ARTIFICIAL INTELLIGENCE (AI) ADOPTION: AN EXTENDED COMPENSATORY LEVEL OF ACCEPTANCE

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ABSTRACT

This paper uses a new measurement of AI's intelligence related to task performance to examine how expectations about the operating efficiency of an AI technology influence the intention to adopt it. We suggest four levels of user acceptance/rejection of AI services, including the level of compensatory acceptance. Our conceptual model is specifically designed for the AI context, with two key variables: cybersecurity and anthropomorphism, and three mediating constructs: i) perceived level of AI's intelligence, ii) perceived performance expectancy, and iii) perceived effort expectancy. The hypotheses were tested by surveying 494 potential virtual banking users in Hong Kong and analyzing the data with Structural Equation Modelling (SEM). We find that consumer acceptance of AI services is positively related to perceived performance expectancy and effort expectancy and to the perceived level of AI's intelligence. These findings support an extended behavioral intention: the compensatory level of AI acceptance. Our empirically tested and generalizable results have implications for academics and practitioners.

Keywords: AI adoption; AI's intelligence; Performance expectancy; Effort expectancy; Self-service technology

1. Introduction

Cognitive technologies are products of artificial intelligence (AI) and have been widely penetrating different industries (Lombardi et al., 2020), including the FinTech industry. This disruptive technology enables the FinTech industry to increase its cost-effectiveness and competitive edge, especially transforming traditional banking services dramatically into virtual banking (VB) services without a physical distribution outlet. The growth of the FinTech ecosystem and environment has dramatically sharpened banking services. Given the newness of this banking industry transformation, it is understandable that the level of customer acceptance of AI technology-based banking services is nascent and that academic research into it is limited. According to McKinsey's 2021 Personal Finance Survey, the adoption of digital banking by users in Asia (Mckinsey, 2021, p.4) increased by 88%, which is 65% up from four

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years prior, and more than 60% of consumers have expressed a willingness to switch to a “direct” bank. Even before the Covid-19 pandemic, direct banking services were emerging worldwide, offering cost advantages and operating efficiencies that surpass those of traditional retail banks. With the onset of the pandemic and the social distancing requirements imposed by many governments, consumers were nudged to realize the extent to which non-face-to-face banking could save them queuing and travel time.

In general, an individual can respond to these examples of Self-Service Technology (SST) (Cao et al., 2022; Hsu et al., 2021) in two polar ways: acceptance or rejection. There is limited research examining why and how an individual swings or changes mindset from rejection to acceptance or vice versa in the AI context. Prior extant research primarily focused on the traditional Technology Adoption Model (TAM) with constructs not capturing AI’s machine learning algorithms and AI generative content for instant-process services. As such, it underestimates the complexity of humans responding to AI services if we simply employ conventional information systems adoption constructs to explain behavior in the AI context. While the AIDUA model (Gursoy et al., 2019) incorporates users’ emotions in the adoption of AI services by using a three-stage cognitive appraisal theory (Lazarus, 1991a, 1991b), we believe that the subjectivity and transitoriness of emotion affect the predictability of the outcomes. Furthermore, extant research lacks an explanation for a user who will accept services that are enabled by AI instead of humans. Facing these underlying deficiencies or unknown elements motivates the development of a new AI adoption model.

First, our model extends our understanding of AI consumer behavioral intention by introducing a new concept of a *Compensatory Level of Acceptance* for innovative technologies. “Compensatory” nature of acceptance has been derived from prior research on compensatory consumption (Wooddruff-Burton and Elliot, 2005) to reflect and express the concept of “self-acceptance in resolving self-deficits” (Kim and Gal, 2014), i.e., an individual will accept the challenge to change once they have accepted self-deficits. This implies consumers can both perceive the value offered by technology, high-performance expectancy, and also be willing to put in extra effort to use it, high effort expectancy.

Second, we introduce a new set of determinants and mediating variables that are appropriate to the AI context. One such factor is the AI’s level of intelligence (PERCEAII). This is relevant because users’ perceptions of AI performance have now become key to whether AI technologies are adopted. In addition, one of the critical factors for the adoption of VB by customers is the matter of “trust” (Chang and Fang, 2013; de Matos et al., 2020), and reliance upon high levels of cybersecurity (Alhouti et al., 2016). Security concerns can deter AI adoption because a potential user may worry about the leakage of personal data during information inputting, transmitting, interpreting, and storing. In addition, AI anthropomorphism is another important factor because AI-service interfaces should be comparable to offer an expected human-like experience or even exceptional user service if service providers intend to attract new users by switching them from traditional human service providers.

The rest of the paper is organized as follows: Section 2 outlines the literature review and theoretical foundation of this study. Section 3 presents the research model and hypotheses. Section 4 focuses on research methodology, and Section 5 summarizes the results of data analysis. Finally, key findings and implications are discussed in Section 6, and these are followed up with limitations and future research in Section 7.

2. Literature Review

Over the past 35 years, many researchers have conducted studies into users’ adoption of technology by reference to the most popular TAM models. Despite advances in AI technology development since 2016 and its penetration into different industry platforms, most extant research on technology adoption is still based on constructs derived from the traditional TAM originated by Davis (1986). The voluminous body of work researching technology adoption is, as shown in Appendix A with three phases of development. During the early phase, a generally summarized eight theories have been highlighted in many works (Dwivedi et.al., 2016; Sair and Danish, 2018; Tsai et al., 2013; Venkatesh et al., 2012). As our banking services rapidly emerge and become transformed by AI devices, biometrics, and non-human service interfaces, the traditional model becomes ever less appropriate for explaining fully the customers’ responses and decisions in such a service context. The technology acceptance models e.g., TAM, TPB, IDT, TRA UTAUT, and ITM (see Appendix A) that have informed prior research may not be applicable to studying customers’ willingness to accept the use of AI devices because those models focus on customers’ adoption of non-intelligent functional technologies and Self-Service Technologies (SST) (Stock and Merkle, 2017) for service production and delivery processes. These models are therefore much less applicable to the AI adoption context.

In the second phase, the UTAUT theory has integrated performance expectancy and effort expectancy, social influence, and facilitating conditions and developed from the well-established above eight theories by Venkatesh (2003). More modifications with UTAUT2 (Venkatesh et al., 2012) and extended TAM (Azim et al., 2011) were seen in 2019. Finally, technology adoption theory has included the penetration of AI and robotics, for instance, Artificial Intelligence Device Use Acceptance -AIDUA (Gursoy, 2019). The models have been developed across a variety of disciplines, but their primary focus is on user behavioral intentions to adopt new information technologies. Their constructs are generally extensions and modifications of TAM’s perceived benefits (positive) and perceived risks (negative) rather than from users’ non-quantifiable assessment factors, such as trust, commitment, and compatibility with innovative technology.

The 2 by 2 matrix (illustrated in Figure 1 and Table 1) elaborates four possible consumer behavior outcomes for how users perceive the level of performance expectancy (PE) and the level of effect expectancy (EE) regarding technology innovation.

Table 1: Four Possible Consumers’ Behavioral Outcomes for Technology Adoption and Rejection.

Types	Perceived Level of PE	Perceived Level of EE	Outcomes
Q1	High (positive impact)	Low (negative impact)	Technology Adoption: High Level of Acceptance
Q2	High (positive impact)	High (positive impact)	Technology Adoption: Compensatory Level of Acceptance *The conceptual model*
Q3	Low (negative impact)	High (positive impact)	Technology Rejection: Job Replacement Failure
Q4	Low (negative impact)	Low (negative impact)	Technology Rejection: Functionality Failure

Remarks: Most research focuses on Q1. Q2 is an underdeveloped and underexplored area and a pioneering research concept.

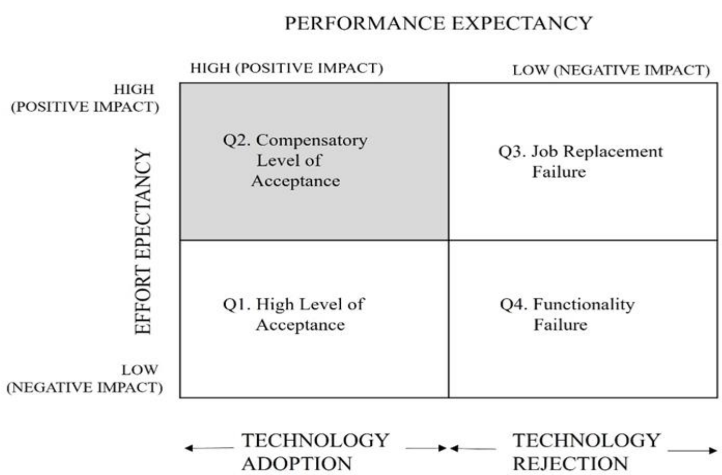

Figure 1: Classification of Consumer Behaviors on Performance Expectancy (PE) and Effort Expectancy (EE) toward Technology Innovation

Based on the above two-by-two matrix grid, there are four quadrants to show the possible outcomes of consumer behavior of AI technology. The compensatory level of acceptance (see Q2 in Figure 1) is a level of acceptance of an AI-enabled service that falls between high-level acceptance and outright rejection. Users may need to re-tune their mindsets and learn certain pre-requisite skills (for instance, how to download an app and enable face recognition) before they can accept and operate AI services. Consumers perceive the value offered by up-to-date technology and make use of it which will require extra effort. This is the opposite of the traditional view of perceived ease of use, which assumes that new technology will take less or even zero effort. The scenario of the Compensatory Level of Acceptance (Q2) exists that signifies high EE and high PE and is yet unmentioned in previous research. In traditional AI adoption literature, the most discussed points were low EE and high PE, then customers will engage in a High Level of Acceptance (Q1). Consumers classify into Q2 because they would like to be better educating themselves in new technology in handling financial matters or obtaining AI services in a self-control manner. Ultimately, they might perceive themselves as more intelligent and superior. Virtual banking operations require a high level of customer involvement and self-operating ability when interacting with an AI interface.

Q3 and Q4 are classified as technology rejection. In the Q3 quadrant of Job Replacement Failure, AI intelligence underperformed human intelligence with high EE and low PE. In this case, even if the customers try hard to interact with the AI, the result will be lower than expected. In the Q4 quadrant of Functionality Failure, it represents that AI services do not deliver any added value with low EE and low PE, possibly with a technology failure. Even though there is no extra effort required by the customers, the output does not provide any benefit to them. We validate the compensatory acceptance (Q2) outcome through the empirical study with hypotheses and data findings in our field research.

Key Constructs for AI-enabled Services

Cybersecurity (CYBERSC)

Cybersecurity refers to the extent to which users perceive that AI devices deliver services that are sufficiently safe, secure, and reliable (June and Cai, 2001; Polatoglu and Ekin, 2001; Rogers, 1976; Sathye, 1999; Walker et al., 2002). The extent of risk perceived by users may be the key determinant factor, and this is related to the functional reliability of the service delivery system. The risk may be associated with concerns about personal privacy and security, such that an AI service that exists without apparent human aid will cause users to lose confidence. In this context, security refers to perceptions about the mechanism for storing and transmitting information (Kolsaker and Payne, 2002) and to technical aspects of assurance like integrity, confidentiality, authentication, and non-recognition of relationships (Casaló et al., 2007). Early research on technology in financial services (Hoffman et al., 1999) focused on ATMs because non-users, especially the elderly, preferred to use a human teller for financial affairs due to fears about a machine's general level of security. There were also concerns that mechanical failure might cause financial loss. An early study that predicted internet banking adoption (Cheng et al., 2006) added one construct (web security) to their TAM-related hypothesis. More recently, Payne, Peltier, and Barger (2018) investigated mobile banking usage by examining the differential effects of a variety of non-technology-based determinants and concluded that security is one of the key attributes for the use of SST.

Users' security perception has a very significant effect on users' attitudes toward the adoption of FinTech services. Indeed, this factor should be treated as the primary variable affecting the use of any digital services because potential users must view an operating platform as safe. Online banks are progressively adopting new biometric-based security measures (Locke, 2017). Facial recognition and voice verification increase the complexity levels of authentication, which not only strengthens protection but offers customers a better experience and more security assurance.

Anthropomorphism (ANTHRO)

Anthropomorphism refers to the extent to which an object has humanlike characteristics, such as appearance, self-consciousness, and emotion (Kim and McGill, 2018). Perceived anthropomorphism is an important determinant of customer behaviors in the context of AI and service robots (Lu et al., 2019; Van Doorn et al., 2017). Its design positively and negatively influences human interactions and consumer attitudes and intentions. Intelligent objects are products that, although not considered human, have an any, shape, actions, and expressions that resemble those of human beings. Familiarity with human features induces comfort, which leads to positive consumer attitudes and purchase intentions (Lu et al., 2019). A review of the extant literature on users' acceptance of anthropomorphic products and services shows two categories of such interfaces: frontline service robots (FSR) and self-service technology. The virtual banking service comes under the latter category, research upon which it is somewhat limited. Hence, we review the importance of perceived anthropomorphism based on the operations of SST in comparison to those of a human frontline employee (FLE) (Stock and Merkle, 2017). Furthermore, Qiu and Benbasat (2009) find that perceived social relationships with highly customized product recommendation agent interfaces will not only meet users' needs but also develop the social and emotional bonding of, say, enjoying "being with others" (Biocca et al., 2003). Hence, humanoid embodiment and human voice-based communication both have a significant impact on the social presence or relationships that influence trusting beliefs, creating perceived enjoyment that leads to TAM-related constructs of perceived usefulness and increasing usage intentions toward the use of a service agent.

The Social Frontline Robot Acceptance Model (Stock and Merkle, 2017) asked users to assess a frontline service robot (FSR) for functionality and trustworthiness. Consistent with the traditional IS adoption of TAM-related constructs, this model uses two determinant variables that disregard the informational, relational, and emotional components and focus mainly on the functional components of perceived usefulness (PU) and perceived ease of use (PEOU) to measure customers' behavioral intentions. With the functionality expectation, customers expect the same deliverables as offered by a human service. But for informational and emotional experiences, customers expect to be offered service by a human rather than a robot. Hence, we believe that a highly customized anthropomorphic object or interface will positively affect the adoption of AI.

Perceived Level of AI's Intelligence

In a review of the extant literature (Gursoy et al., 2019; Lo et al., 2015; Lu et al., 2019; Virabhakul and Huang, 2018), emotion was a variable put forward for leading and explaining different behavior intentions. Further extended to the term emotional intelligence, it is generally defined as the ability to understand and manage your individual emotions, as well as recognize and influence the emotions of those around an individual. The term was coined in 1990 by researchers John Mayer and Peter Salovey and was later popularized by psychologist Daniel Goleman. Both these two terms originated to be applied to human behaviors and could not be able to be directly applied to machine learning behavior. In this study, we adopt a new perspective for our evaluation to measure dimensions of AI's cleverness and emotions: the Perceived Level of AI's Intelligence (PERCEAII). This was first introduced by the AI Job Replacement Theory (Hung and Rust, 2018). It is a controversial topic that has recently been much debated by various scholars and practitioners (Miroshnichenko, 2018; Shuaib et al., 2020; Xu et al., 2020; Mitchell, 2019; Cremer and Kasparov, 2021). This perspective goes beyond the classic measurement of an individual's emotion (as was discussed by Arbib (1992) in the cognitive structure of emotions and Lazarus (1991) in the Theory of Emotion) to suggest four levels of intelligence by which the work performance of AI services may be assessed: mechanical, analytical, intuitive, and empathetic. Mechanical intelligence relates to simple, standardized, repetitive, routine, and transactional tasks (i.e., respond to act and react repetitively). Analytical intelligence relates to logical thinking in decision-making with rule-based tasks (i.e., rational decision-making). Intuitive intelligence relates to experiential and contextual interaction and thinking (i.e., boundedly rational decision-making). Empathetic intelligence relates to social, emotional, communicative, and highly interactive service (i.e., decision-making incorporates emotions). These four specific characteristics may be both "ordinal" and "parallel"." Ordinal characteristics have a higher level of intuitive and empathetic Human Intelligence (HI), while parallel characteristics are at a lower level (mechanical and analytical) of HI.

We replace the commonly discussed variable of "emotions" with this meditating variable because the research trend is currently switching from examining human emotions to looking at AI's cognitive technology-based emotions. This could be a more accurate and effective way of measuring the outcomes of users' behaviors, reflecting how humans respond to AI services, especially at the threshold of the user's negative choice. "AI is unlike psychology because it stresses computation and is different from computer science because of its emphasis on observation, way of thinking, perception, and action" (Suresh and Rani, 2020). We find further support for our use of this theory in Russell and Norvig (2010), who suggest that AI mimics HI in terms of "the ability of knowledge, reasoning, problem-solving, learning, communicating, perceiving and acting." We strongly believe that potential users of an AI banking service would assess and justify the compatibility and cleverness of the AI-enabled services by comparing them with human services. Cognitive technologies (Huang and Rust, 2018) have enhanced personalized customer services through AI by using big data analytics and machine learning to discover customer needs and preferences; customer behavioral and usage data can be quickly collected and analyzed, generating an instant response. This unique level of service allows AI to dominate in the conduct of cognition-based personalization, creating a more satisfying customer experience. This is the ultimate situation from a service provider perspective: using an AI interface to replace human service in the foreseeable future. Hence, we find that the job replacement theory provides a good road map to measure and evaluate AI's intelligence in different stages of development.

Perceived Performance Expectancy (PE)

Performance expectancy in internet banking is defined as the degree to which an individual believes that using internet banking will help them attain gains in performing banking tasks (Rahi et al., 2018). In general, users will perceive a lower performance expectancy for devices when they have a negative evaluation of the use of AI devices, thereby leading to objection to their use. Conversely, a higher level of performance expectancy of AI devices will be perceived by users when they have a positive evaluation of the use of AI devices, leading to a willingness to use them. This is driven by the view that technology adoption always involves gain, and that using a specific system will create specific benefits. Venkatesh and Morris (2000) view PE as "the significant rewards" for users, who benefit from increased service efficiency and convenience. The adoption of virtual banking services provides the expected outcomes online via a 24-hour self-service interface, with personalized financial information being confidentially handled.

Perceived Effort Expectancy (EE)

Effort expectancy is the degree to which users feel that internet banking is easy to use and does not require much effort. Individuals who believe online banking is effortless (i.e., effort expectancy is perceived negatively) are likely to adopt it (Chaouali et al., 2016). Past studies have indicated that effort expectancy has a significant influence on behavioral intention to adopt internet banking (Martins et al., 2014; Rahi et al., 2018; Riffai et al., 2012). However, when users perceive that a high level of effort or more cognition is required to understand the AI interface (i.e., effort expectancy is perceived to be high), they may reject the use of AI services.

Many previous studies on technology adoption (Q1 of the Performance Expectancy Model) stress that the adoption of new technology requires a higher level of positive PE combined with negative EE (i.e., effortlessness). Our study runs counter to this and takes an approach that falls within Q2, being based on a positive perceived EE relationship. We, therefore, ask why AI users are willing to put more effort into learning how to interact with the AI service interface. Traditionally, users would expect their acceptance of new technology to lead to them having to make less effort. Based on the commitment-trust theory of relationship marketing (Morgan and Hunt, 1994), relationship commitment and trust are key mediating variables (KMVs) for explaining cooperative behaviors among stakeholders. When both commitment and trust are present, target users will take action even if these are potentially high effort. Potential users may perceive that AI will ultimately perform much better than the existing human services; hence they are prepared to fully commit themselves to learn how to properly complete self-service tasks because these offer considerable convenience in the future. Another reason that supports such voluntary behavior is that users may view the AI machine as a safer repository than a human for their confidential financial information.

3. Conceptual Framework and Hypotheses

Based on the reviewed theoretical models and the above-mentioned key variables, our proposed research model is illustrated in Figure 2 - The Conceptual Model, with the following constructs: Cybersecurity (CYBERSC), Anthropomorphism (ATHRO), Perceived Level of AI's Intelligence (PERCEAII), Performance Expectancy (PE), and Effort Expectancy (EE). These constructs are moderated by online banking frequency (FREQ). In our empirical investigation, we have reviewed and considered constructs appropriate to the AI context, and intentionally deviated from the conventional TAM-related constructs that are less explanatory and supportive of software-based anthropomorphic service agents (Qiu and Benbasat, 2009).

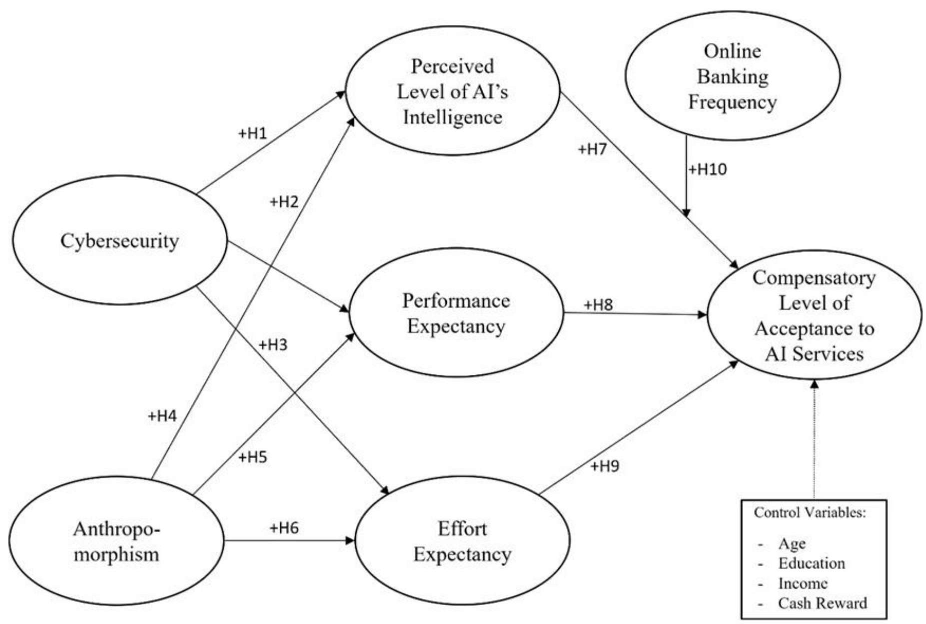

Figure 2: The Conceptual Model

3.1. The Impact of Cybersecurity (H1-3)

The level of perceived trust is the factor most pertinent to whether users avail themselves of AI-enabled services. Previous researchers (Grabner-Krauter and Faullant, 2008; Poon, 2008; Stewart and Jurjens, 2017; Yousafzai et al., 2005) have discussed online data security, information privacy control, and consumer acceptance of internet banking and FinTech services. Consumers' perception of cybersecurity relates to how AI's functionality compares with human intelligence. If users perceive that the AI service provides a high level of technical guarantee, they are less likely to be wary of dealing with its non-human interfaces. In terms of the adoption of internet banking (IB), perceived web security is expected to have a positive relationship with customers' attitudes and intentions to use IB (Cheng et al., 2005). Furthermore, Ng and Kowk (2017) suggest that "a substantial issue for the adoption of FinTech is the lack of regulatory frameworks and safeguards." Users are likely to require more effort to be made when handling the transmission of personal data than when interacting with a human employee. Thus, the following hypotheses are proposed:

***H1**: Cybersecurity has a positive influence on the perceived level of AI's intelligence (PERCEAII)*

***H2**: Cybersecurity has a positive influence on the perceived performance expectancy (PE) of AI services.*

***H3**: Cybersecurity has a positive influence on the perceived effort expectancy (EE) of AI services.*

3.2. The Impact of Anthropomorphism (H4-6)

Anthropomorphization is where human characteristics are incorporated in products or services to increase familiarity or comfort (DiSalvo and Gemperle, 2003). It influences consumer behavior and evaluations positively (Kim and McGill, 2011; Puzakova et al., 2013). According to Goudey and Bonnin (2016), the two most successful types of smart products are virtual interactive agents and domestic robots. The acceptance of these intelligent objects will be subject to the product's resemblance to human characteristics. Users have extensive experience and knowledge of human beings; therefore, they can draw on this experience to easily process information about the usage of an object. The anthropomorphization of internet sites shows that including anthropomorphic elements increases the perceived usefulness of an internet site (Burgoon et al., 2000). In general, humanized products or services help consumers to feel closer to the product, making it easier for them to understand it and interact with it.

Most previous research consistently indicates that software-based/anthropomorphic product recommendation agents, anthropomorphized products, intelligence objects, smart objects, product intelligence (Goudey and Bonnin, 2016), and frontline social robots (FSR: Stock and Merkle, 2017) can create a favorable response with human intelligence features because consumers are adept at recognizing human features on unfamiliar products. This increases their understanding and eases interactions, which increases the perceived ease of use (Goudey and Bonnin, 2016). A highly congruent anthropomorphic image can attract consumers' attention by alerting them to the presence of social interactions.

The terms "intelligence" and "autonomous" are blurred in their respective representations of human beings and objects (Goudey and Bonnin, 2016). AI Job Replacement Theory (Huang and Rust, 2018) shows that customers evaluate AI advanced technologies according to their productivity and level of intelligence. We presume that a smart object perceived to be higher than humans on the four levels of job intelligence will have increased adoption of self-service technologies.

Anthropomorphic features may increase users' perception of the effort required to use AI services (e.g., the effort needed to self-learn a technological device). Users may find that interacting with a human-like agent takes greater effort, as it involves more communication and information transmission. Therefore, anthropomorphized AI service has a positive impact on PERCEAII, PE, and EE. We propose the following hypotheses:

***H4**: Anthropomorphism has a positive influence on the perceived level of AI's Intelligence (PERCEAII).*

***H5**: Anthropomorphism has a positive influence on the perceived performance expectancy (PE) of AI services.*

***H6**: Anthropomorphism has a positive influence on the perceived effort expectancy (EE) of AI services.*

3.3. Compensatory Level of Acceptance to AI Services (H7-9)

We developed a model of a compensatory level of acceptance by incorporating three key factors, including the perceived level of AI's intelligence, EE and PE. The assumption is that traditional bank users rely on human intelligence services; hence there is no need to have strong abilities, skills, or techniques in handling their financial matters. The question is whether customers will forgo the use of SST if they face difficulties and require equipping skills to respond to its interaction. By exploring the concept of compensatory consumption (Rucker and Galinksy, 2013, p. 207; Rustagi and Shrum, 2019), we define a compensatory level of acceptance as the desire for or use of platforms or products to respond to a psychological need or deficit.

The measurement of users' perceptions of AI performance has now become key to whether AI technologies are adopted or rejected. By examining the level of AI Intelligence (PERCEAII), we adopt and adapt the theory of AI job replacement (Huang and Rust, 2018) to assess AI's strengths at performing job tasks based on users' expectations. The theory of AI job replacement describes and predicts the way AI is likely to replace human tasks and jobs. The authors outline and quantify four types of AI intelligence, through which they can effectively compare AI with Human Intelligence (HI) based on the level of job performance. They emphasize that "AI job replacement occurs fundamentally at the task level rather than the job level." Hence, it is claimed that the existing implementation of AI is limited to replacing human labor (e.g., a simple task in a repeating cycle or routine) with tasks that require lower-level (i.e., mechanical and analytical) intelligence. However, human service still has the edge in higher-intelligence tasks that require both intuitive and empathetic intelligence. With a limited level of intelligence, novice users of virtual banking have greater difficulties in using this technology. Perceived AI intelligence, therefore, gives them more motivation to gain a compensatory level of acceptance to AI services. We thus derive our hypothesis:

***H7**: Perceived level of AI's intelligence has a positive influence on the compensatory level of acceptance to AI services.*

AI services may be seen as "the significant rewards that can be obtained from the use of the system" (Venkatesh et al., 2003). The Covid-19 pandemic accelerated the banking institutions' aggressive promotion of I-banking services, with advanced AI technology reducing human interactions. When users perceive that they receive a more rewarding (satisfying) service from using an AI interface, they will perceive it as having a high level of usefulness; this leads directly to their adoption of it.

When users perceive ease of use for technology, they are more inclined to adopt it. All AI-oriented services are directly self-interactive with users. Users of AI-enabled services may expect and encounter extra effort when they switch from traditional human mode to self-service technology. In the internet banking adoption context, Rahi et al. (2018) find the relationship between effort expectancy and behavioral intention to be significant (Moore and Benbasat, 1991). Great effort expectancy does not lead to straight adoption, rather, it may render users have a compensatory level of acceptance. As suggested by compensatory consumption literature, users would be more inclined to adopt intelligence-related products when their intelligence is threatened (Gao et al., 2009; Kim and Gal, 2014; Lisjak et al., 2015). In this case, we argue that users are willing to have a compensatory level of acceptance of the technology although it takes greater effort. Thus, the following hypothesis is proposed:

***H8**: Performance expectancy (PE) has a positive influence on the compensatory level of acceptance to AI services.*

***H9**: Effort expectancy (EE) has a positive influence on the compensatory level of acceptance to AI services.*

3.4. Moderating Variable: Online Banking Frequency

Prior research (Belanche et al., 2019) confirms that basic demographic variables (e.g., age and gender) do not moderate the influence of the intention variables on the use of financial robot advisors. Hence, users' characteristics and their behavioral intentions evince no technological divide. However, we believe that a user's experience on a similar platform (i.e., the usage frequency of internet banking) may affect the expected behavioral outcome.

We assume that the target users of AI banking technologies will be familiar with online banking services, making them more open to accepting the latest non-humanized AI banking technologies. Hence, the moderating variable of online-banking usage frequency plays a role in the conceptual model of monitoring the effects of behavioral intention. For more frequent users of AI banking, they are more frequently exposed to challenges and difficulties in coping with these up-to-date technologies. With greater perceived AI intelligence, they are better assisted to cope with the "intelligent" task and therefore exhibit a compensatory level of acceptance.

***H10**: Online Banking Frequency has a positive influence on the effect of the perceived level of AI's intelligence on the compensatory level of acceptance to AI services.*

4. Methodology

4.1. Sample and Data Collection

Virtual banking (VB) is a highly relevant context for our empirical examination of users' adoption decisions in an industry that is entirely service-oriented. The newly developed platform of virtual banks in Hong Kong is the ideal ground for testing services that are 100% AI-enabled (see Appendix B). The Hong Kong Monetary Authority (HKMA) defines VB as "a bank which primarily delivers retail banking services through the internet or other electronic channels instead of physical branches." The Hong Kong Monetary Authority (HKMA) has issued eight virtual banking licenses to non-traditional, newly-formed banking corporations since March 2019. Most of these players are from non-financial areas and deliver "out of the box" personal financial services that escape the Banking Ordinance regulations. Offering technology-augmented services with reduced compliance costs enables them to increase their effectiveness and efficiency. Traditional banks are fighting aggressively to retain their market share by offering telephone, online, or mobile banking services, but they are losing ground due to a lack of operational efficiency and customer expectations for the real-time execution of 24-hour service. One of the latest innovative developments to increase the competitiveness of traditional bankers is their provision of invisible credit cards or ATM cards. At Hong Kong Fintech Week (2019), HKMA released a finding that "almost 90% of our retail banks have already implemented, or planning to implement, AI in their business applications." Mobile phones are a prerequisite for personalized banking services, and since it appears that most of Hong Kong's mobile users have at least two mobile phone numbers, Hong Kong is an ideal location for the development of the digitalized VB platform.

Studies on the banking industry broadly describe the "Virtual Bank" (VB) as an online bank; this is sometimes interpreted as a mixed category of mobile banking and online banking. However, this study principally defines a virtual bank as one that does not operate from a physical distribution outlet; in short, it is branchless. This characteristic is supplemented by digital banking technologies (including virtual reality (VR), artificial intelligence, big data analytics, robotics, blockchain, the internet of things, voice banking, and biometrics) that lay the groundwork for VB innovative services that will ultimately lead to invisible banking. The VB is 100% digitalized and does not operate as a physical bank outlet. The arena of virtual banking is thus an ideal context for studying users' responses to AI services.

Our survey's target respondents were restricted to Hong Kong citizens because the eight licensed VBs are open to Hong Kong residents only. User classification ranges from non-experienced users to highly experienced users in online banking. To test the instrument, a pilot study was conducted on a group of 10 respondents (recruited from a friendship circle) who were then included in the final data pool. A random sample of 494 responses was received at the end of six weeks. This was then analyzed using SmartPLS.

4.2. Instrument Development

To obtain content validity, we developed measurement items (see Appendix C) based on constructs obtained from the literature review. The items and scales for the CYBERSC constructs were chosen from Casaló, Flavián, and Guinalíu (2007). The items and scales for the ANTHRO, PE, and EE constructs were adapted from Gursoy, Chi, and Nunkoo (2019). The items and scales for the PERCEAII were adapted from Huang and Rust (2018), with self-development questions based on machine intelligence to mimic HI. The proposed research model with hypotheses was tested by collecting users' data with the quantitative method. A customized questionnaire combined our hypotheses with the questions used in previous literature. To strengthen data reliability, we offered an incentive of HK$20 to each consenting qualified (i.e., age 18+ and holding a permanent Hong Kong identity card) respondent. The cash reward was credited to their online bank account after verification of (i) the first four digits of the Identity Card number and (ii) the mobile number given in the survey. Participation in the study was voluntary. Our appointed marketing agency verified each respondent's data to ensure truthfulness before the payment of HK$20 was made via the Faster Payment System (FPS, fps.hkicl.com.hk). Respondents were required to answer all questions in one go. Once an identity card and mobile number had been used in the survey, they could not appear in it again.

The online survey was developed in both English and Chinese, and it was delivered by a Google link. Since it was administered to the general population in Hong Kong, the English version of the instrument was translated into Chinese by online freeware (fanyi.youdao.com). The translation's validity was confirmed via its back-translation into English via Google Translate. The survey was executed by an outsourced online marketing research agency in Hong Kong from 5 March to 18 April 2021 (i.e., over a 6-week period). It consists of two sections. The first relates to demographic characteristics (for further details see Table 2—Demographic Profile of Respondents), including their age, gender, marital status, occupation, education, income range, online/virtual banking experience, and the frequency with which they use such services. The second section contained the main questions in five sub-sections. The closed-end questions took the form of a 7-point Likert scale (interval range of "1-strongly disagree" to "7-strongly agree").

5. Results

5.1. Demographic Profile of Respondents

As presented in Table 2, 63% of the respondents were single females (63.2%) with a degree level of education; 37% of respondents were male. Most respondents were between 18 and 34 years old (66.8%). The most common occupations were student, professional, and managerial (56.9%). Many respondents had bachelor's degrees (40.7%) and had an annual family income in the range of HK$10,000 to HK$20,000 (61.9%). Their monthly earnings were below the average of the Hong Kong working population, with a median monthly wage of HK$18,400 (Hong Kong 2021 Census and Statistics Department). The data show that the trend or tendency to use mobile banking is popular among a younger demographic that might be attracted by the latest AI technology; they are thus the targets of aggressive promotion by the local virtual banks.

Table 2: Demographic Profile of Respondents

Items	Category	Number of Respondents	Distribution (%)
Gender	Male	183	37
	Female	311	63
Age	18-25	196	39.7
	26-34	134	27.1
	35-44	68	13.8
	45-54	58	11.7
	55-64	31	6.3
	65 or above	7	1.4
Marital Status	Single	312	63.2
	Married	143	28.9
	Cohabitee	18	3.6
	Widowed	1	0.2
	Divorced	20	4.0
Occupation	Student	134	27.1
	Professional	64	13.0
	Administrative and Management Personnel	83	16.8
	Sales Staff	43	8.7
	Homemaker	37	7.5
	Self-employed	50	10.1
	Retired	13	2.6
	Others	70	14.2
Education	High School Graduate or Below	117	23.7
	Associate Degree/College Diploma	126	25.5
	Bachelor's Degree	201	40.7
	Master's Degree	38	7.7
	Doctorate Degree or Above	3	0.6
	Others	9	1.8
Monthly Income (HK$)	$10,000 or less	168	34.0
	$10,001- $20,000	138	27.9
	$20,001 -$30,000	109	22.1
	$30,001 -$40,000	42	8.5
	$40,001 -$50,000	11	2.2
	Over $50,000 and above	26	5.3

5.2. Measurement and Structural Model

The unit of analysis was the individual. The measurement reliability and factor loading are presented in Table 3.

Table 3: Factor Loading and Reliability

		Loadings	Alpha
Anthropomorphism	Anthro1	0.922	0.929
	Anthro2	0.923	
	Anthro3	0.926	
	Anthro4	0.858	
Cybersecurity	Cybersc1	0.811	0.944
	Cybersc3	0.831	
	Cybersc4	0.839	
	Cybersc5	0.890	
	Cybersc6	0.889	
	Cybersc7	0.898	
	Cybersc8	0.901	
Performance Expectancy	PerfExp1	0.839	0.894
	PerfExp2	0.871	
	PerfExp3	0.890	
	PerfExp4	0.883	
Effort Expectancy	EffEXP1	0.849	0.839
	EffEXP2	0.866	
	EffEXP3	0.893	
Perceived Level of AI's Intelligence	PerceAii1	0.727	0.919
	PerceAii2	0.808	
	PerceAii3	0.88	
	PerceAii4	0.904	
	PerceAii5	0.888	
	PerceAii6	0.803	

The reliability and validity of the constructs were evaluated using Cronbach's α and confirmatory factor analysis. The Cronbach's α levels were all above 0.7, and the composite reliabilities (CRs) all exceeded 0.80, suggesting high reliability.

Table 4 presents the results of structural equation models, which were analyzed with SmartPLS. We mean-centered all variables (except the control variables) before generating the interaction terms.

Table 4: Results of Structural Equation Models

		Path Coefficient	SD	t	P
H1	Cybersecurity -> perceived level of AI's intelligence	0.118	0.050	2.349	0.019
H2	Cybersecurity -> perceived performance expectancy	0.238	0.042	5.689	0.000
H3	Cybersecurity -> perceived effort expectancy	0.294	0.055	5.340	0.000
H4	Anthropomorphism -> Perceived level of AI's intelligence	0.391	0.055	7.068	0.000
H5	Anthropomorphism -> perceived performance expectancy	0.609	0.035	17.344	0.000
H6	Anthropomorphism -> perceived effort expectancy	0.200	0.057	3.529	0.000
H7	Perceived level of AI's intelligence -> compensatory level of acceptance to AI services	0.364	0.101	3.618	0.000
H8	Perceived performance expectancy -> compensatory level of acceptance to AI services	0.195	0.095	2.047	0.041
H9	Perceived effort expectancy -> compensatory level of acceptance to AI services	0.179	0.074	2.405	0.017
H10	Frequency * perceived level of AI's intelligence -> compensatory level of acceptance to AI services	0.726	0.211	3.439	0.001

As hypothesized, cybersecurity is positively related to the perceived level of AI's intelligence (β= 0.118, $p < 0.05$), perceived performance expectancy (β= 0.238, $p < 0.001$), and perceived effort performance (β= 0.294, $p < 0.001$), supporting H1-3. Anthropomorphism is positively and strongly associated with the perceived level of AI's intelligence (β= 0.391, $p < 0.001$), perceived performance expectancy (β= 0.609, $p < 0.001$), and perceived effort performance (β= 0.200, $p < 0.001$), supporting H4-6. Perceived level of AI's intelligence (β= 0.364, $p < 0.001$), perceived performance expectancy (β= 0.195, $p < 0.05$), and perceived effort performance (β= 0.179, $p < 0.05$) all have significant effects on the compensatory level of acceptance to AI services, supporting H7-9. As shown in Table 4, the moderation effect of online banking frequency on the relationship between the perceived level of AI's intelligence and the compensatory level of acceptance is positive and significant (β= 0.726, $p < 0.001$), so H10 is supported.

6. Discussion

6.1. Discussions of Empirical Results

Firstly, as indicated by the results, we found that both cybersecurity and anthropomorphism would lead to more positive outcomes, such as a higher-level perception of AI's intelligence and performance expectancy. However, these antecedents were found to drive effort expectancy. While research findings of previous studies indicated humanoid or low-risk applications might lead to a greater intention of adoption (Mou et al., 2017; Qiu and Benbasat, 2009), our findings suggest the unique characteristics of AI adoption which may involve significant effort and therefore costs on the user side. Second, the two types of expectancy and perceived level of AI's intelligence were found to make users willing to accept AI services. Our findings are partially consistent with recent studies on the impact of perceived intelligence on continuance intention (Moussawi et al., 2022). In this study, the perceived effort was found positively related to technology adoption. In most studies of traditional technologies, the perceived effort is negatively correlated with technology acceptance (e.g., Zhu et al., 2014), with "ease of use" being one of the key factors in users' acceptance of new technology (e.g., Gursoy et al., 2019). Third, the connection between the perceived level of AI's intelligence and the compensatory level of acceptance of AI services has been strengthened by use frequency. The findings of this study, together with recent research on service robots (Belanche et al., 2020) suggest the contingencies pertaining to the relationship between AI's intelligence and user adoption.

6.2. Theoretical Implications

The most significant contribution of this study is that it provides a micro-analysis of AI adoption by drawing on a theoretical understanding of the compensatory level of acceptance, which is evident in the context of virtual banking assisted with AI technologies. Most of the previous studies are concerned with the straightforward adoption of innovative technologies. Our study aims to develop a new model specifically tailored to AI adoption, with AI-based variables that explain whether consumers will tend to use the self-service technology provided by the virtual bank. We find scant discussion in the literature about whether there is a middle ground between acceptance and rejection of new technology. Indeed, it appears from prior research that there is no transitional state between these two opposites. We posit that consumers' evaluations of technology involve a trade-off between the expectations for perceived performance against the perceived degree of effort. Our results support the existence of a new compensatory level of customers' acceptance behavior.

Secondly, our study provides a model that was constructed based on a new mediating element of AI's intelligence; this has not been used in previous studies to measure and explain consumers' behavioral intention for the adoption of cognitive technologies. Although many studies have examined AI adoption based on TAM-related constructs, many of these works have not been specifically geared to AI-based job or task performance (e.g., Azim et al., 2011; Belanche et al., 2019; Hu et al., 2019; Stewart and Jurjens, 2017; Stock and Merkle, 2017; Walker et al., 2016). The positive effect of effort evident in this study can be explained with a logic of self-improvement (Nussbaum and Dweck, 2008) or more recently, self-repair (Rustagi and Shrum, 2019). When users have higher effort expectations with challenging AI tasks, they may take remedial or defensive actions by trying AI services as compensation or remediation (Kim and Gal, 2014; Nussbaum and Dweck, 2008; Rustagi and Shrum, 2019). The positive side of effort expectation can also be explained by the trust-commitment theory in relationship marketing (Morgan and Hunt, 1994). A recent study of global users of cross-border m-commerce indicates that efforts committed to the relationships with users may stimulate adoption (Cui et al., 2020). Users are willing to make an extra effort to learn the techniques of operating SST if this means they can gain the long-term benefits of a system that allows them to control their finances anytime, anywhere, and any place, so long as there is internet access. Furthermore, their personal financial information can remain completely private, protected by online security measures such as personalized encryption, e.g., face recognition and figure prints.

Third, it is worth noting the debate in prior studies about whether intelligent objects with distinctively human characteristics and/or physical resemblance might upset consumers rather than reassure them. Hence, a partially anthropomorphic robot with its own psychological features that are neither machine-like nor human-like may be easier to accept. Prior study indicates that perceived anthropomorphism is positively related to effort expectancy. Our findings add to this line of research by showing that perceived anthropomorphism is also an important driver of performance expectancy.

6.3. Managerial Implications

The findings of the descriptive statistics and SEM suggest many important implications for banking industry operators, especially for virtual bankers. First, managers should be aware that they can tempt more users to accept AI technology by understating the compensatory level of acceptance. The challenge is to let potential customers become familiar with all forms of SST. Bankers should provide online tutorials or simulation demonstrations to nurture in users a positive experience of self-service. Second, it is strongly recommended that we do not disregard the importance of perceived expected effort, which was positively related to AI adoption. In general, we believe that the new generation of users is in favor of learning new technologies that offer lifestyle enhancement through convenience. Hence, it is easier for SST to penetrate the younger population. This is also evident from our research's random sample, where 66.8% of respondents were between 18-34 years old and had online banking experience. Third, the positive cognitive perception of AI's intelligence can increase the usefulness of measuring AI's intelligence for performance evaluation. Service operators can more effectively measure AI's replacement of human service at the job replacement level. Fourth, users' frequency of usage of online banking has a significant positive impact on users' acceptance of AI adoption. Bankers can use this finding to convert users of online banking to VB. Finally, traditional bankers are now aggressively searching for cost-effective ways to defend their market share positions by offering online services via a technology-driven interface. This was particularly the case during the pandemic. Thus, AI-banking services are unlikely to remain the assets solely of the branchless VB bank. Indeed, our proposed research model can serve as a starting point for broadening the application of SST to industries that are 100% service-based, such as online medical appointments and online teaching. Last, but not least, service providers should properly assess the benefits and costs to the customer of AI or HI by looking at all five variables in our tested model.

7. Conclusions and Future Research

7.1. Contributions

This study extends the traditional knowledge of technology adoption by redefining the AI contextual environment. Some previously common constructs have been revamped with new definitions for the context of SST (i.e., no human-provided service) and branchless virtual banking service. We find that perceived expected performance (PE) increases the acceptance of innovative technology by offering service benefit rewards. We also find that, contrary to prior literature, the perceived expected effort has a positive impact on the compensatory acceptance of technology. The higher the perceived usefulness of technology, the higher the probability of it being accepted and used. To fit into the parameter of AI, a closely fitted mediating element has been employed, namely the perceived level of AI's intelligence, This has a significant impact on the technology's adoption. This factor goes beyond traditional measures of emotion and attitude on behavioral intention.

7.2. Future Research

There are a few limitations to this study that may affect its results. First, the data is cross-sectional; the study, therefore, presents a snapshot of one point in time within a very specific cultural context. This may impair the generalizability of our research findings. Future studies could collect data from respondents of different races and cultural contexts. They could also collect data from actual or active virtual banking users, which would be useful for better understanding users' expectations of SST. Second, the research did not address all potential variables, such as users' social influence and self-concept, perceived social relationship with SST, customer satisfaction, or hedonic motivation. All of these could increase acceptance intention and would be worth exploring in more detail in the future. Further consideration of a similar or modified model is needed to measure consumers' AI adoption by symbolically representing the application of SST. This study measures behavior intention via a questionnaire. It would be very helpful for future research to look instead at actual AI service users (i.e., individuals who have accepted the technology). This could increase the validity of the study results, which would significantly contribute to the development of AI service applications.

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Appendix A: Eight Models Extended from Technology Acceptance Model (TAM) and Its Modifications from 1986 to 2019.

The study of consumers' acceptance of technology is a complex issue involving multi-disciplinary subjects: Psychological, Technology, Marketing, and Social Contexts. Most scholars have developed and modified their research models based on the original TAM, such as the Motivational Model – MM (Davis et al.,1992),), Theory of Planned Behavior – TPB (Schifter & Azjeu 1985; Ajzen, 1991 and 2002, Lee, 2008), Model of PC Utilization – MPCU (Thompson et al., 1991), Innovation Diffusion Theory – IDT (Moore & Benbasat, 1991) or DOI (Rogers, 1995), Theory of Reasoned Action – TRA (Ajzen & Fishbein, 1997); Socio Cognitive Theory – SCT (Compeau & Higgins, 1995), and Decomposed Theory of Planned Behavior – DTPB (Taylor and Todd, 1995).

Item	**Theory**	**Author and Year**	**Eight theories/Models**	**Dependent Variable(s)**	**Constructs**	**Topics - Disciplines**	
1	Expectation Theory and Self-efficacy Theory.	Davis 1986, 1989	1.Techhnology Acceptance Model (TAM)	Intention to use	Perceived usefulness (PU), Perceived ease of Use (PEOU)	Technology Adoption	Management Information System (MIS)
2	Intrinsic Motivation	Davis et al.,1992	2.Motivational Model (MM)	Behavior Intention	Perceived usefulness, Enjoyment, Perceived Ease of Use and Perceived Output Quality	Attitude towards Individual Behavior	Psychology
3	Theory of Planned Behaviour	Schifter & Ajzen 1985; Ajzen 1991	3. Theory of Planned Behaviour (TPB)	Behavior Intention	Attitude toward Behavior, Subjective Norms, Perceived Behavioral Controls (PBC)	Attitude towards Individual Behavior	Psychology
4	Theory of Reasoned Action	Thompson et al.,1991	4.Model of PC Utilization (MPCU)	Behavior Intention	Social factors, Affect, Perceived Consequences (Complexity and Job Fit), Facilitating Conditions, Habit Hierarchies	Utilization of PCs	Management Information System (MIS)
5	Adopted TAM's PEOU	Rogers 1995; Moore & Benbasat 1991	5. Innovation Diffusion Theory (IDT)	Adoption of Technology	Compatibility (perceived to be consistent with perceived needs); Complexity (degree of innovation)	Adoption Process in Organization	Organizational Behavior (OB)
6	Extended TPB	Ajzen and Fishbein 1997; Jiang 2009	6. Theory of Reasoned Action (TRA)	Behavior Intention	Perceived Benefit and Perceived Risk	Attitude towards Individual Behavior	Psychology
7	Intrinsic Motivation	Vankatesh 1999; Compeau and Higgins 1995	7. Social Cognitive Theory (SCT)	Intentions toward using a specific computer technology	Self-efficacy, Outcome Expectation and Effect	Attitude towards Individual Behavior	Psychology
8	Decomposed Theory of Planned Behavior	Taylor and Todd 1995	8.Decomposed Theory of Planned Behavior (DTPB)	Behavioral Intention	Attitude (Relative Advantages, Complexity and Compatibility); Subjective Norm (Normative Influences);	Consumer Adoption Intentions	Marketing Management

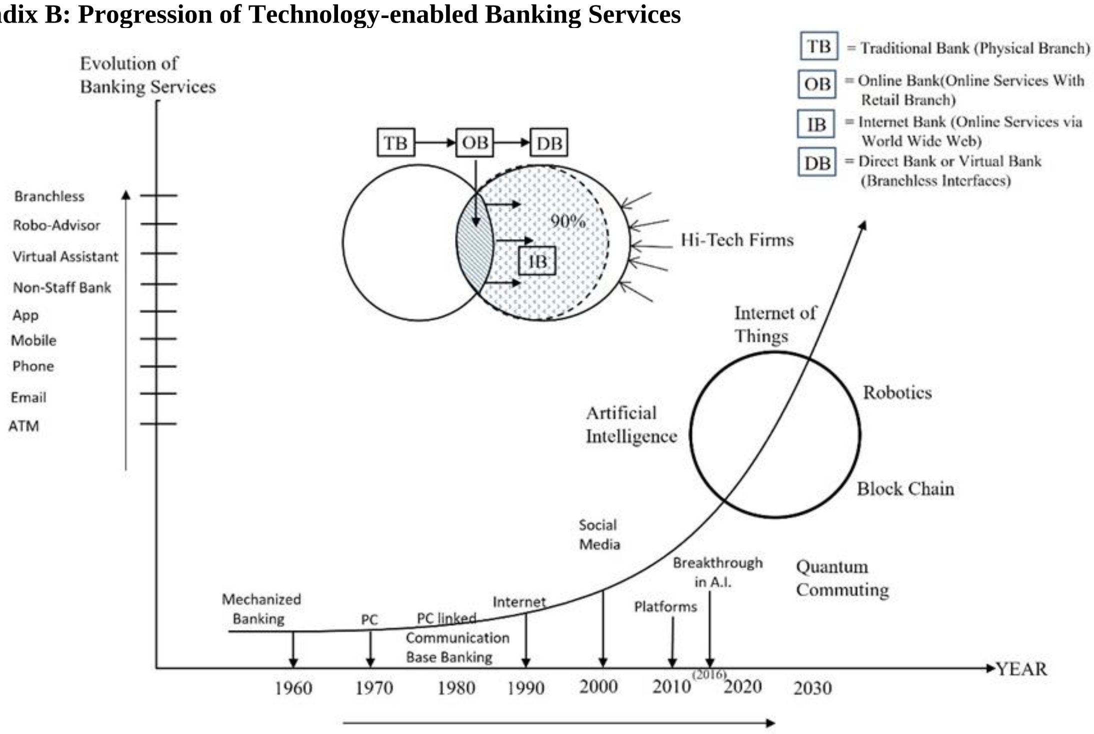
					Perceived Behavioral Control (Efficacy and Facilitating Conditions)		
9	Extended TAM	Venkatesh et al. 2003	Unified Theory of Acceptance and Use of Technology (UTAUT)	Behavior Intention	Performance Expectancy, Effort Expectancy and Social Influence	Attitude towards Individual Behavior	Consumer Behavior
10	Integration of TAM and TPB (Perceived Risk Theory)	Lee 2008	TAM + TPB	Adoption of Internet Banking	Perceived Risk (Performance Risk, Social Risk, Financial Risk, Privacy Risk, Time Risk and Physical Risk). Perceived Benefit: Attitude (Direct Advantages - Financial Benefits, Faster Transaction Speed and Increased Information Transparency); (Indirect Advantages - Perform Banking Transactions Anywhere and Anytime, and More Investment Opportunities)	Intention to use	Consumer Behavior
11	Extended UTAUT	Kim et al. 2009	Initial Trust Model (ITM)	Initial Trust	Environmental factors (Firm Reputation, Structural Assurances and Personal Propensity to Trust)	Adoption of an Innovative Service	Consumer Services Marketing
12	Adopted TAM	Azim, Ali and Sattar 2011	Extended TAM	Adoption of Information Technology based Banking Services	Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Quality of Connection (QI), Attitude Towards Use (ATT), Trust (TR) and Intention to Use (AI)	User Behavior	Consumer Behavior
13	Extended UTAUT	Venkateshand Thong and Xu 2012	UTAUT2	Behavior Intention	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit. Moderating Variables: Age, Gender and Experience.	User Behavior	Consumer Behavior
14	Extended UTAUT	Tiago, Miguel, Manoj & Ales 2014	UTAUT+ITM	Mobile Banking Adoption	UTAUT + TTF + ITM = Firm Reputation (Institution-based Trust), Environmental Forces - Structural Assurances (trustworthiness e.g.,	Technological and Behavioral	Consumer Behavior - Adopt Mbanking at an Individual Level

					service guarantees and social influence) and Personal Propensity (User Personality) to Trust		
15	Adopted TAM + DOI	Walker, Saffu and Mazurek 2016	TAM+DOI	E-Commerce Adoption in Slovakian SMEs	Compatibility, External Pressure, Managerial Productivity, Organizational Readiness, Organizational Support, Perceived Ease of Use (PEOU), Perceived Usefulness (PU) and Strategic Decision Aids.	Adoption vs non-Adoption	Organization Behavior (OB)
16	Adopted TRA	Ryu 2017	TRA	FinTech Continuance Intention	Perceived Benefit: Economic benefit, Seamless Transaction, Convenience. Perceived Risk: Financial Risk, Legal Risk, Security Risk and Operational Risk.	User Behavior	Consumer Behavior
17	Extended TAM	Stewart and Jurjens 2017	Extended TAM	FinTech Adoption (Intention to Adopt FinTech)	Customer Trust (CT), Data Security (DS), Value Added (VA) and User Design Interface (UI, and FinTech Promotion (FP)	User Behavior	Consumer Behavior
18	TAM	Stock and Merkle 2017	Robot-Acceptance-Model (RAM), leading to a Social Frontline Robot Acceptance Model (SFRAM)	Robot Acceptance - Frontline Service Robots (FSR)	Functional Component: Ease of Use, Usefulness. Informational Component: Informativeness of Interaction. Relational Component: Benevolence, User Satisfaction and Understanding	User Perception	Customer's Acceptance of Humanoid Robot Service
19	Extended TAM	Hu, Ding, Li, Chen & Yang 2019	Extended TAM	Adoption Intention of FinTech Services for Bank Users	Perceived usefulness (PU), Perceived ease of Use (PEOU), Attitudes, Trust, Brand Image, Perceived Risk, Government Support and User Innovativeness.	User Behavior	Consumer Behavior
20	Cognitive Appraisal Theory	Gursoy et al. 2019	Artificial Intelligence Device Use Acceptance (AIDUA)	Willingness to Accept or Objection to the Use of Artificial Intelligence (AI) Devices	Primary Appraisal: Social Influence, Hedonic Motivation and Anthropomorphism. Secondary Appraisal to emotion: Performance Expectancy and Effort Expectancy. Outcome	Adoption of AI Devices	Consumer Behavior on AI Services

					Stage: Willingness or Objection.		
21	Adopted TRA + UTAUT + Extended UTAUT	Lu, Cai and Gursoy 2019	Service Robot Integration Willingness (SRIW) Scale	Willingness to use service robots	Performance Efficacy, Intrinsic Motivation, Anthropomorphism, Social Influence, Facilitating Conditions, Emotions	Adoption of A.I.R.	Consumer Behavior on AI Services
22	Extended TAM	Belanche, Casalo and Flavian 2019	Extended TAM	Intention to use (AI Robo-advisors)	Attitude: Perceived Usefulness, Perceived Ease of Use. Subjective Norms. Moderating Variables: Age and Gender.	Adoption of Financial AI Robo-Advisors	Consumer Acceptance of Service Robots

Notes:
Academic theories and models of technology acceptance can classify into three phases of development:
1. Eight Theories / Models of the Technology Acceptance Model (TAM) from 1986 to 2003
2. UTAUT and UTAUT2 from 2003 to 2019
3. AIDUA - Artificial Intelligence Device Use Acceptance from 2019 onwards

Appendix B: Progression of Technology-enabled Banking Services



Appendix - Progression of Technology-Enabled Banking Services

Appendix: Progression of Technology-Enabled Banking Services

A virtual bank is a branchless bank that fully utilizes AI autonomous banking services.

Banking services' distribution channels have undergone a drastic change since the 2016 breakthrough of Artificial Intelligence (AI) technology, which was rapidly applied to the FinTech industry. The term "virtual banking" has not yet been clearly defined. Most research uses online banking (OB), internet banking (IB), and mobile banking (MB);

these offer the banking services that are typically provided by a traditional bank's physical branch (TB) (see Figure 2—Progression of Technology-Enabled Banking Services). Customers can easily locate and visualize the existence of these banks. In this article, we use branchless direct banking to test our theoretical model. This business environment features a disruptive FinTech innovation process that provides the perfect ground for testing potential users' perceptions, attitudes, and behavioral intentions in relation to AI technology.

The branchless Virtual Bank (VB) is experiencing unprecedented growth and is becoming commercially attractive to many financial and/or hi-tech operators. VB services do not need a brick-and-mortar home and are run by a physical cash economy (Sha & Mohamed, 2017). Given the early stage of AI development, few bankers and customers have experience with these disruptive innovations. VB is thus a unique platform for measuring 100% non-human intelligence services. It can provide us with a clear theoretical research model and generalizable empirical findings on users' willingness or rejection of use.

Appendix C: Measurement Items

Construct	Item NO.	Questionnaire	Supporting Literature
Cybersecurity			
	Cybersc1	I think AI device has mechanisms to ensure the safe transmission of its users' information.	Stewart & Jürjens (2018)
	Cybersc2	I think AI device shows great concern for the security of any transactions.	
	Cybersc3	I think AI device has sufficient technical capacity to ensure that no other organization will supplant its identity on the internet.	
	Cybersc4	I am sure of the identity of AI device when I	
	Cybersc5	When I send data to AI device, I am sure that they will not be intercepted by unauthorized third parties.	
	Cybersc6	I think AI device has sufficient technical capacity to ensure that the data I send will not be intercepted by hackers.	
	Cybersc7	When I send data to AI device, I am sure they cannot be modified by a third party.	
	Cybersc8	I think AI device has sufficient technical capacity to ensure that the data I send cannot be modified by a third party.	
Anthropomorphism			
	Anthro1	AI devices have a mind of their own.	Gursoy, et al (2019)
	Anthro2	AI devices have consciousness.	
	Anthro3	AI devices have their own free will.	
	Anthro4	AI devices will experience emotions.	
Performance Expectancy			
	PerExp1	AI devices are more accurate than human beings.	Gursoy, et al (2019)
	PerExp2	AI devices are more accurate with less human errors.	
	PerExp3	AI devices provide more consistent service than human beings.	
	PerExp4	Information provided by AI devices is more consistent.	
Effort Expectancy			
	EffEXP1	Using AI devices takes too much of my time.	Gursoy, et al (2019)
	EffEXP2	Working with AI devices is so difficult to understand and use in services.	
	EffEXP3	It takes me too long to learn how to interact with AI devices	
Perceived Level of AI's Intelligence			
	PerceAii1	I think that AI's device works like a machine.	Huang & Rust (2018)
	PerceAii2	I can communicate well with AI device, and	

		vice versa.	
	PerceAii3	I find that AI device understands my need and response well.	
	PerceAii4	I think that AI device has knowledge with analytical ability.	
	PerceAii5	I have connections like human-like services with AI device.	
	PerceAii6	I can feel that AI device takes care of me and solve my problem.	
	PerceAii7	I can feel that AI device is sensitive to my feeling and acts like humans.	
	PerceAii8	I believe that AI device can accomplish the task well.	
Compensatory Level of Acceptance			
	WillUse1	I am willing to receive AI device services.	Gursoy, et al (2019)
	WillUse2	I will feel happy to interact with AI devices.	
	WillUse3	I am likely to interact with AI devices.	