Internet of Things (IoT) acceptance model – assessing consumers' behavior toward the adoption intention of IoT

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Abstract

Purpose – This study identifies key facets leading to consumers' Internet of Things (IoT) adoption intention.

Design/methodology/approach – Applying four technology acceptance theories (theory of planned behavior, technology acceptance model, pleasure-arousal-dominance theory and technology readiness index), the author uses deductive quantitative research to develop a model, explaining IoT adoption intentions. Administrated questionnaires are distributed in Egypt among generation-Z and millennials in malls. A total of 400 questionnaires are used for hypotheses testing, applying structural equation modeling (SEM) path coefficient analysis.

Findings – Results of this study show that attitude, dominance, perceived usefulness, innovativeness and insecurity impact consumers' IoT adoption intentions; subjective norms, perceived behavior control, pleasure, arousal, perceived ease, optimism and discomfort hold insignificant impact on consumers' IoT adoption intentions.

Research limitations/implications – Exploring IoT facets and how these facets impact consumers' adoption intentions, this study helps grasp technology acceptance in theory and practice, guiding scholar and practitioners (e.g. IoT developers, retailers, marketers and other field experts) to consider consumers' mindset when developing, improving and marketing IoT.

Originality/value – The contribution stems from the incorporation of various frameworks used to explain technology acceptance. By studying several theories jointly, the research extracts and identifies a significant set of facets (technical and psychological) to build a comprehensive theory of IoT acceptance, showing consumers' IoT adoption is not entirely similar to adoption of other past innovations. This understanding allows marketers to focus on content that needs to be promoted to boost consumers' IoT purchase plans. Future researchers could replicate the results to IoT categories (e.g. home appliances, cars, healthcare, education, sportswear, etc.) to improve external validity of the findings, among other future research opportunities.

Keywords Adoption, Behavior intention, Consumer behavior, IoT, Technology acceptance

Paper type Research paper

1. Introduction

Internet of Things (IoT) changed the traditional way of people's operations, performances and lifestyle, compelling ongoing technology advancement, digitization and datafication to make society more efficient, comfortable and reliable (Tsourela & Nerantzaki, 2020). IoT are smart devices; physical objects that contain sensors, software and other technologies to connect and exchange data with other devices and systems over the internet or other information communication technology without needing human-to-human or human-to-computer interaction (Almomani, Mohd, & Rahman, 2022). IoT exist in many forms, such

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as a heart monitor implant in a person, a smart refrigerator that scans and monitors the inside items to recognize the needed grocery stock, built-in automobile sensors to inform the driver about vehicle matters or any products or services that hold an Internet protocol address and capable of transferring data over a network (Tsourela & Nerantzaki, 2020). IoT enhance and facilitate the functionality of different activities among humankind, providing everyday innovative solutions in society, among consumers, businesses as well as government and public entities (Momani, 2020).

Scholars and practitioners claim that IoT improve the quality of life; nevertheless, the diffusion and adoption rate are sluggish in societies, especially in the Arab world (Almomani *et al.*, 2022). There are debates regarding its justification; some researchers claim that it is due to lack of awareness of IoT usage and benefits (Lau *et al.*, 2018). Other researchers claim that it is due to security and privacy encounters that lead to cyber-attacks, risks and vulnerabilities of people and/or their personal data (Kim & Wang, 2021). Fittingly, scholars and practitioners yearn to comprehend the necessary initiatives that can encourage consumers' IoT acceptance; as they see that these devices are indispensable, leading to community development, individual empowerment and circumvent traditional inept processes (Kumar, Tiwari, & Zymbler, 2019). To address this challenge, there is a need for further research to better understand how to stimulate IoT usage. Thus, this study seeks to be a guide to grasp IoT adoption intentions drivers, offering practitioners empirical insights needed for developing, improving and marketing IoT to consumers.

Due to the disruptive nature of advanced technology and its multiple social and economic implications, continuous explorations are requested in this fast-growing area (Flavián, Pérez-Rueda, Belanche, & Casaló, 2022). Acceptance toward innovation varies among products, consumers and circumstances (Momani, 2020). Recurring researches call for more scholars to identify if IoT are similar or not from adoption of other technological innovations; relevant literature have insufficient realization of IoT behaviors (Sepasgozar, Davis, Li, & Luo, 2018; Almomani *et al.*, 2022). Accordingly, this study addresses this research gap, developing empirical insights of how might consumers embrace the general concept of IoT (web-enabled smart devices with sensors to act on data attained from the environment); and if it is with the same motives as other existing technological objects. Existing research studies assess IoT with the technology acceptance model (TAM) and its various extensions (Kim & Wang, 2021); nevertheless, shortcomings in results occur as these theories hold criticisms; scholars claim that more antecedents are needed to be incorporated (Almomani *et al.*, 2022).

Rogers (1983/2003) states that there are many reasons one can adopt to a technology; factors like hedonic and utilitarian stimuli, intrinsic and extrinsic stimuli, functional and psychological stimuli can lead to consumers' acceptance toward various technologies. Therefore, numerous technology acceptance theories and models exist in literature that reflects several facets that could explain people's behavior to embrace new technologies (Flavián *et al.*, 2022). Each theory and model incorporate a single perspective into their respective notion, neglecting an all-inclusive explanation of why consumers might take-up technology and innovation; this leads to limitations, criticisms and the redevelopment operations of theories throughout the years (Almomani *et al.*, 2022). Hence, this study incorporates several frequently adopted theories relating to technology acceptance to bridge the gap in literature that bids to clarify consumers' technology adoption intentions. Two main research questions are steered through convergent reasoning to identify the main facets to theorize consumers' IoT adoption intentions.

RQ1. What are the technological mechanisms that impact IoT adoption intention?

RQ2. What are the psychological mechanisms that impact IoT adoption intention?

The solutions to these research questions allow twofold contribution. First, this study incorporates well-known theories to predict IoT usage. Prior technology researchers suggest that the theory of planned behavior (TPB), TAM, technology readiness index (TRI) and pleasure-arousal-dominance theory (PDA) are significant frameworks that rationalize people's technology acceptance in different contexts; and are previously unexplored together in one study (Belanche, Casaló, & Flavián, 2019). Thus, this study unified these frameworks to tackle the gaps of each theory, constructing a model that is comprehensive yet parsimonious and, thereby, more powerful in describing and predicting IoT adoption intention. The second contribution is to improve the conceptualization of IoT usage cognition, identifying significant advantages, which involves its innovation superiority. These insights aid in the strategy formation for IoT promotion in the market.

The remainder of this article is structured as follows: the following sections seek to review prior IoT literature and explain various technology acceptance theories, leading to the presentation of the proposed research model and the formulated hypotheses. Next, the data collection process and methodology are explained. Then, the main findings are clarified. The final section ends with the research conclusion, implications, limitations and suggested outlines for future studies.

2. Literature review

The diffusion theory of innovation states that users are prepared to accept innovations and technology if it delivers exceptional rewards, extra gains and benefits not found among existing solutions (Rogers, 1983). Research studies clarify that IoT are valuable to individuals, providing promising advantages (Almomani *et al.*, 2022). Kim and Wang (2021) mention that IoT are in the early stage of diffusion; research studies have focused on its technological and economic aspects (Tsourela & Nerantzaki, 2020); though, other studies indicate that psychological factors may impact usage (Arfi, Nasr, Khvatova, & Zaied, 2021), signifying the need for a comprehensive explanation of key technological and psychological facets for adopting this relatively new technology (Almomani *et al.*, 2022).

IoT have initiated a line of research studies (as shown in Table 1), exploring various factors influencing adoption in a wide-range of contexts (Tsourela & Nerantzaki, 2020). Various IoT adoption researches use the TAM as the main adoption theory (Almomani *et al.*, 2022). Perceived usefulness and perceived ease have been recognized to influence IoT behavioral intention in various countries, such as in Turkey (Karahoca, Karahoca, & Aksöz, 2018), Saudi Arabia (bib_al_hogail_2018Al-Hogail, 2018), the Netherland (de Boer, Alexander, Deursen, & Rompay, 2019), India (Dhagarra, Goswami, & Kumar, 2020), Vietnam (Van, 2020), Taiwan (Lian, Chen, Shen, & Chen, 2020) and France (Arfi *et al.*, 2021). However, other research works clarify that the original TAM lacks sufficient intrinsic and extrinsic facets of IoT adoption (Kim & Wang, 2021). Correspondingly, some IoT research studies do not deploy any theory; these research works apply an exploratory nature to pinpoint significant facets not acknowledged formerly; they clarify IoT acceptance is steered by privacy, comfort, security, trust and cost as well as consumers' knowledge, skills and innovativeness (Almomani *et al.*, 2022).

Several IoT literature works highlights various facets (other than the TAM) that are deemed significant to explain people's technology acceptance; these research works emphasize a particular IoT context (not the overall IoT concept). For example, Choi and Kim (2016) reflect on IoT wearables, such as smartwatches. They highlight this new IT product as being high in demand as they are fashionable. In their study, the characteristics of fashion impact intention to wear smartwatches; individuals' desire this IoT for its uniqueness in image. Aldossari and Sidorova (2020) explain that the availability of internet access paves IoT usage, especially in households. They clarify that current home appliances and electronics hold sensors as Internet is found in many households, making IoT able to function

Study	Context	Methodology	The significant IoT predictors
Choi and Kim (2016)	Smartwatches	Quantitative research 562 participants	• Product characteristics • Product image
Karahoca *et al.* (2018)	IoT healthcare	Quantitative research 426 participants	• Perceived advantage • Product image • Perceived ease of use
Belanche, Casaló, and Flavián (2019)	Robot-advisor services	Quantitative research 765 participants	• Mass media • Subjective norms • Perceived usefulness • Product familiarity
Aldossari and Sidorova (2020)	Smart homes	Quantitative research 400 participants	• Performance expectancy • Effort expectancy • Social influence • Hedonic motivation • Price value • Security risk
Carlina and Kusumawati (2020)	Smart garden	Quantitative research 353 participants	• Optimism • Innovativeness • Perceived ease of use • Perceived usefulness
de Boer, Alexander, Deursen and Rompay (2020)	IoT healthcare	Qualitative research 100 participants	• Product knowledge • Internet skills
Lian *et al.* (2020)	Smart lockers	Mixed research 262 participants 50 interviews	• Perceived usefulness • Perceived ease of use • Product function • Product convenience
Tsourela and Nerantzaki (2020)	IoT software application	Quantitative research 812 participants	• Product appropriation • Perceived usefulness • Perceived ease of use
Van (2020)	IoT banking	Quantitative research 290 participants	• Innovative willpower • Perceived usefulness • Perceived ease of use • Product risk
Arfi *et al.* (2021)	IoT healthcare	Qualitative research 68 participants	• Cost of using IoT
Negm (2022)	IoT education	Quantitative research 384 participants	• Optimism • Discomfort • Insecurity
Almomani *et al.* (2022)	IoT healthcare Smart-homes	Quantitative Review 22 researches	• Perceived ease of use • Perceived usefulness • Social influence • Privacy • Attitude • Compatibility • Cost

Table 1.
Summary of current IoT research findings

due to infrastructure. Their research shows that effort expectancy, social influence, trust and hedonic motivation are significant to IoT smart-home acceptance. Lian *et al.* (2020) study IoT in the context of blockchain-based smart lockers. They conclude that it is critical to emphasize the function and opportuneness of IoT when introducing it to potential users. Arfi *et al.* (2021)

justify IoT in the healthcare sector, aiding in well-versed and on-time treatments. They explain that IoT allow hands-on treatments, quick doctor interventions and improve the overall patient-care experience; however, the sluggish IoT usage among patients is due to cost. Negm (2022) focuses on IoT in educational context since the 2020 pandemic changed the educational landscape, making online-learning necessary in the education system. The study focuses on students' technology readiness. Results show that technological optimism, discomfort and insecurity impact IoT adoption. Almomani *et al.* (2022) show that among existing studies, there is no steady agreement on the facets of IoT adoption by users. They analyze existing literature systematically to find the current status of IoT adoption and the main facets that impact adoption. Their results show that usefulness, perceived risk, social influence, privacy, attitude, compatibility, cost and trust are frequently mentioned facets (but not the only facets) that impact IoT adoption.

These reviewed research studies rely either on TAM or have added facets based on exploratory research. Subsequently, this study develops a more comprehensive theoretical model that extends the original TAM. This study assesses other well-known theories related to technology acceptance and incorporates them in a framework to predict IoT usage intention. These theories have been reported to be significant frameworks that rationalize technology acceptance in different outlooks, and are previously unexplored together in one study (Belanche *et al.*, 2019). These theories are merged to overcome each theory limitation (shown in Table 2) to cautiously rationalize IoT acceptance. The following sections explain each of the theory and how the joining theories complete each other.

2.1 Theory of reasoned action (TRA) and theory of planned behavior (TPB)

TRA is one of the first models that emerged to explain the forecast of people's behavior intention (Fishbein, 1967). TRA studies show that a person's attitude (set of emotions and beliefs) toward a particular object is a significant driver of one's actions. In addition, social influence (subjective norms) encourages certain actions of an individual; social pressure by people of importance is a common trigger that can conform individuals' way of thinking and behaving (Ajzen & Fishbein, 1980). In the technology acceptance context, Lau *et al.* (2018) explain that people are accustomed to develop attitudes and get influenced by friends and family. Nevertheless, critics of TRA anticipated that self-determination must be recognized so behaviors can emerge (Tsourela & Nerantzaki, 2020). Thus, TRA was expanded to become TPB (Fishbein & Ajzen, 1975). TPB adds perceived behavior control to TRA, explaining that individual's actions are also inspired by their perceived willpower, self-control and determination (Ajzen, 1991).

Past studies claim that TPB is not wholesome enough to explain human behavior as others variables are deemed important to explain intentions such as fear, mood or past experience (Davis, Bagozzi, & Warshaw, 1989). TPB considers normative influences, but does not take into account environmental, emotional or economic factors that may influence behavior intention (Mehrabian & Russell, 1974; Belanche *et al.*, 2019). While perceived behavioral control is significant to TPB, it does not say anything about actual control over behavior (Venkatesh, Morris, Davis, & Davis, 2003). Correspondingly, studies have built on this theory, developing other branched models (Fishbein & Ajzen, 1975). Furthermore, studies have mentioned a gap in literature, questioning TPB suitability regarding individual's behavior for technology (Sindhu & Namratha, 2019).

2.2 Technology acceptance model (TAM)

When it comes to explaining individuals' behavior toward technology, to fill in the gap found among TRA and TPB, researchers have built upon these theories by establishing TAM (Davis *et al.*, 1989). The goal of TAM is to offer clarifications of the determinants of

Theory	Components of the theory	The limitation of the theory
TPB	The theory explains that people's behavior is connected to various beliefs. The theory pinpoints three main components that shape behavioral intentions: attitude, subjective norms and perceived behavioral control, (Source: Ajzen, 1991)	TPB does not wholesomely explain human behavior as others variables are deemed vital to explain intentions, such as fear, mood, or past experience (Davis *et al.*, 1989) TPB considers normative influences, but does not take into account environmental, emotional, or economic factors that may influence behavior intention (Mehrabian & Russell, 1974; Belanche *et al.*, 2019) TPB may not be suitable for technology as it does not reflect product features (Sindhu and Namratha, 2019)
TAM	The theory explains that there are two factors that determine whether a computer system will be accepted by individuals: perceived usefulness, and perceived ease of use. (Source: Davis, 1989)	TAM ignores the influence of individual differences and environmental variables (Bagozzi, 2007; Marangunić & Granić, 2015; Momani, 2020) TAM focuses on cognition (comprehend through rationalization and experience) rather than affect (comprehend through emotions and moods) (Momani, 2020; Almomani *et al.*, 2022)
PAD	The theory explains that pleasure, arousal and dominance reflect the assorted people's feelings and emotional reactions toward objects. (Source: Mehrabian & Russell, 1974)	PAD measures consumers' emotional responses, ignoring the drive that initially allowed consumers to consider the technology usage (Koufaris, 2002) PAD neglects product-related and environment features that encourage technology acceptance (Momani, 2020) PAD ignores people's propensity to embrace and use new technologies to accomplish goals in home life and at work (Parasuraman, 2000)
TRI	The theory explains the emotions (positive and negative technology-related reactions: optimism, innovativeness, discomfort and insecurity) that consumers feel toward using new technologies, regulating its usage tendency (Source: Parasuraman, 2000)	TRI focuses on consumers' traits in explaining technology usage, neglecting the product features as well purpose (Parasuraman, 2000). TRI does not mention the technology relative importance (Momani, 2020)

Table 2.
Technology acceptance theories and its criticisms

consumers' adoptions that generalize over various forms of innovations and technologies (Tsourela & Nerantzaki, 2020). TAM theorizes that consumers' intention to adopt a particular technology is determined by their attitudes toward technology usage, which is formed by two beliefs: perceived usefulness, "*one believes that using the technology will enhance his/her performance*"; and perceived ease of use: "*one believes that using the technology will be free of effort*" (Davis *et al.*, 1989, p. 982).

TAM has been criticized for its limitations. TAM ignores the influence of individual differences and environmental variables on technology acceptance (Bagozzi, 2007; Marangunić & Granić, 2015). Further, most research using TAM focused on cognition (comprehend through thought, experience and rationalization) rather than affect (comprehend through emotions and moods). Existing researchers say that the emphasis on cognition might be appropriate for technology adoption that is mandated for consumers; consumers have little choice regarding the decision. Nevertheless, it is an inadequate reason for consumers who are free to adopt or reject new technology based on how they feel and how they think (Almomani *et al.*, 2022). Due to TAM limited clarification, studies added on to

TAM, developing other revised models to grasp further consumers technology acceptance (Venkatesh *et al.*, 2003; Sepasgozar *et al.*, 2018; Momani, 2020).

The modifications models of TAM still were considered by research to be partial in explaining technology acceptance (Venkatesh *et al.*, 2003). Momani (2020) claims that intrinsic motivation, such as fun, when used with TAM had a more significant effect on clarifying technology acceptance; emotion(s) are relevant facets to technology adoption. Childers, Carr, Peck, and Carson (2001) propose that both hedonic and utilitarian motives are relevant to consumers' engagement in technology. Thus, studies later added emotional responses to explain consumer technology behavior, filling in some gaps and limitations among various versions of TAM (Almomani *et al.*, 2022).

2.3 Mehrabian–Russell's (1974) PAD

Mehrabian and Russell's (1974) theory claims that all emotional responses can be apprehended with three dimensions of affect: pleasure, arousal and dominance, creating PAD theory of technology acceptance. PAD argues that pleasure, arousal and dominance reflect the assorted human feelings and emotional reactions toward objects in the environments. Studies explain that pleasure reflect consumers experiences with the technology that leads to an enjoyable reaction (feelings of happiness, fun and satisfaction); arousal reflects consumers' mental and physical alertness (feelings of stimulation and anticipation); dominance reflect consumers' sense of control (feeling of power) (Almomani *et al.*, 2022). Research shows that when it comes to IoT usage, many consumers calculate different emotions toward it; their emotions can range from joy, to boldness and courage, to anger and fear at one point to another (Tsourela & Nerantzaki, 2020).

Literature gaps exist among previous PAD studies. For instance, studies claim that the feelings of pleasure and arousal are overstudied, but the dominance dimension has frequently been left out; the dominance factor have been overlooked by researchers (Kulviwat, Bruner, Kumar, Nasco, & Clark, 2007; Almomani *et al.*, 2022). Kulviwat *et al.* (2007) explain that dominance should be studied more often as it can play a significant role toward technology acceptance. Flavián, Pérez-Rueda, Belanche, and Casaló (2022) mention that new technology empowers individuals; with technology, individuals can hold unlimited access to information and can make their voices/opinions heard more loudly, increasing the dominance affect (Almomani *et al.*, 2022), specifically in regards to IoT (Carlina & Kusumawati, 2020).

PAD employed in research measures consumers' emotional responses when using technologies (Koufaris, 2002). Thus, studies have criticized PAD for its limitations, ignoring the drive that initially allowed consumers to consider the technology usage (Almomani *et al.*, 2022). Parasuraman (2000) claim it is important when studying technology acceptance among consumers to be mindfulness about: "*people's propensity to embrace and use new technologies to accomplish goals in home life and at work*" (p. 308). Thus, to reduce PAD limitation regarding consumer behavior toward technology, other studies turned to the psychological technology drivers instead of product-related and environment features (Momani, 2020).

2.4 Technology readiness index (TRI)

Research shows that consumers calculate different mental readiness and emotions toward technology usage; their thoughts can range from joy, to boldness and courage, to anger, skepticism and fear at one point to another (Tsourela & Nerantzaki, 2020). Fittingly, Parasuraman (2000) developed TRI theory to illustrate a paradox of emotions (positive and negative technology-related beliefs) that consumers feel toward the idea of using new technologies; these beliefs regulate a person's tendency to interact with new technology. The beliefs are sorted into four dimensions: optimism, innovativeness, discomfort and insecurity. Optimism is the belief that technology gives more efficiency at work, innovativeness is the belief of being technology pioneer, discomfort is the belief that technology is overwhelming because it is difficult to control and insecurity is the belief of distrust and skepticism toward technology to work properly (Parasuraman & Colby, 2015). TRI reflects personal mental dimensions as antecedents to the cognitive dimensions of TAM, filling another limitation of TAM (Parasuraman & Colby, 2015). Carlina and Kusumawati (2020) state that the dimension optimism and innovativeness bring out positive values of consumers; discomfort and insecurity dimensions make consumers develop negative values. Tsourela and Nerantzaki (2020) explain that these personal beliefs allow consumers to readily accept or counteract the technology; it can be used to explain IoT adoption.

2.5 The proposed research model

Many theories exist to explain technology adoption among consumers (Belanche *et al.*, 2019), whether they relate to product features and function, individual's mental-readiness, social factors or emotional factors (Flavián *et al.*, 2022). Each theory incorporates a certain perspective, neglecting an all-inclusive explanation. Thus, this study uses these four distinctive theories (TPB, TAM, PAD and TRI) under one model (Figure 1) to theorize IoT adoption intentions. Past studies mention that these theories are useful in rationalizing technology acceptance in different outlooks, and are previously unexplored together in one study (Almomani *et al.*, 2022), specifically when it comes to IoT (Kim & Wang, 2021). Thus, this study differs from existing research.

By studying several theories jointly, the developed model satiates the limitations found in each theory. For example, TAM ignores the influence of individual differences and environmental variables on technology acceptance; most TAM research focused on cognition rather than affect (Marangunić & Granić, 2015). TPB considers normative influences, but does not take into account emotional factors that may influence adoption (Belanche *et al.*, 2019). Parasuraman (2000) indicates it is mandatory to study the paradox of emotions toward technology usage. Consequently, the inclusion of TPB, TAM, PAD and TRI would constitute a valuable extension of previously conducted research, considering the main technological and psychological facets.

From this proposed research model, 12 hypotheses are formed; each construct assumes significant impact on consumers IoT adoption intentions. Testing these hypotheses should clarify the main technological and psychological facets; and if IoT adoption intentions are similar to other technology acceptances. With these insights, this study develops and

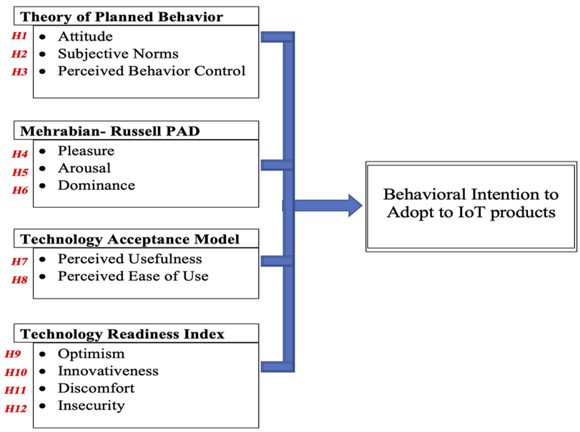

Figure 1.
Proposed research model

validates an extended TAM, specifically designed for IoT that integrates diverse facets to enable systematic prediction of IoT, with implications for the adoption of future pervasive technologies.

3. Research design

This quantitative descriptive research was deductive in nature as hypotheses were formulated from existing theories found in the literature review; to be tested with a positivist approach in philosophy. The researcher sought objective data to conclude: "*law-like generalizations similar to those produced by the physical and natural scientists*" (Saunders, Lewis, & Thornhill, 2009, p. 15). Administrated questionnaires were used to collect the primary data.

Mega-shopping malls in Egypt were the field of focus; these malls contained stores selling various forms of IoT. The study setting was noncontrived. The data were collected during August to October 2021, following a cross-sectional study. The researcher casually stopped individuals in the mall and asked them if they would voluntarily participate in a study, applying convenience sampling; those who agreed were given a pen, the questionnaire to fill-out and hand sanitizer for safeguarding from germs. The studied population were millennials and generation-Z. According to Statista (2021), "*millennials are anyone born between 1981 and 1996; and generation-Z are anyone born between 1997 and 2012*" (p. 1). This population was chosen because researches indicate that millennials and generation-Z enjoy learning about new advanced products; they appreciate social encouragement toward the purchases of various technologies; they are documented as heavy consumers of electronics and advanced technology (Consumer Electronics Association, 2017).

Ethical consideration was mandatory as researcher conducted the data collection. Before allowing the respondents to participate in the study, the researcher required them to read an informed consent paragraph in the cover page of the questionnaire. The paragraph clarified the research topic, the voluntary role of the respondents, the respondents' anonymity, the confidentiality of the responses and the option of withdrawal from the study if chosen at any point. Once the respondents read the paragraph and gave consent for participation, they began to answer the questions.

The questionnaire was offered in several languages to suit the respondents' preferences in questioning – either Arabic (mother tongue language), English (universal language), Spanish or French (second most spoken native language globally) (Statista, 2021). Back translation was used for each version of the questionnaire so to confirm the congruence of ideas and meaning. In addition, a pilot test (50 questionnaires) was steered to confirm the questionnaire's scales' validity and reliability (each variable was assessed by *five-point Likert scale*). This step was vital since the scales were from past research and modified to suit IoT context (Table 5 shows scale source).

4. Research analysis

Out of 500 questionnaires that were distributed, 400 questionnaires were properly completed and used for analysis (80% response-rate). The research used *IBM-SPSS 19* to summarize respondent characteristics and key study variables. The research used *IBM-SPSS Amos 16* to test hypotheses through structural equation modeling (SEM) path coefficient analysis.

4.1 Frequency analysis

Frequency analysis portrayed the participants' backgrounds and IoT standpoints. Based on the analysis (Table 3), the respondents were from different socio-demographic traits and opinions.

Item	Category	Frequency	%	Item	Category	Frequency	%
Age	Born 1981–1989	17	04.250	Average household Income	Less than 2,000	59	15.000
	Born 1990–1996	183	45.750		2,000 – less than 5,000	70	17.000
	Born 1997–2012	200	50.000		5,000 – less than 10,000	85	21.300
					Over 10,000	186	46.500
Gender	Female	172	43.000	Occupation	White collar	86	21.500
	Male	228	57.000		Blue collar	294	73.500
					Other	20	5.000
Marital status	Single	239	59.000	Education	Elementary school	1	0.300
	Married	145	36.000		High school	63	15.8
	Divorced/ Separated	13	3.000		College degree	104	26.0
	Widowed	3	0.800		Graduate degree	102	25.5
					Postgraduate degree	107	26.8
					Other	23	5.8
Reasons for buying IoT	Social influence	63	15.800	Reasons for not buying IoT	Social influence	16	4.000
	Ease of use	104	26.000		Lack of trust	107	26.800
	Trendy	13	3.300		Lack of availability	360	90.000
	Fun	10	2.500		Lack of relevance	104	26.000
	Reliable	361	90.300		Not aware	86	21.500
	Other	16	4.000		Expensive	239	59.000
					Other	13	3.000
IoT owned	Cars	7	1.800	IoT future purchases	Cars	104	54.000
	Fashion/ Accessories	159	39.800		Fashion/ Accessories	102	26.000
	Home appliance	18	4.500		Home appliance	107	25.500
	Home entertainment	107	26.800		Home entertainment	216	26.800
	Smart health-product	7	1.800		Smart health-product	107	26.800
	others	3	0.800		others	18	4.500

Table 3.
Participants' socio-demographics and IoT behaviors

4.2 Normality testing

Before testing any hypotheses, normality tests took place. This test was used to determine if the data set was well-modeled to compute how likely it was for a random variable underlying the data set to be normally distributed. In this study, the *Kolmogorov–Smirnov test of normality* was applied. This analysis assumed that the data was normally distributed if the *p*-value was greater than 0.05. It was called the formal test of normality. Table 4 illustrates the results.

The research tested normality by checking the *skewness and kurtosis values.* A kurtosis value of +/−1 was considered good for most psychometric uses. Skewness reflected distribution of values deviated from symmetry around the mean. If the number of skewness was greater than +1 or lower than −1, this was an indication of a substantially skewed distribution. Table 4 illustrates the result. The data under study were not approximately normal. Therefore, nonparametric tests were used.

The *assumption of multicollinearity* was required to avoid redundancy of information in the model under study. Redundancy occurred when two or more predictors in a model were

Variables	Descriptive statistics Mean	Std. deviation	Skewness Statistic	Std. error	Kurtosis Statistic	Std. error	VIF	Kolmogorov–Smirnov[a] Statistic	df	Sig
1. Attitude	3.265	1.158	−0.297	0.122	−0.954	0.243	2.803	0.287	400	0.000
2. Subjective Norms	3.583	1.073	−0.564	0.122	−0.360	0.243	2.977	0.268	400	0.000
3. Perceived Behavior Control	3.453	1.121	−0.509	0.122	−0.685	0.243	3.012	0.409	400	0.000
4. Pleasure	3.517	0.917	−0.776	0.122	0.449	0.243	2.174	0.300	400	0.000
5. Arousal	3.350	0.997	−0.563	0.122	−0.301	0.243	2.047	0.316	400	0.000
6. Dominance	2.930	0.978	−0.069	0.122	−0.643	0.243	1.418	0.342	400	0.000
7. Perceived Usefulness	4.025	0.731	−1.002	0.122	2.304	0.243	1.936	0.293	400	0.000
8. Perceived Ease of Use	3.915	0.767	−0.890	0.122	1.502	0.243	1.561	0.277	400	0.000
9. Optimism	3.483	1.016	−0.269	0.122	−0.548	0.243	1.256	0.285	400	0.000
10. Innovativeness	3.805	0.743	−0.697	0.122	1.167	0.243	2.803	0.304	400	0.000
11. Discomfort	3.820	0.808	−0.575	0.122	0.496	0.243	2.977	0.260	400	0.000
12. Insecurity	2.930	0.978	−0.509	0.122	−0.685	0.243	3.012	0.316	400	0.000
13. Adoption Intention	4.025	0.731	−0.297	0.122	−0.954	0.243	2.174	0.342	400	0.000

Table 4.
Testing of normality

highly correlated with each other as this leads to problems with understanding which predictors contribute to the variance explained in criterion, and technical issues in calculating multiple regression model. This assumption was tested by variance inflation factor. It was observed (Table 4) that the VIFs of the variables were all less than 5, implying no problem of multicollinearity between variables.

4.3 Reliability and validity testing

Reliability and validity tests indicated how well the scale or test measured the constructs. Reliability explained the consistency of a measuring test. Validity checked the accuracy of the questions – if the questions were truly assessing the issues it claimed to measure (Bryman, 2012). Several reliability and validity tests were conducted in this study: Kaiser–Meyer–Olkin (KMO), average variance extracted (AVE), Cronbach's alpha (α) and discriminant validity. The analyses results (Tables 5 and 6) implied adequate convergent validity, reliability and discriminant validity.

4.4 Confirmatory factor analysis

Confirmatory factor analysis (CFA) was used to illustrate a confident expectation regarding the design of the data obtained (Hair, Hult, Ringle, & Sarsted, 2016). The model fit of the confirmatory factor analysis were computed; it was found that the minimum discrepancy or chi-square divided by the degrees of freedom (CMIN/DF) was 2.234, the probability of getting as larger discrepancy as occurred with the present sample (p-value) was 0.000, goodness of fit (GFI) was 0.942, adjusted goodness of fit index (AGFI) was 0.908, which evaluated the fit of the model versus the number of estimate coefficients or the degrees of freedom needed to achieve that level of fit, the Bentler–Bonett normed fit index (NFI) was 0.984 and the Tucker–Lewis index or Bentler–Bonett nonnormed fit index (TLI) was 0.921, which assessed the incremental fit of the model compared to a null model; the comparative fit index (CFI) was 0.932. The root mean square residual (RMR) was 0.070, which showed the amount by which the sample variances and covariances differ from their estimates obtained under the

Table 5.
Validity and reliability test

Variables/Scale source	KMO	AVE %	α	Variables/Scale source	KMO	AVE %	α
Attitude – adapted from Priester, Nayakankuppam, Fleming, and Godek (2004)	0.890	79.235	0.934	Perceived ease of use- adapted from Meuter, Bitner, Ostrom, and Brown (2005)	0.700	72.520	0.804
Subjective norms – adapted from Nysveen, Pedersen, and Thorbjørnsen (2005)	0.741	82.524	0.894	Optimism- adapted from Grewal, Iyer, and Levy (2004)	0.830	76.070	0.895
Perceived behavior control – adapted from Nysveen *et al.* (2005)	0.753	85.866	0.918	Innovativeness – adapted from Shih and Venkatesh (2004)	0.700	72.720	0.810
Pleasure – adapted from Mehrabian and Russell (1974)	0.724	76.474	0.846	Discomfort – adapted from Spangenberg, Sprott, Grohmann, and Smith (2003)	0.729	78.216	0.861
Arousal – adapted from Mehrabian and Russell (1974)	0.711	78.634	0.863	Insecurity – adapted from Montoya-Weiss, Voss, and Grewal (2003)	0.806	68.354	0.783
Dominance – adapted from French and Raven (1959)	0.806	68.354	0.883	IoT Adopt intention – adapted from Sundar and Kalyanaraman (2004)	0.820	72.520	0.894
Perceived usefulness- adapted from Nysveen *et al.* (2005)	0.820	64.049	0.858				

assumption that the model was correct; the root mean square of approximation (RMSEA) was 0.056, which was an informative criterion in covariance structure modeling and measured the amount of error present when estimating the population. Table 7 shows CFA indicators value and the recommended values.

4.5 Hypotheses testing

The study's hypotheses were tested using correlation and path analysis of SEM. Table 8 shows the hypothesis testing. The outcomes of the path coefficient showed that attitude, dominance, perceived usefulness, innovativeness, insecurity impacted consumers' IoT adoption intentions; the insignificant variables on consumers' IoT adoption intentions were: subjective norms, perceived behavior control, pleasure, arousal, perceived ease, optimism and discomfort.

5. Research conclusion

This study provides thought-provoking insights into IoT literature, showing that the key facets for consumers IoT adoption is not entirely similar to the adoption of other innovations. Two main research questions were sought: *what are the technological mechanisms that impact IoT adoption intention; what are the psychological mechanisms that impact IoT adoption intention?* The results show that consumers' attitudes, their feeling of dominance, their perceived usefulness of the technology, their innovativeness mindset and the level of insecurity toward technology are the key technological and psychological facets that impact IoT consideration. With these findings, a framework is developed, theorizing consumers' IoT adoption intention. This framework shows the technological and psychological mechanisms involved in this relatively new technology, tackling the gaps of past technology theories. This framework is a useful guide for developing, improving and marketing IoT. With the emerged

Table 6. Discriminant validity

	1	2	3	4	5	6	7	8	9	10	11	12	13
Attitude	(0.890)												
Subjective Norms	0.716**	(0.908)											
Behavior Control	0.731**	0.737**	(0.927)										
Pleasure	0.358**	0.416**	0.405**	(0.874)									
Arousal	0.338**	0.350**	0.391**	0.627**	(0.887)								
Dominance	−0.165**	−0.121*	−0.151**	0.269**	0.338**	(0.827)							
Usefulness	0.354**	0.511**	0.436**	0.359**	0.293**	−0.015	(0.800)						
Perceived Ease	0.213**	0.320**	0.270**	0.332**	0.272**	−0.004	0.529**	(0.852)					
Optimism	−0.235**	−0.156**	−0.205**	0.141**	0.130**	0.367**	0.051	0.005	(0.872)				
Innovativeness	0.369**	0.379**	0.384**	0.312**	0.259**	−0.087	0.550**	0.425**	−0.015	(0.853)			
Discomfort	0.384**	0.378**	0.400**	0.369**	0.231**	−0.088	0.541**	0.411**	−0.011	0.712**	(0.884)		
Insecurity	0.716**	0.358**	0.436**	0.468**	0.331**	−0.087	0.521**	0.413**	−0.016	0.728**	0.367**	(0.827)	
Adoption Intention	0.580**	0.578**	0.208**	0.592**	0.571**	0.291**	0.615**	0.545**	0.188**	0.521**	0.582**	0.712**	(0.846)

Note(s): **Correlation is significant at the 0.01 level (2-tailed)
*Correlation is significant at the 0.05 level (2-tailed)

empirical evidence, practitioners and researchers can apply the insights to progress the spread of IoT on larger scale to benefit the society as much as possible.

6. Research discussion

Various theoretical and managerial implications and contributions can be concluded (both theory and practice), aiding scholars and IoT practitioners (e.g. developers, retailers, marketers and other IoT experts) The results in this study imply that when it comes to TPB and TAM, consumers perceive IoT as useful; consumers hold positive attitudes toward IoT as it progresses performance in many aspects of their daily-lives (transport efficiency, easy-access to healthcare and wellness, socialization and job-productivity); regardless of IoT ease-of-use, their own perceived behavior control or what other people around them think. These results correspond with studies by Kumar *et al.* (2019) and Almomani *et al.* (2022); they clarify that IoT are the next generation of products, using artificial data and machine learning to add intelligence to existing products, improving its function, consistency and quality; IoT are practical and advantageous, which leads consumers to consider their usage. Momani (2020) and Kim and Wang (2021) state that advances in technology have heralded new useful and obligatory changes in consumer behavior. So, the study recommends that practitioners promote IoT as a necessary, practical and valuable mechanism that empowers achievement; showing IoT constructiveness and usefulness to boost purchase intention.

When it comes to PAD, the results imply IoT adoptions are not similar to other technologies that are enjoyable and exciting in its purpose. Dominance (psychological–physiological state) is what drives IoT consumption, not the feeling of pleasure or arousal. IoT enable consumers with seamless access to unprecedented amounts of data. Consumers use IoT as development tools and information-exchange so to improve performance and

Table 7. Fit indices and thresholds for measurement model

Measure	Results	Threshold	Measure	Results	Threshold
Chi-square/df	2.234	<3 good	TLI	0.921	>0.85
P-value	0.000	>0.05	CFI	0.932	>0.80
GFI	0.942	>0.80	RMR	0.070	<0.09
AGFI	0.908	>0.80	RMSEA	0.056	<0.10
NFI	0.984	>0.80			

Table 8. SEM path coefficient analysis

Hypotheses	Estimate	*p*	Hypothesis supported
1. Attitude → AI	0.252	***	Supported
2. Subjective norms → AI	−0.229	0.014	Not-Supported
3. Perceived behavior control → AI	−0.086	0.367	Not-Supported
4. Pleasure → AI	−0.042	0.718	Not-Supported
5. Arousal → AI	0.097	0.287	Not-Supported
6. Dominance → AI	0.277	***	Supported
7. Perceived usefulness → AI	0.033	***	Supported
8. Perceived ease of use → AI	0.309	0.069	Not-Supported
9. Optimism → AI	−0.036	0.369	Not-Supported
10. Innovativeness → AI	0.277	***	Supported
11. Discomfort → AI	0.010	0.886	Not-Supported
12. Insecurity → AI	0.939	***	Supported

Note(s): AI reflects adoption intention
*** Reflects hypothesis is significant

quality of life. The Consumer Good Forum (2021) mentions: "*although the idea of machines exchanging data is nothing new, the increasing bandwidth of wireless and mobile networks means consumers can be connected wherever they are, making IoT incredibly powerful at gathering, sharing and enriching data*" (p. 3). Therefore, Mehrabian and Russel (1974) original theory is not fully relevant for explaining IoT usage. It is recommended that practitioners promote IoT, highlighting the sense of dominance and control: "*extending the benefits of the regular internet—constant connectivity, remote control ability, data sharing, and so on—to goods in the physical world*" (Tsourela & Nerantzaki, 2020, p. 1).

In this study, TRI results imply that consumers do not adopt IoT due to the feeling of discomfort nor due to the optimism of technologies; consumers adopt innovative solutions that protect from cybersecurity threat. People are aware that each generation of technology introduced in the market improves over the last (enhancements happen from version to version of products). Product progress is anticipated, making consumers not enthusiastic for development. Kumar *et al.* (2019) mention that advanced technology constantly changes products in the market; changes in products and behaviors are norms. Carlina and Kusumawati (2020) explain that people are reluctant about IoT due to safety. Al-Hogail (2018) claims that: "*consumers are cautious about sharing data for fear that it can be used in any inappropriate ways*" (p. 3). Therefore, IoT practitioners should develop and promote IoT as a new, safe, beneficial and futuristic device that improve the quality of life and daily performance so to enhance wider and faster diffusion.

6.1 Research limitations and proposed suggestions for future studies

This study faced several limitations during the research conduction. This study focused on four TAMs, neglecting other models that could be significant. Thus, it is suggested that future research can study other theories as supplementary insights. This might involve adding further facets or requiring some changes to be made to the model. This study tested IoT in general, not focusing on a specific field or product category. So, upcoming research can conduct assessments on specific domains of IoT products and applications (e.g. smart homes and appliances, smart cars, smart health-devices, smart wearables, etc.). This study explored the factors influencing consumer adoption of IoT in one community, the Egyptian context. Nevertheless, it is known that there may be some variation in opinions, preferences and motives due to cultural beliefs or governmental regulations. Thus, to verify the validity of the developed model presented in this study, future studies can test the model on other communities.

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