The Impact of Functional and Psychological Barriers on Algorithm Aversion – An IRT Perspective

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Abstract. The application of artificial intelligence (AI) in decision-making is regarded as the most impactful disruption in an organization's digitalization. However, the benefits of the algorithmic decision can be leveraged only if the managers of an organization adopt this technology. Research found that despite the superior performance of algorithms, people discount algorithmic decisions either deliberately or unintentionally, a phenomenon known as algorithm aversion. In this regard, the current study seeks to investigate whether managers' innovation resistance, measured by different barriers, has any impact on algorithm aversion. Analyzing the survey data of 167 bank/financial managers, we found that while value barriers, tradition barriers, and image barriers are significantly associated with algorithm aversion, such relationships are absent in the case of usage barriers and risk barriers. The findings of this study have several theoretical and practical implications.

Keywords: Algorithm aversion, Innovation resistance theory, decision making, algorithmic decision-making, artificial intelligence.

1 Introduction

With the advent of the "Data Age," organizations are now inundated with a vast amount of information, which is also expected to grow at a faster pace [1]. Research demonstrated that organizations could grow by utilizing this information in decision-making [2]. To understand how an organization uses information in decision-making, understanding the individual's decision-making process is crucial [3]. Human, being "rational animal," [4] generally tends to make a rational decision through making an exhaustive search of available alternatives and selecting the best one [2]. Simon [5] suggested that an individual's rational choice is bounded because the number of alternatives he must identify is so enormous and the amount of information he must process is so big that even making a rational estimation is quite challenging. However, with the introduction of computing technologies and artificial intelligence (AI), individuals' race towards optimal decision-making has been expedited to a great extent [6]. AI serves two basic functions of organizational decision-making: (i) provides suitable alternative courses of action and (ii) provides information processing power [7]. An AI-based system is capable of learning by itself and can reveal hidden insights thereon [8]. Such insight capability bestows AI to become more rational. Therefore, Lindebaum et al. [9] refer to AI decision algorithms as "supercarriers of formal rationality". Furthermore, the decision-making process and outcomes are highly replicable as they are based on transparent logic and mathematics [6]. Thus, given the calculation prowess, processing speed, ability to self-learn and adapt, and high level of rationality, AI algorithms can be seen as a boon in overcoming the bounded rationality of human and organizational decision-making [9].

The potential benefits of an algorithmic decision can be capitalized on if the managers of an organization adopt it. This study builds on innovation resistance theory (IRT) [10] in the managerial decision-making context to understand what prevents managers from adopting algorithms. There are two reasons why we are considering IRT in our study. First, Mahmud et al. [11] found that although there are some studies about the implications and adoption of algorithmic decision-making in the organizational context, there is no study investigating the impact of functional and psychological barriers perceived by the managers on algorithm aversion. An AI-based algorithmic decision is a relatively new addition to most organizations. Many managers even do not have any prior experience dealing with algorithmic decisions. They perceive several psychological and functional barriers while contemplating following the algorithmic decisions. Second, the algorithmic decision system is a complex technology, which is different from other digital technologies that are "easy-to-use and easy-to-deploy" [12]. Therefore, it is necessary to understand how IRT and algorithm aversion are related to each other. Such understanding will help to implement algorithmic decision systems in an organization.

We conducted a cross-sectional survey of 167 bank/financial managers who regularly make decisions about their businesses. Our study holds both theoretical and practical implications in algorithm aversion literature. In terms of theory, our study is among the first to examine IRT in the algorithmic decision. Further, we respond to the call of Mahmud et al. [11] by addressing the need for algorithm aversion research in real-world settings by developing a measurement scale for algorithm aversion. In terms of practice, our study highlights different barriers that affect the managers in adopting algorithmic decisions.

2 Background

2.1 AI Decision and Algorithm Aversion

Organizations are increasingly using AI algorithms in decision-making [9]. In the prior literature, although AI decision has been discussed to some extent, to the best of our knowledge, AI decision is defined nowhere. An AI decision can be better captured by putting together the definitions of both AI and algorithmic decisions. According to

Mikalef and Gupta [13] "AI is the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals". As follows, algorithmic decision-making or simply algorithm is "an automated process that provides decisions independently without the mediation of humans" [11]. Henceforth, AI-based algorithmic decision-making or AI decision can be defined as *an automated process that can identify, interpret, make inferences, and learn from data to suggest decisions or courses of action*.

Algorithm aversion occurs when people show reluctance to use algorithmic decisions either intentionally being familiar with the superior performance of algorithms [14] or unintentionally out of fundamental distrust towards algorithms [15]. Mahmud et al. [11] defined algorithm aversion as "a behavior of discounting algorithmic decisions with respect to one's own decisions or other's decisions, either consciously or unconsciously" [11]. Such aversion is viewed as a behavioral anomaly, which creates an obstacle to fully leveraging the benefits of algorithmic decision-making [16].

Various factors influence algorithm aversion. Based on a systematic literature review, Mahmud et al. [11] identified that factors related to the algorithm (design, delivery, and decision), task (complex vs. simple; subjective vs. objective), individual (personality, demography), and macro environment (uncertainty, cultural) are responsible for aversion. However, in their study, they did not find any study exhibiting the relationships between perceived functional and psychological barriers and algorithm aversion.

2.2 Innovation Resistance

Although some people are pro-innovation, many are resistant to innovation [10]. Their resistance can be attributed to their satisfactory status quo or conflicting belief structure [10]. Innovation resistance can be referred to as the resistance of an individual to innovation, resulting from a perceived belief of either potential changes in the status quo or potential conflicts with current beliefs [10, p. 6]. Several obstructors stymie the adoption of innovation, and scholars classified those into two groups: functional and psychological barriers [17]. Functional barriers consist of usage barriers, value barriers, and risk barriers and occur when an individual perceives a significant change due to the adoption of innovation. On the other hand, psychological barriers comprise traditional barriers and image barriers and arise when an individual perceives a conflict with his/her prior belief [18].

Existing innovation adoption research is primarily dominated by the investigation of motivators and drivers of adoption, thus the inhibitors that obstruct the adoption of innovations seem to be overlooked by the scholars [17]. Scholars imputed this trend to "pro-innovation bias," whereby it is assumed that "all innovations are good and should be adopted by all" [17]. On the contrary, it is found that the major cause of innovation failure is individuals' resistance to adoption [18]. Therefore, Arif et al. [18] suggest that instead of studying the reasons for adoption, researchers and practitioners should concentrate on what prevents adoption.

Innovation resistance theory has widely been used in understanding the adoption of new technology such as internet banking [18], mobile banking [19], mobile gaming

[20], and e-tourism [21]. Kaur et al. [19] found that IRT is the most sought choice among researchers to investigate innovation resistance. It has a proven explanatory power of why individuals defy to adopt innovation [22]. It addresses all the major sources of barriers to adoption in the form of functional and psychological barriers [22]. This overarching nature of IRT has led us to borrow this theory in explaining why individuals are averse to an algorithmic decision.

3 Model and Hypothesis Development

To examine why individuals show algorithm aversion, we draw on IRT to investigate the relationship between different perceived barriers and algorithm aversion (Fig. 1).

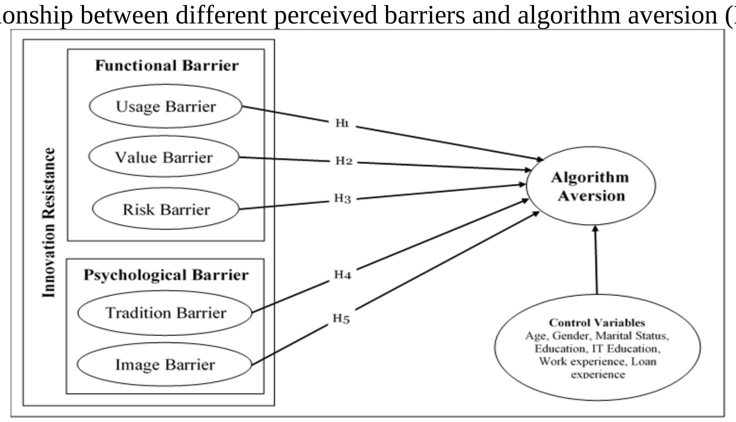

Fig. 1: Proposed research model

3.1 Usage Barrier

The usage barrier is functional and is regarded as the most common cause of innovation resistance [10]. Usage barrier arises when innovation is perceived to conflict with existing practices and requires a change in the status quo [10]. In the case of digital innovation, it is assumed that the usage barrier is related to the perceived complexity and ease of use of innovation [23]. In the context of the current study, being a disruptive innovation, algorithmic decision demands a radical change in existing practice. With the implementation of the algorithmic decisions, managers are expected to forgo their status quo. In addition, an algorithmic decision is complex technology. Therefore, managers need to spend sufficient time learning and getting familiar with the algorithmic decision. Earlier studies suggest that the usage barrier has a significant positive impact on the resistance to technology adoption [17, 21, 24]. Therefore, considering the above discussion and the evidence found in the extant literature, we hypothesize:

H1: Usage barrier is positively correlated with algorithm aversion.

3.2 Value Barrier

The value barrier represents the performance-to-price ratio compared to alternatives [25]. Such representation indicates that the value generated by the innovation should be greater than that of the existing one. Scholars have found a positive relationship between value barriers and innovation resistance in various contexts such as online learning [24], mobile banking [17], and e-tourism [21, 26]. However, the impact of the value barrier has never been studied in the context of algorithmic decision-making. Since using algorithmic decisions is a substantial monetary investment and there is a lack of perceived usefulness due to the black-box nature, we argue that the value barrier discourages managers from adopting algorithmic decisions. Thus, we define our next hypothesis:

H2: Value barrier is positively correlated with algorithm aversion.

3.3 Risk Barrier

The risk barrier represents the risks and uncertainties involved with an innovation [25]. The higher the risk an innovation entails, the slower the adoption of that innovation [10]. The risk barrier is regarded as the most cited barrier to digital innovation adoption [27]. In the context of algorithmic decision-making, managers may perceive various risks and uncertainties in using algorithms. For example, managers tend to work in a highly risky environment, in which they have to pursue decisions considering a lot of uncertainties. Again, many managers lack firsthand knowledge about the accuracy of algorithmic decisions at the pre-adoption stage. Therefore, they perceive uncertainty about the performance of the algorithms. Prior research demonstrates that people abandon even the best possible algorithms if the decision domain and environment are risky and volatile [15]. Extant literature confirmed the positive association between risk barriers and resistance behavior in mobile banking [17], online learning [24], and e-tourism [21]. Therefore, we also argue that the risk barrier obstructs managers to adopt algorithmic decisions. Thus, we propose our next hypothesis:

H3: Risk barrier is positively correlated with algorithm aversion.

3.4 Tradition Barrier

Individuals have their own established daily routines and tradition for their work. They are more comfortable with their habits [24]. Tradition barriers arise when innovation requires changes in this behavior or status quo [23]. John and Klein [28] stated that tradition is deeply ingrained in society and thereby any potential change results in strong repercussions in the form of negative word-of-mouth, boycotts, and even attacks on the change. Therefore, it is assumed that the tradition barrier has a strong negative effect on innovation adoption [29]. In the context of algorithmic decision-making, tradition barriers may arise if the managers are satisfied enough with their conventional way of decision-making and enjoy the discussion with their colleagues and seniors while making decisions. Prior studies found several instances when the tradition barrier is positively related to innovation resistance such as online learning [24], mobile banking [17], and e-tourism [21]. Therefore, bearing on these findings, we define our fourth hypothesis:

H4: Tradition barrier is positively correlated with algorithm aversion.

3.5 Image Barrier

Image is an impression that an entity imprints on the minds of others [30]. It serves as an important cue to evaluate an innovation [24]. If the perceived image is not favorable, then the image can produce a barrier to adoption. Image barriers can emerge from the perception of how difficult or easy to adopt the innovation [25]. In the context of algorithmic decision-making, it is found that negative perception is positively related to algorithm aversion [31]. People have a perception that an algorithm is good at performing objective tasks as it is deviant of subjective judgment capability [32]. Therefore, they trust less on algorithms. Again, people have a negative impression that algorithms may provide biased decisions and lead to some job losses in the future [33]. Prior literature has reported the positive relationship between image barriers and innovation resistance [21, 24]. According to the above discussion, we hypothesize:

H5: Image barrier is positively correlated with algorithm aversion.

4 Methodology

4.1 Measurement Development

Innovation resistance is measured by five constructs: usage barrier, value barrier, risk barrier, tradition barrier, and image barrier. The measurement items for these constructs are adapted from existing scales (see Table 1). For measurement of algorithm aversion, to the best of our knowledge, no previous study has developed scales. Therefore, we construct a five-item algorithm aversion construct following the procedures followed by Mäntymäki et al. [34]. In this regard, we interviewed nine senior bank managers who have experience working in both the information technology and credit department. Four of the interviewees were female and five were male, and their ages varied from 37 to 50 years. We asked them to describe their perceptions and experiences about what characterizes algorithm aversion and what behavior is observed when a user exhibits a reluctance to use algorithmic decision-making. Upon scrutinizing the information collected from interviewees, we identified a list of 7 candidate items measuring algorithm aversion. The items were reviewed by two managers, one Ph.D. student, and two senior academics. In the review process, one item was eliminated as it was deemed redundant by the reviewers. To maintain the quality of the developed items, we employed a card-sorting exercise with 11 managers, who were asked to evaluate the items according to the item's similarity [35]. Participants unanimously labeled five items homogenous and were divided into one item, which was dropped from the final measurement. Finally, five items were accepted to measure algorithm aversion. Consisting of all foregoing constructs and demographic items, a questionnaire was drafted and reviewed by two senior academics. The final survey instrument used in the measurement is presented in Table 1.

Table 1. Measurement items, items loadings, composite reliabilities, and AVEs

Construct	Item	Item loading	CR	AVE
Usage barrier [17, 23]	UB1: *AI Loan Decision Tool* will be difficult to use.	0.82	0.89	0.68
	UB2: The use of *AI Loan Decision Tool* will be inconvenient to use.	0.88		
	UB3: Usage of *AI Loan Decision Tool* will slow my task.	0.84		
	UB4: The process of *AI Loan Decision Tool* is unclear.	0.75		

Value barrier [17]	VB1: The use of *AI Loan Decision Tool* is uneconomical.	0.72	0.91	0.66
	VB2: *AI Loan Decision Tool* will NOT offer any advantages compared to the current way of decision-making.	0.82		
	VB3: The use of *AI Loan Decision Tool* will NOT increase my ability to control my loan decision tasks.	0.87		
	VB4: *AI Loan Decision Tool* is NOT a good substitute for the current way of decision-making.	0.87		
	VB5: *AI Loan Decision Tool* will NOT resolve the problems associated with the current way of decision-making.	0.79		
Risk barrier [39, 40]	RB1: It is probable that *AI Loan Decision Tool* would frustrate me because of its poor performance.	0.84	0.90	0.70
	RB2: Compared with the current way of decision making, using the *AI Loan Decision Tool* has more uncertainties.	0.83		
	RB3: It is uncertain whether *AI Loan Decision Tool* would be as effective as I think. (Dropped)			
	RB4: *AI Loan Decision Tool* might not perform well and create problems.	0.82		
	RB5: Overall, using *AI Loan Decision Tool* would be risky.	0.85		
Tradition barrier [18, 19, 41, 42]	TB1: I am satisfied with my conventional way of loan decision-making.	0.79	0.88	0.72
	TB2: I am so used to evaluating customers' creditworthiness by myself that I will find it difficult to switch to *AI Loan Decision Tool*.	0.85		
	TB3: I think making a loan decision by myself will be more pleasant than following the decision provided by *AI Loan Decision Tool.*	0.89		
	TB4: I enjoy the discussion with my colleagues and seniors about making loan decisions. (Dropped)			
Image barrier [17, 19, 41]	IB1: I have a very negative image of the *AI Loan Decision Tool*.	0.90	0.89	0.73
	IB2: New technology is often too complicated to be useful.	0.74		
	IB3: I have such an image that *AI Loan Decision Tool* is difficult to use.	0.91		
Algorithm aversion (new scale)	AA1: In loan decisions, I will make the decision by myself rather than follow the decision given by *AI Loan Decision Tool*.	0.78	0.89	0.62
	AA2: In loan decisions, I will follow the expert's decision rather than follow the decision given by *AI Loan Decision Tool*.	0.79		
	AA3: In loan decisions, I will follow human decisions rather than follow decisions given by *AI Loan Decision Tool*.	0.83		
	AA4: In loan decisions, I will follow human decisions even human does not provide consistently better decision than *AI Loan Decision Tool*.	0.82		

	AA5: In loan decisions, I will NOT follow decisions given by *AI Loan Decision Tool* even it provides consistently better decisions than humans.	0.72		

4.2 Data Collection and Analysis

The data were collected from the managers of the banking industry of Bangladesh. From a contextual standpoint, the bank is a forerunner in using algorithmic decisions for the core business process such as loan approval and risk analysis [36]. To collect data, an anonymous online survey link was distributed among the bank managers, selected through convenient sampling. At the beginning of the survey, a brief introduction of algorithmic decision-making and how it works were given to the respondents. Subsequently, an AI loan decision tool was demonstrated based on two loan scenarios. We received 193 responses, out of which 26 responses are discarded due to failing in answering attention check questions. Finally, 167 usable responses were considered for analysis. The age of the respondents ranged from 18 and 55 years, with a mean age of 41 years. Their average experience in working with loan approval is 5.40 years.

Collected data were analyzed using the partial least squares (PLS) approach using SmartPLS 3.0 software. To test the reliability and validity, we adhered to the limits recommended by Fornell and Larcker [37]. We maintained each item loading above 0.7, composite reliability (CR) above 0.8, and average variance extracted (AVE) above 0.5 to ensure the convergent validity (Table 1). To test the discriminant validity, we compare the inter-construct correlations and the square roots of the AVE values presented diagonally in Table 2. The lower off-diagonal correlation values against the square roots of the AVE values suggest a discriminant validity of the constructs. We also examined whether loadings are higher than the cross-loadings to ensure the discriminant validity on the item level and found satisfactory results [38].

Table 2: Square root of the AVEs and Inter-construct correlations

Item	Usage barrier	Value barrier	Risk barrier	Tradition barrier	Image barrier	Algorithm Aversion
Usage barrier	**0.822**					
Value barrier	0.726	**0.814**				
Risk barrier	0.713	0.735	**0.834**			
Tradition barrier	0.517	0.523	0.631	**0.847**		
Image barrier	0.657	0.611	0.635	0.586	**0.853**	
Algorithm Aversion	0.385	0.402	0.417	0.48	0.441	**0.787**

5 Results and Discussion

5.1 Hypothesis Test Results

To test our proposed hypotheses and examine the significance of the relationships between the dependent variable and the independent variables, we conducted a structural model test. As hypothesized, the results indicate that the value barrier (β=0.22, $p<0.05$), tradition barrier (β=0.20, p<0.05), and image barrier (β=0.22, p<0.05) have a significant positive effect on algorithm aversion. This result corroborates the findings of existing literature [17, 23]. However, the usage barrier (β=-0.01, ns) and risk barrier (β=0.04, ns) have no significant impact on algorithm aversion. These findings bear a valuable insight for the practitioners and researchers. One explanation for this could be that since bank/financial managers are well-educated, knowledgeable, familiar with the use of technology to some extent, and are used to working in a risky environment, they are less concerned about usage barriers and risk barriers in adopting algorithms. Besides, we also examined the effect of control variables such as age, gender, marital status, education, IT education, work experience, and experience in loan decision-making on algorithm aversion and no such effect was found. The predictors explained 42.30 percent of the variance of algorithm aversion.

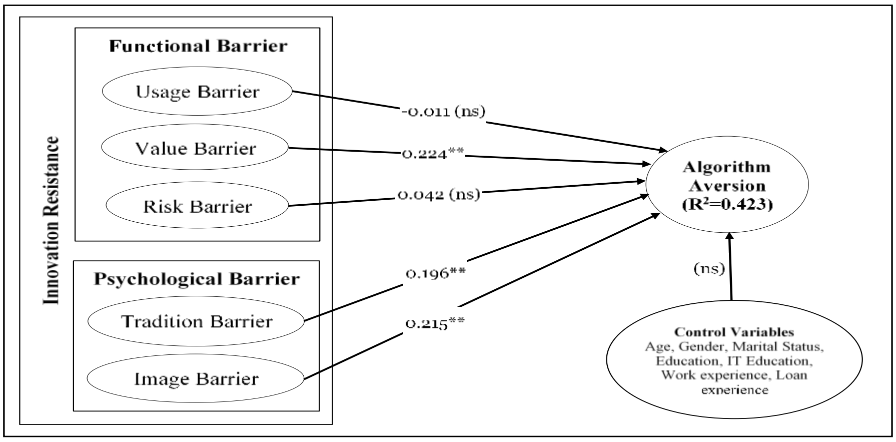

Fig. 2. PLS results

5.2 Implications

Our study lends several contributions that could benefit researchers and practitioners. First, we contribute theoretically by investigating the IRT in the context of algorithm aversion. To the best of our knowledge, potential relationships between different barriers of IRT and algorithm aversion have not been examined in the extant literature. Although the IRT was developed to measure the extent to which different barriers thwart customers to accept technology-based products or services [10], we empirically show that it can be effectively applied in organizational settings to gain an understanding of different barriers to adopting and using technologies for decision making.

Second, developing a new measurement scale is viewed as a significant contribution to information system research [34]. In this study, we made an initial attempt to propose a new measurement scale for algorithm aversion which can be further validated across different contexts. As such, we contribute methodologically by responding to the call of Mahmud et al. [11], thus overcoming the limitation of algorithm aversion research in the real-world context. This construct will help future researchers to conduct algorithm aversion research with the subjects who are subjected to the use of algorithmic decision-making.

Third, our study reveals several important relationships. We found that managers' perceived psychological barriers and value barriers significantly impact algorithm aversion. Contrary to our hypotheses, we also found that usage barriers and risk barriers do not have any impact on algorithm aversion. This finding bears a valuable insight for the practitioners and researchers. One explanation for this could be that since bank/financial managers are well educated, knowledgeable, and familiar with technology use and working in a risky environment, they are less concerned about usage barriers and risk barriers in adopting algorithms. Rather they are skeptical about the potential benefits of using algorithmic decisions. The values of using algorithmic decisions are not evident to them. Furthermore, they might have developed a status quo and formed a negative image of the quality of AI-based decision algorithms.

Fourth, since organizations are gradually employing emerging technology to automate and streamline business operations, an understanding of different barriers to embracing technology will provide useful insights to the entrepreneurs or employers to decide about the appropriate technology-related strategy. In this regard, our study will guide managers while adopting or using algorithmic decision-making in their organizations.

5.3 Limitations and Future Research

Despite multiple implications and study rigor, like any other research, the current study has limitations that also open the avenue for future research. First, the study was cross-sectional. The perception and attitudes toward using technology change over time as the user gains more knowledge and becomes more familiar with it. Such change cannot be captured in a cross-sectional study. Thus, a longitudinal study can be undertaken to mitigate this lacuna. Second, the survey participants were selected using a convenient sampling method and they are predominantly based on a particular industry (banking/financial). In addition, the number of survey responses was not optimal for the findings to be generalized. Future studies can be undertaken by including an expansive set of samples to overcome this issue. Third, in our study, we identified that value barriers, tradition barriers, and image barriers significantly affect algorithm aversion. Future studies can be conducted to see how these barriers can be overcome by incorporating different moderators and mediators in between these relationships.

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