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Mahmud Hasan, Islam A.K.M. Najmul, Luo Xin (Robert), Mikalef Patrick

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# Decoding algorithm appreciation: Unveiling the impact of familiarity with algorithms, tasks, and algorithm performance

Hasan Mahmud [b,*], A.K.M. Najmul Islam [b], Xin (Robert) Luo [a,b], Patrick Mikalef [c,d]

[a] Anderson School of Management, The University of New Mexico, Albuquerque, USA
[b] Software Engineering Department, LUT University, Lappeenranta, Finland
[c] Department of Computer Science, Norwegian University of Science and Technology, Sem Sælandsvei 9, 7034 Trondheim, Norway
[d] School of Economics and Business, University of Ljubljana, Kardeljeva ploščad 17, 1000 Ljubljana, Slovenia

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ABSTRACT

Algorithm appreciation, defined as an individual's reliance or tendency to rely on algorithms in decision-making, has emerged as a subject of growing scholarly interest. Inquiries into this subject are crucial to understanding human decision-making processes as in the era of artificial intelligence, algorithms are increasingly being integrated into decision-making. To contribute to this evolving field, this study examines three factors that might play significant roles in enhancing trust in algorithms: familiarity with algorithms, familiarity with tasks, and familiarity with algorithm performance. Drawing upon prior studies, a conceptual model was developed and empirically tested using a scenario study. Data on 327 individuals showed a strong positive association between familiarity with algorithms and trust in algorithms. In contrast, task familiarity appeared to have no significant influence on trust. Trust, in turn, was identified as a key driver of algorithm appreciation. The study also revealed the moderating role of familiarity with algorithm performance in the relationship between familiarity with algorithms and trust in algorithms. Post hoc analysis highlighted that trust fully mediates the relationship between algorithm familiarity and algorithm appreciation. The study underscores the significance of algorithm familiarity and performance transparency in shaping trust in algorithms. The study contributes theoretically by offering important insights about the influences of different forms of familiarity on trust and practically by prescribing practical guidelines to enhance algorithm appreciation.

## 1. Introduction

Algorithms, defined as automated processes capable of learning autonomously, making decisions, and performing tasks without direct human intervention [1], are becoming increasingly prevalent in our daily lives. Their ubiquity extends from the applications in the governmental and private sectors (e.g., judicial systems [2], medical diagnoses [3], and human resources management [4]) to individual use (e.g., shopping, education, and entertainment), suggesting their influence on shaping human decisions. Such widespread appreciation of algorithms in decision-making has drawn considerable scholarly interest in understanding the factors that influence an individual's reliance on algorithms [5,6].

However, a comprehensive understanding of how different forms of familiarity, such as familiarity with algorithms (FA), familiarity with tasks (FT), and familiarity with an algorithm's performance (FP), influence trust in algorithms and algorithm appreciation remains elusive [2]. Presumably, individuals who possess greater familiarity with the general work process of algorithms, the decision task at hand, or the performance of a specific algorithm are more likely to exhibit greater trust in algorithms. Yet, the existing literature presents mixed findings regarding the relationships between various forms of familiarity and trust in algorithms. Some studies have demonstrated that an individual's FT has no significant impact on trust in algorithms [7,8], while others have shown that individuals familiar with tasks tend to rely less on algorithms [5,9]. Similarly, certain studies have suggested that individuals discount algorithms even when they are familiar with the superior performance of algorithms [10,11], while a separate body of research has shown that individuals appreciate algorithms more when they are familiar with the superior performance of algorithms [2,6,12]. In contrast, findings regarding the positive influence of FA on trust appear to be consistent [13,14]. Given the paradoxical results

* Corresponding author.
*E-mail addresses:* hasan.mahmud@lut.fi (H. Mahmud), najmul.islam@lut.fi (A.K.M.N. Islam), xinluo@unm.edu (X.(R. Luo), patrick.mikalef@ntnu.no (P. Mikalef).

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documented by different studies on the effects of various forms of familiarity on trust in algorithms, it is imperative to investigate these distinct forms of familiarity within a single study. Such an investigation would enhance our understanding of how different types of familiarity influence trust in algorithms, contributing to algorithm appreciation. Therefore, we pose the following research question: *How do FA, FT, and FP influence trust in algorithms and contribute to algorithm appreciation?*

To address the above research question, a conceptual model was developed based on an extensive review of the existing literature. We conducted a vignette-based online experimental study involving 327 participants to empirically examine the model. The study involved a prediction task in which participants were presented with scenarios and asked to make predictions with or without considering algorithmic advice. The experiment manipulated FP, distinguishing between familiar and unfamiliar conditions, to explore its influence on the relationships between FA or FT and trust in algorithms. The findings revealed a significant relationship between FA and Trust, but no significant relationship between FT and trust. We also found that FP moderates the relationship between FA and trust in algorithms. Importantly, trust in algorithms was found to be a significant contributor to algorithm appreciation.

This study advances our knowledge of algorithmic decision-making by examining how different facets of familiarity influence trust, ultimately shaping individuals' algorithm appreciation [1,10]. First, it adopts a comprehensive approach to examine the impact of different forms of familiarity on trust in algorithms, consolidating and synthesizing knowledge within this domain. Second, the findings underscore the importance of increased FP in strengthening the relationship between FA and trust, highlighting the significance of the algorithm's performance transparency. Third, the study results offer insights to address the inconsistencies observed in the effects of FT and FP on trust. Moreover, the study provides practical implications for managers and designers of algorithms in developing the right forms of familiarity to leverage the benefits of algorithms in decision-making processes.

## 2. Theoretical background

### 2.1. Algorithmic decision-making and trust

Algorithmic decision-making, or simply algorithms, refers to an automated process that can learn independently, make decisions, offer recommendations, and perform tasks without the need for direct human intervention [1,15]. Scholars have sought to understand why people accept or reject algorithms from two perspectives: algorithm aversion and algorithm appreciation. Algorithm aversion refers to an individual's reluctance or tendency to discount algorithmic decisions, either consciously—being aware of the high or identical performance of algorithms—or unconsciously out of fundamental distrust toward algorithms [1,15]. For instance, consider a scenario in which a highly accurate medical diagnostic algorithm is available to assist doctors in identifying diseases. Despite this algorithm's proven ability to outperform human diagnosticians, some doctors might hesitate to rely on its recommendations due to a variety of factors, including a preference for traditional diagnostic methods or a lack of trust in the algorithm's decision-making process. Such an aversion to algorithms can have far-reaching implications, potentially leading to suboptimal outcomes and compromising the expected benefits of algorithms [1,10]. On the other hand, algorithm appreciation, as the antithesis of algorithm aversion, can be defined as an individual's reliance or tendency to rely on algorithms in decision-making [2,5]. To illustrate, consider the context of financial investments; an individual who consistently follows the investment recommendations given by a sophisticated algorithm can be seen as demonstrating algorithm appreciation. Another scenario featuring algorithm appreciation could be a user of a streaming platform who regularly relies on the platform's recommendation algorithms to discover new movies or music.

Trust is a psychological state determined by the perceived benevolence, integrity, and competence of the trustee (in this study, algorithms) [16–18]. Benevolence is related to the trustor's belief that the trustee is acting in their best interests, while integrity signifies the trustee's adherence to accepted principles [16]. Competence encompasses factors such as expertise, knowledge, and proficiency within a given task. Trust has long been treated as a cognitive component that prompts individuals' subsequent behaviors. When individuals trust algorithms, they attribute higher levels of benevolence, competency, and integrity to those algorithms, fostering algorithm appreciation. Thus, trust serves as a key determinant of individuals' willingness to appreciate algorithms [2,5,6,10]. Prior research has suggested that individuals who trust algorithms are more likely to appreciate them, even without knowledge of algorithms' performance history [2,5]. Conversely, individuals who lack trust in algorithms are less likely to appreciate algorithms, even when they are aware of the algorithms' superior performance compared to those of human decision-makers [2,6,10,12,19].

### 2.2. Familiarity in algorithmic decision-making

Familiarity refers to one's understanding of a subject, typically stemming from previous direct or indirect engagements, practical experience, and an understanding of the what, who, how, and when aspects of the subject [14,20]. In the context of the algorithmic decision-making literature, Mahmud et al. [1] identified five facets of familiarity: (1) FA, (2) FT, (3) FP, (4) familiarity with prediction outlook (positive vs. negative, gain vs. loss) (FO), and (5) familiarity with the human experts, whose decisions are evaluated and weighted against those of algorithms. The current study limited its scope to examining the first three facets of familiarity in the context of algorithm appreciation. FA refers to individuals' general knowledge and understanding of algorithms and their underlying mechanisms, decision-making capabilities, and associated strengths and weaknesses. For example, in the context of a stock prediction algorithm, FA entails one's experience or deep understanding of how prediction algorithms work and their strengths, limitations, and performance history.

FT pertains to individuals' expertise and comprehension of the specific domain or context in which an algorithm is employed. For instance, in the stock prediction scenario, FT would involve an individual's familiarity with the intricacies of stock markets, financial analysis, and the factors that influence stock prices. This domain-specific familiarity is commonly referred to as domain knowledge. While FA is acquired through one's direct or indirect experience with algorithms, FT is gained through direct or indirect experience with a specific task or domain.

FP relates to individuals' awareness of the accuracy and reliability of a particular algorithm's predictions. For example, in the context of stock prediction, FP would involve an investor's assessment of how consistently accurate and reliable a specific stock prediction algorithm has been in past forecasts. In the context of our study, by FP, we refer to familiarity with an algorithm's superior performance. We distinguish between FA and FP in that while the former indicates knowledge about algorithmic technology in general, such as what algorithms are, how they are designed, what they do, how they execute their protocols, and what their advantages and limitations are, the latter pertains to knowledge about the effectiveness and reliability of a specific algorithm.

Finally, FO entails an individual's awareness of whether a prediction leads to a positive or negative outlook, resulting in either gains or losses. For example, in the context of stock market predictions, FO would mean understanding whether a forecast predicts that a particular stock's value will increase (positive outlook) or decrease (negative outlook).

Individuals' levels of familiarity with various familiarity facets—FA, FT, FP, and FO—hold significant influence over their trust in algorithms. Algorithms are often perceived as "black boxes," which can deter individuals' comprehension of their operation [1,21]. The extant literature suggests that algorithms may benefit from opening the black box, explaining how a black box algorithm works [22]. We assert that individuals who possess FA and have a comprehensive understanding of algorithms' general operational processes are better able to demystify the black box nature of algorithms. While prior research has explored the idea of opening the black box by explaining the inner workings of algorithms (*how*), recent studies have suggested that emphasizing *why* individuals should use algorithms is more important [2,23,24]. We contend that disclosing the performance history of the algorithm's prediction serves as a compelling *why* factor for individuals to embrace algorithms. Castelo et al. [6] considered providing individuals with empirical evidence of algorithms' superior performance for a given task the most intuitive approach to increase algorithm appreciation. Furthermore, an individual's familiarity with the specific task for which an algorithm is employed can significantly impact their ability to assess its suitability for that task [25]. Moreover, the mismatch between an individual's expectations (gain vs. loss) and the outlook (gain vs. loss) indicated by the algorithms' predictions can erode trust in them [26]. Therefore, we argue that the alignment between an algorithm's prediction outlook and an individual's expectations plays a pivotal role in shaping their trust in algorithms. While past research has explored these various forms of familiarity separately, no study has investigated three types—FA, FT, and FP—in a single study, highlighting their potential interactions in building trust in algorithms. Therefore, the current study takes an important initial step in examining these different forms of familiarity in the context of algorithmic decision-making.

## 3. Hypotheses development

### *3.1. Familiarity and trust in algorithms*

Prior research has demonstrated that an individual's FA has a significant impact on their trust in algorithms [1,27,28]. While familiarity is rooted in past experiences, trust is concerned with expectations regarding future behaviors [28]. Familiarity with the past behaviors of algorithms assists individuals in gauging the likelihood of desired future behaviors. Therefore, FA can enhance trust by reducing complexities and the uncertainties involved in the expectations and use of algorithms through an increased understanding of what happened in the past [14,20,27,29,30] and how algorithms work [20]. Furthermore, FA helps to increase trust by building individuals' confidence in the algorithm's competence [14]. Several prior studies have demonstrated that an individual's prior experience with algorithms fosters trust in them. For example, Komiak and Benbasat [14] found evidence that FA increases trust in a recommendation agent's integrity and competence. Therefore, we propose our hypothesis:

**H1a**. There is a significant positive relationship between familiarity with algorithms and trust in algorithms.

FT relates to the experience with the task at hand about which decisions, recommendations, or predictions are made. Although experience with a task increases self-efficacy in using algorithms, such experience does not increase trust in algorithms [1]. Previous studies have shown that experienced people rely less on algorithms for several reasons [5,9]. First, experienced people feel more confident in their abilities; therefore, they prefer to make decisions by themselves [8,9]. Second, experienced people believe that they possess a deeper understanding of the task and the context, allowing them to consider various factors that algorithms may overlook. Due to this egocentric bias rooted in the perception of superior self-understanding, they trust algorithms less [5]. Third, experienced people feel more responsible and accountable for the consequences of their decisions. Therefore, they need to ensure that there are no unintended outcomes of following algorithms that might jeopardize their professional identity [9,31]. Furthermore, due to the inherent opacity and lack of transparency of many algorithms, people may feel uncertain about the decision-making process. Therefore, they cannot blindly follow algorithmic decisions as they are responsible for the resulting outcomes [9]. In contrast to the above findings, several studies have also found insignificant relationships between FT and trust in algorithms [7,8]. Considering the inconsistencies in the above findings, this study aims to examine this relationship. Therefore, we posit the following hypothesis:

**H1b**. There is a significant relationship between familiarity with a task and trust in algorithms.

Individuals' FA can significantly affect their use of algorithms. Numerous studies have observed that individuals shy away from algorithms despite their familiarity with instances of superior, or even identical, performance by algorithms [10,11]. For instance, Dietvorst et al. [10] found that individuals exhibited resistance to algorithmic forecasters, even when these algorithms outperformed human forecasters. Similarly, Longoni et al. [32] found that individuals displayed an aversion to a medical algorithm even when the algorithm's performance was explicitly specified to surpass that of humans. Conversely, Castelo et al. [6] noted that individuals were more inclined to utilize algorithmic advice when they were familiar with the algorithms' performance. To investigate these seemingly inconsistent findings regarding the influence of an individual's FP, the study seeks to examine the moderating impact of FP on the hypothesized relationships between FA or FT and trust. FP has been examined as a moderating factor in several recent studies [2,6]. For example, Castelo et al. [6] found that FP moderates the preference for algorithms when the nature of a task is objective. Similarly, You et al. [2] examined the influence of the communication format of prediction performance (average vs. detailed) on algorithm appreciation. Therefore, we expect that the relationships between FA or FT and trust will be strengthened when individuals are familiar with the superior performance of a specific algorithm. While individuals may possess a general FA—what algorithms are, what they can achieve, and how they operate—they may not be fully aware of the algorithm's actual performance history. In such cases, knowledge about the algorithm's actual performance can instill greater confidence, eventually increasing individuals' trust in algorithms. Similarly, people who are familiar with the task and have more confidence in their decision-making abilities may reconsider their stance on algorithms if they are provided with the algorithm's actual performance information. As a result, we formulate the following hypotheses:

**H2a**. Information about an algorithm's performance moderates the positive relationship between FA and trust.

**H2b**. Information about an algorithm's performance moderates the relationship between FT and trust.

### *3.2. Trust and algorithm appreciation*

The successful integration of algorithms into decision-making processes depends on the trust individuals place in these algorithms. Trust fosters algorithms' adoption by reducing concerns about their ethical conduct [20]. Individuals are more likely to follow the recommendations given by algorithms when they perceive them as competent and free from biases [14]. Trust also instills confidence in the reliability of algorithms and diminishes the perception of risk and uncertainty associated with their use [6]. Given the sensitivity involved in algorithms' handling of extensive data, a higher level of perceived trust may reduce concerns about safety and security, thus contributing to the appreciation of algorithms. Chen and Dibb [27] identified a positive relationship between trust and the intention to use technology. Lastly, individuals are hesitant to embrace algorithms when they perceive them as less competent [11,33]. Thus, we propose the following hypothesis:

**H3**. Trust exerts a significant positive influence on algorithm appreciation.

## 4. Methodology

### 4.1. Experimental design and participants

To test the proposed hypotheses (Fig. 1), we conducted a between-subject experiment via a crowdsourcing platform, which is extensively used in conducting experiments on algorithmic decision-making [1]. We chose Prolific for our experiment because participants on Prolific are relatively more honest than those on other platforms [6]. In designing the experiment, we did not impose any restrictions on participation, except that the participant should be at least a high school graduate and 18 years old. During the experiment, the participants engaged in a carefully designed prediction task that involved estimating the future index value of the S&P 500 one month from the day of the experiment. Specifically, the participants were asked to make predictions on two occasions: first before being exposed to the algorithm's prediction and then after receiving the algorithm's prediction. This sequential arrangement allowed us to measure an individual's degree of algorithm appreciation.

For this study, we developed a scenario for predicting stock market indices based on prior research [6] and pretested the scenario with eight experts (two professors of accounting and information systems, one professor of economics, two doctoral students, a management consultant, a senior banker, and a healthcare development manager). Additionally, to ensure the reliability and credibility of the algorithm's predictions presented in the experimental vignette, a panel of six experts from our initial group—each highly experienced in financial forecasting—was involved. Each expert was asked to predict the value of the S&P 500 Index one month into the future, considering positive and negative outlook conditions. The predicted scores were subsequently averaged for each condition and served as the scores for the algorithmic prediction. By incorporating the insights of domain experts and employing the mean method, the study aimed to ensure that the algorithm's estimations were grounded in a realistic and informed context, reducing the likelihood of random values.

The present study manipulated FP across two experimental groups. Specifically, one group was exposed to the algorithm's prediction and its corresponding performance information, while the other group was not shown such performance information. Additionally, recognizing the potential impact of prediction outlooks on algorithm utilization [21], the study carefully controlled for this variable by manipulating participants' FO in the presence and absence of FP conditions. Upon completion of the experiment, participants were invited to participate in a post-experiment survey. The survey questionnaire included several attention check questions strategically designed to identify and exclude responses lacking careful consideration or provided without due diligence, thereby ensuring the integrity and reliability of the collected data.

Before experimenting, the required minimum sample size was determined by employing G*Power analysis [34] and the inverse square root method [34,35]. G*Power analysis suggested a sample size of 38 for our proposed model, assuming a significance level (α) of 0.05, a power level of 95%, and a medium effect size (0.3). Additionally, the inverse square root method indicated a minimum sample size of 155, based on a minimum path coefficient range of 0.11–0.2 and a significance level of 5%. Nevertheless, to ensure a robust dataset, we aimed to collect at least 300 unique responses, with a minimum of 150 responses per experimental condition. Ultimately, 363 participants completed the study, with 36 participants failing to correctly respond to attention check questions, resulting in a final sample of 327 participants. As an incentive for participation, participants received €2.50 (i.e., a rate of roughly €15/h). Demographic information (Table 1) revealed that the survey population consisted of 51.99% males, with an average age of 29.28 years. Additionally, 66.06% of the participants were employed either full-time or part-time, and 96.64% had at least an undergraduate degree. Table 2 shows the distribution of the participants across different conditions.

### 4.2. Procedures

The design of the experiment was mostly consistent across both conditions, except for the specific interventions employed in each condition. Thus, a detailed description of the design for Condition 1 is provided, followed by a brief explanation of the specific interventions introduced in Condition 2.

**Condition 1: Unfamiliarity with performance.** Before commencing the experiment, we obtained informed consent from all participants. To ensure that participants understood what algorithms are, a short description of algorithms was provided. Additionally, participants were informed of the presence of attention check questions; failure to respond to these questions correctly would result in disqualification from compensation. Subsequently, the participants were briefed about the experimental task. They were asked to act as potential

**Table 1**
Demographics ($N = 327$).

| Gender (% male) | 51.99% | Age | Average: 29.28 |
|---|---|---|---|
| Employment Status | | Education | |
| Employed full-time | 54.13% | High school degree | 3.36% |
| Employed part-time | 11.93% | Undergraduate degree | 67.89% |
| Retired | 0.31% | Graduate degree | 28.75% |
| Student | 18.35% | | |
| Prefer not to say | 2.14% | | |
| Seeking opportunity | 13.15% | | |

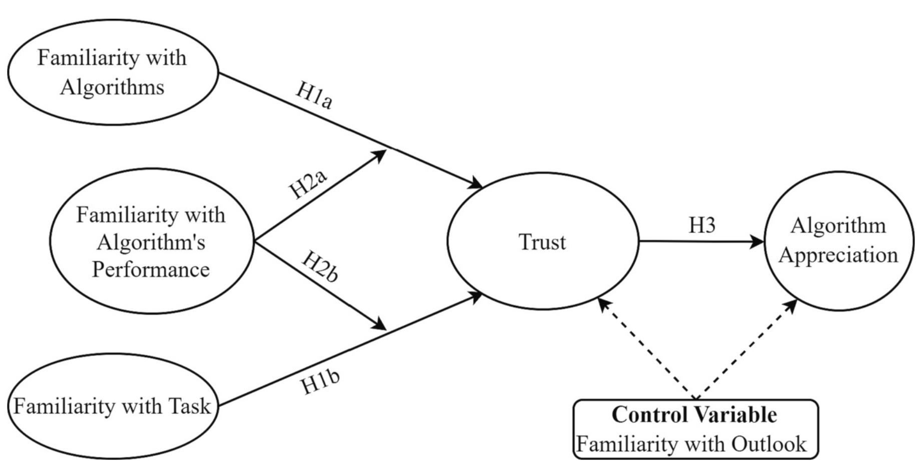


**Fig. 1.** Proposed research model.

**Table 2**
Distribution of respondents.

| | |
|---|---|
| Condition 1: Unfamiliarity with performance (positive outlook: 78, negative outlook: 72) | 150 |
| Condition 2: Familiarity with performance (positive outlook: 82, negative outlook: 95) | 177 |

investors in the stock market and instructed to forecast the index value of the S&P 500 one month from the current date. To facilitate their tasks, a line chart depicting the historical values of the S&P 500 Index was presented. To aid in their understanding of the chart, the following key statistics from the chart were presented in text format (Table 3). The participants were then asked to enter their predictions.

In the following stage, participants were informed about a stock market prediction algorithm developed by a financial investment firm. It was conveyed that, based on the current situation, the algorithm held an optimistic (pessimistic) perspective and provided an estimated value higher (lower) than the current index value. After that, the predicted score of the algorithm was presented, without any information about its accuracy. Hence, we manipulated the experimental condition by ensuring the participants' unfamiliarity with the algorithm's performance and introducing a positive (negative) outlook. Participants were then asked to enter their final predictions based on this new information, with the freedom to either follow or discount the algorithm's prediction. After completing the prediction task, participants were asked to indicate their position on various statements related to the constructs under study and provide demographic information.

**Condition 2: Familiarity with performance.** In this condition, the experimental procedure closely resembled that of Condition 1, except that additional information concerning the rate of accuracy of the algorithm's predictions was provided to manipulate FP. Specifically, participants were informed that the algorithm's estimates were more accurate than those of professional investment advisors about 80% of the time.

### 4.3. Measures

We found two methods in the existing literature for measuring our dependent variable: "algorithm appreciation." The first is called the "binary method," in which individuals are considered to rely on algorithms fully (1) or not fully (0) [15]. For example, in deciding whether a student will pass or fail the next exam, individuals may completely agree (1) or disagree (0) with the prediction of algorithms. The other is called the "non-binary method," in which individuals can apply their discretionary power with more flexibility to decide on the extent to which they would rely on algorithms [15]. This method is also known as the judge–advisor paradigm [36], which is commonly used in the algorithmic decision-making literature [4,5,11]. In the judge-advisor paradigm, the judge (decision-maker) is given a stimulus (stimuli) and invited to provide an initial estimate, which is numerical (e.g., the value of a stock or the exchange rate of a currency) before experiencing the estimate of advisor(s) and an adjusted estimate after receiving the estimate of an advisor. This process allows for the calculation of the weight of advice (WOA) or algorithm appreciation by applying the following formula, which gives a value on a scale from 0 (complete aversion) to 1 (complete appreciation).

**Table 3**
Key statistics provided with the experiment vignette.

| |
|---|
| Today's value |
| Value at 1 year ago today, along with the difference |
| Highest value over the past year, including the date |
| Lowest value over the past year, including the date |
| Maximum increase in points in a given month, along with the month |
| Maximum decrease in points in a given month, along with the month |

$$\text{WOA} = \frac{\text{adjusted estimation} - \text{initial estimation}}{\text{advisor's estimation} - \text{initial estimation}}$$

However, the WOA value may be below 0 or above 1 if decision-makers think that the true value lies outside the range of their initial estimate and the advisor's estimate. Whereas a few studies [11] retained the values as they were, following Logg et al. [5], we winsorized WOA values $>1$ or lower than 0. Aside from algorithm appreciation, we measured FA, FT, and trust using items adapted from the existing literature (Table 4). All constructs were measured using a 7-point Likert scale.

### 4.4. Data analysis

The collected data were initially analyzed using SPSS 28.0.0.0 to assess normality, multicollinearity, and the presence of common method bias (CMB). This step was essential to ensure the suitability of the data for subsequent analysis. In the next stage, SmartPLS 4 was utilized to evaluate construct reliability and validity as well as to test the proposed hypotheses. These analyses followed the partial least squares (PLS) approach to structural equation modeling (SEM). PLS is a suitable approach if the objective of a study is to investigate the validity of a research model and to examine the hypothesized connections within it [34]. The significance of the path coefficients was determined using 5000 bootstrap samples [34].

## 5. Results

### 5.1. Normality, multicollinearity, and common method bias

The normality of the data was confirmed by scanning the skewness and kurtosis values. Scholars lack consensus in determining the acceptable values of skewness and kurtosis to validate the normality assumption of the data. For example, according to Leech et al. [40], skewness values within the range of $\pm 1.0$ are considered normal. According to Kim et al. [41], absolute skewness values $<2$ and absolute kurtosis values $<7$ are considered normal. However, in our case

**Table 4**
Constructs and their measurement items.

| Construct | Item No. | Item | Source |
|---|---|---|---|
| Familiarity with algorithms (FA) | FA_1 | I am familiar with algorithms that provide a prediction. | [11,20,37] |
| | FA_2 | I am familiar with how algorithms provide an estimation. | |
| | FA_3 | I am familiar with receiving estimations from algorithms. | |
| | FA_4 | Overall, I am familiar with algorithms. | |
| Familiarity with tasks (FT) | FT_1 | I know how to predict the value of the stock market index. | [38] |
| | FT_2 | I understand the factors that influence the value of the stock market index. | |
| | FT_3 | I can follow the established practices to predict the value of the stock market index. | |
| | FT_4 | I often do the task of predicting the value of the stock market index. (New) | |
| Trust | Trust_1 | I trust algorithms to be reliable. | [39] |
| | Trust_2 | I trust algorithms to be secure. | |
| | Trust_3 | I believe algorithms are trustworthy. | |
| | Trust_4 | I trust algorithms. | |
| | Trust_5 | Even if algorithms are not monitored, I'd trust them to do the job correctly. (Dropped) | |

**Table 5**
Descriptive statistics, skewness, and kurtosis.

| Variable | Mean (n = 327) | Std. Dev. | Skewness | Kurtosis |
|---|---|---|---|---|
| Familiarity with algorithms (FA) | 4.211 | 1.449 | −0.434 | −0.635 |
| Familiarity with tasks (FT) | 3.304 | 1.333 | 0.129 | −0.890 |
| Trust | 4.606 | 1.109 | −0.505 | −0.269 |
| Algorithm appreciation | 0.448 | 0.385 | 0.069 | −1.543 |

(Table 5), the skewness and kurtosis values were within the recommended range, thus ensuring the normality of the data. There was no multicollinearity issue, as the variance inflation factor (VIF) values for all latent variables ranged between 1.007 and 3.088, which was within the recommended threshold of 5 [42,43].

Finally, to address concerns regarding CMB, several statistical tests were conducted. First, we examined potential CMB issues by observing the correlations between the latent variables. The inter-construct correlation matrix (Table 6) did not indicate any highly correlated factors. The highest correlation was $r = 0.477$, which is much lower than the recommended threshold ($r > 0.90$) [43,44]. Second, the marker variable technique was used to assess the potential threat of CMB. The variable of education was chosen as the marker variable because it does not have any substantive relationship with the endogenous variables under investigation [45]. The results indicated a low average correlation coefficient of −0.042 between the marker variable and other variables, which is below the 0.100 threshold [45]. This suggests that CMB was not significant in this study [46]. Third, a Harman one-factor test [47] was conducted, revealing that a single factor accounted for only 41.99% of the variance, which is well below the 50% threshold [48]. Fourth, the common method factor approach [49] was employed in the measurement model by creating a set of single-indicator constructs, utilizing all indicators of original constructs. These single-indicator constructs were subsequently connected to their respective original constructs. Finally, a method construct was created by utilizing all indicators from each original construct and linking them to all single-indicator constructs. To assess the presence of CMB, careful analysis was conducted on the factor loadings and the variance explained by the method factor concerning the constructs under investigation [50]. The findings indicated that all measurement items exhibited higher loadings on their respective constructs compared to the common method factor, and the variance attributed to the method factor was found to be significantly lower than that of the constructs. Thus, we conclude that CMB has no substantial influence on the outcomes of the study.

### 5.2. Measurement model

To ensure that the constructs' items, which are theoretically related, are also relevant in reality [51], we assessed convergent validity by evaluating item loadings, composite reliability (CR), Cronbach's alpha (CA), and average variance extracted (AVE) (Tables 6 and 7). We maintained a minimum threshold of 0.70 for item loading, 0.8 for CR, 0.7 for CA, and 0.5 for AVE, following the guidelines outlined by Fornell and Larcker [52]. To comply with these criteria, we dropped one item from the trust construct, thus confirming convergent validity.

**Table 6**
Construct reliability, discriminant validity, and correlation matrix.

| | CR > 0.7 | CA > 0.7 | AVE > 0.5 | 1 | 2 | 3 |
|---|---|---|---|---|---|---|
| 1. FA | 0.940 | 0.922 | 0.808 | **0.899** | | |
| 2. FT | 0.931 | 0.877 | 0.723 | 0.477 | **0.850** | |
| 3. Trust | 0.929 | 0.927 | 0.820 | 0.348 | 0.125 | **0.906** |

CR – composite reliability; CA – Cronbach's alpha; AVE – average variance extracted; Bold numbers on the diagonal of the matrix represent the square roots of the AVEs.

**Table 7**
Loadings of measurement instruments.

| Constructs | Indicators | Loadings/cross-loadings | | |
|---|---|---|---|---|
| | | 1 | 2 | 3 |
| 1. Familiarity with algorithms (FA) | FA_1 | **0.902** | 0.451 | 0.289 |
| | FA_2 | **0.885** | 0.484 | 0.255 |
| | FA_3 | **0.900** | 0.429 | 0.306 |
| | FA_4 | **0.909** | 0.376 | 0.376 |
| 2. Familiarity with tasks (FT) | FT_1 | 0.479 | **0.901** | 0.125 |
| | FT_2 | 0.350 | **0.760** | 0.040 |
| | FT_3 | 0.424 | **0.896** | 0.124 |
| | FT_4 | 0.341 | **0.835** | 0.093 |
| 3. Trust | Trust_1 | 0.310 | 0.086 | **0.905** |
| | Trust_2 | 0.343 | 0.176 | **0.868** |
| | Trust_3 | 0.284 | 0.106 | **0.932** |
| | Trust_4 | 0.326 | 0.092 | **0.918** |

Next, to ensure that the items within a construct effectively measured that particular construct [53], we assessed discriminant validity using various methods. First, following the Fornell–Larcker criterion [52], discriminant validity was assessed by comparing the square roots of AVEs with the inter-construct correlations. Table 6 displays these comparisons: the diagonal entries, representing the square roots of AVEs, were consistently higher than the off-diagonal inter-construct correlations, thus confirming the discriminant validity between the constructs [52]. Second, we compared whether the item loadings were higher than the cross-loadings to further ensure discriminant validity [53]. Table 7 also confirms discriminant validity in this regard. Third, AVE was compared with the maximum shared variance (MSV) and the average shared variance (ASV) [54]. The analysis revealed that AVE was higher than MSV and ASV, thus establishing discriminant validity. Additionally, we performed HTMT analysis, in which the values were well below the 0.85 threshold (Table 8) [55], suggesting the discriminant validity of the constructs.

### 5.3. Structural model

A structural model was created to test the strength of the hypothesized relationships and to understand the variance explained by the structural model [51]. Fig. 2 depicts the results of the structural modeling. As expected, the results indicated a significant positive impact of FA on trust in algorithms, thus providing substantial support for H1a ($\beta = 0.240$, $p < 0.01$). However, contrary to our hypothesis (H1b) that there is a significant relationship between FT and trust, the model found an insignificant effect ($\beta = 0.022$, ns). Following this, trust in algorithms ($\beta = 0.325$, $p < 0.001$) was found to have a significant positive influence on algorithm appreciation. Hence, H3 was supported. The moderation analysis indicated that FP significantly moderates the relationship between FA and trust in algorithms (H2a), but no such moderation exists in the relationship between FT and trust (H2b). The interaction effect is presented in Fig. 3. Finally, as for the control variable, the effects of FO on trust and algorithm appreciation were not significant. Altogether, the model explained 15.80% of the variance in trust and 11.30% of the variance in algorithm appreciation. The findings of the hypotheses testing are presented in Table 9.

**Table 8**
HTMT analysis.

| | FA | FT | Trust |
|---|---|---|---|
| FA | | | |
| FT | 0.526 | | |
| Trust | 0.370 | 0.127 | |

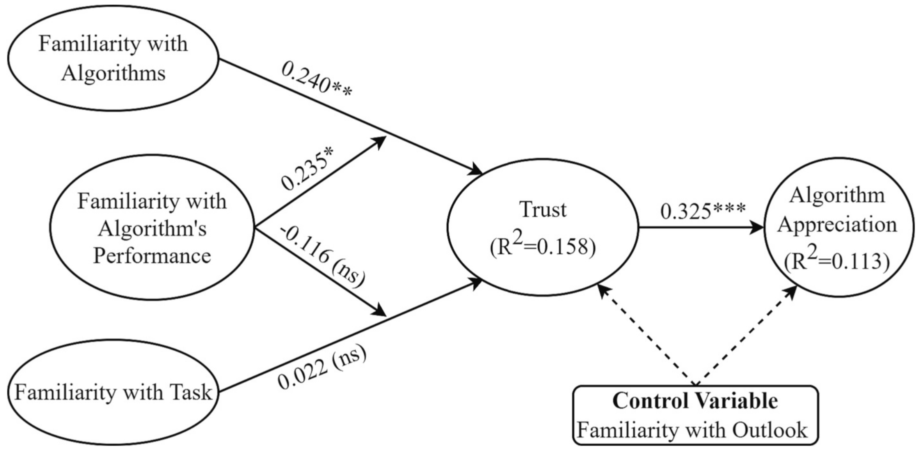


**Fig. 2.** PLS analysis results ***p < 0.001; **p < 0.01; *$p$ < 0.05; ns: not significant.

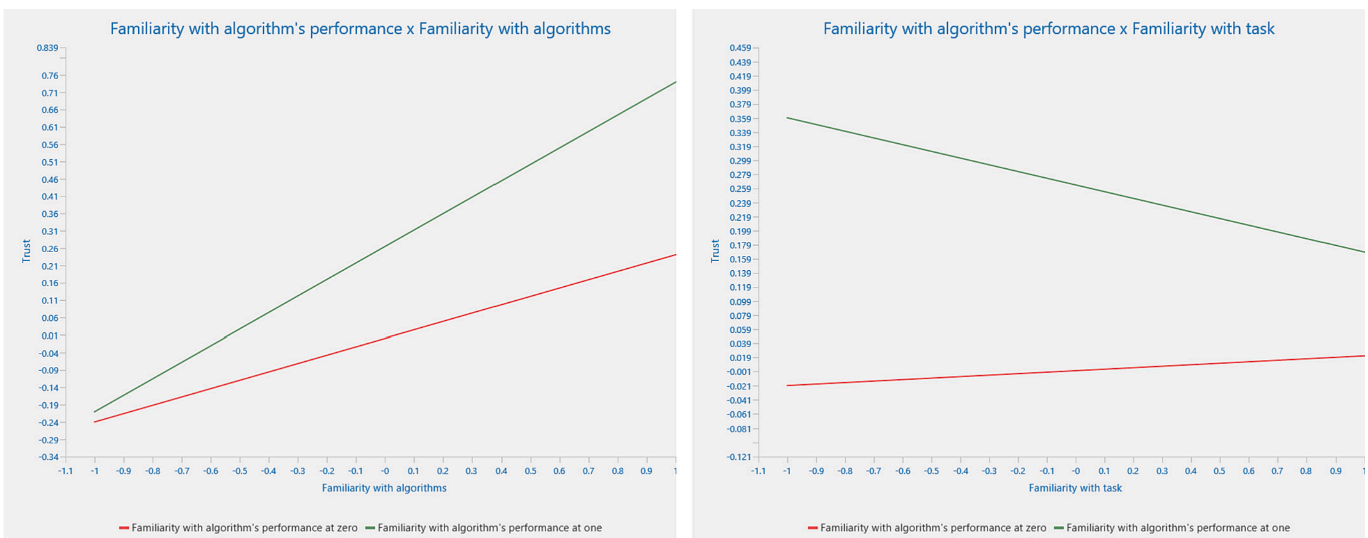


**Fig. 3.** Interaction effect.

**Table 9**
The overall hypothesis testing results.

| Hypotheses | Path | Path coefficient | SD | *P*-values | Conclusion |
|---|---|---|---|---|---|
| H1a | FA → Trust | 0.240 | 0.098 | 0.007 | Supported |
| H1b | FT → Trust | 0.022 | 0.102 | 0.415 | Not supported |
| H2a | FP*FA → Trust | 0.235 | 0.127 | 0.032 | Supported |
| H2b | FP*FT → Trust | −0.116 | 0.127 | 0.180 | Not supported |
| H3 | Trust→AA | 0.325 | 0.051 | 0.000 | Supported |

SD = Standard deviation.

## 6. Post hoc analysis

### *6.1. Mediation and power analysis*

We performed a post hoc analysis to examine both the effect sizes of the mediated relationships and the direct effects of FA and FT on algorithm appreciation. The analysis revealed that FA had no significant direct effect on algorithm appreciation ($\beta = 0.043$, $p > 0.05$), suggesting that the relationship between FA and algorithm appreciation is fully mediated by trust. The mediated effects are illustrated in Table 10. We also found a direct effect of FP on trust ($\beta = 0.264$, $p < 0.01$).

**Table 10**
Indirect (mediated) effects of the model constructs.

| Indirect effects | Effect size | Standard deviation | *p*-value |
|---|---|---|---|
| FA - > Trust - > Algorithm Appreciation | 0.080 | 0.035 | 0.011 |
| FT - > Trust - > Algorithm Appreciation | 0.008 | 0.035 | 0.414 |

Additionally, a post hoc power analysis was conducted to ascertain the sufficiency of both effect sizes and sample size to determine if the model possessed the necessary statistical power. This analysis is important to ensure the model's ability to reject null hypotheses and minimize the risk of Type II errors (i.e., failing to reject a false null hypothesis). The post hoc power analysis indicated a power level of 1, in comparison to 0.95 in the a priori power analysis. This result suggests that the study had an extremely high probability of correctly detecting a statistically significant effect if such an effect truly existed. In other words, it had a 100% chance of correctly rejecting the null hypothesis and finding a true effect.

### 6.2. Robustness check

We conducted several additional analyses to ensure the robustness of our findings. First, to validate the moderation effect, we performed an exploratory analysis. During the experiments, the participants were asked to briefly mention the reasons for adjusting or maintaining their initial estimates after receiving the algorithm's estimate. We found that participants were more likely to change their initial estimates when they learned about the algorithm's success rate. Some of the participants' statements are quoted below:

> "I changed my answer based on the fact that the algorithm predictor has an 80% accuracy rate."
> "The statistics provided about the algorithm state that it is correct 80% of the time. Therefore, I decided to go with it but not put the whole estimated value, since there is still 20% of the time where it's not correct."
> "Because the algorithm is it said to have a higher accurate, which motivated me to change my estimate."
> "Since the algorithm is more accurate than average estimates of professional investors and I'm nowhere close to being an investor, I took the algorithm advice and lowered my final estimate."

Second, robustness was examined by testing an alternative model. In the original model, trust is regarded as a dependent variable with the assumption that FA, FT, and FP can influence an individual's trust in algorithms. In the alternative model, we replaced the dependent variable "trust" with "word-of-mouth intention," as it can also be an outcome variable of different forms of familiarity under investigation [56,57]. Individuals who possess FA and FP are more likely to spread positive word of mouth [58,59]. Similarly, individuals who have FT might not be motivated to share word of mouth because they are more confident in their decision-making capabilities [9]. We ran the alternative model in SmartPLS and found compelling evidence supporting the validity of our research model, thereby enhancing the robustness of our findings.

Third, to establish the validity and stability of our findings, we also performed a robustness check following the procedures outlined by Wang et al. [60]. We assessed the impact of additional demographic factors (i.e., age, education, employment, and gender) on trust and algorithm appreciation by including them in our analysis as control variables. This allowed us to examine potential alterations, if any, in the hypothesized path estimates. Regarding the direction of the relationships and statistical significance, our findings closely mirror those reported in Table 9. Only employment status ($\beta = -0.153$, $p < 0.05$) exhibited a significant negative impact on trust. However, the inclusion of these control variables did not yield any substantial alterations in the results, supporting the robustness of the structural model's results.

### 6.3. Endogeneity

The purpose of the endogeneity test is to identify whether relationships are biased or inconsistent due to the presence of a correlation between the independent variable and the error term of the model [61]. In a regression model, accounting for endogeneity is crucial to ensure the validity of causality [62]. To examine the presence of endogeneity within our model, we employed the Gaussian copula approach, following prior studies [62–64]. First, we assessed whether the independent variables that may exhibit endogeneity were non-normally distributed. The assessment was conducted by performing the Kolmogorov–Smirnov test with Lilliefors correction [65], utilizing the latent variable scores from the original model as inputs. The outcomes indicated that the independent variables did not follow a normal distribution, thus allowing us to adopt Park and Gupta's [64] Gaussian copula approach. The results of the Gaussian copula process with 10,000 bootstrapped samples indicate that the Gaussian copula for FT was significant ($p < 0.05$), while Gaussian copulas for FA and trust were insignificant ($p > 0.05$) across all combinations of Gaussian copulas included in the model.

To address the endogeneity issue, we followed the approach suggested by Hult et al. [62]. According to them, two widely accepted and commonly used approaches are the control variable approach and the instrument variable approach. Since we did not collect data ex ante for an instrument variable that is closely related to the independent variable FT, we employed the control variable approach. We chose education as the control variable because education plays a critical role in shaping an individual's FT. We reran the Gaussian copula process, incorporating education as a control variable for the FT construct. The findings revealed that none of the three predictor constructs of algorithm appreciation yielded significant copulas: 0.303 for trust ($p = 0.157$), 0.276 for FA ($p = 0.160$), and $-1.058$ for FT ($p = 0.052$), suggesting that endogeneity is not a major concern in our model.

## 7. Discussion

### 7.1. Key findings

We systematically examined the direct effects of FA and FT on trust in algorithms. Additionally, we assessed the influence of trust on algorithm appreciation. We also investigated the moderating role of FP in the relationships between FA or FT and trust in algorithms.

Our findings indicate that FA significantly enhances trust in algorithms, a result consistent with previous research [8,13,14,28]. This outcome emphasizes that individuals who perceive algorithms as familiar tend to view them as more reliable and experience fewer uncertainties when engaging with them, leading to elevated levels of trust [13]. However, an interesting discovery emerged from our study: trust mediates the relationship between FA and algorithm appreciation, aligning with previous studies [2,10,14,36,66,67]. These results suggest that FA has no direct relationship with algorithm appreciation. However, this relationship is fully mediated by trust. Therefore, individuals with FA must also place trust in algorithms to implement algorithmic decisions. This novel insight reveals the pivotal role of building trust among individuals to facilitate the integration of algorithms in decision-making.

Interestingly, our data did not support the expected relationship posited in H1b regarding FT and trust. We observed an insignificant relationship between FT and trust, which contradicts the assumption that task experience reduces reliance on algorithms [8,9]. Instead, our findings align with previous studies that also found insignificant relationships between FT and trust [7,8]. This inconsistency among the studies may be explained by the findings of our post hoc analysis, which revealed a significant direct negative relationship between FT and algorithm appreciation. This suggests that, unlike the relationship between FA and algorithm appreciation, the relationship between FT and algorithm appreciation is not contingent on other factors, such as trust in algorithms.

Finally, our results revealed that the relationship between FA and trust is moderated by FP, indicating that the impact of FA on trust is contingent on FP. These findings challenge previous notions [10,32,68] that individuals may be hesitant to rely on algorithms even when they are aware of the superior performance of algorithms. Conversely, our findings corroborate studies [2,6,12] that demonstrated increased trust when individuals were informed about the superior performance of algorithms.

### 7.2. Implications for research

Our study offers several valuable theoretical implications for the field of algorithmic decision-making. First, drawing upon prior research on algorithmic decision-making [1,5,6,10,19], we provide a theoretical framework demonstrating the influences of different forms of familiarity on trust and algorithm appreciation. A unique aspect of our study lies in the concurrent exploration of the distinct effects of FA and FT within a single study. While prior research has examined FA and FT separately in various contexts [9,27], our study fills a crucial gap by comprehensively exploring both aspects within the same study and context [8]. This simultaneous examination enhanced our understanding of their distinctive influences. Furthermore, we introduced FP as a moderating variable and FO as a control variable in our model. By incorporating these three dimensions of familiarity within a single study, we offer a holistic understanding of their impact on trust in algorithms. This effort not only advances the field but also opens avenues for further investigation. Future research might explore these relationships and examine them in different contexts.

Second, our study contributes to the growing body of literature on fairness, accountability, and transparency (FAT) in algorithmic decision-making [69–72]. Algorithms often face criticism for their lack of transparency, and recent regulations are placing greater emphasis on this issue [69]. Our study sheds light on the pivotal role played by increased performance transparency in reinforcing individuals' trust in algorithms, essentially turning the mysterious algorithmic black box into a transparent "glass box." Our empirical findings provide concrete evidence that individuals are more likely to trust algorithms when they are familiar with an algorithm's superior performance [2,12].

Third, our study offers insights to address the inconsistencies observed in the impact of FT and FP on trust. Our results challenge the prevalent assumption that individuals are reluctant to embrace algorithmic advice, even when they are acquainted with the superior performance of algorithms [10,32]. Instead, our findings indicate that individuals who possess FP tend to place greater trust in algorithms [2,6]. Additionally, our study uncovered another unexpected aspect: we found no significant relationship between individuals' FT and trust [7], which contradicts previous findings that FT negatively influences trust in algorithms [5,8,9].

Fourth, our study highlights the pivotal role of trust in understanding algorithm appreciation [2]. Consistent with prior studies [14,66,68,73], our findings suggest the presence of mediating effects of trust in utilizing algorithmic advice. This underscores the importance of building trust among individuals to encourage their adherence to algorithmic advice. Additionally, it opens a future research avenue in algorithmic decision-making. For example, future research might explore specific factors, such as transparency or ethical considerations, that could influence the development of trust in algorithms.

### 7.3. Implications for practice

Our findings have substantial implications for the managers and designers of algorithms in practice. First, it underscores the profound implications for decision-makers and organizations in understanding how individuals trust algorithmic advice [5]. Individuals' trust in algorithms is intrinsically connected to their level of FA [13], emphasizing the importance of individuals' familiarity with algorithms [20]. Thus, our study guides organizations to ensure that their employees are familiar with the values and capabilities of algorithms. In this regard, organizations need to adopt a comprehensive strategy, focusing on educating and training potential users about fundamental aspects of algorithmic advice such as capabilities, accuracy, and performance metrics [9,20]. These strategic measures not only enhance FA but also reinforce trust, which leads to an increased appreciation of algorithms. Increased algorithm appreciation enables organizations to effectively leverage the benefits of algorithms, ultimately strengthening their competitiveness in data-driven business environments.

Second, our study highlights the critical role of FP in nurturing trust in algorithms, a discovery that bears significant importance for managers and algorithm designers. The extent to which individuals trust algorithms is influenced by the transparency of the algorithms' performance [10]. Providing information regarding an algorithm's performance significantly contributes to the increased acceptance and utilization of algorithms [12]. This is particularly crucial to individuals who evaluate algorithms considering not only the algorithms' decisions but also the transparency behind these decisions [68]. Therefore, managers should prioritize transparent communication and documentation of the algorithm's reliability [15] to mitigate individuals' reluctance to follow algorithmic advice. Furthermore, in the ongoing debate about the implications of AI-based systems being perceived as black boxes, our findings suggest that algorithm designers should consider opening the black box, demonstrating algorithm reliability to end users [9]. For example, in healthcare, algorithms are commonly used for disease diagnosis and treatment plans, but their actual usage depends on the perceived accuracy and reliability as assessed by healthcare professionals. This perception is crucial as the decisions pose significant impacts on patients' lives. Sharing performance information such as accuracy rates, success in early disease detection, or comparative studies with human diagnostics can significantly enhance perceived reliability, boosting trust among healthcare professionals.

Third, the results suggest that trust completely meditates the impact of FA on algorithm appreciation, indicating that mere FA is not sufficient to guarantee the use of algorithms. This finding has significant importance for practitioners. Practitioners and managers who want their users to use algorithms need to ensure that their users trust algorithms. To improve user trust, organizations can take several steps, such as ensuring an algorithm's physical presence, transparency, reliability, and human likeness and conducting bias audits to ensure fair and equitable outcomes [74]. For instance, in the finance and banking industry, while professionals and customers are cognizant of algorithms used for risk assessment, fraud detection, and personalized services, the ultimate use of these algorithms hinges on trust. Skepticism about the fairness and equality of algorithmic decisions can discourage their use, considering the substantial impact of these decisions on customer's financial plans. To address this issue, it is advisable to carry out periodic assessments of bias to ensure algorithmic fairness and trust.

## 8. Limitations and future research

Despite the robustness of the study, it has a few limitations that must be acknowledged. First, our study employed a cross-sectional design, which may not fully capture the evolving dynamics of familiarity and trust among individuals. To address this issue, future research could employ a longitudinal approach. Second, our research was confined to a specific context (stock market), which could potentially restrict the generalizability of our findings. Therefore, we recommend that future studies replicate our research in diverse settings to validate our results. Third, the variance explained by the model was in the moderate range. Other scholars may replicate our study by considering additional variables, such as privacy concerns and perceived fairness, to determine whether the model has more predictive power.

Additionally, our findings pave the way for several future research directions that can further expand our knowledge in this area. First, the present study revealed an insignificant relationship between FT and trust in algorithms. To further advance this line of inquiry, future investigations could explore potential mechanisms aimed at enhancing trust among individuals who possess familiarity with the specific task at hand. Researchers may consider experimenting with the length of FT and various moderators and mediators that have the potential to amplify or attenuate this relationship. Second, we posited that algorithm aversion and appreciation are opposites. Future research should measure both constructs and potentially incorporate them into the same model to explore whether they are indeed opposites and share common determinants. Third, although FP has been examined as a moderator in several recent studies [2,6] as well as in our current study, our post hoc analysis revealed a direct effect of FP on trust. This discovery indicates an important relationship that needs further investigation. Fourth, following the study of You et al. [2], we manipulated FP by providing performance information as an aggregated score. Future research could examine the impact of detailed performance information instead. This investigation would help to understand how individuals process and respond to specific performance-related information about algorithms. Fifth, in this study, we examined FA, FT, FP, and FO to understand algorithm appreciation, comparing an individual's own decision with that made by algorithms. However, the appreciation of algorithms may vary if individuals have the option to compare algorithmic decisions with those made by human experts [1]. Therefore, future research could enhance our model by incorporating a dimension of familiarity with human experts. This addition would offer a more comprehensive understanding of how various types of familiarity, including familiarity with human experts, influence the appreciation of algorithms.

## 9. Conclusion

In algorithmic decision-making, understanding how individuals perceive and interact with algorithms is of paramount importance. This study delved into the growing field of algorithm appreciation by examining how different forms of familiarity shape individuals' trust in algorithms. This research presented a comprehensive model, backed by empirical evidence, highlighting three critical factors that influence algorithm appreciation: FA, FT, and FP. The results underlined the pivotal role of FA as a foundation for building trust in algorithms, which in turn drives algorithm appreciation. Notably, the findings indicated an insignificant impact of familiarity with tasks on trust. Furthermore, FP moderates the relationship between FA and trust, underpinning the importance of an algorithm's performance transparency in building trust. Importantly, our research established trust as a full mediator between FA and algorithm appreciation, emphasizing the importance of building trust among individuals to foster algorithm appreciation. As our society increasingly relies on algorithmic decision-making, understanding the drivers of algorithm appreciation is vital in harnessing the benefits of algorithms. Thus, our study contributed to the evolving field of algorithm appreciation by equipping scholars and practitioners with insightful findings that demonstrated strong robustness and consistency.

## Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to improve language and readability, with caution. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

## CRediT authorship contribution statement

**Hasan Mahmud:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **A.K.M. Najmul Islam:** Writing – review & editing, Supervision, Methodology, Data curation, Conceptualization. **Xin (Robert) Luo:** Writing – review & editing, Supervision, Methodology. **Patrick Mikalef:** Writing – review & editing, Supervision.

## 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.

## Data availability

Data will be made available on request.

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**Hasan Mahmud** is a Junior Researcher and doctoral candidate at the Software Engineering Department of LUT School of Engineering Science, LUT University, Finland. Before starting his doctoral studies, he served many years in FMCG and the banking sector. His research interests include artificial intelligence, algorithmic decision, and digital transformation. His research has been published in respected journal such as Technological Forecasting and Social Change.

**A.K.M. Najmul Islam** is a Professor at the Software Engineering Department of LUT School of Engineering Science, LUT University, Finland. His research has been published in top outlets including European Journal of Information Systems, Information Systems Journal, Journal of Strategic Information Systems, Technological Forecasting and Social Change, Computers in Human Behavior, Internet Research, Computers & Education, Journal of Medical Internet Research, Information Technology & People, Telematics & Informatics, Journal of Retailing and Consumer Research, Communications of the AIS, Journal of Information Systems Education, AIS Transaction on Human-Computer Interaction, and Behavior & Information Technology. His research interest includes human–centered computing.

**Xin (Robert) Luo** is a Special Assistant to the Dean for Research Advancement, an Endowed Dean's Professor of Research Excellence, and a Full Professor of Management Information Systems and Information Assurance at the Anderson School of Management of the University of New Mexico, Albuquerque, USA. He received his Ph.D. in Management Information Systems from Mississippi State University, USA. His research has been or will be published in leading IS/ business journals, including the *Information Systems Research, Journal of Operations Management, Production and Operations Management, Journal of Management Information Systems, Journal of the Association for Information Systems, European Journal of Information Systems, Information Systems Journal, Journal of Strategic*

*Information Systems, Journal of Information Technology, Decision Sciences, Decision Support Systems, Information & Management*, and *IEEE Transactions on Engineering Management*. He has served as an ad hoc Associate Editor for *MIS Quarterly* and an Associate Editor for the *European Journal of Information Systems*, and currently serves as an Associate Editor for the *Decision Support System*, *Journal of the Association for Information Systems, Decision Sciences, Information & Management, Electronic Commerce Research*, and the *Journal of Electronic Commerce Research*. He also sits on the Editorial Review Board of *Information Systems Research* and serves as a Guest AE for special issues of *Journal of Management Information Systems* and *Decision Support Systems*. His research interests center around information assurance, innovative technologies for strategic decision-making, and global IT management. He is the Co-Editor-in-Chief of the *International Journal of Accounting and Information Management*.

**Patrick Mikalef** is a Professor in Data Science and Information Systems at the Department of Computer Science. In the past, he has been a Marie Skłodowska-Curie post-doctoral research fellow working on the research project "Competitive Advantage for the Data-driven Enterprise" (CADENT). He received his B.Sc. in Informatics from the Ionian University, his M.Sc. in Business Informatics for Utrecht University, and his Ph.D. in IT Strategy from the Ionian University. His research interests focus the on strategic use of information systems and IT-business value in turbulent environments. He has published his work in over 150 international conferences and peer-reviewed journals including the Journal of the Association for Information Systems, European Journal of Information Systems, Journal of Business Research, British Journal of Management, Information and Management, Industrial Management & Data Systems, and Information Systems and e-Business Management. He serves as a senior editor of the European Journal of Information Systems and as editor of Information of Management. Patrick Mikalef is also a distinguished member of the Association for Information Systems (AIS).