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Delegation Uncertainty in Algorithmic Experience: Conceptualization, Drivers, and Effect on Trust

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Abstract

The objective of this thesis is to expand the understanding of algorithmic experience (AX), focusing on the conceptualization of delegation uncertainty in the AX context. The study set the foundational concept to explore different dimensions of uncertainty where the algorithms highly influence human experience. The transition of agency from human to algorithmic technologies, coupled with the "black box" nature of algorithms, led to novel forms of information asymmetries in the delegation process, identified as intention, technical and coordination uncertainty. Our findings underscore the significance of these uncertainties, revealing that intention uncertainty and coordination uncertainty significantly affect individuals' trust in algorithmic systems. Besides, the effect of technical uncertainty on trust is observable when intention uncertainty and coordination uncertainty diminish.

From the theoretical perspective, this paper explores the various dimensions of uncertainty surrounding algorithms and subsequently investigates the potential enhancement of individuals' algorithmic experiences through delegation transparency enhancing signals. The dissection of the delegation uncertainty concept into intention, technical and coordination sheds light on the multifaceted nature of uncertainty in AX.

Moreover, the results yield practical implications by offering actionable measures to improve the algorithmic experience. These blueprints advocate for incorporating intention, technical and coordination signals within the algorithmic artifacts, thereby fostering greater transparency and comprehension when humans interact with algorithmic systems.

Keywords: Algorithmic experience, uncertainty, information asymmetries, IS delegation, algorithmic transparency, informational signal, trust

Research methods: The initial construct assessment was conducted using two closed card-sorting activities to validate the suitable items within the online news context. After that, the 2x2x2 factorial design study was developed, manipulating three dimensions of information transparency about the algorithm: Intention signals (absent, present), technical signals (absent, present) and coordination signals (absent, present) showcased in the prototypes. A between-subject online survey was set up in Qualtrics and then distributed via Prolific online panel, collecting a convenient sample size of 242 responses.

Table of Contents

Abstract ... *iii*

Table of Contents ... *iv*

List of figures ... *vi*

List of Tables ... *vi*

Preface ... *viii*

Acknowledgments ... *ix*

Chapter 1: Introduction ... *1*

1.1 Context and objective of the research ... 1

1.2 Results and contributions of the research ... 2

1.3 Thesis structure ... 2

1.5. Contribution and responsibility ... 3

Chapter 2: Research Article ... *4*

Abstract ... 4

2.1. Introduction ... 5

2.2. Literature Review ... 8

2.2.1. Uncertainty ... 8

2.2.2. Information asymmetries & signaling ... 9

2.2.3 Algorithmic experience ... 9

2.2.4. Delegation ... 10

2.3. Research Model & Hypotheses ... 11

2.3.1. Trust ... 11

2.3.2. Delegation uncertainty ... 11

2.3.3. Drivers of Delegation Uncertainty ... 13

2.4. Method ... 15

2.4.1. Experimental design ... 15

2.4.2. Procedure ... 21

2.4.3. Measures and Item Development ... 22

2.4.4. Participant recruitment 25

2.5. Result 25

2.5.1. Sample description 25

2.5.2. Measurement validity and reliability 26

2.5.3. Manipulation validity 29

2.5.4. Hypothesis testing 31

2.5.5. Summary of the research model result 39

2.7. Discussion 40

2.7.1. Discussion of the result 40

2.7.2. Contribution, Limitation and Future Research 41

2.8. Conclusion 42

Appendix 43

Bibliography 48

Chapter 3: Managerial Article 53

Algorithmic experience: The impacts of transparency-enhancing signals on people's trust in algorithmic systems 53

Chapter 4: Conclusion 57

4.1 Overview of the results 57

4.2. Limitations 58

4.3 Contributions 58

4.3.1 Theoretical contributions 58

4.3.2. Managerial contributions 58

4.4 Future research 59

Bibliography 60

List of figures

Figure 1. Research model 15
Figure 2. Conditional effects of Technical uncertainty (TechUnc) at values of Intention uncertainty (IntUnc).. 37
Figure 3. Conditional effects of Technical uncertainty (TechUnc) at values of Coordination uncertainty (CoorUnc) 39
Figure 4. Illustration of research model results 40

List of Tables

Table 1. Summary of agentic problems under the delegation process 13
Table 2. Illustration of the 2x2x2 factorial design 16
Table 3. Summary of signaling contents presented by screens 16
Table 4. Illustration of signals manipulation by screens.. 17
Table 5. Final measurement 23
Table 6. Age distribution 26
Table 7. Descriptive statistic for the control variables 26
Table 8. Online new consumption 26
Table 9. Loadings and cross-loadings for related uncertainty construct (Pattern Matrix)............ 27
Table 10. Loading summary for adapted scales.. 28
Table 11. Descriptive and measurement validity.. 29
Table 12. ANOVA for intention signal manipulation 30
Table 13. ANOVA for technical signal manipulation 31
Table 14. ANOVA for coordination signals manipulation... 31
Table 15. Synopsis of Hypotheses and Results 32
Table 16. Summary of signal effects on three dimensions of delegation uncertainty 32
Table 17. The between-subject effects of transparency-enhancing signals to intention uncertainty 33
Table 18. The between-subject effects of transparency-enhancing signals to technical uncertainty 33
Table 19. The between-subject effects of transparency-enhancing signals to coordination uncertainty.. 34

Table 20. Generalized Linear Model (GLM) summary 35
Table 21. Model Summary (Y: Trust, X: Technical uncertainty; W: Intention uncertainty) 36
Table 22. Conditional effects of Technical uncertainty at different values of Intention uncertainty 36
Table 23. Model Summary (Y: Trust, X: Technical uncertainty; W: Coordination uncertainty) 37
Table 24. Conditional effects of Technical uncertainty at different values of coordination uncertainty 38

Preface

This thesis was submitted with the permission of the administrative management of the Master in User Experience program at HEC Montréal. The research project has obtained approval from HEC Montréal's Research Ethics Committee (REC) (Project No. 2024-5164).

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Chapter 1: Introduction

1.1 Context and objective of the research

Technological systems have advanced rapidly and are now more accessible to mainstream users across various fields. At the center of this emergence lies the notion of algorithms, previously enclosed only as a computer's technical terminology but now being used interchangeably with the systems themself. The algorithm or a set of algorithms, is described as the essential building blocks in computer systems that process data and handle complex computational tasks (Hill, 2016). As technology progresses, so do the capabilities of algorithms, which lead to their broader scope of processes and decision-making tasks. Examples include content curation algorithms determining what contents to show users, auto-filter application algorithms facilitating recruitment processes, algorithms managing workers in gig platforms (Möhlmann et al., 2021) or medical diagnosis algorithms assisting healthcare professionals' decisions. Such influential implications of algorithms in human life make them worth throughout research.

The concept of "algorithmic experience" (AX) was introduced by Alvarado & Waern, 2018 to specifically explore how individuals interact with technological systems that are heavily influenced by algorithms. The AX concept has helped highlight the profound impacts of algorithms on the human digital experience. Besides, early studies also suggest that agency effects operate in Human-Computer Interaction (HCI) (McEneaney, 2013). A stream of information system (IS) research has further challenged the notion of human agency primacy in HCI, such as role reversals - reduced human agency when information systems use humans (Demetis & Lee, 2018), cognitive computing systems (Schuetz & Venkatesh, 2020), technological agency (Yu et al., 2021), and agentic IS artifacts - from IS use to IS delegation (Baird & Maruping, 2021). Their suggestions emphasize the bidirectional and agentic interaction between humans and the IS artifacts, where roles and responsibilities between agents are interdependent and transverse.

Along with algorithms' increased agency, the "black box" nature of algorithms and their opaque implementations create friction for human agents when they interact with algorithms. The lack of information and characteristics about this process will potentially create individuals' uncertainty and affect their overall trust in algorithmic systems.

In this context, the primary purpose of this study is to discover and conceptualize uncertainty as a relevant construct within the scope of AX. The research also examined how it affects human assessment of an algorithm's trustworthiness.

1.2 Results and contributions of the research

The research has conceptualized and examined dimensions of delegation uncertainty, including intention, technical and coordination when people interact with algorithmic systems. The outcomes indicated that delegation-transparency signals can reduce their respective dimensions of delegation uncertainty; notably, coordination signals also reduce both technical and coordination uncertainty. The results also confirm that people's trust in algorithmic systems can be enhanced by reducing their uncertainty regarding intention and coordination with an algorithm. Further analysis explains the interaction among the three dimensions of delegation uncertainty on trust. In particular, the influence of technical uncertainty on trust become stronger when intention uncertainty or coordination uncertainty decrease.

The findings of this research contribute to the general understanding of the new form of human-algorithm interaction, developing novel concepts of delegation uncertainty in AX based on the IS Delegation framework and Agency Theory. We suggest the proposed delegation uncertainty construct is worth further study in diverse contexts of the algorithm roles and examination with other salient sociotechnical models.

This research also serves as instructions for manager professionals, algorithm designers, and government officers to take the agentic approach for their work to understand the nuanced relationship between human and algorithmic technologies. By advocating for the integration of intention, technical cues, and coordination signals into the algorithmic artifacts, we expect that the human-algorithm interaction will be more transparent and comprehensive.

1.3 Thesis structure

The thesis contains two articles, one of which is the primary research article, while the other is a managerial-oriented one. The research article in Chapter 2 will present the conceptualization of delegation uncertainty in the AX context and the empirical results on how each dimension affects users' trust in algorithmic systems. A managerial article in Chapter 3 aims to summarize the research's practical implications and make it more accessible to broader audiences such as entrepreneurs, software developers or policymakers whose work is related to algorithm systems and are seeking suitable approaches to improve people's experience with algorithmic technologies. This practitioners-oriented article is in preparation to submit to online managerial magazines such as The Conversation Canada. Finally, Chapter 4 includes a synthesis of the research results, a discussion of its potential contributions and limitations, and suggestions for future research.

1.5. Contribution and responsibility

Please refer to the table below to understand the personal contribution to this thesis.

Steps	Contribution and responsibility
Definition of the research questions	Define the research questions - 80% ● Under the guidance of my supervisor, I proposed the research topic and framed the research questions.
Literature review	Conduct literature review - 90% Constructs conceptualization - 90% Develop research model - 75% ● I reviewed the literature and defined the research model, constructs, and measurements. ● My supervisor gave me feedback and helped me refine it.
Creation of the experiment design	Develop scenarios, design the prototype - 100% Develop and test the questionnaire - 90% ● My supervisor reviewed and advised for adjustments.
Participants recruitment	Conduct online recruitment through an online panel - 20% ● My supervisor suggested the online panel that I used to recruit the participants. ● I set up the protocol based on the panel's information and ensured the recruitment standards.
Pretest and Data collection	Pilot test - 90% Data collection - 90% ● I followed up on errors and reviewed responses of the survey and analyze the pilot test results. ● My supervisor suggested some changes for the official data collection.
Statistical Analysis	Data processing - 100% Data analysis - 80% ● I conduct the analysis, interpret the results, and draft my conclusions. ● My supervisor gave critical input throughout the process.
Writing	Writing - 90% ● I wrote the initial version of the dissertation in its entirety. ● My supervisor provided valuable comments and suggested revisions to enhance the quality of the content.

Chapter 2: Research Article

Delegation Uncertainty in Algorithmic Experience: Conceptualization, Drivers, and Effect on Trust

Abstract

When assessing the user experience of systems heavily reliant on algorithms, the opacity of these algorithms raises significant user concerns and uncertainty. This research focuses on conceptualization and operationalizing uncertainty in the context of algorithmic experiences (AX). Based on prior research about the agentic nature between humans and computers within the Information System (IS) delegation framework, we defined three subconstructs of ***delegation uncertainty*** in algorithmic experience: ***intention uncertainty***, referring to the users' difficulty knowing the purpose or the objective of an algorithm; ***technical uncertainty***, reflecting the users' difficulty understanding how an algorithm operates to achieve or optimize a particular outcome or decision; and ***coordination uncertainty***, relating to users' uncertainty about how they can intervene to influence the outcome produced by an algorithm. Leveraging the theory of information asymmetry and signaling theory, we argue that lowering these three uncertainties through delegation transparency-enhancing signals would increase the user's trust and improve their algorithmic experience. The research model was developed and validated through a factorial survey conducted within the context of using an online news website. The results confirmed that the three proposed uncertainties are distinct and discriminable. The findings revealed that intention uncertainty and coordination uncertainty in AX adversely affect users' trust. Additionally, technical uncertainty shows an impact on trust, particularly when people's uncertainty about the algorithm's intention is less prominent. The study also suggests that delegation transparency-enhancing signals are effective uncertainty mitigators in the context of AX.

2.1. Introduction

In the current digital world, there has been a rising awareness about the power of algorithms as technology continues to advance and play pivotal roles in people's daily lives. An algorithm, defined as "a step-by-step procedure for solving a problem or accomplishing some end" (Merriam-Webster., 2023), is one of the core components of various technological systems. Their pervasive influences appear across digital platforms and decision-making procedures, especially the increased delegation of significant tasks to algorithms in "transformative services" such as social welfare, healthcare education, policing and criminal justice (Marjanovic et al., 2021). As a result of this expansion, the rising use of algorithms in various computerized systems has drawn much attention from scholars. Interestingly, the subject has been discussed among fields closely linked to Information Systems (IS), like Sociology, Information, Communication and Society Studies (Beer, 2017; Willson, 2017; Kitchin, 2017; Bucher, 2018), showcasing the multifaceted impact of algorithmic technologies and how it has transformed human-computer interaction. Within the IS field, a subset of research has studied different topics that indirectly challenge the human agency primacy assumption, which highlighted the potential social injustice effects produced by the use of algorithms, namely, "datafication" in algorithmic decision-making (Newell & Marabelli, 2015), algorithmic pollution (Marjanovic et al., 2021) and algorithmic justice (Marjanovic et al., 2021). A further topic circled the growing use of algorithms in online labour markets, including algorithmic management of work (Möhlmann et al., 2021), algorithmic sensemaking by platform workers (Möhlmannn et al., 2023) and algorithmic control and gig workers (Wiener et al., 2021).

On the other hand, a subset of IS research focuses on developing the argument for challenging the assumption of human agency primacy in the Human-Computer relationship. The research stream suggested different concepts such as role reversals and reduced human agency when IS use humans (Demetis & Lee, 2018), cognitive computing systems (Schuetz & Venkatesh, 2020), technological agency (Yu et al., 2021), agentic IS artifacts / from IS use to IS delegation (Baird & Maruping, 2021). As proposed, the bidirectional nature of the relationship between humans and IS artifacts lies at the heart of theorizing. The relationship now considers interdependencies between agents, focusing more on the dyad and its dynamic when roles and responsibilities are delegated or distributed between agents. The term *agentic IS artifacts* refers to software-based artifacts designed to make autonomous and rational decisions, underlying the ability to perceive and act to achieve preferred outcomes. (Baird & Maruping, 2021). Thus, positioning the algorithmic system as an active agent is a relevant way to examine the human experience with algorithmic technology as it transforms. It is essential to shift from the study of user experience (UX), in which the human agency is assumed, to that of algorithmic experience (AX), which recognizes the prevalence of delegated agency. In summary, ***we propose the concept of AX as the particular form of human-computer relation characterized by the significant delegation of rights, responsibilities, and power from human agents (users) to agentic IS artifacts***.

Algorithmic experiences are particularly different from traditional user experiences because of the algorithm' "black box" nature, hindering the user's uncertainty and lack of control as critical parts of this evolving relationship. A new form of friction emerges as human agency is increasingly being transferred to algorithms, combined with the expansion of complex and opaque capabilities of the algorithms. It is acknowledged that the agentic IS artifact can also use individuals for goal attainment (Baird & Maruping, 2021). Although the algorithms are believed to make things better for the users, they also serve the business goals. When an algorithm conducts a delegated task, the algorithmic decision-making, the systems' inner workings and decision criteria are often hidden or not readily explainable to the end-users (or human agents). That is where the conflict of interests and information asymmetries in AX emerges. The lack of transparency in algorithm task delegations presents challenges not only for understanding the role of the algorithm but also for reasons of accountability. Another issue with algorithmic systems is interpretability, the ability to understand and explain how an algorithm arrives at its conclusions. The reasons for this issue can lie both in the users' limited technical knowledge and in the complexity of the algorithms, especially in machine learning or deep learning models, where comprehending the decision-making processes becomes more difficult as the model evolves. As a result, users may feel uncertain or distrustful when they cannot recognize or validate the rationale behind the delegated algorithmic decisions.

Based on the IS Delegation Theoretical Framework (Baird & Maruping, 2021), we propose that delegation is becoming a new object of uncertainty that is likely to affect people's trust in an agentic IS artifact. Uncertainty results from the lack of pertinent information about any factor that might affect the payoffs of those involved in an exchange (Knight, 1921), in other words from principal-agent perspective, it is driven by hidden information and hidden action (Pavlou et al., 2007) . Thus, we define ***delegation uncertainty as users' difficulty in assessing the delegated role of an algorithm in their digital experience***. Information asymmetries can be mitigated through information signaling as well as designing contracts that formalize roles and responsibilities for each exchange. In the context of AX, where interactions happen constantly, signalling (Spence, 2002) appears to be a more plausible option. For instance, informational signals such as positive ratings and seller popularity can help reduce seller uncertainty in social commerce (Kanani & Glavee-Geo, 2021), online product descriptions and third-party product assurances significantly reduce product uncertainty (Dimoka et al., 2012), and data collection disclosure can reduce privacy uncertainty (Al-Natour et al., 2020). Our research aims to explore different dimensions of delegation uncertainty and uncover its impacts on users' trust in algorithmic systems. Hence, we ask the following questions:

R1: Do individuals consider delegation uncertainty (individuals' difficulty in assessing the delegated role of an algorithm in shaping their digital experience) when assessing the level of trustworthiness of an algorithmic system?

R2: What informational signals can help mitigate delegation uncertainty?

In this research, we identified three dimensions of users' delegation uncertainty: Intention uncertainty (the user's difficulty knowing what the purpose or the objective of an algorithm is), technical uncertainty (the users' difficulty understanding how an algorithm operates to achieve or optimize a particular outcome or decision), and coordination uncertainty (the users' uncertainty about how they can intervene to influence the outcome produced by an algorithm). A 2x2x2 factorial online survey was then designed to study the effect of these constructs. Using a hypothetical online news website, three categories of delegation transparency-enhancing information signals were manipulated (presence and absence conditions) to measure their impact effectively. The results confirmed that the three proposed dimensions of delegation uncertainty in AX are distinct. Intention uncertainty and coordination uncertainty show significant negative impacts on people's trust in algorithmic systems. Besides, the effect of technical uncertainty on trust is moderated significantly by intention uncertainty and marginally by coordination uncertainty.

The rest of this article includes the first literature review section in which each dimension of delegation uncertainty is conceptualized and discussed in depth throughout the review of prior research and established theories. The research model and hypothesis are then presented, followed by research methodology, procedure and measurement development. Details of the research results are summarized in section 2.5. Finally, the last section includes a discussion of the results, the study's contribution and its implications.

2.2. Literature Review

2.2.1. Uncertainty

The concepts of uncertainty and the sources leading to it have been examined in different settings. In economic transaction contexts, uncertainty refers to the limited knowledge regarding an exchange or any other relevant elements (Knight, 1921). Uncertainty is exacerbated in digital settings where the effects of information asymmetry are more pronounced (Ghose, 2009). Technological uncertainty is one salient dimension that has been proposed and examined; it characterizes the individual's perception of being unable to predict or fully comprehend technology environments (Downey & Slocum, 1975; Song & Montoya-Weiss, 2001). In IS research, Venkatesh et al., 2016 applied the uncertainty concept to study the individual's adoption and use of technology, particularly e-government services. They position the three types of uncertainty - task, workflow, and environmental uncertainty, as relevant in this context. Building upon these three uncertainty types, a thematic analysis by Weiler et al., 2019 further explored user uncertainty toward technology's implementation, not only from technical challenges (the lack of understanding of system functionality) but also from socio-psychological factors such as social dynamics, fear of AI, or the non-transparency of the system implementation.

Another theoretical work by Pavlou et al., 2007 uncovered the nature of uncertainty in online exchanges using the principal-agent perspective. The two main agency problems are hidden information and hidden action. In particular, the buyers (principals) delegate responsibility to sellers (agents) who have more information about their characteristics, products, and practices; however, the agents are only partially monitored by the principals. Their work also suggested four antecedents of perceived uncertainty in online buyer-seller relationships: perceived information asymmetry, fears of seller opportunism, information privacy concerns, and information security concerns. Upon this theory, Dimoka et al., 2012 conceptualized seller uncertainty as the consumer's difficulty in assessing the seller's actual characteristics and predicting whether the seller will act opportunistically. Another uncertainty construct refers to product uncertainty, which is the consumer's difficulty in assessing the product characteristics and predicting how it will perform in the future (Dimoka et al. 2012). Finally, privacy uncertainty was developed by Al-Natour et al., 2020 as a distinct construct focusing on the hidden information and hidden action related to data collection, use and protection, referring to consumers' difficulty in assessing the privacy of the data they entrust to others and how it will be maintained.

2.2.2. Information asymmetries & signaling

Information asymmetries are central to agency problems where one party has more information than the other, leading to uncertainty in the exchange. It is suggested that signals can be leveraged to carry information persistently to fill in the information gap in the market, transforming generally from those with more information to those with less information. (Spence, 2002). Thus, signals can mitigate uncertainty from the agency theory perspective (Pavlou et al., 2007). The detail of signals depends on the context and the aspects of the information gap they aimed to mitigate. For instance, information signals like seller ratings can reduce seller uncertainty, product descriptions are leveraged to reduce product uncertainty, or disclosing what data was collected can help mitigate privacy uncertainty.

2.2.3 Algorithmic experience

Within the Human-Computer Interaction (HCI) community, there has been a growing stream of research on human-algorithm interaction or algorithmic experience in recent years. "Algorithmic experience" is a suitable concept for the surge of studies on user experience in which algorithms heavily influence the IS artifacts and environments (Oh et al., 2017). The studies of AX consider user interaction with algorithmic systems as an agentic relationship rather than a simple interaction focused solely on the interfaces' usability and utility (Oh et al., 2017). Aligning with this view, the reframing of AX proposed by Klumbyte et al., 2020 appraises AX as a property of interaction rather than a property of service, in which the interaction regarding AX also includes socio-cultural belonging and context implied in agency distribution and task delegation.

The AX concept was first made explicit in the algorithmic-influenced social media context by Alvarado & Waern, 2018. Their work proposed a framework of five aspects to improve AX, including algorithmic profiling transparency, algorithmic profile management, algorithmic user control, selective algorithmic memory and algorithmic awareness. Overall, these five dimensions imply that users' awareness and user control are critical drivers for the experience with algorithms in social media. In line with this AX concept, many studies were conducted to understand algorithmic experience where users interact with the algorithmic recommendations or content curations (Alvarado et al., 2019, 2020, 2021; Karizat et al., 2021; Vaccaro et al., 2020).

Another work uncovered AX in the context of Online labour platforms (OLPs) uncovered how platform workers experience algorithmic management, in which algorithms take on roles of matching and controlling the worker's performance (Möhlmann et al., 2021) (Park & Ryoo, 2023). To capture the roles that algorithms take on in the social world, Wu et al., 2019 proposed algorithmic personas where human characteristics were used to describe the new roles and explain the algorithms' behaviour. The study suggested three different personas for YouTube's algorithms, including Gatekeepers, a curator that decides what will and will not be seen by the viewers; Agent, a partial judge that will decide if the video will get promoted or not; Drug Dealer, a strategist for increasing user engagement with the platform. Generally, the algorithmic personas helped classify the algorithm by different roles and the objective of the task it was programmed to achieve.

2.2.4. Delegation

Delegation has been proposed as a new focus to understand the interaction between humans and IS artifacts as the agentic primacy (including roles and responsibilities) becomes more fluid, specifically since humans, as well as IS artifacts, can delegate tasks to the other (Baird & Maruping, 2021). The scaffolding of the IS delegation framework was developed to help theorize on specific aspects like willingness to delegate or effective delegation. Considering the dyad relationship in human and IS artifacts interaction, the conditions required for the delegation to take place: (1) a minimum of two agents involved, (2) the agents are brought together as the specific task needed to be completed, and lastly, (3) the roles and responsibilities for the tasks are transferred persistently. It is also suggested that new vocabulary is suitable for the dyad delegation, in which human agents refer to the users and agentic IS artifacts refer to the systems. Whether human or agentic IS artifacts, they are attributed with endowments, preferences and roles. The agents are brought together when a specific task (or a set of tasks) needs to be conducted for the expected outcomes. Then, the delegation happens with the fluidity of roles and responsibilities constructed by three mechanisms: Appraisal, distribution, and coordination.

An important note from Baird & Maruping's framework is that Agentic IS artifacts also have preferences constructed via goals and decision models. These goals are ingrained within the IS artifacts by their designer. Notably, the revelation or hidden of the IS artifacts' preferences holds significant implications for the dynamics of the agentic relationship. Hence, the delegation of tasks and responsibilities to these artifacts is a key area of uncertainty within this context. In particular, we argue that uncertainty surrounding delegation to algorithmic systems constitutes significant challenges in algorithmic experience.

2.3. Research Model & Hypotheses

2.3.1. Trust

In the research model, we selected to explore the dynamic of trust in algorithmic systems and delegation uncertainty, drawing from the premise that trust is a vital determinant of technological acceptance and utilization. Trust and uncertainty are closely related. Trust serves as a means to mitigate uncertainty, while reduced uncertainty helps the establishment of trust (Venkatesh et al., 2016). Establishing trust becomes inherently more challenging when confronted with the ambiguity of the opaque interaction in AX. Prior research considers that trust in technology can be conceptualized using system-like attributes (e.g., functionality, reliability) or human-like attributes (e.g., competence, benevolence). It depends on the type of technology being studied, that trust should be defined accordingly (Gulati et al., 2018). As we have identified the agentic characteristics of the algorithm, we chose the definition of trust in human-like technologies by Gulati et al., 2018 as relevant and suitable in the AX context. Trust, defined in the human-computer trust model as “an individual's willingness to depend on another party because of the characteristics of this other party”, was constructed with four attributes: perceived risk, benevolence, competence and reciprocity. Combining the IS delegation framework (Baird & Maruping, 2021) and the human-computer trust model (Gulati et al., 2018), we proposed trust in algorithmic systems as human agents’ willingness to rely on agentic IS artifacts.

2.3.2. Delegation uncertainty

To conceptualize delegation uncertainty, we draw from the two main agency problems discussed earlier - hidden action and hidden information - to specify each dimension of delegation uncertainty. Hidden information and hidden actions of the agentic IS artifacts, in this case, the algorithm, manifest under the delegation of a specific task.

First, we argue that the nature of the responsibility that is transferred (or the algorithm's roles and preferences) constitutes a first key hidden information. For example, a previous study showed that the hidden existence of the Facebook News Feed filtering algorithm led to user surprise and concerns (Eslami et al., 2015). The absence of this information is likely to generate uncertainty among users, who are the beneficiaries of the task process (in this instance, News Feed filtering), regarding the purpose of the algorithm's integration into the system. This, in turn, can prompt them to question the true intentions behind the algorithm. With endowments, roles, and preferences identified as key attributes of the algorithm's characteristics in the delegation framework, uncertainty might arise in human agents if they are unaware of these attributes in the delegation process. Therefore, we characterize this dimension of delegation uncertainty as ***intention uncertainty***, defined as the user's difficulty knowing what the purpose or the objective of an algorithm is (to whom part of the task is delegated).

Other sources of the algorithm's hidden characteristics and actions stem from the opaque nature of the algorithm. This particular algorithmic opacity is identified as technical illiteracy and the complexity of algorithmic models (Burrell, 2016). More precisely, coding and designing algorithms are specialized skills and knowledge that the majority of the population remains inaccessible. Secondly, algorithmic opacity was formed as the unavoidable complexity of the algorithmic models and the scale of its application to make the algorithmic systems "useful" and accurate. This opacity of algorithms was mostly mentioned in human-computer relationship studies, and it has been previously constructed into the general concept of technological uncertainty, an individual's perception of being unable to predict or fully comprehend technology. It is highlighted that the delegation mechanism helps better understand the task execution being transferred from one agent to another. (Baird & Maruping, 2021). The lack of understanding of how the task is conducted by the agentic IS artifacts or how they function (hidden action) can cause human agents' uncertainty and concerns. In the context of AX, the users generally have limited endowments to comprehend the algorithm execution fully. The algorithm's complexity makes it hard to explain, and uncertainty might arise. Hence, we propose ***technical uncertainty*** as the second dimension of delegation uncertainty in AX, defined as the users' difficulty understanding how an algorithm operates to achieve or optimize a particular outcome or decision.

Finally, coordination is positioned in the IS delegation framework as one of the fundamental mechanisms to present the dynamic relationship between human agents and agentic IS artifacts. For instance, when studying the user experience of challenging content moderation decisions made by algorithms, Vaccaro et al., 2020 highlighted the importance of having appeal systems to allow users to participate in the decision-making process. They suggested that the lack of influence over these decisions causes users to feel fatalism and have a tendency to disengage from the system. Overall, coordination mechanisms effectively allow each agent to receive and direct the task execution for the expected outcomes. The lack of this transparency and information in coordination can create significant uncertainty for the delegation process. In the context of AX, we distinguish this dimension of delegation uncertainty as ***coordination uncertainty,*** defined as the users' uncertainty about how they can intervene to influence the outcome produced by an algorithm.

Table 1. Summary of agentic problems under the delegation process

	Delegation Facet	Agentic Problem	Preference
Intention Uncertainty	What role does the algorithm take on?	Hidden information about delegated role and objectives of the algorithm	Pavlou et al., 2007 & Eslami et al., 2015
Technical Uncertainty	How does the algorithm act on the delegated tasks?	Hidden characteristics and hidden actions stemming from algorithmic opacity	Pavlou et al., 2007 & Burrell, 2016
Coordination Uncertainty	How is coordination with the algorithm carried out?	Hidden information and characteristics of coordination mechanism	Pavlou et al., 2007 Baird & Maruping, 2021

In summary, we have identified and defined three dimensions of delegation uncertainty in AX: intention uncertainty, technical uncertainty, and coordination uncertainty. In circumstances where trust is not yet established, delegation uncertainty is likely to play a pivotal role in trust development. Thus, we propose the following hypotheses:

- H1: Intention uncertainty reduces trust in algorithmic systems.
- H2: Technical uncertainty reduces trust in algorithmic systems.
- H3: Coordination uncertainty reduces trust in algorithmic systems.

2.3.3. Drivers of Delegation Uncertainty

The signaling theory suggests that signals are fundamental in reducing information asymmetry between the two parties (Spence, 2002). In particular, the qualities or characteristics of one party are usually unobservable and need to be communicated to the other parties through signals. In line with this approach, we propose delegation transparency-enhancing signals as specific information cues to make various facets of delegation transparent to humans regarding the algorithm. Each signal type is intended to mitigate its corresponding delegation uncertainty dimensions.

- Intention signals - Information that clarifies the purpose of the algorithm employed in the platform, indicating the algorithm’s scope and its objectives (i.e., what the algorithm aims to achieve)

- Technical signals - Information that streamlines the users' understanding of the algorithm's functions. From the users' standpoint, this type of information should highlight the inputs considered by the algorithm and provide essential insights about its operation (e.g., frequency, data type and weighting)
- Coordination signals - Information or features that demonstrate to users how they can influence the algorithm's processes and results (e.g., feedback loops or algorithm refinement features)

Hence, we propose three hypotheses below:

- H4: Intention signals will minimize users' uncertainty about the algorithm's purpose or its implementation's objective, that is, intention uncertainty.
- H5: Technical signals will reduce users' uncertainty about how an algorithm operates to achieve (or to optimize) a particular outcome (or a decision), that is, technical uncertainty.
- H6: Coordination signals will decrease users' uncertainty about how they can intervene to influence the outcome produced by an algorithm, that is, coordination uncertainty.

The full research model and its proposed concepts are presented in Figure 1 below. We select individuals' IT self-efficacy, IT anxiety and algorithmic awareness as control variables, presuming that each can potentially affect trust in algorithmic systems. IT self-efficacy refers to "a person's belief in his or her capabilities to organize and execute the courses of action required to use information technology" (Compeau et al., 2022). Hence, we expect higher IT self-efficacy to improve people's trust in algorithmic systems. The second control variable is IT anxiety, defined as "one's tendency to be uneasy, apprehensive, or fearful about using technology" (Compeau et al., 2022), which can negatively affect an individual's trust in such systems. Lastly, algorithmic awareness is described as "the extent to which people are aware that algorithms are used in online applications, particularly, a) what algorithms can be used for and b) in what online context algorithms are actually used" (Dogruel et al., 2021). The concept of algorithmic awareness and algorithmic knowledge was proposed by Dogruel et al., 2021 as two dimensions of algorithm literacy that allow users to navigate digital environments effectively. We project that people's trust in algorithmic systems is impacted by their awareness of the algorithm's usage in their lives.

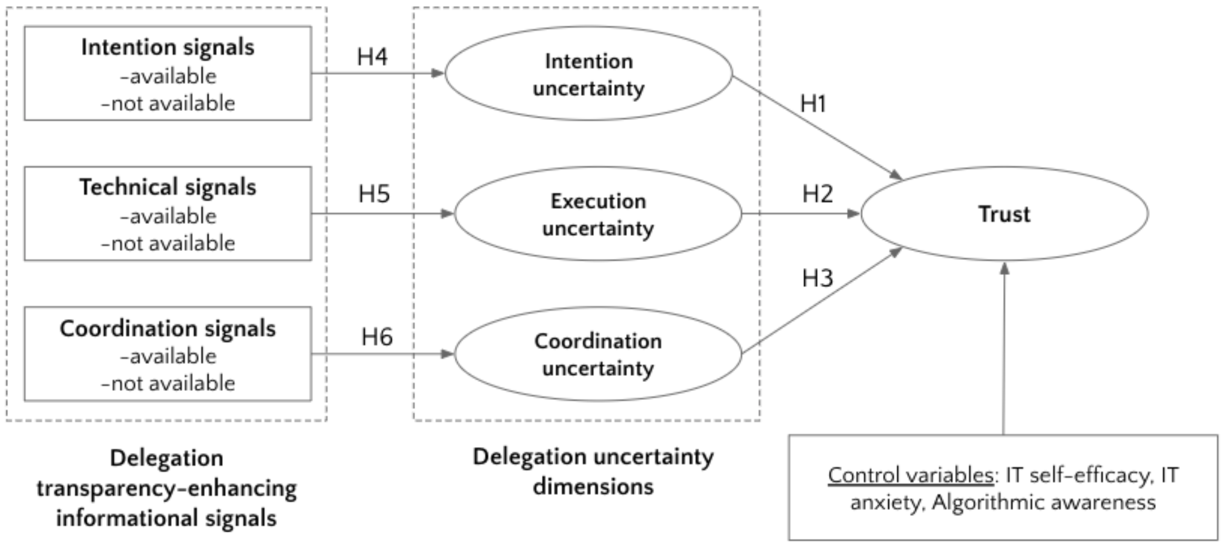


Figure 1. Research model

2.4. Method

2.4.1. Experimental design

To replicate a realistic setting of algorithmic experience, we created a fictional news website called "NewsFlow". We selected the online news context because of the algorithmic news curation has transformed the way in which news is disseminated, personalized and consumed online, significantly impacts on the user experience. Algorithms, fueled by vast amounts of user data and machine learning algorithms, play a central role in determining which news articles are surfaced to users, shaping their information diet and influencing their perceptions. Yet, the algorithms' opacity and lack of information regarding its implementation raise questions and uncertainty among users about their accountability, fairness and potential biases. Thus, the study of delegation uncertainty under the online news setting would be likely to be realistic and resonate well with participants.

The experiment adopts a 2x2x2 fully factorial design with eight separate treatment groups, in which we manipulate intention signals, technical signals and coordination signals in two levels (present vs absent). The experimental conditions are summarized in Table 2 below.

Table 2. Illustration of the 2x2x2 factorial design

Group	Manipulation condition of transparency enhancing signals		
	Intention signals (IS)	Technical signals (TS)	Coordination signals (CS)
1(control)	No	No	No
2	No	**Yes**	No
3	No	No	**Yes**
4	No	**Yes**	**Yes**
5	**Yes**	No	No
6	**Yes**	**Yes**	No
7	**Yes**	No	**Yes**
8	**Yes**	**Yes**	**Yes**

The news website prototypes were developed using Figma design tools. These prototypes featured a series of six onboarding screens, each introducing different parts of the site. The screens varied depending on the treatment group. To replicate the common onboarding information, the technical signals and coordination signals were split into two parts and placed in the narrative sequence of the onboarding. The summarized signaling contents displayed on each screen can be consulted in Table 3 below.

Table 3. Summary of signaling contents presented by screens

Screen 1	Screen 2	Screen 3	Screen 4	Screen 5	Screen 6
No manipulation	Intention signal	1st Technical signal	1st Coordination signal	2nd Technical signal	2nd Coordination signal

The first screen was the site's homepage, as users would typically encounter on their first visit. This screen is the same for every group. The second screen presents a welcoming message and contains intention signal manipulation. In groups with intention signals (Table 2 - groups 5,6,7,8), the news curation algorithm's introduction and detailed information about the algorithm’s objectives were presented. In contrast, participants in groups without intention signals (Table 2 - Group 1,2,3,4) only saw a simple welcome message.

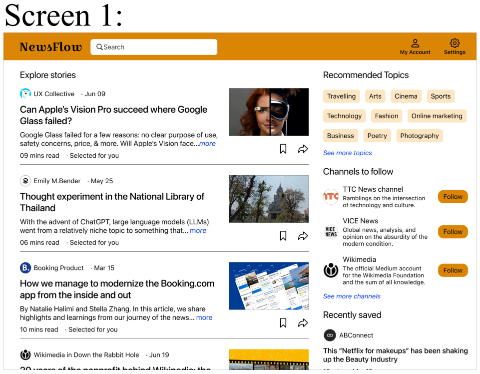
Technical signals were incorporated in the third and fifth screens. In conditions where these signals were present, a thorough explanation of how the algorithm functions was included in the “Explore Stories” and “Recommended Topics” sections. On the other hand, the absence of technical signals meant only general information regarding these sections was provided.

Lastly, the manipulation of coordination signals was positioned on the fourth and sixth screens. In the absent condition of this signal type, there were no options for feedback or refinement towards the news curation algorithm. Conversely, the present condition contained a comprehensive guide on how to interact with these features. The specific manipulation designs are presented in the table below.

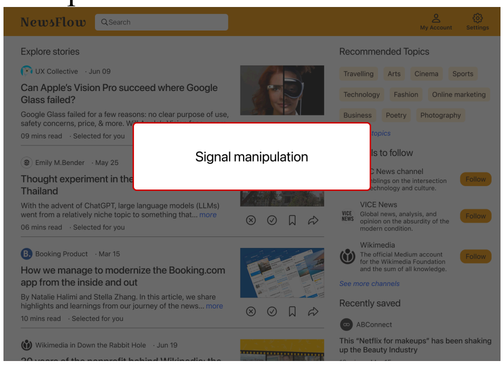
Table 4. Illustration of signals manipulation by screens

<table>
<tr><th>Screen</th><th>Signaling content</th></tr>
<tr><td>

Screen 1:



</td><td>No manipulation</td></tr>
</table>

<table>
<tr>
<td>Screen 2: Intention signal (IS) manipulation:

</td>
<td>Absence of IS: group 1,2,3,4

Welcome to NewsFlow!

Stay up to date with our news curation algorithms.
We are excited to have you on board!

Get Start

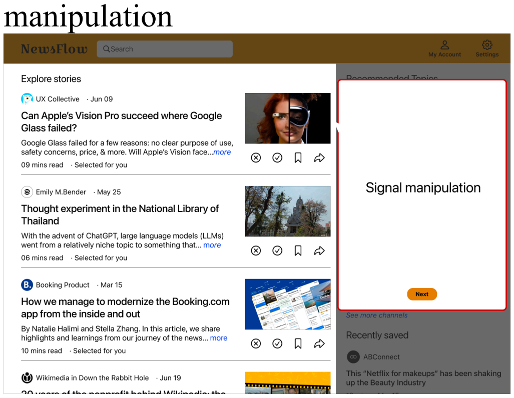
Presence of IS: group 5,6,7,8

Welcome to NewsFlow!

Your personalized news journey begins here.
We are delighted to have you with us!

Our news algorithm is intended to:
• Enhance your news reading experience with personalized content.
• Diversify your content exposure with a board range of topics, news sources
• Filter out repeated and unreliable news
• Present and update the most current and relevant contents

Our ultimate goal?
• Offer you a comprehensive and balanced view of the world, empowering you to stay updated and make well-informed decisions.

Get Start</td>
</tr>
<tr>
<td>Screen 3: Technical signal (TS) manipulation

</td>
<td>Absent of TS: group 1,3,5,7

Browsing news tailored only for you. Let the exploration begin!

Next

Presence of TS: group 2,4,6,8</td>
</tr>
</table>

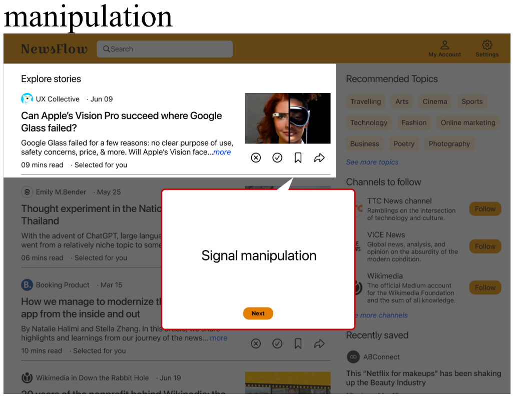
Browsing the personalized news tailored only for you. Let the exploration begin!

Here is how the algorithm works:

- We analyze your browsing history, followed topics, and content interactions to understand your interests and preferences, and tailor the news articles accordingly.
- The data we collect include your browsing history, followed topics and interactions with content, such as articles you have read, liked, or shared.
- The algorithm scans through thousands of news articles from reliable sources, and the contents are selected using a ranking score system based on similarity to the topics you've shown interest in, combined with the article's popularity.
- Our algorithm is updated regularly to reflect the latest trends and news topics around the world.

Next

Screen 4: Coordination signal (CS) manipulation



Absence of CS: group 1,2,5,6

Stay Informed and Share your world here.

Saved the article to your collections for later reading

Share the article for friends or post it on your social account

Next

Presence of CS: group 3,4,7,8

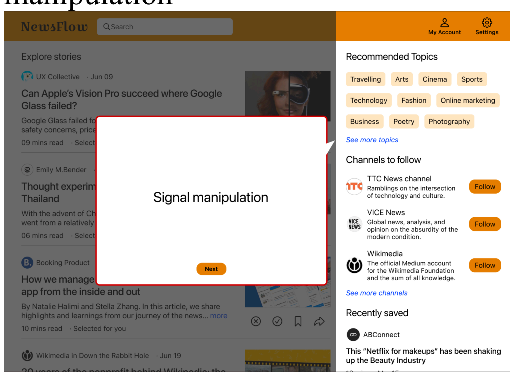
<table>
<tr><td></td><td>Shape the experience by giving your feedback to the news curation algorithm.

Select "Like" for the one that you find interesting and wish to see similar articles more often.

Select "Dislike" for the one that you're not interested and wish to see similar articles less often.

Saved the article to your collections for later reading.

Share the article for friends or post it on your social account.

Next</td></tr>
<tr><td>Screen 5: Technical signal (TS) manipulation
</td><td>Absence of TS: group 1,3,5,7

Here you can find all recommended topics and related channels to follow!

Next

Presence of TS: group 2,4,6,8

Here you can find all recommended topics and related channels to follow!

Here is how the algorithm works:

• We analyze and determine preference from our data pool. Linkage models are leveraged to define the topics and channels that our users, who have references similar to you, are more likely to follow and interact with, in order to recommend the most relevance one for you.
• The data include your browsing history, followed topics, interactions with content, such as articles you have read, liked, or shared.
• The algorithms is updated regularly to take into account emerging topics or channels that are relevant to you.

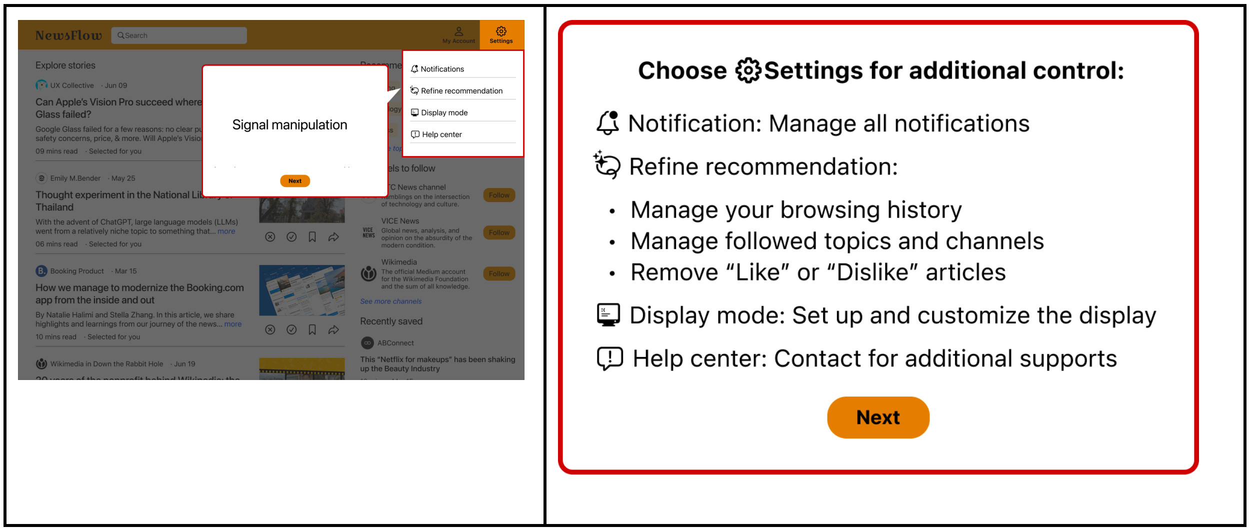
Next</td></tr>
<tr><td>Screen 6: Coordination signal (CS) manipulation</td><td>Absence of CS: 1,2,5,6

Choose Settings for additional control:

Notification: Manage all notifications
Display mode: Set up and customize the display
Help center: Contact for additional supports

Next

Presence of CS: 3,4,7,8</td></tr>
</table>



Participants were randomly assigned to one of the treatment groups through an online survey. The news website's onboarding prototypes varied based on the presence or absence of the aforementioned delegation transparency-enhancing signals. After being exposed to the prototypes, participants were asked to answer a set of questions capturing the constructs specified in the research model.

2.4.2. Procedure

Initially, 242 participants were recruited through an online panel called Prolific. The participants must be 18 years old or older and currently live in North America to be eligible. At the beginning of the survey, participants were briefed about the study's objective, researcher contact information and what to expect when participating in this survey. They were informed of the survey's anonymity, the data collection and the use of data from this study. After agreeing to participate in the study, the introduction was presented. To avoid biasing the participants' attention solely to the algorithmic aspect of the website, we chose not to prime them specifically in the question. Instead, both the scenarios and the questions encompassed the entirety of the website experience. A comprehension check question was given with two trials to ensure that the participants paid attention and fully understood the scenario. If they failed both attempts, their answers were excluded from the study. Following the introduction, participants were randomly assigned to one out of eight treatment groups where the prototypes with manipulated transparency-enhancing signals were presented. After carefully reviewing the provided information, participants answered a sequence of questions about their thoughts and preferences about the news website. To ensure the quality of the response, we embedded two attention-check questions within the questionnaire; participants were excluded if they failed both questions.

2.4.3. Measures and Item Development

2.4.3.1. Measures for Trust in algorithmic systems

The measurement of trust in algorithmic systems selected for this study was referenced from the human-computer trust scale by Gulati et al., 2019. The 12-item scale from the Human-Computer Trust Model (HCTM) (Gulati et al., 2019) was selected because of its relevance in defining trust in modern user-technology interactions. The scale measures four aspects of human trust in technological interaction: Perceived risk, Benevolence, Competence, and Reciprocity, which reflect a greater sense of parity and a more harmonious human-computer relationship.

2.4.3.2. Measures for Delegation Uncertainty

We developed items based on the measurement of privacy uncertainty (Al-Natour et al., 2020), including manipulation check questions and items to assess intention uncertainty, technical uncertainty and coordination uncertainty. The 7-point Likert scales with five items were used to measure each dimension of delegation uncertainty.

2.4.3.3. Control variables

In addition to the measurements of the research model, we selected online news consumption (Pew Research Center, 2020), IT self-efficacy (Compeau et al., 2022), IT anxiety (Compeau et al., 2022) and algorithmic awareness (Dogruel et al., 2021) as the control variables. The ordinal scale was selected to measure participants' frequency of online news consumption. IT self-efficacy and IT anxiety are updated constructs by Compeau et al., 2022 to contemporary IS research. In particular, IT self-efficacy refers to "a person's belief in his or her capabilities to organize and execute the courses of action required to use information technology" (Compeau et al., 2022) and IT anxiety was defined as the erroneous beliefs about one's ability surround various activities in using information technology across its life cycle. (Compeau et al., 2022 - Adapted from Heinssen et al., 1987; Storm & Storm, 1987). We expected that these constructs would be relevant when examining the individual's uncertainty in the AX context. Another construct - Algorithmic awareness, was selected as the emerging concept in studying human-algorithm relationships, capturing "the extent to which people are aware that algorithms are used in online applications, particularly, a) what algorithms can be used for and b) in what online context algorithms are actually used" (Dogruel et al., 2021). We consider that these control variables can enhance or influence the effects between delegation uncertainty and trust in algorithmic systems.

2.4.3.4. Developing and testing the instruments to measure delegation uncertainty constructs

Because of the novelty of the AX context and delegation uncertainty concept, we set out to test the scales we created for the three dimensions of delegation uncertainty. In particular, two rounds of closed card-sorting activities were conducted with two convenience samples of 12 and then 8 participants (a mix of master's students and faculty members at the university). The card-sorting exercises were completed through an online tool called The Optimal Workshop. Participants were presented with our list of 35 randomly organized items and with the definitions of trust, intention uncertainty, technical uncertainty and coordination uncertainty. They were asked to match the item cards with their respective definition. The items were shown in random order, and participants could set any item aside if they felt that it did not match any definition. This option helped avoid forced answers. The detailed results and revisions can be consulted in section A1 and A2 in the appendix.

The final items of all measurements were summarized in the table below.

Table 5. Final measurement

Construct	Item	Scale	Reference
Trust in algorithmic system	Indicate the extent to which you agree or disagree with the following statements: "If I use NewsFlow, …." 1. …I believe that it would act in my best interest." 2. … I believe that it would do its best to help me." 3. … I think that its algorithm would be competent and effective in choosing the suitable news for me." 4. …I think that its algorithm would perform the role of a news curator very well." 5. ...I think I would be able to depend on it completely." 6. …I would be able to completely depend on it for choosing suitable news for me." 7. …I would always be able to rely on this news curation algorithm for choosing the news that I would consume." 8. …I would be able to trust the content selection made by its news curation algorithm. 9. …I feel that I would need to be cautious when using it."	7-point Likert (1. Totally disagree - 7. Totally agree)	Gulati et al., 2019

Intention uncertainty	Indicate the extent to which you agree or disagree with the following statements: 1. I am uncertain about the purpose of having a news curation algorithm on NewsFlow. 2. I am unclear why NewsFlow has decided to implement a news curation algorithm in it. 3. I believe NewsFlow hasn't given enough information about why they use a news curation algorithm. 4. I am unsure why a news curation algorithm is put in place on NewsFlow. 5. I have trouble understanding the goal of using the news curation algorithm on NewsFlow.	7-point Likert (1. Totally disagree - 7. Totally agree)	Al-Natour et al., 2020
Technical uncertainty	Indicate the extent to which you agree or disagree with the following statements: 1. I am not sure if I can fully understand how the algorithm selects content on NewsFlow. 2. I am uncertain how the news curation algorithm functions on NewsFlow. 3. I find it's unclear what information is taken into account in the news 4. curation algorithm. 4. I am struggling to understand how the news curation algorithm operates. 5. I find it's unclear what information is taken into account in the news curation algorithm.	7-point Likert (1. Totally disagree - 7. Totally agree)	Al-Natour et al., 2020
Coordination uncertainty	Indicate the extent to which you agree or disagree with the following statements: 1. I am struggling to know how to interact with the news curation algorithm on NewsFlow. 2. I feel that I don't know how to work around the news curation algorithm on NewsFlow to my advantage. 3. I am finding it difficult to figure out how to effectively engage with the news curation algorithm on NewsFlow. 4. I find it hard to discover ways to interact with this news curation algorithm for my own benefit. 5. I am uncertain as to how I can work with the news curation algorithm on NewsFlow to suit my preferences.	7-point Likert (1. Totally disagree - 7. Totally agree)	Al-Natour et al., 2020
Online news consumption	How often do you get news from online sources such as news websites or apps? 1. daily 2. several times a week 3. weekly 4. several times a month 5. once a month 6. less often than once a month	Ordinal scale	Pew Research Center, 2020
IT self-efficacy	Rate how certain you are that you can do each of the things described below by selecting the appropriate number on the scale 1. Install/Set up technologies 2. Learn to use unfamiliar technologies 3. Use technologies for advanced tasks 4. Troubleshoot problems 5. Show people arround me how to use it	From 0 to 100 (0. Can not do it at all - 100. Highly certain I can do it	Compeau et al., 2022

IT anxiety	Please indicate the extent to which you agree or disagree with the following statements: "When I am using technology, I feel…" 1. Anxious 2. Uneasy 3. Nervous 4. Worried 5. Itimidated	7-point Likert (1. Totally disagree - 7. Totally agree)	Compeau et al., 2022
Algorithmic awareness	Part 1. There is a large amount of data that can be used in the development and application of algorithms. Here you can see a selection of possible sources. Which of them are being used in the development and application of algorithms? 1. Smart speaker (e.g. Alexa) 2. Smart TV 3.Wearable computing devices such as activity trackers, heart rate monitors 4. Internet-Browsers (e.g. Internet Explorer, Firefox, Opera, Google Chrome) 5. Electronic payment (credit-, debit cards) 6. Cell Phone Towers 7. Computer Games Part 2. Algorithms are already being used in very different areas. Do you know which of the following functions are often performed by algorithms? 1. To create weather forecasts 2. To make product recommendations 3. To create financial news (stock markets) 4. To personalize advertisements	1. Is used 2. Is not used 3. Don't know	Dogruel et al., 2021

2.4.4. Participant recruitment

Participants were recruited from Prolific, an online research panel for this study. After their completion was approved, participants received compensation directly through the platform. The eligibility criteria included that the participants lived in North America, were at least 18 years old and proficient in English.

2.5. Result

2.5.1. Sample description

Our sample (N=242) was constructed to ensure a fairly balanced representation of males and females. Of the participants, 49.2% identified as male, 46.7% as female, 2.5% as non-binary, and 1.7% preferred not to disclose their gender. Participants ranged from 18 to 65 years old. Data regarding online news consumption, IT self-efficacy, IT anxiety, and algorithmic awareness were also collected to analyze as control variables. Descriptive statistics for our sample are presented in the tables below.

Table 6. Age distribution

Age range	Frequency	Percent	Cumulative Percent
From 18-24	53	21.9	21.9
From 25-34	89	36.8	58.7
From 35-44	51	21.1	79.8
From 45-54	24	9.9	89.7
From 55-64	17	7.0	96.7
65 or older	6	2.5	99.2
Prefer not to say	2	.8	100.0
Total	242	100.0	

Table 7. Descriptive statistic for the control variables

Control variables	Minimum	Maximum	Mean	Std. Deviation
IT Self-efficacy	8	100	74.12	16.92
IT Anxiety	1	6	2.24	1.25
Algorithmic awareness	0	11	8.05	2.44

Table 8. Online new consumption

Online news consumption	Number of responses	Percentage
Daily	132	54.55
Several times a week	55	22.73
Weekly	22	9.09
Several times a month	17	7.02
Once a month	7	2.89
Less often than once a month	9	3.72
Total	224	100.0

2.5.2. Measurement validity and reliability

To confirm that intention, technical and coordination uncertainty were distinct and discriminable, an exploratory factor analysis using Promax rotation was performed. The results presented in Table 9 confirmed the three dimensions of uncertainty about the intention, technical and coordination are distinct.

Table 9. Loadings and cross-loadings for related uncertainty construct (Pattern Matrix)

	Component		
	1	2	3
INT_UNC_1	0.138	-0.139	**0.830**
INT_UNC_2	-0.003	0.007	**0.884**
INT_UNC_3	-0.076	0.011	**0.861**
INT_UNC_4	-0.017	0.050	**0.860**
INT_UNC_5	0.032	0.261	**0.620**
TECH_UNC_1	-0.068	**0.894**	0.058
TECH_UNC_2	-0.147	**0.952**	0.079
TECH_UNC_3	0.072	**0.766**	0.057
TECH_UNC_4	0.154	**0.867**	-0.123
TECH_UNC_5	0.127	**0.861**	-0.044
COOR_UNC_1	**0.839**	0.070	-0.056
COOR_UNC_2	**0.861**	0.117	-0.080
COOR_UNC_3	**0.900**	-0.025	0.075
COOR_UNC_4	**0.907**	-0.088	0.109
COOR_UNC_5	**0.903**	-0.008	0.005

INT_UNC: Intention uncertainty
TECH_UNC: Technical uncertainty
COOR_UNC: Coordination uncertainty
Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization

To assess item reliability for the adapted scales, the loadings of each measurement item were evaluated on their targeted construct. The results are presented in Table 10. All measurement loadings for intention uncertainty, technical uncertainty, and coordination uncertainty are higher than the recommended threshold of 0.7 (Nunnally, 1978).

Table 10. Loading summary for adapted scales

Constructs	No	Items	Loading
Trust in algorithmic systems: The human agents' willingness to rely on agentic IS artifacts.	1	If I use NewsFlow, I believe that it would act in my best interest.	0.764
	2	If I use NewsFlow, I believe that it would do its best to help me."	0.736
	3	If I use NewsFlow, I think that its algorithm would be competent and effective in choosing the suitable news for me."	0.814
	4	If I use NewsFlow, I think that its algorithm would perform the role of a news curator very well."	0.778
	5	If I use NewsFlow, I think I would be able to depend on it completely."	0.810
	6	If I use NewsFlow, I would be able to completely depend on it for choosing suitable news for me."	0.792
	7	If I use NewsFlow, I would always be able to rely on this news curation algorithm for choosing the news that I would consume.	0.781
	8	If I use NewsFlow, I would be able to trust the content selection made by its news curation algorithm."	0.841
	9	If I use NewsFlow, I feel that I would need to be cautious when using it."	0.406
Intention Uncertainty: user's difficulty knowing what the purpose or the objective of an algorithm is (or to whom part of the task is delegated).	1	I am uncertain about the purpose of having a news curation algorithm on NewsFlow.	0.705
	2	I am unclear why NewsFlow has decided to implement a news curation algorithm in it.	0.797
	3	I believe NewsFlow hasn't given enough information about why they use a news curation algorithm.	0.721
	4	I am unsure why a news curation algorithm is put in place on NewsFlow.	0.805
	5	I have trouble understanding the goal of using the news curation algorithm on NewsFlow.	0.705
Technical Uncertainty: the users' difficulty understanding how an algorithm operates to achieve (or to optimize) a particular outcome (or a decision).	1	I am not sure if I can fully understand how the algorithm selects content on NewsFlow.	0.816
	2	I am uncertain how the news curation algorithm functions on NewsFlow.	0.847
	3	I find it's unclear what information is taken into account in the news curation algorithm.	0.771
	4	I am struggling to understand how the news curation algorithm operates.	0.824
	5	I find it's unclear what information is taken into account in the news curation algorithm.	0.861

Coordination Uncertainty: the users' uncertainty about how they can intervene to influence the outcome produced by an algorithm.	1	I am struggling to know how to interact with the news curation algorithm on NewsFlow.	0.770
	2	I don't know how to work around the news curation algorithm on NewsFlow to my advantage.	0.829
	3	I am finding it difficult to figure out how to effectively engage with the news curation algorithm on NewsFlow.	0.879
	4	I find it hard to discover ways to interact with this news curation algorithm for my own benefit.	0.856
	5	I am uncertain as to how I can work with the news curation algorithm on NewsFlow to suit my preferences.	0.842

The descriptive analysis and reliability results of each construct measurement are presented in Table 11 below. The score for each construct was calculated by taking the average score of its selected items, except the Algorithmic Awareness Scale, which is the sum of corrected answers, ranging from 0 to 11. The square roots of AVE of each construct were larger than the correlations between the constructs, indicating adequate discriminant validity.

Table 11. Descriptive and measurement validity

Construct	Values	Cronbach's Alpha	Mean (Std. Dev)	AVE*	1	2	3	4	5	6
1. Trust (9)	1 - 7	0.93	4.2 (1.15)	0.78	**0.881**					
2. Intention uncertainty (5)	1-7	0.9	2.83 (1.26)	0.76	-0.36	**0.871**				
3. Technical uncertainty (5)	1-7	0.93	3.04 (1.34)	0.79	-0.313	0.599	**0.891**			
4. Coordination uncertainty (5)	1-7	0.94	2.83 (1.31)	0.80	-0.377	0.547	0.623	**0.894**		
5. IT self-efficacy (5)	0-100	0.92	74.12 (16.92)	0.83	0.145	-0.155	-0.107	-0.205	**0.910**	
6. IT anxiety (5)	1-7	0.95	2.24 (1.25)	0.87	-0.127	0.216	0.189	0.261	-0.48	**0.934**

Diagonal element in bold are square roots of the Average Variance Extracted
Number of measurement items in parentheses
*Average Variance Extracted

2.5.3. Manipulation validity

To ensure that the manipulation of each delegation transparency-enhancing signal (intention, technical, coordination) was effective, manipulation check questions were included in the survey after prototype exposure. Three univariate analyses of variance (ANOVA) were conducted, one for each manipulation check question as a dependent variable. The interaction of these transparency-enhancing signals was also examined. It was expected that the absence or presence of one signal type would significantly influence its respected manipulation check question. The data presented in Table 12, 13 and 14 show that our manipulations were successful in signaling the expected information and avoiding unwanted cross-effects between signals.

Table 12. ANOVA for intention signal manipulation

Dependent variable: IS manipulation check

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	30.286*	7	4.327	2.985	0.005	0.082
Intercept	7021.694	1	7021.694	4843.959	<.001	0.954
Intention Signal (IS)	**22.086**	**1**	**22.086**	**15.236**	**<.001**	**0.061**
Technical Signal (TS)	0.3	1	0.3	0.207	0.65	0.001
Coordination Signal (CS)	0.171	1	0.171	0.118	0.732	0.001
IS * TS	5.48	1	5.48	3.78	0.053	0.016
IS * CS	0.908	1	0.908	0.626	0.429	0.003
IS * CS	1.321	1	1.321	0.911	0.341	0.004
IS * TS * CS	0.091	1	0.091	0.063	0.803	0
Error	339.201	234	1.45			
Total	7396	242				
Corrected Total	369.488	241				

*R Squared = 0.082 (Adjusted R Squared =0 .055)
Intention signal manipulation check question: “The information provided to introduce NewsFlow to its new users clearly describes what is the purpose and motivation for using a news curation algorithm in NewsFlow.”

Table 13. ANOVA for technical signal manipulation

Dependent variable: TS manipulation check

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	58.225*	7	8.318	5.286	<.001	0.137
Intercept	7276.064	1	7276.064	4623.634	<.001	0.952
Intention Signal (IS)	2.635	1	2.635	1.675	0.197	0.007
Technical Signal (TS)	**46.539**	**1**	**46.539**	**29.573**	**<.001**	**0.112**
Coordination Signal (CS)	1.099	1	1.099	0.698	0.404	0.003
IS * TS	2.029	1	2.029	1.289	0.257	0.005
IS * CS	2.528	1	2.528	1.606	0.206	0.007
TS * CS	3.029	1	3.029	1.925	0.167	0.008
IS * TS * CS	0.379	1	0.379	0.241	0.624	0.001
Error	368.238	234	1.574			
Total	7714	242				
Corrected Total	426.463	241				

*R Squared = 0.137 (Adjusted R Squared = 0.111)
Technical signal manipulation check question: "The information provided to introduce NewsFlow to its new users clearly describes how the news curation algorithm works in NewsFlow."

Table 14. ANOVA for coordination signals manipulation

Dependent variable: CS manipulation check

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	20.131*	7	2.876	2.27	0.03	0.064
Intercept	8180.712	1	8180.712	6456.261	<.001	0.965
Intention Signal (IS)	0.5	1	0.5	0.394	0.531	0.002
Technical Signal (TS)	0.404	1	0.404	0.319	0.573	0.001
Coordination Signal (CS)	**17.025**	**1**	**17.025**	**13.436**	**<.001**	**0.054**
IS * TS	0.008	1	0.008	0.006	0.938	0
IS * CS	1.813	1	1.813	1.431	0.233	0.006
TS * CS	0.158	1	0.158	0.124	0.725	0.001
IS * TS * CS	0.002	1	0.002	0.002	0.965	0
Error	296.501	234	1.267			
Total	8497	242				
Corrected Total	316.632	241				

* R Squared = 0.064 (Adjusted R Squared =0 .036)
Coordination signal manipulation check question: "The information provided to introduce NewsFlow to its new users clearly describes how can I interact with the news curation algorithm so that it better supports my news interest."

2.5.4. Hypothesis testing

Table 15 below summarizes the research model results. Sections 2.5.4.1 and 2.5.4.2 provide detailed information about hypothesis testing.

Table 15. Synopsis of Hypotheses and Results

Hypothesis	Result	β /F	Significance level
H1: Intention uncertainty → Trust in algorithmic systems	Supported	β = -0.179	0.009
H2: Technical uncertainty → Trust in algorithmic systems	Not supported	β = -0.043	0.532
H3: Coordination uncertainty → Trust in algorithmic systems	Supported	β = -0.191	0.005
H4: Intention signals → Intention uncertainty	Supported	F = 8.740	0.003
H5: Technical signals → Technical uncertainty	Supported	F = 20.780	<0.001
H6: Coordination signals → Coordination uncertainty	Supported	F = 5.433	0.021

2.5.4.1. The effects of delegation transparency-enhancing signals on delegation uncertainty dimensions (H4, H5, H6)

Mean scores and standard deviations for the three types of uncertainties across signalling conditions are summarized in Table 16. Besides, an ANOVA analysis was performed separately for each uncertainty dimension. This analysis aimed to explore how intention, technical, coordination signals, and interactions affected the three distinct dimensions of uncertainty.

Table 16. Summary of signal effects on three dimensions of delegation uncertainty

	Condition (sample size)	Intention uncertainty	Technical uncertainty	Coordination uncertainty
Intention signals (IS)	Absent (N=120)	**3.07 (1.32)***	3.13 (1.38)	2.93 (1.32)
	Present (N=122)	**2.60 (1.14)***	2.94 (1.29)	2.73 (1.29)
Technical signals (TS)	Absent (N=121)	2.93 (1.20)	**3.40 (1.37)***	2.85 (1.29)
	Present (N=121)	2.73 (1.29)	**2.67 (1.20)***	2.81 (1.33)
Coordination signals (CS)	Absent (N=122)	2.90 (1.29)	**3.26 (1.38)***	**3.03 (1.37)***
	Present (N=120)	2.77 (1.22)	**2.81 (1.25)***	**2.63 (1.22)***

* The result is significant at 5%
The mean score is presented outside the parentheses. The standard deviation is presented inside the parentheses

The ANOVA results presented in Table 17 indicate that the provision of intention signals significantly reduces intention uncertainty (p=0.003); **providing support for hypothesis 4**. There are no additional effects from other signals or their interaction on intention uncertainty.

Table 17. The between-subject effects of transparency-enhancing signals to intention uncertainty

Dependent Variable: Intention uncertainty

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	20.109*	7	2.873	1.871	.075	.053
Intercept	1944.076	1	1944.076	1266.088	<.001	.844
Intention Signal (IS)	**13.420**	**1**	**13.420**	**8.740**	**.003**	**.036**
Technical Signal (TS)	2.529	1	2.529	1.647	.201	.007
Coordination signal (CS)	1.000	1	1.000	.651	.420	.003
IS * TS	1.839	1	1.839	1.198	.275	.005
IS * CS	.512	1	.512	.334	.564	.001
TS * CS	.735	1	.735	.478	.490	.002
IS * TS * CS	.035	1	.035	.023	.879	.000
Error	359.307	234	1.535			
Total	2321.760	242				
Corrected Total	379.416	241				

* R Squared = .053 (Adjusted R Squared = .025)

Similarly, our results also confirmed that the presence of transparency-enhancing signals about technical (TS effect with $p < 0.001$) would decrease technical uncertainty, thus, the results presented in Table 18 **support Hypothesis 5**. The results also suggest that coordination signals help diminish technical uncertainty (p=0.004).

Table 18. The between-subject effects of transparency-enhancing signals to technical uncertainty

Dependent Variable: Technical uncertainty

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	60.122*	7	8.589	5.419	<.001	.139
Intercept	2232.426	1	2232.426	1408.460	<.001	.858
Intention Signal (IS)	2.204	1	2.204	1.391	.240	.006
Technical signal (TS)	**32.936**	**1**	**32.936**	**20.780**	**<.001**	**.082**
Coordination signal (CS)	**13.093**	**1**	**13.093**	**8.261**	**.004**	**.034**
IS * TS	1.215	1	1.215	.767	.382	.003
IS * CS	5.629	1	5.629	3.552	.061	.015
TS * CS	4.765	1	4.765	3.006	.084	.013
IS * TS * CS	.517	1	.517	.326	.569	.001
Error	370.893	234	1.585			
Total	2660.920	242				
Corrected Total	431.014	241				

* R Squared = .139 (Adjusted R Squared = .114)

The final ANOVA analysis on coordination uncertainty is presented in Table 19 below. The results **supported hypothesis 6** predicting that the presence of coordination signals would decrease coordination uncertainty (p = 0.021).

Table 19. The between-subject effects of transparency-enhancing signals to coordination uncertainty

Dependent Variable: Coordination uncertainty

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	16.072*	7	2.296	1.356	.225	.039
Intercept	1939.847	1	1939.847	1145.551	<.001	.830
Intention signal (IS)	2.408	1	2.408	1.422	.234	.006
Technical signal (TS)	.148	1	.148	.087	.768	.000
Coordination signal (CS)	**9.199**	**1**	**9.199**	**5.433**	**.021**	**.023**
IS * TS	.168	1	.168	.099	.753	.000
IS * CS	3.517	1	3.517	2.077	.151	.009
TS * CS	.082	1	.082	.048	.826	.000
IS * TS * CS	.443	1	.443	.262	.609	.001
Error	396.250	234	1.693			
Total	2352.400	242				
Corrected Total	412.321	241				

* R Squared = .039 (Adjusted R Squared = .010)

2.5.4.2. The effect of intention, technical and coordination uncertainty on trust (H1, H2, H3)

Before running a Generalized Linear Model (GLM) analysis, we centered the three independent variables: intention uncertainty, technical uncertainty and coordination uncertainty, by subtracting the variables from their mean. The centering method was aimed to address multicollinearity, reducing the correlation between intention uncertainty, technical uncertainty and coordination uncertainty. Additionally, and more importantly, centering around the means also improves the interpretability of coefficients in the model. Control variables were also added to the model, including IT self-efficacy, anxiety, and algorithmic awareness.

The results of GLM, presented in Table 20, reveal a significant effect of intention uncertainty (p = 0.009) and coordination uncertainty (p = 0.005) on trust, thus **confirming hypotheses H1 and H3**. In contrast, **H2 was not supported** as technical uncertainty's effect on trust was found to be insignificant.

Besides, algorithmic awareness was found to decrease trust (p = 0.004) significantly. This finding indicates that the more aware people are of the presence of algorithms in their daily lives, the less likely they are to trust an algorithmic platform. IT self-efficacy had a marginal effect ($p<0.1$), while IT anxiety had an insignificant effect on trust ($p=0.8$).

Table 20. Generalized Linear Model (GLM) summary

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig. (p)
(Intercept)	4.188	.4383	3.329	5.047	91.306	1	.000
Intention uncertainty*	-.179	.0682	-.313	-.045	6.873	1	.009
Technical uncertainty*	-.043	.0683	-.177	.091	.390	1	.532
Coordination uncertainty*	-.191	.0679	-.324	-.058	7.940	1	.005
IT self-efficacy	.008	.0046	-.001	.017	3.123	1	.077
IT anxiety	.016	.0611	-.104	.135	.064	1	.800
Algorithmic Awareness	-.080	.0280	-.134	-.025	8.086	1	.004
(Scale)	1.036[a]	.0942	.867	1.238			

Dependent Variable: Trust in algorithmic systems
Model: (Intercept), Intention uncertainty, Technical Uncertainty, Coordination uncertainty, IT Self-efficacy, IT anxiety, Algorithmic awareness
*The variables were centered around their mean value
a. Maximum likelihood estimate.

2.5.4.3. Post-hoc analysis for the effect of technical uncertainty on trust

In light of these results, we conducted an additional analysis to explore whether the insignificant effect of technical uncertainty on trust (H2) was due to the competing effects from the other two dimensions of delegation uncertainty. To do so, a Conditional Process Analysis (Hayes, 2022), PROCESS in short, was used to investigate whether the effect of technical uncertainty would become significant at low levels of intention uncertainty and coordination uncertainty.

Thus, we first run a PROCESS Analysis (Model 1) with intention uncertainty as a moderator of the technical uncertainty to trust effect. The results, reported in Table 21, indicate a significant interaction between technical uncertainty and intention uncertainty ($p = 0.0025$), suggesting that the effect of technical uncertainty on trust varied at different levels of intention uncertainty. Overall, this suggests that intention uncertainty significantly moderates the relationship between technical uncertainty and trust. We analyze this effect in more detail below.

Table 21. Model Summary (Y: Trust, X: Technical uncertainty; W: Intention uncertainty)

Model: 1 (Sample size: 242)

Outcome variable: Trust
Model Summary

R	R-sq	MSE	F	df1	df2	p
0.4203	0.1767	1.0936	17.0216	3.0000	238.0000	0.0000

Model

	Coeff	se	t	p	LLCI	ULCI
Constant	4.0718	0.0766	53.1869	0.0000	3.9210	4.2227
Technical uncertainty (TU)	-0.1552	0.0634	-2.4465	0.0152	-0.2802	-0.0302
Intention uncertainty (IU)	-.2682	0.0675	-3.9742	0.0001	-0.4011	-0.1352
TU x IU	0.1119	0.0366	3.0608	**0.0025**	0.0399	0.1840

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
TU* IU	0.0324	9.3687	1.0000	238.0000	**0.0025**

Technical uncertainty and intention uncertainty were centered around its mean value
Level of confidence for all confidence intervals in output: 95%
MATRIX procedure: PROCESS Procedure for SPSS Version 4.2 - Written by Andrew F. Hayes, Ph.D. www.afhayes.com
Documentation available in Hayes (2022). www.guilford.com/p/hayes3

As Table 22 further shows, at a higher level of intention uncertainty (i.e., one standard deviation above the mean), the effect of technical uncertainty on trust is not significant ($\beta = -0.0144$, $p = 0.8445$). However, at both low (one standard deviation below the mean) and mean levels of intention uncertainty, the effect of technical uncertainty to trust becomes significant ($\beta = -0.2953$, $p < 0.001$ and $\beta = -0.1549$, $p < 0.05$, respectively). Figure 2 further illustrates the effect of technical uncertainty on trust is stronger when intention uncertainty decreases.

Table 22. Conditional effects of Technical uncertainty at different values of Intention uncertainty

Conditional effects of the focal predictor (technical uncertainty) at values of the moderator (intention uncertainty):

Intention uncertainty (IU)	Effect (β)	se	t	p	LLCI	ULCI
-1.517	**-0.2953**	0.0829	-3.5642	**0.0004**	-0.4585	-0.1321
0.0031	**-0.1549**	0.0634	-2.4416	**0.0154**	-0.2798	-0.0299
1.2578	-0.0144	0.0734	-0.1963	0.8445	-0.1591	0.1302

Technical uncertainty and intention uncertainty were centered around its mean value
Level of confidence for all confidence intervals in output: 95%
Intention uncertainty (IU) values in conditional tables are the mean and +/-SD from the mean
MATRIX procedure: PROCESS Procedure for SPSS Version 4.2 - Written by Andrew F. Hayes, Ph.D. www.afhayes.com
Documentation available in Hayes (2022). www.guilford.com/p/hayes3

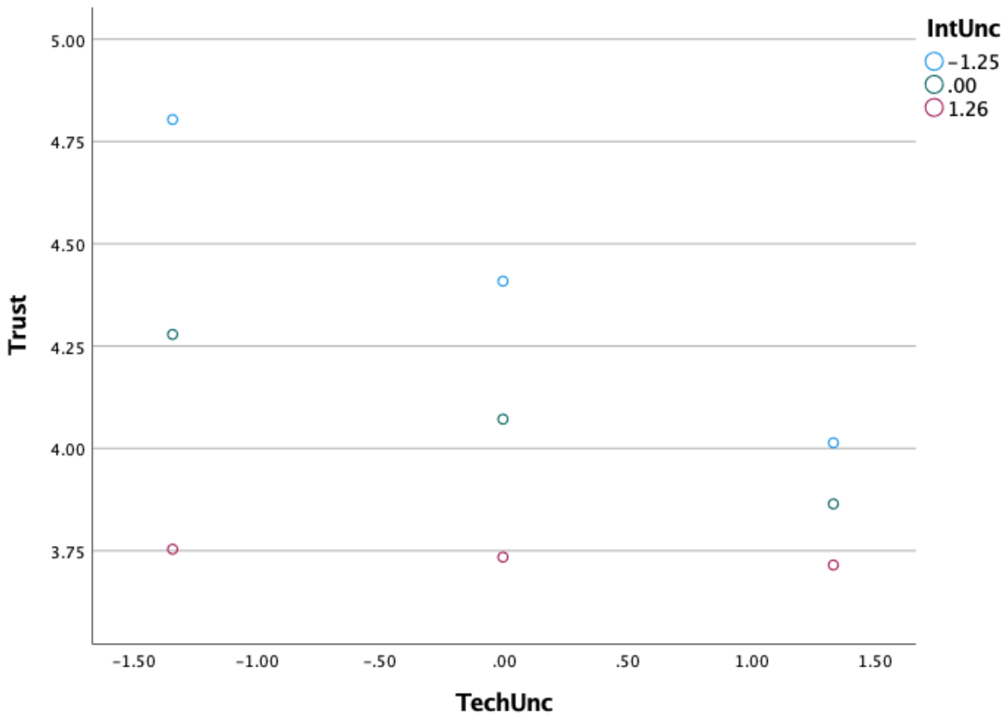


Figure 2. Conditional effects of Technical uncertainty (TechUnc) at values of Intention uncertainty (IntUnc)

The second similar analysis was conducted with coordination uncertainty as a moderator variable moderating the effect of technical uncertainty on trust. The model summary is presented in Table 23 below. The interaction effect between coordination uncertainty and technical uncertainty was found to be marginal (p= 0.0994) at the 95% confidence level. Hence, this analysis suggests that coordination uncertainty marginally moderates the relationship between technical uncertainty and trust.

Table 23. Model Summary (Y: Trust, X: Technical uncertainty; W: Coordination uncertainty)

Model: 1 (Sample size: 242)

Outcome variable: Trust							
Model Summary							
	R	R-sq	MSE	F	df1	df2	p
	0.4022	0.1617	1.1134	15.3060	3.0000	238.0000	0.0000
Model							
		Coeff	se	t	p	LLCI	ULCI
	Constant	4.1192	0.0782	52.6423	0.0000	3.9650	4.2733
	Technical uncertainty (TU)	-0.1147	0.0651	-1.7630	0.0792	-0.2429	0.0135
	Coordination uncertainty (CU)	-.2739	0.0669	-4.0910	0.0001	-0.4058	-0.1420
	TU x CU	0 .0594	0.0359	1.6540	0.0994	-0.0114	0.1302

Test(s) of highest order unconditional interaction(s):					
	R2-chng	F	df1	df2	p
TU*CU	0.0096	2.7357	1.0000	238.0000	0.0994

Technical uncertainty and coordination uncertainty were centered around their mean value
Level of confidence for all confidence intervals in output: 95%
Run MATRIX procedure: PROCESS Procedure for SPSS Version 4.2 - Written by Andrew F. Hayes, Ph.D.
www.afhayes.com
Documentation available in Hayes (2022). www.guilford.com/p/hayes3

We analyze the effect in more detail and the result is presented in Table 24. At the mean and high (one standard deviation above the mean) levels, the effect of technical uncertainty on trust is not significant (β = -0.1146, p = 0.0794 and β = -0.0369, p = 0.6382, respectively). However, at a low level of coordination uncertainty, the effect of technical uncertainty becomes significant (β = -0.1924, p < 0.02). This effect is further illustrated in Figure 3. Overall, this supports the idea that although technical uncertainty does not have a general significant influence on trust in the presence of coordination uncertainty, the strength of its effect seems to be increasing as coordination uncertainty diminishes.

Table 24. Conditional effects of Technical uncertainty at different values of coordination uncertainty

Conditional effects of the focal predictor (technical uncertainty) at values of the moderator (coordination uncertainty):

Coordination uncertainty (CU)	Effect(β)	se	t	p	LLCI	ULCI
-1.3066	**-0.1924**	0.0821	-2.3433	**0.0199**	-0.3541	-0.0306
0.0014	-0.1146	0.0651	-1.7618	0.0794	-0.2428	0.0135
1.3094	-0.0369	0.0784	-0.4708	0.6382	-0.1913	0.1175

Technical uncertainty and coordination uncertainty were centered around their mean value
Level of confidence for all confidence intervals in output: 95%
Coordination uncertainty (CU) values in conditional tables are the mean and +/-SD from the mean
Run MATRIX procedure: PROCESS Procedure for SPSS Version 4.2 - Written by Andrew F. Hayes, Ph.D.
www.afhayes.com
Documentation available in Hayes (2022). www.guilford.com/p/hayes3

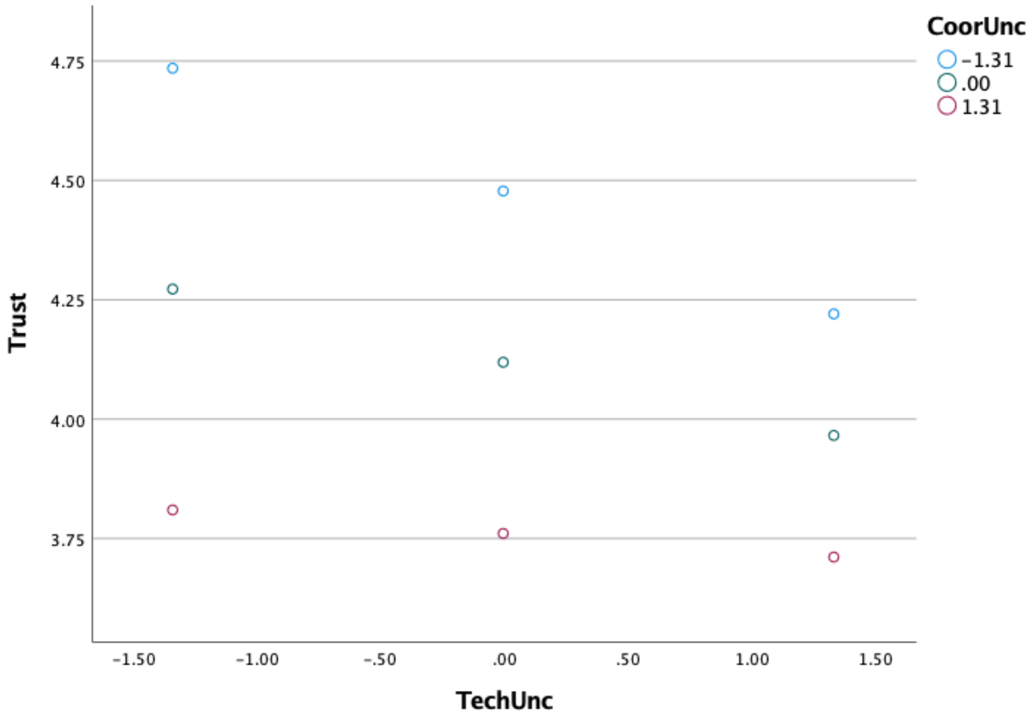


Figure 3. Conditional effects of Technical uncertainty (TechUnc) at values of Coordination uncertainty (CoorUnc)

In summary, the post-hoc analysis emphasizes the complex interplay between the three dimensions of delegation uncertainty in AX and their effects on trust. In particular, we found that the strength of technical uncertainty effects on trust varied depending on the level of intention uncertainty and coordination uncertainty. When the level of intention uncertainty and coordination uncertainty were high, the impact of technical uncertainty on trust was negligible. We suspect that this might occur because when the other two dimensions of delegation uncertainty are high, their effects on trust mask the effect of technical uncertainty. We have shown that this was particularly salient in the context of technical uncertainty interacting with intention uncertainty.

2.5.5. Summary of the research model result

Overall, the findings are illustrated in Figure 4 below. We confirm the significant impacts of delegation transparency-enhancing signals in reducing the respective uncertainty (H4, H5, H6 is supported). Furthermore, the analysis also shows a significant effect of coordination signals in mitigating technical uncertainty. Intention uncertainty and coordination uncertainty can significantly reduce trust in algorithmic systems (H1 and H3 are supported), while technical uncertainty does not significantly affect trust (H2 is not supported). However, post-hoc analysis has uncovered a significant effect of intention uncertainty and a marginal effect of coordination uncertainty in moderating technical uncertainty's effect on Trust. Finally, the results emphasize algorithmic awareness as a significant control variable, while the effect of IT self-efficacy as a control variable is marginal.

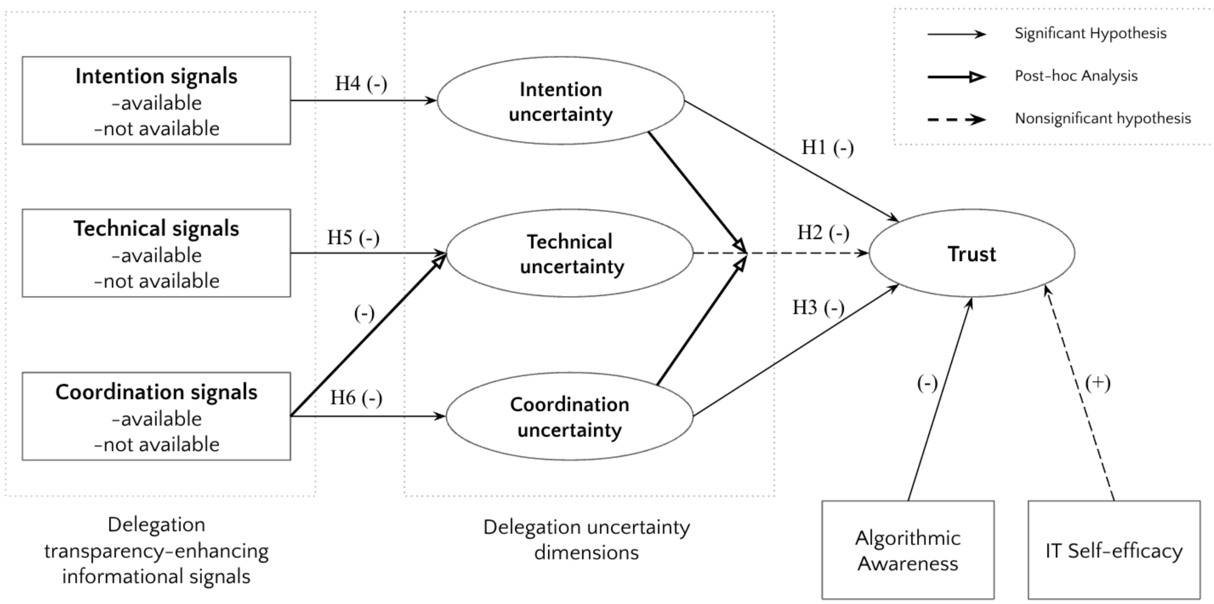


Figure 4. Illustration of research model results

2.7. Discussion

2.7.1. Discussion of the result

The study highlights the importance of delegation uncertainty in the context of AX. First, we found that delegation transparency-enhancing signals about the algorithm's intention, technical aspects, and coordination mechanisms can effectively mitigate uncertainty in an individual's algorithmic experience. It should be noted that coordination signals can significantly reduce users' uncertainty about how an algorithm functions (technical uncertainty) in addition to mitigating coordination uncertainty.

Secondly, intention uncertainty and coordination uncertainty significantly impact how an individual perceives the algorithm's trustworthiness during their experience. Thus, trust in algorithmic systems can be best enhanced by reducing uncertainty about intention and coordination. Even though the primary model's results indicate the insignificant impact of technical uncertainty, further analysis uncovered that technical uncertainty's effect on users' trust is significant and observable when an individual's intention uncertainty diminishes. Similarly, the lower level of coordination uncertainty also suggests stronger effects of technical uncertainty on trust in algorithmic systems. Hence, we suggest possible competing effects on trust in algorithmic systems among the three dimensions of delegation uncertainty.

2.7.2. Contribution, Limitation and Future Research

This research contributes to the theoretical study of human interaction with modern algorithmic technology, more precisely, algorithmic experience. Extending from the human-computer interaction literature, agency theory and the agentic IS delegation framework, we refined the AX concept to capture a comprehensive nature of the dyadic dynamic between human and algorithmic technologies. Moreover, this study proposed delegation uncertainty as a novel concept worth noticing in improving people's trust in algorithmic systems.

The conceptualization of delegation uncertainty dimensions helps explore critical aspects that can affect human trust in algorithmic systems. More precisely, the results help guide developers and designers in the future development of algorithmic systems. By defining the three subconstructs of delegation uncertainty, including intention, technical and coordination, the study revealed varying effects and underscored critical aspects for future study. First, the effectiveness of delegation transparency-enhancing signals, including intention, technical and coordination in reducing delegation uncertainty in AX. Second is the pronounced effect of intention uncertainty and coordination uncertainty on people's trust in algorithmic systems. Lastly, we discovered the potential interaction of the three dimensions of delegation uncertainty in impacting trust, precisely, a significant interaction between technical uncertainty and intention uncertainty and a marginal interaction between technical uncertainty and coordination uncertainty.

One limitation of this study is that we only examine the research model in one specific AX context, the online news curation algorithm. It is essential to note that the algorithmic experience is highly contextualized because of the flexibility in the IS delegation framework, traversing from the tasks, roles and responsibilities between human agents and the agentic IS artifacts. Further study for different archetypes of agentic IS artifacts would be beneficial to understand how this study's results are generalizable in other circumstances. In addition, the scope of this exploratory research focused solely on manipulating different delegation transparency-enhancing signals by intention, technical and coordination. We have not explored the potential different effects when each type of signal is further classified. For instance, coordination signals like algorithm refinement options might affect coordination uncertainty more strongly than the system's feedback loops.

Finally, one presumption in the scope of this study is that the difference between typical online transactions and algorithmic experiences makes little intersection between privacy uncertainty and delegation uncertainty. For future studies, we encourage exploring the interaction between privacy uncertainty and delegation uncertainty and their effects on human trust in the context of AX. Another direction for future research could be exploring execution as a source of uncertainty in the implementation of algorithmic systems. This uncertainty type is related to the challenges in validating whether the platform owners execute the algorithmic practices as they have claimed.

2.8. Conclusion

By further exploring the existing human-computer interaction literature, agency theory, and the agentic IS delegation framework, we have refined the AX concept and introduced Delegation Uncertainty as a pertinent construct to understand the evolving agency dynamics within human-computer interaction. The study marks significant work in exploring AX by concentrating on delegation uncertainty as a pivotal aspect of the human-algorithm relationship. We have developed a research model outlining three dimensions of delegation uncertainty—intention, technical, and coordination—in the context of AX. Additionally, drawing upon signalling theory, we propose three delegation transparency-enhancing signals to address each dimension of delegation uncertainty. The study uncovered that trust in algorithmic systems can be improved by effectively reducing an individual's intention and coordination uncertainty through the respected delegation transparency-enhancing signals. Besides, technical uncertainty's indirect effect on trust was figured with the moderation of intention uncertainty. This research sets a foundation for further exploration and refinement of the conceptual model of AX, aiming to enhance and optimize human interactions with transformative algorithmic technology.

Appendix

Appendix A1. First card sorting for measurement items

Card	Correct (%)	Results
Intention uncertainty is defined as the users' difficulty understanding what (the outcome, the decision, etc.) an algorithm is intended to achieve or optimized.	-	Keep and reword
I am unsure why a content curation algorithm is put in place on the news website	58.33%	Keep
I feel that the news website is not clear with respect to the reasons for implementing a content curation algorithm	50.00%	Remove
I have trouble understanding the goal of the content curation algorithm embedded in this news website	58.33%	Keep
I am unsure what the content curation algorithm is designed to achieve or optimize	50.00%	Remove
I am uncertain as to the purpose of having a content curation algorithm on the news website.	75.00%	Keep
I am unclear why the news website has decided to implement a content curation algorithm.	66.67%	Keep
I feel that the news website has not provided sufficient information about the rationale for employing a content curation algorithm.	50.00%	Keep and reword
I am having difficulty understanding the benefits of the content curation algorithm on this particular news website.	50.00%	Remove
Technical uncertainty is the users' difficulty understanding how an algorithm achieves or optimizes a particular outcome (or a decision)	-	Keep and reword
I am unsure about how the content curation algorithm operates	41.67%	Remove
I am afraid I can't clearly grasp how the algorithm curates content on the news website	50.00%	Keep and reword
I am uncertain how the content curation algorithm functions.	58.33%	Keep
I feel that the news website is not clear with respect to how the content is curated	33.33%	Keep and reword
I am unclear on the inner workings of the content curation algorithm.	50.00%	Remove
I am struggling to comprehend how the content curation algorithm operates.	58.33%	Keep and reword
I am not sure I fully grasp how the algorithm chooses which stories to showcase.	58.33%	Keep and reword
I am finding it difficult to comprehend how the algorithm decides which articles to feature.	50.00%	Remove
Coordination uncertainty refers to the users' uncertainty about how they can intervene to influence the outcome produced by an algorithm	-	Keep and reword
I am struggling to know how to interact with the content curation algorithm	66.67%	Keep
I feel that I don't know how to work around the content filtering algorithm to my advantage	66.67%	Keep
I am finding it difficult to figure out how to effectively engage with the content curation algorithm.	66.67%	Keep
I am uncertain as to how I can work with the content filtering algorithm to suit my preferences.	58.33%	Keep
I am struggling to discover ways to interact with the content curation algorithm in a way that benefits me.	50.00%	Keep and reword

I am unsure how to tailor the content curation algorithm to my preferences and needs	58.33%	Remove
Trust is defined and explained as the user's willingness to depend on an algorithm to assist them in their task.	-	Keep and reword
I feel I must be cautious when using this news curation algorithm	41.67%	Keep
It is risky to rely on this news curation algorithm	75.00%	Keep
I believe that this news curation algorithm will act in my best interest	100.00%	Keep
I believe that this news curation algorithm will do its best to help me	75.00%	Keep
I believe that this news curation algorithm is interested in understanding my needs and preferences	41.67%	Keep
I think that this news curation algorithm is competent and effective in choosing the suitable news for me	58.33%	Keep
I think that this news curation algorithm performs its role as a news curator very well	58.33%	Keep
I believe that this news curation algorithm has all the functionalities I would expect from a news curator	66.67%	Keep
If I use this news curation algorithm, I think I would be able to depend on it completely	91.67%	Keep
I think I can completely depend on this news curation algorithm for choosing suitable news for me	91.67%	Keep
I can always rely on this news curation algorithm for choosing news that I consume	75.00%	Keep
I can trust the content selection made by this news curation algorithm	91.67%	Keep
I believe that there could be negative consequences when interact with the news curation algorithm	25.00%	Remove

Appendix A2. Second card sorting for measurement items

Card	Correct (%)	Final result
Intention uncertainty is defined as the users' difficulty knowing what is the purpose or the objective of using algorithm in the given context	-	-
I am unsure why a content curation algorithm is put in place on the news website	88.89%	Select
I have trouble understanding the goal of the content curation algorithm embedded in this news website	100.00%	Select
I am uncertain as to the purpose of having a content curation algorithm on the news website.	88.89%	Select
I am unclear why the news website has decided to implement a content curation algorithm.	100.00%	Select
I believe the news website hasn't given enough information about why they use a content curation algorithm	100.00%	Select
Technical uncertainty is the users' difficulty understanding how an algorithm operates to achieve (or to optimize) a particular outcome (or a decision)	-	-
I am not sure if I can fully understand how the algorithm selects content on the news website.	77.78%	Select
I am uncertain how the content curation algorithm functions.	88.89%	Select

I find it's unclear what information is taken into account in the news curation algorithm	77.78%	Select
I am struggling to understand how the content curation algorithm operates.	88.89%	Select
I am not sure how the news is curated by the algorithm in this website.	88.89%	Select
Coordination uncertainty refers to the users' uncertainty about how they can intervene to influence the outcome produced by an algorithm	-	Select
I am struggling to know how to interact with the content curation algorithm	100.00%	Select
I feel that I don't know how to work around the content filtering algorithm to my advantage	100.00%	Select
I am finding it difficult to figure out how to effectively engage with the content curation algorithm.	88.89%	Select
I am uncertain as to how I can work with the content filtering algorithm to suit my preferences.	88.89%	Select
I find it hard to discover ways to interact with the content curation algorithm for my own benefit.	88.89%	Select
Trust is defined as users's willingness to rely on algorithmic technology due to their perceived competence and effectiveness	-	
I feel that I must be cautious when using this news curation algorithm	55.56%	Select
It is risky to rely on this news curation algorithm	55.56%	Remove
I believe that this news curation algorithm will act in my best interest	100.00%	Select
I believe that this news curation algorithm will do its best to help me	100.00%	Select
I believe that this news curation algorithm is interested in understanding my needs and preferences	55.56%	Remove
I think that this news curation algorithm is competent and effective in choosing the suitable news for me	66.67%	Select
I think that this news curation algorithm performs its role as a news curator very well	66.67%	Select
I believe that this news curation algorithm has all the functionalities I would expect from a news curator	44.44%	Remove
If I use this news curation algorithm, I think I would be able to depend on it completely	88.89%	Select
I think I can completely depend on this news curation algorithm for choosing suitable news for me	100.00%	Select
I can always rely on this news curation algorithm for choosing news that I consume	88.89%	Select
I can trust the content selection made by this news curation algorithm	100.00%	Select

Appendix B1. Summary of manipulation check

		Manipulation check for Intention signal	Manipulation check for Technical signal	Manipulation check for Coordination signal
Role signal	No (N=120)	**5.09 (1.40)***	5.38 (1.47)	5.77 (1.19)
	Yes (N=122)	**5.69 (0.97)***	5.59 (1.17)	5.86 (1,11)
Execution signal	No (N=121)	5.36 (1.18)	**5.05 (1.47)***	5.86 (1.06)
	Yes (N=121)	5.42 (1.30)	**5.93 (1.01)***	5.77 (1.23)
Coordination signal	No (N=122)	5.36 (1.36)	5.43 (1.47)	**5.55 (1.25)***
	Yes (N=120)	5.42 (1.11)	5.55 (1.33)	**6.08 (0.96)***

* The result is significant at 5%
The mean score is presented outside the parentheses. The standard deviation is presented inside the parentheses
Manipulation check questions:

- Intention: "The information provided to introduce NewsFlow to its new users clearly describes what is the purpose and motivation for using a news curation algorithm in NewsFlow."
- Technical: "The information provided to introduce NewsFlow to its new users clearly describes .how the news curation algorithm works in NewsFlow."
- Coordination: "The information provided to introduce NewsFlow to its new users clearly describes how can I interact with the news curation algorithm so that it better supports my news interest."

Appendix B2. Summary of manipulation check per treatment groups

Treatment group	N	Manipulation check for Intention signal	Manipulation check for Technical signal	Manipulation check for Coordination signal
1: Control group	30	4.87 (1.50)	4.73 (1.68)	5.67 (1.27)
2: Technical signal (TS) only	31	5.13 (1.57)	6.10 (1.14)	5.52 (1.41)
3: Coordination signal (CS) only	30	4.93 (1.17)	4.97 (1.40)	5.97 (0.81)
4: TS + CS	29	5.41 (1.32)	5.72 (1.25)	5.93 (1.16)
5: Intention signal (IS) only	30	5.93 (0.79)	5.00 (1.60)	5.57 (1.19)
6: IS + TS	31	5.52 (1.24)	5.84 (0.969)	5.45(1.18)
7: IS + CS	31	5.68 (0.75)	5.48 (1.09)	6.23 (0.81)
8: IS + TS + CS	30	5.63 (1.03)	6.03 (0.556)	6.20 (1.03)

The mean score is presented outside the parentheses
The standard deviation is presented inside the parentheses

Appendix C. Summary of delegation uncertainty by treatment groups

Treatment groups	N	Intention uncertainty	Technical uncertainty	Coordination uncertainty
1: Control group	30	3.41 (1.27)	3.84 (1.37)	2.98 (1.27)
2: Technical signal (TS) only	31	2.95 (1.40)	2.59 (1.15)	3.03 (1.43)
3: Coordination signal (CS) only	30	3.11 (1.14)	3.31 (1.32)	2.88 (1.15)
4: TS + CS	29	2.81 (1.45)	2.80 (1.39)	2.84 (1.47)
5: Intention signal (IS) only	30	2.70 (1.09)	3.72 (1.39)	3.16 (1.37)
6: IS + TS	31	2.54 (1.25)	2.94 (1.25)	2.94 (1.44)
7: IS + CS	31	2.53 (1.21)	2.76 (1.19)	2.41 (1.28)
8: IS + TS + CS	30	2.63 (1.15)	2.35 (095)	2.43 (0.90)

The mean score is presented outside the parentheses
The standard deviation is presented inside the parentheses

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Chapter 3: Managerial Article

Algorithmic experience: The impacts of transparency-enhancing signals on people's trust in algorithmic systems

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The use of algorithms in technological systems has become more common, from personalized recommendation systems that appear to know our specific preferences to AI-powered technologies in critical sectors such as finance, medical care, and even governments' justice systems. As our world becomes increasingly interconnected and digitalized, algorithms actively shape how people perceive and engage with their surrounding environment.

However, algorithms remain a "mystery", perceived as incomprehensible due to their technical complexity and opaque nature. The expanding authority granted to algorithms raises profound questions about ethical practices, algorithmic biases, and discrimination. Transparency and clear explanations about the algorithm's implementation are generally considered important factors in establishing people's trust in algorithmic systems. But how exactly should it be done? What is the right approach?

First, what are algorithmic experiences (AX)?

Algorithms are generally described as the system's computational process and its optimization for specific system outcomes. They are the backbone of the system, determining how it functions and responds to external input. We should acknowledge that the interaction with algorithmic systems is fluid, as such systems are no longer inert tools but active agents that influence humans who engage with them. Scholars and professionals have directed to agency perspective to illustrate the bidirectional delegation of roles and responsibilities between human agents and agentic systems (in this instance, the algorithms).

The concept of algorithmic experience seems to be suitable, described as *the particular form of human-computer relation characterized by the significant delegation of rights, responsibilities, and power from human agents (users) to agentic IS artifacts (the algorithmic systems)*.

What are the key friction points in AX?

As mentioned, the lack of information about the algorithm and the delegation process poses challenges and creates uncertainty when individuals interact with these systems. Using agency theory and information system (IS) delegation framework, our research identified three dimensions of delegation uncertainty in AX. Overall, *delegation uncertainty refers to individual users' difficulty in assessing the delegated role of an algorithm in their digital experience*. Delegation uncertainty is captured in three dimensions:

- **Intention uncertainty** - the user's difficulty knowing what is the purpose or the objective of an algorithm (to whom part of the task is delegated).
- **Technical uncertainty** - the users' difficulty understanding how an algorithm operates to achieve or optimize a particular outcome or decision.
- **Coordination uncertainty** - the users' uncertainty about how they can intervene to influence the outcome produced by an algorithm.

We conducted an online survey experiment through Prolific panel, with a sample size of 242 participants. The experiment unfolds in a stimulated scenario where respondents engage with the onboarding process of an online news website, featuring an algorithm for content curation. Delegation transparency-enhancing signals about intention, technical, and coordination were manipulated, expecting to mitigate delegation uncertainty.

We found that uncertainty about intention and coordination can significantly reduce trust in algorithmic systems. Thus, efforts to mitigate uncertainty about what the algorithm aims to achieve (intention) and how to interact with an algorithm (coordination) can effectively improve people's overall trust in an algorithm. Besides, the effect of technical uncertainty on trust in algorithmic systems is varied.

What transparency signals can reduce uncertainty?

Based on uncertainty segmentation, the following transparency-enhancing signals are effective mitigators for uncertainty in AX.

- Intention signals - Information that clarifies the purpose of the algorithm employed in the platform, indicating the algorithm's scope and its objectives (i.e., what the algorithm aims to achieve)
- Technical signals - Information that streamlines the users' understanding of the algorithm's functions. From the users' standpoint, this type of information should highlight the inputs

considered by the algorithm and provide essential insights about its operation (e.g., frequency, data type and weighting)

- Coordination signals - Information or features that demonstrate to users how they can influence the algorithm’s processes and results (e.g. feedback loops or algorithm refinement features)

Each signal type can mitigate its corresponding uncertainty. Notably, providing information on how to collaborate with the algorithm (coordination signals) not only reduces the users’ coordination uncertainty but also mitigates their uncertainty relating to the algorithm's technical complexity (technical uncertainty).

Implications to Enhance Trust in Algorithmic Systems

The findings show that user trust is best achieved through transparently communicating what the algorithm aims to optimize (reducing intention uncertainty) and enabling users to engage with the algorithm effectively (reducing coordination uncertainty). While detailed explanations about the algorithm’s technical functionality benefit users, we recommend prioritizing transparency efforts to address the algorithm’s intention and coordination mechanisms.

However, while technical uncertainty has a less significant impact, it still plays a role in shaping people’s trust in an algorithm. Technical uncertainty affects trust more strongly when people are less uncertain about what the algorithms tend to achieve (low intention uncertainty) or how to interact with the algorithm (low coordination uncertainty). We suggest a balancing act to ensure transparency about the technical aspects of the algorithm.

What more to consider in improving AX?

For future development of algorithmic systems, it is essential to remember that there is no universal formula for great algorithmic experience. Our study focused on recommendation algorithms in online news. Several contextual factors should be further explored for that specific circumstance, including the domain in which the algorithm operates, the nature of the task it undertakes, and the human attributes relevant to task execution.

Adapting transparency signals to particular contexts would seem like a desirable thing to do in order to improve people’s trust in algorithmic systems. We illustrate different transparency signals using three examples of the algorithm’s implication in the table below:

	The algorithm curates content in online news platforms	***The algorithm assesses worker's performance in gig work platforms***	***The algorithm allocates the government's utility discount to citizens***
Intention signals	***Purpose:*** - Personalized content based on users' preferences. - Diversify users' content exposure. - Filter out repeated and unreliable news. - Update the most current and relevant content.	***Purpose:*** - Assess the workers' overall performance to ensure the quality of the services. - Speed up the evaluation process with a high level of accuracy and unbiasedness. - Make sure underperformance is addressed and quickly improved.	***Purpose:*** - Decide a suitable utility discount amount for the citizens. - Speed up the application evaluation, ensuring accuracy and that only suitable applicants receive the right discount amount.
Technical signals	***How the algorithm works:*** - Data input: browsing history, followed topics, content engagement. - Ranking score systems based on the similarity of the user's interested topics and the article's popularity. - The algorithm is updated regularly to reflect the latest trends or topics.	***How the algorithm works:*** - Data input: Total of success tasks, task completion rate, number of late completions, customer's review score. - The assessment information in comparison with the standard performance. - All data is captured at the same time to reflect accurate work performance.	***How the algorithm works:*** - Data input: Multiple financial proofs and information such as annual after-tax income, the utility spent within a fiscal year, and average utility prices in the applicant's living area. - The evaluation reviews applicants' information: it compares and matches them with the program requirements; the discount amount is then calculated based on the pre-defined rate and allocated budget. - Data are captured by fiscal year.
Coordination signals	***Coordination mechanisms:*** - Features allow user engagement with the article such as Like, Dislike, Save or Share the article. - Refine recommendation options where user can manage their browsing history, manage their followed topics, remove "Like" or Dislike" article.	***Coordination mechanisms:*** - Early notification for workers to adjust their work regarding the aspects that they underperform. - Performance Report options: Report the wrong task record, Flag feud customer review. - Contestability and Reviewability: Appeal and re-evaluation process if needed.	***Coordination mechanisms:*** - Review information in the systems. - Report functions for wrong input. - Contestability and Reviewability: Appeal and re-evaluation process if needed.

Besides delegation uncertainty, other research should further explore additional forms of uncertainty that might impede trust in AX, such as privacy uncertainty or execution uncertainty. While platform owners may claim the intention and technical information of the algorithms, as well as offer coordination mechanisms, it can be challenging to verify their actual practices. Thus, execution uncertainty may arise, questioning whether the platform owners actually do like what they have declared. One possible solution for this is to involve third parties, such as independent technical auditors or regulatory organizations, to ensure the scrutiny and accuracy of algorithmic decisions.

Chapter 4: Conclusion

The primary objective of this research was to explore and conceptualize uncertainty as one of the critical constructs in AX. We have identified delegation uncertainty *as* ***the individual's difficulty in assessing the delegated role of an algorithm in shaping their experience***. This uncertainty is clustered in three dimensions: *intention, technical and coordinatio*n, particularly when individuals engage with algorithmically driven products or services. Delegation transparency-enhancing signals of each dimension were manipulated to examine the effect of their presence and absence on intention, technical and coordination uncertainty. Lastly, the study focused on uncovering how each dimension of delegation uncertainty in AX influences individuals' perception of an algorithm's trustworthiness.

4.1 Overview of the results

As recognized, three dimensions of delegation uncertainty from hidden action and hidden characteristics in AX are intention, technical, and coordination. The findings uncovered insightful understandings of how people perceive an algorithm's trustworthiness in their digital experience. The delegation transparency-enhancing signals about intention, technical and coordination are effective uncertainty mitigators. Interestingly, coordination signals help people feel less uncertain not only about how to coordinate with an algorithm but also about the technical aspects of it. The results also recognize intention uncertainty and coordination uncertainty as significant detrimental factors on users' trust in their algorithmic experience.

Besides, it was discovered that technical uncertainty influences users' trust under the moderating effects of intention uncertainty. More precisely, when people are less uncertain about the algorithm's intention, technical uncertainty becomes a significant factor affecting their trust in an algorithmic system. Similarly, coordination uncertainty also marginally affects the relationship between technical uncertainty and people's trust. We suggest this is the competing effect among intention, technical, and coordination uncertainty. The presence of uncertainty regarding intention and coordination with the algorithm shows radical impacts on people's trust in an algorithmic system; while the influence of technical uncertainty is more subdued but not entirely negligible.

In addition, the findings denoted algorithmic awareness as a significant factor in people's trust in algorithmic technologies, while IT self-efficacy has a marginal effect.

4.2. Limitations

This study is limited to the archetype of algorithmic systems that we use to explore delegation uncertainty in AX. As also acknowledged in the IS delegation framework (Baird & Maruping, 2021), the relationship between humans and agentic IS artifacts is accommodating depending on specific context as well as how much of the tasks and responsibilities delegated to the agentic technological systems. The dimensions of delegation uncertainty might need to be adaptive in the respective circumstances.

Another limitation of this research scope is the presumption that privacy uncertainty and delegation uncertainty have little convergence due to the different settings between traditional online transactions and algorithmic experience. Further examination of the intersections between privacy uncertainty and delegation uncertainty would complement the existing study on AX.

4.3 Contributions

4.3.1 Theoretical contributions

This research contributes to the fundamental understanding of the dyadic relationship between human and algorithmic systems. Our work combines current knowledge of AX with the IS Delegation Framework and applies agency theory to conceptualize delegation uncertainty as a novel construct that significantly influences how individuals perceive and interact with algorithms. Notably, our study models and examines three dimensions of delegation uncertainty, including intention, technical and coordination, exploring how they impede an individual's trust in algorithmic systems. We also verify the implication of the signaling theory in the context of AX, where delegation-transparency signals are confirmed to be effective mitigators of delegation uncertainty. The findings denote important directions for enhancing people's trust when they experience algorithmic technologies.

4.3.2. Managerial contributions

This research also provides important insights into the managerial implications of future design and development of algorithmic systems. More precisely, the findings highlight coordination mechanisms as effective signals to reduce two dimensions of delegation of uncertainty: technical and coordination. It also showed that intention uncertainty and coordination uncertainty are strong negative factors influencing individuals' trust during their digital experience. Thus, we encourage efforts to make algorithms more explainable by ensuring that users are aware and understand the algorithm's objectives and motivation for its implementation (intention signals), as well as providing more effective coordination mechanisms to the users.

In addition, it should be note that the analysis does not completely reject the impact of technical uncertainty. In the situation when people feel less uncertain about algorithm intention or coordination but profoundly concerns about technical aspects of the algorithms, it is also challenging for them to establish trust with an algorithm.

4.4 Future research

For future research, we recommend exploring and comparing delegation uncertainty's effects on individuals' trust in different archetypes of algorithmic systems. The classification of types of signals is also recommended for further exploring the most effective type to mitigate delegation uncertainty. For instance, coordination signals can be incorporated under different mechanisms or features in the systems (e.g., feedback loops, report function or refinement options), and their effects on users' trust might be varied.

With the discovery of algorithmic awareness's effect on trust in algorithmic systems, we suggest another direction for research that can further explore the relationship between delegation uncertainty and the respective constructs, such as algorithmic awareness or algorithmic literacy. We expect this will open further discussions on the importance of improving people's awareness about algorithm implementations and the potential impacts the algorithms can make on them as users or recipients of algorithm technologies.

As mentioned as one of the research limits, we encourage future studies to expand the examination of delegation uncertainty in the context of AX with conventional uncertainty constructs in online transaction settings, such as privacy uncertainty, product uncertainty, and seller or provider uncertainty.

We also acknowledge execution as another form of uncertainty. Execution uncertainty can be a subject for future research on AX, which is related to the potential gap between the actual practices of the algorithm system's owners and what they have claimed to do.

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