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Debiasing anchoring bias in the context of telemedicine

Abstract: Clinical decision-making in the context of asynchronous 'store-and-forward' telemedicine can be susceptible to the cognitive shortcut of anchoring bias. This paper aims to (1) examine the effect of cognitive style, cognitive ability, and information breadth on anchoring bias in telemedicine, (2) validate the effectiveness of a composite debiasing strategy, (3) investigate how the extent of debiasing is affected by cognitive style, cognitive ability, and information breadth. A pretest-posttest experiment was conducted among 72 medical students with a composite debiasing strategy as an intervention. Results indicated that information breadth increased individuals' susceptibility to anchoring bias. The composite debiasing strategy was successful in reducing anchoring bias. The debiasing effect was particularly pronounced among individuals with high cognitive ability. Furthermore, cognitive style interacted with cognitive ability to affect the reduction in anchoring bias. The debiasing worked best for high cognitive ability and intuitive cognitive style. The paper draws on the literature on cognitive psychology and clinical decision-making to contribute as one of the earliest efforts to study anchoring bias in telemedicine.

Keywords: anchoring bias; healthcare information technology; information overload; health professionals; medical informatics; telemedicine.

1. Introduction

Telemedicine became popular amid city-wide lockdowns and travel restrictions during the height of the COVID-19 outbreak. By making remote consultation and diagnosis easily available through technology, patients could remain in the comfort of their homes without the risk of exposing to the virus. With its convenience, efficiency, accessibility and inclusivity, telemedicine looks set to be firmly cemented in the healthcare landscape even after the pandemic has receded (Elkefi & Layeb, 2023; Tensen et al., 2024).

Nonetheless, integrating technology into medicine comes with unique challenges and decision-making quirks (Haimi et al., 2018; Khoong et al., 2022). In particular, unlike synchronous telemedicine, asynchronous telemedicine using a store-and-forward approach bears no resemblance to an actual in-person consultation (Tensen et al., 2024). There is no provision for dynamic clinical interactions. Medical information is first collected and then transmitted for diagnosis and treatment recommendations. With no opportunity for real-time dialogue, communication difficulties are amplified between clinicians and patients, and among clinicians across departments (Haimi et al., 2018). When clinicians are not co-located, they can only rely on less nuanced communication modalities such as briefly written notes. Decisions are made without the benefit of considering subtleties that lie beyond cold, hard data. This opens the door to using cognitive shortcuts (Hansen et al., 2020), potentially resulting in anchoring bias.

Anchoring bias is the tendency in decision-making to overly rely on an initial point of reference, known as an anchor, even though the anchor is arbitrary (Tversky & Kahneman, 1974). It is notoriously deep-seated and has profound ramifications. For example, staff performance evaluations could be severely biased (Cantarelli et al., 2020), and clueless online buyers unwittingly relied on banner advertisement to make price estimates (Wu et al., 2012).

In the medical context, anchoring bias can manifest as diagnostic momentum, which refers to a clinician's inclination to accept a previously made diagnosis, often by a colleague, without thorough scrutiny (Satya-Murti & Lockhart, 2015). Exacerbated by time constraints, fatigue, or simply choosing to take mental shortcuts, anchoring bias raises safety concerns due to delays in delivering appropriate care and contributes to medical errors (Croskerry, 2003; Satya-Murti & Lockhart, 2015; Singh et al., 2014; Loncharich et al., 2023). For example, a female patient who experienced dramatic weight loss was wrongly diagnosed and treated for anorexia nervosa (Groopman, 2007). Exemplifying anchoring bias, every clinician thereafter saw her through the lens of a neurotic patient with disordered eating even though she was actually suffering from coeliac disease. The result was 15 years of futile treatment (Wright & Sittig, 2008).

Healthcare information technologies have hitherto been mostly studied from the perspective of user adoption (Albarrak et al., 2021; Bao & Lee, 2024; Werner & Karnieli, 2003; Zhang et al., 2020). The focus has been on factors that promote or hinder individuals' willingness to accept and use. Relatively scant attention has been paid to examining the consequences after these technologies are adopted. As healthcare becomes increasingly digitized, this paper is motivated by the need to understand how the asynchronous 'store-and-forward' mode of telemedicine might create an environment conducive to anchoring bias for clinicians and the extent to which this problem could be mitigated. Such an effort is timely given that human error is known to be a key contributor to adverse events in healthcare (Croskerry, 2003; Singh et al., 2014).

In addition, the paper considers three factors: cognitive style, cognitive ability, and information breadth. Cognitive style and cognitive ability are important to study given that they are inherently associated with susceptibility to cognitive biases (Stanovich & West, 1998; Trippas et al., 2015). Information breadth is another pertinent factor because decision-making in telemedicine must contend with the volume of information available (Naeem & Bhatti, 2020). Results from investigative diagnoses such as bloodwork and imaging tests represent a wider information breadth compared to those collected from bedside history-taking and physical examination alone (Croskerry, 2002). Yet, the effect of information breadth on cognitive biases in telemedicine remains unknown.

Therefore, set in the context of asynchronous 'store-and-forward' telemedicine, this paper has three purposes. The first is to examine the effect of two human factors, namely, cognitive style and cognitive ability, in conjunction with the situational factor of information breadth on anchoring bias. The second is to empirically validate the effectiveness of a composite debiasing strategy to reduce anchoring bias. The third is to investigate how the extent of debiasing is affected by cognitive style, cognitive ability, and information breadth. Specifically, the following research questions (RQs) are formulated for investigation:

RQ1: How is anchoring bias affected by cognitive style, cognitive ability, and information breadth?

RQ2: To what extent can anchoring bias be reduced using a composite debiasing strategy?

RQ3: How is the extent of debiasing influenced by cognitive style, cognitive ability, and information breadth?

A pretest-posttest experiment was conducted to address the research questions. A composite debiasing strategy served as the intervention. The significance of this paper is two-fold. Theoretically, it adds to the literature by studying healthcare information technology beyond the perspective of user adoption. It expands the general understanding of anchoring bias in the hitherto-unexplored context of telemedicine by studying the effectiveness of a composite debiasing strategy in tandem with human factors and information breadth. On the practical front, the results offer insights for clinicians to improve the way they process information. Medical educators could also draw attention to the pitfalls of anchoring bias and infuse the composite debiasing strategy into their curricula.

2. Literature Review

2.1. Human interaction with healthcare information technologies

The literature on how people interact with healthcare information technologies can be broadly divided into two clusters. One includes works that focus on the use of healthcare information technologies by patients. The use of question-answering websites and discussion fora on health-related information exchange among patients has been widely studied (e.g., Demner-Fushman et al., 2020; Elnaggar et al., 2020). Patients' adoption of emerging technologies such as AI-driven healthcare systems and mobile health services has also received scholarly attention (e.g., Esmaeilzadeh, 2020; Zhang et al., 2020). When it comes to telemedicine in particular, patients' willingness to use such services has been a recurring theme in the literature (e.g., Chae et al., 2000; Eikelboom & Atlas, 2005).

The other cluster, to which the current paper contributes, includes works that focus on the use of healthcare information technologies by clinicians. How clinicians use social media and online health communities has been a burgeoning theme (e.g., Bautista et al., 2022; Ghalavand et al., in press; Panahi et al., 2016). A stream of research suggests that the use of healthcare information technologies could give rise to cognitive load (e.g., Hennington et al., 2011; Stadin et al., 2021). The greater the cognitive load, the more likely cognitive biases among clinicians could be induced. This in turn could result in diagnostic and treatment errors (Croskerry, 2003; Singh et al., 2014). While prior studies have shed light on clinicians' willingness to adopt telemedicine (e.g., Albarrak et al., 2021), how cognitive biases arise from the use of telemedicine and the extent to which clinicians can be debiased have remained largely overlooked.

2.2. Cognitive shortcuts and anchoring bias

The dual process theory suggests that individuals' thought processes can be dichotomized into System 1 and System 2 (Kahneman, 2011; Norman et al., 2014; O'Sullivan & Schofield, 2018). The former solves diagnostic problems quickly through heuristic judgements and is thought to be responsible for as much as 85% of all decision-making while the latter is characterized by conscientious analytic reasoning (Chowdhury et al., 2023; Griffith et al., 2020). Reliance on cognitive shortcuts is usually a manifestation of System 1 thinking (Kahneman, 2011).

While cognitive biases have been widely demonstrated in environments such as word-of-mouth opinions (e.g., Yin et al., 2016) and social media algorithms (e.g., Alsaad et al., 2018), there is a dearth of studies in a high-stakes medical decision-making environment that demands specific subject matter expertise. How the peculiarities of asynchronous store-and-forward telemedicine, characterized by the absence of visual cues of the patient and the lack of prospect for target questioning (Haimi et al., 2018), could predispose one to the cognitive shortcut of anchoring bias has not been explored.

As a research theme, anchoring bias has attracted much attention. A dominant stream of investigation examines its antecedents including personality styles (Welsh et al., 2014) and educational background (Calikli & Bener, 2014). Anchoring bias could also be traced to individual differences such as cognitive style and cognitive ability (Appelt et al., 2011; Stanovich & West, 1998).

Cognitive style, defined as the preferred mode of gathering and evaluating information, is commonly measured on an analytic-intuitive spectrum (Allinson & Hayes, 1996), paralleling the System 1-2 dichotomy. Individuals who refrain from responding intuitively have been shown to make fewer inferential mistakes (Djulbegovic et al., 2014). In the same vein, analytic cognitive style is known to lead to reduced cognitive biases (Trippas et al., 2015), as well as a reduced propensity for religious and supernatural beliefs (Pennycook et al., 2012). Thus, cognitive style may influence anchoring bias in telemedicine. Specifically, individuals with analytic cognitive style are expected to be less susceptible to anchoring bias than those with intuitive cognitive style.

Cognitive ability is conceived as the mental capacity for reasoning (Ree et al., 2001). Unsurprisingly, it has been featured in several heuristics and bias studies. For example, cognitive ability was found to be related to cognitive biases such as outcome bias and hindsight bias (Stanovich & West, 1998). However, its link to myside bias was tenuous (Stanovich et al., 2013). It may seem that the higher the cognitive ability, the less likely an individual will be under the influence of cognitive biases. Still, whether cognitive ability has any effect on anchoring bias therefore remains an open question.

Another factor that could influence anchoring bias has to do with decision characteristics (Appelt et al., 2011). In telemedicine, a salient decision characteristic is the breadth of information presented. A quick bedside assessment yields limited patient information such as temperature and heart rate but a formal workup involving an array of investigations to choose from such as laboratory parameters and imaging procedures offers a wider information breadth to support diagnosis (Croskerry, 2002). Obviously, this gives clinicians greater confidence in their assessment of the situation. However, on the downside, a wider information breadth creates the problem of information overload (Naeem & Bhatti, 2020). The notion of 'paradox of choice' describes how an abundance of choices ironically leads to poorer decision-making and greater dissatisfaction (Li, 2016; Schwartz, 2004). Unfortunately, extant literature on anchoring bias has yet to consider the roles played by cognitive style and cognitive ability in conjunction with information breadth.

2.3. Strategies to reduce cognitive biases

Strategies to reduce cognitive biases in clinical practice can be categorized as extrinsic and intrinsic. Extrinsic methods rely on an external impetus such as teachings and checklists. Unfortunately, didactic teachings showed little clinical utility while checklists must be customized specifically for differential diagnoses to be effective (O'Sullivan & Schofield, 2018).

In contrast, intrinsic methods that entail conscious, self-driven cognitive debiasing appear more promising. One common technique is to slow down and naturally segue into System 2 thinking (Norman et al., 2014). For example, in a study involving first- and second-year medical students (Mamede et al., 2010), the introduction of forced slow deliberation was found to effectively reduce diagnostic errors stemming from experimentally induced bias.

A second technique is to practice metacognition by entertaining different possibilities, re-examining decision making as new data emerges, and looking for disconfirming evidence (Croskerry, 2003; Sherbino et al., 2011). Consider-the-opposite strategies have also been empirically proven effective in reducing bias (Mussweiler et al., 2000), albeit not specifically in the context of clinical decision-making.

A third technique, relying on Bayesian reasoning, hinges on the principle that the predictive value of any diagnostic test is determined by its sensitivity and specificity—the ability to pick up true positives and true negatives respectively (Pewsner et al., 2004). Knowledge of sensitivity and specificity of tests are combined with initial pre-test clinical impressions to derive accurate post-test probabilities of the medical condition (Pines, 2006). A randomized controlled trial among paediatric psychiatrists who employed Bayesian reasoning showed promising results in cognitive debiasing (Jenkins & Youngstrom, 2016).

While each of these methods has been studied singularly, the three techniques have neither been synergistically dovetailed nor investigated in tandem with other possible causes of anchoring bias such as cognitive style, cognitive ability, and information breadth. Hence, this paper develops a composite debiasing strategy described in Section 3.2.

3. Methods

3.1. Research design

This study adopted a pretest-posttest experimental design with the debiasing strategy as intervention. It would have been ideal to invite participation from doctors. However, due to the practical challenges of accessibility and scheduling, medical students in Year 3 and above were involved. The deliberate exclusion of freshmen and sophomores ensured that participants possessed the requisite clinical expertise needed for this study.

Evenly distributed across the pretest and the posttest were a total of 12 unique medical case vignettes adapted from PubMed real-life case reports (e.g., Mcfarlane et al., 2013) and a textbook (Morris & Fletcher, 2009). Some cases were incidents of reported misdiagnosis while others were developed by meshing actual and fictitious details. The cases were iteratively written and checked by experienced clinician-educators to ensure realism and fidelity to the literature. These were divided equally between those containing investigative (wide information breadth) and non-investigative (narrow information breadth) medical results.

An erroneous diagnosis was presented at the beginning of each vignette to serve as an anchor for diagnostic momentum. Each anchor was developed from either the possible differential diagnoses in the textbook or the false initial diagnosis highlighted in the case reports. However, the contents were deliberately scripted to contain not only disconfirming evidence to rule out the wrong initial diagnosis but also sufficient evidence pointing to a more compelling alternative. Participants were not told the source of the diagnoses. Their task was to rate the level of agreement with the erroneous initial assessment given in each case on a 10-point scale, adapted from a prior study (Mamede et al., 2008). The higher the level of agreement, the higher the anchoring bias. Hence, reduction in anchoring bias was computed by taking the difference between the mean pretest and posttest scores.

Sequences of the cases were randomized to minimize order effect. Informed by prior works (Sherbino et al., 2014), an additional four dummy cases, two positive and two negative, were inserted to reduce demand characteristic. These were intended to break the potential misperception that the cases were consistently presented as either misdiagnoses or correct diagnoses. Evenly and randomly distributed across the pretest and the posttest, the positive dummy had an unmistakably correct initial diagnosis while the negative one was obviously off the mark. Responses to these dummy cases were excluded from the analyses.

3.2. Debiasing strategy as intervention

The debiasing strategy integrates three extant approaches: slowing down (Mamede et al., 2010; Norman et al., 2014; O'Sullivan & Schofield, 2018), metacognition (Croskerry, 2003; Mussweiler et al., 2000), and Bayesian reasoning (Pewsner et al., 2004; Pines, 2006; Jenkins & Youngstrom, 2016). Thus, it encompasses three steps. The first is to slow down the thought process, making a deliberate effort to be methodical. Next, the focus shifts to metacognition, which is the awareness of one’s own thinking. Different alternatives are weighed before jumping to conclusions prematurely. Disconfirming evidence is actively sought to eliminate any erroneous opinion initially held. The final step considers the sensitivity and specificity of the evidence presented. The idea is to consider whether it is specific enough to rule in or sensitive enough to rule out a certain differential diagnosis.

3.3. Procedure

After having obtained ethics approval from the Institutional Review Board, participation for the experiment was solicited via advertisement in social media groups of clinical year (Year 3, 4, 5) students in two medical schools in Southeast Asia. To be eligible, participants must be older than 21 years of age, and in Year 3 or above so that they possessed the requisite clinical knowledge to evaluate the cases. To reduce self-selection bias, multiple waves of invitation were sent, first to all eligible students and thereafter targeting Dean's Listers, which was used as a proxy for high cognitive ability. A carefully managed approach of tracking the progress of data collection dynamically helped ensure fair representations across gender, year of study as well as cognitive ability.

To reflect the asynchronous store-and-forward telemedicine modality where clinicians analyze cases in an electronic format without meeting patients in real time, an online questionnaire comprising a series of medical case vignettes was sent. After obtaining informed consent, participants—whose identities were anonymized—were led through four steps. First, they were asked to provide demographic details such as gender, year of study, and whether they had been a Dean's Lister. Additionally, they were required to complete a 15-item Cognitive Style Index (Allinson & Hayes, 1996).

In step two, they were shown eight medical case vignettes (3 investigative cases reflecting wide information breadth + 3 non-investigative cases reflecting narrow information breadth + 2 dummy cases) individually with a time limit of one minute imposed on each to induce intuitive thinking. This time limit was chosen based on a similar study where participants were given an average of 72 seconds per case (Norman et al., 2014). A pilot study involving five participants confirmed that the time limit was reasonable, all the cases were of comparable level of complexity, and investigative cases with details such as blood report had greater information breadth than non-investigative ones. A countdown timer was displayed prominently on each page to help participants manage their time. To prevent invalid results and ensure the time variable remained constant, participants were not allowed to progress to the next page before the time was up. The cases consisted of an initial wrong diagnosis followed by information such as presenting complaint, past medical, drug, family, and social history, as well as physical examination findings. Cases with investigative results (wide information breadth) carried additional details such as blood counts and radio-imaging, where appropriate. For each case, participants indicated their level of agreement with the initial assessment on a 10-point scale (Mamede et al., 2008). Two sample cases, one investigative and the other non-investigative, are shown in Figure 1.

In step three, participants were introduced to the debiasing strategy. It was shown as a pop-up window accompanying each case with unlimited time to read and digest the description of the strategy. Specifically, participants were instructed to slow down their thinking, look out for disconfirming evidence wherever possible, and consider the sensitivity and specificity of the evidence before making a judgement. Thereafter, they were instructed to adhere to these techniques as they went through another eight case vignettes (3 investigative cases reflecting wide information breadth + 3 non-investigative cases reflecting narrow information breadth + 2 dummy cases). As with the previous step, they rated their level of agreement with the initial diagnosis on the same 10-point scale (Mamede et al., 2008).

Finally, as an induction check, participants responded to three closed-ended question to confirm they had followed the instructions to slow down, to deliberately look for disconfirming evidence, and to consider the sensitivity and specificity of the evidence when going through each case. Following that, they were debriefed about the purpose of the study.

Name: Chester Tan Sex: Male Age: 13 Ethnicity: Chinese	
Diagnosis Acute appendicitis	
History of presenting complaint - 3 days abdominal pain that began in the epigastrium but later became localized in the right iliac fossa - Associated with fever, body aches, malaise, and vomiting	
Past Medical History & Drug History - None of relevance	
Family History - None of relevance	
Social History - None of relevance	
Physical Examination findings - Vitals: 38°C, HR 109 bpm, BP 120/80 - Abdominal: generalised tenderness with marked tenderness in the right iliac fossa	
Investigations - Abdominal ultrasound: no findings **FBC**	

Parameters	Result	Reference range
RBC	4.81	4.50 – 5.75 X 10^{12}/L
WBC	2.02	4.30 – 10.40 X 10^9/L
Hb	12.7	13.1 – 16.8 g/dL
HCT	36.7	40.3 – 50.0 %
MCV	87.5	80.6 – 96.1 fL
MCH	29.0	26.1 – 32.1 pg
MCHC	32.6	30.8 – 34.9 g/dL
PLT	104	180 – 397 x 10^9/L

Name: Brenda Lim Sex: Female Age: 39 Ethnicity: Chinese	
Diagnosis Acute episode of migraine	
History of presenting complaint - 24 hours sudden severe generalised headache pulsating to the back of the neck, score 9/10 - Vomited at the onset of the headache and still feels nauseated - Small improvement with rest in a dark and quiet room - No fever, visual impairment, or altered mental state	
Past Medical History & Drug History - 2-year history of migraines usually preceded by alterations in her vision following which she gradually develops a throbbing left-sided headache, associated with vomiting - Breast cancer 5 years ago for which she underwent bilateral mastectomy - Drugs: Aspirin and sumatriptan PRN for migraines	
Family History - Mother and sister also has a history of migraines	
Social History - Smoker of 30 pack years - Occasional social drinking	
Physical Examination findings - Vitals: 36.5°C, HR 90 bpm, BP 107/60 - Glasgow Coma Scale 15/15, no meningeal signs, no neurological deficit - Normal examination of the fundi and tympanic membranes	
Investigations - Awaiting CT head	

Figure 1: Sample investigative (left) and non-investigative (right) cases

3.4. Measures

Cognitive style was dichotomized into analytic and intuitive based on median split of the Cognitive Style Index scores (Allinson & Hayes, 1996). The purpose was to divide the sample into two groups: those who exhibit a more analytical cognitive style and those who are relatively more intuitive. Cognitive ability was dichotomized into Dean's Listers and Non-Dean's Listers. The former comprised those students who had been ranked the top 15% of their cohort based on final examinations performance in any previous year in medical school. In the absence of letter grades and grade point averages, the Dean's List is the only standardized indicator of students' ability to process medical information both in theory and in practice, relative to their counterparts. As a reliable proxy for general mental ability (Cole et al., 2003) and an early predictor of clinical performance (Carr et al., 2014), the list represents an expedient way to capture cognitive ability. Anchoring bias for each case vignette was measured as the agreement with the erroneous initial anchor while the effectiveness of the debiasing strategy was determined by the difference in anchoring bias between the pretest and the posttest responses.

3.5. Analyses

To address the research questions RQ1 and RQ3, two sets of 2x2x2 mixed factorial ANOVA were used. The between-participants factors were cognitive style (analytic vs intuitive) and cognitive ability (Dean's Lister vs Non-Dean's Lister). The within-participants factor in RQ1 was the pretest anchoring bias score (wide vs narrow information breadth) while that for RQ3 was reduction in score (wide vs narrow information breadth). A paired-samples t-test between pretest and posttest scores was used to address RQ2.

4. Results

Of the 83 who participated, responses from 11 participants were rejected either due to incompleteness or failure at the induction checks. Of the 72 valid responses, 38 (52.77%) were male and 34 (47.22%) were female. The distribution of participants across Year 3, Year 4 and Year 5 were 24 (33.33%), 39 (54.17%) and 9 (12.5%) respectively. G*Power was used to carry out a post-hoc power analysis of the sample size of 72 in detecting statistically significant differences (Faul et al., 2009). With a medium effect size and a significance level of 0.05, the power value was above the recommended threshold of 0.8. Results from the induction checks showed that all participants understood and responded affirmatively to the three closed-ended questions, confirming they had followed the instructions.

Gender and year of study were statistically confirmed using t-test and ANOVA respectively to be non-confounding factors to both average pretest and posttest scores. In terms of cognitive style, 35 (48.61%) were considered analytic while 37 (51.39%) were intuitive. As for cognitive ability, 31 (43.06%) had been on the Dean’s List, while 41 (56.94%) had not.

Statistical assumptions for the two mixed factorial ANOVA analyses used in RQ1 and RQ3 were checked. Box's M statistic remained non-significant. This confirmed that for each level of the between-participants variable, the pattern of intercorrelations among the levels of the within-participants variable was the same. Levene's test of equality of error variances consistently yielded a non-significant result, confirming that the assumption of homogeneity of variance was not violated. Greenhouse-Geisser epsilon correction was applied to account for the violation of the sphericity assumption, as denoted through Mauchly’s Test of Sphericity. The statistical assumption of using paired t-test to address RQ2 was not a problem given the sample size of over 30 (Pallant, 2005).

The descriptive statistics are given in Table 1. Pretest anchoring bias scores under investigative and non-investigative conditions were computed as the average rating of the three cases with wide information breadth and that of the three cases with narrow information breadth respectively. Posttest anchoring bias scores under investigative and non-investigative conditions were also computed using the same approach. Scores for the dummy cases were not considered.

Table 1: Descriptive Statistics

Cognitive Style	Cognitive Ability	N	Pretest*		Posttest*		Reduction (= Pretest - Posttest)	
			Wide info breadth	Narrow info breadth	Wide info breadth	Narrow info breadth	Wide info breadth	Narrow info breadth
Analytic	Dean's Listers	15	6.27 ± 1.94	4.56 ± 1.30	5.60 ± 1.76	4.20 ± 1.42	0.67 ± 1.46	0.36 ± 2.09
	Non-Dean's Listers	20	6.95 ± 1.43	5.08 ± 1.28	6.05 ± 1.72	4.97 ± 1.53	0.90 ± 1.51	0.12 ± 1.70
Intuitive	Dean's Listers	16	6.85 ± 1.45	4.79 ± 1.47	5.13 ± 2.01	3.77 ± 1.67	1.73 ± 2.64	1.02 ± 1.56
	Non-Dean's Listers	21	6.16 ± 1.09	4.78 ± 1.71	6.00 ± 1.34	4.48 ± 1.54	0.16 ± 1.62	0.30 ± 1.70

* Scored on a 10-point scale

RQ1 was addressed through a 2 (cognitive style: analytic vs intuitive) x 2 (cognitive ability: Dean's Lister vs Non-Dean's Lister) x 2 (pretest score: wide vs narrow information breadth) mixed factorial ANOVA. The between-participants main effects of cognitive style and cognitive ability on anchoring bias were not statistically significant. Neither was the interaction effect between cognitive style and cognitive ability ($F(1, 68) = 3.84$, $p = 0.054$, $\eta_p^2 = 0.053$). However, the within-participants effect of information breadth was statistically significant, Wilk's Lambda = 0.58, $F(1, 68) = 49.65$, $p < 0.001$, $\eta_p^2 = 0.422$. Greater susceptibility to anchoring bias was seen in the wide information breadth condition (6.56 ± 1.48) than in narrow information breadth condition (4.82 ± 1.44). Information breadth did not significantly interact with either cognitive style or cognitive ability. The three-way interaction was also non-significant.

RQ2 was addressed through a paired samples t-test that compared the average anchoring bias in the pretest with that in the posttest. A significant result arose, $t(71) = 4.52$, $p < 0.001$, Cohen's $d = 0.53$. Anchoring bias in the pretest (5.69 ± 1.04) exceeded that in the posttest (5.07 ± 1.34). This shows the effectiveness of the proposed composite debiasing intervention regardless of cognitive style, cognitive ability, and information breadth.

RQ3 was addressed through a 2 (cognitive style: analytic vs intuitive) x 2 (cognitive ability: Dean's Lister vs Non-Dean's Lister) x 2 (reduction score: wide vs narrow information breadth) mixed factorial ANOVA. The between-participants main effect of cognitive style and the within-participants main effect of information breadth on the reduction in anchoring bias was non-significant. The between-participants main effect of cognitive ability was nonetheless significant, $F(1, 68) = 4.73$, $p = 0.033$, $\eta_p^2 = 0.065$. For investigative cases, the reduction in anchoring bias was greater among Dean's Listers (1.22 ± 2.18) than Non-Dean's Listers (0.52 ± 1.60). Similarly, for non-investigative cases, the reduction was greater among Dean's Listers (0.70 ± 1.83) than Non-Dean's Listers (0.21 ± 1.68).

The interaction effect between cognitive style and cognitive ability on the extent of debiasing was also significant, ($F(1, 68) = 4.68$, $p = 0.034$, $\eta_p^2 = 0.064$. The reduction in anchoring bias was the highest among intuitive Dean's Listers. As evident from the interaction plots, this was true for both investigative (1.73 ± 2.64, cf. Figure 2) and non-investigative cases (1.02 ± 1.56, cf. Figure 3). Except for Non-Dean's Listers with intuitive style, all participants saw greater anchoring bias reduction for investigative cases (wide information breadth) than non-investigative ones (narrow information breadth). All other interactions were non-significant.

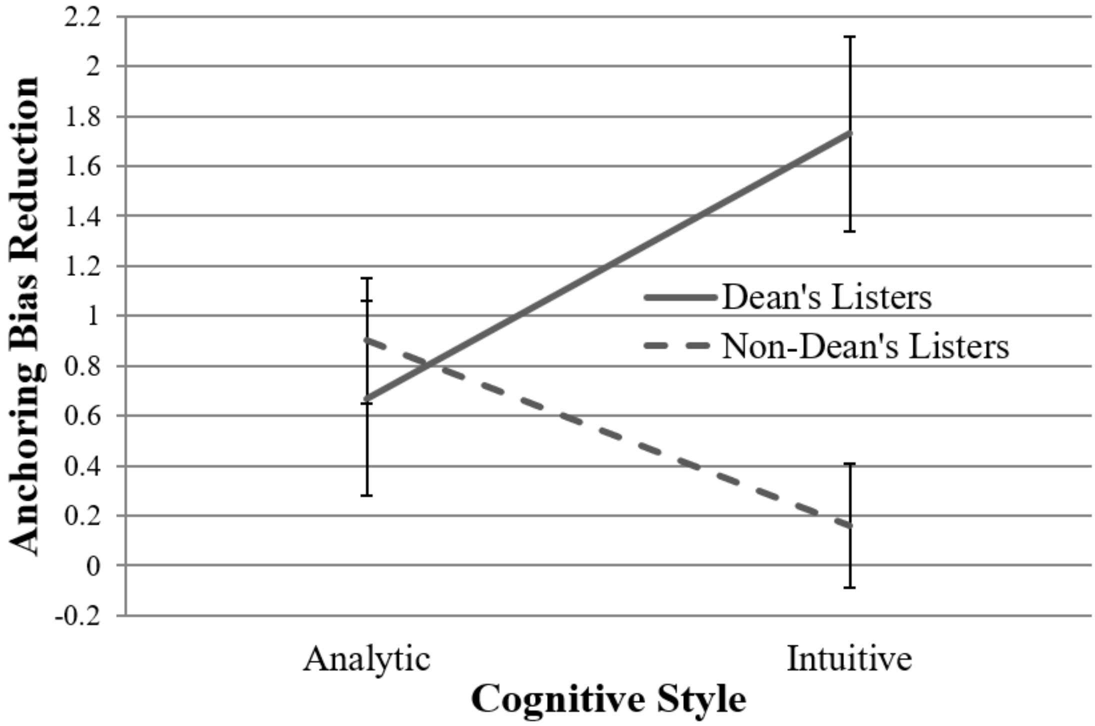

Figure 2: Cognitive style x cognitive ability interaction plot for investigative cases

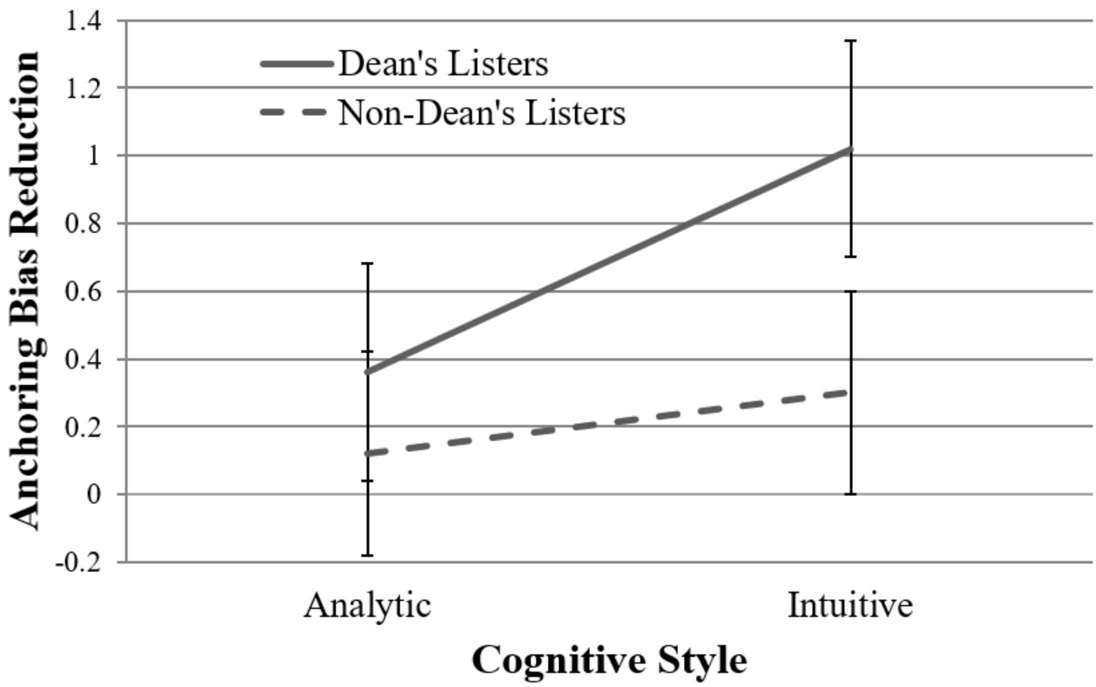

Figure 3: Cognitive style x cognitive ability interaction plot for non-investigative cases

5. Discussion

Three key findings emerge from the results. First, neither cognitive style nor cognitive ability were significant contributors of anchoring bias under time crunch. Even though anchoring bias represents a flawed cognitive processing, this finding is consistent with a prior study that found cognitive ability to have little relationship with the cognitive pitfall of myside bias (Stanovich & West, 2008). In other words, even decision makers with a relatively higher cognitive ability are not spared from falling victim to anchoring bias. In terms of cognitive style, the relationships between Systems 1-2 thinking with anchoring bias are not entirely causal. Intuitive thinkers may make accurate judgements by following their instincts while analytic thinkers could overemphasize few shards of evidence and draw faulty conclusions. Thus, in fields like medicine and forensic science which demand specialized knowledge, the link between anchoring bias and cognition-related attributes seems tenuous.

Second, anchoring bias was more pronounced when a wider breadth of information was presented. With more data points to be processed, there is a greater tendency to look for confirming evidence in support of a preliminary diagnosis, albeit an erroneous one. In fact, previous research has shown that ambiguous information tends to be interpreted in a way that conforms to the preconceived notion especially when a copious amount of information is available (Klayman and Ha, 1987). This is likely the consequence of being overwhelmed by information overload (Li, 2016; Naeem & Bhatti, 2020).

Third, the debiasing strategy was effective in reducing anchoring bias. Unlike singular techniques used previously (Mamede et al., 2010; Norman et al., 2014; Sherbino et al., 2011)—all involving medical students, the debiasing strategy in this study addresses the fallacy of anchoring bias by combining three complementary techniques. Slowing down provides opportunities for metacognition and Bayesian reasoning, while metacognition helps overcome any persistent bias even after slowing down. Bayesian reasoning, in turn, provides a framework for incorporating new evidence and updating beliefs systematically. Norman et al. (2014) and Sherbino et al. (2011) found singular techniques to be ineffective in increasing diagnostic accuracy among medical students. However, the composite debiasing strategy proposed in this paper proved effective. It is also worth noting that the effectiveness of the debiasing strategy was more pronounced among Dean's Listers. Their greater cognitive ability, compared with Non-Dean's Listers, perhaps enabled them to make the most of the intervention.

A particularly interesting finding was that among Dean's Listers, those with an intuitive cognitive style experienced greater anchoring bias reduction than those with an analytical style. Thus, being intuitive rather than analytic is not all gloom and doom. One possible explanation is that intuitive Dean's Listers, who are likely to have greater cognitive flexibility (Colzato et al., 2006), were more adept at embracing the debiasing strategy than their analytic counterparts.

Non-Dean's Listers with intuitive cognitive style fared better than those with analytic cognitive style only under narrow information breadth. However, under wide information breadth, the opposite was true. What analytic Non-Dean's Listers lacked in cognitive flexibility, they perhaps made up for by being meticulous in adhering to the debiasing strategy. Investigative data points available might have enabled them to avoid anchoring bias more than their counterparts could.

6. Conclusions

Set in the context of telemedicine, this paper had three purposes: (1) To examine the effect of cognitive style, cognitive ability, and information breadth on anchoring bias, (2) To empirically validate the effectiveness of a composite debiasing strategy, (3) To investigate how the extent of debiasing is affected by cognitive style, cognitive ability, and information breadth. Based on an experimental setup involving 72 medical students, it was found that cognitive style and cognitive ability did not matter but information breadth increased individuals' susceptibility to anchoring bias. The composite debiasing strategy was successful in reducing anchoring bias. Cognitive style interacted with cognitive ability to affect the reduction in anchoring bias. Specifically, the debiasing effect was the highest among individuals with high cognitive ability and intuitive cognitive style.

This paper holds implications for both research and practice. Theoretically, it draws on the literature on cognitive psychology (e.g., Mussweiler et al., 2000; Stanovich & West, 2008) and clinical decision-making (e.g., Djulbegovic et al., 2014; Pines, 2006; Sherbino et al., 2014) to contribute as one of the earliest efforts to study anchoring bias in telemedicine. To do so, it considers not only the human factors of cognitive style and cognitive ability but also the situational factor of information breadth. This advances the literature on healthcare information technologies beyond user adoption studies, which has hitherto been the predominant focus in the literature (Albarrak et al., 2021; Bao & Lee, 2024; Werner & Karnieli, 2003; Zhang et al., 2020). It also extends the literature on clinicians' interaction with healthcare information technologies (e.g., Bautista et al., 2022; Ghalavand et al., in press; Panahi et al., 2016) by shedding light on the consequences after these technologies are adopted.

The paper further dovetails ongoing research (e.g., Norman et al., 2014; O'Sullivan & Schofield, 2018; Sherbino et al., 2011) by showing both cognitive style and cognitive ability to be non-contributors of anchoring bias. Furthermore, extending prior research that has considered different debiasing interventions singularly (e.g., Mamede et al., 2010; Jenkins & Youngstrom, 2016), the intervention used in this paper synergistically dovetails three independent techniques to develop a composite strategy which was found to be effective. Several new findings emerged. Cognitive ability affected the effectiveness of the debiasing strategy, but cognitive style did not. This suggests that anchoring bias and its reduction efforts might transcend some individual differences.

Additionally, this paper introduces the notion of information breadth in telemedicine and highlights that having a wide array of data points could increase individuals' susceptibility to anchoring bias. It further found that intuitive Dean's Listers experienced greater anchoring bias reduction than analytic Dean's Listers. More research is needed to better understand the reasons for these new findings.

On the practical front, this paper casts the spotlight on the cognitive shortcut of anchoring bias in telemedicine. To avoid making diagnostic errors, clinicians must first be cognizant of such a bias. One suggestion to generate awareness is through in-house seminars where past cases of anchoring bias could be highlighted. At the individual level, clinicians could consider the proposed composite debiasing strategy as they process telemedical information in their day-to-day duties.

For medical educators, this study draws attention to the need to enrich the curricula with the concept of cognitive pitfalls in general and anchoring bias in particular given its deep-seated nature. Furthermore, medical educators should encourage students to sharpen their instincts rather than completely abandoning intuition in favour of an analytic cognitive style. After all, intuitive individuals, specifically Dean's Listers, were found to be debiased more readily compared with those who were analytic.

Findings from this study must be interpreted in light of three limitations. The first is the nature of the experimental setup which was uncertainly not identical to that of an actual clinical setting. Also, the scope was confined to the anchoring bias in context of asynchronous store-and-forward telemedicine. Interested researchers may consider authentic settings such as hospital-based real-time telemedicine and home-based telemedicine monitoring where other types of cognitive biases including availability bias, framing bias and overconfidence bias could be explored.

Two, participants in this study were drawn from a limited sample of medical students who are expected to practice in hospitals after graduation. Further research could involve experienced clinicians and other healthcare professionals to check for the problem of anchoring bias. To do so, it is necessary to engage with the institutional hierarchy and secure support for resources, time allowances, and recognition for research activities, making participation more feasible and rewarding. Findings from different anchoring bias studies could then be juxtaposed for comparative analysis.

Three, the debiasing strategy proposed in this study involve slowing down to process medical information at hand. In reality, however, clinicians may not always have the luxury of time. This calls for some flexibility to adapt the debiasing strategy for actual use. Future research could also consider supplementing data collection with qualitative approaches such as one-on-one interviews at critical juncture of the study to gain textured insights into how participants process information in each medical case vignette, as well as why different clinicians respond differently to the debiasing strategies.

Going forward, the future of telemedicine is poised to transform healthcare delivery through the integration of chatbots and AI-enabled decision-making tools. These innovations help clinicians analyze complex medical data, identify patterns, and recommend personalized treatment options. Hence, it would be interesting to investigate how cognitive biases shape the interaction between clinicians and AI, with the focus on decision confidence, override behaviors, and reliance patterns.

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