Literature Review:

How AI's role and an innovation orientation influence auditor reliance on a hybrid specialist team's advice

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Research Question:

In this study, we examine whether the role of AI and a Human specialist in a Hybrid specialist team influences auditor reliance on hybrid specialist team advice. We additionally examine whether lack of transparency regarding AI's role in a specialist team influences end reliance. Further we examine if any negative influences of certain workflows of a hybrid specialist team on auditor reliance are mitigated when the auditor has a higher innovation orientation.

Introduction

Artificial Intelligence (AI) is likely to transform how audits are conducted. Investment in technology by audit firms is growing (EY Global 2021, KPMG 2021, PwC 2021, Deloitte 2022), recognizing the potential of advanced algorithms like AI to leverage big data, compare companies, and execute complex calculations. Auditing standards require auditors to consider relevant industry, regulatory, economic, and market information when evaluating client estimates (AS 2501.16, ISA 620). The constantly improving ability of AI to accumulate and analyze data suggests that complex estimates present a suitable application for AI technologies (Ding, Lev, Peng, Sun, and Vasarhelyi 2020). A particularly promising area for AI applications is in aiding valuation specialists in generating advice for the audit team.[1] We propose that the role of AI in such AI-influenced specialist advice—i.e., a preparing role versus a reviewing role —is an important factor in how the auditor interprets and relies upon this advice.

Additionally, audit firms, regulators and professional organizations have increasingly begun to focus on innovation as an important skill for auditors (EY 2020, 2024; KPMG 2021,

[1] AI's ability to gather and synthesize large amounts of data as well as evaluate estimates in comparison to other clients within the firm and companies within an industry, means that AI has the capability to both autonomously develop estimates based on trained or programmed methodology as well as assess the estimate of a client. Thus, in this capacity, we expect AI to be able to effectively perform similarly to a human firm specialist.

2024; Deloitte 2022; PwC 2022). The way practice defines this skill is "an ability to utilize creativity and flexibility in thinking to solve problems" (CAQ 2018; EY 2024). We posit an individual's orientation towards innovation may influence how an auditor is willing to incorporate AI-driven specialist advice. Thus, in this study we examine how the role of AI in a hybrid specialist team and the level of an individual's innovation orientation may affect auditor reliance on specialist advice.

There is ongoing discussion about AI's role in the workplace and how roles for AI and humans may be structured (Wesche & Sonderegger 2019; Chugunova & Sele 2020; Trunk, Birkel, & Hatmann 2020; Langer & Landers 2021; Raisch & Krakowski 2021; Tongi 2023). Traditionally, AI has been viewed as a performer of tasks, suggesting that it would primarily serve as an initial preparer within a workflow (Kokina & Davenport 2017; Raisch & Krakowski 2021; Deranty & Corbin 2024), leaving humans to take on a reviewing role. In the context of firm specialist advice, this would involve a specialist reviewing an AI-generated estimate to ensure its appropriateness and provide any necessary modifications before presenting a final recommendation to the auditor. Conversely, there is also emerging discussion about use of AI in a supervisory or reviewer capacity (Wesche & Sonderegger 2019; Lanz, Briker, & Gerpott 2023; Lewis Silkin 2023). PwC's Partner of Data and Technology, Mona de Boer, highlights a paradigm shift in AI utilization, stating "Don't think of AI as just a tool to be implemented…it helps us look at our work in a fundamentally different way" (PwC 2023). In a specialist setting, utilizing AI as a reviewer would involve the specialist developing their estimate independently, while AI serves as a quality control mechanism, identifying flaws or confirming the credibility of a human-developed estimate.

According to auditing standards, an auditor must understand specialist methods and bases for judgements, including instances where technology is relied upon to draw conclusions (e.g., AS 1210). It follows that the role of AI should be clearly delineated and transparent to auditors in specialist communications, as auditors bear ultimate responsibility for evaluating its credibility, similar to their evaluation of a human specialist.[2] Within a hybrid specialist team composed of both a human and an AI counterpart, it is important to understand how AI's role—as either a preparer or a reviewer—may influence audit judgments. We consider a situation where the human specialist and the AI have reached consensus on an estimate (i.e., the reviewer agrees with the work performed by the preparer)[3]. However, we expect that utilizing AI in a preparer role within a hybrid specialist team may lead to lower reliance by an auditor on the resulting advice in comparison to when AI is used as a reviewer. This is because AI in a preparer role may trigger auditor algorithm aversion, in turn amplifying the auditor's perceptions about the human specialist's overreliance on the AI, and subsequently decreasing the auditor's assessed credibility of resulting advice from the hybrid specialist team. This raises the concern that auditors might discount AI-influenced specialist advice when AI serves as a preparer, even if the advice is of high quality, as they lean on the heuristic perspective that AI-driven advice is risky or of low quality.

Given that AI's ability to calculate complex estimates continues to advance, it becomes crucial for auditors to not let algorithm aversion bias their judgements. Something that may counteract this heuristic tendency against AI and improve auditor's reliance on high-quality hybrid advice, is an innovation orientation. Though traditionally, accounting has not been seen as a very innovative field (Bryant, Stone, & Wier, 2011), there has been an increased focus on innovation by both regulators and firms (CAQ 2018; Deloitte 2024; EY

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[2] Though we generally expect the use of AI to be transparent to the auditor, we also examine a control condition where the auditor is aware that the specialist team utilizes AI but is not given specific information about the role of AI on the specialist team.

3 We consider a situation where there is agreement rather than disagreement as we can better measure the auditor's perceived credibility/reliability of the hybrid specialist team's advice rather than each piece of advice separately. Additionally, we expect that by the time an auditor receives a fair value memo, it is likely that sources of disagreement among the specialist team may be solved and thus less transparent to the auditor.

2023; KPMG 2021; PwC 2024). There is some research suggesting innovation could be both beneficial and tricky for auditors (Kachelmeier et al. 2008; Herron & Cornell 2021; Bibler, Carpenter, Christ, & Gold 2024; Bonk & Schmidt 2024) thus this concept begs for more understanding on how it can interact with an auditor's job and audit quality. Though encouraging innovation may be one way to enhance innovation among auditors, another way could be to focus hiring practices on more innovative individuals. One such concept that firms may consider at an individual level is an auditor's innovation orientation. Innovation orientation at the individual level should include more open-minded and flexible thinking. This open-mindedness could be essential for embracing the perspectives of both the human and the AI specialist counterparts and for being more open to adopting strategies that are less rooted in prior experience and routine behaviour. An innovation orientation may be a key part in an individual feeling comfortable trusting hybrid specialist-sourced advice, incorporating data from diverse sources, and accepting some uncertainty when incorporating AI into the process. We expect that auditors showing a heightened openness to new ideas, uncertainty, and creative approaches due to a higher innovation orientation likely have less aversion to AI-generated advice.

To test our predictions, we perform a 3x2 between-participants experiment involving auditor participants from a Dutch audit firm. Participants are presented with a hypothetical auditing engagement and the task to evaluate management's fair value estimate. They receive case background information about the task, the client, and management's current fair value estimate, along with the rationale behind it. Subsequently, participants receive advice via a fair value memo from their firm's hybrid specialist team. We manipulate role by varying whether the human specialist or AI specialist acted as the initial preparer versus reviewer in the workflow, or whether the workflow is not made explicit (control condition). We measure each participant's innovation orientation using a validated scale (Thomas et al. 2024).

After reviewing the background and fair value memo, participants are asked to provide their evaluation of management's estimate, their final estimate, and any rationale to support their final conclusions. Subsequently, they will complete a questionnaire where they assess various aspects of the advice received, including the competency of each advisor, the quality of the advice, and their reliance on the advice/advisors. Our main dependent variable is the distance between auditors' final estimate and management's estimate. Given that the advice from the hybrid specialist team is conservative compared to management's preference, a greater distance from management's estimate indicates higher reliance on the received advice and a greater willingness to challenge management. We will also examine the rationale provided by participants and their responses to the post-experimental questionnaire to gain additional insight.

This study contributes to the auditing literature by examining whether algorithm aversion persists in scenarios where both humans and technology are involved in the advice workflow, and how this impacts auditor reliance on advice received from a hybrid specialist team. While prior research on technology-sourced advice has typically framed human and technology as an either/or choice (e.g., Commerford et al. 2021), we seek to understand auditor reliance on advice generated by a human-technology ("hybrid") team (Emmanouilidis, Waschull, Bokhorst, & Wortmann 2021). This novel approach fills a gap in the existing literature, which has not yet examined the dynamics of hybrid advice sourced jointly from human and technology. We, therefore, contribute to the scarce body of research in the auditing literature concerning to algorithm aversion and appreciation, and their effects on auditor decision-making (Commerford et al. 2021; Commerford & Holman 2022; Peters 2022).

Additionally, we examine how innovation orientation may be increasingly important among auditors and one aspect that this individual perspective could influence is openness to

AI-influenced advice, regardless of the role of AI as a preparer or reviewer in the workflow. This contributes to limited research on the impact of innovation on auditing judgements (Bibler, Carpenter, Christ, Gold 2024). This also contributes to the more general discussion in the literature regarding creativity in accounting (Bryant, Stone, and Weir 2011) and expands our understanding of how this traditionally rigid profession could benefit from exploring innovative thinking as a way to improve judgements.

Furthermore, we contribute to the human-computer interaction (HCI) literature by examining a third party's perception of a hybrid output. Unlike studies that focus directly on a human-technology team (Rebensky et al. 2022; Hemmer et al. 2021; Krügel et al. 2023), our study examines the indirect impact of a hybrid team on auditor's perceptions, influenced by team members' roles and an innovative firm culture. Overall, our study contributes to a deeper understanding of specialist advice and technology use on audit engagements, making it relevant for academics, regulators, and firms alike.

Background & Theory Development

Auditor-engaged Specialists

Auditors often engage the work of firm specialists when evaluating complex estimates that require unique expertise (PCAOB 2015). The areas in which auditors engage specialists' help can cover a variety of topics, generally regarding areas where there is valuation complexity and a degree of subjectivity. Auditors often leverage both the specialist's skills regarding complex calculations (such as goodwill, stock options, or complex financial instruments) as well as expertise in certain industries (such as oil & gas, insurance reserves, or real estate). Auditing standards state that auditors are responsible for assessing the sufficiency of the knowledge, skill, and capabilities of specialists and ensuring that assumptions and conclusions specialists are in line with the auditor's understanding of the client and related information (PCAOB 2022, ISA 620). As such, auditors cannot simply rely on specialist conclusions but rather are encouraged to use specialist advice as an input to their own judgments as they are ultimately responsible for all resulting determinations regarding complex estimates. The auditor and specialist relationship and resulting judgments can be influenced by numerous factors, both audit-related and personal (e.g., Griffith 2019; Gold, Kadous, and Leiby 2024). Hence, it is important to understand how auditors assess specialists and how this assessment factors into end reliance of the auditor on specialist advice, which directly impacts the quality of judgments related to complex estimates.

Auditor Reliance

When deciding whether to rely on the work of a specialist, auditors are encouraged to evaluate the quality of the specialist (IAASB 2009, 2013; PCAOB 2015; Gold, Kadous, and Leiby 2024). Research in psychology confirms that credibility is a significant factor advisees consider when making decisions and taking advice (e.g. Chaiken and Maheswaran 1994; Bonaccio and Dalal, 2006; Gino and Schweitzer 2008; Petty and Briol 2008). We expect that agreement among a human and AI specialist will impact an auditor's perception of advice credibility depending on the workflow. In conditions of uncertainty (such as an estimate, in this context), individuals tend to feel a heightened need for cognitive closure (Larson, Tindale, & Yoon 2020). The need for cognitive closure is described as a "stopping mechanism" that allows a judgment to solidify rather than needing to seek additional information or exert additional effort to get to a final judgment (Kruglanski & Fishman 2009). Cognitive closure creates a situation where people latch onto information that reduces uncertainty and allows them to make a judgment without exerting additional cognitive effort. This leads to consensus striving in situations with multiple group members, as agreement decreases uncertainty (Kruglanski & Fishman 2009). These considerations suggest that in a situation where there are multiple advisors (as is the case in the setting of a specialist team), an advisee (in this case the auditor) may reach a confident conclusion in a situation where the advisors' advice converges, resulting in low uncertainty. We argue that obtaining advice from multiple advisors is effectively the case when there are AI and human roles in a hybrid specialist team and that this consensus among an AI and human specialist would increase credibility, but only in the case where the workflow is one where the human is in the preparer role. In a situation with an AI (Human) preparer and a Human (AI) reviewer role, if the reviewer finds the preparer's estimate to be appropriate, the general expectation based on advice literature would be that this enhances advice credibility as two advisors have reached the same conclusion. However, though agreement is often seen as the preferred scenario, we expect that this agreement among a hybrid specialist team may be viewed negatively when AI acts as a preparer in a hybrid specialist team workflow, as opposed to when the human is in the preparer role, as described next.

We consider a situation where the human specialist and the AI have reached consensus on an estimate, regardless of their role (i.e., the reviewer agrees with the work performed by the preparer). However, this advice diverges from management's estimate, creating potential motivations for the auditor to discount or under-rely on the advice as often shown to be the case in prior research (Austin, Hammersley, and Ricci 2020; Griffith, Kadous, and Young 2021). Furthermore, research in similar settings has demonstrated auditor under-reliance on technology (Commerford et al. 2021). Specifically, Commerford et al. (2021) show that auditors tend to rely more on advice received from a human specialist compared to an AI specialist, providing evidence that auditors experience algorithm aversion and use AI involvement as a heuristic cue to assess advice credibility as low and under-rely on advice generated by this technology. However, examining a scenario where specialist advice originates from a hybrid specialist team, comprising both a human and AI, adds complexity to auditors' responses. When assessing auditor reliance on converging advice from such a team, auditors are likely to first form perceptions about the extent to which the human specialist relied on the AI.

We expect that a variation in roles of human and AI counterparts in a hybrid specialist workflow will influence auditor reliance and willingness to conflict with management's preference. Humans and machines are unlikely to be viewed as equals in hybrid decision-making and, accordingly, there will be a difference in the level of responsibility attributed to each party (O'Neill, McNeese, Barron, & Schelble 2022, Krügel, Ostermaier, Uhl 2023). We believe the level of attributed responsibility could be highly dependent on the role that the AI and Human specialist team members are given and that this will in turn impact an auditor's perceived credibility of advice received from a hybrid specialist team. We expect that an AI-prepared workflow will lead to significantly less auditor reliance on hybrid specialist advice than a human-prepared workflow.

Role in the Workflow

Vinokur and Ajzen (1982) identified the "causal primacy effect" which suggests that the order of events in a chain influences perceived importance. More specifically, in a causal chain, the initial action is given more weight of importance when assessing the cause. This suggests that an initial preparer in a workflow may be perceived as the driver of the end outcome and thus change the perceived or actual role of an individual. Johnson, Ogawa, Delforge, and Early (1989) also saw this to be the case when participants were asked to attribute fault in a legal case. Anderson (1965) used information integration theory to posit that there is a primacy effect in impression formation. Steiner (1970) argued that attribution of cause increases with perceived freedom of action of an individual. When one starts working on a task they go from somewhat of a "blank slate" and perform the work they see fit. If a secondary individual then inherits this task to review, they will likely be perceived as having less freedom as there will be a tendency to leverage and anchor on what is done by the former. Thus, outcomes are perceived to be driven by the initial individual's work in a muti-party workflow. [4] If we situate these studies in an environment where the initial (preparer) and secondary (reviewer) roles are either a human or AI specialist in an audit engagement, the user of hybrid advice (the auditor) likely perceives the initial preparer of the estimate as the driver of the quality of the estimate. Thus, if an AI specialist is in a corrective role (i.e. reviewing the human specialist's work in the workflow), then the human specialist is seen as the driver of the end quality of the work. Vice versa, if a human specialist is in a corrective role, then the AI specialist may be perceived as having more contribution towards the end outcome.

The importance given to the initial team member within a workflow, coupled with an auditor's tendency towards algorithm aversion, would suggest that when an AI specialist is in the preparer role and a human specialist is in the reviewer role, an auditor evaluating the work may suffer from algorithm aversion. Algorithm aversion in this case is the tendency for an auditor to be weary or "averse" to a technology source in comparison to a human source (Commerford et al. 2021). As Commerford et al. (2021) finds that auditors tend to discount judgmental advice received from AI in comparison to a human specialist, we would expect that in the condition where the human specialist reviews an AI specialist's work and comes to agreement, this would result in similar algorithm aversion to the advice, even when a human specialist is involved, as it is perceived to be primarily driven by AI. Thus, we expect in an AI-prepared workflow, the core auditor attributes more of the work quality to the technology. This likely results in the auditor relying on the work of the hybrid specialist team less when a human is in a corrective (secondary) role (as opposed to when a human is in the preparer/initiator role).

[4] Though some impression formation research has also shown recency effects, we argue that in this context, where a second specialist is inheriting and reviewing a task prepared by another specialist in a workflow, the primacy effect will dominate, as the first specialist has higher perceived freedom to execute the task than the second specialist.

In addition to the discussed primacy effect and algorithm aversion, the core auditor may perceive a human specialist inheriting work done by an AI specialist to suffer from automation bias. Automation bias has been defined as “the tendency to use automated cues as a heuristic replacement for vigilant information seeking and processing” (Mosier and Skitka 1996). Thus, when exhibiting this bias, an individual will exert lower effort because they over-rely on the technology. Though we discussed core auditor algorithm aversion to an AI preparer role in the prior paragraph, this aversion could also result in increased sensitivity to any perceived automation bias on the part of the human specialist, as it again indicates the advice is driven by the technology rather than the human. It is important for this argument to consider that we expect a core auditor to suffer from algorithm aversion. However, we expect this to also increase their sensitivity to the perception that a human specialist over-relies on technology. Thus, when there is an estimate prepared by an AI specialist and a human specialist is reviewing it and comes to agreement, the core auditor may have a tendency to perceive the human specialist to be passively relying on AI. Therefore, algorithm aversion in a core auditor could be linked to perceived automation bias in a human specialist. This could result in the core auditor being more sensitive to over-reliance than under-reliance of the human specialist on the technology, as a result of their own algorithm aversion which leads them to be somewhat distrustful of an AI specialist (Commerford et al. 2021).

Conversely, in a workflow where the human specialist acts as the preparer, agreement by an AI specialist reviewer may signal the accuracy and credibility of the human specialist, which is important given auditors’ general tendency to be algorithm averse (Commerford et al. 2021). In this situation, the AI specialist’s evaluation merely acts as a “confirmation” of the human specialist’s work and the human will inherently be perceived as playing the dominant role. When the human precedes the AI specialist, the auditor, even if suffering from algorithm aversion, will likely view the human specialist's advice as uncorrelated with the AI specialist's as they had no opportunity to rely on the AI specialist's advice prior to forming their own judgment. In this workflow, the sources are viewed as independent and thus agreement therefore likely results in easy cognitive closure due to reduced uncertainty by receiving similar signals from both the AI and Human without concern that the human over-relied on AI. In addition to agreement easing the path to cognitive closure when the human specialist is the preparer, in this workflow the human and the technology will likely both be viewed as distinct sources and this convergence in opinion of two distinct parties gives decision-makers more confidence in end conclusions (Surowiecki 2004, 2005; Mannes 2009). Thus, this scenario likely results in relatively high reliance by the auditor.

In this situation where the human is in the preparer role, the auditor perceives they are receiving independent judgments from both a human and an AI specialist. As a result, their algorithm aversion is likely to be less pronounced as they are not being asked to rely on technology alone for a judgment. Rather, they are being asked to leverage two distinct sources, one technology and one human. In this case, as we expect that an auditor is not suffering from strong aversion to the AI specialist given independent human involvement, they may have a high expectation of the technology and expect it to play an important role in addition to the human specialist. For example, individuals not experiencing aversion often have a tendency to view automation with a "perfect" schema and thus be less error-prone (Dzindolet et al. 2002, Madhavan and Wiegmann 2007, Peters 2022).[5] If the view that technology is credible and plays a meaningful role dominates in Human-prepared workflow, then convergent advice from the hybrid specialist team likely further supports confidence in the human judgment and thus leads to high reliance by the auditor.

[5] It is important to note that although algorithm aversion is present when technology is viewed alone or viewed as having a main role, we posit that when viewed as working subsequently to and in collaboration with a human specialist, this aversion will be mitigated as the human remains "in the loop".

Though we predict the above when the role is known by the auditor, there is also a likely scenario where the role is not made explicit. For example, the auditor may be aware that their firm's valuation specialists utilize an AI team mate but not at what capacity. Thus, we are also interested in how the opacity of the role may influence auditor reliance on hybrid Human-AI advice. We posit that this opacity will lead to lower reliance than either condition above where the role is transparent. Auditors are generally uncertainty averse as they must be accountable for their end judgements and the uncertainty of the roles of AI vs. Human does not allow the auditor the control of assessing the output/advice of each specialist. This may also contradict with their current understanding of the regulation and their obligation to assess the credibility of their specialists (PCAOB 2022). Further, advice-taking literature shows that perceived uncertainty leads advisees to avoid acting on the advice because it seems less definitive (Bonaccio & Dalal 2006). Thus, this lack of control and exposure to higher uncertainty likely leads the auditor to quicker discount the advice received from this specialist. Additionally, when it comes to AI involvement, higher uncertainty leads to lower reliance on AI advisors (Dietvorst & Bharti 2020, Commerford WP). Additionally, we know auditors, are already prone to algorithm aversion in a judgemental advice context (Commerford et al. 2021), thus this aversion to technology may be exacerbated if they do not know AI's exact role in producing the advice. Transparency around AI's role could allow auditors to better contextualize their decisions, while opacity might trigger instinctive skepticism (Dzindolet et al., 2002). Thus, we expect this uncertainty in general to have a negative effect and especially given the context associating the uncertainty with AI, will give auditors much more caution when presented with hybrid advice, thus leading to lower reliance.

Innovative Culture and Algorithm Aversion

As we predict that in an AI-prepared workflow, the auditor will have lower reliance on advice due to lower perceived credibility of the hybrid specialist team, this may have negative implications on audit quality, especially if the advice is of high quality. Though these roles in the workflow may signal to the auditor that advice is less credible, this in itself does not actually dictate the credibility of the advice. Thus, if a firm intends to use a hybrid workflow where AI prepares a task, there may be a need to address algorithm aversion, as to not have an auditor discount credible advice simply due to the perceived roles of a human and AI specialist.

As this threat to credibility is likely due to an auditor's aversion to relying on AI, it would be useful if firms had better understanding into the types of individuals that may or may not be impacted by this heuristic bias. One such individual trait that may influence the level of an auditor's openness to utilizing AI is innovation orientation. The concept of innovation has been introduced in practice as an important skillset for auditors but the understanding of the implication of an innovative perspective on judgements is very limited (Bibler, Carpenter, Christ, and Gold 2024). Though accounting and innovation may not be an intuitively important combination, there are reasons to believe being oriented towards innovation may help auditors make more well-rounded and open-minded judgements.

Tendency to discount algorithms can happen for a variety of reasons, including overconfidence, sensitivity to uncertainty, lack of familiarity, improper incentives, and loss of control (Burton, Stein, and Jensen 2023). Several of these sources of algorithm aversion may be alleviated for an individual that is prone to more open-minded and flexible thinking. In a situation where an auditor is being pushed to rely on AI-influenced advice, they may feel a tendency to root in their own expertise, and prior experience which may lead to discounting AI-driven advice because it is "different" or "risky". If an auditor leans more naturally to thinking innovatively, they may be less influenced by unfamiliarity and uncertainty and be more willing to accommodate AI's unique perspective. Thus, we expect that some of the drivers of algorithm aversion will be absent or mitigated for auditors with a higher innovation orientation and thus the effect of algorithm aversion in the AI-first workflow will be mitigated when auditors are more innovative.

Innovation can be examined either at the object or subject level (i.e. innovative outcomes versus innovative processes). Within the subject level, innovation can also be examined at different levels including country, industry, organization, or individual levels (Norris & Ciesielska 2019). One such subject-focused concept related to innovation that has been studied is innovation-orientation. Hurley and Hult (1998) refer to innovation orientation as a construct that includes openness to new ideas and change through adopting new technologies, resources, skills and administrative systems (Hult, Hurley, & Knight 2004, Norris & Cielsielska 2019). Though a majority of innovation orientation literature has focused on the organizational level (Siguaw Simpson & Enz 2006, Norris & Cieselska 2019), existing research on individual orientations and individual innovativeness (Hurt et al. 1977, Agarwal & Prasad 1998, Yi, Fiedler & Park 2006, Nisula & Kianto 2015, Ali 2019, Sankose & Turkmen 2020, Llopis & Déste 2022) suggests this concept also exists at the individual-level. It is not unheard of for organizational orientations to be mapped to individual orientations, such as the Blanka 2019 work linking organizational entrepreneurship orientation to individual entrepreneurship orientation (referred to as intrapreneurship). In fact existing research has already begun to make the bridge between innovation orientation at the organizational level and the individual level (Dreschler, et al. 2021, Thomas et al. 2024).

Thomas et al. 2024 refers to individual Innovation Orientation as an individual's tendency to innovation, including their "aptitude for learning new things", "a proclivity for approaching tasks creatively", and optimising novel methods and ambiguous situations where such methods may be useful. If we consider the context where an auditor is given advice from a hybrid Human-AI advisor, the above characteristics of Innovation Orientation such as desire to try new things, novel methods, and approach tasks differently would suggest that auditors higher in Innovation Orientation would. Given we expect algorithm when the AI precedes the human in the hybrid advisor workflow, we would expect this aversion to be mitigated for those individuals exhibiting a higher innovation orientation. Though this prediction is largely based on the logic that an individual more open to innovation will likely be more open to relying on technology, there is also some research suggesting this will be the case. Though much research related to innovation orientation has examined business performance, more recent research has also linked it with other important factors such as knowledge management and learning (Norris & Cielsieska 2019). Given the advice from the hybrid advisor will be of high quality in all conditions, the evidence that innovation orientation can lead to better quality outcomes further suggests that auditors will be more likely to be open to quality hybrid advice when they have this type of orientation.

Conclusion & Contributions

This study aims to make several contributions to both practice and the literature. First, it extends existing research on algorithm aversion (Commerford et al., 2021) by examining the nuances of hybrid human-AI teams in auditing. Unlike prior studies that compare human and AI advisors as distinct sources, our study focuses on the complexities introduced by human-AI collaboration, particularly in the division of preparer and reviewer roles. Additionally, by introducing innovation orientation as a moderating factor, we contribute to the growing research on how individual traits, such as openness to new technologies and creative problem-solving, affect audit quality. We also add to the burgeoning topic of creativity in accounting and auditing and how this can be beneficial (Bibler et al. WP 2024).

Further, our study adds to the Human-Computer Interaction (HCI) literature by exploring the indirect effects of hybrid human-AI collaboration on third-party perceptions—

in this case, auditors. While most HCI studies focus on direct interactions between humans and technology (Rebensky et al., 2022), we examine how an auditor's reliance on advice is shaped by the roles assigned to human and AI specialists within a team. As AI adoption increases in auditing, understanding how auditors perceive AI's role in collaborative workflows is critical. Our findings offer practical insights for audit firms aiming to optimize human-AI interactions. Specifically, firms should consider how to assign roles within hybrid teams to maximize the intended use of AI-Human hybrid advice. Additionally, fostering innovation-oriented thinking among auditors could further facilitate the integration of AI technologies, improving audit judgment and overall quality.

References

Anderson, N. H. (1965). Primacy effects in personality impression formation using a generalized order effect paradigm. Journal of Personality and Social Psychology, 2(1), 1–9. https://doi.org/10.1037/h0021966

Baker, S. M., & Petty, R. E. (1994). Majority and minority influence: Source-position imbalance as a determinant of message scrutiny. Journal of Personality and Social Psychology, 67(1), 5–19. https://doi.org/10.1037/0022-3514.67.1.5

Bamber, E. M., & Iyer, V. M. (2007). Auditors' Identification with Their Clients and Its Effect on Auditors' Objectivity. AUDITING: A Journal of Practice & Theory, 26(2), 1–24. https://doi.org/10.2308/aud.2007.26.2.1

Bandura, A. (1999), Self-Efficacy: The Exercise of Control, W.H. Freeman and Company, NewYork, NY.

Bauer, T. D. (2014). The Effects of Client Identity Strength and Professional Identity Salience on Auditor Judgments. The Accounting Review, 90(1), 95–114. https://doi.org/10.2308/accr-50863

Bauer, T. D., Estep, C., & Malsch, B. (2019). One team or two? investigating relationship quality between auditors and it specialists: implications for audit team identity and the audit process. Contemporary Accounting Research, 36(4), 2142–2177. https://doi.org/10.1111/1911-3846.12490

Bhattacharjee, S., & Brown, J. O. (2017). The Impact of Management Alumni Affiliation and Persuasion Tactics on Auditors' Internal Control Judgments. The Accounting Review, 93(2), 97–115. https://doi.org/10.2308/accr-51816

Bibler, S., Carpenter, T., Christ, M. H., & Gold, A. (2024). Thinking Outside of the Box: Engaging Auditors' Innovation Mindset to Improve Auditors' Fraud Judgments and Actions in a Data-Analytic Environment. Working Paper. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4311283

Bonaccio, S., & Dalal, R. S. (2006). Advice taking and decision-making: an integrative literature review, and implications for the organizational sciences. Organizational Behavior and Human Decision Processes, 101(2), 127–151. https://doi.org/10.1016/j.obhdp.2006.07.001

Bonk, Katrin & Schmidt, Martin. (2024). The "Dark Side" of Creativity in Auditing. Working Paper. EAISM 10th Workshop on Audit Quality

Bryant, S. M., D. Stone, & B. Wier. (2011). An exploration of accountants, accounting work, and creativity. Behavioral Research in Accounting, 23(1), 45–64.

Burton, J. W., Stein, M., & Jensen, T. B. (2019). A systematic review of algorithm aversion in augmented decision making. Journal of Behavioral Decision Making, 33(2), 220–239. Portico. https://doi.org/10.1002/bdm.2155

Burton, J. W., Stein, M.-K., & Jensen, T. B. (2023). Beyond Algorithm Aversion in Human-Machine Decision-Making. Judgment in Predictive Analytics, 3–26. https://doi.org/10.1007/978-3-031-30085-1_1

Cannon, N. H., & Bedard, J. C. (2016). Auditing challenging fair value measurements: Evidence from the field. The Accounting Review, 92(4), 81–114. https://doi.org/10.2308/accr-51569

Cassia, F., & Magno, F. (2021). Antecedents of professionals' self-efficacy in professional service firms: effects of external source credibility and content quality. Journal of Business & Industrial Marketing, 36(13), 187–198. https://doi.org/10.1108/jbim-11-2019-0485

Center for Audit Quality (CAQ). (2018). Your road to discover audit – Workbook. Skills that lead to endless opportunities. Discover Audit. https://www.thecaq.org/mindset-

behaviors-knowledge-skills-building-roadmap-auditor-future/ Retrieved on 4/5/2023.
Chaiken, S. and Maheswaran, D. (1994), "Heuristic processing can bias systematic processing: effects of source credibility, argument ambiguity, and task importance on attitude judgment", Journal of Personality and Social Psychology, Vol. 66 No. 3, pp. 460-473
Chugunova, M. and Sele, D. (2020) We and It: An Interdisciplinary Review of the Experimental Evidence on Human-Machine Interaction (September 14, 2020). Max Planck Institute for Innovation & Competition Research Paper No. 20-15, ETH Zurich Center for Law and Economics Working Paper Series No. 12/2020, Available at SSRN: https://ssrn.com/abstract=3692293 or http://dx.doi.org/10.2139/ssrn.3692293
Commerford, B. P., Dennis, S. A., Joe, J. R., & Ulla, J. W. (2021). Man Versus Machine: Complex Estimates and Auditor Reliance on Artificial Intelligence. Journal of Accounting Research, 60(1), 171–201. Portico. https://doi.org/10.1111/1475-679x.12407
Commerford, B. P., & Holman, B. (2022) Evidence Specificity and Auditors' Heuristic Responses To Human and Non-Human Specialists https://www.nhh.no/globalassets/centres/digaudit/activities/commerford-and-holman-2022-april--evidence-specificity-and-auditors-heuristic-responses-to-human-and-non-human-specialists.pdf
Danaher, J. (2019). The rise of the robots and the crisis of moral patiency. AI & Society, 34(1), 129–136. http://dx.doi.org/10.1007/s00146-017-0773-9
De Cremer, D., Kasparov, G. (2021) AI Should Augment Human Intelligence, Not Replace It. Harvard Business Review. Available at: https://www.daviddecremer.com/wp-content/uploads/HBR2021_AI-Should-Augment-Human-Intelligence-Not-Replace-It.pdf
Dechow, P. M., Myers, L. A., & Shakespeare, C. (2010). Fair value accounting and gains from asset securitizations: a convenient earnings management tool with compensation side-benefits. Journal of Accounting and Economics, 49(1-2), 2–25. https://doi.org/10.1016/j.jacceco.2009.09.006
Deloitte. 2022. Audit Innovation. Available at: https://www2.deloitte.com/us/en/pages/audit/topics/audit-innovation.html?icid=top_audit-innovation
Ding, K.; B. Lev; X. Peng; T. Sun; and M. A. Varsarhelyi. (2020). Machine Learning Improves Accounting Estimates: Evidence from Insurance Payments. Review of Accounting Studies 25:1098–134. https://doi.org/10.1007/s11142-020-09546-9
Dohmke, T. (2023). "Universe 2023: Copilot Transforms Github into the AI-Powered Developer Platform." The GitHub Blog, Available at github.blog/2023-11-08-universe-2023-copilot-transforms-github-into-the-ai-powered-developer-platform/.
Dunning, D. (2011). The Dunning–Kruger Effect. Advances in Experimental Social Psychology, 247–296. https://doi.org/10.1016/b978-0-12-385522-0.00005-6
Dzindolet, M. T., Pierce, L. G., Beck, H. P., & Dawe, L. A. (2002). The perceived utility of human and automated aids in a visual detection task. Human Factors, 44(1), 79-94.
Emmanouilidis, C., Waschull, S., Bokhorst, J., & Wortmann, H. (2021). Human in the AI Loop in Production Environments. In A. Dolgui, A. Bernard, D. Lemoine, G. von Cieminski, & D. Romero (Eds.), Advances in Production Management Systems: Artificial Intelligence for Sustainable and Resilient Production (pp. 331-342). (IFIP Advances in Information and Communication Technology; Vol. 633 IFIP). Springer. https://doi.org/10.1007/978-3-030-85910-7_35

Estep, C., Griffith, E. E., & MacKenzie, N. L. (2023). How do financial executives respond to the use of artificial intelligence in financial reporting and auditing? Review of Accounting Studies. https://doi.org/10.1007/s11142-023-09771-y

EY. (2023). Audit Innovation. https://www.ey.com/en_se/audit/innovation Retrieved on 3/28/2024.

EY Global. (2021). EY Value Realized: Reporting progress on global impact 2021. Available at: https://www.ey.com/en_gl/global-review/value-realized-2021

Fogliato, R., Chappidi, S., Lungren, M., Fisher, P., Wilson, D., Fitzke, M., Parkinson, M., Horvitz, E., Inkpen, K., & Nushi, B. (2022). Who Goes First? Influences of Human-AI Workflow on Decision Making in Clinical Imaging. 2022 ACM Conference on Fairness, Accountability, and Transparency. https://doi.org/10.1145/3531146.3533193

Frey D (1986) Recent research on selective exposure to information. Berkowitz L, ed. Advances in Experimental Social Psychology (Academic Press, New York), 41–76.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Gino, F. and Schweitzer, M.E. (2008), "Blinded by anger or feeling the love: how emotions influence advice taking", Journal of Applied Psychology, Vol. 93 No. 5, pp. 1165-1173.

Gold, A., Kadous, K., Leiby, J. (2024) Does Status Equal Substance? The Effects of Specialist Social Status on Auditor Assessments of Complex Estimates. Forthcoming in *The Accounting Review*. Available at SSRN: https://ssrn.com/abstract=3578700

Griffith, E. E., Hammersley, J. S., & Kadous, K. (2015). Audits of complex estimates as verification of management numbers: how institutional pressures shape practice. Contemporary Accounting Research, 32(3), 833–863.

Griffith, E. E. (2018). When do auditors use specialists' work to improve problem representations of and judgments about complex estimates? Accounting Review, 93(4), 177–202. https://doi.org/10.2308/accr-51926

Griffith, E. E. (2020). Auditors, Specialists, and Professional Jurisdiction in Audits of Fair Values. Contemporary Accounting Research, 37(1), 245-276. https://doi.org/10.1111/1911-3846.12506

Gurman, Mark. (2024). "Apple's AI Plans: Github Copilot Rival for Developers, Tool for Testing Apps." Bloomberg.Com, Bloomberg www.bloomberg.com/news/articles/2024-02-15/apple-s-ai-plans-github-copilot-rival-for-developers-tool-for-testing-apps.

Harkins, S., & Petty, R. (1987). Information utility and the multiple source effect. Journal of Personality and Social Psychology, 52, 260–268.

Harris, S. B. "Technology and the Audit of Today and Tomorrow." 2017. Speech delivered at PCAOB/AAA Annual Meeting: Washington DC, April 20, 2017. Available at https://pcaobus.org/News/Speech/Pages/Harris-statement-PCAOB-AAA-4-20-17.aspx.

Hemmer, P., Schemmer, M., Vössing, M., and Kühl, N. Human-AI Complementarity in Hybrid Intelligence Systems: A Structured Literature Review (2021). PACIS 2021 Proceedings. 78. https://aisel.aisnet.org/pacis2021/78

Herron, E. T., & R. M. Cornell. (2021). Creativity amidst standardization: is creativity related to auditors' recognition of and responses to fraud risk cues? Journal of Business Research, 132, 314–326.

Hilton, A. S., & O'Brien, P. C. (2009). Inco Ltd.: Market Value, Fair Value, and Management Discretion. Journal of Accounting Research, 47(1), 179–211. https://doi.org/10.1111/j.1475-679x.2008.00314.x

IAASB. (2009). International Standard on Auditing 620 – Using the Work of An Auditor's Expert New York, NY: IFAC.

IAASB. (2013). Clarified International Standards on Auditing – Findings from the Post-Implementation Review New York, NY: IFAC.

IAASB. (2021). IAASB issues support material to help auditors address risk of overreliance on technology. IFAC. Available at: https://www.iaasb.org/publications/addressing-risk-overreliance-technology-arising-use-automated-tools-and-techniques-and-information

Janis IL (1972) Victims of Groupthink (Houghton Mifflin, Boston).

Joe, J. R., Vandervelde, S. D., & Wu, Y.-J. (2017). Use of high quantification evidence in fair value audits: Do auditors stay in their comfort zone? The Accounting Review, 92(5), 89–116. https://doi.org/10.2308/accr-51662

Johnson, J. T., Ogawa, K. H., Delforge, A., & Early, D. (1989). Causal primacy and comparative fault: The effect of position in a causal chain on judgments of legal responsibility. Personality and Social Psychology Bulletin, 15(2), 161–174. https://doi.org/10.1177/0146167289152003

Uma R. Karmarkar, Zakary L. Tormala, Believe Me, I Have No Idea What I'm Talking About: The Effects of Source Certainty on Consumer Involvement and Persuasion, Journal of Consumer Research, Volume 36, Issue 6, April 2010, Pages 1033–1049, https://doi.org/10.1086/648381

Kachelmeier, S.J., B. E. Reichert, & M. G. Williamson. (2008). Measuring and motivating quantity, creativity, or both. Journal of Accounting Research, 46(2), 341–373.

Karmarkar, U. R., & Tormala, Z. L. (2010). Believe Me, I Have No Idea What I'm Talking About: The Effects of Source Certainty on Consumer Involvement and Persuasion. Journal of Consumer Research, 36(6), 1033–1049. https://doi.org/10.1086/648381

KPMG. (2021). Our commitment to an open innovation mindset. https://info.kpmg.us/news-perspectives/advancing-the-profession/open-innovation-mindset.html Retrieved on 2/26/24.

KPMG. (2021). Transparency Report 2021. Available at: https://assets.kpmg/content/dam/kpmg/xx/pdf/2021/12/transparency-report-2021.pdf

Krügel, S., Ostermaier, A., & Uhl, M. (2023). Algorithms as partners in crime: a lesson in ethics by design. Computers in Human Behavior, 138, 107483–107483. https://doi.org/10.1016/j.chb.2022.107483

Kruglanski A. W., Fishman S. (2009). The need for cognitive closure. In Leary M. R., Hoyle R. H. (Eds.), Handbook of individual differences in social behavior (pp. 343–353). New York, NY: Guilford Press.

Larson, J. R., Tindale, R. S., & Yoon, Y.-J. (2020). Advice taking by groups: The effects of consensus seeking and member opinion differences. Group Processes & Intergroup Relations, 23(7), 921–942. https://doi.org/10.1177/1368430219871349

Madhaven, P., & Wiegmann, D. A. (2007). Similarities and differences between human–human and human–automation trust: an integrative review. Theoretical Issues in Ergonomics Science, 8(4), 277-301

Maheswaran, D., & Chaiken, S. (1991). Promoting systematic processing in low-motivation settings: Effect of incongruent information on processing and judgment. Journal of Personality and Social Psychology, 61(1), 13–25. https://doi.org/10.1037/0022-3514.61.1.13

Mannes, A. E. (2009). Are We Wise about the Wisdom of Crowds? The Use of Group Judgments in Belief Revision. Management Science, 55(8), 1267–1279. http://www.jstor.org/stable/40539285

Martin, R. D., Rich, J. S., & Wilks, T. J. (2006). Auditing fair value measurements: a synthesis of relevant research. Accounting Horizons, 20(3), 287–303.

Mosier, K. L., Skitka, L. J. (1996) Human decision makers and automated decision aids: made for each other. In: R Parasuraman, M Mouloua, eds. Automation and Human Performance: Theory and Applications. Hillsdale, NJ, England: Lawrence Erlbaum Associates; 1996: 201–220.

Müller, Vincent C. (2012), ‘Autonomous cognitive systems in real-world environments: Less control, more flexibility and better interaction’, Cognitive Computation, 4 (3), 212-15. http://www.sophia.de – http://orcid.org/0000-0002-4144-4957

O’Neill, T., McNeese, N., Barron, A., & Schelble, B. (2022). Human–Autonomy Teaming: A Review and Analysis of the Empirical Literature. Human Factors, 64(5), 904–938. https://doi.org/10.1177/0018720820960865

PCAOB. 2015. The Auditor’s Use of the Work of Specialists. Staff Consultation Paper No. 2015 – 01. Washington, D.C.: PCAOB.

PCAOB. 2018. Amendments to Auditing Standards for Auditor’s Use of the Work of Specialists. PCAOB Rulemaking Docket Matter No. 044. Washington, DC: PCAOB.

PCAOB. (2015). The Auditor’s Use of the Work of Specialists. Staff Consultation Paper No. 2015-01-. Washington, D.C.: PCAOB. Available at https://pcaobus.org/Standards/Documents/SCP-2015-01_The_Auditor%27s_Use_of_the_Work_of_Specialists.pdf

PCAOB. (2022). AS 1210: Using the Work of an Auditor-Engaged Specialist (Amended). Washington, D.C. Available at https://pcaobus.org/oversight/standards/auditing-standards/details/AS1210

Peters, Christian P. H., Auditor Automation Usage and Professional Skepticism (December 9, 2022). Available at SSRN: https://ssrn.com/abstract=4309348 or http://dx.doi.org/10.2139/ssrn.4309348

Petty, R.E. and Briol, P. (2008), “Persuasion: from single to multiple to metacognitive processes”, Perspectives on Psychological Science, Vol. 3 No. 2, pp. 137-147.

Price, P. C., & Stone, E. R. (2003). Intuitive evaluation of likelihood judgment producers: evidence for a confidence heuristic. Journal of Behavioral Decision Making, 17(1), 39–57. Portico. https://doi.org/10.1002/bdm.460

Pulford, B. D., Colman, A. M., Buabang, E. K., & Krockow, E. M. (2018). The persuasive power of knowledge: Testing the confidence heuristic.Journal of Experimental Psychology: General, 147(10), 1431–1444. https://doi.org/10.1037/xge0000471

PwC. 2021. Global Annual Review 2021. Available at: https://www.pwc.com/gx/en/about-pwc/global-annual-review-2021/downloads/pwc-global-annual-review-2021.pdf

PwC. (2024). How auditors combine tech know-how and finance skills to drive innovation. https://www.pwc.com/us/en/tech-effect/automation/audit-technology-and-digital-skills.html

Rebensky, S., Carmody, K., Ficke, C., Carroll, M. and Bennett, W. (2022) Teammates Instead of Tools: The Impacts of Level of Autonomy on Mission Performance and Human–Agent Teaming Dynamics in Multi-Agent Distributed Teams. Front. Robot. AI 9:782134. doi: 10.3389/frobt.2022.782134

Smith, S. M., & Petty, R. E. (1996). Message Framing and Persuasion: A Message Processing Analysis. Personality and Social Psychology Bulletin, 22(3), 257–268. https://doi.org/10.1177/0146167296223004

Smithson, M. (1999). Conflict aversion: preference for ambiguity vs conflict in sources and evidence. Organizational Behavior and Human Decision Processes, 79(3), 179–198. https://doi.org/10.1006/obhd.1999.2844

Van Swol, L. M., & Sniezek, J. A. (2005). Factors affecting the acceptance of expert advice. British Journal of Social Psychology, 44(3), 443–461. https://doi.org/10.1348/014466604X17092

Stasser G, Titus W (1985) Pooling of unshared information in group decision-making: Biased information sampling during discussion. J. Personality Soc. Psych. 48(6):1467–1478.

Stefaniak, C. M., Houston, R. W., & Cornell, R. M. (2012). The Effects of Employer and Client Identification on Internal and External Auditors' Evaluations of Internal Control Deficiencies. AUDITING: A Journal of Practice & Theory, 31(1), 39–56. https://doi.org/10.2308/ajpt-10179

Steiner, I. (1970) Perceived Freedom. Advances in Experimental Psychology. 5, 187-248

Surowiecki, J. (2004). The wisdom of crowds: Why the many are smarter than the few and how collective wisdom shapes business, economies, societies, and nations. New York, NY: Random House.

Surowiecki, J. (2005). The wisdom of crowds (First Anchor books). Anchor Books, a division of Random House.

Sutton, S. G., Arnold, V. and Holt, M. (2022), An Extension of the Theory of Technology Dominance: Understanding the Underlying Nature, Causes and Effects (April 30, 2022). Available at SSRN: https://ssrn.com/abstract=4101835 or http://dx.doi.org/10.2139/ssrn.4101835

Svanberg, J., & Öhman, P. (2015). Auditors' identification with their clients: Effects on audit quality. The British Accounting Review, 47(4), 395–408. https://doi.org/10.1016/j.bar.2014.08.003

Tan, S. K., & Tan, H. T. (2008). Effects of Exposure to Subsequently Invalidated Evidence on Judgements of Audit Workpaper Preparers and Reviewers. Contemporary Accounting Research, 25(3), 921–946. https://doi.org/10.1506/car.25.3.10

Tenney, E. R., MacCoun, R. J., Spellman, B. A., & Hastie, R. (2007). Calibration Trumps Confidence as a Basis for Witness Credibility. Psychological Science, 18(1), 46-50. https://doi.org/10.1111/j.1467-9280.2007.01847.x

Thomas, L. Jr. (2017) At BlackRock, Machines Are Rising Over Managers to Pick Stocks. The New York Times. Available at: https://www.nytimes.com/2017/03/28/business/dealbook/blackrock-actively-managed-funds-computer-models.html

Thomas, A., Khatri, P., Dabas, V., & Coniglio, I. M. (2024). Capturing innovation orientation in knowledge workers: development and validation of a measurement scale. Journal of Knowledge Management. https://doi.org/10.1108/jkm-12-2023-1276

Tormala, Z. L., DeSensi, V. L., Clarkson, J. J., & Rucker, D. D. (2009). Beyond attitude consensus: The social context of persuasion and resistance. Journal of Experimental Social Psychology, 45(1), 149–154. https://doi.org/10.1016/j.jesp.2008.07.020

Tsai, M-H., Bendersky, C. 2016. The Pursuit of Information Sharing: Expressing Task Conflicts as Debates vs. Disagreements Increases Perceived Receptivity to Dissenting Opinions in Groups. Organization Science 27(1):141-156. https://doi.org/10.1287/orsc.2015.1025

Vinokur, A., & Ajzen, I. (1982). Relative importance of prior and immediate events: A causal primacy effect. Journal of Personality and Social Psychology, 42(5), 820–829. https://doi.org/10.1037/0022-3514.42.5.820

Yaniv, I. (2004b). Receiving other people’s advice: influence and benefit. Organizational Behavior and Human Decision Processes, 93, 1–13.
Ziegler, R., Diehl, M., & Ruther, A. (2002). Multiple Source Characteristics and Persuasion: Source Inconsistency as a Determinant of Message Scrutiny. Personality and Social Psychology Bulletin, 28(4), 496–508. https://doi.org/10.1177/0146167202287007