ideas and behaviors. Individuals from cultures scoring high on UA tend to avoid and reduce uncertainty in all forms [87]. The MF dimension works under the assumption that masculine cultures emphasize the importance of work goals, such as receiving promotions and being assertive, whereas feminine cultures emphasize nurturance and personal goals such as maintaining a friendly environment [84]. The ID dimension refers to the relationship between the individual and the group and is used to indicate the extent that personal self-interests are prioritized over the concerns of the group. In individualistic cultures, people tend to be self-oriented and are more likely to expect individual decisions, whereas in collectivist cultures group cohesion and consensus are more highly valued. Moreover, a collectivist will likely pay more attention to the opinions of others than an individualist, due to a need to gain group approval [85]. LTO measures the willingness to delay short-term social and material gains and sacrifice emotional gratification for the sake of future benefits, as well as the ability to connect the past with the future to solve problems. Cultures high in LTO value self-discipline, perseverance, saving, and being able to adapt to the changing environment [92].

A number of studies have already begun to investigate the impact of cultural differences on technology adoption. For example, cultures with high UA and PD (including Japan) tend to have slower acceptance rates of new technologies, and these cultures require a more centralized decision making process in order to enhance acceptance [93]. The specific properties of the technology, however, must be taken into consideration when attempting to predict cultural influences [94]. For example, if a technology's benefit is linked to accomplishing a goal, then it is more likely to be favored by higher masculinity cultures (e.g., Japan), whereas benefits oriented towards enhancing interpersonal communications are likely more attractive to higher femininity cultures (e.g., the U.S., in comparison with Japan). Regarding UA, if the adoption procedure is not clearly directed by individuals or institutions with recognized authority or social standing, then individuals from high UA cultures (including most East Asian cultures) tend to be more reluctant to adopt. Based on this reasoning, because HEMS is goal orientated and HEMS adoption has little social presence, the Japanese will likely be slower to embrace it in comparison with U.S. residents.

More relevant to our research, several studies on technology adoption have examined how cultural differences influence the impacts of other important variables, including most of those proposed in our three-dimensional framework. To simplify our hypotheses, our discussion focuses on the connection between the identified factors and adoption intention instead of WTP based on cultural dimensions because we assume WTP is influenced by adoption intention. A multicultural study with data from 25 locations around the world found that while PU and PEOU are generally positively associated with technology adoption intention, their effects can be nullified in cultures with low UA, high masculinity, high PD, and high collectivism [95]. The authors reasoned that if UA is low enough, it may make both PU and PEOU irrelevant. Meanwhile, when an authority requests the adoption of a specific technology, people from high PD cultures may not require any additional information. People from high masculinity cultures, on the other hand, may focus more on whether the technology can help accomplish their goals instead of considering whether the technology is easy to use. Lastly, people from collectivist cultures may be more willing to endure lower usability or greater difficulty if adoption is required due to larger goals valued by their culture in general. In another study on green technology adoption, attitudes toward saving resources and saving money had a stronger effect on purchase intention for U.S. participants than for Japanese participants because of the individualist culture of the former, whereas Japanese participants were more likely to be motivated by subjunctive norms [96]. This finding is in line with Hassan et al., who compared the effectiveness of TPB variables across cultures and concluded that the relationship between subjective norms and intention is influenced by PD, with a stronger relationship in high PD cultures [97]. However, they did not find that the effect of attitudes varies across cultures [97]. In another study, social norms were discovered to have a stronger effect on the behaviors of individuals with feminine and high UA cultural values than those in masculine cultures with lower UA values [98].

As for trust, evidence shows that UA and LTO moderate the effects of trust on e-commerce use intention more than Hofstede's other dimensions [99]. More specifically, high UA cultures typically feel threatened by uncertain situations and are, therefore, slower to build personal trust with officials. Meanwhile, cultures with high LTO emphasize building relationships, for which trust is essential. For these reasons, we predict that trust in utilities or organizations should be more important for Japanese society than for the U.S. Furthermore, it is also likely that their collectivist culture encourages Japanese residents to value group cohesion and trust greater than other cultures might.

Privacy and cybersecurity concerns are a significant barrier to adoption for high UA cultures because those who are concerned about privacy tend to be concerned about unexpected problems in general [82]. As mentioned earlier, trust is related to privacy and cybersecurity concerns, so we expect cultural dimensions to also affect the privacy and cybersecurity concerns on HEMS adoption. We also expect the impact of these concerns to be higher in U.S. society because of its high individualism, low LTO (people try less to sacrifice emotional gratification), and low PD (e.g., believing inequity should be minimized), despite the U.S. having lower UA. Additionally, U.S. society may emphasize interpersonal communications more than highly masculine cultures such as Japan; therefore, the concerns for privacy and cybersecurity might be greater. Moreover, empirical studies have shown that privacy has had a direct and negative effect on smart meter acceptance in the U.S. [7], while its effect was not that significant for Hong Kong [100] or Germany [66], where the UA levels are actually higher.

2.6. The present study

This study's contribution to the technology adoption literature is threefold. First, it examines how social-psychological and demographic factors drive residents' intention to adopt and pay for HEMS. This is done by examining variables in three dimensions: technology attribute interaction, attitudes and perceptions, and system and infrastructure expectations. This can be accomplished by integrating three theories, namely, the TPB, the TAM, and the TAF. Second, this study adds to the collective body of knowledge on the role of PU, PEOU, attitudes, norms, and PBC, in addition to the variables of trust technology anxiety, energy-efficiency behavior in technology adoption, and WTP; few studies have attempted this kind of holistic approach to this topic. Third, the study investigates cultural differences in technology adoption by connecting cultural dimensions with various factors which can influence technology adoption. Naturally, there is an enormous variety—culturally, economically, and historically—both within and between Western and Eastern Countries. No one city can fully represent another. However, as Tokyo and New York are each iconic cities within their own cultural spheres, and are somewhat similar in general ways, such as their size and economic clout, we hope that the patterns of differences and similarities which our analysis reveals might suggest fruitful ways to educate the public about the benefits of HEMS, and overcome obstacles related to energy-saving technology in both cultures. This paper strives to provide valuable cross-cultural insights for cultural similarities and differences in technology adoption through the use of a comprehensive three-dimensional framework and statistical analyses. We propose the following hypotheses and research questions, focusing mainly on behavioral intention because we assume it influences WTP. Our hypotheses were derived from the theoretical frameworks (i.e., TPB, TAM and TAF), and findings of the empirical studies discussed in 2.5.

H1: N.Y. residents have higher HEMS adoption intention than Tokyo residents.

H2: PU has a positive effect on HEMS adoption in general, but it has a stronger positive effect for N.Y. residents than Tokyo residents.

H3: PEOU has a positive effect on HEMS adoption in general, but it has a stronger positive effect for N.Y. residents than Tokyo residents.

H4: Technology anxiety is negatively associated with HEMS adoption intention in general, but it has a greater effect on Tokyo residents than N.Y. residents.

H5a, H6a, H7a: The three TPB variables, attitudes (H5a), social norms (H6a), and PBC (H7a), have positive effects on HEMS adoption for both Tokyo and N.Y. residents.

H5b: The effect of positive attitudes towards HEMS is greater in N.Y. than in Tokyo;

H6b: The effect of social norms on HEMS adoption is greater in Tokyo than in N.Y.;

H7b: The positive effect of PBC on HEMS adoption is similar for Tokyo and N.Y. residents.

H8: Trust has a positive effect on HEMS adoption in general, but the effect is stronger for Tokyo residents than N.Y. Residents.

H9: Privacy and cybersecurity concerns are negatively associated with HEMS adoption in general, but they have a greater effect on adoption for N.Y. residents than for Tokyo residents.

RQ1: Does the impact of energy-efficient behaviors differ in N.Y. and in Tokyo, even though Japanese residents historically have higher energy-saving intentions?

3. Method

3.1. Survey design and data collection

We conducted an internet-based survey (n = 2,419) through Qualtrics Panel Services, an online data collection platform frequently used by researchers. Our survey started with a brief explanation of what HEMS is and does, after which participants were asked about their intention to adopt HEMS, WTP for different services, and their attitudes towards various social-psychological variables which could potentially influence the decision, such as perceived usefulness and ease of use, social norms, and PBC (see details in section 3.2). The survey was first developed in English and then translated into Japanese for Tokyo participants, and was distributed to homeowners in the greater New York and Tokyo metropolitan areas. Demographic information was collected at the end of the survey. Back-translation was performed to ensure consistency of the question contents [101]. Responses were excluded when the participants missed more than 10% of the survey questions, or if they indicated they did not understand what HEMS was after reading the introduction. The final valid responses include 1,193 homeowners in New York (N.Y.) and 1,226 in Tokyo.

Among N.Y. participants, 49.7% were female and 50.3% were male. The largest age groups were 35–39 (14.9%), 65–69 (14.8%), and 30–34, 60–64 (both 12.9%). The largest income group in N.Y. was $100,000-$149,999 (22.5%), followed by $75,000-$99,999 (18.9%), $50,000-$74,999 (18.0%), and $35,000-$49,999 (11.4%). Other income groups contained smaller proportions of participants. Among Tokyo participants, 47.7% were female and 52.3% were male. The largest age groups were 55–59 (17.5%), 45–49 (16.3%), and 50–54 (16.2%). The largest income group for the Japanese participants was $25,000-$34,999 (17.4%), followed by $35,000-$49,000 (17.2%), $50,000-$74,999 (14.6%), $15,000-$24,999 and $75,000-$99,999 (both 10.9%). Other income groups contained smaller proportions of participants.

3.2. Measures

In this study, we measured two dependent variables (HEMS adoption intention and WTP for HEMS) and a series of social-psychological variables that potentially predict those DVs (see Table 1), as well as demographic variables including age, gender, and income. All the variables except demographics were measured using multiple questions (at least 3) to ensure reliability. All measures except WTP were based on participants' responses to a 5-point Likert scale, where 1 indicates "*strongly disagree*," "*very unlikely*," or "*never*" and 5 indicates "*strongly agree*," "*very likely*," or "*very often*." To begin, exploratory factor analysis (EFA) was conducted on each social-psychological variable set. Results of the EFA indicate uni-dimensionality for each factor; the factor loadings of all items range from 0.64 to 0.95 for the U.S. sample and from 0.64 to 0.99 for the Japanese sample. Cronbach's α values are all above 0.75 (see Table 1), indicating an overall good reliability level. Another EFA was conducted for all of the independent variables (IVs) containing ten emergent factors with eigenvalues larger than 1.0, and the result indicated independent loadings of the IVs with no cross-loadings higher than 0.3. These results suggest good construct validity for the IVs. Table 1 presents a list of the items used for DVs and IVs, along with their means, standard deviations (*SD*s), factor loadings, and Cronbach's α values.

WTP, as previously mentioned, was measured using a different scale. Three items, each corresponding to a different HEMS feature (Table 1), were presented to the participants to learn how much they would be willing to pay per month for an HEMS with each of the three

Table 1
Factor loadings, means and standard deviations for major variables.

	New York			Tokyo		
Dependent Variables (DVs)	*Loading*	*Mean*	*S.D.*	*Loading*	*Mean*	*S.D.*
Willingness to Pay (WTP)		2.34	2.42		1.99	2.04
Cronbach's α: N.Y. = 0.96 Tokyo = 0.96						
HEMS can visualize and monitor electricity usage to help you save money	0.95	2.36	2.49	0.94	1.88	2.09
HEMS can automatically control your appliances	0.95	2.43	2.55	0.93	2.15	2.17
HEMS can help reduce your community's household electricity consumption and the environmental impact	0.94	2.34	2.51	0.94	1.94	2.14
Intention to Use		3.87	0.93		3.56	0.78
Cronbach's α: N.Y. = 0.92 Tokyo = 0.92						
Using HEMS service is worthwhile	0.81	4.12	0.90	0.78	3.81	0.77
It is likely that I will use HEMS services in the future	0.95	3.80	1.03	0.99	3.53	0.87
For sure, I would use HEMS services in the future	0.92	3.69	1.08	0.89	3.34	0.90
Independent Variables (IVs)	***Loading***	***Mean***	***S.D.***	***Loading***	***Mean***	***S.D.***
Perceived Usefulness (PU)		3.87	0.80		3.69	0.74
Cronbach's α: N.Y. = 0.90 Tokyo = 0.93						
HEMS helps the residents proactively without human intervention	0.84	3.79	0.86	0.90	3.73	0.78
HEMS provides auto-adjusted control	0.90	3.91	0.86	0.92	3.64	0.80
With HEMS, I can control home appliances through simple operation	0.85	3.90	0.91	0.90	3.69	0.79
Perceived Ease of Use (PEOU)		3.68	0.88		3.37	0.76
Cronbach's α: N.Y. = 0.91 Tokyo = 0.93						
Learning to live with HEMS will be easy for me	0.87	3.71	0.96	0.90	3.37	0.79
Interacting with HEMS will not require a lot of mental effort	0.83	3.65	0.97	0.90	3.38	0.84
I will find HEMS easy to use	0.92	3.68	0.95	0.90	3.37	0.80
Technology Anxiety		2.82	1.03		2.87	0.72
Cronbach's α: N.Y. = 0.92 Tokyo = 0.89						
Working with HEMS will make me nervous	0.90	2.85	1.07	0.81	2.93	0.78
New technology like HEMS will make me feel uncomfortable	0.94	2.80	1.12	0.92	2.84	0.76
I hesitate to use new technology like HEMS, for fear of making major mistakes	0.82	2.81	1.15	0.84	0.28	0.82
Cost concerns		3.94	0.84		3.74	0.76
Cronbach's α: N.Y. = 0.93 Tokyo = 0.95						
HEMS basic installation fee	0.85	3.81	0.93	0.93	3.74	0.78
Additional HEMS service fee	0.93	4.00	0.88	0.96	3.73	0.78
HEMS maintenance fee	0.93	4.00	0.88	0.91	3.76	0.81
Attitudes toward HEMS		3.59	1.00		3.37	0.77
Cronbach's α: N.Y. = 0.95 Tokyo = 0.93						
Using HEMS will be beneficial to me	0.96	3.70	1.04	0.97	3.45	8.30
Using HEMS will be helpful to me	0.95	3.73	1.03	0.92	3.51	0.83
Using HEMS will be important to me	0.88	3.36	1.10	0.81	3.13	0.83
Perceived Behavioral Control (PBC)		3.58	0.89		3.31	0.70
Cronbach's α: N.Y. = 0.88 Tokyo = 0.76						
I will be able to adopt HEMS services	0.84	3.56	0.98	0.64	3.43	0.80
Adopting HEMS services is entirely within my control	0.82	3.66	0.95	0.72	3.41	0.88
I have the resources and ability to adopt HEMS services	0.88	3.52	1.03	0.79	3.08	0.85
I feel confident in the brand of my utility company	0.90	3.61	0.94	0.90	3.08	0.89
Social Norms		3.44	0.94		3.04	0.74
Cronbach's α: N.Y. = 0.93 Tokyo = 0.92						
My family would think I should use HEMS to save money or electricity	0.88	3.53	1.03	0.76	3.16	0.83
My close friends would think I should use HEMS to save money or electricity	0.94	3.43	0.99	0.97	3.00	0.78
My close neighbors who are important to me, would think I should use HEMS to save money or electricity	0.90	3.37	1.00	0.93	2.95	0.78
Energy Efficiency Behaviors		4.40	0.74		3.79	0.92
Cronbach's α: N.Y. = 0.75 Tokyo = 0.87						
Buy energy-efficient light bulbs	0.77	4.44	0.84	0.88	3.80	1.02
Buy energy-efficient household appliances	0.77	4.36	0.81	0.88	3.77	0.94
Trust in Utilities		3.57	0.79		3.07	0.78
Cronbach's α: N.Y. = 0.90 Tokyo = 0.93						
My utility company is reliable	0.78	3.97	0.80	0.89	3.21	0.85
My utility company always keeps promises and commitments	0.84	3.52	0.87	0.92	3.11	0.83
My utility company always keeps the customer's best interests in mind	0.80	3.23	1.02	0.82	2.87	0.84
I feel confident in the brand of my utility company	0.90	3.61	0.94	0.90	3.08	0.89
Privacy and Cybersecurity Concerns		3.38	0.96		3.74	0.78
Cronbach's α: N.Y. = 0.92 Tokyo = 0.96						
Some cyber hackers would break into HEMS network to access and misuse my personal information	0.91	3.49	1.01	0.96	3.75	0.80
Some cyber hackers will break into HEMS network to manipulate my usage information	0.90	3.30	1.04	0.96	3.72	0.80
Some cyber hackers will bring down HEMS to make the system unusable	0.87	3.36	1.04	0.93	3.76	0.82

features (Table 1). The three specific features shall henceforth be referred to as "monitoring," "automation," and "social benefits" for simplicity (see Table 1). Participants chose from "0 = *I'm not willing to pay for this service*," "1 = $0.01-0.99 per month," "2 = $1.00–1.99 per month," all the way to "8 = $7.00 or more per month," with each item increasing by a 1-dollar interval. In the Japanese survey, WTP was scaled in Japanese Yen (100 JPY = 0.88 USD).

4. Results

4.1. Variable overview

Figs. 1 and 2 show the detailed distributions of intention to adopt HEMS and WTP. Interestingly, while many respondents (~70% in N.Y. and ~ 50% in Tokyo) chose "likely" or "extremely likely" to adopt

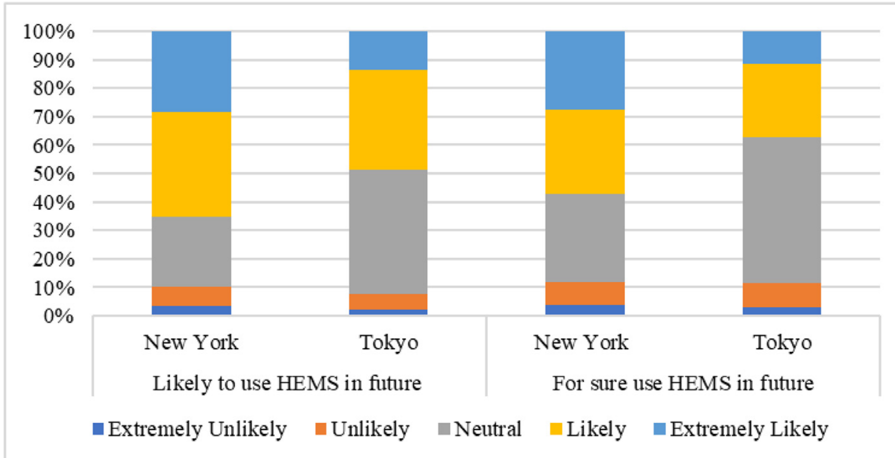

Fig. 1. Distribution of the intention to use HEMS.

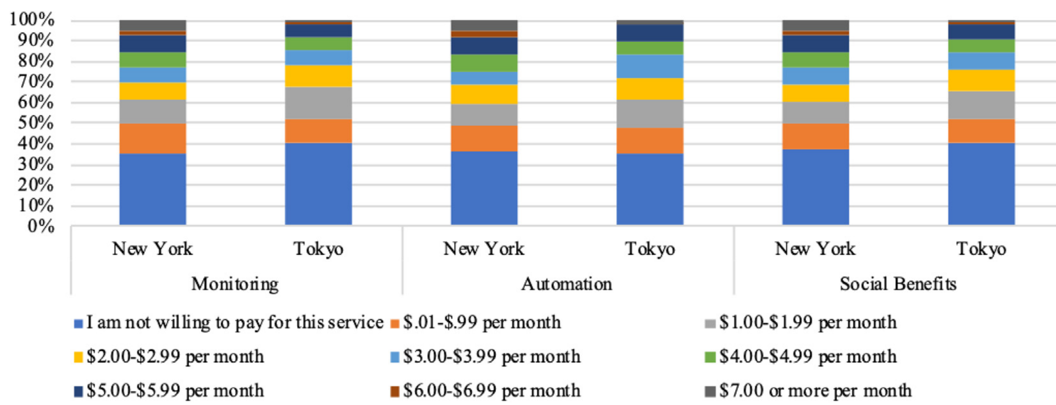

Fig. 2. Distribution of the WTP for specific services.

HEMS, a substantial portion (~35%) of the respondents in both areas indicated they were unwilling to pay anything. N.Y. residents expressed higher adoption intention (M = 3.75, SD = 1.02) than Tokyo residents (M = 3.44, SD = 0.86), t (2417) = 8.04, p < .001, supporting H1. In response to the negative skew of the WTP scores and to make the results more interpretable, WTP was treated as a categorical variable. The three categories are: first, "not willing to pay anything," second, " would pay $0.01-$2.99" (later referred to as "a small amount"), and third, "would pay $3.00-$7.00+" (later referred to as "a larger amount"). N.Y. residents also reported higher WTP than Tokyo residents, χ^2 (2) = 7.61, p < .05. The two averaged variables, intention and WTP, correlated positively in both N.Y. (Kendall's τ = 0.42, p < .001) and Tokyo (Kendall's τ = 0.31, p < .001) areas.

Fig. 3 is a box plot that shows the maximum, minimum, mean, and quartiles for each social-psychological variable. Independent-sample t-tests were conducted to compare the means of those variables between the two locations. The results suggest that N.Y. participants had a more positive attitude towards HEMS (t = 6.28, p < .001) and higher PBC for using HEMS (t = 8.41, p < .001). N.Y. participants also indicated a stronger level of social norms (t = 11.84, p < .001), a higher level of cost concerns (t = 5.97, p < .001), and better energy-efficiency behaviors (t = 17.97, p < .001) than the Tokyo participants. Participants in N.Y. also viewed HEMS as more useful (t = 5.79, p < .001), easier to use (t = 9.17, p < .001), and indicated they were more likely to trust their utility companies (t = 15.83, p < .001) than their Tokyo counterparts, who were more concerned about privacy and cybersecurity breaches (t = -10.02, p < .001) than the N.Y. participants. Anxiety about the new technology was equal for both areas.

Table 2 presents the correlations for all variable pairs. The upper triangle contains the correlation coefficients for the N.Y. area, and the lower triangle contains the correlation coefficients for the Tokyo area. In the N.Y. area, attitudes and intention, attitudes and PU, attitudes and social norms, and PBC and PEOU had the highest correlations (r > 0.70). In the Tokyo area, only the correlation between PU and attitudes reached this level (r > 0.70).

4.2. Regression diagnostics

We performed Ordinary Least Squares (OLS) linear regression to identify factors influencing adoption intention, and multinomial logistic regression to determine the factors influencing WTP. We produced regression diagnostics for both of the regression models, and in our diagnoses of the OLS linear regression model, we found no multicollinearity, with variance inflation factors (VIFs) well under the recommended limit of 10 [102]. Similarly, the P-P plots showed no major breach of the normality assumption, with the expected cumulative probability being slightly above the observed cumulative probability for smaller values and somewhat under the observed probability for larger values. The multinomial logistic regression for WTP also displayed no significant issues regarding multicollinearity because the VIFs, as mentioned above, were well below the recommended limit. When inspecting for potential outliers, the P-P plots showed a slight deviation from normality around the tails, but were otherwise normal. Note that multinomial logistic regressions do not assume normality or homoscedasticity. Because the large sample size has made the data quite robust, we decided not to remove outliers or use bootstrapping for either regression.

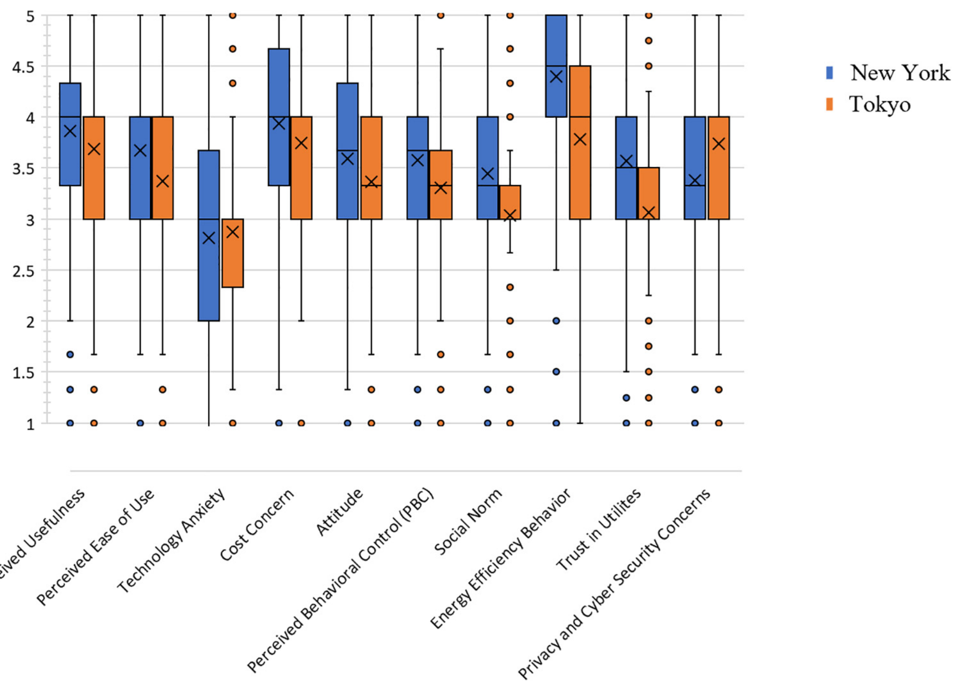

Fig. 3. Boxplot of social-psychological variables for N.Y. and Tokyo residents.

4.3. Multilinear regression results on adoption intention

The regression models were significant for both N.Y. and Tokyo residents, $F_{\text{-}N.Y.}(13, 1145) = 121.89$, $p < .001$, $F_{\text{-}Tokyo}(13, 1127) = 95.17$, $p < .001$. In both countries (Table 3), PU positively affected HEMS adoption intention with other predictors held constant. A one-unit increase in the rating of PU on a 5-point Likert-like scale led to a 0.15-unit increase in the rating of intention in N.Y. and a 0.07-unit increase in Tokyo. To test the magnitude of difference between the effects of PU in the two countries, we fit the same regression model on the combined data from N.Y. and Tokyo and added two more predictors- a location variable (N.Y. vs. Tokyo) and an interaction term between PU and location. If the interaction term was significant, then we could conclude that the effect of PU differs significantly between the two locations. It turned out that the interaction term was not significant ($B = -0.03$, $p = 0.357$), failing to support the second part of H2. PEOU, on the other hand, showed no effect on adoption intention, which failed to support H3. Additionally, H4 was partially supported in that technology anxiety only negatively affected the Japanese residents, where a one-unit increase in the rating of technology anxiety led to a 0.15-unit decrease in adoption intention; the N.Y. residents did not seem discouraged by technology anxiety. Cost concerns were positively associated with adoption intention in both locations. As with PU, we tested the differences in the effect of cost concerns between the two locations by adding locations and an interaction term of cost concerns and location into the regression model, and then fitting the model on the combined data set. Results showed that the interaction term was not significant ($B = 0.04$, $p = 0.220$), meaning that the effect of cost concerns did not differ significantly between the two locations.

The overall effects of positive attitudes (H5a) and social norms (H6a) on adoption intention were supported. Most notably, a one-unit increase in the rating of positive attitudes led to a 0.49-unit increase in the rating of intention in N.Y. and a 0.42-unit increase in Tokyo We further tested the differences of the effects between the two locations and found that neither the interaction between attitude and location ($B = -0.03$, $p = 0.333$) nor the interaction between social norms and location ($B = -0.02$, $p = 0.576$) was significant. In other words, the effect of attitudes or social norms did not differ significantly between the two areas, lending no support for H5b or H6b. On the other hand, PBC only had a positive association with adoption intention among Tokyo residents, a result which failed to support H7a or H7b. In contrast to H8, trust did not positively affect adoption intention with other predictors held constant. Instead, it had a negative association with adoption intention among the N.Y. residents. Meanwhile, H9 was partially supported in that privacy and cybersecurity concerns were found to negatively influence adoption intention, but only among the N.Y. residents. Lastly, in response to our research question, the results of the regression model indicated that energy-efficiency behaviors had no effect on HEMS adoption intention.

Our results contain two counter-intuitive findings. The first, and most notable, was that when holding other predictors constant, there was a positive correlation between cost concern and adoption intention for both areas. This finding also holds true in the simple correlation analysis for Tokyo residents (Pearson's $r = 0.29$, $p < .001$) and N.Y. residents with a much weaker effect (Pearson's $r = 0.07$, $p < .05$). The second unexpected result was that among the N.Y. residents, adoption intention decreased with the level of trust. However, the negative relationship was reversed in simple correlation analysis (Pearson's $r = 0.12$, $p < .001$). Therefore, this finding needs to be interpreted in the context of all other predictors being considered in this study.

4.4. Multinomial logistic regression results on WTP

A multinomial logistic regression was conducted for both N.Y. and Tokyo respondents using the "not willing to pay" group as the reference group for each. These models performed significantly better than an intercept-only model: for N.Y., χ^2 (26, $N = 1159$) = 572.63, *Nagelkerke* $R^2 = 0.44$; for Tokyo, χ^2 (30, $N = 1141$) = 350.34, *Nagelkerke* $R^2 = 0.30$. In predicting the likelihood of being willing to pay a small amount (i.e., less than \$3 per month) versus being unwilling to pay anything at all, attitudes proved to be the only significant factor for the N.Y. residents. The results show that (Table 4), holding other predictors constant, a one-unit increase in the rating of positive attitudes on a 5-point Likert-like scale nearly doubled the odds of being willing to pay a small amount (1.79 times). For the Tokyo residents, positive attitudes and higher PU were associated with higher odds of willingness to pay a small amount versus nothing. Higher technology anxiety and higher PEOU, on the other hand, correlated negatively with willingness to pay

Table 2
The correlation matrix among major variables.

Tokyo	New York 1[a]	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1[a] WTP	–	0.38***	0.37***	0.30***	−0.06*	−0.12***	0.47***	0.35***	0.39***	−0.04	0.14***	−0.06*	−0.26***	0.11***	0.13***
2 Intention to Use	0.27***	–	0.59***	0.50***	−0.17***	0.06*	0.73***	0.51***	0.61***	0.13***	0.12***	−0.14**	−0.25***	0.06*	0.14***
3 PU	0.29***	0.56***	–	0.58***	−0.21***	0.06	0.73***	0.57***	0.62***	0.16***	0.22***	−0.09**	−0.23***	0.04	0.10***
4 PEOU	0.21***	0.54***	0.49***	–	−0.32***	0.02	0.66***	0.71***	0.55***	0.17***	0.26***	−0.10***	−0.29***	0.13***	0.19***
5 Technology Anxiety	−0.06*	−0.16***	−0.09**	−0.29***	–	0.22***	−0.16***	−0.23***	−0.10***	−0.05	0.12***	0.49***	−0.05	−0.07*	−0.10**
6 Cost concerns	0.00	0.29***	0.34***	0.23***	0.19***	–	−0.01	0.01	0.02	0.15***	0.02	0.32***	0.06*	0.00	−0.02
7 Attitudes	0.33***	0.67***	0.74***	0.61***	−0.10***	0.27***	–	0.66***	0.72***	0.12***	0.22***	−0.15***	−0.34***	0.08**	0.18***
8 PBC	0.24***	0.57***	0.50***	0.67***	−0.22***	0.17***	0.63***	–	0.60***	0.14***	0.32***	−0.07*	−0.26***	0.15***	0.26***
9 Social Norms	0.27***	0.54***	0.48***	0.44***	−0.03	0.16***	0.66***	0.56***	–	0.13***	0.27***	−0.07*	−0.32***	0.07*	0.14***
10 Energy Efficiency Behaviors	0.04	0.19***	0.21***	0.19***	−0.04	0.24***	0.19***	0.23***	0.12***	–	0.12***	0.06*	0.12***	−0.06*	0.02
11 Trust in Utilities	0.11***	0.16***	0.18***	0.19***	0.07*	0.06*	0.22***	0.25***	0.27***	0.02	–	0.08**	−0.04	0.03	0.05
12 Privacy & Cybersecurity Concerns	−0.01	0.13***	0.17***	0.16***	0.14***	0.51***	0.06	0.14***	0.01	0.28***	0.00	–	−0.02	0.02	−0.01
13 Age	0.02	−0.00	−0.01	−0.02	−0.02	−0.02	−0.06*	0.06*	−0.03	0.11***	0.02	0.06*	–	−0.04	−0.12***
14 Gender	0.04	0.08*	−0.04	0.08**	−0.14***	−0.07*	0.00	0.14***	0.05	−0.06*	−0.07**	0.03	0.28**	–	0.18***
15 Income	0.09***	0.15***	0.10***	0.17***	−0.11***	−0.04	0.17***	0.22***	0.13***	0.07*	0.07*	0.02	−0.04	0.06*	–

Note: The correlation coefficients between willingness to pay and other variables were based on Kendall's Tau tests, while others used Pearson's correlation coefficients. * $p < .05$; ** $p < .01$; *** $p < .001$.
[a] The numbers correspond with the adjacent variable.

a small amount. Also, men in Tokyo were less likely to be willing to pay a small amount than women.

In predicting the likelihood of being willing to pay a larger amount (i.e., $3.00 per month or higher) versus being unwilling to pay anything, New Yorkers were more likely to pay a larger amount if there were concomitant increases in the levels of positive attitudes, social norms, and PU, but were proportionally less likely to pay a larger amount with increases in age, PEOU, cost concerns, and energy-efficiency behaviors, holding other variables constant. Also, a higher income was found to increase respondents' likelihood of being willing to pay a larger amount over being unwilling to pay anything. Likewise, for Tokyo residents, positive attitudes and social norms increased the odds of willingness to pay a larger amount, whereas higher cost concerns reduced these odds. In sum, based on the number of significant predictors and the magnitude of effects, distinguishing the residents who were willing to pay a small amount from those unwilling to pay anything has proven more difficult than identifying those willing to pay a larger amount from those unwilling to pay anything. This situation is especially true among the N.Y. residents. Overall, attitudes, social norms, PU, PEOU, and cost concerns had emerged as the essential predictors in both areas. Age, income, and energy-efficiency behaviors only had useful predictive value for the N.Y. residents' WTP. Technology anxiety, on the other hand, was only significant for Tokyo residents.

The above contains two counter-intuitive findings. First, higher PEOU correlated with being unwilling to pay in both areas. However, this result should be interpreted with caution because it only applies to the context of this particular regression model with other predictors held constant. In simple correlation analyses, PEOU related positively with WTP in both N.Y. (Kendall's $\tau = 0.30$, $p < .01$) and Tokyo (Kendall's $\tau = 0.23$, $p < .01$). Second, while one could reasonably assume that cost-conscious individuals would be willing to pay more for HEMS, as it has the potential to reduce electricity bills, it turned out that cost concerns and a tendency towards energy-efficiency behaviors were, in fact, negatively related to WTP. Among the simple correlations of these variables with WTP, one was significant: cost concerns correlate negatively with WTP in N.Y. (Kendall's $\tau = -0.11$, $p < .01$). This finding is particularly interesting when being considered together with our previous finding that cost concerns were positively associated with adoption intention.

5. Discussion

5.1. Summary of findings

Based on the three dimensions factored into our analysis, we have identified four key takeaways: *First*, after accounting for several demographic and social-psychological variables, we have found that the majority of participants are willing to adopt HEMS even when their cost concerns are high, but this is not true of WTP. Both N.Y. and Tokyo residents with high cost concerns are less willing to pay a "larger" amount (i.e., more than $3 per month) for HEMS, indicating that WTP is indeed influenced by more practical factors than just attitude and social norms. Previous research has proven that factors such as purchasing power [103], reference price, and expected quality [104] all affect WTP. People could report high intention to make a purchase while rating the product as less valuable [105]. An important takeaway is that neither adoption intention nor WTP is a perfect proxy of actual adoption behavior; therefore, researchers may benefit from considering both of these variables to make better predictions of actual adoption behavior and identify the barriers to adoption.

Second, looking at the technology attribute dimension, we have found specific cultural differences in preferences for certain types of technology and WTP. Regarding adoption intention, while N.Y. participants are mostly driven by the PU of automation features, Tokyo participants are mostly influenced by technology anxiety. This may be

Table 3
OLS linear regression results for HEMS adoption intention among N.Y. and Tokyo residents.

	N.Y.				*Tokyo*			
Independent variables	B	*SE*	*t*	*VIF*	B	*SE*	*t*	*VIF*
PU	0.15	0.04	3.94***	2.37	0.07	0.04	2.00*	2.35
PEOU	0.05	0.04	1.29	2.56	0.07	0.04	1.90	2.18
Technology Anxiety	−0.03	0.02	−1.11	1.63	−0.15	0.03	−5.47***	1.28
Cost concerns	0.09	0.03	3.51***	1.18	0.14	0.03	4.86***	1.58
Attitudes	0.49	0.04	13.66***	3.43	0.42	0.04	9.78***	3.51
Social Norms	0.18	0.03	5.54***	2.34	0.16	0.03	4.68***	1.94
PBC	0.02	0.04	0.68	2.55	0.15	0.04	3.72***	2.41
Energy-efficiency Behaviors	0.05	0.03	1.90	1.12	0.02	0.02	0.89	1.19
Trust in Utilities	−0.05	0.03	−1.98*	1.23	−0.03	0.03	−1.36	1.13
Privacy & Cybersecurity	−0.05	0.02	−1.98*	1.46	0.04	0.03	1.24	1.49
Age	−0.01	0.01	−0.56	1.24	−0.01	0.01	−0.54	1.13
Gender	0.00	0.04	0.05	1.06	0.06	0.04	1.64	1.17
Income	0.00	0.01	0.11	1.11	−0.00	0.01	−0.09	1.07
R^2	0.58				0.52			
R^2_{adj}	0.58				0.52			
F	121.89				95.17			

Note: $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

because Japanese culture tends to be higher in both LTO (e.g., expecting future outcomes) and collectivism (e.g., valuing social information more), which tend to reduce the impact of the characteristics of the technology itself [92]. Higher UA in Japan may not have as much influence as the aforementioned cultural dimensions because consumers in high UA cultures would presumably like to know more about the technology to reduce uncertainty. It may also be due to Japan's disproportionately large elderly population; a recent study conducted in four Asian countries found that the elderly are prone to high technology anxiety, which negatively affects their intention to use smart homes for health care purposes [60]. Similarly, another study has shown that those who are younger and more open to new experiences show greater willingness to adopt smart home technologies [106]. Future research should continue to explore the problems posed by technology literacy issues among underserved communities (e.g., elderly and low-income communities). For WTP, PU is equally critical for both areas in determining who is willing to pay a more considerable amount and who is unwilling to pay anything, but PU is also important for Japanese residents in predicting who is willing to pay a small amount versus being unwilling to pay anything. PEOU is not a significant predictor of adoption intention for either of these areas; however, it is essential for the N.Y. residents' WTP. Overall, the effect of PEOU does not seem to hold for the Japanese residents, most likely due to the cultural characteristics of high PD, high collectivism, and high masculinity. People who focus on collectivism are more willing to suffer lower usability to achieve the goals valued by others while focusing less on their own

Table 4
Multinomial logistic regression results for WTP among N.Y. and Tokyo residents.

Predictors	WTP Level: [a]Zero vs.	New York			Tokyo		
		OR	[b]*CI*	*p*	*OR*	[b]*CI*	*p*
Perceived Usefulness	Small	1.33	(0.98, 1.81)	0.07	**1.56**	(1.15, 2.13)	0.01
	Larger	**1.57**	(1.08, 2.27)	0.02	**1.99**	(1.36, 2.91)	0.00
Perceived Ease of Use	Small	0.86	(0.64, 1.16)	0.32	**0.72**	(0.53, 0.98)	0.04
	Larger	**0.66**	(0.46, 0.95)	0.03	0.78	(0.54, 1.13)	0.19
Technology Anxiety	Small	0.92	(0.74, 1.15)	0.47	**0.72**	(0.56, 0.93)	0.01
	Larger	1.18	(0.92, 1.52)	0.19	0.91	(0.68, 1.22)	0.52
Cost concerns	Small	0.83	(0.67, 1.04)	0.11	1.06	(0.81, 1.37)	0.68
	Larger	**0.52**	(0.40, 0.67)	0.00	**0.53**	(0.39, 0.73)	0.00
Attitudes	Small	**2.79**	(2.07, 3.77)	0.00	**2.61**	(1.80, 3.79)	0.00
	Larger	**4.58**	(3.08, 6.83)	0.00	**3.31**	(2.10, 5.24)	0.00
Perceived Behavioral Control	Small	0.99	(0.75, 1.32)	0.97	1.23	(0.88, 1.73)	0.23
	Larger	1.38	(0.96, 1.98)	0.08	1.33	(0.88, 2.01)	0.18
Social Norms	Small	1.27	(0.98, 1.63)	0.07	1.23	(0.92, 1.64)	0.17
	Larger	**1.69**	(1.23, 2.32)	0.00	**1.79**	(1.25, 2.55)	0.00
Energy Efficiency Behaviors	Small	0.93	(0.74, 1.17)	0.55	0.88	(0.73, 1.04)	0.14
	Larger	**0.71**	(0.55, 0.93)	0.01	0.84	(0.68, 1.03)	0.09
Trust in Utilities	Small	0.98	(0.78, 1.24)	0.90	1.10	(0.89, 1.36)	0.40
	Larger	1.10	(0.84, 1.45)	0.48	1.25	(0.97, 1.60)	0.09
Privacy & Cyber Concerns	Small	0.97	(0.78, 1.19)	0.74	1.14	(0.89, 1.45)	0.30
	Larger	0.95	(0.75, 1.21)	0.70	1.12	(0.84, 1.48)	0.44
Age	Small	0.95	(0.88, 1.02)	0.15	0.96	(0.89, 1.04)	0.35
	Larger	**0.83**	(0.76, 0.91)	0.00	1.06	(0.97, 1.17)	0.19
Gender	Small	1.10	(0.79, 1.52)	0.59	**0.71**	(0.52, 0.99)	0.04
	Larger	1.39	(0.95, 2.02)	0.09	1.17	(0.81, 1.70)	0.40
Income	Small	1.04	(0.95, 1.13)	0.44	1.05	(0.98, 1.13)	0.19
	Larger	**1.12**	(1.01, 1.24)	0.03	1.08	(0.99, 1.17)	0.09

The bolded numbers indicate significant results.
[a] The reference group "zero" is "Unwilling to pay anything".
[b] The multinomial result uses a 95% confidence interval.

efforts [95].

Third, on the dimension of attitudes, behavior, and social influence, attitudes appear to be the strongest predictor of adoption intention and WTP for both areas. The effects of attitudes are statistically the same in both areas, contrary to the expectation that it would be stronger in individualistic cultures. This may be because HEMS is a personal technology; therefore, adoption is also a personal decision. Social norms, as an indicator of social influence, positively predicts adoption intention, which is consistent with previous research [72,88,89,107,108]. However, the effect is not stronger in a typical collectivist culture like Japan. This suggests that, when faced with a new and closely life-related technology like HEMS, social information and support are essential, regardless of culture differences. As for WTP, we are surprised that social norms only positively influence the N.Y. residents, mattering little for the Tokyo residents. It seems like other factors such as technology anxiety, gender, PU and attitudes are more likely to sway the WTP of the Tokyo residents. In addition, PBC is only significant for Tokyo residents in predicting HEMS adoption intention, probably due to their cultural tendency towards higher levels of technology anxiety and UA; therefore, a lack of PBC would seem to be more of an obstacle to adoption. Surprisingly, energy-efficiency behavior is not related to adoption intention. However, this study only measures the purchase of energy-efficient light bulbs and appliances as an indicator; future research could explore the relationship using a more robust sampling of energy-efficiency behaviors. It is also likely that HEMS is perceived as more than just an energy-efficiency measure. Future research could explore which features of HEMS have the greatest influence on how people perceive it.

Fourth, regarding system and infrastructure expectations, only N.Y. residents' adoption intention is negatively affected by privacy and cybersecurity concerns. This appears contrary to Japan's significantly higher UA score and other cultural dimensions, such as collectivism, but MF, PD and LTO are more important than UA in this case. As hypothesized earlier, we found that privacy and cybersecurity are more important in the N.Y., which might be explained by its individualistic and more-feminine culture, emphasizing personal goals, self-interests, and interpersonal communication. Another factor that may explain this result is the low PD culture in the U.S., making their residents less tolerant of the utility authority exerting control over them. Our findings are in line with a variety of other empirical studies regarding privacy (e.g., [7,100]). This is probably because concerns about privacy and cybersecurity are close to other values, such as personal freedom and individualism, which are significant in American culture, thereby superseding the need to simply reduce uncertainties. Some U.S. residents have been noted to be rather paranoid in regards to large corporate entities, perhaps believing utility companies might record their energy consumption patterns and monitor them like "Big Brother" [7]. In contrast to our hypothesis, trust in utilities does not enhance adoption intention, suggesting privacy and cybersecurity concerns outweigh trust, possibly because participants consider privacy and security as the utility provider's responsibility. As a result, privacy and security concerns are embedded into the variable of trust, but are more directly related to our DVs of interest. Regarding WTP, trust or privacy and cybersecurity concerns are not significant predictors for either New York or Tokyo. In summary, the factors influencing adoption intention and WTP overlap in some aspects, but are somewhat different across cultures.

For both cultures, social-psychological factors are more important than demographic factors (e.g., age, gender, and income) for predicting adoption intention and WTP. Among demographic groups, older and higher-income New Yorkers (as opposed to younger, lower-income residents) are more willing to pay a larger amount rather than nothing. Men in Tokyo are more willing to pay a smaller amount (versus not paying anything) than women. Both the dimension of technology attribute interaction and the dimension encompassing attitudes, behavior, and social influence are more important than the dimension of system and infrastructure in influencing the WTP of the N.Y. residents. In contrast, the dimension of technology attribute interaction, particularly technology anxiety and cost concerns, affect the WTP of the Tokyo residents. That is, when a monetary cost is involved, the Tokyo residents care more about the attributes of interacting and operating with technology than personal attitudes, energy-related behaviors, and social influence.

5.2. Limitations and future research

Several limitations to this research need to be addressed, and these can provide some direction for future research. First, our study only samples one large, urban city in two countries, which is not enough to safely extrapolate meaningful conclusions regarding differences in Eastern and Western culture. More countries from Asia and Europe need to be considered in future research, ideally while paying some attention to smaller cities and rural areas. Second, this study assumes that the two major benefits of HEMS are automation and control, and the measures of PU and PEOU have been designed around these two benefits. Future researchers could expand the dimensions and empirically test how other aspects of PU and PEOUs, such as thermal comfort, mobility, and community communication, affect HEMS adoption. Additionally, different energy-efficiency practices (e.g., EV, solar adoption) and curtailment behaviors (e.g., turning off lights and appliances when not in use) could be measured in future studies. Third, we did not find any connection between trust in utilities and adoption intention or WTP, and our research design does not allow us to delve into the reasons for this. Studies using more qualitative methods, such as focus groups and interviews, could provide more details about the underlying social-psychological aspects behind this tendency. Fourth, our participants had not adopted HEMS, and their attitudes and behaviors are likely different from those who already had some experience with HEMS or smart home systems. Future research could test our models, or use an expanded model, to include those who have already adopted this type of technology, perhaps considering different levels of service and installation costs. This study did not measure the installation cost because our participants are from more than 20 towns in the greater N.Y. and Tokyo areas, and the cost is determined by local utilities' policies and HEMS developers. Finally, although we measured certain social-psychological variables, such as attitudes, norms, PBC, and privacy and cybersecurity concerns that are culturally specific, more measures related to local cultures (e.g., technology independence, decentralization energy system, family-living style with parents and/or grandparents) could be integrated into a future cross-cultural comparison to expand the explanatory power of culture on technology adoption and WTP.

5.3. Policy implications

This work highlights the following suggestions, which could be of interest to smart home industry practitioners and policymakers: *First*, to promote HEMS, an easy-to-operate and straightforward user interface, as well as a simple education tutorial, should be developed, especially for Tokyo residents, where technology anxiety seems to be more prevalent. Moreover, specific needs resulting from different demographics and social-psychological factors need to be considered. For example, system design should focus on simplicity rather than broad functionality for the elderly or those with lower technology literacy. Developing a simple, interactive, intuitive HEMS design, and increasing education about HEMS itself, could help lower anxiety towards technology while also increasing PBC and adoption rates in some societies (e.g., Japan).

Second, the fact that people with higher cost concerns are more willing to adopt HEMS but less willing to pay for it suggests that promoting adoption intention and resident use of services require different approaches. Introducing HEMS with affordable fees is of critical importance to the actual rollout of the technology. Yet, the broader social and well-being benefits (e.g., reducing carbon emissions, promoting a healthier lifestyle, convenience, and saving time) should be emphasized in addition to the technological benefits, so that policymakers and industry can promote HEMS based on a broader set of advantages. Our results suggest that potential users depend not only on technology-based attributes but also on attitudes, social norms, and PBC to form their behavioral intention and WTP. Emphasizing the overall benefits of HEMS and the social influence of friends and family seems to be an essential mechanism for its promotion.

Third, technology developers and utilities need to treat privacy and security concerns more seriously during the design and implementation process because customers' concerns about these issues are increasing, and privacy and security concerns are significant barriers to trust in energy providers. Utilities and policymakers need to continue to develop the most up-to-date hardware and software to ensure data privacy and cyber system security across all facets, as at this time, many smart home products do not include sufficient safeguards [109]. More importantly, customers need to be informed about these procedures in plain, transparent language. For example, addressing issues related to customers' energy data, who can access that data, and what happens if it falls into the wrong hands will require cooperation between the industry and policymakers [65]. Additionally, policymakers can assist by developing best practice guidelines while working with consumer rights organizations to better meet customers' needs [110].

Finally, policymakers need to develop strategies to solve the issue of integrating HEMS into existing or older homes without smart appliances while promoting HEMS, either through existing policies or developing new ones. For example, in the U.S., the Energy Policy Act of 2005, the Energy Independence and Security Act of 2007, and the American Recovery and Reinvestment Act of 2009 all provide tax incentives, credits, or deductions for residential energy efficiency upgrades [111]. Making sure the public understands these policies can remove some of the adoption barriers. Another critical barrier to widespread adoption stems from a lack of industry-accepted device communication and interoperability standards [111]. This is a barrier local policymakers and industry need to cooperate on to overcome [111].

6. Conclusion

This study examines the issue of HEMS adoption along three dimensions: technology attribute interaction; attitudes, behavior, and social influence; and system and infrastructure interaction to investigate the impact of specific social-psychological and demographic variables on adoption intention and WTP. Understanding these factors from the social-technical perspective can help researchers and policymakers promote energy efficiency technologies and reduce carbon emissions at the household level. We have attempted to cast some light on the Western and Eastern cultural differences in technology adoption and WTP by comparing two large but disparate metropolitan areas, N.Y, and Tokyo. Analyzing the attitudinal and behavioral differences regarding the same technology in these two distinct cultural spheres can provide valuable perspectives in achieving the goals of reducing energy-use and carbon emissions. Finally, a comprehensive framework integrating the functional, instrumental, and social-technical aspects with a wide range of factors, while also considering the public service and utility sectors, is much needed [33]. To thoroughly analyze an integrated HEMS or smart home system, future researchers need to consider the adoption of other renewable energy technologies, including electric vehicles, solar photovoltaics systems, and/or home wind turbines.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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