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# Why do people avoid and postpone the use of voice assistants for transactional purposes? A perspective from decision avoidance theory

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ABSTRACT

Consumers increasingly adopt artificial intelligence (AI) enabled voice assistants (VAs) for transactional and non-transactional uses due to these devices' inherent affordances, such as their ease of use and convenience. Despite the widespread adoption of VAs in recent times, consumers continue to avoid using VAs for transactional purposes. Currently, we have a limited understanding of the various antecedents and consequences of consumer decision avoidance in the context of VAs. This study aims to bridge this gap by adopting the decision avoidance theory as a theoretical lens and a convergent mixed-methods approach to identify the antecedents (i.e. cognitive biases and nudging) and consequences (i.e. rejection of VAs for transactional purposes and intention to adopt VAs for transactional purposes) of consumer decision avoidance (i.e. consumer inertia and procrastination). The study findings suggest a positive association of cognitive biases with consumer inertia, procrastination and rejection. While nudging is positively associated with procrastination and intentions, it shares a negative association with rejection. Consumer inertia is positively associated with rejection and negatively associated with intentions. Meanwhile, procrastination shares a positive association with intention and a negative association with rejection. Technology comfort has a significant moderating (negative) influence on the association between cognitive biases and intentions.

## 1. Introduction

Consumers have shown noticeable interest in the adoption of artificial intelligence- (AI) enabled voice assistants (VAs), popularly known as smart speakers, such as Alexa (Amazon's Echo), Siri (Apple) and OK Google (Malodia et al., 2021; McLean et al., 2021). The use of VAs is expected to revolutionise consumer engagement by redefining the ways in which consumers interact with firms and engage in various shopping activities (Hoy, 2018). The potential for this transformation is evident in the steep increase in the percentage of consumers owning VAs. For example, in the USA, the ownership rate of VAs exceeded 30% in 2020 (Kinsella, 2020). Similarly, in Japan, 3.7 million households owned VAs in 2018, and this number is expected to grow by approximately 500% and cross the 22 million mark by 2024 (Francis, 2019).

While the adoption of VAs is impressive, the majority of consumers continue to hold various apprehensions, concerns and biases about using VAs in their day-to-day lives (PwC Report, 2018). The most common apprehensions and biases against VAs include safety and privacy concerns and various financial risks (PwC Report, 2018). Consequently, the actual usage of VAs remains limited to non-transactional activities, such as searching for information, listening to music and checking weather and news updates. In Japan, a recent report suggests that only 17.5% of those who own VAs frequently use them for transactional purposes (e.g. shopping online, making payments and carrying out financial transactions; Zhang & Itoyama, 2020). The same report further suggests that more than 60% of consumers either avoid using VA for transactional purposes or at least wish to postpone the use of VAs for transactional purposes, such as shopping, paying bills, etc. However, the reasons for

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avoiding and postponing the use of VAs for transactional purposes remain largely unknown.

Scholars have observed that consumers' decisions to avoid or postpone the use of a given product or service are often driven by factors that are distinct from the factors that influence their adoption behaviour (Claudy et al., 2015; Talwar et al., 2021). In the prior extended consumer behaviour literature, consumer avoidance of any product or service is termed 'consumer inertia' (Henderson et al., 2021), whereas postponement is termed 'procrastination' (Akerlof, 1991; Azimi et al., 2020). Scholars argue that understanding the underlying factors of avoidance and postponement (collectively termed 'consumer resistance') is as important as understanding the factors influencing adoption (Talwar et al., 2021).

Because consumer inertia and procrastination may result in lost opportunities for marketers (e.g. delayed adoption, slow diffusion of innovative products, etc.), it demands a deeper investigation (Anderson, 2003; Henderson et al., 2021). Consequently, understanding the possible antecedents and consequences of consumer decision avoidance (i.e. consumer inertia and procrastination) is important, especially in the context of VA usage for transactional purposes. Thus, this is a timely and essential research agenda for service providers, retailers and market practitioners. Prior literature has suggested decision avoidance theory as a theoretical framework for the conceptualisation of consumer inertia and procrastination (Anderson, 2003). The decision avoidance theory also offers insights into consumers' choice deferral behaviour (Maeng et al., 2020; Nel & Boshoff, 2021; Seth et al., 2020). However, scholars have yet to explore its applicability in the context of digital assistants, such as smart speakers and VA.

Prior literature on consumer decision avoidance suggests that cognitive biases and nudging are two important antecedents that reinforce or mitigate the influence of consumers' decision avoidance (i.e. inertia and procrastination; Jung et al., 2018; K. Lee & Joshi, 2017; Nel & Boshoff, 2021). The literature on the influential role of cognitive biases is extensive, but the current academic understanding of nudging's influence is limited (Schneider et al., 2020; Stryja & Satzger, 2019). Amirpur and Benlian (2015) demonstrated the influence of nudging on consumer buying behaviour in the context of digital transactions by providing evidence of the positive influence of nudging on deal choice. Similarly, our qualitative study found that practitioners have utilised various nudging techniques (such as default selection, reminders, etc.) to counterbalance consumers' apprehensions and concerns and even motivate them to use VAs more extensively (including using them for transactional purposes; Tussyadiah & Miller, 2019). It is not known, however, whether and, if so, how nudging techniques are effective in mitigating the negative influence of consumer decision avoidance (i.e. inertia and procrastination) in the context of the transactional VA use. However, scholars have also noted a fine line between nudging and nagging; if nudging is not properly implemented, it can backfire (Ingendahl et al., 2021). Therefore, it is important to investigate whether nudging can effectively reduce consumer inertia and procrastination in the context of VAs.

In sum, we identify three main research gaps in the prior literature. First, we observe a limited understanding of the influential role of decision avoidance in the case of innovative products in general and in the context of VAs specifically. Furthermore, scholars have scarcely studied the possible antecedents and outcomes of consumers' decision avoidance. Second, most of the existing VA studies have focused on VA intentions and usage in non-transactional contexts. Meanwhile, little prior research has examined the factors reinforcing or mitigating the transactional uses of VAs. Third, the boundary conditions that reinforce or mitigate the associations between antecedents and decision avoidance also remain unexplored.

The present study proposes to address these three research gaps by answering three main research questions (**RQs**): **RQ1**. How are cognitive biases and nudging associated with decision avoidance (i.e. consumer inertia and procrastination) and outcomes (rejection and intentions to use) in the context of VAs? **RQ2**. How are consumer inertia and procrastination associated with outcomes, i.e. intentions to adopt or reject the use of VAs for transactional purposes? **RQ3**. Does technology comfort negatively moderate the association between (a) cognitive biases and consumer inertia and positively moderate the association between (b) nudging and consumer inertia?

To develop our research framework, we first identified VA-specific cognitive biases and the nudging strategies marketers use through a qualitative study. In doing so, we drew upon the discussion points from Seth et al. (2020), which we contextualised in the context of VAs. Next, we extensively reviewed the literature to understand the conceptualisation of cognitive biases, nudging, consumer inertia and procrastination. This qualitative study and in-depth review of literature helped us to develop a finer understanding of issues related to consumer inertia and procrastination in the context of VAs.

We adopted a mixed-method approach (Harrison & Reilly, 2011) and proposed a conceptual framework accordingly. We propose cognitive biases and nudging as the antecedents of consumer inertia and procrastination. Because the antecedents remain under-explored in the context of VAs, we collected data via 29 in-depth interviews. Further, we propose the rejection of VAs for transactions and the intention to use VAs for transactions as outcomes of consumer inertia and procrastination. Finally, we propose technology comfort as a moderating variable. Our model also controlled for age and gender. To empirically validate our research framework and seek answers to the above research questions, we collected data using a cross-section survey (N = 301) and a research panel situated in Japan. Addressing the above research gaps and identifying the antecedents and consequences of consumer inertia and procrastination offers both theoretical and practical benefits. Further, a deeper understanding of the above issues will provide critical insights to marketers by illuminating the reasons for consumer inertia and procrastination towards using VAs for transactional purposes. Marketers must understand these specific reasons and develop strategies to enhance transactional usage among VA owners.

The rest of the paper is organised as follows. The second and third sections review the literature and discuss the relevant hypotheses and conceptual framework. The fourth and fifth sections detail the empirical results and methods, while the sixth section presents the study's managerial and theoretical implications. Finally, the study's limitations are discussed in the sixth section, along with future research directions.

## 2. Background literature

### *2.1. Voice assistants (VAs)*

A VA refers to a bundle of artificially intelligent software agents that uses natural language processing algorithms and operates through a purpose-built device, i.e. a smartphone or a smart speaker (Hoy, 2018). While smartphones are more personal in nature, smart speakers can be used by all members of a household. Therefore, the use of VAs through smartphones is expected to be more personalised than the use of VAs through smart speakers (Edwards, 2021). VAs are programmed to listen continuously for a wakeup word—for example, OK, Google' or 'Hey, Alexa'. Upon hearing the word and being activated, VAs are able not only to carry out real-time conversations with consumers but also to execute various tasks, such as searching for and reading the requested information (e.g. online news, weather, reports etc.), controlling Internet of things- (IoT-) enabled devices, playing music, booking a cab, placing an online order and so on. In addition to interactions aimed at executing search commands or completing tasks, consumers also report experiencing an emotional bond with their human-like VAs (Schweitzer et al., 2019). For example, consumers have even proposed marriage to their VAs or declared their love towards their anthropomorphised virtual agents (Schweitzer et al., 2019).

As the proliferation and advancement of technology proceed through all spheres of life, consumers' interactions with AI-enabled smart devices is constantly rising (Guzman, 2019). Amidst a wide variety of technologies, VAs have gained popularity and found acceptance among consumers via both smart speakers and mobile applications on smartphones (Moriuchi, 2019). VAs offer consumers a convenient medium of interaction with their service providers (McLean et al., 2021). In addition, consumers can multi-task by giving voice commands to their VAs without experiencing any interruptions in their own activity (Strayer et al., 2017). For example, consumers can respond to emails or request traffic updates while driving, order groceries online while cooking and book a cab without taking out their mobile phones. AI-enabled VAs are capable of personalising their interactions with consumers on both a cognitive and emotional level (Moriuchi, 2019). Thus, VAs provide opportunities for marketers to engage with consumers using voice technology.

The academic literature examining the behavioural dimensions associated with the use of VAs remains scant (McLean & Osei-Frimpong, 2019; K. Lee et al., 2019). Adopting the uses and gratification (U&GT) framework, McLean & Osei-Frimpong (2019) explored the underlying dimensions that motivate consumers to adopt VAs. Moriuchi (2019) mined the technology acceptance literature to investigate the effect of VAs on consumer engagement in the context of online shopping. Although VAs are easy to use, convenient and efficient, and the adoption of voice assistants is increasing steadily, many consumers remain apprehensive about this new technology (McLean & Osei-Frimpong, 2019; Moriuchi, 2019). These apprehensions result in consumer inertia, which restrains consumers from utilising VAs for transactional purposes. Despite the rapid surge in the use of VAs, consumers' behavioural motives and inertia towards using VAs for transactional purposes remains unaddressed. The present study aims to bridge this gap, utilising the decision avoidance theory to understand the various factors that result in consumer inertia and procrastination in the context of VAs.

### 2.2. Decision avoidance

Anderson (2003) postulated decision avoidance as '*a tendency to avoid making a choice by postponing it or by seeking an easy way out that involves no action or no change*'. When facing difficult choices, consumers typically enter a decision avoidance mode to escape the feeling of discomfort (Van Putten et al., 2013). The decision avoidance theory is based on three psychological measures: '*inertia*' or the '*status quo bias*' (K. Lee & Joshi, 2017; Samuelson & Zeckhauser, 1988), '*inaction*' or the '*omission bias*' (Van Putten et al., 2013; Ritov & Baron, 1992; Tykocinski et al., 1995) and '*delay*' or '*choice deferral*' (Dhar & Nowlis, 1999). Building upon the decision avoidance theory, Joseph (2005) argued that inertia might manifest in the non-adoption or 'rejection' of an innovation. Further, Alós-Ferrer et al. (2016) found that inertia is positively associated with repeat behaviour, resulting in sub-optimal choices and the rejection of superior alternatives. Another important decision avoidance option is deferring a decision for a particular period of time (Anderson, 2003). The literature on innovation resistance identifies choice deferral, i.e. postponement or procrastination, as passive resistance to adopting innovative products and services (Laukkanen et al., 2009).

The decision avoidance theory is a suitable theoretical lens for the current research for two main reasons. First, this theory allows us to identify the two important dimensions of decision avoidance, i.e. consumer inertia and procrastination. Second, the extant literature has found these two dimensions highly relevant and useful in the context of innovative products and services (Alós-Ferrer et al., 2016; Laukkanen et al., 2009). Thus, these dimensions have been applied in the context of VAs.

## 3. Research model and hypotheses development

### 3.1. Qualitative study

We identified context-specific dimensions of inertia and procrastination through a qualitative study that involved 29 in-depth interviews. We interviewed senior executives (n = 5) (Table 1) working with popular brands of VAs and consumers (n = 24; females = 45.8%; students = 5, professionals = 19) who regularly used VAs in past 6 months. The interviews revealed that their usage included tasks such as controlling home automation, seeking traffic updates while driving, listening to music, voice search, booking a cab service etc. Furthermore, it was found that consumers using VAs were using it both through their smart phones as well as smart speakers. Amazon eco was the most popular smart speaker among our respondents (eco = 17, OK Google = 4, whereas, 3 consumers were using Apple Siri as their VA only through their phones). Because our objective was to understand why people who own VAs limit their usage to non-transactional purposes, we conducted in-depth interviews with precisely these consumers to understand the conscious as well as sub-conscious factors that led them to reject or postpone their decision to use VAs for transactional purposes. We developed the interview questions through an extensive review of the academic literature, popular press articles and industry reports related to VAs. The interview questions for consumers were designed to understand their experiences using VAs as well as their apprehensions towards VAs. Meanwhile, the interview questions for the service provider executives aimed to understand (from the service providers' perspective) the issues and challenges of VA non-adoption for transactional purposes.

Interviewing consumers and service providers helped us develop a holistic understanding of the issues related to the non-adoption of VAs for transactional purposes. The questions allowed us to assess consumers' inertia mindset and procrastination towards the use of VAs for transactional purposes. Follow-up questions sought to understand various types of biases that consumers hold towards VAs. Finally, we asked the service providers questions regarding the nudging strategies they have adopted to overcome consumers' inertia towards the use of VAs.

We employed Colaizzi's (1978) seven-step phenomenological process to analyse the qualitative data (Talwar et al., 2021). The seven steps are as follows: (1) the authors independently analysed the transcripts of the interviews to develop a deeper understanding of the issues associated with not using VAs for transactional purposes; (2) each author developed open codes based on the keywords, phrases and sentences they deemed important; (3) each author analysed the open codes and independently articulated their meanings; (4) this process was repeated for all transcripts to generate recurring themes; (5) next, the authors independently integrated the recurring themes to develop a cohesive description of the phenomenon under investigation; (6) thereafter, the authors collectively examined and compared the themes proposed by the individual authors and developed a coherent explanation of consumers' inertia and procrastination behaviour in the context of using VAs for transactional purposes; (7) finally, the authors asked respondents to review the findings and incorporated their feedback into the explanation of the phenomenon Fig. 1. We present a sample of themes that emerged in our qualitative analysis in Table 2.

**Table 1**
Profile of senior executives.

| Profile of respondent | Age & gender |
|---|---|
| Senior product marketing manager (VA skills developer marketing) | 35–40, Female |
| Product marketing manager (VA) | 45–50, Male |
| Business analyst | 40–45, Male |
| Country head, research & measurement (voice-based products) | 40–45, Male |
| Product manager (voice products) | 35–40, Female |

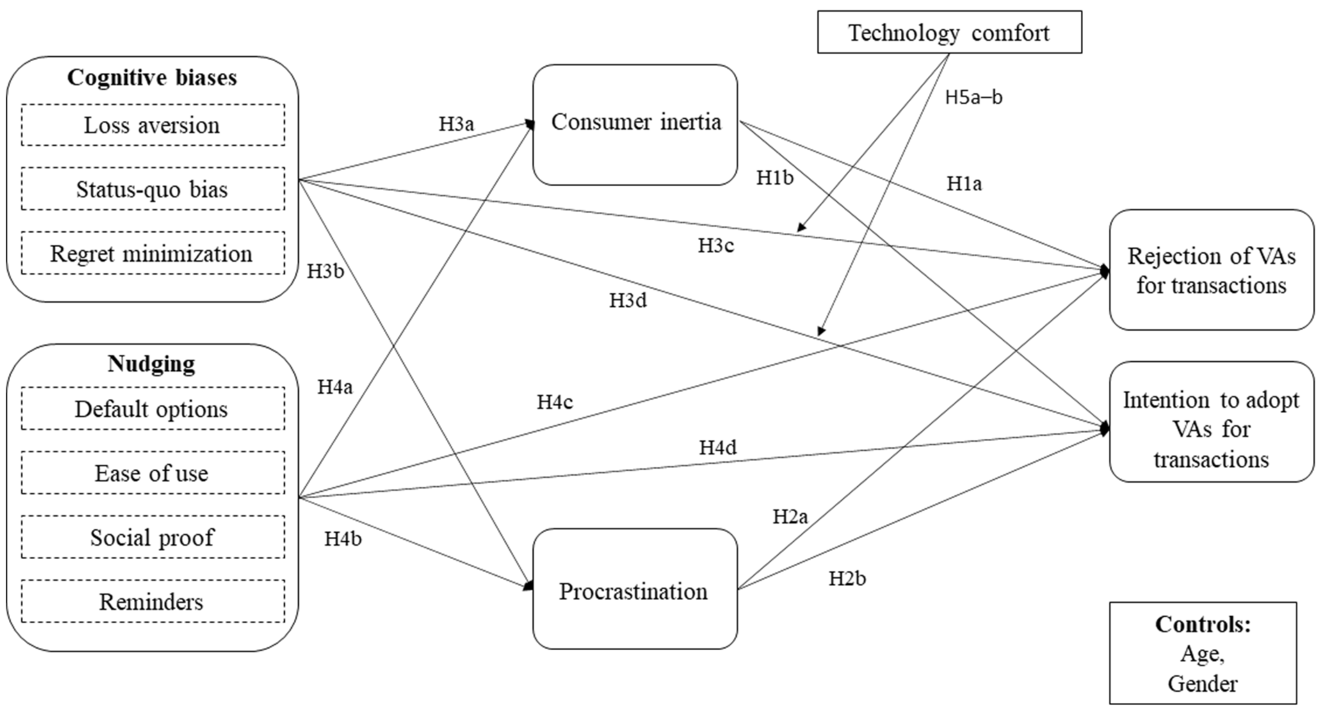


**Fig. 1.** Conceptual model.

**Table 2**
Interview insights: Sample responses from users of VAs and corresponding themes.

| Theme | Sample comments |
|---|---|
| Loss aversion | *"I am worried my kids will start ordering things using Alexa if I register my payment details with her. Maybe once my kids grow up a little I'll do so."* *"What if Alexa does not understand my command and orders wrong stuff."* |
| Regret minimisation | *"I don't' want to make mistakes and my friends to laugh at me. Ordering food using my mobile is tried and tested, why take the risk and use Alexa"* |
| Status quo bias | *"When it is easy to shop online, why use Alexa. None of my friend group use Alexa for shopping."* |
| Inertia | *"I know, I can use Alexa for ordering my pizza, but I am habitual of ordering it using my mobile. However, I believe I'll soon be using Alexa for this."* *"Shopping through my laptop is more convenient, why take the risk and use Alexa."* |
| Procrastination | *"My friends keep asking me to use Alexa for ordering Uber. It's just a matter of habit, but I'll use Alexa more and more in the near future."* *"I will be using Alexa for making payments in the future if my friends are doing so."* |
| Default Rules | *"While the smart speaker comes with some default rules. For example, if you order your toilet paper, it will show you stock options at Amazon. However, users can change the default options."* |
| Ease of Use | *"One thing that we boast about is the convenience and ease of using our VA. Even while you are driving, you can ask it to not only read the email for you, but it can also book a dinner table for you at your favourite restaurant."* |
| Reminders | *"Once you start ordering things using our VA. Let us continue with the example of toilet paper. After 2 or 3 orders, it will know exactly when you need toilet paper next time, and it will give you reminders appropriately."* |
| Social Proof | *"You must have seen our recent advertisement of VA being used by an old couple, kids at home, etc. These all communication attempts are aimed at creating social proof for our users. Soon we are going to launch a series of advertisements that will show people carrying out transactions using their smart speakers."* |

The themes identified from the qualitative analysis were as follows: loss aversion, status-quo bias, regret minimisation, ease of use, need for social proof, reminder's function, default options, delay tactics, postponement of difficult choices etc. These themes were further bucketized, and the process helped us operationalise consumer inertia and procrastination and synthesise the underlying biases of inertia and procrastination. Further, we identified nudging practices the industry has utilised to overcome consumer inertia and procrastination towards using VAs for transactional purposes. Next, we solicited feedback by appointing an expert panel of three industry representatives working as senior product managers for voice-related products. The feedback from the expert panel, along with an extensive review of the extant literature, enabled us to identify specific scale items to operationalise and measure our proposed constructs.

### 3.2. Inertia

The origins of the concept of inertia can be traced to the theory of status quo bias (SQB) (Samuelson & Zeckhauser, 1988). Inertia refers to the predisposition of consumers to continue to follow certain practices irrespective of the availability of superior alternatives (Seth et al., 2020). Inertia has also been described as the 'path of least resistance' (Samuelson & Zeckhauser, 1988), 'resistance to change' (Mesquita and Urdan, 2019) and 'status quo maintenance' (De Guinea & Markus, 2009). The current literature identifies multiple factors that can drive inertia, such as convenience, habit, loss aversion, regret minimisation, and uncertainty avoidance (Henderson et al., 2021; Huang & Yu, 1999; K. Lee & Joshi, 2017). Scholars have further classified the above factors into cognitive biases and affective biases (Seth et al., 2020).

Cognitive biases represent an individual's conscious decision to maintain the status quo even when the choice of a better alternative is available (Amoroso & Lim, 2017). On the contrary, effective biases represent a continuation of the status quo to avoid a stressful situation (Amoroso & Lim, 2017). The prior literature examining investment behaviour observed that inertia could significantly explain the behaviour of investors who stick to a set of investment options and refrain from investing in newer options to avoid risk (Auger et al., 2016). Similarly, the current literature has argued that inertia may result in continuance intentions towards an existing product and the rejection of a new product (Greenfield, 2005; Henderson et al., 2021; Polites & Karahanna, 2012). Furthermore, Gong et al. (2020) demonstrated that consumer inertia is negatively associated with the intention to use mobile payments. On the contrary, Gray et al. (2017) observed a paradoxical relationship wherein consumer inertia is negatively associated with switching intentions but fails to predict the actual switching behaviour when consumers switch their service provider in less than one year. While it is thus reasonable to assume that inertia may not always result in rejection, inertia does make the switching decision difficult (Gray et al., 2017). Based on the above empirical evidence, we extend the concept of inertia in the context of VAs and expect inertia to result in the rejection of VAs for transactional purposes and to act as a barrier towards consumers' intentions to use VAs for transactions. Hence, we advance the following hypotheses:

**H1a**. Consumer inertia is positively associated with the rejection of VAs for transactional purposes.

**H1b**. Consumer inertia is negatively associated with the intention to use VAs for transactional purposes.

### 3.3. Procrastination

The marketing literature has defined procrastination as a prevalent tendency to postpone or delay purchase decisions (Mzoughi et al., 2007), and it has identified avoidance and indecision as two significant dimensions of procrastination (Darpy, 2000). Scholars have observed procrastination as a widespread tendency among consumers; however, procrastination is not always associated with negativity. Rather, the marketing literature often imbues procrastination with positive connotations and classifies it as a functional delay and hence it is often positively associated with behavioural intentions (Azimi et al., 2020; Choi & Moran, 2009). For example, scholars have argued that consumers employ procrastination as a strategy to avoid rushed decisions under conditions of uncertainty (Azimi et al., 2020; Bernstein and Bernstein, 1996). The current literature argues that procrastination involves an element of behavioural intention with a general tendency to defer decision-making (Anderson 2003). Based on the above argument and in the context of VAs, we define procrastination as a conscious decision to delay and not to completely reject using VAs for transactional purposes. Consumers intentionally delay using VAs for transactions because they want to collect more information and avoid uncertain outcomes. Hence, we propose the following hypotheses:

**H2a**. Procrastination is positively associated with the intention to use VAs for transactions.

**H2b**. Procrastination is negatively associated with the rejection of VAs for transactions.

### 3.4. Cognitive biases

Cognitive biases refer to a cognitive phenomenon that manifests in irrational thinking and quick decision-making (Kliegr et al., 2021). Research has shown that cognitive biases are deep-rooted, and in the absence of well-articulated choices, consumers rely on their cognitive biases to make decisions (Biswas & Grau, 2008; Tversky & Simonson, 1993). Previous literature examining consumer decision-making has indicated that irrational cognitive biases often affect consumers' judgements (Åstebro et al., 2007; Lee, 2014; Messner & Vosgerau, 2010). The status quo bias is a cognitive bias that refers to an individual's preference to maintain the current situation (Samuelson & Zeckhauser, 1988). Though some scholars consider the status quo bias to be irrational, the counter-argument states that adhering to tried and tested choices is not only a safe decision but also an easy decision, especially in situations with limited information, choice overload, high uncertainty, hidden costs, etc. (Dean et al., 2017; Nebel, 2015). In the context of mobile shopping, Nel and Boshoff (2021) observed that cognitive biases, especially the status quo bias, significantly influence consumers' inertia from online purchases to mobile shopping. Bekir and Doss (2020) also argued that the status quo bias might lead to procrastination. Similarly, studies in the behavioural economics literature have found that procrastination is often associated with individuals' cognitive biases (Chuah & Devlin, 2011; De Meza et al., 2008).

The second category of cognitive bias discussed in the literature is regret minimisation (Seiler et al., 2008). Regret minimisation refers to an ego-defensive mechanism that propels an individual to uphold his or her previous decisions and behaviours to avoid regretful situations (Inman & Zeelenberg, 2002). The current literature identifies inertia and procrastination as the two major consequences of regret minimisation (Anderson, 2003; Janis & Mann, 1977; Henderson et al., 2021). Janis and Mann (1977) reported that when individuals anticipate a regretful situation, they are likely to collect more information before making a final decision; hence, they proposed that anticipatory regret may result in procrastination. Similarly, Henderson et al. (2021) found that individuals with a higher amount of regret minimisation operate according to an inertia mindset, which further manifests in consumer inertia.

The third important cognitive bias discussed in the current literature is loss aversion (Andersson et al., 2016; Lee and Joshi, 2017). Loss aversion holds that in situations of loss, the pain individuals experience is likely greater than the gains they enjoy (Kahneman & Tversky, 1979). The marketing literature has explored the impact of loss aversion for technology products, observing that consumers often delay their purchase decision because they anticipate that the same product will be available at a lower price when a newer version is launched, and hence, they hope to avoid incurring a loss by paying the current regular price (Zeelenberg & Putten, 2005 Similarly, because they are loss averse, consumers are reluctant to purchase regular price products from brands that are known to offer discounts (Tversky & Kahneman, 1992). Further, in the context of implementing new information systems or information and communication technology (ICT) projects, Polites and Karahanna (2012) observed that loss aversion leads consumers to exhibit inertia towards purchasing newer technology products because they perceive surrendering their current product as a loss. The question of whether cognitive biases in the context of VAs lead to consumer inertia or procrastination requires further examination. Therefore, we propose the following hypotheses:

**H3a**. Cognitive biases are positively associated with consumer inertia in the context of using VAs.

**H3b**. Cognitive biases are positively associated with procrastination in the context of using VAs.

Nevertheless, the impact of cognitive biases on consumers' decisions to use VAs for transactional purposes or reject them or transactional purpose remains uncertain. However, since our qualitative interviews suggest a connection between these constructs, we assume that it would be interesting to examine the following hypotheses:

**H3c**. Cognitive biases are positively associated with the rejection of VAs for transactions.

**H3d**. Cognitive biases are negatively associated with the intention to use VAs for transactions.

### 3.5. Nudging

Nudging refers to alterations or modifications in the choice architecture, which aim to influence consumer choices through subtle interventions, such as default options, positive reinforcements and indirect suggestions (Ingendahl et al., 2021; Thaler & Sunstein, 2008). The different types of nudging interventions include default options, social proof, ease of use, reminders, etc. (Sunstein, 2019). In the context of online retailing, Demarque et al. (2015) found that nudging is an effective tool by which marketers can influence consumers to purchase eco-friendly products online. Default options are preselected, which requires consumers to de-select them if they do not require them (Schneider et al., 2020). Previous studies have found that consumers are likely to retain the default option(s), making it a successful nudging strategy (Cronqvist & Thaler, 2004; Sunstein, 2019). For example, in permission marketing, marketers utilise default opt-ins as a nudge for enrolling consumers in various updates and services (Johnson et al., 2002). Similarly, by default, VAs are always on a listening mode, and by default, Alexa would suggest ordering from Amazon, or when the user asks Alexa to book a cab, Alexa would suggest ordering an Uber.

Rooted in the theory of social influence, social proof is another type of nudging strategy marketers frequently use to signal the demand for and popularity of a product or a service (Roethke et al., 2020; Schneider et al., 2020). Cialdini and Trost (1998) argued that, in situations of uncertainty, consumers are likely to make decisions on the basis of social proof. Marketers frequently use social proof as a marketing cue not only to counter consumers' concerns but also to build trust in their products and services (Burtch et al., 2018; Schneider et al., 2020). For example, e-commerce firms utilise social proof as a nudging strategy by publishing testimonials and product reviews (Burtch et al., 2018; Roethke et al., 2020). It was reported during our qualitative interviews that providers of VAs are aggressively utilising social proof as their marketing communication strategy to nudge consumers to use VAs for transactional purposes. Hence, it is reasonable to assume that social proof will impact consumers' decision avoidance in the context of VAs.

Next, Sunstein (2014) suggested ease and convenience as effective nudging tactics. Prior literature has argued that consumers are likely to make choices that are easy and convenient (Sunstein, 2014). Additionally, consumers are more inclined towards choices that supplement ease of use and convenience with entertainment value (Sunstein, 2019). Moreover, during our qualitative interviews, respondents focused on ease of use as an important nudge strategy to promote usage of VAs. Therefore, we include ease of use as an important nudging tactic in the context of VAs.

Finally, reminders represent a well-known nudging tactic (Damgaard & Gravert, 2018). Reminders are used to curb individuals' forgetful behaviour by continuously informing them to complete a task or an activity (Sunstein, 2014). The prior literature has demonstrated empirically that reminders can induce behaviour change in multiple contexts, such as encouraging fitness center attendance (Calzolari & Nardotto, 2017), promoting energy conservation (Allcott & Rogers, 2014; Gilbert & Zivin, 2014), increasing charitable giving (Sonntag & Zizzo, 2015) and promoting savings behaviour and timely payments (Karlan et al., 2015; Karlan et al., 2016). Users can program their VAs to set reminders for various activities, and hence, in the context of VAs, reminders can be considered as an important nudge.

With the growing integration of technology into everyday life, decision inertia has become a pressing concern for service providers (Jung et al., 2018). The current literature on nudging proposes that providers can reduce decision inertia by manipulating consumers' choice architecture (Jung et al., 2018; Sunstein, 2014). Research related to behavioural economics, information systems, marketing, psychology, and other disciplines has employed the concept of nudging (Ingendahl et al., 2021). Furthermore, prior literature on nudging argues that nudging is an effective tool to combat procrastination behaviour (Friedman & Wilson, 2022; Rodriguez et al., 2019). Studying academic procrastination among the student population, Rodriguez et al. (2019) found that information technology can be used not only to overcome procrastination but it can also to induce positive and self-reinforcing behavioural change among individuals. Similarly, Friedman and Wilson (2022) provided empirical evidence for using compensation as a nudge to overcome procrastination behaviour among participants who were procrastinating a medical procedure. Based on the above literature, we propose the following hypotheses:

**H4a**. Nudging is negatively associated with consumer inertia in the context of using VAs.

**H4b**. Nudging is negatively associated with procrastination in the context of using VAs.

**H4c**. Nudging is negatively associated with the rejection of VAs for transactions.

**H4d**. Nudging is positively associated with the intention to adopt VAs for transactional purposes.

### *3.6. The moderating role of technology comfort*

Our initial qualitative inquiry also helped us understand the potential moderating role of technology comfort in the relationship between cognitive biases and the decision to use VAs for transactions (i.e. the rejection of VAs for transactions or the intention to adopt VAs for transactions). Akhter (2015) examined the role of technology comfort in the context of online shopping and defined technology comfort as the level of comfort that individuals have in handling computers and the Internet. The extant literature has argued that consumers desire a minimum level of technology comfort when dealing with service providers (Lassar et al., 2005). Spake et al. (2003) found that technology comfort positively affects the outcomes of marketing interventions. The literature has also documented the positive effects of technology comfort on consumer behaviour and consumer satisfaction (Lloyd & Luk, 2011; Spake et al., 2003). Studies in consumer psychology have suggested that technology comfort helps consumers overcome anxiety, puts them at ease and reduces tension (Akhter, 2015; Simmons, 2001). Further, the literature has observed that technology comfort makes the outcomes of transactions more predictable to consumers, allowing them to feel relaxed and confident about their decisions to engage in online transactions (Akhter, 2015). The above findings from the literature are relevant in the context of VA usage for transactional purposes due to the following reasons: a) prior literature has suggested technology comfort moderates the adoption of new technology, and VA is a fast emerging technology, and its usage is increasing. However, our qualitative inquiry suggests that though people are owning VAs, they are anxious about trusting fully trusting their VAs; b) while VA is a new technology that can operate through smart speakers, mobile phones, tablets, laptops, etc., and hence, the findings of Akhter (2015), can be extended in the context of VAs. Based on the above arguments, we assume that technology comfort will positively moderate the association between cognitive biases and the outcome variables. Hence, we advance the following hypotheses:

**H5**. Technology comfort positively moderates (a) the association between cognitive biases and the rejection of VAs for transactional purposes and (b) the association between cognitive biases and the intention to adopt VAs for transactional purposes.

## 4. Data and methods

### *4.1. Measures*

A multi-pronged approach was used to develop the survey instrument. First, an item pool was created through qualitative research. The items were then matched with the pre-existing scales through an extensive literature review. Three cognitive biases were shortlisted: loss aversion, regret minimisation and status quo bias. We operationalised loss aversion with three items (Mrkva et al., 2020), regret minimisation with three items (Henderson et al., 2021) and status quo bias with three items (Lee & Joshi, 2017). Similarly, we operationalised default rules using four items adapted from Berger et al. (2020), ease of use with four items adapted from Weinmann et al. (2016), social norms with five items adapted from Tussyadiah and Miller (2019) and reminders with five items adapted from Namazu et al. (2018). Consumer inertia was measured using six items from Carter et al. (2016) and Wang et al. (2020). Measures of procrastination were adopted from Zanjani et al. (2016) and were operationalised using five items. The English version of the questionnaire was translated into Japanese, and data collection was conducted in Japanese using the back translation method (Dhir et al., 2015). A panel of three researchers, inclusive of a native Japanese professor, also an expert in bilingual translation, i.e. English-Japanese-English, were involved in the process of back-translation. Further, we conducted a pilot study with a sample of 24 respondents from the target group to ensure that respondents were comfortable understanding the translated version of the questionnaire. This also helped us ensure that the scale items were relevant to the context of VAs and that the respondents understood the intended measures of the scale items. All items were measured on a seven-point Likert scale.

### 4.2. Data collection

Data were collected from residents of Japan through a leading marketing research company 'Macromill'. A screening survey was conducted to identify frequent users of VAs (VAs used through smartphones as well as smart speakers) who nevertheless did not use VAs for transactions. The screening was conducted in February 2021. Emails were sent to 118,322 pre-registered members of the Macromill research panel, and 21,290 participants were collected based on a first-come, first-served basis. Of the 21,290 participants, 1,254 qualified to proceed to the final survey by there at least twice weekly VA usage. The final questionnaire was conducted in March 2021. Of the 1,254 participants obtained from the screening survey, a random sample of 520 respondents was invited to participate in the final survey, and 330 questionnaires were obtained on a first-come, first-served basis. Of these, 29 responses were removed.

### 4.3. Data analysis

Covariance based structural equation modelling (CB-SEM) was deemed suitable to analyse the data. The suitability of the method was assessed on the basis of sample size and conformity of the assumptions for using multivariate analysis. The analysis proceeded in three stages. First, data were further cleaned to address missing values, unengaged respondents and outliers. A final sample of 301 respondents was found suitable for the data analysis (Table 2). The demographics of the sample are presented in Table 1. At this stage, we also checked the assumptions for carrying out multivariate analysis, i.e. data were tested for normality (kurtosis values were within $\pm$ 2), and homoscedasticity was tested by plotting residuals. Second, we built a measurement model using confirmatory factor analysis (CFA), and third, we tested the path relations in the proposed research framework using the structural equation model (SEM; Anderson & Gerbing, 1988). We relied on the CFA to test the reliability and validity of constructs in the research framework, while the SEM helped us examine the strength and significance of the structural paths proposed in the research framework.

## 5. Results

### 5.1. Measurement model

We conducted CFA using the maximum likelihood method via AMOS to establish validity measures of the proposed measurement model and to assess goodness of fit and construct reliability. CFA allowed us to examine the psychometric properties of the latent constructs while assuming all factors as first-order factors. The analysis produced satisfactory model fit indices ($CFI = 0.90$; $TLI = 0.89$; $RMSEA = 0.06$; $\chi^2/df = 2.06$). Despite satisfactory overall model fit indices, the model's observed validity and reliability was concerning. The critical ratio (CR) values for loss aversion and status quo bias were 0.55 and 0.64, respectively, which were below 0.70 (Hair et al., 2006). Similarly, the average variance extracted (AVE) values for loss aversion and status quo bias were 0.32 and 0.40, respectively, which were below 0.50 (Hair et al., 2006). The model did not pass the discriminant validity and convergent validity test due to highly correlated factors. Hence, we decided to hypothesise cognitive biases and to nudge as second-order factors (Byrne, 2001).

Next, we tested the second-order factor model following the recommendations of Rindskopf and Rose (1988). A hierarchical approach was adopted wherein we tested four different models. Model 1 was hypothesised as a single-factor model with all scale items loading on cognitive biases and nudging directly. In Model 2, we hypothesised that all factors (three factors for cognitive biases and four factors for nudging) were separate uncorrelated factors. Model 3 hypothesised the seven factors as separate correlated factors. Model 4 tested a second-order factor model of cognitive biases and nudging. Comparing the four models, we observed that Model 1 and Model 2 failed to produce acceptable model fit indices. Comparing Model 3 and Model 4, we observed that Model 4 exhibited better model fit indices (Table 3) and also satisfied the validity and reliability measures. Therefore, we adopted the latter for the analysis.

In addition to the measurement model results, the reliability of the constructs, their uni-dimensionality, and validity was assessed using the AVE and CR (Table 4). Fornell-Larcker's (1981) criteria were used to assess discriminant validity. According to Fornell and Larcker (1981), the square root of the AVE should be greater than all correlation coefficients of the latent construct. The CR values all exceeded the recommended cut-off value of 0.70 Table 5 (Hair et al., 2006). Finally, an assessment of multi-collinearity confirmed that multi-collinearity was absent from our model (O'Brien, 2007). Hence, a satisfactory model fit was obtained.

**Table 4**
Model fit indices.

| Model | TLI | RMSEA | $\chi^2$/df |
|---|---|---|---|
| Model 3 | 0.89 | 0.06 | 2.06 |
| Model 4 | 0.92 | 0.05 | 1.80 |

**Note:** CFI = Comparative fit index, TLI = Tucker-Lewis index, RMSEA = Root mean square error of approximation.

**Table 3**
Sample characteristics.

| | | Total | Percentage |
|---|---|---|---|
| **Gender** | Male | 162 | 53.82% |
| | Female | 139 | 46.18% |
| **Age** | *18–24* | 66 | 21.93% |
| **(in years)** | *25–34* | 78 | 25.91% |
| | *35–44* | 63 | 20.93% |
| | *45–54* | 51 | 16.94% |
| | *≥55* | 43 | 14.28% |
| **Total** | | 301 | 100% |

**Table 5**
Factor loadings, reliability and validity (Model 4) .

| First-order factors | Measurement items | Factor loadings | CR | AVE |
|---|---|---|---|---|
| **Loss aversion (LA;** Mrkva et al., 2020**)** | The convenience offered by VA is too little as compared to the privacy risk posed by VA. | 0.65 | 0.72 | 0.46 |
| | Though VA is reliable, I don't want it listening to my conversation all day. | 0.71 | | |
| | I think the risks associated with the use of VA outweigh the potential benefits. | 0.68 | | |
| **Regret minimisation (RM;** Henderson et al., 2021**)** | If I made a shift towards using a VA, and then upon further information, I realised that I had made a mistake, I would experience the feeling of discomfort. | 0.89 | 0.93 | 0.82 |
| | If I adopt a VA in my day-to-day life and later I realise that I had made a mistake, I would feel bad. | 0.90 | | |
| | If I adopt a VA in my day-to-day life, and then upon further information, I realise that I had made a mistake, I would feel regret. | 0.92 | | |
| **Status quo bias (SQB;** Lee & Joshi, 2017**)** | My smartphone fully meets my requirements, and I do not need a voice assistant. | 0.84 | 0.79 | 0.57 |
| | Traditional digital gadgets are enough for me. | 0.64 | | |
| | I do not really need a VA because my existing digital gadgets are sufficient. | 0.76 | | |
| **Default options (DO;** Berger et al., 2020**)** | The recommendations offered by my VA help me in decision-making. | 0.70 | 0.79 | 0.49 |
| | The default settings of my VA are useful to me. | 0.84 | | |
| | When I ask my VA to play some random music for me, I like the selection of music most of the time. | 0.64 | | |
| | When I ask my VA to read news and updates for me, most often, the information is of interest to me. | 0.60 | | |
| **Ease of use (EU;** Weinmann et al., 2016**)** | Using my VA is intuitive. | 0.60 | 0.83 | 0.55 |
| | Using my VA to complete a task is very easy. | 0.78 | | |
| | I quickly learned VA skills. | 0.81 | | |
| | Learning to use a VA is not a complex task. | 0.77 | | |
| **Social proof (SP;** Tussyadiah & Miller, 2019**)** | I am informed about how to search for information/shopping via the Internet effectively via VA. | 0.74 | 0.86 | 0.56 |
| | The use of voice assistants among people around me is growing fast. | 0.72 | | |
| | I have heard a lot about the features and benefits of using VAs. | 0.77 | | |
| | I am well informed about how to use VAs for searching for information and shopping. | 0.76 | | |
| | I get a lot of encouragement from people around me for using my voice assistant. | 0.74 | | |
| **Reminders (REM;** Namazu et al., 2018**)** | I like the alarm function of my VA. | 0.63 | 0.87 | 0.57 |
| | The reminder function in my VA is helpful to me. | 0.84 | | |
| | The routine function in my VA makes me more efficient. | 0.84 | | |
| | Integration of my calendar events is an important function of my VA. | 0.73 | | |
| | The list function of my VA is an important tool for me. | 0.67 | | |
| **Consumer inertia (CI;** Carter et al., 2016; Wang et al., 2020**)** | I continue using online shopping to purchase products or services instead of using my VA to place an order. | 0.89 | 0.95 | 0.76 |
| | I continue placing orders myself when shopping online to purchase products instead of using my VA because that is what I have always done when purchasing from the online retailer. | 0.94 | | |
| | I continue placing orders myself when shopping online to purchase products instead of using my VA because it is part of my normal routine when purchasing from the online retailer. | 0.87 | | |
| | When it comes to my status quo use of online shopping versus using my VA for shopping, I feel 'it is better to be safe than sorry'. | 0.88 | | |
| | I continue placing orders myself when shopping online to purchase products instead of using my VA, even if I know it is not the best way to purchase from the online retailer. | 0.84 | | |
| | I continue placing orders myself when shopping online to purchase products instead of using my VA, even if it is costly. | 0.81 | | |
| **Procrastination (PRO;** Zanjani et al., 2016**)** | I take a lot of time on trivial matters before getting to the final decision when it comes to new technology such as VAs. | 0.71 | 0.91 | 0.66 |
| | Even after I have made a decision to adopt new technology such as VAs, I delay acting upon it. | 0.88 | | |
| | When I have to make a decision to use new technology such as VAs, I wait a long time before starting to think about it. | 0.87 | | |
| | I delay making decisions until it is too late while adopting new technology such as VAs. | 0.81 | | |
| | I put off making decisions related to adopting new technology such as VAs. | 0.78 | | |
| **Rejection of VAs for transactions (REJ;** Talwar et al., 2021**)** | It is unlikely that I will use a VA for transactional purposes in the near future. | 0.79 | 0.94 | 0.79 |
| | Using a VA for transactional purposes is not for me. | 0.90 | | |
| | I don't need a VA for doing transactions. | 0.93 | | |
| | I don't think that I will use a VA ever for transactions. | 0.92 | | |
| **Intention to adopt VAs for transactions (IA)** | I expect my use of VA to increase in the future. | 0.78 | 0.86 | 0.60 |
| | I intend to use a VA for online shopping in the future. | 0.66 | | |
| | I intend to use a VA for online transactions in the future. | 0.84 | | |
| | If I have an opportunity to use a VA, I will use a VA for shopping. | 0.80 | | |
| **Second-order factors** | **Variables** | **Standardised loading** | **CR** | **AVE** |
| **Cognitive bias (CB)** | Loss aversion | 0.74 | 0.75 | 0.50 |
| | Regret minimisation | 0.73 | | |
| | Status quo bias | 0.65 | | |
| **Nudging (NUD)** | Default options | 0.69 | 0.88 | 0.65 |
| | Ease of use | 0.91 | | |
| | Social proof | 0.87 | | |
| | Reminders | 0.72 | | |

**Note:** CR = Composite reliability, AVE = Average variance extracted.

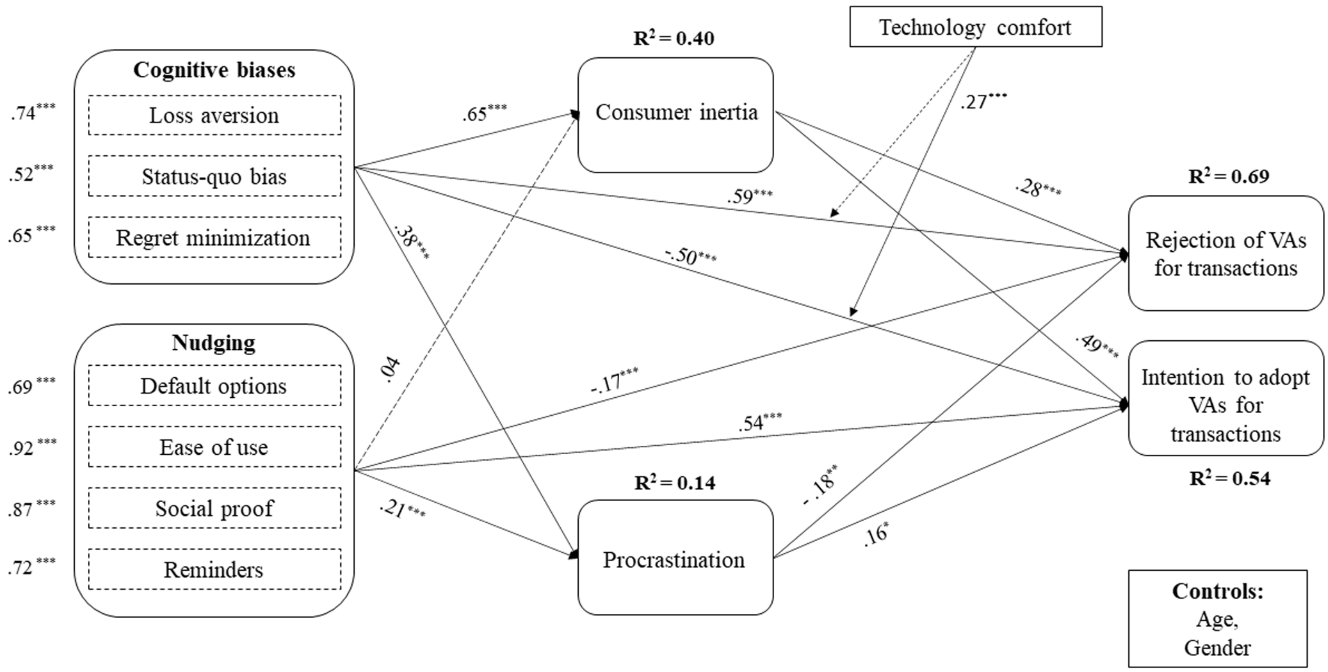


**Fig. 2.** Results of hypothesis testing.

**Table 6**
Discriminant validity.

| | MSV | ASV | CB | PRO | CI | REJ | NUD | IA |
|---|---|---|---|---|---|---|---|---|
| **CB** | 0.40 | 0.22 | **0.71** | | | | | |
| **PRO** | 0.10 | 0.02 | 0.31 | **0.81** | | | | |
| **CI** | 0.46 | 0.18 | 0.63 | −0.05 | **0.87** | | | |
| **REJ** | 0.46 | 0.17 | 0.61 | −0.03 | 0.68 | **0.89** | | |
| **NUD** | 0.41 | 0.08 | −0.33 | 0.09 | −0.17 | −0.42 | **0.80** | |
| **IA** | 0.41 | 0.12 | −0.32 | 0.02 | 0.08 | −0.32 | 0.64 | **0.78** |

**Note:** MSV = Maximum shared variance, ASV = Average shared squared variance, CB = Cognitive biases, PRO = Procrastination, CI = Consumer inertia, REJ = Rejecting VAs for transactional purposes, NUD = Nudging, IA = Intention to adopt VAs for transactional purposes, MSV = Maximum shared variance, Bold values on diagonal = SQRT (AVE), off-diagonal = correlation coefficients.

### 5.2. Common method bias

The data collected for the study were vulnerable to common method bias because they include self-reported behavioural constructs (Podsakoff et al., 2003). Hence, we attempted to address the issue by using a multi-pronged approach suggested by Chang et al. (2010). First, we randomised the questionnaire items and sought to reduce ambiguity in the instrument (Kaushik & Rahman, 2015). Second, we informed the respondents that the purpose of the study was academic and assured them that their identity would remain anonymous. We also informed respondents that there was no right or wrong answer, and we were interested only in knowing their perceptions about the various aspects of using VAs (Podsakoff et al., 2003). Upon completing the data collection, we conducted a post hoc Harman's single-factor test and found that the variance explained by the single factor was well below the cut-off value of 50% (Harman, 1967). Finally, when we included a common latent factor, the fit indices (GFI = 0.69; *TLI* = 0.68; *RMSEA* = 0.19) indicated a poor model fit. Hence, no common method bias was observed (Podsakoff et al., 2003). Therefore, we assumed that common method variance was absent and that further correction for common method variance was not required while testing the structural model.

### 5.3. Controls

The model controlled for the confounding effects of two demographic variables, i.e. age and gender, on two dependent variables REJ (Rejecting VAs for transactional purposes) and IA (Intention to adopt VAs for transactional purposes) and two mediating variables CI (Consumer inertia) and PRO (Procrastination). Consistent with the findings of previous studies on the use of VAs (McLean & Osei-Frimpong, 2019). However, the control variables did not show a significant effect on the dependent variables or on the mediating variables.

### 5.4. Structural model

The research model (Fig. 2) was empirically validated using the SEM equation with the maximum likelihood method. The results revealed a model fit with acceptable indicators. The chi-square was significant ($\chi^2/df$ = 3.66), and the other model fit indices, such as *RMSEA* = 0.06, *CFI* = 0.97, *TLI* = 0.97, fell within the recommended cut-off values (Browne & Cudeck, 1993; Hair, Ringle & Sarstedt, 2011; Hu & Bentler, 1999).

### 5.5. Mediation and moderation analyses

We examined the mediation effect of consumer inertia and procrastination on the associations between the two independent variables (cognitive biases and nudging) and the outcome variables, i.e. rejection of VAs for transactional purposes and intention to adopt VAs for transactional purposes. We adopted Hayes and Rockwood's (2017) approach to conduct the mediation analysis and used PROCESS macro to

**Table 7**
Mediation analysis.

| **CB → CI → REJ** | | | | | | |
|---|---|---|---|---|---|---|
| | *β* | *se* | *t* | *p* | *LLCI* | *ULCI* |
| CB → CI | 1.67 | 0.09 | 17.55 | 0.000 | 1.48 | 1.86 |
| CB → REJ | 1.28 | 0.08 | 15.44 | 0.000 | 1.12 | 1.45 |
| CI → REJ | 0.18 | 0.36 | 5.16 | 0.000 | 0.11 | 0.25 |
| Total effect | 1.59 | 0.06 | 26.14 | 0.000 | 1.47 | 1.71 |
| **CB → PRO → REJ** | | | | | | |
| | *β* | *se* | *t* | *p* | *LLCI* | *ULCI* |
| CB → PRO | 0.54 | 0.08 | 6.31 | 0.000 | 0.37 | 0.70 |
| CB → REJ | 1.83 | 0.05 | 35.77 | 0.000 | 1.73 | 1.93 |
| PRO → REJ | − 0.44 | 0.03 | −13.52 | 0.000 | −0.51 | −0.38 |
| Total effect | 1.59 | 0.06 | 26.14 | 0.000 | 1.47 | 1.71 |
| **CB → CI → IA** | | | | | | |
| | *β* | *se* | *t* | *p* | *LLCI* | *ULCI* |
| CB → CI | 1.67 | 0.09 | 17.56 | 0.000 | 1.49 | 1.86 |
| CB → IA | −1.33 | 0.11 | −12.48 | 0.000 | −1.55 | −1.12 |
| CI → IA | 0.46 | 0.05 | 10.07 | 0.000 | 0.37 | 0.55 |
| Total effect | −0.57 | 0.09 | −6.55 | 0.000 | −0.74 | −0.40 |
| **CB → PRO → IA** | | | | | | |
| | *β* | *se* | *t* | *p* | *LLCI* | *ULCI* |
| CB → PRO | 0.54 | 0.08 | 6.31 | 0.000 | 0.37 | 0.70 |
| CB → IA | −0.66 | 0.09 | −7.22 | 0.000 | −0.84 | −0.48 |
| PRO → IA | 0.17 | 0.06 | 2.88 | 0.004 | 0.05 | 0.28 |
| Total effect | −0.57 | 0.09 | −6.55 | 0.000 | −0.74 | −0.40 |
| **NUD → CI → REJ** | | | | | | |
| | *β* | *se* | *t* | *p* | *LLCI* | *ULCI* |
| NUD → CI | −0.46 | 0.14 | −3.25 | 0.001 | −0.74 | −0.18 |
| NUD → REJ | −0.68 | 0.07 | −9.21 | 0.000 | −0.83 | −0.54 |
| CI → REJ | 0.52 | 0.03 | 17.42 | 0.000 | 0.46 | 0.58 |
| Total effect | −0.93 | 0.10 | −8.92 | 0.000 | −1.13 | −0.72 |
| **NUD → PRO → REJ** | | | | | | |
| | *β* | *se* | *t* | *p* | *LLCI* | *ULCI* |
| NUD → PRO | 0.16 | 0.10 | 1.63 | 0.103 | −0.03 | 0.34 |
| NUD → REJ | −0.93 | 0.10 | −8.88 | 0.000 | −1.13 | −0.72 |
| PRO → REJ | 0.01 | 0.06 | 0.18 | 0.853 | −0.11 | 0.14 |
| Total effect | −0.93 | 0.10 | −8.92 | 0.000 | −1.13 | −0.72 |
| **NUD → CI → IA** | | | | | | |
| | *β* | *se* | *t* | *p* | *LLCI* | *ULCI* |
| NUD → CI | −0.46 | 0.14 | −3.25 | 0.001 | −0.74 | −0.18 |
| NUD → IA | 1.26 | 0.07 | 18.69 | 0.000 | 1.13 | 1.40 |
| CI → IA | 0.15 | 0.03 | 5.42 | 0.000 | 0.09 | 0.20 |
| Total effect | 1.19 | 0.07 | 17.21 | 0.000 | 1.06 | 1.33 |
| **NUD → PRO → IA** | | | | | | |
| | *β* | *se* | *t* | *p* | *LLCI* | *ULCI* |
| NUD → PRO | 0.16 | 0.10 | 1.63 | 0.103 | −0.03 | 0.34 |
| NUD → IA | 1.20 | 0.07 | 17.23 | 0.000 | 1.07 | 1.34 |
| PRO → IA | −0.05 | 0.04 | −1.06 | 0.288 | −0.13 | 0.04 |
| Total effect | 1.19 | 0.07 | 17.21 | 0.000 | 1.06 | 1.33 |

**Note:** CB = Cognitive biases, PRO = Procrastination, CI = Consumer inertia, REJ = Rejecting VAs for transactional purposes, NUD = Nudging, IA = Intention to adopt VAs for transactional purposes.

deconstruct the association between the independent variables and the outcome variables. We observed that consumer inertia and procrastination partially mediated the association between the independent variables and the outcome variables. However, procrastination failed to mediate the association between nudging and the outcome variables. The statistical indicators of the mediations analysis appear in Tables 6 and 7.

Next, we tested the moderation effect of technology comfort on the associations between the independent variables and the outcome variables using the Hayes PROCESS macro method (Hayes, 2012). We used 5000 bootstrap samples at a confidence interval of 95% to assess the moderating effect. We observed that technology comfort moderated the association between cognitive biases and intention to adopt VAs for transactional purposes ($\beta = 0.27, p < .05$, se = 0.11, $t = 2.28$, *CI* [0.04 – 0.50]). We present the visualisation of the moderation effects in Fig. 3. Table 8.

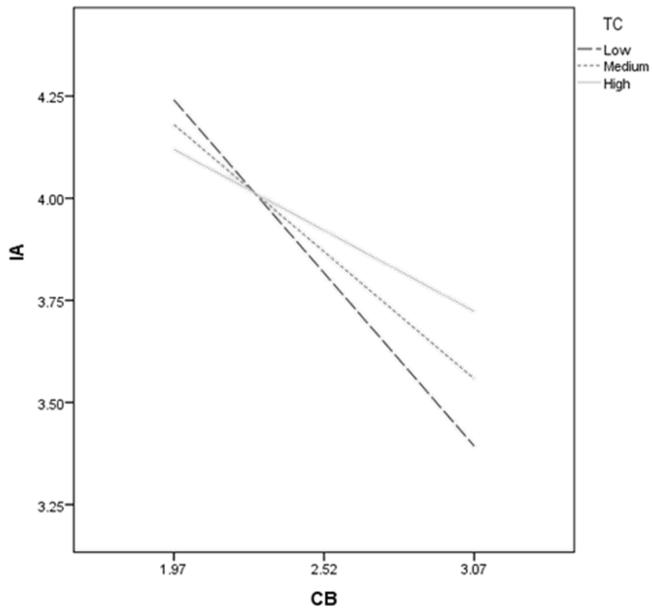


**Fig. 3.** Association of cognitive biases (CB) and intention to adopt VAs for transactions (IA) moderated by technology comfort (TC).

**Table 8**
Indirect effects between DVs and IVs .

| | *Effect* | *se* | *LLCI* | *ULCI* |
|---|---|---|---|---|
| CB → CI → REJ | 0.31 | 0.07 | 0.18 | 0.45 |
| CB → PRO → REJ | −0.24 | 0.05 | −0.33 | −0.15 |
| CB → CI → IA | 0.77 | 0.09 | 0.60 | 0.96 |
| CB → PRO → IA | 0.09 | 0.04 | 0.01 | 0.17 |
| NUD → CI → REJ | −0.24 | 0.08 | −0.38 | −0.06 |
| NUD → PRO → REJ | 0.001 | 0.14 | −0.03 | 0.03 |
| NUD → CI → IA | −0.07 | 0.03 | −0.13 | −0.02 |
| NUD → PRO → IA | −0.01 | 0.11 | −0.03 | 0.01 |

**Note:** CB = Cognitive biases, PRO = Procrastination, CI = Consumer inertia, REJ = Rejecting VAs for transactional purposes, NUD = Nudging, IA = Intention to adopt VAs for transactional purposes.

## 6. Discussion

### 6.1. *Theoretical implications*

While the previous literature has focused on the consumer decision-making process and behavioural intentions to use AI-enabled innovative products and services, research on decision avoidance and the reason for postponing or rejecting innovative products or services remains scant (Kleijnen et al., 2009; Laukkanen, 2016). This study aimed to contribute to the previously under-utilised decision avoidance theory (Anderson, 2003) by empirically validating the framework in the context of VA usage for transactional purposes. The study brings novel insights because the sample respondents were active users of VAs and used their VAs solely for non-transactional purposes, whereas the extant literature has focused more on innovation resistance in the context of non-users (Laukkanen, 2016).

This study theorises two types of decision avoidance: customer inertia and procrastination. From a theoretical perspective, the study makes four major contributions. First, it examines the predictors of consumers' rejection of and intention to adopt VAs for transactional purposes. In this study, we examined the role of customer inertia (H1) and procrastination (H2) as predictors of rejection and intention to adopt VAs. We found that customer inertia and procrastination significantly predict the proposed outcomes variables. The conceptual model significantly predicts rejection of VAs for transactional purposes ($R^2 = 0.69$) and intention to adopt VAs for transactional purposes ($R^2 = 0.54$).

The results of this study reinforce the findings of Nel and Boshoff (2021) and align with the resistance adoption inertia continuance (RAIC) framework proposed by Seth et al. (2020). Additionally, the previous literature on the role of procrastination has suggested a positive association between procrastination and behavioural intentions (Lay & Brokenshire, 1997; Sirois, 2004); while our findings align with these previous studies, we observed a negative association between procrastination and rejection behaviour, which is a signification contribution to the literature on procrastination as well as the predictors of rejection behaviour.

Second, our study of cognitive biases and nudging as antecedents of customer inertia and procrastination significantly advances the theoretical framework of decision avoidance. As a predictor of customer inertia ($R^2 = 0.40$), cognitive biases exhibit a significant positive association with customer inertia (H3a). However, nudging is not significantly associated with customer inertia (H4a). Examining the predictors of procrastination ($R^2 = 0.14$), we found that cognitive biases are significantly and positively associated with procrastination (H3b). While we had hypothesised that nudging reduces procrastination and is negatively associated with procrastination, our results revealed a significant positive association between nudging and procrastination (H4b). Further, we found support for H3c (cognitive biases significantly affect the rejection of VAs for transactional purposes), H3d (cognitive biases negatively affect intentions to adopt VAs for transactions), H4c (nudging significantly reduces rejection of VAs for transactional purposes) and H4d (nudging significantly enhances intentions to adopt VAs for transactional purposes). The previous literature, though, has documented the effects of inertia, suggesting that inertia results in the continuance of past consumption practices irrespective of the availability of superior alternatives (Ascarza et al., 2016). While the findings of this study resonate with the previous literature, its novel insights identify customer inertia as a significant predictor of behavioural intentions. We also offer new insights into the predictors of customer inertia. While previous studies related to customer inertia have offered a limited theoretical explanation for the construct (Polites & Karahanna 2012), we extend this understanding by testing three cognitive biases—loss aversion, regret minimisation and status quo bias—to disentangle the underlying cognitive foundations of customer inertia. Further, examining the link between cognitive biases and customer inertia and procrastination extends the understanding of decision avoidance. The previous literature has identified uncertainty and lack of information as major predictors of decision avoidance (Nutt & Wilson, 2010). However, in the context of innovative products such as VAs, where consumers experience information overload, decision avoidance is mainly influenced by consumers' cognitive biases (Acciarini et al., 2020). Therefore, this research provides evidence of a crucial link between cognitive biases and decision avoidance, i.e. customer inertia and procrastination behaviour. Similarly, examining the impact of nudging on decision avoidance, the previous literature has proposed nudging as an effective strategy to tackle decision avoidance (Mirsch et al., 2017). Previous studies in the context of innovative products and services have provided evidence in favour of nudging and suggested that nudging strategies, such as default rules, effectively guide consumers to make decisions (Mirsch et al., 2017). However, the findings of this study conflict with the extant literature about nudging. This suggests a thin line between nudging and nagging, opening an important field of investigation for future academic research.

Third, this study contributes theoretically as well as methodologically in defining and measuring cognitive biases and nudging as second-order constructs. Although second-order models are not complex in terms of conceptualisation and testing, studies on the adoption of innovation and innovation resistance have yet to fully utilise the capabilities and insights such models offer. Previous studies that have included cognitive biases and nudging in their research models have measured them as latent constructs and hence have failed to capture the multidimensionality of these constructs. We thus offer a more comprehensive explanation of cognitive biases and nudging.

Finally, testing the moderation effect of technology comfort on the association of cognitive biases and nudging with the outcome variables (H5a–d), we observed that technology comfort negatively moderates the association between cognitive biases and intention to adopt VAs for transactions (H5b). In other words, cognitive biases are less likely to negatively affect the intention to adopt VAs for transactional purposes among consumers with greater technology comfort.

### 6.2. Managerial implications

From the practitioner's perspective, understanding how decision avoidance affects consumers' rejection of and behavioural intentions to use VAs for transactional purposes enables marketers to design the attributes of their VAs to enhance the utilisation of unused or less used features of such products. Building on the previous literature regarding the negative consequences of innovation resistance (Heidenreich et al., 2016), this study helps product managers understand the predictors of decision avoidance. It is important for product managers to factor in the cognitive biases that consumers hold when they are presented with innovative products, such as VAs.

At present, consumers fail to fully exploit the potential of VAs due to the apprehensions they hold. Our results suggest that loss aversion is the most important factor contributing to cognitive biases. Marketers thus must develop an effective marketing communications strategy to overcome this mindset. For example, marketers might create a sense of urgency by capitalising on consumers' fear of missing out (FOMO) in their marketing campaigns, promoting the usage of VAs for transactional purposes. Similarly, marketers can use limited-time offers, social proof, discount coupons, etc., to overcome loss aversion and hence promote using VAs for transactional purposes. Additionally, marketers must utilise effective marketing tools, such as self-visualisation (Dahl & Hoeffler, 2004) and mental stimulation (Hoeffler, 2003), to reduce the fear of anticipated regret among VA users in the context of transactional use of VAs. Further, a deeper understanding of cognitive biases may help marketers deal with consumers' procrastination behaviour. Our findings also indicate that marketers should attend to the anticipated regret that consumers may experience after using VAs and should devise strategies to maximise VA users' positive brand evaluations. Finally, marketers must make systematic attempts to understand the underlying causes of status quo bias and devise strategies to effectively deal with it—for example, by using the framing effect or strengthening cognitive as well as emotional appeals in marketing communications.

Our findings further suggest that existing nudging strategies are not sufficiently effective in addressing consumers' decision avoidance, specifically customer inertia. Hence, marketers must devise innovative nudging strategies to reduce procrastination behaviour and overcome customer inertia. Finally, our findings suggest that technology comfort positively moderates the association between cognitive biases and the intention to adopt VAs for transactional purposes. Therefore, marketers can benefit from our findings by helping consumers develop greater comfort with their technology platforms; for example, marketers might design campaigns to enhance consumers' familiarity with and knowledge of VAs. Boosting technology comfort will help consumers overcome their fears about VAs and thus increase their adoption of VAs for transactional purposes.

## 7. Limitations and future research directions

While the findings of our research offer multiple insights regarding decision avoidance among VA users and provide implications for both theory and practice, efforts to generalise the results of our study must factor in certain limitations. First, the study was conducted with users of VAs. While VAs are classified under AI-enabled devices and can be considered appropriate to explain decision avoidance behaviour, the findings from this category cannot be generalised into other categories such as fast-moving consumer goods (FMCG) products, high involvement products, including automobiles, or investment products, including mutual funds. Future scholars might test the model with multiple categories and present a comparative analysis across product categories.

Second, the sample for the study was taken from Japan, and hence, the findings can be generalised only in the context of countries that exhibit similarities with the cultural and economic conditions of Japan. In the future, it would be interesting to conduct a comparative study on decision avoidance and resistance to technology adoption across different countries. A multi-country study would advance our understanding of decision avoidance across cultures, political, economic and environmental factors.

Third, in this study, we focused predominantly on cognitive biases as a predictor of customer inertia. Future scholars may predict customer inertia with other psychological factors. Finally, adding new moderators, such as trust in AI, consumer innovativeness and risk perception, has the potential to offer novel insights. Fourth, in this study, we used a cross-sectional sample and hence, the study does not capture how the behaviour of users evolved after using VAs for some time. Therefore, in future, scholars can adopt lagged approach to overcome this limitation.

## CRediT authorship contribution statement

**Suresh Malodia:** Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. **Puneet Kaur:** Conceptualization, Data curation, Formal analysis, Project administration, Writing – original draft, Writing – review & editing. **Peter Ractham:** Writing – review & editing, Writing – original draft, Project administration, Formal analysis, Conceptualization. **Mototaka Sakashita:** Conceptualization, Data curation, Writing – original draft, Writing – review & editing. **Amandeep Dhir:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization.

## Declaration of Competing Interest

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

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