Information Overload in the Age of Algorithmic Solutions: The Effect of Patients' Information Processing Capability on Their Perceived Quality of Healthcare

Stefanie H. Gante
Durham University, United Kingdom, stefanie.h.gante@durham.ac.uk

Spyros Angelopoulos
Durham University, United Kingdom, spyros.angelopoulos@durham.ac.uk

INFORMATION OVERLOAD IN THE AGE OF ALGORITHMIC SOLUTIONS: THE EFFECT OF PATIENTS' INFORMATION PROCESSING CAPABILITY ON THEIR PERCEIVED QUALITY OF HEALTHCARE

Stefanie H. Gante
Durham University, Durham, United Kingdom
Stefanie.H.Gante@durham.ac.uk

Spyros Angelopoulos
Durham University, Durham, United Kingdom
Spyros.Angelopoulos@durham.ac.uk

Abstract

To facilitate successful adoption of algorithmic solutions for medical decision-making, we need to identify strategies for engaging patients, who are the beneficiaries of such solutions. In this paper, we investigate how the quantity and complexity of information related to the inner mechanics of algorithmic solutions for medical decision-making can impact patients' perceived quality of healthcare. We propose an inverse U-shaped relationship between possessed information and perceived quality of healthcare of algorithmic solutions for medical decision-making. We develop a theoretical framework based on organizational information processing theory and protection motivation theory, that can inform the optimal level of information shared with patients to increase their perceived quality of healthcare, while considering patient-specific characteristics. Our findings contribute to the literature on human-algorithm interactions and the broader field of health information systems. We discuss the theoretical and practical implications of our work and delineate an agenda for future research on the topic.

Keywords: algorithmic solutions, medical decision-making, human-algorithm interaction, protection motivation theory, organizational information processing theory, information overload

1.0 Introduction

Scepticism related to the adoption of algorithmic solutions for decision-making has been prevailing for years, through the academic (Cave & Dihal, 2018; Dietvorst et al., 2015) and mainstream literature (Cave & Dihal, 2019), as well as the local folktales and legends around the world (Cave & Dihal, 2018). Consequently, algorithmic solutions for medical decision-making have also become subject to such scepticism (DeCamp & Tilburt, 2019). Understanding the risks and shortcomings of algorithmic solutions, however, is a premise for their successful adoption and responsible use (Kumar et al., 2021; Siala & Wang, 2022; Wang et al., 2020), while categorically rejecting their use for medical decision-making and mistrusting their recommendations can hinder opportunities for improving the quality of healthcare (Schaffter et al., 2020). The preference towards human decision-makers over algorithmic-based ones, even when the expected value of following the recommendation of the latter is higher, has been defined as *algorithm aversion* (Dietvorst et al., 2015). As the topic is timely and vital for the quality of healthcare provision, the extant information systems (IS) literature increasingly highlights the urgency for further insights on the joint decision-making between humans and algorithmic solutions, to generate sorely needed insights on how they can cooperate responsibly and efficiently (Mikalef et al., 2022).

When it comes to the adoption of algorithmic solutions for medical decision-making, the extant IS literature has explored the perspective of clinicians, as they are the main *users* of such solutions (Huisman et al., 2021; Wang et al., 2021). This line of research, however, falls short on differentiating between *clinicians as users*, and *patients as beneficiaries* of such solutions. As beneficiaries, patients are not preoccupied with the use of algorithmic solutions and, thus, do not have any direct interaction with them. Patients, however, can be affected by the potential implementation within clinical pathways, which makes vital the impact that such solutions have on their perceived quality of healthcare for generating clinical diagnoses. Consequently, the successful human-algorithm collaboration requires a better understanding of the factors that could drive or impede patients' perceived quality of healthcare towards recommendations generated by algorithmic solutions. Scepticism and mistrust towards algorithmic solution for decision-making is often argued to be rooted in a lack of transparency due to the increased complexity of their inner mechanics (Cutillo et al., 2020). Consequently, we would expect that increased transparency on the inner mechanics of algorithmic solutions for medical decision-making would increase patients' perceived quality of healthcare. The extant literature on *algorithm aversion*, however, suggests that increased information on the inner mechanics of algorithmic solutions does not always increase the acceptance that stakeholders perceive and can even negate it (Dietvorst et al., 2018). We further contribute to this line of research by focusing on patients—as the main beneficiaries of algorithmic solutions for medical decision-making—and the impact that the complexity and quantity of information on the inner mechanics of algorithmic solutions can have on their perceived quality of healthcare. Thus, the broader research question we aim to answer here is:

How does the available information on the inner mechanics of algorithmic solutions for medical decision-making impact patients' perceived quality of healthcare?

Drawing upon organizational information processing theory (OIPT) and protection motivation theory (PMT), we argue that increased transparency on the inner mechanics of algorithmic solutions does not necessarily contribute towards an increase in patients' perceived quality of healthcare. The extant literature on *information overload* suggests that having more information than one can adequately assimilate will negatively impact the capability to process it efficiently without incurring costs of increased stress, errors, or inferior decision-making (Edmunds & Morris, 2000). We suggest, therefore, that there is an inverse U-shaped relationship between the transparency on the inner mechanics of algorithmic solutions for medical decision-making and the perceived quality of healthcare due to their recommendations. The level of provided information on the inner mechanics of algorithmic solutions for medical decision-making, therefore, will only benefit the perceived quality of healthcare up until a certain degree, after which it will exceed an individual's ability to adequately assimilate the information, which may result in overstraining their understanding and reduce their perception on the quality of received healthcare. We expect that this relationship is moderated by the capability of individuals to process such complex information. We argue that it is crucial for beneficiaries of such solutions to experience a high level of perceived quality of healthcare to allow for the successful implementation of such solutions in clinical pathways, as we globally move towards more patient-centric healthcare systems (Saraswat et al., 2022). In doing so, we develop a theoretical framework that provides novel insights on information sharing with patients regarding the inner mechanics of algorithmic solutions to optimise their perceived quality of healthcare. Contrary to established theoretical understandings and practical intuitions, we find that maximum transparency does not guarantee increased perceived quality of healthcare as provided by algorithmic solutions. Instead, we demonstrate that the optimal amount of information quantity and complexity, which implicitly influences the required effort of information processing, ultimately depends on the individual patient, who can generally fall into certain categories and can be individually targeted accordingly.

Our study is positioned within the broader IS research agenda (Struijk et al., 2022) and our findings contribute to the emerging body of knowledge on human-algorithm interactions in general (Fügener et al., 2022; Gante & Angelopoulos, 2022; Tarafdar et al., 2022) and more specifically on algorithmic solutions for medical decision-making (Cai et al., 2019). Concurrently, the practical implications of our work align with the aims for the future of healthcare (Donnelly, 2019; Topol, 2019), while we address the need for further insights into how algorithmic solutions impact patients' perceived quality of healthcare. The insights we share, thus, can address the problem of sustainable adoption of algorithmic solutions for medical decision-making, aid in decreasing healthcare costs, and increase the quality of patient care, while freeing up clinicians' capacities.

The rest of the paper is organized as follows. In the next section, we provide a review of the literature on algorithmic solutions for medical decision-making, and further illustrate the importance of patients' perspectives for their sustainably successful adoption in clinical settings. We then develop a theoretical framework with the respective propositions, drawing upon OIPT, and PMT. In the penultimate section, we elaborate on our theoretical framework, and discuss its merits as well as limitations, while we provide an outlook of how our theoretical framework can be further validated. We conclude the paper with a discussion of the theoretical and practical implications of our work, while we delineate an agenda for future research on the topic.

2.0 Theoretical Framework

The healthcare sector has been increasingly transforming and shifting away from a focus on treatment towards a patient-centric focus on prevention (Donnelly, 2019; Goetzel, 2009). Such a transformation is accelerated through the consumerization of digital technologies (Gregory et al., 2018), which enables patients to track their health and detect abnormalities, and clinicians to have access to such information through the use of electronic healthcare records (Appelboom et al., 2014; Ganju et al., 2022). Concurrently, such a transformation empowers patients by allowing them to become decision-makers equal to clinicians and giving them the right to choose (Donnelly, 2019). Consequently, the implementation and adoption of algorithmic solutions for medical decision-making that take into consideration the perspectives of patients and actively address their concerns becomes timely and topical. The importance of patients' perspectives on diagnoses by algorithmic solutions has received scant attention since patients are not the users of such solutions; they are, however, the main beneficiaries. Failing to incorporate patients' perspectives when designing an algorithmic solution, thus, can ultimately lead to outcomes that are not patient-centric and fail to address efficiently and sustainably the issues they are designed to solve. To further contribute to the patient-centric focus of both theory and practice on the topic, and to help future endeavours in avoiding possible uninformed consequences of introducing algorithmic solutions in clinical settings, which can be as impactful as intended ones (Monteiro et al., 2022), we emphasise the importance of patients' perceived quality of healthcare and investigate the factors that may impact it. In doing so, we draw upon the theoretical underpinnings of information overload, as well as OIPT and PMT, and we present a theoretical framework (see Figure 1) along with six related theoretical propositions. In the following section, we elaborate on the theoretical underpinnings and the generation of our theoretical framework.

2.1 Perceived Quality of Healthcare

Prior to investigating the generation of our theoretical framework, we need to establish a consensus regarding our dependent variable (DV), which we define as *perceived quality of healthcare*. Previous research on *algorithm aversion* shows that humans tend to prefer a human agent over an algorithmic solution, even when they are aware that the expected value of following the recommendation of the algorithm will be higher (Dietvorst et al., 2015). Based on these insights, we reason that even if a patient expects that the diagnosis accuracy provided by an algorithm is high, this does not necessarily imply that their perceived quality of healthcare increases. Hence, patients may still not be comfortable with receiving a diagnosis that has been generated with the help of an algorithmic solution, as they might fear an overall decrease on the quality of healthcare.

In this paper, we investigate how information on the inner mechanics of algorithmic solutions for medical decision-making can increase the perceived accuracy of diagnoses, as well as the quality of healthcare and, consequently, patients' acceptance of integrating such solutions into clinical pathways. Therefore, our DV—perceived quality of healthcare—provides a theoretically flexible lens to capture a broad range of various concepts that may impact the benevolence that patients may experience towards the adoption of algorithmic solutions for medical decision-making.

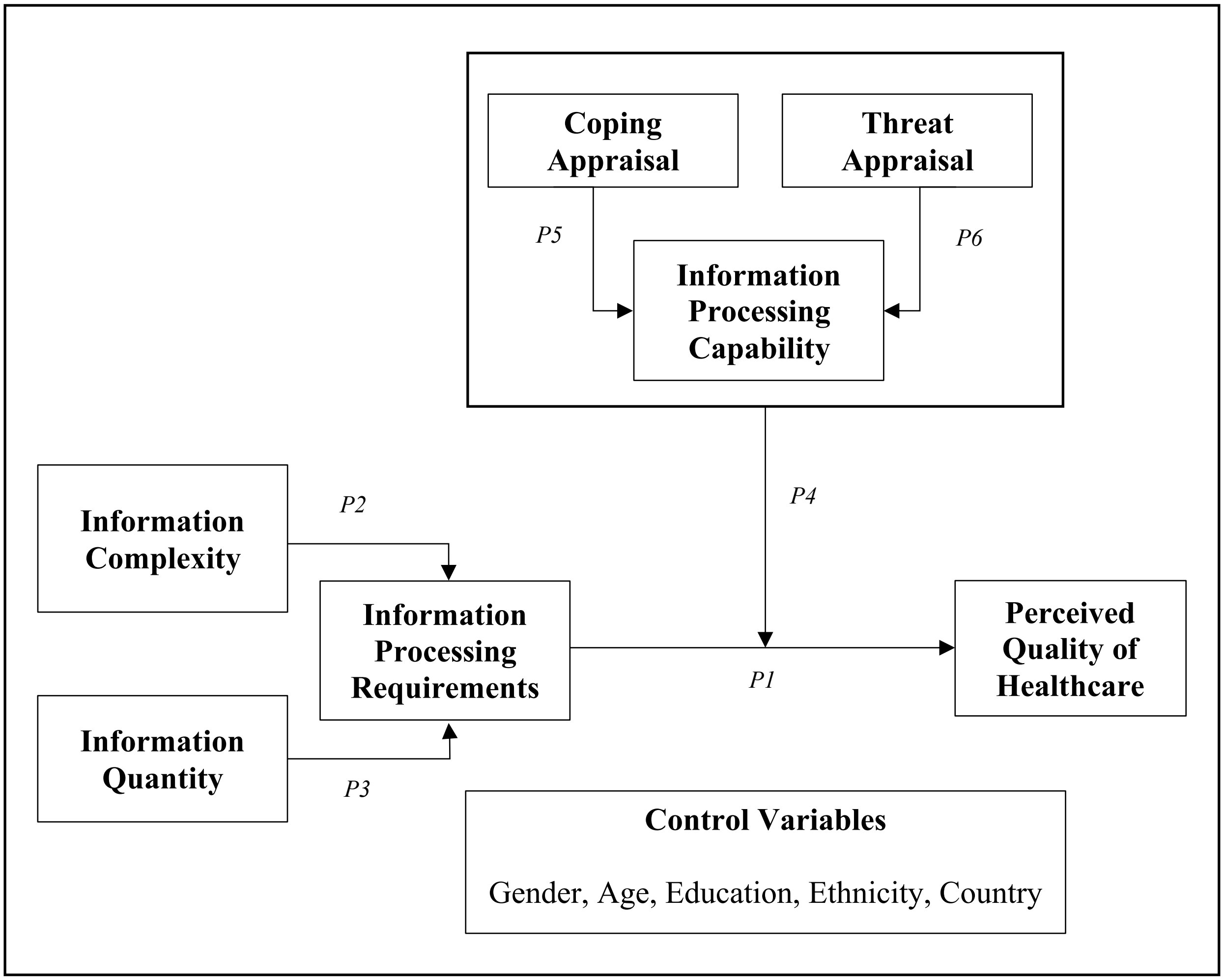

Figure 1. Theoretical Framework

2.2 Information Overload

Information on the inner mechanics of algorithmic solutions, which is also often referred to as *transparency* (de Bruijn et al., 2022; Fernandez et al., 2020), is a fundamental factor for stakeholders' understanding and acceptance of such solutions. Prior studies have suggested that sharing information on how algorithms are designed and make decisions can generally increase their acceptance (de Bruijn et al., 2022; Shin, 2021). The access to information of increased volume, variety, and velocity, however, has brought to the fore the concept of *information overload* (Edmunds & Morris, 2000). Theoretical insights from information overload suggest that excess information can also be harmful and cause confusion and overload, if the recipient is unable to process it accordingly (Schmitt et al., 2018). Information that is possessed implies the need for an equivalent information processing requirement. If the information processing requirements exceed the information processing capabilities in terms of quantity or complexity, an information overload may occur, which can negatively impact the quality of decision-making (Struijk et al., 2020; 2023). In our context, we associate high quality of decision-making with a high level of perceived quality of healthcare. In doing so, our work assumes that allowing an algorithmic solution to contribute to the generation of a clinical diagnosis will increase its accuracy (Killock, 2020; Schaffter et al., 2020), as the expected value of consulting an algorithmic solution exceeds the expected value of rejecting it. Hence, when we refer to a decrease in the perceived quality of decision-making, we refer to a decrease in patients' perceived quality of healthcare, as the rational decision in our context is to approve of the use of the algorithmic solution to improve patient care. Prior research has demonstrated that information under- and over-load can impede decision-making, implying a U-shaped relationship between the complexity and quantity of information and the quality of the resulting decision (O'Reilly III, 1980). In the frame of our research, we expect that an overload of information can exceed an individual's capability to process relevant information and, thus, antagonise the rational reaction of approval of use. Concurrently, an information underload will likely fail to resolve potential misconceptions or prevailing scepticism toward algorithmic solutions. Consequently, we expect the level of diagnosis quality as perceived by the patients can increase up to a certain point, after which additional information related to the inner mechanics of algorithmic solutions will trigger an overload of the individual, causing the perceived quality of healthcare to decrease thereafter. Henceforth, our first proposition is:

P1: There is an inverse U-shaped relationship between information processing requirements and the perceived quality of healthcare.

2.3 Information Complexity

Complexity and quantity of information can be potential sources for information overload. The literature suggests that decision-makers consider the effort of making a decision against the benefit of generating an appropriate outcome (Vessey, 1994). Hence, with increased complexity of information, the effort needed to process that information also increases. Consequently, the perceived benefit of processing the information must outweigh its effort for the recipient to engage with it. Algorithmic solutions for medical decision-making, however, are intrinsically complex

(Adadi & Berrada, 2018; Heising & Angelopoulos, 2021; 2022), and understanding their inner mechanics implies processing complex information, especially when the decision-maker has no prior knowledge on the topic. Therefore, there are two competing forces of increased information complexity on algorithmic solutions for medical decision-making: i) an increased insight into the inner mechanics of algorithmic solutions, as well as ii) an increase in the required information processing capacity to allow for an understanding of such insight, which may overburden the decision-maker. Based on these, our second proposition is the following:

P2: An increase of information complexity increases information processing requirements.

2.4 Information Quantity

Another factor impacting the requirements for information processing is the quantity of information that needs to be processed. The literature suggests that people experience a *need for cognition* (Allen & Wilson, 2003), referring to the extent to which individuals experience a desire for structure and understanding of their environment and things impacting their lives, which fuels the intrinsic motivation for seeking information. Contextual factors such as the importance of the information on decisions, as well as the subjective importance of the information for the individual can impact the need for cognition (Cacioppo et al., 1996). Furthermore, we expect individuals to seek more information in settings where there is high uncertainty and *vice versa*. A higher quantity of information, however, can also increase the information processing requirements, which can overstrain the information processing abilities and, therefore, may negatively impact decision-making. Therefore, our third proposition is the following:

P3: An increase in the quantity of information increases information processing requirements.

2.5 Protection Motivation Theory

The extant OITP literature demonstrates that the effect of information on decision-making depends on the quality of information, and the capability of individuals to process it (Struijk et al., 2020; 2023). The capability for information processing may be influenced by various factors, such as cognitive skills, potentially also shaped through experience, as well as mental or emotional factors that may equally impact how information is received and analysed. To account for an individual's processing capability, we propose a construct that draws upon PMT and captures individual characteristics that may impact how information is processed. PMT captures how individuals react to a perceived health-threat (Prentice-Dunn & Rogers, 1986), based on the idea that their response depends on how the threat is perceived (threat appraisals) and their ability to cope with the threat (coping appraisals). As threat in our context, we perceive the risk of an undetected health concern, which could be mitigated through the use of an algorithmic solution. Notably, PMT has received increasing attention in the IS literature (Ou et al., 2022; Vance et al., 2012), and, thus, provides a flexible approach for investigating the opposing effects of coping and threat appraisals, as it allows the consideration of health concerns along with a clear IS component (Fox & Connolly, 2018).

In PMT, coping and threat appraisals determine behavioural intention of individuals. We focus on patients as beneficiaries of algorithmic solutions for medical decision-making, who are however not central to their actual use. We, therefore, adapt the original PMT model, in which coping, and threat appraisals predict behavioural intention, and we further substitute behavioural intention with information processing capabilities. The idea that coping and threat appraisals will influence behavioural intention cannot apply in our context, as we assume that the beneficiaries of algorithmic solutions have no control over the usage decision and behaviour. Nevertheless, we expect that beneficiaries' coping and threat appraisals can still be triggered, which may influence the way information is processed (information processing capabilities) and ultimately have an effect on the perceived quality of healthcare. The significant difference between ability and capability we establish is the influence that a coping or threat appraisal may have. We distinguish between the two, by referring to ability as the potential that individuals exhibit intrinsically, while capability reflects the true behaviour at an executive level, after the influence of a coping or threat appraisal. In our theoretical framework, processing capability moderates the inverse U-shaped relationship between information processing requirements and perceived quality of healthcare, as suggested in P1. Our fourth proposition, therefore, is:

P4: The information processing capability of individuals will moderate the relationship between information processing requirements and the perceived quality of healthcare.

2.6 Coping Appraisals

Within the setting of our study, coping appraisals refer to the own perception of individuals related to correctly interpreting and acting upon provided information. In PMT, coping appraisals compose of three factors, namely: response efficacy, response cost, and self-efficacy (Prentice-Dunn & Rogers, 1986). Response efficacy captures the perceived benefit of eliminating the threat through a coping action. As the threat in our context is the potential miss of a health concern, the perceived benefit of eliminating should be high, given that the patient comprehends this potential benefit. Response cost captures the cost that individuals face through executing a coping behaviour (*ibid)*. In our context, the cost is the effort of analysing and comprehending the provided information regarding the inner mechanics of algorithmic solutions for medical decision-making. Closely linked to this is the concept of effort expectancy, which is also referred to as perceived ease of use (Venkatesh et al., 2003). As our context considers the decision-making of beneficiaries (patients) rather than users (clinicians), the concept of perceived ease of use is less appropriate for our research question. Finally, self-efficacy refers to the degree to which the decision-maker considers themselves as capable of implementing a protective behaviour, or in our context, capable of processing and understanding the information provided. Self-efficacy is a prominently discussed concept within technology adoption studies and is frequently considered a decisive variable in the question of successful technology adoption (John, 2013). Another concept linked to self-efficacy, which is frequently considered in the context of technology adoption is experience (Venkatesh et al., 2003). In the context of algorithmic solutions for medical decision-making, however, experience with such solutions is likely to be low, making the consideration of self-efficacy more appropriate and highlighting yet again why the use of PMT in our framework is most appropriate. Jointly, these coping appraisals will impact an individual's capability of processing information; therefore, our fifth proposition is:

P5: An individual's perceived coping appraisals will positively impact their information processing capability.

2.7 Threat appraisals

The second variable predicting an individual's information processing capability are threat appraisals. Threat appraisals, also referred to as fear appraisals (Rogers, 1975), have received significant attention in the literature as persuasive messages that signal the significance of a threat, with the objective to divert behavioural intentions of individuals (Johnston & Warkentin, 2010). As such, threat appraisals are frequently used in medical context to mitigate risks such as spreading infectious diseases (e.g., coronavirus) or to reduce detrimental behaviours (e.g., smoking) (Johnston & Warkentin, 2010). In our context, threat appraisals impact the information processing capability, as the perception of a threat motivates individuals to collect more information related to the threat to reduce uncertainty. There are three types of threat appraisals, namely: severity of a threat, vulnerability, as well as intrinsic and extrinsic rewards of maintaining the unwanted behaviour (Prentice-Dunn & Rogers, 1986). The severity of a threat relates to the degree of harm that the threat can cause. If the potential harm is low, there is little incentive to act upon a threat. Another fear appeal is the vulnerability to the threat, which refers to the extend an individual considers themselves susceptible. In our context, there may well be a correlation between the perceived vulnerability of a healthcare threat and the existing health status of individuals, which may impact the reaction of a patient to a threat appraisal. The literature, however, has opposing views on whether an existing medical condition may positively or negatively impact openness towards novel technology solutions in healthcare. While some argue that an existing medical condition can motivate the patient to seek any potential contributor to improving their health (Angst & Agarwal, 2009), others mention that existing health concerns can increase privacy concerns that might eventually prevent patients from considering emerging technological solutions (Fox & Connolly, 2018). Finally, intrinsic, and extrinsic rewards for maintaining an unwanted or harmful behaviour are theorised to decrease the impact of the fear appeal. In our context, intrinsic rewards can refer to the ‘peace of mind’ that a patient might perceive by not being preoccupied with potential health risks, and not processing any information on algorithmic solutions for medical purposes in general. Simultaneously, an extrinsic reward can stem from the social appreciation one may receive through practicing general scepticism toward algorithmic solutions, and therefore rejecting to analyse related information. Jointly, these threat appraisals can enforce the desire of individuals to receive and process information on algorithmic solutions for medical decision-making, and therefore our final proposition is the following:

P6: An individual’s perceived threat appraisals will positively impact their information processing capability.

2.8 Control Variables

Finally, there are some demographic factors which we control for, that could possibly influence the outcome of our theoretical framework, namely: age, gender, education of individuals and ethnicity and country of residence.

2.8.1 Age

The age of *users* has been a predictive variable in previous seminal work on technology adoption (Venkatesh et al., 2003). Prior research has shown that while getting older, people become less open towards the use of novel technologies, potentially due to a decrease in perceived self-efficacy and coping appraisals (Berkowsky et al., 2017), implying a negative relationship between age and patients' perceived level of healthcare. Nevertheless, such an assumption stands in contrast with the notion that older people have a higher exposure to life-threatening diseases with increased age (Kenny & Connolly, 2017). Hence, older people experience threat appraisals more strongly. Therefore, we expect that older individuals are more proactive in counteracting health risks, which may positively impact their openness towards solutions that are targeted at improving the detection of diseases, such as algorithmic solutions for medical decision-making. Therefore, we further consider the impact of age as a control variable in our theoretical framework.

2.8.2 Gender

In the broader technology adoption literature, gender has been identified as a moderator of the relationship between performance expectancy, effort expectancy, and behavioural intention of *users* (Venkatesh et al., 2003). This line of work further argues that men tend to be very task- and performance-oriented, implying that their behavioural intention will be largely defined by their perception of increased performance due to the use of an algorithmic solution. In other words, men (as opposed to women) are more likely to focus their consideration of algorithmic solutions use mainly on the question if it benefits a defined goal (e.g., improving accuracy of diagnoses), rather than other related factors, such as, for instance, ethical concerns of usage. Literature on gender, however, suggests that this performance- and task-orientation stems from socialisation, rather than a biological gender divide (*ibid*). We choose to control for gender, rather than considering it as a moderator in our theoretical framework, because gender roles and potentially associated behavioural patterns have evolved significantly since the publication of prior seminal work on the topic, and to also rule out any impact that gender may have on the perceived quality of healthcare.

2.8.3 Education

An increased understanding of the inner mechanics of algorithmic solutions, in general, can facilitate the information processing effort. Such an increased understanding can be generated through experience, however, we already established that patients' experience with algorithmic solutions for medical decision-making is likely to be very limited. Complementarily, we consider the possibility that patients are more likely to have been exposed to algorithmic solutions, and thus, have critically analysed the impacts of their usage, if they have attended higher education. Therefore, the effects of education on our theoretical framework must be controlled for.

2.8.4 Ethnicity and Country of Residence

As previously annotated, the adoption of an algorithmic solution can be sensitive to the context of the healthcare system it is being implemented in. As such, we may find that patients from countries with limited healthcare capacities experience more openness towards the use of algorithmic solutions, as the pressure of developing alternative treatment methods is high. Another important argument to consider is that the accuracy with which an algorithm operates is dependent on the quality of the data it is being trained on. Companies will ensure that the dataset used for training purposes of the algorithm is representative of the population of potential patients. In other words, if an algorithmic solution is targeted toward the European market, the dataset will most likely contain more cases of Caucasian patients than, for instance, other ethnic minorities within that region, and *vice versa* (Willemink et al., 2020). As a result, receiving treatment in a country where the patient is part of such an ethnic minority may imply an inferior quality of healthcare provision when using an algorithmic solution, due to the limited representativeness of the own ethnicity in the training dataset (Panch et al., 2019). While the operationalization of fairness for the adoption of algorithmic solutions for medical decision-making (e.g., Heising & Angelopoulos, 2021, 2022) goes beyond the scope of this paper, it has one crucial implication that we should further consider:

If a patient is part of an ethnic minority in their country of residence and, moreover, is aware of the potential implications of algorithmic solutions use, their perceived quality of healthcare may be negatively impacted by default. Therefore, we consider additionally the control variables of ethnicity as well as the country of residence to account for any potential relationships.

3.0 Discussion

3.1 Key Findings

Our work contributes to the extant IS literature by introducing a theoretical framework that delineates the optimal level of information sharing for improved support of algorithmic solutions for medical decision-making. Prior studies highlight the need for further inclusion of patients in research targeting such products (e.g., Gante & Angelopoulos, 2022). Concurrently, the adoption of algorithmic solutions in clinical settings remains timely and topical from a practical perspective. As such, our work entails a phenomenon-driven theorizing approach (Gregory & Henfridsson, 2021), while it aligns with recent calls for research that has a clear IS element and presents theoretical as well as practical implications (Struijk et al., 2022). Furthermore, our study has been inspired by reflections on algorithm aversion and also contributes to this line of research.

The theories that we incorporate in our framework—OIPT and PMT—are well-established and widely adopted in IS studies, which resonates with the deductive approach we undertake. In Table 1, we delineate an overview of our framework propositions and their theoretical foundations. The novelty of our theoretical framework is introduced through i) considering patients as beneficiaries in the adoption of algorithmic solutions for medical decision-making, and ii) adapting the construct of PMT accordingly, replacing behavioural intention with information processing capabilities. Shedding light on the perception of patients on algorithmic solutions for medical decision-making and acknowledging their importance for their successful implementation coincides with the goal of giving patients more control and autonomy in the design of their healthcare (Topol, 2019). It is also a step towards a society where academics strive to make the world a better place (Walsham, 2012) by enabling the creation of sustainable and ethically responsible digital technologies, that can help individuals, organizations, and society at large to progress. Our findings entail theoretical and practical implications, which we elaborate on in the following sections.

#	Theoretical Foundation	Proposition
P1	Information Overload	*There is an inverse U-shaped relationship between information processing requirements and perceived quality of healthcare.*
P2	OIPT	*An increase of information complexity increases information processing requirements.*
P3	OIPT	*An increase of quantity of information increases information processing requirements.*
P4	OIPT	*The information processing capability of individuals will moderate the relationship between information processing requirements and perceived quality of healthcare.*
P5	PMT	*An individual's perceived coping appraisals will positively impact their information processing capability.*
P6	PMT	*An individual's perceived threat appraisals will positively impact their information processing capability.*

Table 1. Overview Propositions

3.2 Theoretical Implications

Our work brings together two well-established theories in the IS literature, OITP and PMT, and extends their applicability while making considerable theoretical contributions to both. The combination of these two theories provides a flexible approach to explore the adoption of novel algorithmic solutions that have, thus far, received limited attention in the literature. Additionally, by bridging OITP and PMT, we provide an alternative lens on our knowledge, by replacing the *adhuc* established concept of 'behavioural intention' with our novel concept—for this context—of 'information processing capability'. Such a novel perspective can shed light on the relevance of PMT when the subjects of the study are unable to react to a threat autonomously, and it highlights the role of beneficiaries in the adoption of novel digital technologies. Our theoretical framework, thus, can help in identifying the optimal level of information on the inner mechanics of algorithmic solutions for medical decision-making, for increasing patients' perceived quality of healthcare.

3.3. Practical Implications

Our work suggests that complete transparency and explainability of algorithmic solutions will not maximise patient support for the inclusion of such products in clinical pathways. Moreover, the optimal degree of information quantity and complexity varies between individuals, depending on their information processing capabilities. To maximise patient support for the use of algorithmic solutions, the patients need to be adequately informed in advance through information carefully crafted by the developers of the solution, while healthcare providers must develop strategies to share such information with patients. In doing so, one essential step is to identify the information processing capabilities of individual patients and identify solutions to optimally share information. Notably, there are currently no legal obligations for healthcare providers to inform their patients when incorporating an algorithmic solution in the generation of their diagnosis, however, it can be expected that with increased application of such solutions in clinical pathways, legal frameworks will change and require patients to actively choose either opt in or out of the use of such solutions in the frame of their individualised treatment. By developing strategies for communicating information on algorithmic solutions to patients, such products can become future-proof and enable the facilitation of the best possible healthcare provision for patients moving forward.

3.4 Limitations and Future Research

Although we followed a structured and thorough design, our work presents limitations that need to be acknowledged. First, our work is theoretical, which implies that there has been no primary data collection to test our propositions. We suggest, thus, that future research should further validate our framework. Moving forward, we plan to validate our theoretical framework by undertaking a mixed-method approach. We currently conduct semi-structured interviews with developers of algorithmic solutions for medical decision-making, which shall generate deeper insights and allows us to design and conduct vignette experiments with patients for further testing.

Additionally, our findings point to the importance of adequate communication strategies for sharing information with patients for the optimal support of algorithmic solutions in medical settings. Furthermore, some research suggests that the strategy of communicating information can have an impact on the processing of the information by the decision-maker (Maltz, 2000). As such, a patient might differently process the received information, depending on whether it is i) communicated by a clinician or another stakeholder, ii) shared verbally or in written form, or iii) communicated all at once or over a certain time period, to name a few. In our theoretical framework, we do not distinguish among the various approaches to information sharing, which may impact the way the information is received. We believe that understanding what information should be communicated is a first step to paving the way for future research on this matter.

Finally, our work assumes that the use of algorithmic solutions for medical decision-making will improve healthcare provision. However, there are more facets, rather than only superior product performance, that can determine whether this goal can be achieved. For instance, aspects such as hospital infrastructure and product implementation can also determine the applicability of the solutions, while adequate training and clinicians' willingness to use them can impact their sustainably successful adoption. There are, thus, multiple future research avenues for paving the way toward sustainable adoption of algorithmic solutions for medical decision-making.

4.0 Conclusion

We address the timely and topical question of how information quantity and complexity on the inner mechanics of algorithmic solutions for medical decision-making can impact patients' perceived quality of healthcare. In doing so, we pave the way to increase perceived quality of healthcare due to the implementation of such solutions in clinical pathways and further contribute to the broader literature on health information systems as well as human-algorithm interactions. We draw upon OIPT and PMT to present a theoretical framework along with six propositions, that add insights into the factors that negatively and positively impact perceived quality of healthcare. We reason the deductive approach of our theoretical framework with the high level of establishment of the theories used, and we highlight a need for future research to test our framework and investigate the contexts in which the assumptions that we make may be challenged.

Acknowledgements

The development of the study that is presented here has been supported by a UKAIS Grant.

References

Adadi, A., & Berrada, M. (2018). *Peeking inside the black-box: a survey on explainable artificial intelligence (XAI)*, IEEE Access, 6 52138-52160.

Allen, D., & Wilson, T. D. (2003). *Information overload: context and causes.* The New Review of Information Behaviour Research, 4(1) 31-44.

Angst, C. M., & Agarwal, R. (2009). *Adoption of electronic health records in the presence of privacy concerns: The elaboration likelihood model and individual persuasion,* MIS quarterly, 339-370.

Appelboom, G., Camacho, E., Abraham, M. E., Bruce, S. S., Dumont, E. L., Zacharia, B. E., D'Amico, R., Slomian, J., Reginster, J. Y., & Bruyère, O. (2014). *Smart wearable body sensors for patient self-assessment and monitoring,* Archives of public health, *72*(1) 1-9.

Berkowsky, R. W., Sharit, J., & Czaja, S. J. (2017). *Factors predicting decisions about technology adoption among older adults*, Innovation in aging, 1(3).

Cacioppo, J. T., Petty, R. E.., Feinstein, J. A., & Jarvis, W. B. G. (1996). *Dispositional differences in cognitive motivation: The life and times of individuals varying in need for cognition.* Psychological Bulletin, 119(2), 197-253.

Cai, C. J., Reif, E., Hegde, N., Hipp, J., Kim, B., Smilkov, D., Wattenberg, M., Viegas, F., Corrado, G. S., & Stumpe, M. C. (2019). *Human-centered tools for coping with imperfect algorithms during medical decision-making*, in Proceedings of the 2019 chi conference on human factors in computing systems, Glasgow, Scotland.

Cave, S., & Dihal, K. (2018). *Ancient dreams of intelligent machines: 3,000 years of robots*, Nature, 559(7715) 473-475.

Cave, S., & Dihal, K. (2019). *Hopes and fears for intelligent machines in fiction and reality*, Nature Machine Intelligence, 1(2) 74-78.

Cutillo, C. M., Sharma, K. R., Foschini, L., Kundu, S., Mackintosh, M., & Mandl, K. D. (2020). *Machine intelligence in healthcare—perspectives on trustworthiness, explainability, usability, and transparency*, NPJ digital medicine, 3(1) 1-5.

de Bruijn, H., Warnier, M., & Janssen, M. (2022). *The perils and pitfalls of explainable AI: Strategies for explaining algorithmic decision-making*, Government Information Quarterly, 39(2) 101666.

DeCamp, M., & Tilburt, J. C. (2019). *Why we cannot trust artificial intelligence in medicine*, The Lancet Digital Health, 1(8) 390.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). *Algorithm aversion: people erroneously avoid algorithms after seeing them err*, Journal of Experimental Psychology: General, 144(1) 114.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). *Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them*, Management Science, 64(3) 1155-1170.

Donnelly, T. (2019, 21.12.2022). *Empowering people in their care*. NHS.

Edmunds, A., & Morris, A. (2000). *The problem of information overload in business organisations: a review of the literature*. International journal of information management, 20(1) 17-28.

Fernandez, C., Provost, F., & Han, X. (2020). *Explaining data-driven decisions made by AI systems: the counterfactual approach*. arXiv preprint arXiv:2001.07417 1-33.

Fox, G., & Connolly, R. (2018). *Mobile health technology adoption across generations: Narrowing the digital divide*, Information Systems Journal, 28(6) 995-1019.

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2022). *Cognitive challenges in human–artificial intelligence collaboration: investigating the path toward productive delegation*, Information Systems Research, 33(2) 678-696.

Ganju, K. K., Atasoy, H., & Pavlou, P. A. (2022). *Do electronic health record systems increase medicare reimbursements? The moderating effect of the recovery audit program.* Management Science, 68(4) 2889-2913.

Gante, S., & Angelopoulos, S. (2022). *Paving the way toward Human-Algorithm Interactions: Understanding AI-CAD adoption for breast cancer detection*, in Proceedings of European Conference on Information Systems (ECIS), AIS, Timisoara, Romania.

Goetzel, R. Z. (2009). *Do prevention or treatment services save money? The wrong debate*, Health Affairs, 28(1) 37-41.

Gregory, R. W., & Henfridsson, O. (2021). *Bridging Art and Science: Phenomenon-Driven Theorizing,* Journal of the Association for Information Systems, 22(6) 1509-1523.

Gregory, R. W., Kaganer, E., Henfridsson, O., & Ruch, T. J. (2018). *IT consumerization and the transformation of IT governance*, MIS quarterly, 42(4) 1225-1253.

Heising, L., & Angelopoulos, S. (2021). *Early diagnosis of mild cognitive impairment with 2-dimensional convolutional neural network classification of magnetic resonance images,* in Proceedings of Hawaii International Conference on Information Systems (HICSS), AIS, Maui, USA.

Heising, L., & Angelopoulos, S. (2022). *Operationalising fairness in medical AI adoption: detection of early Alzheimer's disease with 2D CNN*, BMJ Health & Care Informatics, 29(1) 1-7.

Huisman, M., Ranschaert, E., Parker, W., Mastrodicasa, D., Koci, M., Pinto de Santos, D., Coppola, F., Morozov, S., Zins, M., & Bohyn, C. (2021). *An international survey on AI in radiology in 1,041 radiologists and radiology residents part 1: fear of replacement, knowledge, and attitude*, European radiology, 31(9) 7058-7066.

John, S. P. (2013). *Influence of computer self-efficacy on information technology adoption,* International Journal of Information Technology, 19(1) 1-13.

Johnston, A. C., & Warkentin, M. (2010). *Fear appeals and information security behaviors: An empirical study*, MIS quarterly, 549-566.

Kenny, G., & Connolly, R. (2017). *Towards an inclusive world: Exploring m-health adoption across generations,* in Proceedings of European Conference on Information Systems (ECIS), AIS, Guimaraes, Portugal.

Killock, D. (2020). *AI outperforms radiologists in mammographic screening*, Nature Reviews Clinical Oncology, 17(3) 134-134.

Kumar, P., Dwivedi, Y. K., & Anand, A. (2021). *Responsible artificial intelligence (AI) for value formation and market performance in healthcare: The mediating role of patient's cognitive engagement*, Information Systems Frontiers, 1-24.

Maltz, E. (2000). *Is all communication created equal?: An investigation into the effects of communication mode on perceived information quality*, Journal of Product Innovation Management: An International Publication Of The Product Development & Management Association, 17(2) 110-127.

Mikalef, P., Conboy, K., Lundström, J. E., & Popovič, A. (2022). *Thinking responsibly about responsible AI and 'the dark side' of AI*, European Journal of Information Systems, 31(3) 257-268.

Monteiro, E., Constantinides, P., Scott, S., Shaikh, M., & Burton-Jones, A. (2022). Editor's Comments: Qualitative Methods in IS Research: A Call for Phenomenon-Focused Problematization. *MIS quarterly*, *46*(4), iii-xix.

O'Reilly III, C. A. (1980). *Individuals and information overload in organizations: is more necessarily better?*, Academy of management journal, 23(4) 684-696.

Ou, C. X., Zhang, X., Angelopoulos, S., Davison, R. M., & Janse, N. (2022). *Security breaches and organization response strategy: Exploring consumers' threat and coping appraisals,* International journal of information management, 65 1-17.

Panch, T., Mattie, H., & Celi, L. A. (2019). *The "inconvenient truth" about AI in healthcare*, NPJ digital medicine, 2(1) 1-3.

Prentice-Dunn, S., & Rogers, R. W. (1986). *Protection motivation theory and preventive health: Beyond the health belief model*, Health education research, 1(3) 153-161.

Rogers, R. W. (1975). *A protection motivation theory of fear appeals and attitude change,* The journal of psychology, 91(1) 93-114.

Saraswat, D., Bhattacharya, P., Verma, A., Prasad, V. K., Tanwar, S., Sharma, G., Bokoro, P. N., & Sharma, R. (2022). *Explainable AI for healthcare 5.0: opportunities and challenges*, IEEE Access.

Schaffter, T., Buist, D. S., Lee, C. I., Nikulin, Y., Ribli, D., Guan, Y., Lotter, W., Jie, Z., Du, H., & Wang, S. (2020). *Evaluation of combined artificial intelligence and radiologist assessment to interpret screening mammograms*, JAMA network open, 3(3) 1-15.

Schmitt, J. B., Debbelt, C. A., & Schneider, F. M. (2018). *Too much information? Predictors of information overload in the context of online news exposure*, Information, Communication & Society, 21(8) 1151-1167.

Shin, D. (2021). *The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI*, International Journal of Human-Computer Studies, 146 1-10.

Siala, H., & Wang, Y. (2022). *SHIFTing artificial intelligence to be responsible in healthcare: A systematic review,* Social Science & Medicine, 296 1-15.

Struijk, M., Angelopoulos, S., Ou, C., & Davison, R. M. (2020, June). *Influencing information quality: Evidence from a military organization*, in Proceedings of European Conference on Information Systems (ECIS), AIS, Marrakech, Morocco.

Struijk, M., Ou, C. X., Davison, R. M., & Angelopoulos, S. (2022). *Putting the IS back into IS research*, Information Systems Journal, 32(3) 1-4.

Struijk, M., Angelopoulos, S., Ou, C. X., & Davison, R. M. (2023). *Navigating Digital Transformation Through an Information Quality Strategy: Evidence From a Military Organization*. Information Systems Journal, 33(4), 1-41.

Tarafdar, M., Page, X., & Marabelli, M. (2022). *Algorithms as co-workers: Human algorithm role interactions in algorithmic work*, Information Systems Journal.

Topol, E. (2019). *The Topol Review: Preparing the healthcare workforce to deliver the digital future*, Health Education England.

Vance, A., Siponen, M., & Pahnila, S. (2012). *Motivating IS security compliance: Insights from habit and protection motivation theory*, Information & Management, 49(3-4) 190-198.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). *User acceptance of information technology: Toward a unified view*, MIS quarterly, 425-478.

Vessey, I. (1994). *The effect of information presentation on decision making: A cost-benefit analysis*, Information & Management, 27(2) 103-119.

Walsham, G. (2012). *Are we making a better world with ICTs? Reflections on a future agenda for the IS field*, Journal of Information Technology, 27(2) 87-93.

Wang, W., Chen, L., Xiong, M., & Wang, Y. (2021). *Accelerating AI adoption with responsible AI signals and employee engagement mechanisms in health care*, Information Systems Frontiers, 1-18.

Wang, Y., Xiong, M., & Olya, H. (2020). *Toward an understanding of responsible artificial intelligence practices*, in Proceedings of the Hawaii International Conference on System Sciences (HICSS), Maui, USA.

Willemink, M. J., Koszek, W. A., Hardell, C., Wu, J., Fleischmann, D., Harvey, H., Folio, L. R., Summers, R. M., Rubin, D. L., & Lungren, M. P. (2020). *Preparing medical imaging data for machine learning*, Radiology, 295(1) 4-15.