Registered Report Proposal

How Does Generative AI Automation Affect Auditors' Motivation and Judgment Quality?

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ABSTRACT

Generative AI ("Gen AI") technology has significant potential to enhance audit practices. However, there are also risks that need to be addressed. We leverage self-determination theory and predict that auditors' use of Gen AI automation lowers their autonomous motivation, which comes at the cost of auditors' judgment quality. We design two experiments that collectively allow us to investigate these predictions. The first experiment will test the effects of Gen AI automation on auditors' autonomous motivation. The second experiment will test the effects of Gen AI automation on judgment quality in a subsequent audit task. The second experiment uses a moderation-of-process design to test whether an autonomous motivation prompt can attenuate the negative effects of Gen AI automation. This provides process evidence for our theory and also informs audit firms about interventions they can use to mitigate negative effects of Gen AI usage.

Use of non-public PCAOB data

Does your proposal require the use of PCAOB's non-public data: **No**

I. INTRODUCTION

Audit firms invest billions of dollars in new technologies to improve the effectiveness and efficiency of audits (e.g., Austin, Carpenter, Christ, and Nielson 2021; Deloitte 2023; Maurer 2023). For example, many firms are building bespoke generative AI ("Gen AI") technologies that can improve efficiency by automating certain audit tasks (Iacone 2023). While still in its nascent stages, the use of automation technologies, such as Gen AI, is rapidly shifting the design of audit work. Audit firms are upskilling their staff to work with automation technologies in the field; however, firm leadership may be concerned about deskilling of audit staff in other crucial areas (e.g., Sutton, Arnold, and Holt 2023). For example, auditors develop critical audit judgment skills on the job (Earley 2001; Westermann, Bedard, and Earley 2015; Dierynck, Kadous, and Peters 2024), starting with early career tasks that are prime candidates for automation (Zhang, Thomas, and Vasarhelyi 2022). In this study, we examine whether automation of audit procedures using Gen AI (hereafter, "Gen AI automation") affects auditors' judgment quality. We posit that Gen AI automation affects judgment quality through a reduction in auditors' motivation; as such, we further examine whether increasing auditors' autonomous motivation attenuates the effects of Gen AI automation on auditor judgment quality (e.g., Kadous and Zhou 2019).

We leverage Self-Determination Theory (SDT) to examine how Gen AI automation can affect auditor motivation. SDT postulates that individuals' motivation stems from satisfaction of three basic psychological needs: autonomy, which relates to the desire to have control; competence, which relates to skill development; and relatedness, which relates to connections with others (e.g., Deci and Ryan 1980, 1985, 2000; Ryan 1993; Sheldon and Elliott 1999). Based on SDT, Gen AI automation likely changes audit work design in ways that impact satisfaction of these three basic needs and thereby ultimately affecting auditor motivation.

Gen AI automation may impact auditors' feeling of competence by reducing the ability to learn the audit work from hands-on experience (e.g., Westermann et al. 2015). Despite firms' efforts to train auditors in the use of advanced tools, auditors may feel less competent using Gen AI automation systems that are inherently complex and opaque, which affects auditors' ability to understand and analyze the output of the technology (e.g., Holmstrom 2024). Gen AI automation may reduce autonomy as auditors shift from a preparing role to a more reviewing role (Christ et al. 2021; Boritz and Stratopoulos 2023). Additionally, Gen AI automation can introduce a level of dependence on the systems, which could further constrain auditor autonomy if auditors over-rely on Gen AI automation (e.g., Peters 2024). Gen AI automation likely affects relatedness as auditors increasingly engage with systems instead of people. This may for instance happen when junior auditors ask Gen AI automation instead of colleagues to help them, or if auditors spend less time on site with clients because Gen AI automation takes on more of the tasks. Overall, we expect that Gen AI automation reduces auditors' motivation through its effects on competence, autonomy, and relatedness. Importantly, we examine whether automation affects auditors' motivation in a subsequent task, not only motivation within an automated task.

We further expect that Gen AI automation has a negative impact on audit judgment quality. While Gen AI automation has shown to have performance benefits for some complex tasks in professional services (Dell'Acqua, McFowland, Mollick, Lifshitz-Assaf, Kellogg, Rajendran, Krayer, Candelon, Lakhani 2023), recent survey research has pointed out that the use of Gen AI may also lead to procrastination, memory loss, and reductions in performance (Abbas, Jam, and Khan 2024). In auditing contexts, research shows that increasing auditors' intrinsic motivation affects audit judgment quality (Kadous, Proell, Rich, and Zhou 2019; Kadous and Zhou 2019). Intrinsic motivation is a form of autonomous motivation and is the most self-determined type of motivation (Deci et al. 2017, p. 20). Autonomous motivation can be extrinsically motivated by contingent rewards or to avoid punishment, but autonomous motivation will be lower if employees do not feel a sense of choice (Deci et al. 2017). Thus, we expect that Gen AI automation affects audit judgment quality through the hypothesized decrease in motivation, relative to when tasks are conducted without automation.

We employ a moderation-of-process design which allows us to test the link between Gen AI automation and audit judgment quality using a moderating variable that is closely related to the hypothesized mediating variable (Asay, Guggenmos, Kadous, Koonce, and Libby 2022). Namely, we examine whether increasing auditors' autonomous motivation attenuates our hypothesized effect of Gen AI automation on audit quality. If our theory holds, an autonomous motivation prompt should increase audit judgment quality more when auditors use Gen AI automation, since we expect that Gen AI automation decreases auditor motivation relative to non-automated techniques.

We test our hypotheses using two novel experiments designed to test the causal links between Gen AI automation, auditors' autonomous motivation, and audit judgment quality and to provide process evidence (Asay et al. 2022). In Experiment 1 we will conduct a 1 x 2 between-subjects experiment using junior auditors to test the effect of our first independent variable (Gen AI automation) on auditors' motivation. In Experiment 2 we will conduct a 2 x 2 between-subjects experiment using more senior auditors to test the effects of Gen AI automation on audit judgment quality and test the attenuating effect of our second independent variable (i.e., an autonomous motivation prompt) on audit judgment quality. In both experiments, we manipulate Gen AI automation by having auditor participants either complete a task related to allowance for loan losses or prompt Gen AI to complete the task. We design the experiment such that the task is suitably completed by the auditor or Gen AI without needing human intervention. In Experiment 1, participants complete a cognitive reflection test and respond to work motivation scales (adapted from prior research) to examine the effects of Gen AI automation on autonomous motivation and cognitive processing. In Experiment 2, we also manipulate autonomous motivation using prompts consistent with prior literature by asking participants to rank order items from a list of intrinsic motivators (e.g., Amabile 1985; Amabile, Hill, Hennessey, and Tighe 1994; Kadous and Zhou 2019). In the control group, participants are asked to rank something not related to auditing, to keep time and task constant across conditions (e.g., Amabile 1985; Kadous and Zhou 2019).

We contribute to literature in several ways. First, a growing body of accounting research examines the effects of auditors' usage of advanced technologies on auditors' decision-making (Commerford, Dennis, Joe, and Ulla 2022; Commerford, Eilifsen, Hatfield, Holmstrom, Kinserdal 2024; Peecher et al. 2023; Holmstrom 2024; Peters 2024). To our knowledge, this is the first paper to examine the effects of automation and Gen AI on auditor motivation and audit judgment quality. Prior research finds that auditors exhibit algorithm aversion and rely less on contradictory evidence provided by AI systems compared to the same evidence provided by a human specialist (e.g., Commerford et al. 2022). Importantly, our study examines how Gen AI automation affects audit judgment quality through its effects on motivation, not through auditors' reliance on technology relative to humans (i.e., motivational effects rather than source effects). We also further contribute to understanding the link between auditor motivation and judgment quality (Kadous and Zhou 2019; Kadous et al. 2019).

Our research also has practical implications for firms. For audit firms to reap the efficiency and audit quality gains they hope from Gen AI automation, it is imperative to understand how automation affects auditor judgment. These effects may have an outsized effect on skill development and performance of (more junior) auditors. While the combination of Gen AI and human auditors likely outperforms either one of them on their own (e.g., KPMG 2016; Dell'Acqua et al. 2023), we investigate whether the usage of Gen AI automation may also reduce auditors' basic needs and autonomous motivation, thereby potentially reducing judgment quality in other parts of the audit. This is informative to audit firms as it helps them to navigate the difficult trade-offs related to the behavioral ramifications of Gen AI adoption in the audit. We also contribute by testing a theoretical countermeasure, i.e., an autonomous motivation prompt. Audit firms can carefully generalize from our theory to design interventions that can alleviate the potentially negative effects of Gen AI adoption.

Our research has significant implications not only for audit firms but also for regulatory bodies such as the PCAOB and audit inspectors. As Gen AI becomes more integrated into audit practices, it is crucial for regulators to understand how these technologies impact auditor behavior, specifically motivation and judgment quality. This understanding can help shape future PCAOB practices and guidelines regarding the use of Gen AI in audits. Inspectors will need to develop new assessment frameworks that consider the impact of Gen AI on auditors' work. This includes evaluating how AI-generated workpapers are supervised and how the audit organization's system of quality control deals with auditor supervision of AI-generated outputs.

II. THEORY AND HYPOTHESIS DEVELOPMENT

Artificial Intelligence and Audit Work Design

Recent developments in big data, machine learning, artificial intelligence, and blockchain are significantly changing the practice of the audit profession (Zhang, Xiong, Xie, Fan, and Gu 2020; Austin et al. 2021; Commerford et al. 2022; Fedyk, Hodson, Khimich, and Fedyk 2022; Zhang et al. 2022). Audit companies are investing billions in advanced tools and techniques (EY

2018; KPMG 2019; PwC 2019; Deloitte 2023; Iacone 2023; Maurer 2023). The motivations behind these investments are multifaceted, with improvements in audit quality, efficiency, and the ability to provide clients with new insights being key drivers. For instance, Deloitte developed its Omnia cloud-based system to digitize audits and efficiently integrate and analyze client data, and they recently released DARTBot, a firm-developed Gen AI platform that can provide audit guidance and research complex accounting topics (Deloitte 2023). In a similar vein, PwC has the AI Audit Lab to improve audit quality, automation levels, and operational efficiency (PwC 2018; Zhang et al. 2020). As a final example, KPMG auditors can use the firm's Dynamic Risk Assessment platform, which employs AI and advanced analytics, and MindBridge, a third-party AI-based financial risk assessment platform, to assess client risks (KPMG 2023). Many of the firms' advanced technologies utilize AI and Gen AI to automate audit and assurance tasks. Gen AI can help draft audit documentation, provide guidance and research on accounting and auditing standards, read and summarize complex content, and automate reviews and data analyses, among others (Eulerich, Sanatizadeh, Vakilzadeh, and Wood 2023; Isack 2024).

Empirical evidence suggests Gen AI automation can significantly improve audit processes in certain areas (e.g., Appelbaum, Kogan, and Vasarhelyi 2017; Fedyk et al. 2022; Eulerich et al. 2023). For instance, Fedyk et al. (2022) find that investing in AI improves audit quality and reduces fees but displaces some human auditors. Research also finds that automated tools and techniques can improve audit quality and efficiency in inventory counting (Christ, Emmett, Summers, and Wood 2021) and in generating accurate accounting estimates (Ding, Lev, Peng, Sun, and Vasarhelyi 2020). Audit firms cite AI benefits such as time savings, increased accuracy, and the ability to provide enhanced client service (e.g., Munoko, Brown-Liburd, and Vasarhelyi 2020; Austin et al. 2021; Commerford et al. 2024). Recent research also highlights auditors' reticence to rely on advanced technologies and automated tools due to "algorithm aversion" (Commerford et al. 2022, 2024; Peecher, Pietsch, Stirnkorb, and Yamoah 2023) or due to the opacity inherent in many technologies (Holmstrom 2024), both of which reduces auditors' understanding of and in turn comfort relying on output from the technologies.

The unprecedented investments in new cognitive technologies raise the question of how these technologies affect the audit process. Some discussions regarding the effects of AI and digitalization often highlight the potential for significant job losses and auditor replacements (e.g., O'Neill 2016; Chandi 2017; Zhang et al. 2020). Yet, others argue that the actual situation is more nuanced, with digitalization impacting specific tasks within auditing rather than wholesale replacing entire jobs (KPMG 2016; ICAEW 2018; Jesuthasan and Boudreau 2018; Christ et al. 2021; Zhang et al. 2022). Consequently, audit companies stress that the role of automation is to augment rather than replace the human auditor, boosting their productivity and precision in work. Ultimately, it is the auditors who are responsible for making pivotal decisions, providing essential analysis, and delivering insights (PwC; 2017; Deloitte 2022; KPMG 2023).

Yet, Gen AI automation is changing audit work design in ways that have the potential to decrease the development of critical audit skills, thereby potentially diminishing if not negating the effectiveness and efficiency gains from the use of automated technologies. Automating routine tasks that were previously performed by auditors shifts the skill sets required of auditors (Fedyk et al. 2022), such that auditors may not learn the fundamentals of auditing through experience but may instead need to learn it through training or vicariously (e.g., Dierynck et al. 2024). Additionally, integrating Gen AI can change the nature of collaboration within audit teams. As auditors increasingly engage with systems instead of people, their chance to learn from others on the job is similarly affected. Since AI has exploded in variety and complexity, the models and outcomes are likely intelligible only to some but remain opaque to others (e.g., Castelvecchi 2016; Berente et al. 2021; Holmstrom 2024). This complexity can make it difficult for auditors to understand how conclusions are reached, potentially affecting their ability to fully scrutinize the AI's analysis and recommendations. Further, advanced technologies and methods like Gen AI are progressively gaining the ability to operate independently or even evaluate and control humans (Berente et al. 2021; Möhlmann et al. 2021). Auditors may become overly dependent on AI-generated insights related to data processing, analysis, and even decision-making processes without fully understanding or questioning the underlying algorithms and data integrity (e.g., Peters 2024).

Automation and Auditor Motivation

We draw on self-determination theory (SDT) to investigate how the potential changes to auditors' work design from Gen AI automation affect auditor motivation. According to SDT, motivation is fundamentally linked to the extent to which individuals can satisfy three basic psychological needs: autonomy, competence, and relatedness (e.g., Deci and Ryan 1980, 1985, 2000). Autonomy refers to the desire to have control over one's actions and to have activity be concordant with one's integrated sense of self (e.g., Sheldon and Elliott 1999). Competence involves an individual's ability to control their environment and acquire new skills. Relatedness encompasses the need for connection with others, including both caring for others and receiving care in return (e.g., Ryan 1993). According to SDT, the three needs constitute motivation and are the basis for the energization of action. SDT differentiates between autonomous and controlled motivation (Deci, Olafsen, and Ryan 2017). Autonomous motivation is defined as "being engaged in an activity with a full sense of willingness, volition, and choice" (Deci et al. 2017, p. 20). It is often intrinsic (but can also be extrinsic), whereas controlled motivation is often more externally regulated through contingent rewards and power dynamics (Deci et al. 2017).

Basic needs satisfaction subsequently affects motivation. Autonomy supports the internalization of motivation, making activities more self-determined and intrinsically rewarding, thereby increasing intrinsic motivation. Intrinsic motivation is a specific type of autonomous motivation and refers to activities for which the motivation lies in the behavior itself rather than in extrinsic outcomes associated with the behavior (Deci et al. 2017). When individuals experience competence, they are more likely to be intrinsically motivated to engage in activities that challenge their skills, leading to growth and learning. Fulfilling the relatedness need can enhance both intrinsic motivation (engaging in activities for their own sake) and extrinsic motivation (engaging in activities for external outcomes); the latter holds especially when the activities are aligned with fostering or maintaining important relationships. SDT posits that when these three basic needs are satisfied, individuals will exhibit higher levels of autonomous (including intrinsic) motivation.

We argue that in the audit setting, Gen AI automation lowers auditors' basic needs (i.e., autonomy, competence, and relatedness). First, Gen AI automation may reduce autonomy as it can take over some of the analyses and judgments that were previously made by auditors. Second, Gen AI automation may also reduce auditors' competence, as Gen AI automation is structurally conducting some parts of the audit process, making it less likely for auditors to learn from experience. As it is often not transparent how Gen AI automation reaches its conclusion, auditors' feelings of competence related to working with Gen AI may be hampered (e.g., Abbas et al. 2024). Third, the integration of Gen AI automation may reduce relatedness as it changes the nature of collaboration in audit teams from human-human collaboration increasingly to human-AI collaboration.

Hence, based on the predicted reduction in basic needs satisfaction, we expect that Gen AI automation shifts auditors' motivation from more autonomous to more controlled motivation. When the process underlying an audit procedure is more automated by Gen AI, auditors are less directly required to engage in effort related to completion of the audit procedure, especially when the automation performs not only technical tasks but also provides audit conclusions. A critical point is that we expect Gen AI automation to impact auditors' general motivation and development of key audit skills from on-the-job learning, not just motivation on the task automated by Gen AI. Taken together, we propose that audit procedure automation using Gen AI can reduce autonomous motivation in auditors because auditors will assume their efforts to gather and understand information are less likely to affect audit outcomes (i.e., affect their perceived autonomy) and reduce feelings of competence and relatedness. This leads to our first hypothesis:

> **Hypothesis 1:** Gen AI automation in audit tasks reduces auditors' autonomous motivation.

Auditor Motivation and Auditor Judgment Quality

Prior research in auditing shows that auditors' motivation is associated with behaviors necessary for complex judgments, professional skepticism, and audit quality (Kadous and Zhou 2019; Kadous, Proell, Rich, and Zhou 2019). Auditors whose intrinsic motivation is more salient will attend to a broader set of information cues, process them more deeply, and consider more relevant evidence before reaching a conclusion (Kadous and Zhou 2019). Furthermore, auditors' intrinsic motivational orientation positively affects their willingness to raise significant audit issues (Kadous, Proell, Rich, and Zhou 2019). In general, autonomously motivated individuals tend to have a more open mind towards new information (Hennessey 2000; Cerasoli, Nicklin, and Ford 2014), analyze information in a deeper way (Graham and Golan 1991), and collect more evidence to support their conclusion (Condry and Chambers 1978). Autonomous motivation is also associated with less burnout (Fernet et al. 2010), more work satisfaction and less turnover intentions and emotional exhaustion (Richer et al. 2002; Fernet et al. 2012), more knowledge sharing (Foss et al. 2009), and higher job performance (Van den Broeck et al. 2021).

That said, research shows that Gen AI automation can have performance benefits for some complex tasks (Dell'Acqua et al. 2023), but its usage can also have a negative effect on cognition and performance (Abbas, Jam, and Khan 2024). For example, Dell'Acqua et al. (2023) find that generative AI improves performance on consultancy tasks. Abbas, Jam, and Khan (2024) find that usage of ChatGPT by students has a negative impact on students' academic performance and results in memory loss.

Given that we expect Gen AI automation reduces auditors' autonomous motivation, we further expect that Gen AI automation reduces auditors' judgment quality. As noted, we expect that Gen AI automation reduces auditors' general motivation, not just motivation and judgment quality on the task completed by Gen AI, which could be explained by algorithm aversion and reticence to rely on output from the Gen AI automation tool (e.g., Commerford et al. 2022). Rather, we expect Gen AI automation to impact motivation and judgment quality in other, subsequent tasks that are not conducted by Gen AI. This leads us to our second hypothesis.

> **Hypothesis 2:** Gen AI automation in a given audit task reduces auditors' judgment quality in a subsequent audit task.

Autonomous Motivation Intervention

Next, we examine whether the potential negative effects of Gen AI automation on auditors' judgment quality can be attenuated by an autonomous motivation prompt. That is, in our theoretical framework – as displayed in Figure 1 – we expect that the effect of Gen AI automation on auditor judgment quality is mediated by autonomous motivation, which is associated more with intrinsic motivation than extrinsic motivation (e.g., Deci and

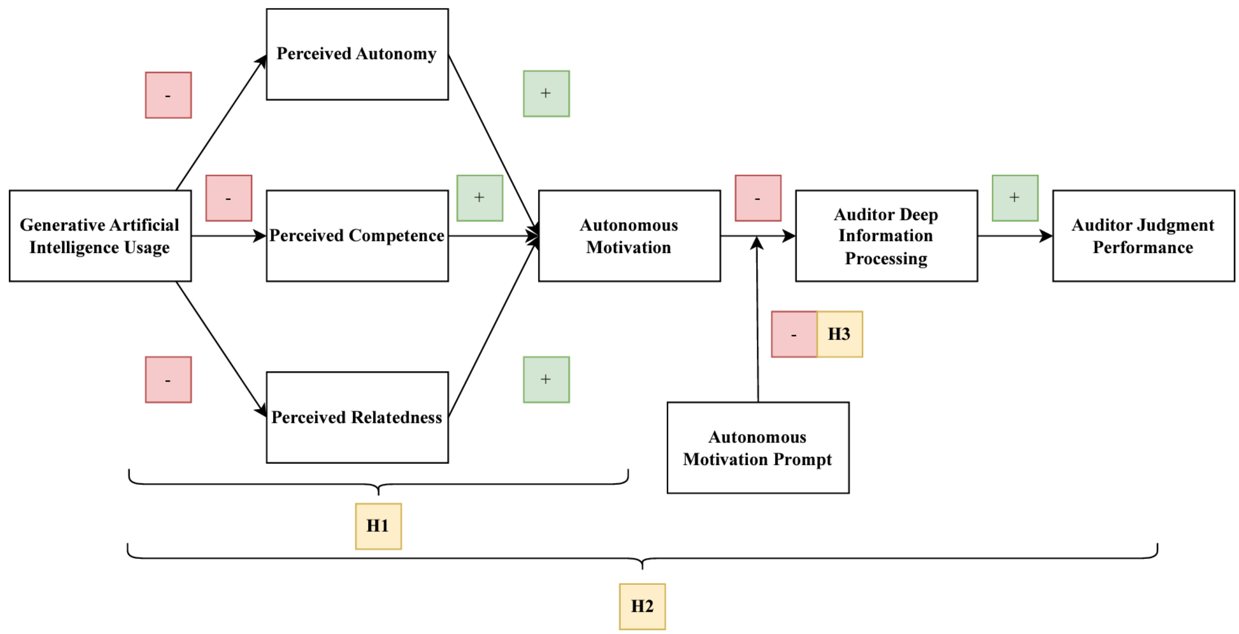
Ryan 2001). Hence, to attenuate the potential negative behavioral ramifications of Gen AI automation, we design an autonomous motivation intervention to moderate the mechanism. Such a moderation-of-process intervention, which uses an independent variable that affects the theorized process and changes the magnitude of a cause-effect relationship, is also useful in identifying the causal mechanism and providing more information about the causal process at play (Asay et al. 2022). If the causal mechanism at play indeed runs through autonomous motivation, we expect that an autonomous motivation prompt will attenuate the negative effects of Gen AI automation usage on auditors' judgment quality. Testing this intervention further provides information about the extent to which our inferences can be generalized through self-determination theory. The above leads us to our third and final hypothesis.

> **Hypothesis 3:** The effects of Gen AI automation on judgment quality are attenuated by an autonomous motivation prompt, compared to a control group with no autonomous motivation prompt.

Figure 1 displays the theoretical mechanism and predicted hypotheses.

FIGURE 1

Theoretical Mechanism and Hypotheses



Notes: Figure 1 displays the theoretical mechanism (with arrows) and hypotheses (H's) of our study. The costructs and hypotheses are described in Section 2, the operationalizations of our constructs are further described in Section 3. The +'s (in green) show a positive predicted relationship between the variables and the –'s (in red) a negative predicted relationship. Furthermore, the hypotheses are indicated in yellow.

III. RESEARCH DESIGN

Experimental Methodology

We use a multiple-studies approach to separately test different sections of our causal chain and provide process evidence (Asay et al. 2022). In our first experiment we will conduct a 1 x 2 between-subjects experiment to test the first link of our theoretical mechanism, i.e., the effect of our independent variable (Gen AI automation) on auditors' motivation and basic needs (i.e., H1). In our second experiment we will conduct a 2 x 2 between-subjects experiment to test the link between our independent variable (Gen AI automation) and auditors' deep information processing (unobtrusively measured) and their judgment quality (i.e., H2). In the second experiment we will also test the attenuating effect of an autonomous motivation prompt (i.e., H3). This multiple-studies approach mitigates potential carryover effects of mediators on dependent variables, and thereby bolsters the internal validity of our inferences (Asay et al. 2022). We next describe the experimental procedures of both experiments sequentially.

Independent Variables

In the first experiment, participants will assume the role of an auditor at a hypothetical audit firm and to conduct certain steps for an audit of the estimate of the allowance for loan losses at a hypothetical client; namely, analyzing information related to loan loss estimates for a sample of individual loans in the client's portfolio. Our first manipulation, *Gen AI Automation*, varies whether Gen AI completes the initial audit steps for the loan loss allowance, or not. Specifically, in the *Control* condition there is no usage of any Gen AI automation, and participants complete the steps of the allowance for loan losses audit by themselves. In the *Gen AI Automation* condition, however, auditors see how most of the task is conducted by an embedded ChatGPT-type application programming interface and only have to document the outcome based on the input provided by the ChatGPT-type application. Importantly, we keep the total time that participants spent on the task equivalent across conditions, such that if participants work faster, they will complete more loan loss estimates. However, we design the steps to complete one loan loss estimate in the *Control* condition and *Gen AI Automation* condition such that they take approximately the same amount of time across Gen AI conditions. In doing so, we control both the time spent on the task as well as the number of loan losses examined. After this task auditors answer questions adapted to our setting from the Basic Needs Satisfaction scale (Deci and Ryan 2000; Deci et al. 2001; Gagné 2003), the multidimensional work motivation scale (MWMS, Gagné et al. 2015), and prior work on motivation in auditing (e.g., Becker 1997; Kadous and Zhou 2019).[1]

[1] Example items from the Basic Needs Satisfaction scale include "I feel like I can make a lot of inputs to deciding how my job gets done." (autonomy): "[w]hen I am working I often do not feel capable" (competence, reverse-coded): and "I pretty much keep to myself when I am at work" (relatedness, reverse-coded). We will adapt the

In our second experiment, we test the effect of Gen AI automation on auditors' information processing and judgment quality. In Experiment 2, participants start with the same experimental instructions and client background information and again conduct the same steps in the audit of allowance of loan losses. During the audit of the loan losses, they are also subject to the *Gen AI Automation* manipulation. However, as the goal of the second experiment is to investigate whether *Gen AI Automation* affects auditors' information processing and judgment quality in a subsequent task, we similarly fix the total time that participants have for this task, and after this task they move on to a second task. Before moving to the second task, they are also subject to the *Autonomous Motivation* manipulation, which we use as a moderation-of-process variable. That is, if *Gen AI Automation* indeed reduces auditors' autonomous motivation (H1), a theoretical countermeasure that prompts autonomous motivation should restore some of the motivation and counter the negative effect of Gen AI automation. The manipulation is similar to prior research, where auditors rank order items from a list of intrinsic motivators for conducting a task (e.g., Amabile 1985; Kadous and Zhou 2019), whereas in the control condition participants rank something irrelevant to motivation.

After our manipulations, auditors in Experiment 2 will conduct a second task in which their information processing and judgment quality is measured. Measuring participants' judgment quality in a separate task is necessary since judgment quality in the first task (i.e., loan loss evaluations) would be impacted by actually completing the task on one's own (*Control* condition) or not (*Gen AI Automation* condition). Specifically, as a second task auditors form a judgment related to the allowance for loan losses for a different client (cf. Commerford et al. 2022). To

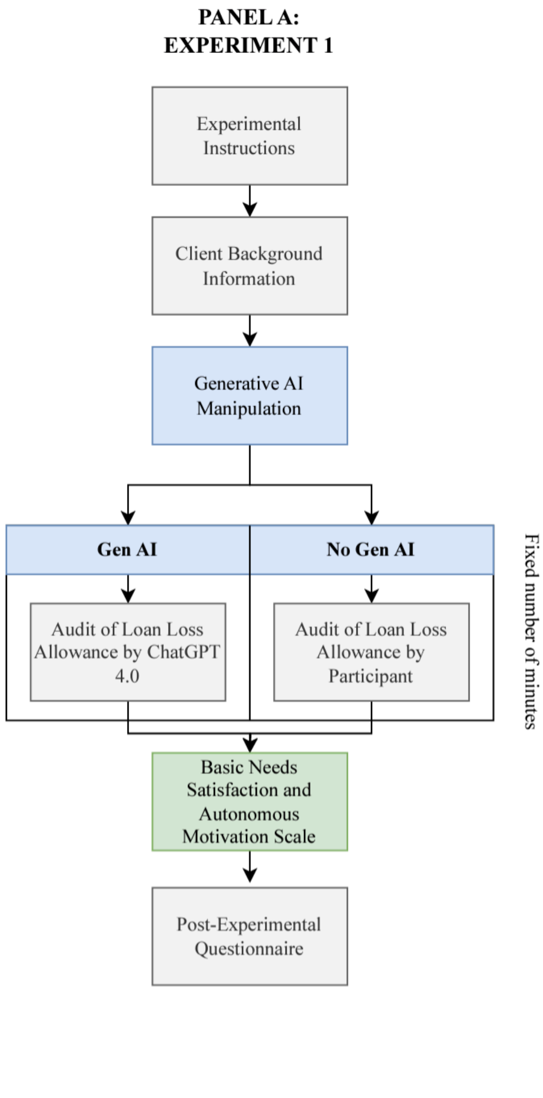
MWMS to our setting and ask, "Why do you or would you put efforts into your task if you had to do the same task again?" An example item from the MWMS is "[b]ecause the work I do is interesting" (intrinsic motivation).

prevent any performance or experience effects, we design the tasks such that there is no overlap between the information in the first and second task. They receive excerpts of real estate market, bank industry, and client information as well as management's loan loss provision and underlying assumptions. Dependent variables consist of variable measures for the likelihood of an audit adjustment, the perceived bias in the management estimate, confidence in the auditor's judgment, and to what extent the auditors believe the audit evidence is of high quality (measured with Likert-type scales). Additionally, we ask them which cues help them to justify their decision (e.g., Griffith et al. 2015; Kadous and Zhou 2019). The case presents several embedded issues suggesting the projections might have been overly optimistic, potentially inflating the value. There are both evident and subtle indicators, the identification of which depended on the level of cognitive effort exerted. When analyzing the extent to which valid cues were identified, we take into account the (i) total number of cues identified, (ii) the number of peripheral cues identified (explained later): (iii) the number of deep cues identified (explained later): (iv) the number of valid evidence requests, (v) the overall reasonableness of the fair value, and (vi) the decision what steps to take next (Kadous and Zhou 2019).

Importantly, using this case has a clear advantage. That is, the case allows us to unobtrusively assess participants' information seeking behavior. As the case contains multiple information cues that can be accessed, we can measure how much time is spent on each information cue. Next to that, the case has both deep and surface level seeded issues. Whereas service level issues can be identified based on information that is prominent and can be directly extracted from the case (e.g., market conditions), deep issues require the auditor to connect multiple pieces of information (e.g., combination of asset type returns and geographic location developments). The deeper issues need more cognitive processing, and as we theoretically predict that Gen AI automation affects judgment quality through motivation and information processing, having this distinction allows us to examine whether the type of cognitive processes used differs between conditions. Hence, the case also allows us to examine the type of information collected by participants.

Following their assessment of the judgments and proposed audit adjustment, auditors are given a post-experiment questionnaire to capture insights on their basic needs satisfaction, autonomous motivation, other process variables (including manipulation checks), variables related to their personality, and demographic details. Other questions probe their views on (generative) artificial intelligence and experience with the audit tasks. For instance, we will elicit participants' level of comfort with Gen AI, participant's prior experience with Gen AI, and how receptive participants are to Gen AI in the work setting, both using scaled and open-ended questions. Additionally, we include items that elicit whether the auditor uses Gen AI in non-firm sactioned ways at work, especially to generate audit evidence. Demographic queries cover age, gender, professional experience, position within their firm, and any certifications held. Figure 2 displays the instrument flow for Experiment 1 (in Panel A) and Experiment 2 (in Panel B).

FIGURE 2
Instrument Flow



Notes: Figure 2 presents the instrument flow of Experiment 1 (in Panel A) and Experiment 2 (in Panel B). The blue boxes represent independent variables (manipulations), and green boxes represent dependent variables.

We will do post-hoc analysis to test whether the randomization was successful based on observable demographics. If there is a randomization failure, we will address this by using the specific variable where the randomization failed as a covariate in our analyses. Also, with respect to potential missing variables, we will use validations to ensure that all the important variables are filled in by participants. If participants forget or choose to not fill in a question, they will not be able to proceed. If participants principally do not want to answer a question, we allow options for it, such as “Prefer not to say.” Also, unfinished observations will be excluded from all analyses; finishing the experiment is one of the inclusion criteria of our proposed study. We will conduct analyses using observable variables whether the dropping out is at-random or not-at-random. If dropping out is not-at-random (e.g., in one condition more likely than in another), we can use techniques such as weighting and survival analysis to correct for the dropouts. In our design, we will try to reduce attrition by simplifying procedures. We will also transparently report the rates of attrition across conditions.

Furthermore, in our experimental instrument we will aim to minimize the risk of outliers by using validated scales and bound certain judgments within parameters (e.g., Likert-type scales). However, for some variables, such as the time spent on certain information, there may be outliers. In these cases, we may use robust statistical techniques such as median or IQR or central tendency and variability. Next to that, we can use non-parametric estimation such as Mann-Whitney *U* (Wilcoxon rank-sum) tests as replacement for t-tests and Kruskal-Wallis *H* test as the non-parametric alternative to one-way ANOVA in cases where there is a risk of outliers. Finally, in the case of outliers we will conduct sensitivity analyses both with and without the outliers to assess their impact on the results. This can provide insights into how robust the findings are to the presence of outliers.

We will use several statistical methods with the following underlying assumptions:

- Analysis of Variance (ANOVA) – independence of observations, normality of residuals, homoscedasticity (tested with Bartlett’s test): group sizes approximately equal.
- Ordinary Least Squares (OLS) regression – independence of observations, linearity, homoscedasticity, normality, no multicollinearity.
- Mann-Whitney *U* test – independence of observations, ordinal or continuous data, homogeneity of variances (optional but preferred).
- Kruskal-Wallis *H* test – independence of observations, ordinal or continuous data, homogeneity of variances (optional but preferred).

- Analysis of Covariance (ANCOVA) – independence of observations, linearity, homogeneity of regression slopes, normality of residuals, homogeneity of variances, no multicollinearity.
- [-3 1 1 1] Contrast coding – linearity, independence of observations, homoscedasticity, normality of residuals, no multicollinearity, appropriately defined contrasts (we will not use custom contrasts [Guggenmos, Piercey, and Agoglia 2018], orthogonality (optional).
- Structural Equation Modeling (SEM) – independence of observations, linearity, correct model specification, normality of residuals, no multicollinearity, homoscedasticity, measurement model assumptions (e.g., discriminant validity).
- Negative binomial regression model: count data, independence of observations, overdispersion, mean-variance relationship, no multicollinearity, and linearity in log-mean.

Data and Participants

As we use a multiple-study approach to better research the causal mechanism at play, we need more participants than most single-study approaches. We deem it important to use auditor participants for our main experiment (i.e., Experiment 2). One of the authors has access to a pool of junior auditors and likely has access to a pool of more senior auditors at a Big 4 audit firm in Western Europe. If the pool of more senior authors is confirmed, this pool is used for Experiment 2 and the pool of junior auditors is used for Experiment 1. In the unlikely and unfortunate case that the more senior pool is not available, we will use the junior auditors for Experiment 2 and use final-year accounting students to conduct Experiment 1. The latter would still be appropriate as our dependent variable in Experiment 1 is not an audit judgment, but instead measured motivation and basic needs satisfaction (e.g., Asay et al. 2022, p. 37). Our study does not need any PCAOB data, and institutional review board (IRB) approval will be obtained at both authors' institutions.

Each of the experiments will take between 30 and 45 minutes, and we expect to gather the data in a total timeframe of three months. We aim to recruit 120 auditors for each experiment, as this allows us to have 30 participants in each cell. The experimental participants are most likely recruited at one or multiple training sessions of a Big 4 audit firm (in the case of the more senior auditors) and at a professional certification course for auditors (in the case of more junior auditors). We will program our experiment using oTree software (Chen, Schonger, and Wickens 2016), which allows us to embed Open AI's ChatGPT 4.0 using API access in our experiment (e.g., Van Pelt 2023). Participants can participate using their own laptop. We will embed a script in our experiment that checks whether participants are in the experimental environment or not to make sure that participants do not make use of Gen AI automation outside the experimental environment. We envision the following set of tables, figures, and appendices:

- *Appendix A* – Overview of Experimental Instrument
- *Appendix B* – Variable Definitions
- Figure 1 – Theoretical Predictions
- Figure 2 – Instrument Flow
- Figure 3 – Observed Interaction Plot – Experiment 1
- Figure 4 – Observed Interaction Plot – Experiment 2
- Table 1 – Sample Descriptive Statistics
- Table 2 – Basic Needs Satisfaction by Gen AI automation
- Table 3 – Autonomous Motivation by Gen AI automation
- Table 4 – Information Processing by Gen AI automation and Autonomous Mindset Intervention
- Table 5 – Judgment quality by Gen AI automation and Autonomous Mindset Intervention
- Table 6 – Structural Equations Model for Experiment 2

IV. INTERPRETING RESULTS

We will start by analyzing the results of Experiment 1. First, we will analyze each of the three basic needs by *Gen AI automation* condition. These results allow us to see which basic needs are significantly affected by Gen AI automation, which can inform audit firms about what aspects of Gen AI automation reduce auditors' autonomous motivation. For instance, if there is a significant negative effect of Gen AI automation on autonomy, audit firms can think of ways to create more autonomy in the final decision. As another example, when relatedness is affected, they can think about ways to anthropomorphize their Gen AI automation systems. Next, we analyze the effect of Gen AI automation on auditors' autonomous motivation and how this relationship is mediated by the three basic needs.

Next, we analyze the results for Experiment 2. First, we will test whether, in the conditions without the autonomous mindset intervention, there is a significant difference between Gen AI automation conditions for each of the dependent variables. Next, we also test whether our variables for autonomous motivation (in the case of Experiment 2 this mediator is measured ex-post, which has its limitations) and the total time spent on information cues (unobtrusively measured). Finally, we test the interaction effect of the autonomous motivation intervention. For both experiments, we will report the results of manipulation checks and comprehension checks, as well as participant demographics and results of key post-experimental questionnaire measures.

If our analyses deviate from our predictions, we will carefully analyze how they deviate and conduct post-hoc tests to see if we can find an explanation that is consistent with one of the other theories. There are several theories that align closely with or are sub-theories of self-determination theory, such as cognitive evaluation theory, goal setting theory, control theory, and expectancy-value theory. For each of such theories, we will carefully map out what the predictions of these theories are, and if they are distinct, we will carefully collect process evidence that helps us to better tease out which theoretical mechanism is at play.

To the best of our knowledge, there is no evidence yet about how the usage of Gen AI affects auditor judgment quality in the auditing setting. To this end, our study has both a theoretical as well as a practical contribution. First, the study informs prior literature about how the implementation of Gen AI in an audit affects judgment quality in subsequent tasks. This also adds to the literature on AI and other automated tools and techniques in the auditing profession more generally, which focuses on source effects in the focal task instead of how it affects other tasks (e.g., Cao, Duh, Tan, and Xu 2022; Commerford et al. 2022, 2024). Second, our study also has the potential to clearly investigate the theoretical mechanism through which Gen AI automation may affect judgment quality and tests a theory-driven intervention using a moderation-of-process design that can help understand how the potential negative effects of Gen AI automation on judgment quality can be attenuated. As we base our predictions on an often-validated theory adapted to the auditing setting, the theory allows us to generalize our inferences using our theoretical framework (Asay et al. 2022).

Our study also has the potential to inform practice. Most notably, audit firms are currently investing billions in the adoption of Gen AI automation in audit procedures. Although the combination of Gen AI and human auditors likely outperforms either one of them on their own (e.g., KPMG 2016; Dell'Acqua et al. 2023), Gen AI automation may also reduce auditors' basic needs and autonomous motivation, thereby potentially reducing judgment quality in other parts of the audit. Next to that, we also evaluate a theory-based intervention that addresses this negative effect. Regulators and audit firms can use this intervention or design new interventions built on the theoretical mechanism to alleviate judgment quality skepticism reductions following auditors' use of Gen AI. An important caveat is that our aim of this study is not to run a horserace between auditors and Gen AI automation. Our experiment does not lend itself to drawing valid conclusions with respect to such questions.

Our study is also subject to some limitations. Within the context of auditing, numerous automated tools, techniques, team member roles, and specific auditing tasks exist. Our research, constrained by the experimental design's inherent limitations, explored a selection of these elements to offer directional insights. Consequently, readers should exercise caution when extending these findings to different auditing tasks, recognizing the study's scope and the potential variability across various audit contexts. Second, the research assesses auditors' responses to a relatively new form of AI. There is a likelihood that this novelty effect might diminish as auditors become more familiar with these AI systems through repeated use, potentially leading to a decrease in the observed effects over time. Hence, readers will need to interpret our inferences with caution. These limitations also offer fertile grounds for future research.

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