Counteracting dark sides of robo-advisors: justice, privacy and intrusion considerations

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Abstract

Purpose: Under the pressure of dynamic business environments, firms in the banking and finance industry are gradually embracing Fintech such as robo-advisors, as part of their digital transformation process. While robo-advisory services are expected to witness lucrative growth, challenges persist in the current landscape where most consumers are unready to adopt and even resist the new service. The study aims to investigate resistance to robo-advisors through the privacy and justice perspective. The human-like attributes are modeled as the antecedents to perceived justice, followed by the subsequent outcomes of privacy concerns, perceived intrusiveness, and resistance.

Design/methodology/approach: An online survey was conducted to gather consumer responses about their perceptions of robo-advisors. Two hundred valid questionnaires were collected and analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM).

Findings: The results revealed that (i) perceived anthropomorphism and perceived autonomy are the positive determinants of perceived justice, (ii) perceived justice negatively impacts privacy concerns and perceived intrusiveness, and (iii) privacy concerns and perceived intrusiveness positively influence resistance to robo-advisors.

Originality/value: The present study contributes to robo-advisory service research by applying a privacy and justice perspective to explain consumer resistance to robo-advisors, thereby complementing past studies that focused on the technology acceptance paradigm. The study also offers practical implications for mitigating resistance to robo-advisors.

Keywords: Robo-advisors, Fintech, Artificial intelligence, Privacy concerns, Justice, Resistance
1. Introduction
The potential of artificial intelligence (AI) technology has been unleashed into the financial and banking services industry, compelling the growth of Financial Technology (Fintech), which brings disruptive changes to the industry. One of the most popular Fintechs that have risen to prominence is robo-advisors (Aw et al., 2023; Belanche et al., 2019). A robo-advisor can be understood as an automated financial service, covering service spectrums ranging from investment to banking. From a broader perspective, on top of serving as an automatic service or tool, a robo-advisor is equipped with a human interface that instills a sense of human touch. The primary purpose of a robo-advisor is to guide consumers through a self-assessment process and mold their wealth and financial management behavior toward attaining goal-based decision-making, with the support of sophisticated algorithms (Jung et al., 2018).

Robo-advisors have enticed tremendous venture capital due to their cost-cutting potential, and financial and banking firms see robo-advisors as the next frontier of their operational strategies (Isaia and Oggero, 2022). Thus far, Betterment and Wealthfront represent the two most prominent robo-advisors, with an estimated $440 billion of assets (The Robo Report, 2019). It is expected that by 2025, assets under the management of the robo-advisory service market will hit a record of over 16 trillion dollars, nearly three times the amount of assets managed by BlackRock, the largest asset manager in the globe. Recently, it has been reported that Bank of America’s robo-advisor has $26 billion in assets with 361,000 accounts under management (Welsch, 2022). Robo-advisory services offer a comprehensive and tailorable wealth management plan for a comparatively low fee, and the services can be easily accessible via a web browser or an app (Hildebrand and Bergner, 2021). The emergence of robo-advisors is resolving problems faced by the financial and banking service industry that mainly relies on humans, as traditional human advisory services often charge fees for additional services that do not meet the investors’ needs and human advisors are often in favor of servicing clients with greater portfolios (Jung et al., 2018). In addition, due to the scale of automation, robo-advisors are expected to offer better quality and more transparent financial advice to consumers (Hildebrand and Bergner, 2021).

Despite the numerous benefits described, the market share of robo-advisors remains suboptimal, whereby many banking and financial services customers are holding back toward embracing robo-advisors (Hildebrand and Bergner, 2021; Jung et al., 2018; Zhang et al., 2021). It has been shown that many consumers tend to maintain the status quo and expect
human advisory services to be offered. It is inevitable for banking and financial service firms to take on the trend of downsizing human advisory operations, except for high net-worth clients. Hence, robo-advisors could be the alternative for general consumers to access banking and financial services in the future. The existing literature on robo-advisors has mainly focused on the technological attributes of robo-advisors (Belanche et al., 2019; Zhang et al., 2021). For instance, Belanche et al. (2019) found attitude and subjective norms as significant predictors of behavioral intention on robo-advisors, where attitude is formed by perceived usefulness and perceived ease of use. Another line of research on robo-advisors emphasized designing the optimal algorithms to attain ideal investment performance (Day et al., 2018; Musto et al., 2015). However, resting on the technology acceptance paradigm could be a fallacy because it has been deemed oversimplistic without incorporating the AI attributes and relevant concerns into its conceptual structure. Adhering to the notion of past literature that shifting sensitive communication processes (i.e., financial services) from a human to technology ground entails effective management of expectations (Jung et al., 2018). It is imperative to undertake the prospects’ perspective so that the banking and financial service providers can tailor their strategies to encounter resistance toward robo-advisors.

Modern marketing and operational practices in the banking and finance industry are hardly separable from the utilization of digital technologies, including AI and customer data (Quach et al., 2022). However, the trend has raised consumers’ privacy concerns about banking and financial service providers’ data behaviors and actions, holding consumers from adopting innovations offered and thus impeding the diffusion. This is particularly relevant for the application of AI-based services in the high involvement industry such as banking and finance because the scale of the privacy risk and intrusiveness is radically different compared to other technologies employed in the past (Yuan et al., 2022). Quach et al. (2022) advocated that further research is essential to understand how emerging innovations such as robo-advisors threaten consumers’ information and privacy. As noted by Jung et al. (2018), transparency, trust, and balancing of information asymmetries constitute the core foundation of consumer expectations of robo-advisory, giving rise to the need to undertake a justice perspective. Moreover, relationship variables such as justice have been established as an essential determinant of technology adoption (Asare et al., 2016). However, the extant literature has yet to establish theoretical models to explain how consumers react to privacy and intrusiveness threats in the robo-advisor context.
To this end, we undertake the human-like perspective of robo-advisors in approaching this phenomenon because robo-advisors are the fusion of humans and technology (Chuah et al., 2021). More specifically, robo-advisors encompass the dialogue-based process of financial advisory, which mimic human-to-human conversations (Hildebrand and Bergner, 2021). Therefore, given the increasing blurring line between smart technology and humans, it is imperative to set the study ground beyond the pure functional capacities of robo-advisors by considering their human-like attributes. In particular, we probe into the anthropomorphic and autonomous characteristics of robo-advisors. As noted by Novak and Hoffman (2019), understanding human-like characteristics is imperative for fostering customer experience in interacting with AI objects, representing a significant avenue of research in marketing and psychology. While a few research has identified the positive implications derived from anthropomorphism, an emerging school of thought refutes the idea and advocates that human-like attributes incur undesirable consumer responses and experiences with AI objects. We seek to explore further this stream of research in relation to robo-advisor resistance.

To sum up, grounded in the Computers as Social Actors (CASA) theory (Reeves and Nass, 1996), we model two human-like attributes, namely perceived anthropomorphism and perceived autonomy as the antecedents to perceived justice. Additionally, we adopt the Justice Theory approach (McFarlin and Sweeney, 1992) by exploring the role of perceived justice in addressing consumers’ privacy concerns and perceived intrusiveness, and determining the outcome of interest (i.e., resistance to robo-advisors). The next section presents the conceptual development of the study. Subsequently, we discuss the research methodology and statistical results. The study is concluded with result discussions, implications, and suggestions for future research.

2. Conceptual Development

2.1 Theoretical Background

Our study is underpinned by the S-O-R framework (Mehrabian and Russell, 1974). The framework encompasses three elements, namely stimuli, organism, and response. The core essence of the S-O-R framework articulates the mechanism by which the environmental and informational stimuli (S) evoke a person’s internal state of cognitive and affective reactions (O), which sequentially lead to the formation of particular behavioral outcomes (R) (Jacoby, 2002). In the present study, we consider the human-like attributes of robo-advisors (i.e., perceived anthropomorphism and perceived autonomy) as the stimuli; perceived justice,
privacy concerns, and perceived intrusiveness as the organisms; and the resistance to robo-advisors as the response.

The S-O-R framework has been widely applied in the field of human-technology interaction to comprehend consumers’ behavioral responses (i.e., approach vs. avoidance) and internal states (i.e., emotions, experiences, and perceptions) arising from external stimuli embedded in products or services (Hew et al., 2018; Lo et al., 2022; Nguyen et al., 2022). More importantly, the S-O-R framework extends the assumption of direct effects of stimulus (i.e., perceived anthropomorphism and perceived autonomy) to include the internal states of consumers (i.e., perceived justice, privacy concerns, and perceived intrusiveness) as an explanation of how robo-advisor attribute variables relate to usage resistance, thus aiding a finer theoretical understanding to the phenomenon. A resistance decision infers a state of opposition, defiance, and rejection of an innovation (Ogbanufe and Gerhart, 2022). As consumers always engage in a mental cost and benefit analysis to draw a decision to adopt or resist the innovation, the S-O-R framework offers an appropriate theoretical foundation that manifests the process and supports the inter-relationships between variables proposed in our study.

Following past studies that advocated for a theory integration approach, we integrate the CASA Theory (Reeves and Nass, 1996) to support our reasoning for investigating human-like attributes, namely perceived anthropomorphism and perceived autonomy as the antecedents of perceived justice. According to the CASA Theory, humans tend to mindlessly apply social rules when interacting with computers that demonstrate human-like social cues such as anthropomorphism and autonomy. The social cues are likely to trigger cognitive heuristics that determine consumers’ judgments pertaining to the nature and content of the interaction in relation to the computers (Kim et al., 2013). Robo-advisors ascribed with anthropomorphic and autonomous features may exhibit a sense of warmth and functionality, enhancing perceived benefit and fairness in the service exchange process (Aw et al., 2022; Slepchuk et al., 2022).

In general, marketing interactions embrace the central tenets of exchange (Bagozzi, 1975), and we argue that the data collection and usage by robo-advisors follow the same idea. Given the risks incurred from personal information sharing, consumers’ perceptions of fairness are critical to robo-advisor usage (Slepchuk et al., 2022). To explain, consumers’ information shared during robo-advisor usage constitutes an input of exchange. In return,
they would expect outcomes such as better investment performance through robo-advisors. Thus, consumers’ privacy and intrusiveness concerns will be considered in a fairness/justice judgment. Justice Theory is appropriate in explaining individual behaviors when encountering conflicts (Son and Kim, 2008), including how people react to a firm’s decisions from a fairness perspective. Justice Theory highlights the importance of fairness during an exchange process (i.e., product/service consumption) in interpersonal or inter-organizational relationships (Konovsky, 2000; McFarlin and Sweeney, 1992). Fair decisions are crucial for achieving favorable relational development and enhancement outcomes, such as intention to use, satisfaction, and loyalty (Wan et al., 2022; Zhao et al., 2012) in different consumption stages. Given that the aim of the study is to understand resistance to robo-advisors through consumers’ justice perception, as well as privacy and intrusiveness concerns, we argue that the Justice Theory can provide an appropriate theoretical ground for this investigation.

2.2 Perceived Anthropomorphism

The marketing literature has established the importance of the consumer-object relationship wherein studies have been undertaken to understand consumers’ responses to objects’ sensual appeal (Blut et al., 2021). In correspondence, AI objects in the market (e.g., service robots, voice assistants, and robo-advisors) are anthropomorphized (featured human-like attributes) to facilitate consumer-object interaction and relationship development. In the present study, we refer to anthropomorphism as the extent to which consumers perceive robo-advisors as human-like (Blut et al., 2021). Novak and Hoffman (2019) argued that people’s tendency to anthropomorphize objects is particularly salient in the context of smart objects (e.g., robots and AI virtual systems). In particular, the AI objects possess human-like appearance interaction following the underlying principles and expectations for human social interactions, thereby increasing the perception of social presence (Blut et al., 2021). Empirical evidence has articulated that perceived anthropomorphism facilitates consumers’ adoption and engagement of AI objects (Aw et al., 2022).

On the contrary, another school of thought has emerged, supporting Mori’s (1970) uncanny valley hypothesis, which postulates that consumers may perceive human-like AI objects as creepy and uncanny, thereby evoking the feeling of eeriness or discomfort. Consistent with the Task–Technology Fit Theory (Goodhue and Thompson, 1995), we argued that anthropomorphism might yield negative impacts in the robo-advisors context due to the functional role of robo-advisors. To explain, consumers tend to favor human-like AI entities for social roles but machine-like AI entities for functional roles (Goetz et al., 2003).
Moreover, according to Thomaz et al. (2020), anthropomorphic technology can lead to the sense of losing self-control. Elevated perceived anthropomorphism can result in consumers’ experience of discomfort and a sense of intrusiveness to their human identity (Blut et al., 2021). Hence, it is hypothesized that:

H1: Perceived anthropomorphism will negatively influence perceived justice.

2.3 Perceived Autonomy

Autonomy denotes the ability of robo-advisors to function independently (Parasuraman et al., 2000). The level of autonomy determines the extent to which technology objects can make and execute decisions independently without human intervention (Novak and Hoffman, 2019). Automated decision aids tasks, ranging from collecting, transforming, or interpreting information, thereby reducing human efforts for complex and time-consuming tasks (Basha et al., 2022). While robo-advisor usage from consumers requires discretionary input (e.g., financial goals and risk appetite), the primary advantages of the robo-advisors are grounded in their fully automated process, ranging from risk evaluation to portfolio management (Hildebrand and Bergner, 2021). Past research has revealed that automated robo-advisory services enhance investment performance by limiting the confounding influence of human emotions and idiosyncratic biases in financial decision-making (Bhatia et al., 2021).

Besides, losing adequate control over a situation (e.g., collection and use of personal information or exposure to certain content/information) fosters a sense of restriction and powerlessness, signaling freedom restriction and triggering the state of reactance. For example, early research has delineated pop-up advertisements during web browsing to be intrusive for consumers, thereby resulting in the avoidance of advertisements (Edwards et al., 2002). The main characteristic of robo-advisors as a class of financial advisors operating with minimal human intervention raises consumers’ concerns about the loss of control (Bhatia et al., 2020). This is due to people’s innate ability to retain partial control of the task despite the reduced effort if the task is delegated to other parties (Rijsdijk and Hultink, 2003; Ruhr et al., 2020). AI objects’ autonomy prompts them to actively collect and use data from different available sources, including their users, to facilitate task performance while minimizing human efforts (Hu et al., 2021). Given the privacy and security challenges that arise from collecting and storing personal financial data for automated advice, there presents a likelihood of violation in transparency, trust, and information symmetry. As articulated by Rühr et al. (2019), people are likely to perceive a fully automated system (i.e., robo-advisor)
as risky, given their relatively low flexibility in reacting to changes and inability to incorporate human intuition. Therefore, it is hypothesized that:

H2: Perceived autonomy will negatively influence perceived justice.

2.4 Perceived Justice

Perceived justice is vital to the development and maintenance of channel relationships and technology adoption (Asare et al., 2016). The notion of justice is rooted in Social Exchange Theory, advocating the imperative role of fairness and equity in social exchange. Supported by the Signaling Theory (Spence, 1973), perceived justice can be formed throughout pre-, during, and post-consumption stages (Crisafulli and Singh, 2016). For instance, it has been shown that consumers can develop justice perceptions toward a firm by inferring the firm’s motives through its policy (Kukar-Kinney et al., 2007). Justice is heralded as the cornerstone of information exchanges during product/service consumption and technology usage (Slepchuk et al., 2022). Early research on privacy theorized that consumers would disclose personal information in exchange for benefits if they believed that organizations would use their information reasonably and that they would not suffer negative consequences in the future (Laufer and Wolfe, 1977).

In general, the justice literature concurs that three justice dimensions exist, namely distributive, procedural and interactional justice (Blodgett and Tax, 1993; Colquitt et al., 2001). To explain, distributive justice refers to the perceived fairness of an exchange engendered from the input-output balance assessment compared to the reference group. Guided by the Equity Theory (Huppertz et al., 1978), all the relationships (i.e., firms and consumers) are governed by a psychological contract that manages fairness expectation, in which a party who has devoted a large number of resources should receive more compared to their counterpart who has invested less. In short, outcomes are considered fair under the premise that the value derived from the good or service received exceeds the information provided (Slepchuk et al., 2022). The violation of the psychological contract is expected to result in breached trust and relationship, eventually leading to negative behaviors (i.e., avoidance).

Procedural justice concerns fairness in the decision-making process (Colquitt et al., 2021; Wan et al., 2022). Unlike distributive justice, procedural justice is assessed in accordance with the control over the process and decisions toward achieving an outcome instead of the outcome itself. A just procedure can even buffer the implications arising from a
negative outcome (Cropanzana et al., 2007). In the context of this study, procedural justice manifests the perceived fairness in processes, procedures, and policies during robo-advisor usage (Wang et al., 2021). It has been shown that the presence of procedural justice in AI robot usage can foster value perception toward public service (Wang et al., 2021).

Interactional fairness is defined as one’s perception of fairness toward the interpersonal treatment received during interactions, encompassing the concepts of respect, honesty, dignity, and politeness (Colquitt et al., 2001). Interactional justice is strongly tied to trust because parties involved in a mutual exchange rely on each other to execute agreed-upon procedures in a reliable manner to derive a fair distribution of the benefits (Slepchuk et al., 2022). In this study, interaction fairness concerns the perceived quality of interaction during the implementation of procedures (i.e., robo-advisor usage). For example, consumers may draw judgment on interactional justice from their perception of whether robo-advisory services make efforts to protect their data.

Perceived justice is particularly relevant when uncertainty prevails, whereby people rely on justice judgment to manage uncertainties (Zhao et al., 2012). According to the Justice Theory, people tend to feel dissatisfied and respond negatively when they sense injustice. In the retail setting, Pizzi and Scarpi (2021) found that consumers’ acceptance of new retail technologies such as facial recognition and smart mirrors depends on their perceived fairness (i.e., evaluation of benefits received and amount of personal information disclosed). In a B2B inter-firm technology adoption context, a perception of injustice can arise when other firms ask partners to adopt technology that is of limited value, leading to resistance to technology adoption (Asare et al., 2016).

Drawing upon the core assumption of justice theory, consumers face a trade-off between the costs and benefits of information disclosure and sharing, suggesting that privacy disclosure decision depends on the weight attributed to risks and benefits associated with information disclosure and sharing (Dinev and Hart, 2006; Pizzi and Scarpi, 2021). Past research has delineated that people who have received fair treatment from their counterparts, either an individual or an organization, tend to reciprocate (Wan et al., 2022). For instance, perceived interpersonal justice (e.g., sincere communication) facilitates the formation of helping behavior and organizational citizenship behavior by fostering relationship development (Colquitt, 2001; Wan et al., 2022). Using a qualitative method, Bhatia et al. (2021) discovered that consumers generally are highly skeptical of information security with
digital platforms (i.e., robo-advisors), but some opine that the disclosure of private information is inevitable when trading online. Taken en mass, we argue that more benefits provided to consumers through robo-advisor usage might lead consumers to perceive higher justice, thus diminishing their privacy concerns (Pizzi and Scarpi, 2021). The following hypothesis is formed:

H3: Perceived justice will negatively influence privacy concerns.

Fair practices implemented by firms and service providers signal assurance for consumers that their data will be collected, used, and stored appropriately, which eventually leads to trust development in consumer-firm exchange relationships (Slepchuk et al., 2022). Although privacy concerns over personal financial information remains an obstacle, perceptions of justice address the issue by backing that consumer information would be intact with robo-advisor usage and handled appropriately (Slepchuk et al., 2022), hence reducing the sense of intrusiveness. With this, it is hypothesized that:

H4: Perceived justice will negatively influence perceived intrusiveness.

2.5 Privacy concerns

AI technologies offer firms an opportunity to leverage consumer data for value creation and delivery, but they have incurred concomitant costs for consumers, particularly in terms of privacy. According to Westin (1967, p. 10), privacy refers to an individual’s ability “to decide what information about himself should be communicated to others and under what condition.” Consumers’ assessments of their relationship with firms are primarily hinged on the vulnerability and severity of privacy risks (Hew et al., 2017; Quach et al., 2022). In other words, if consumers perceive more significant privacy risks due to their data being collected and used, they tend to engage in privacy-protective behaviors, manifesting avoidance responses toward adopting products/services from the firms (Cham et al., 2022). In the robo-advisor context, the developers require a collection of a huge amount of data to optimize robo-advisors’ algorithms and performance (Bhatia et al., 2020), thereby raising increasing privacy concerns that lead to robo-advisor resistance:

H5: Privacy concerns will positively robo-advisor resistance.

2.6 Perceived Intrusiveness

AI technologies can pose threats by being intrusive, whereby such violations are increasing, given the rise of AI usage in consumers’ personal and physical spaces (Quach et al., 2022).
According to Mani and Chouk (2017), perceived intrusiveness in the smart technology context is defined as the preoccupation and invasion of consumers’ private life. The information processing capabilities of the robo-advisors encompass collecting, storing, using, and sharing information, which demonstrates competence but also reveals its intrusive nature. Certain robo-advisor’s specific features, including regular notifications (e.g., to remind of market performance and portfolio management) may interrupt consumers. Collectively, the concern about robo-advisors’ intrusiveness may instigate reactance from consumers, thereby resulting in status quo decisions with human advisory service usage. Ogbanufe and Gerhart (2022) are of the view that the proximity of devices and information shared inhibit the adoption of smart devices.

According to Quach et al. (2022), AI technologies and service robots (e.g., robo-advisors) are endowed with the ability to produce intelligent automation, learn, and adapt, through sophisticated data modeling and programming technologies. The autonomy instilled in AI technologies enables value creation and enhancement by improving marketing and operational performance (e.g., personalized recommendation) (Davenport et al., 2020). The AI technologies, including robo-advisors, feed on enormous amounts of data collected from consumer interactions, and the data extraction for predictive analytics is mainly autonomous, thereby threatening information privacy. While service providers leverage advanced automated technology to increase efficiency and performance, consumers sometimes see automated service threatening their freedom. Consequently, they look for balance in justice to restore freedom by resisting adoption (Ogbanufe and Gerhart, 2022). Given the above reasoning, the following hypothesis is proposed:

H6: Perceived intrusiveness will positively robo-advisor resistance.

3. Methodology

3.1 Data Collection and Sample Characteristics

We recruited participants by disseminating the survey link via social media (e.g., Facebook) and research participant recruitment websites. By adopting the purposive sampling technique, we restricted the sample to non-robo-advisor users given that the primary aim of the study is to understand factors of robo-advisor resistance (Ogbanufe and Gerhart, 2022). To obtain accurate responses, we inserted a video and a brief definition of robo-advisors at the beginning of the survey. Respondents were explained the research objectives and ensured
confidentiality. A total of 217 responses were obtained. After dropping 17 responses identified with the straight-lining issue, the final sample size was 200. Based upon the path coefficients obtained from later Partial Least Squares Structural Equation Modelling (PLS-SEM) analysis, a post-hoc power analysis using the inverse square root and gamma-exponential methods (α = 0.05 and power = 0.80) suggested a minimum sample size of 170 and 156, respectively (Kock and Hadaya, 2018). Therefore, the sample size of the present study is considered sufficient in terms of statistical power. The sample comprised a majority of consumers aged below 32 years (59%), with the majority being male (56%). Most of the respondents (64%) had a bachelor’s degree.

3.2 Measures

All measurements used in the present study were carefully adapted from prior literature. The measures for anthropomorphism were adapted from Chuah et al. (2021), while the measures for autonomy were taken from Lucia-Palacios and Pérez-López (2021). We measured privacy concerns, perceived intrusiveness, and resistance to robo-advisors using scales from Mani and Chouk (2019). Perceived justice was measured using the items adapted from Slepchuk et al. (2022). A seven-point Likert scale, with 1 = ‘strongly disagree’ to 7 = ‘strongly agree’, was applied to all measurement items.

4. Data Analysis

4.1 Common Method Bias

In order to address the common method bias threat, Harman’s Single Factor test was conducted. The results revealed that the total variance extracted was 24.77, and there is not a single factor accounting for the majority of covariance (Podsakoff et al., 2003). We also performed the full collinearity test suggested by Kock and Lynn (2012). The highest full collinearity variance inflation factor (VIF) value was 1.986, which was lower than the conservative threshold of 3.3. The results from the tests conducted indicated minimal threat of common method bias.

4.2 PLS-SEM

We employed PLS-SEM in analyzing the proposed research model for several reasons. Firstly, PLS-SEM is deemed more appropriate compared to covariance-based SEM (CB-SEM) under the condition where theory extension and exploration instead of theory testing is the study’s goal (Hair et al., 2019). Secondly, the capability and nature of PLS - SEM that balance between machine learning methods and factor-based SEM, which is fully prediction-
oriented and theory confirmation-oriented, respectively, render the method appropriate for applied research disciplines such as marketing (Sarstedt et al., 2022). Thirdly, PLS-SEM has a comparatively minimal requirement for data assumptions, which often are inapplicable in the realm of social science (Hair et al., 2019). A two-step approach was taken to execute the analysis.

4.3 Measurement Model

The internal consistency for all variables was assessed based on the composite reliability scores. As shown in Table 1, all variables exhibited satisfactory internal consistency, with composite reliability values recorded above 0.70. Besides, factor loadings of constructs were above 0.7, and average variance extracted (AVE) values exceeded the threshold of 0.5 (Hair et al., 2019), implying good convergent validity (see Table 1). Further, discriminant validity was assessed using the heterotrait-monotrait ratio of correlations (HTMT) criterion (Henseler et al., 2015). As demonstrated in Table 2, all HTMT values were below the conservative threshold of 0.85, thereby confirming the discriminant validity of variables in the model (Hair et al., 2019).

4.4 Structural Model

Following the suggestion of Hair et al. (2019), a multicollinearity test was performed prior to assessing the structural model. The results indicated that VIF values of all variables were in the range between 1.129 and 1.531, indicating a minimal threat of multicollinearity issue. As shown in Table 3, the model explains 20.5 percent of the variance in the key endogenous variable (i.e., resistance to robo-advisors). The model is considered to have predictive relevance for resistance to robo-advisors, given that the Stone-Geisser’s $Q^2$ values were greater than 0. We did not find support for our first and second hypotheses, which asserted that perceived anthropomorphism ($\beta = 0.368, p < 0.001$) and perceived autonomy ($\beta = 0.331, p < 0.001$) are negatively related to perceived justice, given that the effects turned out to be positive. Our third and fourth hypotheses for the effects of perceived justice on privacy concerns ($\beta = -0.251, p < 0.001$) and perceived intrusiveness ($\beta = -0.218, p < 0.001$) were supported. Also, we found support for the fifth and sixth hypotheses proposed, which posit that privacy concerns ($\beta = 0.191, p < 0.01$) and perceived intrusiveness ($\beta = 0.314, p < 0.001$) exert a positive effect on robo-advisor resistance.
5. Discussion

Robo advisors have been deemed the next frontier of wealth management in the banking and finance industry. Robo-advisors are expected to facilitate consumers in making better investment decisions and reducing advisory costs (Belanche et al., 2019). While the banking and finance sector is on the verge of a service revolution with the embrace of robo-advisors, the outlook is rather grim, whereby most consumers are not ready to adopt robo-advisors. Similar to the roll-out of other disruptive innovations in the initial stages, only a minority of early adopters are willing to replace traditional practices of using human financial advisors with robo-advisors (Belanche et al., 2019; Bhatia et al., 2021). Instead, consumers expect banking and financial service providers to continue offering human advisory services and retain physical presence for service operations (Jung et al., 2018). The situation has posed challenges to banking and financial service providers who are planning to downsize advisory operations for resource optimization purposes and improve service accessibility.

The first and second hypotheses pertaining to the negative effects of human-like attributes of robo-advisors (i.e., perceived anthropomorphism and perceived autonomy) on perceived justice are unsupported. The finding refutes earlier research that found human-like attributes (e.g., anthropomorphism and autonomy) in smart objects could induce psychological costs and negative feelings such as a threat to human identity and discomfort (Leung et al., 2018; Uysal et al., 2022). Our findings challenge this school of thought in the AI literature by demonstrating the positive effects of human-like attributes in the robo-advisor context. The Theory of Mind Perception put forth that people tend to perform mind inferences and attribute minds to others, including non-human entities (Gray et al., 2007; Uysal et al., 2022). Based on the theory, the findings can be possibly explained by the fact that the anthropomorphic and autonomous features of robo-advisors are likely to trigger consumers’ responses that are guided by human social rules, and form the belief that they are interacting with and served by social beings instead of machines. The perceived similarity engendered may generate a sense of closeness and perception of justice. This proposition requires further exploration, though.

Next, the findings suggest that perceived justice negatively influences privacy concerns and perceived intrusiveness, thus H3 and H4 are supported. Consumers engage themselves in assessing the input-output ratio in an exchange process, thereby forming the
perception of objectivity and equality, which is decisive in resource exchanges (e.g., expenditure of time and effort to adopt robo-advisors). However, the unfulfillment of a sense of justice can drive them to perceive the exchange as unfair and induce resistance behavior. Our findings concerning the countering effects of perceived justice on privacy concerns and intrusiveness lend support to past research that advocated fairness in technology usage as essential to justify the “cost” of personal information disclosure (Pizzi and Scarpi, 2022).

Lastly, the statistical findings support H5 and H6, confirming our earlier expectation that privacy concerns and perceived intrusiveness impede the adoption of robo-advisors. According to Uysal et al. (2022), due to the inherent properties of AI assistants that collect, store, and use sensitive personal data, they appear to be invasive to consumers’ privacy, which in turn potentially induce consumers’ mental strain and avoidance behavior.

### 5.1 Theoretical Implications

Mani and Chouk (2019) noted that understanding consumer resistance is crucial for the successful diffusion, development, and sustainability of smart products and services. Resistance to innovation is the primary reason for the failure of new products and services. In response to calls by prior studies for more research to be conducted from the consumer perspective, the present study explored consumers’ resistance to robo-advisors and identified the relevant mechanism. Thus far, due to its parsimonious nature, the technology acceptance model (TAM) and extensions have been adopted to explain consumers’ attitudes and adoption toward robo-advisors (Belanche et al., 2019; Zhang et al., 2021). However, it has been argued that the TAM and its extension pose drawbacks as it overlooks many relevant aspects of the adoption and non-adoption of technology, such as consumers’ privacy concerns which are highly relevant for AI objects (Pizzi and Scarpi, 2022). The gap has prompted the current study to depart from probing the positive aspects of robo-advisors as motivators for its adoption to explore the “dark sides” of robo-advisors in understanding consumer resistance. To this end, adhering to the suggestion of past research (Thomaz et al., 2020; van Doorn et al., 2017), we contribute to the robo-advisor literature by validating a research framework showcasing perceptions about a robo-advisor’s human-like attributes (i.e., anthropomorphism and autonomy) and how they influence consumer outcomes.

Moreover, the present study explores resistance to robo-advisors from a justice and privacy perspective. Grounded in the Status Quo Bias Theory (Samuelson and Zeckhauser, 1988), resistance to innovation can be understood through the prism of a risk-benefit
assessment, whereby consumers may favor retaining the status quo to minimize losses if privacy and intrusion risks are significant. This perspective is highly relevant given robo-advisors are in their nascent stage of development, and financial decisions are highly consequential, entailing consumers to disclose significant sensitive information in exchange for optimal and personalized financial advisory services. Therefore, understanding robo-advisor resistance through the lens of justice and privacy enriches the body of knowledge on robo-advisor diffusion.

Given the privacy and intrusiveness concerns of robo-advisor usage, the present research aims to address the gap by identifying their antecedents and outcomes. There is a dire need to focus on consumer justice perception (i.e., whether they perceive the received benefits are worthy in exchange for the information shared for robo-advisor usage) (Pizzi and Scarpi, 2021). To date, scant studies have addressed the orchestration of robo-advisors attributes, and there is an increasing need to relook into this perspective in understanding consumer responses (Glaser et al., 2019; Shanmuganathan, 2020). To the authors’ knowledge, this is among the first piece of work that articulates how human-like attributes (i.e., perceived anthropomorphism and perceived autonomy) can be used to counteract barriers to robo-advisor acceptance.

5.2 Practical Implications
Robo-advisor adoption and usage are at a nascent stage. The diffusion of robo-advisors represents a challenging issue for banking and finance sector while revealing a golden opportunity for service providers (e.g., banks and Fintech companies) to expand and revitalize their existing business model. Understanding how service providers and marketers might cope with such an array of strains motivates the present study. Based on the findings obtained, service providers should instill human-like attributes into robo-advisors for information processing services because anthropomorphism and autonomy are beneficial to the formation of justice perception toward robo-advisor. Therefore, managers should not be fearful of the uncanny valley effect that a human-like artificial intelligence system will induce resistance to robo-advisor adoption. Instead, more work should be done on the algorithms and data incorporated to improve the human-likeness so to elevate consumer confidence and perceived goodwill. More specifically, customized human-like features, including voices, tones, and slangs, and even the capability to detect emotions may be integrated to make robo-advisors more adaptive to the dynamic human-computer interaction. Practitioners should consider the potential of integrating autonomous product solutions to
reduce user intervention in their financial management. The value incurred from the autonomy attribute may counteract the cost of supplying personal information during the robo-advisory service usage, thereby fostering the justice perception.

6. Limitations and Future Research Directions

Despite the richness of the findings, some limitations should be acknowledged, and there are many interesting yet unexplored avenues for research. First, the study is limited in terms of the research design employed (i.e. cross-sectional). Future studies can use longitudinal designs to explore the temporal effect of anthropomorphism and autonomy on relevant outcomes through different stages of robo-advisors diffusion. Second, the present study did not consider the spill-over effect of robo-advisors’ perceptions. In reality, perceptions toward robo-advisors may impact consumers’ perceptual and behavioral responses to banking and financial service providers that employ robo-advisors such as customer trust and customer experience. For example, how do service failures and transgression (e.g., data abuse and leakage) caused by robo-advisors impact service providers? We suggest future research to develop relevant privacy regulatory frameworks or policies in addressing the issues of fairness and accountability in robo-advisor usage. The spill-over effect can be taken a step further by probing the branding aspect of robo-advisors (Aw and Chong, 2019; Cham et al., 2020a,b; 2021).

Third, the current study is limited to the understanding of consumers’ perception toward features of robo-advisors. As articulated by past research, a more comprehensive lens should be taken to understand consumer resistance. For example, consumer personal characteristics such as personality traits (e.g., affinity for technology interaction), demographic variables (e.g., income and educational level), and financial literacy can be explored (Aw et al., 2023). Furthermore, future studies could take the current research model further by examining other important outcomes, such as attachment and negative emotions (e.g., tension, worry, and anger), given their relevance to smart technology adoption (Ooi et al., 2018). Fourth, it would be fruitful to explore whether different configurations of robo-advisors attributes are needed in catering to the need of different consumer segments of different countries, given that cultural differences might foster varying consumers’ perceptions, beliefs, and values (Chuah et al., 2022). Finally, in line with Quach et al. (2022), we believe that the majority of consumers are willing to engage in some trade-offs between loss of privacy and optimal robo-advisor usage experience, thus authors of future research
might embark on this research direction to identify the optimal solution to achieve a win-win situation for both firms and consumers.
References


Figure 1. Research model
### Table 1. Reliability and Convergent Validity

<table>
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<tr>
<th>Latent variables</th>
<th>Items</th>
<th>Loadings</th>
<th>CR</th>
<th>AVE</th>
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<td>0.705</td>
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<td></td>
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<td>0.926</td>
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<td>ANTI3</td>
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<td>ANTI4</td>
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<td>ANTI5</td>
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<td></td>
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### Table 2. Discriminant Validity (HTMT r2)

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<th>Perceived justice</th>
<th>Privacy concerns</th>
<th>Resistance</th>
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<td>intrusiveness</td>
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<td></td>
</tr>
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<td>Justice</td>
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<td>Std. Beta</td>
<td>T Statistics</td>
<td>Effect Size (f²)</td>
<td>Variance Explained (R²)</td>
<td>Predictive relevance (Q²)</td>
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<td>H1</td>
<td>Perceived anthropomorphism -&gt; perceived justice</td>
<td>0.368</td>
<td>5.604***</td>
<td>0.178</td>
<td>0.327</td>
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Note: ***p < 0.001; **p < 0.01; * Not significant